Essays on the labour market impacts of the green transition

By

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ABSTRACT

This thesis is consist of four empirical studies that explore the labour market impact of green economy transition, with special attention to the important role of green jobs in a greening economy. Following a brief introduction in Chapter one, Chapter two provides the overall trend of green jobs in the Dutch labour market for the period 2000 to 2018. Based on a task approach, we show that the share of green jobs accounts for about 16% of the total employment in the Dutch labour market, and this share has increased steadily during 2000 to 2011, and remained relatively stable from 2013 to 2018. In Chapter three, we investigate the employment effect of environmental taxes at sector level for the period 2000 to 2016. Our empirical results show that there is no statistically significant evidence of environmental taxes destroy total jobs, but we show that environmental taxes increase number of green jobs, and hence the share of green jobs at sector level. Similarly, we examine the employment effect of eco-innovation at firm level for the year 2006 to 2010 in Chapter four. We found that eco-innovation has no impact on the overall employment, however, compared to non-eco-innovators there is an increase in the number of green jobs, and hence increase in the share of green jobs. In Chapter five, we explore the characteristics and distribution of green jobs in the Dutch labour market using detailed individual data. Specially, we provide a gendered perspective into an analysis of occupation segregation and wage differential in the green employment. Policy implications have been discussed in each chapter, and last chapter concludes.

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Chapter One

Introduction

The past few decades have seen dramatic changes across the world, with millions of people being lifted out of the poverty, and many countries reaching their middle-income status. Such enormous economic growth, however, is at the cost of damage to the environment, and has led to economic, social, and environmental imbalances. According to the World Counts, the world population is 7.2 billion and is increasing; however, the total resources of earth can only support 2 billion people at the current consumption rate, which means we are using two to three times more resources than what is sustainable.

The growing use of energy and natural resources has led to resource depletion, environmental degradation, and global warming, which is pushing our planet to its environmental limits. Due to the COVID19 pandemic, our world is currently facing the most serious recession in almost a century and we need a strong, sustainable and inclusive growth more than ever to restore the economies of those countries that are suffering from both severe recession and growing environmental problems. Reducing these imbalances requires a shift from an unsustainable development path to a smarter, greener, inclusive growth pattern.

One of the key elements for countries to develop sustainably is to transition towards a greener economy.[1] A transition towards a green economy, that is accompanied by a mix of green growth policies will have a range of economic consequences. It will generate new opportunities for investment, innovation, and to develop the skills needed for a transition to a low carbon, greener economy. More specifically, it will reshape the labour market in a way that creates more so called green jobs, relocate and reshape exiting jobs, but also reduce inequalities and skill gaps, and ultimately support decent work for all (ILO 2011).

This thesis focuses on the labour market consequences of a green economy transition, with special attention given to the impact on so called green jobs. To support the transition, governments have used a variety of green growth policy tools, including environmental regulation, subsides for eco-innovation, fiscal measures such as environmental taxes and so on. Different environmental polices and market-based instruments may affect the labour market in different ways. It may change the level or the composition of overall labour demand, and may increase demand for specific jobs. These impacts are also likely to vary across sectors, occupational groups, and different categories of workers. However, the empirical evidence of how different environmental polices affect employment, especially the impact on the so called green jobs, is still limited.

Green job creation is a common slogan that was revealed in recent policy pledges in many countries. Yet the definition and measurement of green jobs are still far from consistent. Defining and measuring what can be considered as a green job is a great challenge (Deschenes 2013). According to ILO, green jobs are broadly defined as "decent jobs in any

[1] Terms such as green, environmental and sustainable are often used interchangeably. As stated by ILO (2012*b*), green economy is not a replacement for sustainable economy, but is an important tool to achieve a sustainable economy.

economic sector (e.g. agriculture, industry, services, administration) which contribute to preserving, restoring and enhancing environmental quality".

Existing literature has shown that green jobs are better jobs with higher wages and higher skills (e.g., Consoli et al. 2016, Peters 2014, Vona et al. 2019). They are more likely to be found in high-tech areas, and one additional green job is found to be related to 4.2 new jobs in other sectors (Vona et al. 2019). These findings are suggestive of green jobs are higher quality employment in addition to positive job creation spillovers, which support policymakers' belief that green job creation is something worthy to be actively encouraged. However, who are those green workers, how they are distributed across sectors and occupational groups, and why they are important are still not widely known.

Against this backdrop, this thesis empirically examines the labour market implication of green economy transition, particularly focusing on the important role of green jobs in the Netherlands. The Netherlands is perfect country for our study primarily due to the exceptional micro-data base that allows us to fill this gap in the literature. More specifically, we have the tax record for the whole population, which allows us to link employees with employers, and further link it to different datasets at different levels. Besides, Netherlands is an interesting country to study green labour markets. On the one side, the Netherlands is famous for its high stringent environmental policies. For example, the share Dutch environmental taxes over total taxes is the highest in Europe. On the other sides, the Netherlands is also very active in green innovation, who ranks very top in the EU27 eco-innovation scoreboard. All these features makes Netherlands an interesting context to study the labour market impacts of the green transition.

Specifically, Chapter two provides a broad picture of the overall trends and distribution of green jobs by sector and occupational groups in the Dutch labour market for the period 2000 to 2018. Taking a task-based approach, we utilise the Green Economy Program and Green Task Development Project from the O*NET, and create a green occupation list with task-based greenness indices by ISCO job classification. By applying a green occupation list to the Dutch Labour Force Survey (LFS), we show that green jobs account for approximately 16% of the total employment in the Dutch labour market, and this share has increased steadily from 2000 to 2011, and remained relatively stable from 2013 to 2018. A high share of green jobs is observed in Secondary sectors and 'Manager' occupational groups. In terms of trends, we find the share of green jobs increased in most sectors and occupational groups in the first period (2000 to 2011), and remained relatively stable in Tertiary sectors and high-skilled occupational groups, while slightly decreasing in Secondary sectors and low-skilled occupational groups in the second period (2012 to 2018).

Chapter three builds upon our task-based measurement of green jobs, and empirically studies the effect of environmental taxes on employment at the sector level. In recent years environmental taxes have become a central pillar of green growth policies. However, the impact of environmental taxes on the labour market is not well understood. Opponents claim that environmental taxes have destroyed jobs while proponents believe that such taxes help to create more high quality, cleaner and greener jobs. Therefore, we examine the impact of environmental taxes on total employment, the number of green jobs, and the share of green jobs in the Dutch labour market between 2000 and 2016. The results from our sector level analysis are that there is no statistically significant effect of environmental taxes on the total number of jobs but there is a positive impact on the number of green jobs and share of green jobs. More specifically, our 3SLS estimates show that a 10% increase in an environmental tax leads to a 1.62% increase in the number of green jobs, equivalent to 1,004 additional green jobs. Further results show this green job creation is mainly through the creation of new green jobs in non-industrial sectors, where we find a 10% increase in an environmental tax lead to 967 job losses across the industrial sectors and the creation of around 2,200 green jobs in non-industrial sectors.

In Chapter four, we link eco-innovation activities with (green) employment at the firm level in the Netherlands. Governments believe that eco-innovation has an important role to play in helping their economies experience a smooth transition to a sustainable growth path while at the same time creating a large numbers of high quality jobs. However, evidence on job creation from eco-innovation is far from clear. In Chapter four, we investigate the relationship between eco-innovation and employment at the firm level for the period 2006 to 2010. Our results show that, although eco-innovators have no impact on total employment, there is an 18.2% increase in green jobs (equivalent to 12 new green jobs for the average firm) compared to non-eco-innovators. This change in job composition translates into 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 decrease in non-green jobs and a smaller but still significant increase in the number of green jobs. In other results we find that policy induced eco-innovation is positively correlated with the number of green jobs and the share of green jobs with the largest impact from eco-innovation subsidies.

In the final empirical chapter, Chapter five explores the characteristics and distribution of green jobs with special attention given to the gender difference in terms of occupational segregation and wages in green jobs in the Netherlands. Based on the same task approach, we link detailed individual level data with green occupational from O*NET, and show that workers employed in green occupations are, *ceteris paribus*, more likely to be men, non-foreign-born, higher skilled, and are less likely to be female, especially married or with children. For people who hold green jobs, female green workers are also more likely to be observed in high skilled occupational groups compared to male green workers. In terms of wages, we find green jobs are better paid compared to non-green jobs, and this wage gap is increasing over time. The gender wage gap is smaller in green jobs compared to the gender wage gap in all jobs in the Dutch labour market. To study the gender wage gap in green jobs, we decompose the wage within occupation (intra-occupational) and across occupation (inter-occupational) for the sample of workers who hold green jobs based on a Brown decomposition method. Most of the wage differential are justified within and between occupations, i.e. most of the gender wage gap can be explained by difference in human capital. We also find that it is inter-occupational distribution difference drives the overall wage differential between male/female green workers.

Finally, the last chapter concludes. Following a brief summary of the main finding, the last chapter discusses the policy implications and the limitations of the thesis. Suggestions for the future research are presented.

Chapter Two

Evolution of green jobs in the Dutch labour market

2.1 Introduction

According to United Nations Conference on Sustainable Development (Rio+20), a transition towards a green economy is one the most important ways to achieve sustainable development. In recent years, there have been increasing national and international efforts to promote a green economy transition. The Netherlands is seen as one of the pioneers in terms of the implementation of the green growth indicators proposed by OECD (2011*b*). In October 2011, the Government of the Netherlands launched a Sustainability Agenda to explore how key sectors could enable the country to achieve green growth. The Green Deal Program, which is part of the Sustainability Agenda, intends to integrate the private sector in the green transition. The Dutch Government aims, for instance, to achieve zero-carbon emission in dairy chain by 2020.[1]

[1] See link https://www.oecd.org/greengrowth/greengrowthinactionthenetherlands

The impact of the green economy transition that is promoted by a mix of green growth polices is enormous, and the labour market was particularly affected (Bowen & Kuralbayeva 2015). Structural change in the labour market accompanied an expansion of green sectors, vanishing dirty sectors, and a transformation of many sectors was expected. More specifically, the so called green jobs will be created, some jobs will be eliminated, and many of jobs will be substituted or transformed in terms of skills, work content both within/between sectors and occupational groups (ILO 2011). Against this backdrop, the question arises as to the percentage and distribution of those green workers whose daily tasks and skills are considered as 'green' and important for green activities. It is important to understand how this share evolves over time and does it increase as the government expected?

Green jobs are considered as a win-win solution to both economic and environmental challenges that our world is facing (Jones 2009). Existing literature have found green jobs are high quality jobs with higher paid wages (Peters 2014). The skill content of such jobs involves more abstract skills, more formal education, working experience and on-the-job training compared to that of non-green jobs (Consoli et al. 2016). Besides, green jobs are found more likely to be concentrated in high-tech areas and have very large job multipliers (Vona et al. 2019). As it is shown in Vona et al. (2019), one additional green job is associated with 4.2 new jobs in the non-tradable non-green sector.

Understanding the proportion of green workers in the labour market, and how it develops over time is important so that policy makers could have a idea of whether the supply is sufficient to meet current demand, and whether the transition towards a green economy is on the right path. However, defining a green job is challenging. There are several conceptual problems. As ILO (2012*b*) point out, there is no unified definition of a green job, but the need for a systematic, consistent and reliable measure green jobs is urgent.

The existing empirical literature has tended to take one of three 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., 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 accordingly. The third approach defines green jobs at the occupational level 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). The aim of this chapter is to measure the share of green jobs and how it evolve over time across different sectors and occupational groups in the Dutch labour market. Therefore, we use the Green occupation approach based on a task measure that can consistently and continuously identify green jobs spanning multiple sectors, and different occupational groups across several years.

Following the methodology of Vona et al. (2019), we utilise the Green Economy Program and Green Task Development Project from Occupational Information Network (O*NET). First, we construct a task-based greenness index at 8-digit O*NET-SOC level (Standard Occupational Code in O*NET). Then we transform the greenness index to 4-digit ISCO (International Standard Classification of Occupation) level by using correspondence tables between O*NET-SCO and SOC, and between SOC and ISCO. Next, we utilise the Dutch Labour Force Survey (LFS) and Tax Register Data (TRD) for the period 2000 to 2018. To this end, we identify green workers by applying the green occupation list to the matched LFS and TRD and examine the percentage of green jobs, and how they evolve across different sectors and occupational groups for the year 2000 to 2018. To summarise our results, we find:

1. During our sample period, green employment accounts for approximately 16% of total Dutch employment on average. This share increased steadily in the first period (2000-2011), and remained relatively steady in the second period (2012-2018).

2. The secondary sector that includes 'manufacturing', 'construction' and 'utilities' had the highest share of green jobs over time. The share of green jobs in the secondary sector increased steadily in the first period (2000-2011), and dropped slightly in the second period (2012-2018).

3. The highest share of green jobs was found in occupational group 'Manager'. Male jobs are more likely to be found in occupational groups with one exception group 'Service and sale workers', where female green worker and male green worker account for similar proportions.

4. In terms of trend across occupational groups, we show that most occupational groups followed the overall trend (that presented in point (1)) for the first period, while only high skilled occupational groups followed a similar trend in the second period. In other occupational groups, we show that the share of green jobs dropped slightly for the second period, except for 'Service and sale workers', where we see share green jobs, even though relatively small, increased steadily in the second period.

The remaining of this chapter is organised as following: Section 2.2 describes the challenges to define a green job and reviews the existing definition of green jobs; Section 2.3 illustrates how we measure green jobs in this chapter; Section 2.4 demonstrate the overall trend of share of green jobs, and that by different sectors and occupational groups. The last section concludes.

2.2 Defining green jobs

Defining what is meant by a green job is not a straight-forward process. There are several conceptual challenges. Firstly, it is hard to distinguish green jobs from non-green jobs within the same sector. For example, a bus driver can be thought of as a greener job than a taxi driver because it has smaller adverse impact per passenger on the environment although the vehicle itself is likely to be more polluting than a single taxi. However, driving a diesel powered bus is still carbon intensive and polluting so could be considered a dirty sector even though it is potentially taking a large number of gasoline powered cars off the roads. Furthermore, making a distinction between the green job and non-green jobs that perform the same tasks on a daily basis across different sectors is also challenging. For example, an administrator's job might be considered green if that person works in the renewable energy sector as the work contributes to the conservation of natural resources and benefits the environment. However, it could be considered as non-green if the administrative work was done while employed in a dirty manufacturing sector. Nevertheless, the tasks that the administrative worker undertakes would not be considered polluting by themselves.

Another major conceptual issue is that there is little agreement on whether employment in 'supply chains', or the so called 'induced' and 'indirect' jobs should be included in a measure of green jobs (Connolly et al. 2016). For instance, employees of a geothermal energy plant are normally considered as green jobs. For the plant to function well, there will be demand for the goods from firms that supply computers and stationery etc.. These induced employees will normally not be regarded as green jobs at first glance, however, they are from intermediate industries, and are part of the supply chain for green activities. Therefore, they will be affected by green economy transition when a government invests massively in green activities.

As the International Labour Organisation (ILO) points out, it is not easy to make a distinction between green jobs and non-green jobs in sectors across all occupational categories (ILO 2011). They argue that low carbon intensive sectors like education and finance are normally considered as green sectors. However, jobs in those sectors do not normally have any direct link to a reduction in GHG emissions or have any noticeable beneficial impact on the environment. Likewise, there are some high carbon intensive sectors such as the chemical industry, that may employ chemists that are developing cleaner and less polluting fertilisers that have a direct environmental benefit. Unfortunately, as pointed out by ILO, a detailed classification that would allow a researcher to make these distinctions is not currently available (ILO 2011).

Leaving aside the challenges of how to define a green job, Table 2.1 presents some examples of official definitions of green jobs. As we can see, existing definitions of green jobs have common themes such as preserving and restoring the environment. The OECD (1999) definition focus is on employment in Environmental Goods and Services Sectors (EGSS). Considering a sector, and hence all employees in that sector, to have green jobs is also known as Green Sector Approach. This approach is commonly used by national Bureau of Statistics in European countries. According to OECD (2011*b*), employment in EGSS is an important green growth indicator for monitoring progress towards a greener economy. In the Netherlands, the employment in Environmental Goods and Services Sectors has increased from 1.66% to 1.80% from 2001 to 2013, and it contributed around 126,000 full-time equivalent jobs to the economy in 2013 (CBS 2015) .

[Table 2.1 about here]

Some studies have developed their own terminology that is similar to industry definition. For instance, Yi (2013), Yi & Liu (2015) use Green Sector definition developed by the Pew Charitable Trusts to examine green jobs in the US and China respectively. Connolly et al. (2016) refined this approach by applying a hybrid approach that combines 'top down' (that uses a list of industry classification from the top) and 'bottom up' (that uses a variety of survey data on employment and firms at the industry level from the bottom) methods to examine the evolution of green jobs in Scotland.

The EGSS definition or Green Sector Approach defines green jobs between sectors. One obvious limitations of this approach is that it tends to over-estimate green jobs in green industries given that firms normally produce multiple products and services that could include both green and non-green goods and services. As the OECD (1999) states, only when we are able to identify every green activity in the potentially green firms can we accurately talk about environmental industries. Besides, this approach also ignores jobs in firms in non-green sectors but involve green production processes. Therefore, this binary approach cannot accurately measure green jobs and will either underestimate or overestimate green jobs in the economy.

In 2007, the ILO/UNEP/IOE/ITUC collaboratively established 'Green Job Initiative' to enhance green jobs and decent work for all in a greening economy transition. ILO (2012*b*)'s definition states that green jobs can be created in any sectors and all types of firms that contributes to conserving and restoring the environment. What is more, they emphasize that green jobs should be decent jobs, and any jobs that are not decent, i.e. jobs with unfair social justice, bad working conditions, and fail to pay living wage can hardly be considered as green jobs.

The other two green job measures shown in Table 2.1 have been developed with the support of US Department of Labour. This first green job initiative was conducted by US Bureau of Labour Statistics (BLS). BLS combines two approaches to measuring green jobs: (1) Green Product Approach that identifies green products and services, and hence the associated jobs in firms that produce green goods and services; (2) Green Process Approach that identifies environmentally friendly production processes, and hence associated jobs in firms that involve green production processes. Papers that have used BLS definition include Deschenes (2013) and Elliott & Lindley (2017). Based on the BLS Green Goods and Services Survey, green employment accounted for 2.4% of total employment in the US in 2010 and 2.6% of total US employment in 2011 (Elliott & Lindley 2017). The BLS definition is more comprehensive than the Green Industry definition. However, as these surveys are only conducted in the US, it is impossible to make comparable studies for other countries. Besides, these kind of surveys are resource intensive, therefore it is unlikely that there will be measure of green jobs that is consistent over time.

The final type of measure is the one we use in the chapter which looks at green jobs in terms of O*NET occupations.[2] O*NET defines three types of green occupations:

1. Green Increased Demand (Green ID) occupations, which are occupations that will

[2]The O*NET database contains detailed information on the tasks and skills associated with a given occupation

increase in demand because of a green economy, but will not require changes in work tasks or work content.

2. Green Enhanced Skills (Green ES) occupations, which are occupations that are expected to change in work content like tasks, skills and knowledge etc., and may or may not change in demand.

3. Green New and Emerging (Green NE) occupations, which are occupations that will be newly created because of a greening economy.

The Green ID occupations are normally considered as indirect green jobs as they do not involve any green tasks (Consoli et al. 2016).[3] Based on the O*NET broad definition of green jobs which includes all three types of occupations, 19.4% of total employment can be classified as green employment in the US labour market (Bowen et al. 2018). Focusing on only direct green jobs, Consoli et al. (2016) estimate around 11% of total employment can be considered as green employment without reweighting the employment by greenness. If one use the continuous approach proposed by Vona et al. (2019), who weight the employment by greenness, and again focus on direct green jobs, only around 3% of the employment share can be considered as green jobs in the US labour market during the period 2006 to 2014.

In conclusion, the share of green employment in one economy varies depending on different definitions ranging from 1% to 19%. It is hard for one to agree that jobs in EGSS can be all considered as green job. The US BLS approach seems to be more comprehensive compared to the EGSS approach. However, it is hard to use their definition to qualify or

[3]The issue with Green ID occupations is that how the indirect effect is measured was not clear in O*NET system. To estimate both direct and indirect employment effects, the input-output (I-O) tables are the most widely employed (Harsdorff & Phillips 2013) or local multipliers (Vona et al. 2019). Unfortunately, it is not clear how the indirect green jobs is measured in O*NET.

characterize green jobs continuously over time in other countries.

Hence, in this chapter we use the O*NET definition. First, the O*NET green jobs classification does not just consider jobs in green sectors, but also captures jobs in brown sectors that perform green tasks on their daily basis. Second, green occupations in the O*NET database are captured by O*NET-SOC, which allows us to use the crosswalk between O*NET-SOC and more internally used ISCO code to identify green jobs in the Dutch labour market. Finally, using the task-based approach proposed by Vona et al. (2019) measures green jobs in a continuous pattern, which can be used as a proxy for the time that a worker spends on green activities.

2.3 Measuring green jobs

In order to measure green jobs in the Dutch labour market, we use two main data sources. First, we make use of the Dutch Labour Force Survey (LFS) and Tax Register Data (TRD) from the confidential Dutch Micro-database. The Dutch LFS is a large sample survey that includes detailed information on the Dutch labour workforce. In addition to detailed individual characteristics such as: gender, age, marital status, and so on, the Dutch LFS also provides important information on an individual's current occupation, which can be identified using a detailed 4-digit ISCO2008 classification.[4] The TRD is also a very informative dataset that includes more than 10 million jobs every year. It has the tax records for every

[4]The International Standard Classification of Occupations (ISCO) is a four-level classification of occupation groups managed by the International Labour Organisation (ILO). The latest version of ISCO is ISCO2008 dating from 2008. Therefore, the 4-digit level of ISCO code is the most detailed hierarchy in ISCO job classification system.

worker who is actively paying tax. By matching the LFS with the TRD, we know which firms workers are working at, which means we can be confident that we have a representative.[5]

The next stage is to identify green jobs in the Dutch merged LFS and TRD. To do so, we make use of the Green Economy Program in the O*NET 23.0 database. There are 1,100 occupations in the O*NET-SOC job classification scheme in this database, and 204 of these occupations are defined as green occupations, of which 64 are Green Increased Demand (ID) occupations, 62 are Green Enhanced Skilled (ES) occupations. and 78 are Green New & Emerging (NE) occupations. The Green Task Development Project of O*NET further divides the tasks associated with a given green occupation into green tasks and non-green tasks for Green ES and Green NE occupations.[6] The Green ID occupations are not included in the project as they will only affected by greening economy through demand, which means the work content and work skills stays the same.

This chapter uses the approach outlined in Vona et al. (2019), who define green jobs based on a tasked-based Greenness index. Following Vona et al. (2019), we first calculate the greenness of each occupation by calculating the green tasks intensity within an occupation weighted by importance scores:

[5]The TRD database is an extension of the Social Statistics Survey (REOS) conducted by the Statistics Netherlands. The unit records of the Social Statistics Survey database are very detailed and informative about 10 million jobs per year. Each job is a matched combination of employer/business entity data with employee data and recorded start/end date. Therefore, when combine LFS with TRD, we are able to know which firms workers are currently working at.

[6]The Green Task Statements and Task Rating files from the O*NET resource centre are available at: https://www.onetcenter.org/reports/GreenTask.html

$$Greenness_i = \sum_{j=1}^{n} w_{ij} * green_j \tag{2.1}$$

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.[7]

Next, we compile a green occupation list based on ISCO by transforming a greenness index based on O*NET-SOC to ISCO concordance. To do so, we first 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 by assuming workers are evenly distributed across detailed O*NET-SOC occupational groups. For example, 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 with greenness 0 and "11-1101.03, Chief Sustainability officers" which is defined as a green job with greenness 1. In this chapter we calculate the average greenness for SOC "11-1011" as the simple average

[7] As an example, 17 tasks are required for occupation "11-1021.00 General and Operations Managers", of which 2 are green tasks and 15 are non-green tasks. The importance score is associated with each task in a given occupation which is a score given by job incumbents or Occupational Expert, and has been normalised sum up to one in the calculation. For instance, one of the green tasks for occupation "11-1021.00 General and Operations Managers" is 'Manage the movement of goods into and out of production facilities to ensure efficiency, effectiveness, or sustainability of operations' with task ID '20708'. The original important score 3.83 while the normalised important score for this task is 0.0613 (The normalised procedure means the summation of the normalised important score of the 17 tasks would be one). The greenness is a weighted average across normalised important scores of green tasks and non-green tasks, which will give us 0.1134 for occupation "11-1021.00 General and Operations Managers". More examples of green tasks is given in Appendix to Chapter Two Table A.1

between of the two O*NET-SOC codes, which in this case would be 0.5.

The next 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 greenness score of 0.5 (from above), “11-1021, General and Operations Managers” with a SOC greenness score of 0.1134, and “11-9161, Emergency Management Directors” with a SOC greenness score of 0. Hence, the average broad greenness score for ISCO “1112” is 0.2045. Following this approach, of the 436 ISCO occupations, 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 in Appendix to Chapter Two Table A.2.[8]

Table 2.2 reports the total number of occupation categories and number of occupations that are classified as occupations with a positive greenness index (i.e. with greenness > 0) by 1-digit ISCO code. As we can see from Table 2.2, there are no green occupations in occupational groups ‘Clerical support workers’, ‘Skilled agricultural, forestry and fishery workers’ and ‘Armed forces occupations’. Besides, green occupations are more prevalent in the high skilled occupations which may involve more analytical and technical skills such as managers, professionals and technicians and associate professionals, while green occupations

[8] In the Dutch LFS, there are a small number of workers with occupation information available at the 2 or 3 but not 4-digit level. To include these individuals in our sample we aggregate our ISCO 4-digit greenness indices to the 2 and 3-digit level by calculating the sample average greenness score for each group based on the ISCO greenness scores associated with each occupation at the 4-digit level. This process is repeated for both the 2 and 3-digit levels.

are less prevalent in service occupations.

[Table 2.2 about here]

After we merge the greenness indices to the matched LFS and TRD data according to the ISCO classification, each individual has a greenness index for their current job in our final sample. In this chapter we consider an individual to be a green worker if their corresponding occupational greenness score is greater than the average greenness.[9] That means a task-based green job is occupations with a greenness index greater than 0.034. If a worker has more than one job, we keep the job with the the longest job duration. As Dutch LFS is a rotating panel with five waves, we keep the most recent information of an individual, and replicate personal characteristics from the previous waves if the most recent information of an individual is missing. Each worker is only counted once in each year. At end of this process, we end up with a large sample of around 57,000 workers a year covering the period 2000 to 2018.

2.4 Trends of green jobs

The aim of this study is to determine the share of green jobs in the Dutch labour market and how it has evolved over time across different sectors and occupational groups.[10] We examine the trends for two periods: 2000 to 2011, and 2012 to 2018. This is because,

[9]The threshold for greenness is arbitrary. By using the average as our threshold, we exclude those occupations with very few green tasks in the green occupation list.

[10]Note that we generate the share of green jobs from a sample not whole economy. Therefore, this survey-based estimates should be interpreted and used with caution and all the trends should be taken as indicative only.

in 2012, Statistics Netherlands changed the LFS questionnaire for occupation and sectors.[11] As the Dutch LFS is a rotating panel with five waves, we count each individual only once each year dropping the same individual who appears in both the current year and in the last wave of the previous year. So those who both exist in 2011 and 2012 cannot be dropped in 2012. Therefore, we examine the percentage of green jobs separately for the two periods. [12]

Consider figure 2.1, for the first period time (figure on the left), we see share of green jobs gradually increasing over time. It remained relatively stable from 2000 (17.16%) to 2005 (17.52%), and started to rise from 2006 to 2008 ranging from 17.27% to 18.67%. Then, it dropped slightly in 2009 and remained relatively stable thereafter. Turning to second period (figure on the right), starting 2013, we see share of green jobs slightly decrease range from 2013 (15.01%) to 2018 (14.77%), but this decrease is relatively small. Therefore, generally speaking, the share of green jobs increased slightly in the first period, and remained relatively stable in the second period.[13]

[Figure 2.1 about here]

[11] Before 2012 the LFS interview was face-to-face or by telephone, after 2012 the Statistics Netherlands also included internet-interview in the LFS. The old LFS questionnaire was not sufficient for internet interview, therefore, they had to change the LFS questionnaire to make internet-interviews possible. This results in, however, more observations in the sample in year 2012 and more workers occupational information only available at broader level.

[12] Note that this will not be a problem after 2012 as we are able to drop all duplicates for 2013 and onwards. Unfortunately, TRD is not available after 2016. Therefore, we merge LFS with TRD for the first period only.

[13] The plunge between 2011 and 2012 is due to the fact that the Statistics Netherlands changed the LFS questionnaire in 2012. This leads to more observations in 2012 and more workers occupational information available at broader, i.e. 2- or 3-digit level.

2.4.1 Sectors

Figure 2.2 presents the trends in the share of green jobs for three broad economic sectors. The primary sector, which corresponds to Dutch SBI division A-B, are sectors involving extracting raw materials.[14] Examples of activities within this sector includes agriculture, fishing and mining. The secondary sector corresponds to Dutch SBI division C-F relating to the production of finished goods, e.g. manufacturing, construction and utilities. The tertiary/service sector corresponds to Dutch SBI division G-U and it includes providing goods and services to customers in wholesale and retail trade, transport, and government, financial, professional, and personal services such as education, health care, and real estate services.[15]

Focusing on Figure 2.2, the secondary sector remained the sector that had the highest share of green jobs, ranging from 25% to 29% for both periods. The first period (2000-2011) saw share of green jobs gradually increase over time, while for the second period (2013-2018), the share of green jobs has dropped since 2012.[16]

[14] The Dutch Standaard Bedrijfsindeling (SBI 2008) is based on the activity classification of the European Union (Nomenclature statistique des activités économiques dans la Communauté Européenne, NACE) and on the classification of the United Nations (International Standard Industrial Classification of All Economic Activities, ISIC). The first four digits of the SBI are the four digits of NACE and the first two digits of the SBI and NACE are the same as the first two digits of ISIC. See link: https://www.cbs.nl/en-gb/our-services/methods/classifications/activiteiten/standard-industrial-classifications--dutch-sbi-2008-nace-and-isic--

[15] Our classification of three economy sectors is based on the Metadata Glossary of World Bank. According to World Bank, industry corresponds to ISIC divisions 10-45 (ISIC V3.1), and this is corresponding to first digit of ISIC division C-F. See link:https://databank.worldbank.org/metadataglossary/wdi-database-archives-(beta)/series/NV.IND.TOTL.CD. Services correspond to ISIC divisions 50-99, which is equivalent to first digit of ISCI G-U. see link: https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NV.SRV.TOTL.ZS.

[16] Note that we display 2012 here is because the series break in 2012 is not prominent when we break our

For the first period, the tertiary sector was the second largest in terms of the share of green jobs. Green jobs account for approximately 15% of total employment in the tertiary sector, and first period saw it rising slightly over time. For the second period, the tertiary sector became the third largest sector in term of share of green jobs, and the share of green jobs remained relatively stable between 2013 to 2018.[17]

The primary sector was the smallest sector in terms of share of green jobs for the first period, with share of green jobs ranging from 9% to 14%.The share of green jobs slightly increase over time except for a drop in 2009. For the second period, we see share of green jobs first dropped between 2013 to 2014, and started to increase slightly after 2014 that lead to the primary sector becoming the second largest sector in term of share of green jobs in the Dutch economy.[18]

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sample into three economics sectors. We further see total jobs drop and green jobs remain stable for the first period, therefore, the increase in share of green jobs was through a decrease in non-green jobs rather than an increase in green jobs between 2000 and 2011. For the second period time, we see total jobs remain relatively stable between 2013 and 2017, and start to rise in 2018, while green jobs slightly dropped between 2013 and 2017, and started to rise in 2018. Therefore, the decrease in share of green job was through a slight decrease in green jobs for the second period

[17]For the first period, there are generally increasing trends in both total jobs and green jobs, hence the increase in share is because the increase in green jobs is higher than that of total jobs. For the second period, there is a slight increase in total jobs and green jobs. However, for the second period, total jobs and green jobs are generally trending together leading to no change in the share of green jobs.

[18]The first period shows a generally decreasing trend in total jobs in primary sector and a slightly increasing trend in green jobs. Therefore, this increase in share is through both decrease in non-green jobs as well as a small increase in green jobs. The second period shows the total jobs remain relatively stable over year 2013 to 2018, while green jobs show a tiny increase over time, and this leads to a general increase in share of green jobs.

[Figure 2.2 about here]

To summarise, the number of green jobs is approximately 17% in the first period, and around 15% of the total Dutch employment for the second period.[19] The secondary sector remains the largest in terms of the share of green jobs, especially Sector D "Energy supply", and Sector E "Water supply", where both are less labour-intensive but have a high percentage of green jobs. The overall trend in the share of green jobs has increased in the first period and remained relatively stable for the second period. These trends generally hold when we break sample into three broad sectors. [20]

2.4.2 Occupational groups

Our classification of occupational groups is based on ISCO2008. ISCO2008 divides occupations into 10 major groups based on their similarity in terms of skill levels and skill specialization required to do the job. Figure 2.3 shows the distribution of the number of total jobs and green jobs by 10 major occupation groups for the periods ending 2011 and

[19]Note that the O*NET occupational classification is much detailed than that of ISCO, given there are more than 1,000 occupational categories in the O*NET classification compared to only 436 occupational categories in the ISCO job classification scheme. Therefore, using crosswalk between SOC and ISCO may introduce measurement error where we may include more non-green jobs at broader level. What we did is we exclude the jobs with greenness below the average mean, and count the number of jobs. By doing so, we could balance out the measurement error to some extent. Our share of green jobs estimates is slightly higher than that in Consoli et al. (2016), who focus on the same direct green jobs and estimate around 11% of total employment can be considered as green employment in the US labour market. Alternatively, we could use the continuous measure following Vona et al. (2019), who reweight the employment by greenness. In the section A.4 of Appendix to Chapter two, We obtain the similar percentage to Vona et al. (2019) by weighting the number of green jobs by their greenness within each ISCO categories. See section A4 for details.

[20]Trends fluctuate more when we further disaggregate in detailed sectors

2018, respectively. As we can see from figure 2.3, there are no green jobs in the occupation groups "Clerical support workers", "Skilled agricultural, forestry and fishery workers", and "Armed forces occupations".

[Figure 2.3 about here]

Figure 2.4 presents the trends in share of green jobs, share of male green jobs and share of female green jobs for the 7 major occupation groups for the first period and second period, respectively. Except for "Service and sales workers", we see male green workers dominates in the other 6 major occupation groups, especially for "Craft and related trades workers" and "Plant and machine operators, and assemblers", where almost all the green jobs are male jobs.

Occupational groups "Manager", "Professional" and "Technicians and associate professionals" are considered as higher skilled occupations.[21] Focusing on high skilled occupational groups, green jobs account for a large proportion of jobs in the group "Manager", ranging from 65% to 80%. The first period saw the share of green jobs gradually increase over time, and this increase was driven by a combination of a larger increase in female green workers and a small decrease in male green jobs. For the second period, the share of green jobs in "Manager" remained relatively stable, and this stable pattern is same for both share of male green jobs and female green jobs.

People who work in the major group "Professional" and major group "Technicians and associate professionals" are normally considered as human resources in science and technol-

[21] See Correspondence table of ISCO-08 major groups to skill levels in Appendix to Chapter Two

ogy (HRST).[22] In the major group "Professionals", the share of green jobs (18% on average) is relatively moderate, considering that the total jobs are relatively high in this group. From Figure 2.3, we see total jobs in "Professionals" were expanding, ranging from 21% of total employment by the end of first period and 26% by the end of the second period. In the first period, green employment grew faster than total jobs, as we see a rise in the proportion of green jobs during this period. Growth in male and female green employment contributed to this rise. The share of green employment remained relatively constant in the second period as we see green jobs were trending along with total jobs. This stable trend is similar for both male green jobs and female green jobs.

The share of green jobs in the major group "Technicians and associate professionals" is slightly higher than that in the major group "Professionals"(20% on average). We see these two groups share the same trend in terms of share of green jobs in both periods, that is there is an increasing trend in the first period, and relatively stable trend in the second period.

The share of green jobs in the major group "Service and sales workers" is very low, and accounts for only 1% of total jobs in this group in the first period. The second period sees a steadily increasing pattern in the percentage of green jobs ranging from 1.5% to 2.5%. Notably, this is the only sector that male jobs and female jobs account for similar proportion in green jobs.

The major group "Craft and related trade workers" includes workers mainly in the

[22]See https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Human_resources_in_science_and_technology_(HRST) Professional knowledge and experience in the fields of physical and life sciences, or social sciences and humanities are required in the primary tasks of occupations in these two groups.

field of mining and construction. Male green jobs dominate in this occupation. We see the proportion of male green jobs increasing over time in the first period, ranging from 20% to 25%, while this share has been decreasing in the second period.

Occupations in the group "Plant and machine operators and assemblers" often involve tasks like operating and monitoring on-the-spot or remote-controlled industrial and agricultural machinery and equipment, driving and operating trains, motor vehicles, and mobile machinery and equipment, or assembling products. Green male jobs dominate in this group. In the first period, we see share of green jobs gradually increasing, ranging from 35% to almost 40%. While in second period, green jobs decrease from 30% to 22% between 2013 and 2016, and then increase again in 2017 and 2018.

The major group "Elementary occupations" usually consists of workers whose tasks are mainly routine-based that primarily involve the use of hand-held instruments and some physical effort. We see the share of green jobs decreasing in the first period, ranging from 22% to 17%, and continuing to drop slightly to almost 15% in second period.

[Figure 2.4 about here]

To summarise, green jobs are male dominated in almost all occupational groups except “Service and sales workers”. The occupational group with the highest share of green employment are observed in managerial jobs. The trends in occupational groups that are normally considered as high skilled such as “Manager”, "Professional" and "Technicians and associate professionals" display the similar trends to the overall trend for the whole sample, where we show the share of green jobs has increased from 2000 to 2011, and remained relatively stable for the period 2013 to 2018. While for certain occupation groups require less skills like "Craft and related trade workers" and "Plant and machine operators and assemblers", we see share of green jobs increased in the first period, and dropped slightly in the second period. The other two groups show the opposite pattern, where we find the share of green jobs (relatively small) fluctuated in the first period and increased steadily in the second period for “Service and sales workers", while we see share of green jobs decreased in the first period, and continued dropping slightly in second period for "Elementary occupations".

2.5 Conclusions

In this study, we provide descriptive evidence of the share of green jobs in the Dutch labour market between 2000 to 2018. Using on a task-based approach, we create a green occupation list from the ISCO classification system by linking O*NET green occupation code to more internationally-widely used ISCO code. We then identify green jobs in the merged Dutch LFS and TRD and empirically estimate the trend in the share of green jobs in the economy, by economics sectors and by occupational groups, respectively.

Our results show that green employment that involves green tasks in their work content accounts for about 16% of Dutch total employment on average during our sample period. We show the share of green jobs grew in the first period (2000 to 2011), and remained relatively stable for the second period (2012 to 2018). The secondary sector that includes ‘manufacturing’, ‘construction’ and ‘utilities’ remain the top sectors that have the highest share of green jobs over time. In terms of trends in the secondary sector, we show this share increased in the first period, but dropped slightly in the second period.

By different occupational groups, we show occupational group ‘Manager’ has the highest share of green jobs among all the other occupational groups over time. Male green jobs dominate in almost all the occupational groups except in 'Service and sales workers', although, green jobs only account for a very small percentage of total jobs in this group (1%). In terms of trends, we show that trends in the percentage of green jobs in most occupational groups share the same pattern as the trend for the whole sample for the first period, but only high skilled occupational groups followed the the whole sample trend for the second period, where share of green jobs decreased slightly in lower skilled occupational groups (with the exception of 'Service and sales workers', where we find share of green jobs, even though relatively small, increased steadily in the second period).

This chapter is motivated by the belief among government and policymakers that green jobs will be created as part of the transition to a greener economy. Green jobs are created, which are expected not only to benefit the environment but also stimulate future economic growth. However, the evolution of green jobs could display different pictures in different time periods.

It is useful to illustrate with a specific example. Consider the renewable energy sectors. If the renewable energy sectors continue to grow and achieve technical maturity, one can expect that jobs that develop and maintain those renewable energy devices will drop. For example, Connolly et al. (2016) show that the installed capacity of renewable generation doubled between 2007 and 2012 in Scotland, while the number of jobs in Low Carbon Environmental Goods and Services decreased. This could be a sign of technical maturity of these green activities.

It is also important to note that green jobs pay higher wages (see e.g. Peters (2014), Vona et al. (2019)). This means employing more green workers will increase labour costs, and hence will only be profitable if the outputs produced by green workers are valued more highly. If green jobs are found to be less profitable than other jobs, green jobs are more likely to be cut than non-green jobs during difficult times. This may explain the drop we observe in share of green jobs in some sectors and occupational groups in the second period.

As a result, when we try to evaluate the effectiveness of green growth policies, instead of only focusing on the number of certain type of jobs (i.e. green jobs) being created, one could also consider the broader spillover implications for the economy. More specifically overall employment, the number of indirect green jobs and induced green jobs that are created. As long as we are interested in the labour market effect of the green economy transition, specially the effect of green growth policies on green jobs, a united, consistent and reliable measurement of green jobs is needed. Only when are able to measure green jobs in a consistent way can we actually justify policies aiming at green job creation. In this chapter, we have developed a consistent way of measuring green jobs based on tasks of occupations, which we believe is an improvement for the development of estimates of green jobs, especially for European countries.

Table 2.1: Definitions of green jobs

Authorities	Definition
OECD (1999)	Employment in Environmental Goods and Services Sectors(EGSS), which includes activities to produce goods and services that measure, prevent, limit, minimise or correct environmental damage to water, air and soil as well as problems related to waste, noise and ecosystems. This includes cleaner technologies, products and services which reduce environmental risk and minimise pollution and resource use.
ILO (2012*b*)	Any decent job that contributes to preserving or restoring the quality of the environment in any economic sector such as agriculture, industry, services, and administration.
US Bureau of Labor Statistics (2010)	Jobs in establishments that produce goods and services that benefit the environment, or perserve the natural resouces; and jobs in establshments that invovles environmentally friendly production process.
US O*NET (2009)	Occupations that already exist but will increase in demand or change in work and worker requirements, or that are newly generated because of the impact of green eocnomy activites.

Table 2.2: Number of green occupations by 1-digit ISCO code

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

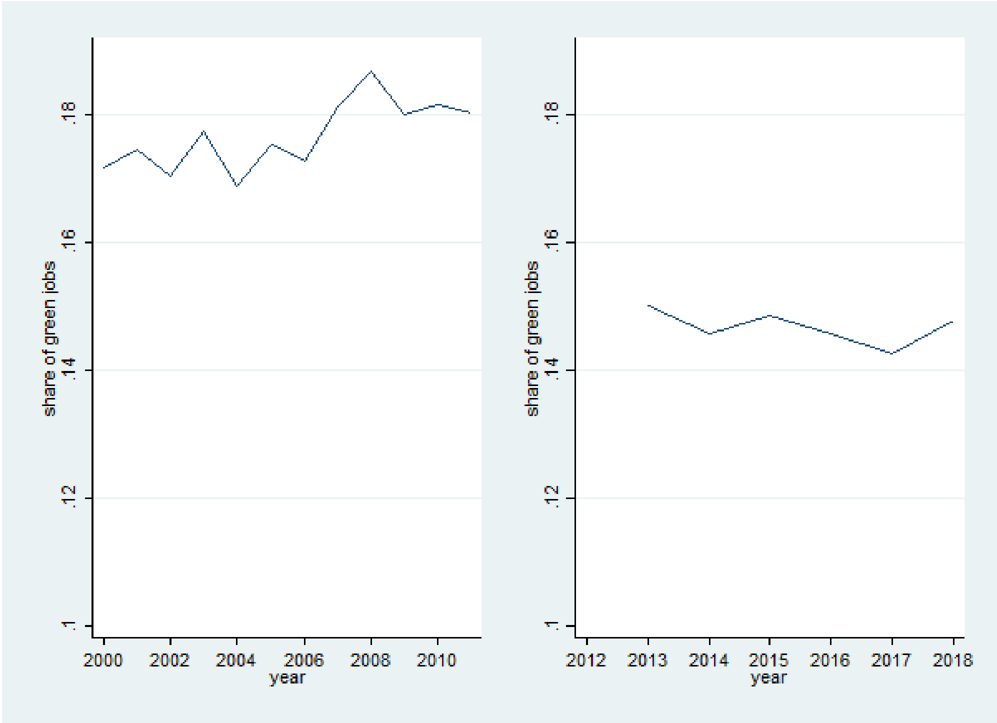


Figure 2.1: Share of green jobs (2000 - 2018)

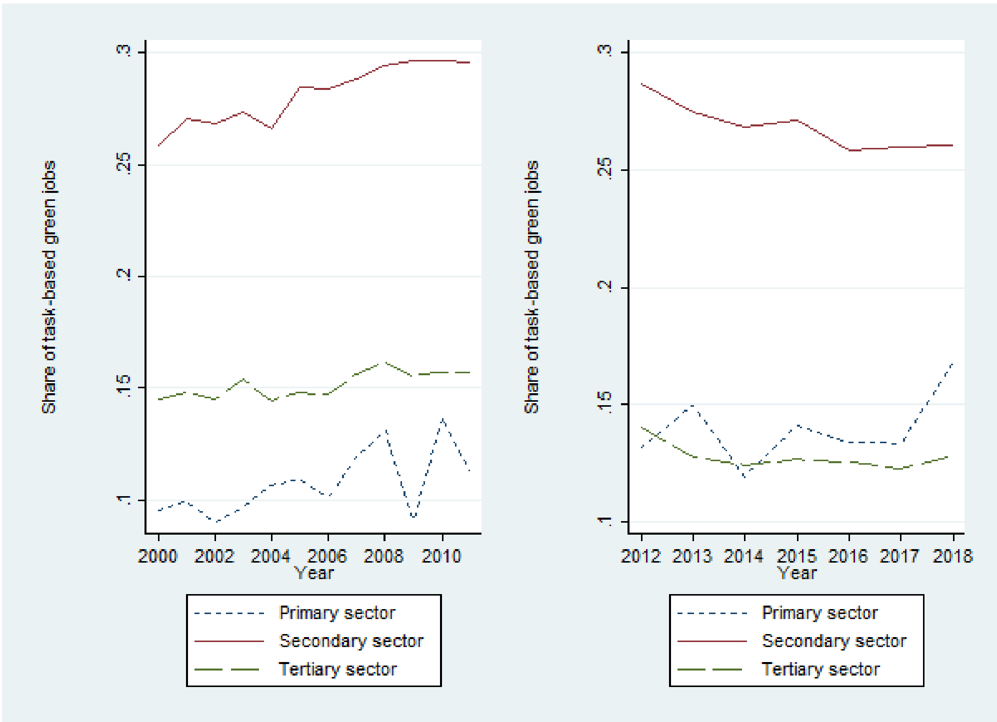
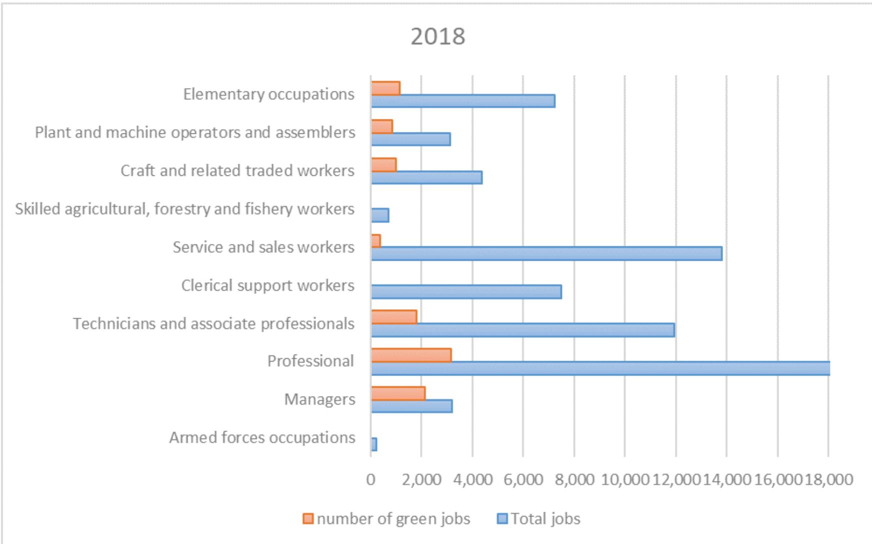


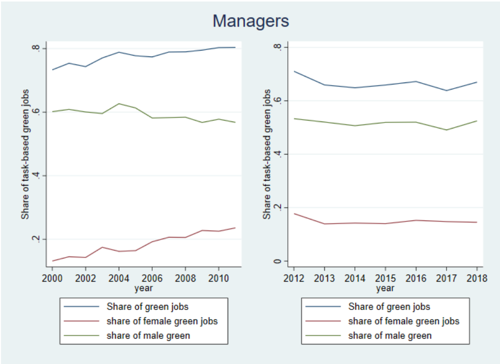
Figure 2.2: Share of green jobs by sectors (2000 - 2018)

(a) 2011



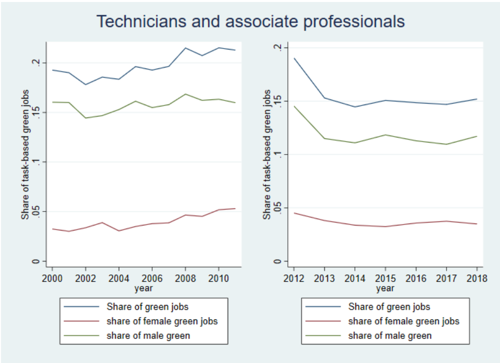
(b) 2018

Figure 2.3: Green jobs distribution by occupational groups (2011 & 2018)

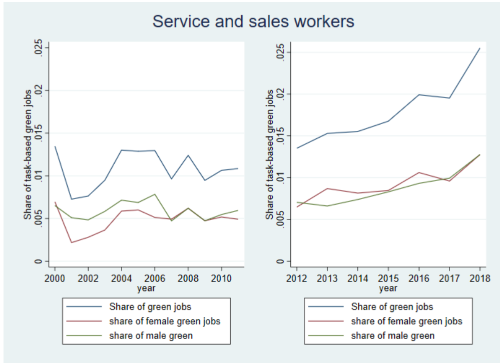


(a) Managers

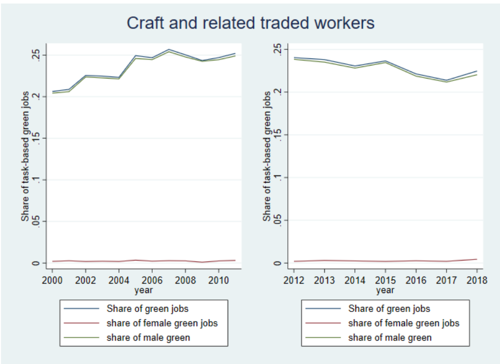
(b) Professionals



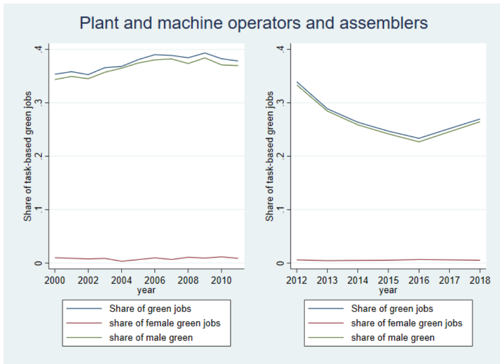
(c) Technicians



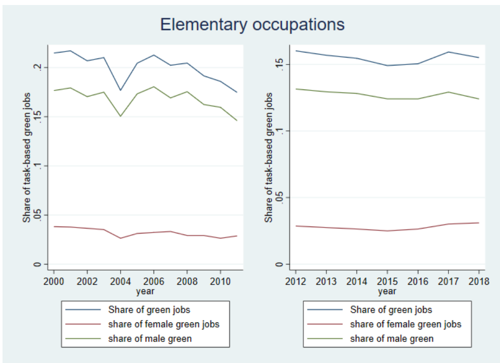
(d) Service



(e) Trade



(f) Machine operators



(g) Elementary occupation

Figure 2.4: Share of green jobs: Major Occupational Groups (2000 - 2018)

Chapter Three

Environmental tax and employment: A sector level analysis

3.1 Introduction

Ever since the 2016 Paris agreement on climate change, it has become clear that governments will need to use various policy initiatives if their economies are to undergo the necessary green transition. The recent COVID-19 crisis has once again pushed the idea of a green transition to the forefront of the policy agenda as part of plans for a broader green recovery. For example, the OECD recently stated that a green recovery could significantly increase the resilience of economies, resolve the jobs crisis and address increasing environmental challenges (OECD 2020*c*).

Prior to COVID-19 crisis, the ILO estimated that 24 millions jobs could be created by 2030 as part of a transition to a greener economy through the use of green growth policies (ILO 2018). The policy most often associated with a green growth strategy is the levying of environmental taxes and which the OECD argue should be considered a central pillar of any green transition (OECD 2020*b*). For example, environmental taxes were considered a vital and effective fiscal measure that stimulated the UK's transition to a greener economy (Spelman et al. 2011).[1] However, to date there has been very little research done on the impact of environmental policies on employment and whether they create or destroy jobs and whether the jobs created are so-called green jobs. Given the stated objective of the green transition is the creation of better and greener jobs it is important to consider the empirical evidence.

According to ILO, the primary benefit that comes with green jobs is related to the improvement in energy and natural resource efficiency, limiting greenhouse gas emissions, minimising waste and pollution, and protecting, restoring the environment. In terms of effects on individual workers, existing literature suggests that green jobs are high-quality jobs with higher-paid wages (Peters 2014, Vona et al. 2019). The work content of such jobs involves more abstract skills, more formal education, working experience, and on-the-job training compared to that of non-green jobs (Consoli et al. 2016). They are found more likely to be concentrated in high-tech areas and have very large job multipliers (Vona et al. 2019). These findings are suggestive of green jobs are higher quality employment in addition to positive job creation spillovers.

The purpose of this chapter is to provide a detailed understanding of the employment impact of previous environmental policies. More specifically, based on administrative level data from the Netherlands we investigate how environmental taxes have effected total employment, the number employed in green jobs, and share of green jobs at the sector-level.

[1] In response to the Covid-19 pandemic, the UK's Prime Minister Boris Johnson set out a ten points plan for a green industrial revolution which will mobilise £12 billion of government investment to create and support up to 250,000 highly-skilled British green jobs as part of the COVID-19 recovery plan

By combining the Dutch Labour Force Survey (LFS), the Tax Register Data (TRD), and other open data published by Dutch government, Eurostat and Comtrade we are able to show how environmental taxes impacted employment from the period when such taxes were first introduced in 2000 to 2016.

Our contribution is three-fold. First, we provide a reliable and consistent definition and measure of green jobs over time and across different industries and regions using a task-based measure of green occupations introduced by Vona et al. (2019). Second, based on a simple model by Yamazaki (2017), we analyse the relationship between environmental taxes (distinguishing between all environmental taxes and an energy tax) and employment, looking at both the traditional polluting industries but also the relatively clean sectors. Third, there are several existing studies examining the sectoral employment effect of environmental policies (e.g., Kahn & Mansur 2013, Walker 2013). However, what less understood is the effect on green jobs within sectors. We are the first, to the best of our knowledge, to analyse the effect of environmental taxes on green jobs and share of green jobs at the sector level instead of looking only at aggregate employment effects.

The economic rationale for the use of environmental taxes is generally well known. The simple idea is that a tax is designed that is able to internalise environmental costs by putting a price on activities that are thought to harm the environment. As a result people and firms are encouraged to adapt their behaviour in ways that are less damaging to the environment.

However, the impact of environmental taxes on the labour market is less well understood. On the one hand, the tax interaction effect (output effect) of a tax may reduce employment because, by their nature, taxes increase the cost of polluting, and as a result discourage the production and consumption of the previously produced goods and services. Proponents of environmental taxes, on the other hand, believe that environmental taxes, as with other environmental regulations, have the potential to create jobs through the process of revenue recycling and the so-called double dividend that was firstly put forward by Pearce (1991). The first of the double dividends relates to the expected improvement in environmental quality, and the second is derived from the idea that tax revenues can be used to offset or reduce pre-existing distortionary taxes while maintaining a constant overall level of tax revenue e.g. shifting the tax burden away from distortionary taxes such as corporate or personal income taxes.[2]

To date, there are a small number of studies that have examined the relationship between carbon taxes and employment such as Metcalf (2019), Metcalf & Stock (2020), Yamazaki (2017), Yip (2018) but there are few studies that have looked at the impact of environmental taxes or environmental policies in general on green employment. This gap in the literature is due mainly to issues of data availability and the difficulty in overcoming the challenge of measuring to what extent an occupation can be considered green. Studies that do exist have tended to focus on the US where data is more readily available (see e.g. Bowen et al. (2013), Vona et al. (2019), Yi (2013)).[3]

[2]Based on their Global Economic Linkages (GEL) model, ILO (2012*b*) estimates that up to 14 million net new jobs could be created if a tax on emissions was imposed and the tax revenues were used to offset labour taxes.

[3]There is a small but growing literature that examines the relationship between environmental regulations and employment although this has tended to concentrate on dirty industries (e.g. Berman & Bui (2001), Greenstone (2002), Martin et al. (2014), Morgenstern et al. (2002)). As Hafstead & Williams III (2018) point out, concentrating on only polluting sectors may be misleading as it ignores the economy-wide employment effect.

Given one of the reasons for a relative scarcity of research examining the employment effects of environmental taxes is data issues, the first stage of our analysis is to develop a reliable and consistent definition of green jobs that varies over time and across different industries and regions. Our solution is to follow the novel task-based approach proposed by Vona et al. (2019), who make use of the Green Task Development Project from US Occupational Information Network (O*NET). O*NET provided a list of green occupations by ONET-SOC code. The Green Task Development Project provides further information on the green and non-green tasks attached to each occupation. Based on this information, Vona et al. (2019) create a greenness index for each occupation, calculated as the number of importance-weighted green tasks over total tasks. This provides us with a continuous measure of green jobs which we use as a proxy for the amount of time that any given worker spends on green activities in the workplace (Vona et al. 2019).

We first construct our greenness index at the 8-digit O*NET-SOC level (Standard Occupational Code in O*NET), before generating a greenness index at the 4-digit ISCO (International Standard Classification of Occupation) level using correspondence tables between O*NET-SOC and SOC, and SOC and ISCO. As most of the cross-walks do not have a one-to-one correspondence, we calculate the average greenness of each broad occupation category.[4] Once we have a greenness index for each of the 436 ISCO occupations it is possible to categorise an employee as belonging to a green occupation by applying the green occupation list to individuals in the matched TRD and LFS data. We then aggregate from the individual level data to the sectoral level.

The Netherlands represents an ideal country for our analysis for at least two reasons. First, the environmental policies of the Netherlands have always been considered to be

[4]See section 2.3 of Chapter two for details of our concordance strategy.

among the most stringent. This is also evident by the fact that Dutch environmental taxes as a percentage of total taxes is the highest in Europe (CBS 2015). Second, over the last twenty years or so, there has been a significant reduction in the number of people that are employed in the more traditional manufacturing type industries and an increase in the number of workers in sectors such as education and financial services.[5] In this chapter we want to understand whether environmental taxes, although helping to reduce emissions, were also partly responsible for the decline in traditional dirty industry employment. We also want to understand whether environmental taxes helped to create newer green jobs and if so, in which sectors these jobs were created.

To briefly summarise our results, we find no evidence to suggest that environmental taxes reduced overall employment levels. However, we do find that although there is no significant change in total employment on average for all sectors, there is an increase in the proportion of green jobs in the economy. In general, we show that a 10% increase in environmental taxes would create 1,004 more green jobs on average, which is equivalent to a 0.664% increase in the share of green jobs in the economy. In further results we show that the increase in green jobs is mainly driven by the creation of more jobs in the non-industrial sectors where we show that a 10% increase in environmental taxes would lead to approximately 967 job losses in the more traditional industrial sectors that would be offset by an increase of 2,200 more green jobs in non-industrial sectors. Therefore, although environmental taxes do not destroy jobs there are compositional changes as non-green dirtier jobs are replaced by greener jobs in non-industrial sectors.

The remainder of this chapter is organised as follows. Section 2 reviews the literature on environmental tax and employment while Section 3 outlines the data and methodology.

[5] Overall trends in Dutch employment by sector can be found at: https://opendata.cbs.nl/statline

Section 4 presents the results and the final section concludes and discusses the policy implications.

3.2 Literature review

3.2.1 Environmental taxes and employment

It is widely acknowledged that environmental taxes can have a positive or negative effect on employment. First, there can be a negative tax interaction effect, also known as the output effect (Bento & Jacobsen 2007, Williams III 2002, Yamazaki 2017). In this case, an environmental tax impacts labour demand through a negative output effect from the tax induced increase in marginal costs which leads to higher prices and a reduction in demand for the firm's output and labour. Second, there can be a positive employment effect if the tax revenues are effectively redistributed as outlined in the double dividend hypothesis. The potential for a double divided was first proposed by Pearce (1991) who argues that environmental taxes can improve environmental quality (the first dividend) and increase the efficiency of the tax system by using the revenues to offset or reduce pre-existing distortionary taxes while maintaining a constant level of total tax revenue (the second dividend). Such a policy is thought to be particularly effective if it is able to shift the tax burden away from distortionary taxes on labour (Bovenberg & De Mooij 1994, Carraro et al. 1996, Yamazaki 2017).

The impact of an environmental tax has also been illustrated by Yamazaki (2017) who use a simple model to show how an environmental tax can impact sectors differently. In this simple model, it is assumed that there are two industries in a long run competitive equilibrium. Industry A is an energy-intensive sector with higher price elasticity of demand, and industry B is a less energy-intensive industry facing relatively inelastic demand.[6]

First, an environmental tax will increase the marginal cost for both industries by putting a price on their polluting products and processes. The subsequent increase in costs will reduce output in both industries, but the reduction will be higher in industry A. This is because (1) the increase in marginal costs is larger in industry A than industry B because it is more energy-intensive; (2) The upwards shift in the marginal cost curve will drive down output in both industries but this effect will be larger for industry A because industry A is more sensitive to price changes as it is more demand elastic. Therefore, one would expect to see a reduction in output in both industries through the output effect but that this reduction would be much larger in industry A than industry B.

On the other hand, if environmental tax revenues were used to shift the tax burden from distortionary taxes on labour (such as corporate or income taxes) then after the tax revenues had been redistributed to consumers they would be free to spend the extra income on goods and services from both industries increasing demand for the products from both industries. This positive effect shifts the demand curve upwards and increases output in both industries. Under certain circumstances it is possible to envisage a scenario where demand increases in industry B outweigh the negative output effect leading to a positive overall effect.

The overall employment effect is the addition of the output and recycling effects across both sectors and could be positive, negative or neutral if the effects cancel each other out

[6] Industry A can be thought of as manufacturing that is both energy intensive and trade intensive, while industry B is the service sector that is less energy intensive and less trade intensive

(which depends on the size of these offsetting effects across industries). Therefore, the aggregate employment effect of environmental tax is theoretically ambiguous.

Empirically, the "Environmental Policy versus Jobs" debate has been widely studied. The majority of existing studies examine the effect of regulation (rather than taxes) on employment using either plant/establishment level or industry level data for the US, UK, and more recently China with an emphasis on directly regulated (highly polluting) industries. One notable paper by Berman & Bui (2001) examine the employment effect of air quality regulations in Los Angeles between 1979 and 1992 based on a partial static equilibrium model that describes the mechanism through which employment is affected by environmental regulation. Using a unique plant-level dataset, Berman & Bui (2001) find no evidence that more stringent environmental regulations caused a reduction in employment.

Following Berman & Bui (2001), Cole & Elliott (2007) and Gray & Shadbegian (2014) use a similar theoretical framework to examine industry level employment changes. Treating environmental regulations as both exogenous and endogenous, Cole & Elliott (2007) find no evidence that environmental regulations had a negative impact on employment for UK manufacturing industries. In a similar study for the US, Gray & Shadbegian (2014) show that while environmental regulations had a statistically significant and negative effect on employment at the industry level, the economic effects were very small (Gray & Shadbegian 2014). More recently, Sheng et al. (2019) include corruption as an input into the firm's employment decision and show that environmental regulations adversely affect employment in Chinese manufacturing firms although the impact of regulations is weakened by higher levels of corruption (Sheng et al. 2019).

In terms of specific policies, the 1970 Clean Air Act Amendments of 1970 has been carefully studied. For example, Greenstone (2002) use a difference-in-difference model with plant level data to show that US manufacturing plants in non-attainment areas experienced a relative decline of 590,000 jobs compared to equivalent industries in attainment areas. Using the same empirical approach and establishment level data, Gray et al. (2014) examine the impact of the Environmental Protection Agency's (EPA) Cluster Rule on labour demand in the highly regulated pulp and paper sector in the US.[7] Their results indicate that the Cluster Rule reduced labour demand in these two sectors but that the effects were sometimes statistically insignificant. A more recent paper is given by Liu et al. (2017) examines the impact of environmental regulations on labour demand in the directly regulated textile printing and dyeing industry in China and found evidence that labour demand fell by approximately 7% in these two industries as a result of the implementation of more stringent environmental standards.

Studies that investigate the impact of environmental taxes have tended to examine the impact of taxes on emissions (e.g. Andersson (2019), Lin & Li (2011), Rivers & Schaufele (2015)), or on GDP (e.g. Bernard et al. (2018), Metcalf (2019), Metcalf & Stock (2020)). Other papers attempt to verify the Double Dividend hypothesis (e.g. Bento & Jacobsen (2007), Williams III (2002).) A much smaller number of studies consider the impact of environmental taxes on employment.

Of the studies that examine the impact of environmental taxes on employment, Yamazaki (2017) examines the employment effect of British Columbia's revenue-neutral carbon tax implemented in 2008 using industry level data and conclude that the carbon tax adversely

[7] The Cluster Rule is an integrated regulation that aimed to reduce both air and water pollution from the pulp and paper industry implemented by US EPA in 1998.

affected employment through the output effect but positively affected employment through the redistribution effect when all industries are considered. At the sector level he shows that employment fell the most in carbon-intensive and trade-intensive industries while it rose in clean services industries. In a related study Yip (2018) also examines the labour market effect of British Columbia's revenue-neutral carbon tax using individual data and explores the impact of the tax on labour outcomes. In contrast to Yamazaki (2017), Yip (2018) show that the carbon tax increased unemployment and that it was less-educated male workers who suffered the most.

Finally, in a Europe wide study, Metcalf & Stock (2020) consider the effect of a carbon tax on various economic outcomes including GDP, total employment and emissions and find no evidence of a negative effect of a carbon tax on GDP, or total employment. It is worth noting that they also test for a possible benefit of a carbon tax through the recycling of tax revenue by looking at those countries that used tax revenues to reduce taxes in other areas and find a modest positive effect on economic outcomes.[8]

To summarise, the majority of the existing literature has found no effect or a negative effect of environmental policy on labour demand, with the exception of Yamazaki (2017) who finds an overall positive effect of a carbon tax. Methodologically, studies have tended to estimate a reduced form specification based on the partial equilibrium model of Berman & Bui (2001) or take a difference-in-difference (DiD) approach comparing regulated with unregulated sectors.[9]

[8]It is worth noting that while they find a small positive effect they, recommend caution when interpreting the results as the standard errors are large and that they do not have a measure of the actual use of the tax revenues.

[9]Note, the DiD method has cons (Hafstead & Williams III 2018). Studies of regulated industries only provide the effect of environmental regulation on specific sectors rather than capture the effect on the whole

3.2.2 Environmental taxes and green employment

Although there are a number of studies that have looked at how environmental policies affect employment, what has been only rarely discussed is the relationship between environmental policy and green jobs. One possible reason for this is overcoming the challenge of how to measure both environmental policy and green jobs especially when different studies have defined green jobs in different ways, making comparisons difficult. Based on O*NET definition of green jobs, recent literature have attempted to examine the relationship between regional diversification and green employment in US metropolitan areas (Barbieri & Consoli 2019), and the relationship between eco-innovation activities and green jobs in Dutch firms (Elliott et al. 2021).

Of the small number of studies that have looked at the relationship between environmental policies and green jobs, Yi (2013) consider the effect of state and local clean energy policies on green jobs across US metropolitan areas using a sectoral definition of green jobs developed by the Pew Charitable Trust. By creating a state clean energy policy index that combines different policy instruments (emission caps, standards for energy efficiency, tax incentives, and public funding for renewable energy etc.), Yi (2013) found that both state and local clean energy policies had a positive and significant effect on the number of green jobs. In contrast, Bowen et al. (2013) find no significant effect of state renewable energy portfolio standards (RPS) on green job growth using the BLS definition of green jobs although they

economy. Hence, applying a difference-in-difference approach may be misleading if the control group is unregulated sectors such that the increase in employment in unregulated industries could be mistakenly be interpreted as a larger fall in those employed in regulated sectors.

did show that the adoption of RPS promotes an increase in the number of green businesses at the state level. This result is similar to Yi (2014) who found that the presence of RPS was positively correlated with the number of green business in the US.

More recently, Vona et al. (2019) examined the effect of environmental policies on green jobs growth in the US using a task-based definition of green jobs using the O*NET classification. By analysing both direct emission regulations and local green subsidies within the American Recovery and Reinvestment Act (ARRA), they found that green subsides were the main driving force of green jobs growth in metropolitan and non-metropolitan areas, while direct environmental regulation is a secondary factor (Vona et al. 2019). These results are consistent with Elliott et al. (2021), who show that subsidy-driven eco-innovation is positively correlated with the number and share of green jobs at firm level rather than a regulation-driven eco-innovation. In an earlier study, Vona et al. (2018) explore the role of environmental regulations on green skills for US metropolitan and non-metropolitan areas based on the O*NET Green economy program and although they found no impact on overall employment, a significant relationship between environmental regulation and demand for green skills was found (Vona et al. 2018).

To summarise, the literature that investigates the relationship between environmental policy and green jobs is rather limited, and often based on certain regions. More specifically, to the best of our knowledge there are no studies of the impact of environmental taxes on green jobs.

3.3 Data and methodology

3.3.1 Data

To estimate the impact of environmental taxes on total employment, the number of green jobs, and share of green jobs at sector level we combine the following data: Confidential individual-level data from the Dutch Labour Force Survey (LFS) and the Dutch Tax Register Data (TRD), and publicly available sector-level data from StataLine, Eurostat and Comtrade.[10] The Dutch LFS is a large household survey. In addition to demographic characteristics, the LFS also provides occupational information at the 4-digit ISCO level. By matching the green occupation list constructed by O*NET, we are able to create a greenness index for each employee in the Dutch LFS.

We link the LFS with the TRD to identify those workers who were active in the labour market between 2000 and 2016. [11] By merging the LFS with the TRD, we are able to trace the entire employment history of each worker at firm level. By matching the same green occupation list constructed in Chapter two, we are able to identify green jobs in the merged LFS and TRD. To analyse the sector-level employment effect of an environmental tax, we aggregate the individual level information up to sector level based on the first digit of the SBI classification. We then merge this dataset with other sector level data. The result is a sample than contains 15 sectors over 17 years.[12]

[10]See TableB.1 in Appendix to Chapter Three for details of the data sources for each variable.

[11]Note that TRD are not available after 2016. This will limit our research period to 2000 to 2016. As it is illustrated in Chapter Two, CBS changed the questionnaire of LFS in 2012, however, this would not result in a serious series break when we disaggregate at sector level. Details to see Table B.1 in Appendix to Chapter Three for sample consistency. On top of this, we control the year dummies and sector dummies in the regression to reduce the potential effect of change of questionnaire.

[12]The SBI is the Dutch classification of economic activity. The first digit of Dutch SBI 2008 is consistent

To have a better understanding of key variables in our sample, we present some descriptive evidence; first on the distribution of employment by sector. Figure 3.1 shows the distribution of workers and share of green jobs by sector for 2016. The primary sector (sector A 'Agriculture, forestry and fishing' and B 'Mining and quarrying') has a relatively low share of green jobs in sector A but relatively high percentage in sector B (although the number of workers is fairly small). The secondary sector (sector C 'Manufacturing', D 'Energy supply', E 'Water supply', and F 'Construction') has a relatively large share of green jobs especially in Sector D 'Energy supply' (34.68%) and Sector E 'Water supply' (51.04%).[13] As a service-based economy, a large number of jobs are in the tertiary/service sectors. However, the share of green jobs tends to be relatively small.

[Figure 3.1 about here]

Our key explanatory variable is the total value of environmental taxes by sector, obtained from the official database of Statistics Netherlands (StatLine). According to CBS (2015), an environmental tax has the following definition: "*A tax whose tax base is a physical unit (or a proxy of a physical unit) of something that has a proven, specific negative impact on the environment*". Based on the Eurostat (2013) classification, total environmental taxes

with the economic activity classification of the NACE classification and the international standard industrial classification of all economics activities (ISCI).

[13]For simplicity, sector D 'Electricity, gas, steam and air conditioning supply' is refereed to as 'Energy supply' and sector E 'Water supply; sewerage, waste management and remediation activities' is referred as 'Water supply'. It is not surprising that sector D 'Energy supply' includes a large number of green activities as it includes the generation of energy from wind, nuclear, bioenergy and other renewable resources. Sector E 'Water supply' includes activities associated with the water supply, sewerage management and waste recycle and disposal and so on. These activities tend to be less labour intensive but can involve a large number of green tasks.

can be broken down into four main categories: energy taxes (including tax on fuel for transport); transport taxes (excluding fuel for transport); pollution taxes; and resource taxes. While the categories used by the CBS differ from those of the Eurostat categories, by using a correspondence table we are able to match the Dutch and Eurostat classifications.[14]

Figure 3.2 presents the distribution of four kinds of environmental taxes (in million Euros) by sector. What is evident is that environmental taxes were mainly paid by the energy and transport sectors. Perhaps surprisingly at first glance, Sector 'N administrative and support services' pays the highest total environmental taxes, however this is due primarily to the large amount paid as a transport tax as this sector includes the renting and leasing of motor vehicles. Sector 'H Transportation and storage sectors' pays the second highest total with the tax revenues coming mainly from energy (fuel for transport mostly). Manufacturing sectors pay the third highest level of tax, again driven by taxes on energy use.

[Figure 3.2 about here]

Now, we turn to our key variables. We split the sample into industrial and non-industrial sectors.[15] Figure 3.3 shows that total employment increased slightly in the non-

[14] In this chapter we use the Eurostat classification because it is the most commonly used and is easier to understand and interpret. Details Eurostat's environmental tax categories and the correspondence table with the Dutch classification can are presented in table B.5 and table B.6 in Appendix to Chapter Three, respectively.

[15] Industrial sectors are classified according to the Metadata Glossary of the World Bank which classifies industrial sectors as ISIC divisions 10-45 (ISCI V3.1) which corresponds to the first digit of ISCI divisions C-F. See https://databank.worldbank.org/metadataglossary/wdi-database-archives-(beta)/series/NV.IND.TOTL.CDfordetails. Such a categorization allows us to roughly split the sample into sectors that are more energy intensive and trade intensive and those that are not (the non-industrial sectors).

industrial sectors but fell for the traditional manufacturing sectors. It is worth noting that the absolute level of employment is also much higher in the non-industrial sectors. Turning to figure 3.4, the left panel shows a small decreasing trend in scaled environmental tax revenues for non-industrial sectors with a larger fall from 2006 until 2013 after which time revenues started to increase again.[16] The right panel shows scaled environmental tax revenues for the industrial sector remained relatively stable.

[Figure 3.3 about here]

[Figure 3.4 about here]

Figure 3.5 and figure 3.6 presents trends in the number of green workers and the share of green workers by non-industrial and industrial sectors, respectively. We see for the non-industrial sector that the number of green jobs first increased dramatically between 2000 and 2008 before falling back to 2005 levels after the financial crisis before recovering slightly in 2014. For the industrial sector the number of green jobs is much lower and remained relatively stable until 2011 when it started to fall. The story changes somewhat when we look a the shares of green workers in figure 3.6. The trends in the share of green jobs are fairly similar for both sectors with increases until around 2012 and then a decrease.[17]

[Figure 3.5 about here]

[Figure 3.6 about here]

[16]The sharp decrease between 2006 to 2013 is driven by a both a decrease in total environmental tax revenues and an increase in total GVA

[17]The falling share of green jobs after 2012 might reflect the view that green workers are not considered essential and that they are more likely to be lost during the post-financial crisis downturn.

3.3.2 Methodology

Given the trends in environmental taxes and employment, disentangling the impact of environmental taxes on employment is a challenge not least because of a number of possible endogeneity concerns. The first endogenity concern is that certain sectors may lobby the government to lower the stringency of environmental regulations (reduce environmental taxes) (Cole & Elliott 2007, Ederington & Minier 2003). Second, sectors that have a high number or a high share of green workers may have greater innovation capacity that could lead to at least two different impacts on environmental tax that can be thought of as a scale and technique effect. On the one hand, sectors may be more competitive because they employ more high skilled green workers, and hence are more productive, which leads to a scale effect by which these sectors pollute more and hence have to pay more in environmental tax in absolute terms. On the other hand, more innovative green workers increase the likelihood that the sector will introduce environmentally friendly production processes that will reduce emissions per capita and hence reduce the overall environmental tax burden.

To examine the impact of environmental taxes on employment at the sector level, we initially estimate Equation (2) jointly with Equation (3) using a three stage least squares (3SLS) approach following Cole & Elliott (2007). The use of 3SLS rather than 2SLS is essentially down to efficiency. If there is an endogeneity concern, both 2SLS and 3SLS can produce consistent estimates, but 3SLS is more efficient as it allows correlations between unobserved disturbances across various equations (Bakhsh et al. 2017).[18]

[18] 3SLS is only more efficient than 2SLS if no homoskedasiticity is assumed as the weight matrix used in the standard 3SLS approach assumes homoskedastic errors. Therefore, we first perform a heteroscedasticity test by using iterated GLS with only heteroskedasticity, which produces maximum-likelihood parameter estimates that allows us to do a LR test. Based on the LR test, our main equations have no heteroskedasticity issues so we use 3SLS rather than 2SLS.

$$ln(EMP_{it}) = \delta_i + \gamma_t + \beta_1 ln(ENTAX_{it}) + \beta_n Z^n_{it-1} + \epsilon_{it} \tag{3.1}$$

$$ln(ENTAX_{it}) = \delta_i + \gamma_t + \beta_1 ln(EMP_{it}) + \beta_n X^n_{it-1} + \epsilon_{it} \tag{3.2}$$

Where EMP_{it} denotes the level of total employment, green employment or share of green employment in industry i, year t. $ENTAX_{it}$ denotes the environmental tax revenue in industry i, year t. Sector fixed effects δ_i and year fixed effects γ_t are included. Z_{it-1} is a vector of control variables, which are the factors expected to affect sector level employment while X_{it-1} is a vector of control variables that are expected to affect the level of environmental tax levied. Both control variables are lagged by one year to further mitigate potential endogeneity concerns following Cole & Elliott (2007).

We have three dependent variables: (1) log of the total number of workers (*Total employment*); (2) log of the number of green workers (*Green employment*); and (3) the share of green workers (*Share of green jobs*). We include three dependent variables because we are not only interested in the effect of environmental taxes on overall employment rates but also on compositional changes across sectors.

As for controls, we include several variables that are likely to impact sector level employment. These include hourly wage rate ($Wage_{t-1}$) and GVA (GVA_{t-1}) in industry i and year t-1, where wage captures the quality of workers in each sector and GVA is a proxy for sector size. We also control for the growth of wages ($Wagegrowth_{t-1}$) and the GVA growth rate ($GVAgrowth_{t-1}$). In addition, we also control for net operational surplus ($Surplus_{t-1}$) as a proxy for sector profitability, a measure of trade openness ($Openness_{t-1}$), and net exports as a share of GVA ($Netexport_{t-1}$), where the measures of trade status can also be thought of as a proxy for sector demand elasticity (Yamazaki 2017).[19] Finally, we control capital stock ($Capital_{t-1}$) to measure the capital intensity of a sector. Sector fixed effects and year fixed effects are included.[20]

The control variables in vector X are included to help address the endogeneity concerns mentioned above. Under the assumption that larger and more powerful industries may have a greater ability to lobby government to reduce environmental taxes we include the log of gross value added GVA (GVA_{t-1}) and net operation surplus ($Surplus_{t-1}$) to capture the profitability of an industry. We also include the growth rate of GVA ($GVAgrowth_{t-1}$) as an industry that is growing more slowly may also have an incentive to lobby for lower taxes as an appeal to government to help them save jobs (Cole & Elliott 2007). In addition, sluggish economic growth *per se* may encourage a government to reduce the tax rate to improve the international competitive of firms (Metcalf & Stock 2020). Net exports ($Netexport_{t-1}$) and trade openness ($Openness_{t-1}$) are included to capture the degree of trade protection that

[19]Trade openness is calculated by import value plus export value as a share of GVA.

[20]The majority of previous studies have used a partial static equilibrium model based on Berman & Bui (2001) to analyse the role of environmental regulation on the labour demand, in which material, labour and capital are treated as 'variable factors', and environmental regulation cost is treated as a 'quasi-fixed' factor. By assuming a cost-minimising firm who chooses the level of variable inputs and 'quasi-fixed' inputs, the first order condition gives the demand for labour as a function of output, prices and quantity of 'qausi-fixed' inputs. In Berman & Bui (2001), regulation can affect labour through inputs prices. However, when the input market is sufficiently large and competitive, this effect drops out. In this chapter, we include a number of service sectors so we are not able to include a material price index as Cole & Elliott (2007), Morgenstern et al. (2002).

may manifest itself in the form of environmental regulation (Ederington & Minier 2003). As the level of environmental taxes raised is likely to be proportionate to overall energy use, we also include the log of GHG emissions (GHG_{t-1}). Finally, we include the share of high skilled workers ($Highskill_{t-1}$) to control for the innovation capacity of a sector as a skilled workforce is one of the important factors that contributes to innovation performance (Fu 2008, González et al. 2016).

3.4 Empirical results

The first step is to examine the impact of environmental taxes on overall employment at the sector level. Table 3.1 presents the results of our 3SLS estimations for the whole sample, industrial sample and non-industrial sample respectively.[21] Columns (1) to (3) examine the relationship between environmental taxes and the number workers, the number of green jobs, and share of green workers respectively in the whole sample.[22]

Focusing on our key explanatory variable, the log of total environmental taxes (*Entax*), we find that there is no statistically significant effect of environmental taxes on total employment (*Total employment*). However, the environmental tax is significantly and positively correlated with number of green workers in a sector (*Green employment*) and the share of green jobs (*Share of green jobs*). These results suggest that the effect of environmental taxes on employment at sector level is captured by a compositional change, that is although

[21] Summary statistics and a correlation matrix can be found in Table B.3 and Table B.4, respectively

[22] Standard errors are presented in the table rather than robust standard errors because we use 3SLS under the assumption of homoskedastic errors, and according to LR test, we do not have heteroskedastic issues in the regressions. Therefore, standard errors are used in the results tables of the chapter

there is no significant change in overall employment, there is an increase in the number and proportion of workers that are in so-called green jobs. More specifically, everything else being equal, a 10% increase in environmental tax revenues leads to a 1.62% increase in number of green jobs (equivalent to approximately 1,004 green jobs on average at sector level given the average number of green jobs is 62,000), and this is also approximately equal to 0.664% increase in the share of green jobs across all sectors.

Turning to our controls, we find the wage rate ($Wage_{t-1}$) is significantly and negatively correlated with total employment but that has no significant effect on the number of green workers or the share. Not surprisingly, higher wages means fewer workers are employed. As expected, GVA (GVA_{t-1}) is significant and a positive determinant of total employment but also the number of green workers although there is no significant effect on the share of green jobs (as green and non-green jobs are both increasing proportionately). The growth rate of GVA is found to be negatively correlated with total employment, but positively correlated with the share of green jobs. This suggests that the positive effect on the share is driven by a decrease in non-green jobs rather than an increase in green jobs. Net operational surplus ($Surplus_{t-1}$) is found to be negatively and significantly correlated with total employment and number of green jobs but this has an impact on both in equal proportions so there is no effect on the share of green jobs.[23] Finally, net exports as a share of GVA ($Netexport_{t-1}$) is significantly and negatively correlated with total employment, but positively correlated with share of green jobs. The negative is likely to be capturing the fact that the manufacturing sector is the main exporter but also the more traditional sector that has seen an overall decline in employment. The remaining controls are insignificant.

[23] An inverse hyperbolic sine function is used to transform net operation surplus as it includes a number of zeros.

The existing literature has shown that the effect of environmental taxes on employment differs across sectors due to differences in emission intensities and demand elasticities (Greenstone 2002, Morgenstern et al. 2002, Yamazaki 2017). Our descriptive evidence shows that total employment fell in the industrial sectors while it gradually increased across the non-industrial sectors. In addition, the industrial sector is known to be relatively more energy and trade intensive. Therefore, to test for possible heterogeneity in the relationship between environmental taxes and employment we split our sample into broad industrial and non-industrial categories.

Column (4) to (10) of table 3.1 present the results for industrial and non-industrial sectors separately. Now we find that environmental taxes have a negative and statistically significant impact on the total employment in industrial sectors but no significant effect on overall employment in the non-industrial sectors. More importantly, the results suggest that environmental taxes significantly increase the number of green workers (and hence share of green workers) in the non-industrial sectors. More specifically, we find can infer that a 10% increase in environmental taxes will result in a 0.319% decrease in the total of workers in the industrial sector, which is approximately equivalent to 967 workers. As there is no significant reduction in the number of green workers we can infer that the jobs lost were primarily non-green. In the non-industrial sector we can infer that a 10% increase in environmental taxes will result in a 4.24% increase in the number of green workers, which is equivalent to 2,200 new green workers in the non-industrial sector. Reflecting on the results from Table3.1 it appears that the increase in green workers for the whole sample is driven by a small decrease in the number of non-green workers across the industrial sectors and an increase in green workers across the non-industrial sectors and that these numbers, in the case of the Netherlands over this period pretty much balance out.

Turning to the controls in split samples, for the industrial sector, the employment effect of the log of GVA and the net operational surplus are found similar to the whole sample, while in the non-industrial sectors, the log of GVA is found to also be positively correlated with the share of green workers, while net operational surplus is found to be negatively correlated with share of green workers. The wage rate has a different impact. Wage is positively correlated with the number of green workers and the share of green workers in the industrial sector but negatively correlated with total employment in the non-industrial sector. A similar result is found for the net export variable, which also acts differently across samples, where it is found to be positively correlated with total employment in the industrial sector but negatively correlated with total employment and positively correlated with the number of green workers and hence the share of green workers in the non-industrial sector. These results are consistent with green workers being paid more and being relatively more skilled. The results for net exports are consistent with the relatively high trade intensity of the industrial sector and the generally well known result that exporters are larger.

[Table 3.1 about here]

The next stage is to examine the effect of energy/carbon taxes (*Energytax*) only on employment. We focus on taxes on energy because: (1) It makes it easier to compare with European countries where taxes on energy account for more than three-quarters of the total revenues from environmental taxes.[24] In the Netherlands, energy taxes account a large percent of total environmental tax revenues. For example, in 2016, 62.58% of total environmental tax revenues came from taxes on energy, while 25.21% comes from transport, 10.91% from pollution abatement costs, and 1.30% from resources; (2) The majority of the existing

[24]See Environmental tax statistics from Eurostat: https://ec.europa.eu/eurostat/statistics-explained/index.php/Environmental_tax_statistics

literature examines the effect of energy taxes, the majority of which considers the effect of carbon taxes (see e.g. Metcalf (2019), Metcalf & Stock (2020), Yamazaki (2017), Yip (2018)).

Table 3.2 presents the results from a 3SLS model on the relationship between energy taxes and employment for the whole sample, and the industrial and non-industrial samples, respectively. For the whole sample, energy taxes are found be positively correlated with total employment (at the 10% level) and the number of green jobs but have no impact on the share of green employment (this indicates that total jobs and green jobs were created in similar proportions). When we split the sample into industrial and non-industrial sectors, we find that energy taxes have no statistically significant impact on industrial sector total employment, the number of green workers, or the share of green jobs. However, we find a strong positive and significant effect of energy taxes on the number and share of green jobs in non-industrial sectors. Treating energy tax endogenously, it appears that the positive impact of energy taxes on green job creation in the non-industrial sectors is driven by energy taxes (see Table 3.1).

[Table 3.2 about here]

3.5 Robustness checks

To ensure that the green employment creation effects of environmental taxes we found so far are robust to different measure of green jobs, we repeat our 3SLS estimation equation but based on a broader definition of green jobs.[25] The broad measure of green jobs include

[25]An alternative method to measure green jobs is to use different greenness as the thresholds instead of the average (0.034). We have used following greenness as thresholds: 0.001, 0.024, 0.044, 0.05, 0.1, 0.146

three types of green occupations from O*NET: Green ID occupations, Green ES occupations, and Green NE occupations. Following the same strategy laid out in Chapter two, we convert these three types of green occupations from O*NET-SOC to ISCO based on a binary measure.[26]

Table 3.3 presents the 3SLS estimation results for the whole sample, industrial and non-industrial sectors respectively. For the whole sample environmental taxes are significantly and positively correlated with the number of green jobs and the share of green jobs based on the broad definition at the sector level matching the findings from the 3SLS results in Table 3.1. More specifically, a 10% increase in the environmental tax will lead to a 1.69% increase in number of green jobs (equivalent to 1775 green workers), approximately equal to 0.992% increase in the share of green workers at the sector level. The magnitudes are just a little larger than those found in Table 3.1 as we expected because using broad measure means we include more indirect green jobs. This leads to a larger employment effect of environmental taxes than those are found above.

Column (3) to (6) gives the 3SLS estimation results when we split our sample into industrial and non-industrial sectors. Slightly different from before, where we only show environmental tax decreases total employment in industrial sectors, now we show it also increases the share of green jobs in industrial sectors based on a broader definition. [27] This

(one SD from the mean), 0.258 (two SD from the mean). The main empirical results for the number and share of green jobs is qualitatively similar when the greenness is less than and equal to 0.146. We lose the effect on share of green jobs when the greenness is above 0.146 due to the variation in the share being too small.

[26]We also run the same regressions that treat environmental tax exougenously using Fixed effect model, which can be found in Appendix to Chapter Three

[27]Note that the results for total employment would not change when we use different measure of green

significant increase in share is through a decrease in non-green jobs rather than increase in green jobs. Besides, similar results are found in the non-industrial sector, where we find environmental taxes significantly and positively affect the number and share of green jobs. More specifically, a 10% increase in environmental taxes will result in a 4.05% increase in number of green jobs, this is equal to 3,240 new broad green workers in non-industrial sector(also is equivalent to 1.32% increase in share of green jobs). Again, we find a larger effect of environmental tax on green jobs in industrial/non-industrial sectors when we use the broad definition. This indicates that the green employment effect of environmental tax is economy-wide that not just create direct green jobs, but also indirect green jobs.

[Table 3.3 about here]

Finally, we examine the relationship between energy taxes and green employment based on a broad definition for the whole sample, and the industrial and non industrial samples in Table 3.4. Results are broadly consistent with those found in Table 3.2. For the whole sample, energy taxes are found to have a significant and positive effect on the number of green workers(with similar coefficients), but no effect on the share of green jobs. Same as before, we believe energy taxes increase total employment and green employment for the same proportion. When we split the sample into industrial and non-industrial sectors, we show energy taxes have no effect no number of green jobs in industrial sectors but increase number of green jobs in non-industrial sectors. Besides, a positive and significant effect on the share of green jobs is found in both sectoral groups. The results suggest that energy taxes are driving the sectoral differences found in Table 3.3.

[Table 3.4 about here]

jobs. Therefore, columns for total employment are not reported here.

3.6 Conclusions

Environmental taxes are designed to tax environmentally harmful behaviour and are considered to be a useful policy tool in the fight against climate change, local air pollution and as a tool to encourage the economy to shift to a greener growth path. The advantage of using taxes as a policy tool is that they are seen as effective, efficient, and that revenues can be recycled to offset other distortionary taxes and they are transparent (OECD 2011*a*). However, there are many that remain concerned that environmental taxes place an unfair burden on firms forcing them to invest in costly pollution control measures that damage competitiveness of firms and the economy more broadly. These concerns often manifest themselves in terms of the potential loss of jobs that accompany any increase in taxes.

This chapter explores the employment effect of environmental taxes on the Dutch labour market between 2000 to 2016. More specifically, we quantify the impact of environmental taxes on total employment as well as the impact on the number of green workers at the sector level. We treat environmental taxes both endogenously and find that for the economy overall, environmental taxes have no effect on total sectoral employment, but does stimulate the creation of green jobs (and hence increases the share of green jobs in the economy). The increase in the share is therefore driven by compositional changes in the economy. Put another way, environmental taxes have no impact on total employment because the jobs losses in non-green workers as a result of the taxes are matched by an increase in the number of green jobs.

To understand this compositional change in more detail we investigate the impact of environmental taxes on industrial and non-industrial sectors, respectively. Our results show that environmental taxes decrease total employment in the more traditional industrial sectors (mainly non-green jobs), but creates more green jobs, and hence increases the share of green jobs, in non-industrial sectors. When considered along side the results for the whole sample we can say that the overall increase in green workers that we found for the whole sample is driven by a relatively small percentage decrease in the number of non-green jobs (from a large initial number) in industrial sectors and a larger percentage increase in green jobs in non-industrial sectors that, for this time period, just about balance each other out.

Our results are broadly consistent with existing literature where the majority of studies found no overall employment effect of environmental policy. More importantly, we are able to explore what happened within the 'black box' of this result, that is, we find that environmental taxes trigger green job creation in non-industrial industries but reduce the number of non-green jobs in the dirtier industrial sectors.

In the current Covid-19 crisis, the international organisation and policy makers argue that we need to "build back better" and improve societal and economic resilience to further shocks. A popular solution is to push for a green recovery plan in their stimulus packages. According to a preliminary analysis conducted by OECD in August 2020, there are at least 30 OECD and Key Partner countries that have included a Green Deal as part of their national strategy to help the country overcome the economic crisis while also addressing climate and environmental challenges (OECD 2020*a*). However, the OECD country level report also state that 24 national governments have announced recovery measures that are likely to have an adverse impact on environment, including reducing or abandoning environmentally-related taxes, fees and charges (OECD 2020*c*).

The ongoing COVID19 crisis has shifted policy-makers' attention away from the environmental concerns to the problem of unemployment. The reduction in environmentally-related taxes, fees and charges of many countries is the evidence of policy shift. However, our results show that the effect of environmental taxes on employment is mainly compositional in nature and that there is no evidence that environmental taxes reduce aggregate employment but does increase the proportion of green jobs that are more highly paid and highly skilled. Policy-makers who are eager to return their economies to a sustainable growth path need to carefully consider whether reducing or waiving environmentally-related taxes is worth the environmental damage that such a policy would inflict on their countries and the world.

Table 3.1: Environmental taxes and employment: 3SLS

	Whole sample			Industrial sectors			Non-industrial sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs
Entax	-0.0590	0.162*	0.0664***	-0.0319**	-0.0362	-0.00567	-0.0723	0.424**	0.102**
	(0.0425)	(0.0685)	(0.0135)	(0.0107)	(0.0343)	(0.0121)	(0.0826)	(0.154)	(0.0328)
$Wage_{t-1}$	-0.0247***	-0.00956	0.000701	-0.00380	0.0355**	0.0234***	-0.0263***	-0.0117	0.000634
	(0.00350)	(0.00580)	(0.00106)	(0.00419)	(0.0122)	(0.00468)	(0.00369)	(0.00704)	(0.00147)
GVA_{t-1}	0.647***	0.427**	0.0183	1.316***	1.097***	-0.116	0.334**	0.656**	0.157**
	(0.0977)	(0.165)	(0.0355)	(0.0878)	(0.236)	(0.0859)	(0.130)	(0.235)	(0.0478)
$Wagegrowth_{t-1}$	0.00135	-0.00262	-0.0000791	0.00112	-0.00177	-0.00282	-0.00152	-0.00455	-0.000110
	(0.00290)	(0.00325)	(0.000782)	(0.00199)	(0.00391)	(0.00171)	(0.00299)	(0.00487)	(0.000542)
$GVAgrowth_{t-1}$	-0.162*	0.0956	0.0690*	-0.111	-0.244	-0.0568	-0.125	-0.0164	0.0306
	(0.0725)	(0.127)	(0.0277)	(0.0599)	(0.178)	(0.0627)	(0.0691)	(0.134)	(0.0279)
$Surplus_{t-1}$	-0.203***	-0.164*	-0.00241	-0.314***	-0.306**	0.00183	-0.189***	-0.227*	-0.0415*
	(0.0432)	(0.0745)	(0.0160)	(0.0390)	(0.106)	(0.0386)	(0.0526)	(0.0985)	(0.0194)
$Openness_{t-1}$	0.00979	-0.0361	-0.00899	-0.0136	0.0258	0.0134	-0.00211	-0.0176	-0.00712
	(0.0127)	(0.0222)	(0.00481)	(0.00997)	(0.0279)	(0.0101)	(0.0146)	(0.0283)	(0.00586)
$Netexport_{t-1}$	-0.196**	0.210	0.0577*	0.153*	-0.0229	-0.0199	-0.323***	0.326*	0.0779*
	(0.0755)	(0.132)	(0.0286)	(0.0649)	(0.188)	(0.0670)	(0.0798)	(0.155)	(0.0323)
$Capital_{t-1}$	-0.00584	0.000154	0.000562	-0.00514	-0.0445	-0.0257	-0.00999*	0.00394	0.0000413
	(0.00377)	(0.00456)	(0.000827)	(0.0155)	(0.0362)	(0.0150)	(0.00407)	(0.00695)	(0.00120)
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	64	64	64	176	176	176

* p<0.10 ** p<0.05 *** p<0.01; Standard errors in parentheses; Constants are not reported

All the variables are logged except ratios; All the control variables are lagged for one period

Column (1) to (3) for whole sample

Column (4) to (6) for industrial sample, and column (7) to (9) for non-industrial sample

Table 3.2: Energy taxes and employment: 3SLS

	Whole sample			Industrial sectors			Non-industrial sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs
$Energytax$	0.138*	0.260**	0.0215	-0.0285	-0.0348	-0.00828	-0.00592	0.442***	0.0751**
	(0.0659)	(0.0975)	(0.0171)	(0.0148)	(0.0452)	(0.0164)	(0.0720)	(0.132)	(0.0288)
$Wage_{t-1}$	-0.0158**	0.00220	0.000572	-0.0104	0.0243	0.0209**	-0.0266***	0.00133	0.00330
	(0.00608)	(0.00916)	(0.00159)	(0.00733)	(0.0194)	(0.00736)	(0.00494)	(0.00970)	(0.00196)
GVA_{t-1}	0.490***	0.277	0.0192	1.389***	1.151***	-0.113	0.392***	0.388	0.0647
	(0.138)	(0.210)	(0.0377)	(0.0843)	(0.227)	(0.0845)	(0.113)	(0.208)	(0.0429)
$Wagegrowth_{t-1}$	0.000968	0.000324	-0.000801	0.00116	-0.000442	-0.00237	0.000538	-0.00150	-0.000683
	(0.00154)	(0.00245)	(0.000867)	(0.00203)	(0.00385)	(0.00170)	(0.00259)	(0.00390)	(0.000498)
$GVAgrowth_{t-1}$	0.0766	0.284	0.0325	-0.131	-0.280	-0.0769	-0.124	0.0483	0.0433
	(0.120)	(0.184)	(0.0323)	(0.0822)	(0.247)	(0.0894)	(0.0696)	(0.136)	(0.0278)
$Surplus_{t-1}$	-0.108	-0.109	-0.0137	-0.326***	-0.304**	0.00677	-0.187***	-0.141	-0.0171
	(0.0592)	(0.0931)	(0.0166)	(0.0406)	(0.109)	(0.0404)	(0.0531)	(0.101)	(0.0204)
$Openness_{t-1}$	-0.0119	-0.0375	-0.00169	-0.0202	0.0156	0.0113	-0.00462	-0.0422	-0.00962
	(0.0163)	(0.0249)	(0.00439)	(0.0106)	(0.0293)	(0.0109)	(0.0161)	(0.0311)	(0.00642)
$Netexport_{t-1}$	-0.125	0.162	0.0198	0.194**	0.0156	-0.0130	-0.321***	0.410**	0.0891**
	(0.0949)	(0.145)	(0.0256)	(0.0636)	(0.191)	(0.0702)	(0.0802)	(0.156)	(0.0321)
$Capital_{t-1}$	-0.00219	0.000441	0.000638	-0.00732	-0.0350	-0.0218	-0.00756*	0.00181	0.000191
	(0.00192)	(0.00381)	(0.00108)	(0.0195)	(0.0448)	(0.0176)	(0.00322)	(0.00461)	(0.000867)
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	64	64	64	176	176	176

* p<0.10 ** p<0.05 *** p<0.01; Standard errors in parentheses; Constants are not reported

All the variables are logged except ratios; All the control variables are lagged for one period

Column (1) to (3) for whole sample

Column (4) to (6) for industrial sample, and column (7) to (9) for non-industrial sample

Table 3.3: Environmental tax and green employment (Broad measure): 3SLS

	Whole sample		Industrial sample		Non-industrial sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	Green employment	Share of green jobs	Green employment	Share of green jobs	Green employment	Share of green jobs
Entax	0.169*	0.0992***	0.0217	0.0283**	0.359*	0.134**
	-0.0766	-0.0208	-0.0201	-0.00968	-0.163	-0.0416
$Wage_{t-1}$	-0.0188**	2.81E-05	0.0175	0.0207***	-0.0140*	0.000551
	-0.00579	-0.00139	-0.00962	-0.00429	-0.00688	-0.00157
GVA_{t-1}	0.728***	0.0492	1.465***	0.104	0.739**	0.142*
	-0.18	-0.0537	-0.157	-0.0759	-0.26	-0.0684
$Wagegrowth_{t-1}$	-0.00093	0.0003	0.00111	-0.00196	-0.00014	0.00000383
	-0.00289	-0.00068	-0.00297	-0.00164	-0.00284	-0.000839
$GVAgrowth_{t-1}$	0.125	0.128**	-0.0454	0.0228	0.0529	0.0768*
	-0.134	-0.0399	-0.106	-0.048	-0.143	-0.0376
$Surplus_{t-1}$	-0.212**	-0.0015	-0.417***	-0.0744*	-0.246*	-0.0198
	-0.076	-0.0231	-0.0712	-0.034	-0.105	-0.0297
$Openness_{t-1}$	0.0767**	0.0147*	-0.00262	0.0103	0.105***	0.0261**
	-0.0235	-0.00697	-0.0184	-0.00832	-0.0307	-0.00822
$Netexport_{t-1}$	-0.519***	-0.0583	0.234*	0.0771	-0.594***	-0.0672
	-0.14	-0.0415	-0.114	-0.0499	-0.167	-0.045
$Capital_{t-1}$	-0.0111*	-0.00138	-0.0541	-0.0484**	-0.0103	0.000101
	-0.00473	-0.00189	-0.034	-0.0172	-0.00561	-0.00204
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	64	64	176	176

* p<0.10 ** p<0.05 *** p<0.01; Standard errors in parentheses; Constants are not reported

All the variables are logged except ratios; All the control variables are lagged for one period

Column (1) to (2) for whole sample

Column (3) to (4) for industrial sample, and column (5) to (6) for non-industrial sample

Table 3.4: Energy tax and green employment (Broad measure): 3SLS

	Whole sample		Industrial sample		Non-industrial sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	Green employment	Share of green jobs	Green employment	Share of green jobs	Green employment	Share of green jobs
$Energytax$	0.288**	0.0376	0.0508	0.0388**	0.405**	0.132***
	(0.111)	(0.0213)	(0.0322)	(0.0149)	(0.140)	(0.0362)
$Wage_{t-1}$	-0.00548	0.00184	0.0354*	0.0310***	-0.00507	0.00307
	(0.0101)	(0.00196)	(0.0168)	(0.00776)	(0.00976)	(0.00256)
GVA_{t-1}	0.484*	0.0367	1.458***	0.0476	0.442	0.0562
	(0.242)	(0.0472)	(0.180)	(0.0830)	(0.227)	(0.0606)
$Wagegrowth_{t-1}$	-0.000177	-0.000487	0.00161	-0.00267	-0.000435	-0.000279
	(0.00196)	(0.00105)	(0.00421)	(0.00200)	(0.00299)	(0.00104)
$GVAgrowth_{t-1}$	0.341	0.0908*	0.109	0.108	0.0859	0.0839*
	(0.207)	(0.0397)	(0.172)	(0.0791)	(0.140)	(0.0367)
$Surplus_{t-1}$	-0.109	-0.0178	-0.461***	-0.0811*	-0.113	0.0112
	(0.101)	(0.0206)	(0.0889)	(0.0412)	(0.103)	(0.0287)
$Openness_{t-1}$	0.0743**	0.0241***	0.0126	0.0178	0.0839*	0.0198*
	(0.0280)	(0.00538)	(0.0235)	(0.0109)	(0.0328)	(0.00859)
$Netexport_{t-1}$	-0.574***	-0.109***	0.192	0.0394	-0.536***	-0.0474
	(0.163)	(0.0315)	(0.129)	(0.0591)	(0.163)	(0.0429)
$Capital_{t-1}$	-0.00319	-0.00187	-0.0920	-0.0572*	-0.00337	0.000180
	(0.00467)	(0.00164)	(0.0495)	(0.0231)	(0.00465)	(0.00185)
$Sector$	Yes	Yes	Yes	Yes	Yes	Yes
$Year$	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	64	64	176	176

* p<0.10 ** p<0.05 *** p<0.01; Standard errors in parentheses; Constants are not reported

All the variables are logged except ratios; All the control variables are lagged for one period

Column (1) to (2) for whole sample

Column (3) to (4) for industrial sample, and column (5) to (6) for non-industrial sample

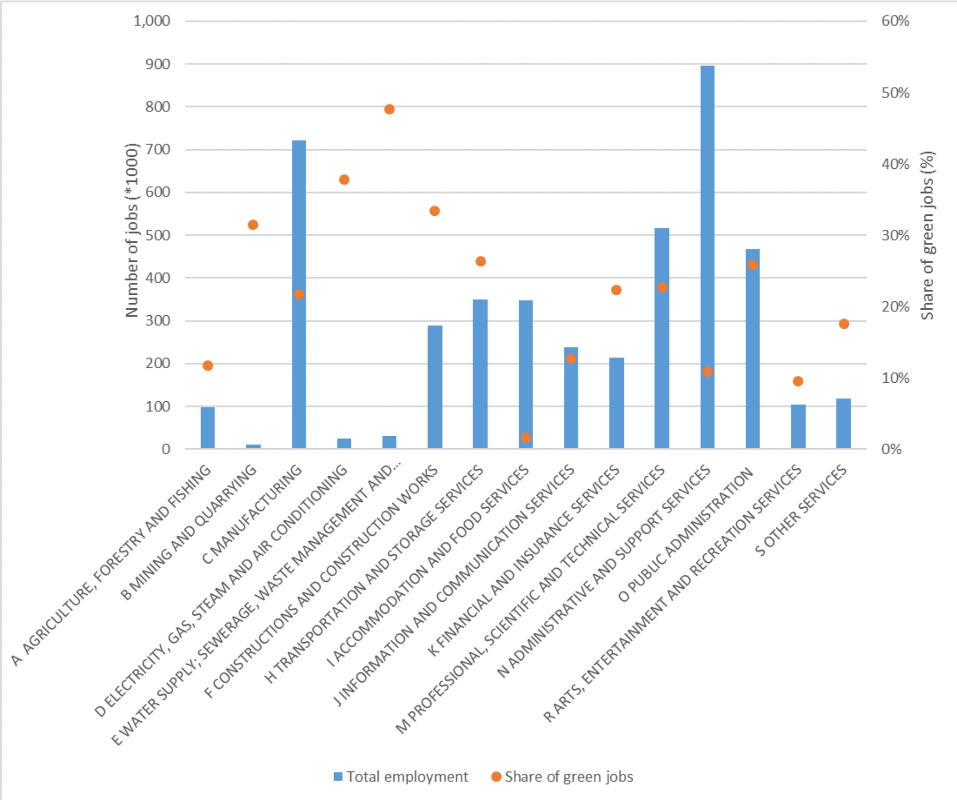


Figure 3.1: Distribution of total employment and the share of green jobs by sector in 2016

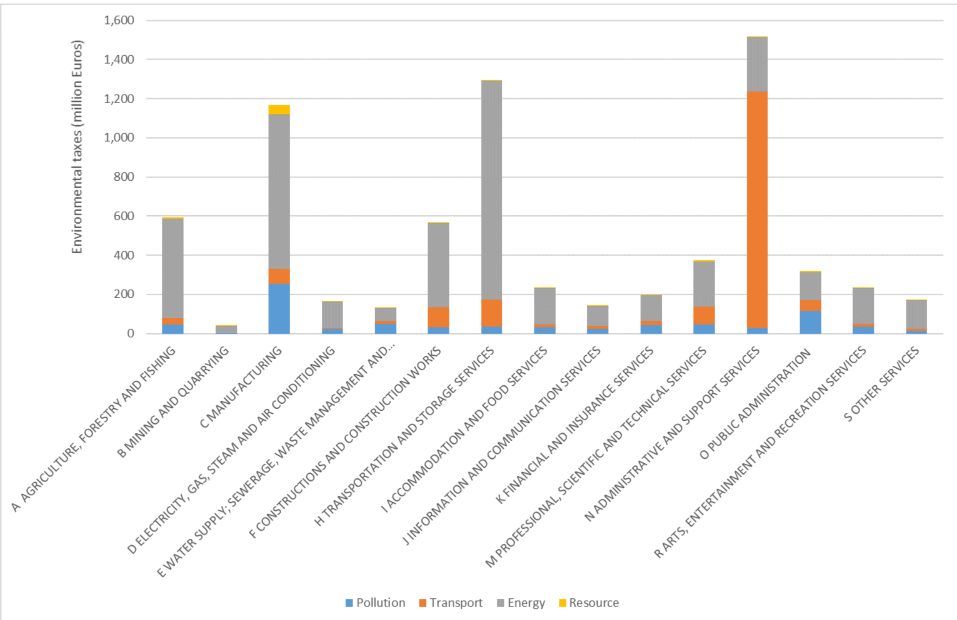


Figure 3.2: Distribution of environmental tax by sector in 2016

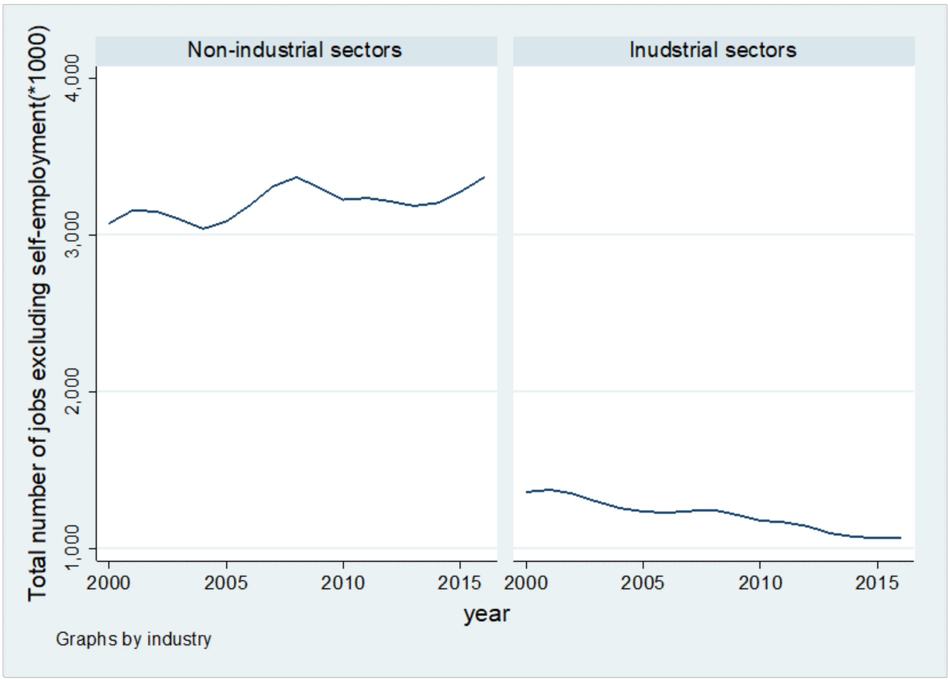


Figure 3.3: Total employment by sector (2000 - 2016)

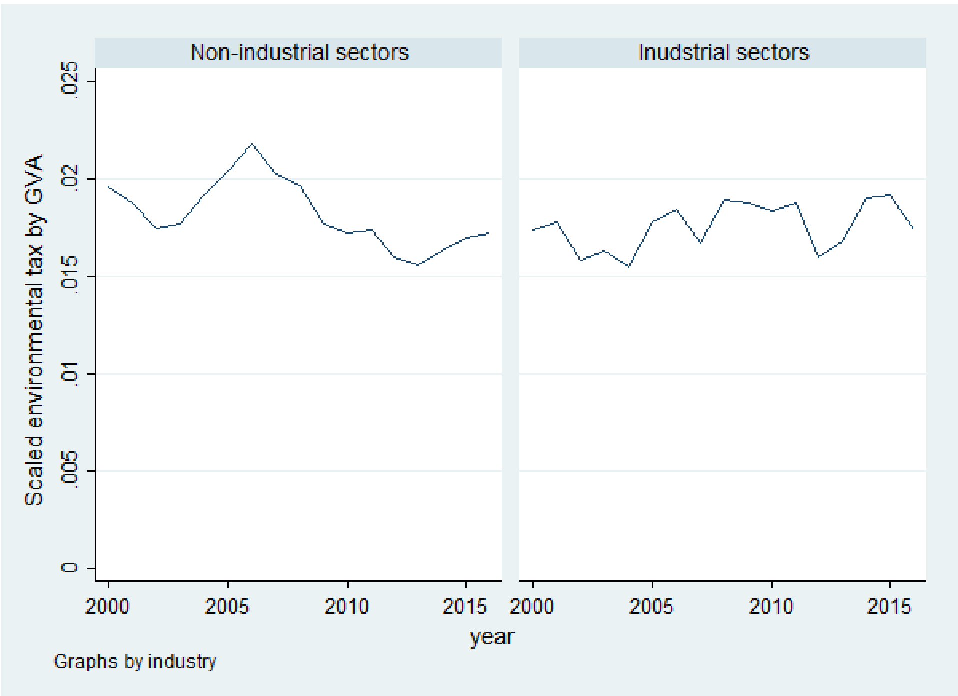


Figure 3.4: Total environmental tax scaled by GVA (2000 - 2016)

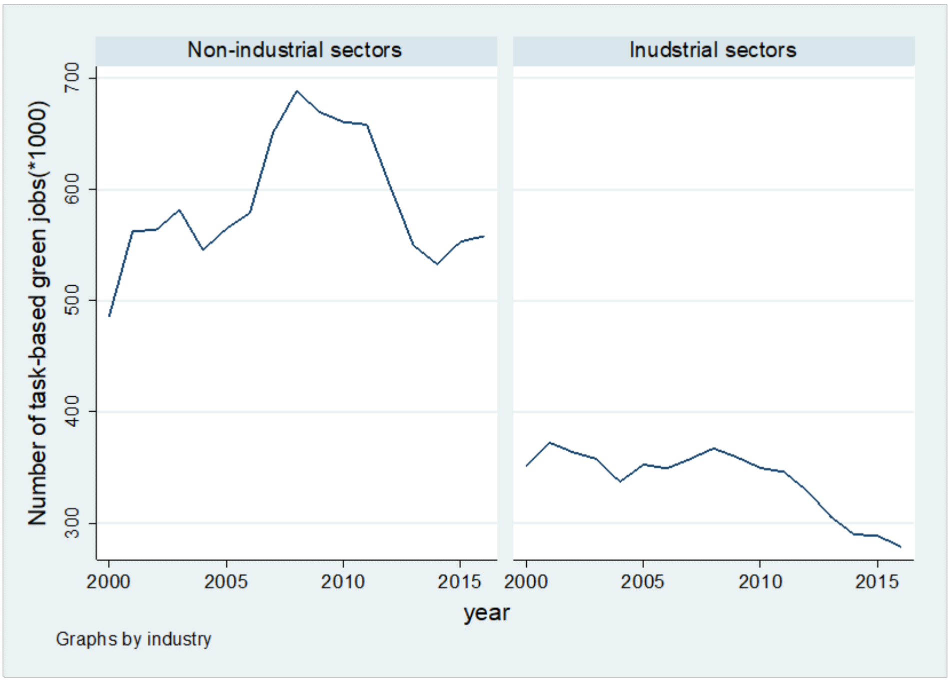


Figure 3.5: Green employment (2000 - 2016)

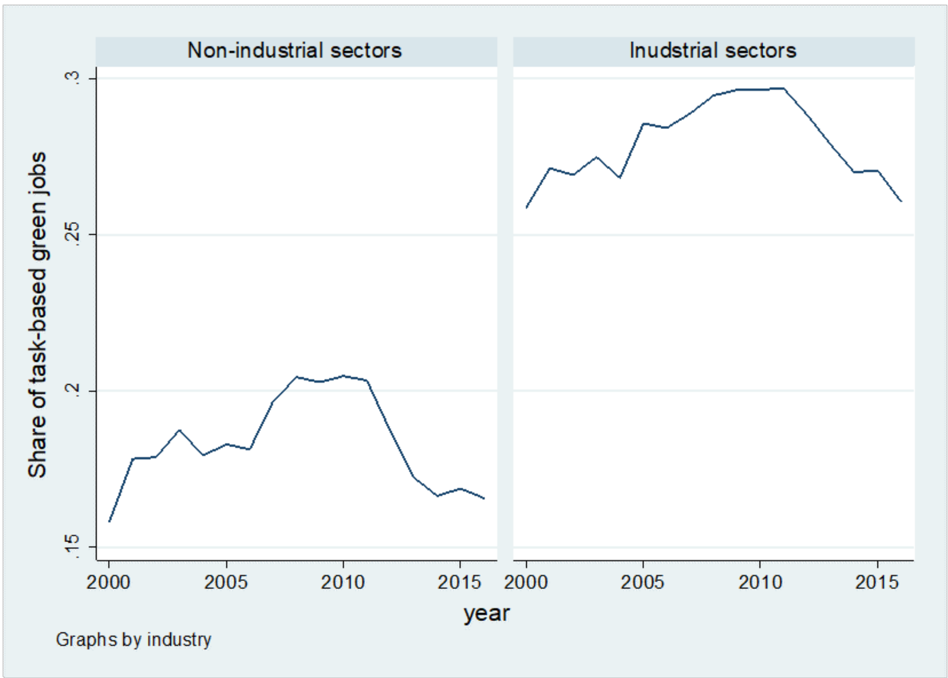


Figure 3.6: The share of green employment (2000 - 2016)

Chapter Four

Eco-innovation and employment: A firm level analysis

4.1 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. 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 chapter 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 chapter 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 (n.d. *b*) 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 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 n.d.). 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 (2012*b*) 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

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

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 chapter is organized as follows: Section 2 explains how we 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.

4.2 Literature review and definitions

4.2.1 Measuring green jobs in the Dutch labour market

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 chapter, 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).

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

[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 chapter we use the O*NET 23.0 Database released in August 2018.

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, using the task-based definition, we are able to identify green jobs that involve at least one green task on their daily basis. Finally, each green occupation is given a corresponding O*NET-SOC code so we can use the US classification for the Netherlands.[3]

[3]SOC stands for the Standard Occupational Classification. One of the challenges of this chapter 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 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 chapter 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.

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 (Bowen et al. 2018, Peters 2014, 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.

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.[4] To provide a little background, of the 1,100 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.

[4]Details of matching O*NET-SOC with ISCO and a full list of green occupations and associated greenness scores (different definitions) can be found in Appendix to Chapter Four. 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 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 C.2 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).

A number of studies have used the O*NET task-based definition of green occupations to characterize green jobs. 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. More recently, 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). Finally, 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 education and also have a wage premium over those working in non-green occupations. This largely descriptive evidence underpins the popular belief of policy-makers that green job creation is something to be actively encouraged.

4.2.2 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 chapter, 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 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., Dachs & Peters 2014, Evangelista & Savona 2003, Harrison et al. 2014, Lachenmaier & Rottmann 2011, Van Reenen 1997), 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 et al. (2004), Rennings & Zwick (2002) 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 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. (2018) use the O*NET green skills classification to examine the role of environmental regulation on the demand for green skills in 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. More recently, 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.

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 n.d.). 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.

4.3 Data

4.3.1 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.[5]

More specifically, in one of the CIS2008 modules, firms are asked whether they undertook an innovation that had environmental benefits. We therefore 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 chapter 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 4.1 presents a schematic representation of how we map the relationships between different innovation categories.

[Figure 4.1 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 chapter, 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

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

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 (Elliott et al. 2019, Isogawa et al. 2012, Lachenmaier & Rottmann 2011). 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.[6]

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.[7] Matching the green occupation list with the LFS2010 means that all of the occupations listed

[6]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).

[7]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.

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 chapter 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 4.2 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.[8] Figure 4.3 plots the skill intensity (average share of high skilled workers) of each occupation against the task-based greenness index. The circles in Figure 4.3 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.[9]

[8]Similar figures for broad and core green jobs can be found in Appendix to Chapter Four. 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.

[9]Equivalent figures for broad and core green jobs can be found in Appendix to Chapter Four.

[Figure 4.2 about here]

[Figure 4.3 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.[10] 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.[11] 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

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

[11] 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.

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 n.d.*e*). Of the rest, only 10.61% of gross value added came from the manufacturing sector (WB n.d.*d*), 19.90% from industry including construction (WB n.d.*c*) and 1.72% from Agriculture, forestry, and fishing (WB n.d.*a*).[12]

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 n.d.*b*), and an increase in unemployment which rose from 3% in 2008 to 4.5% in 2010 (OECD n.d.*a*). 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. However the effects of the crisis are unknown, therefore needs to be borne in mind when interpreting our results.

4.3.2 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., Harrison et al. 2014, Horbach & Rennings 2013, Licht & Peters 2013); (2) the log of the number of employees (e.g., Kunapatarawong & Martínez-Ros 2016, Lachenmaier & Rottmann 2011); or (3) a discrete variable to capture employment dynamics (e.g., Horbach & Rennings 2013, Rennings et al. 2004). As we are

[12]See Appendix to Chapter Four for details of the distribution of firms by size and sector.

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.

4.3.3 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 innovation 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 4.4 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 4.4 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 4.1 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 4.1 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 4.1 about here]

4.3.4 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 C.4 and C.5 of Appendix to Chapter Four provide a description of our dependent and independent variables and a correlation matrix of our key variables of interest, respectively.

4.4 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:

$$\Omega = \begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{0u} \\ \sigma_{1u} & \sigma_1^2 & . \\ \sigma_{0u} & . & \sigma_0^2 \end{bmatrix} \tag{4.1}$$

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).[13] The log likelihood function for regimes 0 and 1, given the assumption about the distribution of the error terms, is as follows:

$$\begin{aligned} \ln L = \sum_i (I_i \omega_i [\ln F(\eta_{1i}) + \ln f(\epsilon_{1i}/\sigma_1)/\sigma_1] + \\ (1 - I_i)\omega_i [\ln 1 - F(\eta_{0i}) + \ln f(\epsilon_{0i}/\sigma_0)/\sigma_0]) \end{aligned} \tag{4.2}$$

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 [14]

$$\eta_{ji} = \frac{(\alpha Z_i + \rho_j \epsilon_{ji}/\sigma_j)}{\sqrt{1 - \rho_j^2}} \tag{4.3}$$

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.

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

$$E(Employment_{1i} \mid X_{1i}) = \beta_1 X_{1i} \tag{4.4}$$

$$E(Employment_{0i} \mid X_{0i}) = \beta_2 X_{0i} \tag{4.5}$$

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

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

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:

$$\begin{aligned} E(Employment_{1i} \mid innovator = 1) &= E(Employment_{1i} \mid \alpha Z_i + u_i > 0) \\ &= E(Employment_{1i} \mid u_i > -\alpha Z_i) \\ &= \beta_1 X_{1i} + E(\epsilon_{1i} \mid u_i < \alpha Z_i) \\ &= \beta_1 X_{1i} + \sigma_{1u}[\frac{f(\alpha Z_i)}{F(\alpha Z_i)}] \end{aligned} \tag{4.6}$$

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

$$\begin{aligned} E(Employment_{0i} \mid innovator = 0) &= E(Employment_{0i} \mid \alpha Z_i + u_i \leq 0) \\ &= E(Employment_{0i} \mid u_i \leq -\alpha Z_i) \\ &= \beta_2 X_{0i} + E(\epsilon_{0i} \mid u_i \leq -\alpha Z_i) \\ &= \beta_2 X_{0i} - \sigma_{0u}[\frac{f(\alpha Z_i)}{1 - F(\alpha Z_i)}] \end{aligned} \tag{4.7}$$

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:

$$\frac{\partial E(Employment_{1i} \mid Innovator = 1)}{\partial x_{1i}} = \beta_{1i} - [\alpha_i \sigma_{1u} (\frac{f(\alpha Z_i)}{F(\alpha Z_i)})(\alpha Z_i + \frac{f(\alpha Z_i)}{F(\alpha Z_i)})] \qquad (4.8)$$

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.

4.5 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 4.2 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 to Chapter Four.

[Table 4.2 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.[15]

[15]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

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 4.2), 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.[16] Test statistics and information on each test are provided in Appendix to Chapter Four.

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 4.3 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), differ-

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.

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

entiate 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 4.3 (although only at the 10% significance level). We find no effect on employment (green or otherwise) for eco-innovation that is undertaken voluntarily.

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 4.3 about here]

4.6 Sensitivity checks

As part of our analysis we perform a series of sensitivity checks. First, Table 4.4 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.[17]

[Table 4.4 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 in Tables 4.5 and 4.6, respectively. Table 4.5 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 4.2) 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

[17]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.

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 4.5 about here]

Table 4.6 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 4.6 about here]

4.7 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 chapter 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 greenness 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 4.1: 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 4.2: Eco-innovation and employment: Baseline results (Task-based measurement)

	(1)	(2)	(3)	(4)	(5)	(6)
	Total employment	Green employment	Share of green jobs	Total employment	Green employment	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. Constants are not reported. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

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.

Table 4.3: 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. Constants are not reported. $^{***}p < 0.01;^{**} p < 0.05;^{*} p < 0.1$.

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 Table4.2.

Table 4.4: Eco-innovation and employment: Heterogeneity tests (Task-based measurement)

	Manufacturing			Non-manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total employment	Green employment	Share of green jobs	Total employment	Green employment	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. Constants are not reported. $^{***}p < 0.01;^{**} p < 0.05;^{*} p < 0.1$.

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 Table4.2.

Table 4.5: 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. Constants are not reported. $^{***}p < 0.01;^{**} p < 0.05;^{*} p < 0.1$.

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 Table4.2, and also for space reason.

Other controls are included but not reported as they are similar to Table4.2.

Table 4.6: 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. Constants are not reported. $^{***}p < 0.01;^{**}p < 0.05;^{*}p < 0.1$.

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 Table4.2, and also for space reason.

Other controls are included but not reported as they are similar to Table4.2.

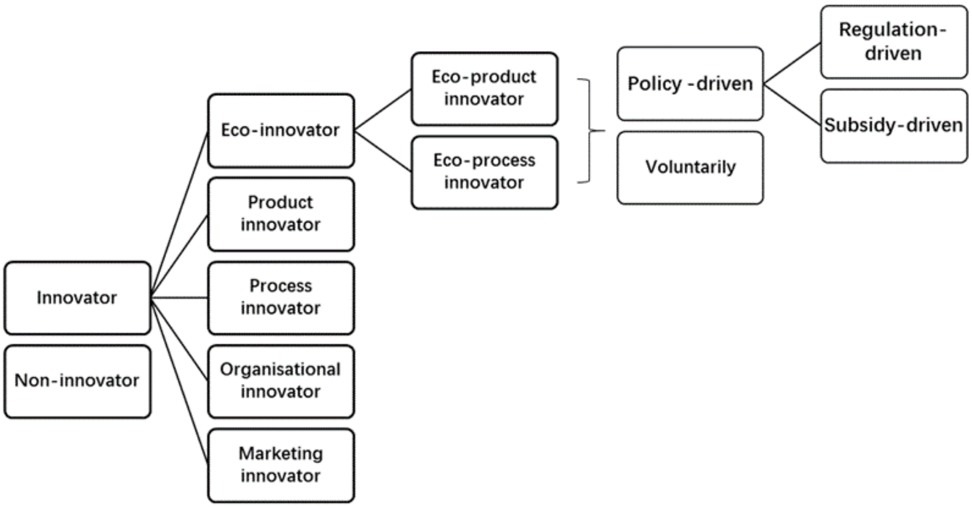


Figure 4.1: Relationship between different innovation categories

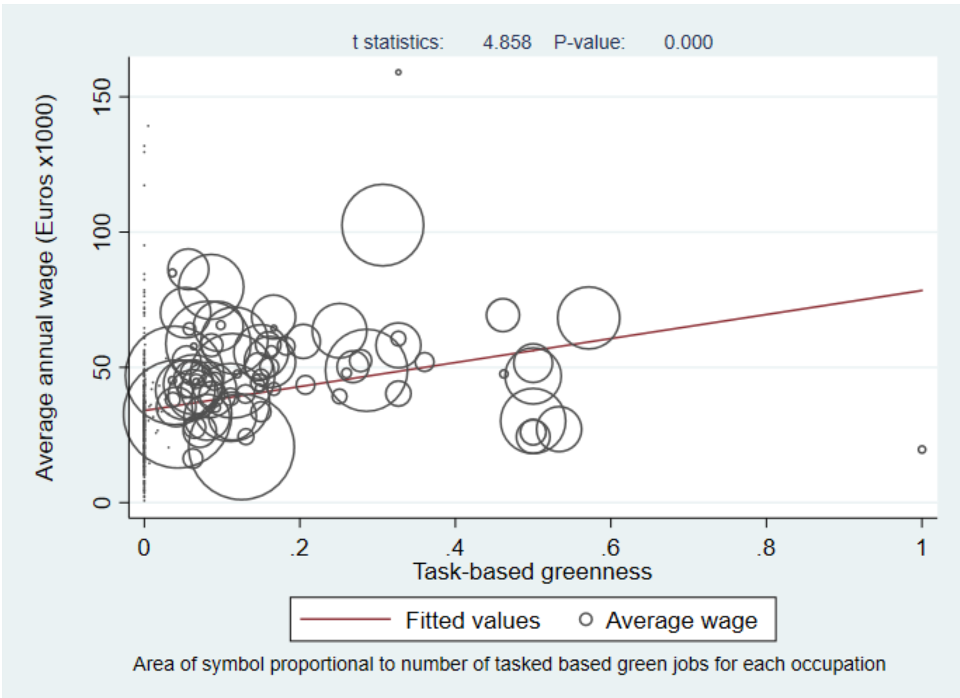


Figure 4.2: Wage and greenness for occupations

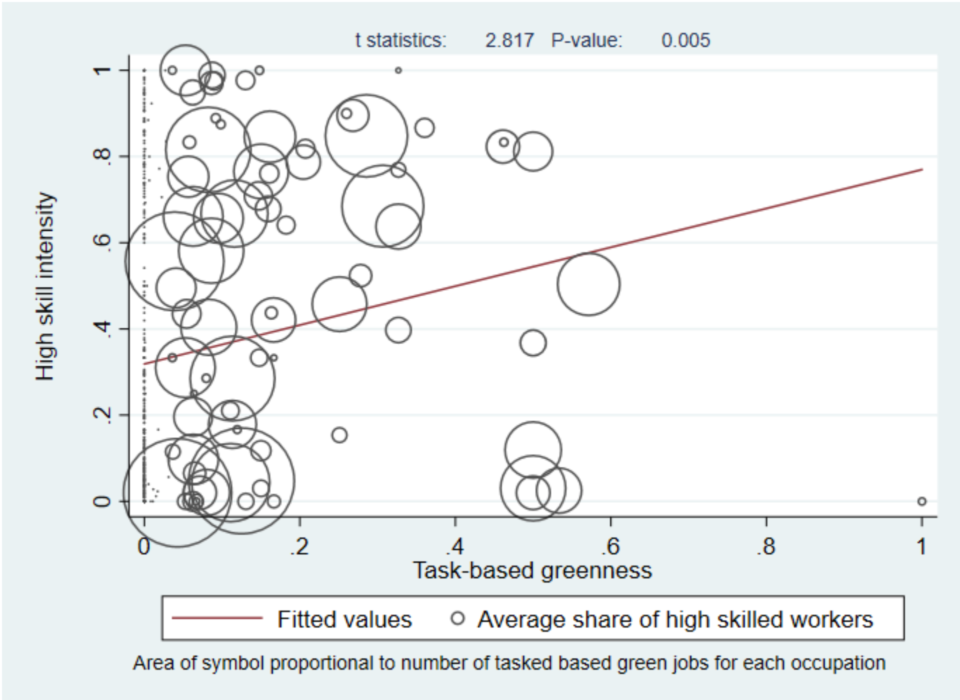


Figure 4.3: High skill intensity and greenness for occupations

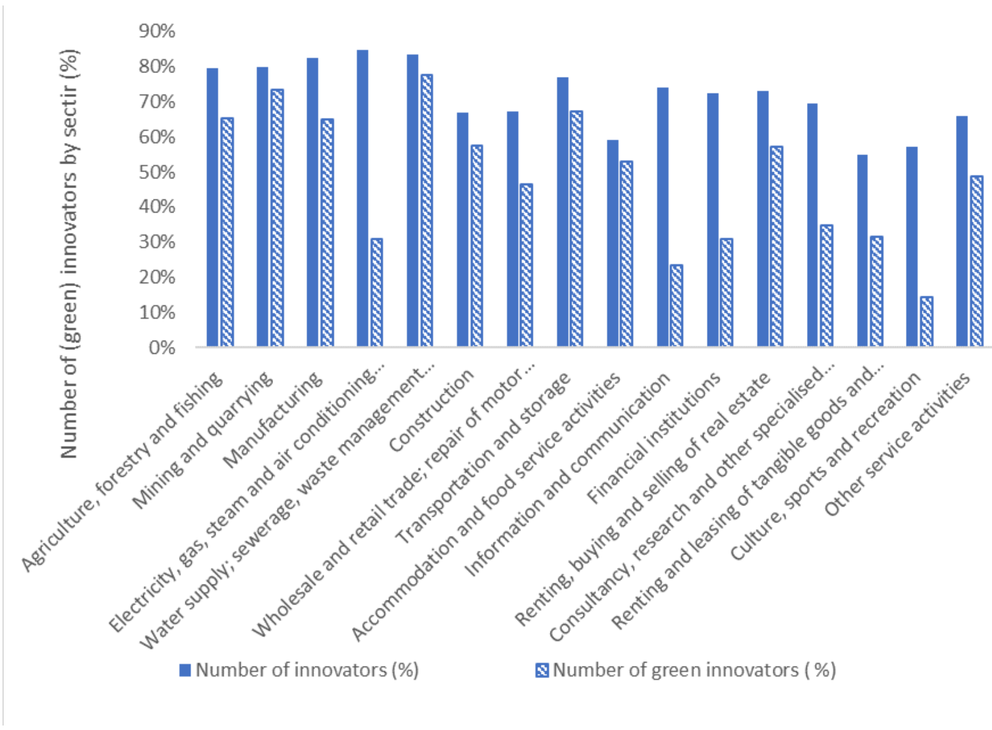


Figure 4.4: Number of innovators and eco-innovators by sector

Chapter Five

Characterising Green jobs: An individual level analysis

5.1 Introduction

In recent years, the economic policies of many nations have started to focus much more on the 'green economy' and 'green jobs', in an attempt to meet both environmental and economic goals (Deschenes 2013). In a post-COVID19 world, many nations especially are attempting to minimise the economic damage, boost economic activity, and create more green jobs by promoting a green recovery policy packages. According to a preliminary estimate from the OECD (2020*c*), USD 312 billion of public resources have been committed to invest in green recoveries in OECD member countries. For example, the UK Prime Minister Boris Johnson has set out a ten-point strategy for a green industrial revolution that will mobilise £12 billion government funds which with the aim of creating and supporting up to 250,000 high skilled British green jobs.

Given the increase attention of policymakers on the green economy and green jobs, it is important to understand what is meant by a green economy and a green job. The current literature still have no clear definition of green jobs although there are common themes. Apart from the environmental aspects, the term 'decent' also appears in most definitions. As stated by Sweeney & Kubit (2008), green job are decent jobs with decent wages, a secure working environment, reasonable career prospects, and worker rights. A job that is unfair, deleterious, fails to pay a living wage, and thus lead workers to a life of poverty can hardly be considered as green. However, the socio-economic characteristics of green workers who hold green jobs, whether they are high skilled and high paid, and how they are distributed among occupations in the labour market are not well particularly understood and rarely studied.

More recent studies have started to use the O*NET database to examine the characteristics and distribution of green jobs (Bowen et al. 2018, Consoli et al. 2016, Peters 2014). O*NET is a free online database that provides detailed occupational information on the tasks and skills associated with any given jobs. Green occupations in the O*NET database are defined as those occupations that are affected most by a greening economy, either through increasing demand, changing skills requirements or those that are newly created. Those occupations are identified by 8-digit O*NET-SOC codes. A list of green tasks each with a task code associated with a green occupation is also included in the database. The unique structure of the O*NET database allows scholars to understand green occupations from a task-based approach, and apply it to countries other than US (Hillage & Cross 2015).

The existing literature that uses the O*NET green jobs classification have addressed a number of different questions. For example, effect of environmental policies on green job growth/green skills demand (Vona et al. 2019, 2018), the role of regional diversification on green jobs growth (Barbieri & Consoli 2019), and the local green job multiplier (Vona et al. 2019). These studies focus on US labour markets combining green occupation data from O*NET to regional-occupation data, and industry-occupation data. There are a small amount of studies have examined the skill distance between green jobs and non-green jobs (Bowen et al. 2018), with special focus on jobs that have the potential to transition to a green job (Bowen & Kuralbayeva 2015, Rutzer 2020).

Another strand of the literature, although still limited, focuses on the characteristics of green jobs based on the O*NET definition. Peters (2014) is the first paper to provide some socio-economic characteristics of jobs that intensively use green tasks from O*NET, and show that green intensive jobs are male dominated, are high quality that pay a higher average wage. The rest of literature tries to characterise green jobs based on job requirements or job descriptors from O*NET (e.g. Consoli et al. (2016), Vona et al. (2019)). For instance, of Consoli et al. (2016) use occupational specific descriptors such as required years of education, required years of training and required years of experience etc. from O*NET to analyse the skill content of green jobs. They show that green jobs involve higher levels of cognitive and interpersonal skills and require more education, working experience, and on-the-job training relative to non-green jobs (Consoli et al. 2016).

The existing literature that uses the O*NET definition of green jobs use occupational specific descriptors or requirements to characterise green jobs. The green occupation information from O*NET is then linked to regional-occupation data, or industry-occupation data but almost always has a focus on the US. However, the are demographic and socio-economic characteristics of those green workers and how they are distributed among occupational groups are not well particularly known, especially for countries other than the US. Therefore, in this chapter, we fill this gap by con-cording O*NET-SOC green occupations to the more internationally used ISCO job classification, and link the green occupation list to individual-level data to investigate the characteristics of green workers in the Netherlands. This enables us to document who are the green workers, how they are distributed among occupational groups, and whether these jobs really are decent jobs with higher skill requirements and higher wages.

Furthermore, we also provide gendered perspective by calculating wage by gender in green jobs to investigate whether there exist an unfair treatment towards women in terms of occupation segregation and earnings in green employment. As ILO (2012*b*) states that women and men should enjoy equal access to skills and employment opportunities in a greening economy, to understand how male workers differ from female workers that are employed in a green job in terms of occupation segregation, and hence how the possible differences between male/female green worker occupational distribution affect the potential male/female green wage differential is of great importance. The results have potentially important policy implications that clarifies whether the policy emphasis should be focused on the equal pay within green occupations, or should be focused on equal access for male/female into occupations in order to ensure equality between male/female in a greening economy.

To briefly summarise our results, our findings are in line with the existing literature that use the O*NET definition of green job showing that green jobs are male dominated, are higher skilled, and are higher paid. What is more, we find:

1. The people working in green jobs, *ceteris paribus*, are more likely to be married males, higher skilled, non-foreign born, and less likely to be female, especially unlikely to be married females and female with children.
2. Despite the disparity in the representatives of female workers in green jobs, female green workers, *ceteris paribus*, are more likely to be found in 'Managers' and 'Professionals'; and male green workers are more likely to be observed in 'Managers', 'Craft and related

traded workers' and 'Plant and machine operators and assemblers'. [1]

3. Green workers are found earn higher wages than non-green workers on average, and this wage gap is expanding over time. Within green jobs, female green workers, *ceteris paribus*, are generally paid less than male green workers. In our further wage decomposition results that consider the occupation distribution as endogenously determined, we show that the gender wage difference within occupation groups are mostly justified by characteristics differences and the inter-occupational distribution difference decreases the gender wage gap, which dominates the explanation of the overall wage differential between male/female green workers.

The reminder of the chapter is organized as follows: Section 2 reviews the existing literature on green jobs mainly focus on papers using the O*NET definition. Section 3 presents the data and examines the characteristics and distribution of green workers. Section 4 decompose the wages in green jobs by gender. The final section concludes.

5.2 Literature Review

While there is a growing demand for both conceptual guidelines and statistical data on measurement of green jobs, a systematic, clear and precise definition of what compose a green job is far from consistent. Examining the diverse definitions and expected goals of green jobs, we find the primary common theme of existing definitions is preserving and restoring the environment (e.g. Sweeney & Kubit (2008)). [2] Green jobs are also expected

[1]Note, both are relative to the default 'Elementary occupation'.

[2]For instance, according to Sweeney & Kubit (2008), green jobs are defined as "any decent job that contributes to preserving or restoring the quality of the environment in any economic sector such as agriculture, industry, services, and administration." Other definitions of green jobs can be found in Bowen (2012), Bowen & Kuralbayeva (2015), Peters et al. (2011)

to be decent jobs that can achieve both social and economic goals (Peters et al. 2011). For instance, the 'Green Job Initiative' promoted by ILO/UNEP/IOE/ITUC [3], argues that a transition with green jobs will provide a great opportunity to tackle the current poverty and social inequality, and make significant contribution to inclusive growth and to decent work for all.

Despite the various definitions of green jobs, there are three main measures of green jobs that stand out in the existing literature. One is mainly used in Europe and the other two are developed by the US Department of Labour. The European countries consider green jobs to be those in Environmental Goods and Services Sectors (EGSS) (e.g. CBS (2015)). This is also known as the Green Industry Approach. This approach normally combines 'top down' and 'bottom up' approaches that use a list of industry classifications from the top and survey data on employment and firms at the industry level from the bottom. The shortcomings of the Green industry approach is that it tend to over-estimate green jobs in green industries and neglects potential green jobs in non-green industries.

The other two ongoing green job measures are developed in the support of the US Department of Labour. This first green jobs initiative is conducted by US Bureau of Labour Statistics (BLS). The BLS incorporates two strategies to measure green jobs: (1) Green Product Approach that identifies green products and services, and subsequently related jobs in businesses that produce green goods and services; (2) Green Process Approach that identifies environmentally friendly production process, and hence associated jobs in businesses that involve a green production process. The BLS definition is more comprehensive than Green Industry definition, however, as these surveys are only carried out in the US, it is

[3]The International Labour Organization (ILO); The United Nations Environment Programme (UNEP); The International Organization of Employers (IOE); The International Trade Union Confederation (ITUC)

impossible to make comparisons with other countries.

The final approach, and the one used in this chapter, measures green jobs based on occupations, as well as tasks within occupations, which is developed by the US Occupational Information Network (O*NET). To understand the changing world of work as a result of the greening of an economy, the National Centre of O*NET Development preformed an extensive research and screening process to classify - so called green occupations (Deschenes 2013, Dierdorff et al. 2009). The O*NET Green Economy Programme identifies three types of green jobs in its taxonomy: (1) Green Increased Demand (ID) occupations that are occupations expected to only increase in demand because of the green economy transition; (2) Green Enhanced Skilled (ES) Occupations that are occupations that require changes in skills and work content because of green economy and may or may not involve a change in demand; and (3) Green New & Emerging (NE) occupations that are new and emerging because of a greening economy. Green ID occupations are generally considered as indirect green jobs (Bowen et al. 2018, Vona et al. 2018) as they do not include any green tasks within the job content. In the following part, we will focus on existing studies that use the green job definition from O*NET.

Peters (2014) was the first to examine green occupation taken from O*NET database 16.0 based on a task-based approach. Using Hierarchical agglomerative cluster analysis, Peters (2014) shows that although green tasks are found in 176 out of nearly 1000 occupations, only 70 of theses green occupations can be considered as green intensive, and the rest can only be described as ‘marginally’ green. By linking O*NET occupational data with industry and employment data from the BLS and the US Census Bureau, Peters (2014) also provides some demographic and socio-economic characteristics evidence for green jobs. He shows that green jobs that intensively use green tasks are high skilled jobs, i.e. jobs are full time, pay higher than average wages, and have health insurance. He also find the majority of green jobs are dominated by male workers, but they are ethnically and racially diverse (Peters 2014).

Consoli et al. (2016) follow Peters (2014) and use O*NET 17.0 to compare the skill content of green jobs with non-green jobs within similar 3-digit SOC classification by regressing a set of skill measures of occupations on a Green ES dummy and Green NE dummy (Dummies take value of 1 if occupations are identified as Green ES occupations and Green NE occupations). By using occupational descriptors such as required level of education, training and work experience, they show green jobs exhibit higher levels of non-routine analytical skills that involve high level of abstract, cognitive and interpersonal skills, and green jobs generally require more years of education, work experience and on-the-job training compared to non-green jobs within the same SOC classes (Consoli et al. 2016).

More recently, Vona et al. (2018) identify a set of green skills that are used intensively in green occupations based on the same Green Economy Program in O*NET database 17.0. They first construct a Greenness index by calculating the ratio between green specific tasks over the total number of tasks associated with a given green occupation. Then they identify the so called General Green Skills (GGS) that are used intensively in a given green occupation by regressing the importance score of each general skill on the Greenness index within 3-digit SOC class. Basically, a positive and significant coefficient on the Greenness index indicates that those skills are used more intensively in greener occupations. Then, by grouping 16 GGS into four major groups, namely 'Engineering and Technical', 'Science', 'Operation Management' and 'Monitoring' using Principal Component Analysis, they compare the skill differences between green jobs and brown jobs (i.e. jobs are found in pollution intensive industries), and show the skill gap between green jobs and brown jobs are generally small within the same group.

In addition, Vona et al. (2018) construct a GGS index at the regional level by linking the GGS of each occupation with regional-occupation data from the BLS Occupational Employment Statistics (BLS-OES henceforth), and assess the effect of environmental regulations on both overall employment and green skills demand for US metropolitan and non-metropolitan areas over the period 2006 -2014. Their results suggest there is no overall employment effect of environmental regulation, but there is a statistically significant positive effect of environmental regulations on green skill demand, especially for technical and engineering green skills.

In an extension of their earlier work, Vona et al. (2019) examine the nature, drivers and effect of green employment in the US labour market for the period 2006 -2014. Instead of focusing on green skills, they concentrate on analysing green jobs by using a binary category based on a task-based Greenness index from the O*NET Green Economy Program. To do so, they first construct Greenness index through an analysis of specific green tasks over the number of total tasks associated with a green occupation weighted by importance scores. Then they construct the share of green employment at the regional and industry level by linking green occupation with occupational-employment data broken down by metropolitan and non-metropolitan areas, and by industry from BLS-OES database. Their stylised facts show around 3% workers in the US labour market are found to be green employment over the period 2006 to 2014. They also show green jobs grow faster than non-green jobs except during the recession period, and green jobs are more geographically concentrated than comparable non-green jobs. What is more, they also find green jobs are high quality jobs with higher wages, where they show green jobs pay an average 4% wage more relative to similar non-green jobs.

Furthermore, based the green job measure mentioned above, Vona et al. (2019) empirically assess the drivers of green employment growth at regional level with special attention to the effect of various environmental policies. Their estimation results show that environmental regulation is less effective than direct green subsides in stimulating local green employment growth. They further assess the local green job multiplier, i.e. they use the green investment as a industrial policy shock to assess the effect of one additional green jobs on the local employment in the non-tradable sectors. They find one additional green jobs could generate 4.2 new jobs in the non-tradable non-green sector, which implicitly indicates that the green subsides are a strong policy tool to support the local labour market multiplier given its strong correlation with green job creation (Vona et al. 2019).

Barbieri & Consoli (2019) follow the same method used by Vona et al. (2019) and calculate the spatial green employment share and link it with occupational-employment by metropolitan areas from the BLS-OES to analyse the effect of regional diversification on green employment growth for US metropolitan areas over the same period 2006 to 2014. Their results show that regional diversification is generally found positively to be correlated with green employment growth. Similarly, in a more recent study, Elliott et al. (2021) examine the relationship between eco-innovation and green employment at firm level following the same task approach of Vona et al. (2019). By converting O*NET-SOC to ISCO, they link green occupations with individual level data from Dutch Labour Force Survey and show eco-innovation activities are positively correlated with green employment, and the share of green jobs at firm level. In their further results, they find similar results as in Vona et al. (2019) that subsidy-driven eco-innovation is more effective than regulation-driven eco-innovation in stimulating green jobs.

Following Vona et al. (2019, 2018), who mainly focus on direct green occupations, namely Green ES and Green ID, Bowen et al. (2018) first estimate that 19.4% of the US labour force can be considered to be the green workers in the US using the broad definition of green jobs that also includes indirectly Green ID occupations. Bowen et al. (2018) expand the green occupation categories in O*NET into five categories by breaking non-green jobs into 'Green Rival' occupations (GR) and non-green jobs, where GR are occupations that have at least one similar skill to green occupations, and are considered as occupations with green potential. They show that there are a few differences between non-green jobs and their green counterparts in terms of specific skill-aspects, but it is easier for existing GR occupations to transition to indirect Green ID jobs rather than direct green jobs as GR occupations are found to be more similar to indirect Green ID occupations in terms of required skills and education.

More recently, Rutzer (2020) refined this approach by applying several machine learning algorithms to estimate the green potential of employment in the US labour market. They first follow Vona et al. (2018) to identify green skills that are intensively used in green occupations, and then they train four machine learning algorithms to predict the green potential of occupations in the US labour market. They show that high green potential occupations are those occupations that involve a large number of technical skills. If one occupation with a green potential index above 0.6, they consider it having a large green potential. In their further results, 4.8% of US work force are found having large green potential with a green potential index above 0.6.

To summarize, the existing literature that uses the O*NET classification of green jobs have examined the drivers of green employment growth/ green skill demand with special focus on environmental polices and regional diversification while a few studies have explored the green potential of non-green occupations. Existing studies that characterise green occupations in O*NET mainly use occupational descriptors and requirements from O*NET, and then link green occupation data from O*NET to regional-occupation data, or industry-occupation data in the US. To the best of our knowledge, no existing literature has examined the socio-economic characteristics of green jobs by linking green occupation data from O*NET to individual-occupation dataset in a country other than US.

5.3 Some Facts about Green Jobs

5.3.1 Data and Sample

To examine who are the green workers in a country other than US, we first need to construct a list of green occupations based on the ISCO job classification scheme. Same as what we did in Chapter Two, we follow Vona et al. (2019) and measure green jobs based on tasked-based Greenness index. We construct the greenness of each occupation by calculating the green tasks intensity within an occupation weighted by importance scores, and then convert O*NET-SOC to ISCO.

One of the objectives of this chapter is to examine the socio-economic characteristics of those that work in green jobs, and how they distribute across occupations, with special attention to the differences between male/female green workers. To do so, we make use of two confidential micro datasets from the Netherlands. The first dataset is Dutch Labour Force Survey (LFS). The Dutch LFS is a yearly dataset that contains individual information in the labour market, including detailed socio-economic characteristics, household characteristics, and most importantly the current position of a worker in the labour market which can be identified by detailed 4-digit ISCO job classification codes. In the Dutch LFS, there is a personal identification number called 'Rinpersoon' for each observation that allows us to match the LFS with other datasets. In this chapter, we use this id to match it with the Social Statistics Database (SSD) that is composed of Tax Register Data (TRD) and Dutch municipality registrations (GBA). The TRD is a very informative dataset that includes more than 10 million jobs in each year. By matching the LFS with TRD, we can identify workers who are currently paying tax. By matching the LFS with the GBA, we create an employer-employee dataset that allows us to identify firms that employees are currently working at, and their firm size and average wage at the firm level.

Workers in the data are aged between 15 to 65. If a worker has multiple jobs, we keep the job with the longest tenure. As the Dutch LFS is a rotating panel with five waves, we keep the most recent information of an individual, and replicate personal characteristics from the previous waves if the most recent information of an individual is missing. Each worker is only counted once in each year. Given the LFS is not a longitudinal dataset, we append the cleaned LFS with TRD and GBA for the years 2001 to 2016. [4] The top 1% and bottom 1% of hourly wage rate are dropped out of the sample. By combing the pooled datasets with the ISCO green occupations list, we then identify green workers with a dummy in the final sample.

Our final sample covers 854,237 workers for the period 2001 to 2016, of which 145,674

[4]The reason we choose the start year in 2001 is because that the variable standing for proportion of the day worked in a year (deeltijdfactorbaanid) is missing before 2001 while it is important for us to generate the hourly wage variable. The Dutch TRD is not available after 2016, therefore, our final pooled datasets covers the period 2001 - 2016.

are green workers and account for 17.05% of the sample. Table 5.1 provides summary statistics for characteristics of green workers and non-green workers also differentiated by gender. Among 145,674 green workers in the sample, only 19.95% are female, which indicates green workers are male dominated. Green workers are more likely to be in high skilled jobs compared to non-green workers. This is especially true for female green workers, where we show 58.23% of female green workers are high skilled while only 28.35% of female non-green workers are high skilled jobs. Furthermore, workers employed in green occupations tend to be native workers, married (mainly male green workers) with children under 12, older, and have longer tenure compared to non-green workers. Furthermore, there is not much difference between green workers and non-green workers in terms of household size. Finally, in terms of firms' characteristics, we show firms who hire green workers are generally smaller, but pay higher average wages.

[Table 5.1 about here]

Table 5.2 presents the occupational distribution of green workers and non-green workers also broken down by gender. These show that green workers are absent in occupational groups 'Clerical support workers', 'Skilled agricultural, forestry and fishery workers' and 'Armed forces occupations'. Green workers are more likely to be found in high skilled occupational groups such as 'Managers', 'Professional' and 'Technicians and associate professionals'. Notably, both male green workers and female green workers are more likely to be found in 'Managers' and 'Technicians and associate professionals', and female green workers are especially more likely to be employed in 'Professional' occupations. For the female dominant occupational group 'Service and sales workers', green workers are virtually absent, especially for male green workers. For male dominant occupational groups 'Craft and related traded workers' and 'Plant and machine operators and assemblers', there are more male green workers in ‘Plant and machine operators and assemblers’ while less male green workers are found in ‘Craft and related traded workers’ compared to male non-green workers. Finally, for ‘Elementary occupations’, there more male green workers than female green workers, and the differences between non-green workers are relatively small.

[Table 5.2 about here]

Table 5.3 provides the mean of hourly wage difference between green workers and non-green workers and broken down by gender. The first panel shows the mean wage differential in the whole sample and by different time periods. We find green workers pay higher average hourly wage than non-green workers, and this is true for both female green workers and male green workers in the whole sample. Breaking down into four time periods, we show average hourly wage level is increasing over time as expected. It is worth noting that the wage gap between green workers and non-green workers is expanding where the wage gap is 1.56 Euros in the early years, and it has risen to 3.57 Euros in the recent period. We also show green female workers pay slightly higher than male green workers. Though the wage differential is rather small when we break the sample into different periods. [5]

The second panel of table 5.3 shows the wage differential between green workers and non-green workers and broken down by occupational groups. For high quality occupational groups that includes ‘Managers’, ‘Professional’ and ‘Technicians and associate professionals’ occupations where hire more green workers, we find the hourly wage rate of green workers outweighs non-green workers in ‘Managers’ and ‘Professional’ occupations. For female dom-

[5] In our sample, we find male workers earn much higher annual wage than female workers, but male workers also work more days than female workers in a year. When we calculate the hourly wage rate, female workers are found to pay slightly higher hourly wage than male workers on average.

inant occupational group 'Service and sales workers', we show green workers pay less than non-green workers on average. For male dominant occupational groups 'Craft and related traded workers' and 'Plant and machine operators and assemblers', we find green workers pay higher wages in 'Plant and machine operators and assemblers' and pay less wages in 'Craft and related traded workers'. Finally, green workers are found pay less than non-green workers in 'Elementary occupations', and this is both true for female green workers and male green workers.

[Table 5.3 about here]

5.3.2 Characteristics and Distribution of green workers

In order to examine the socio-economic characteristics of green workers more closely, we apply a logit model to describe what constitutes a green worker in the Netherlands using following equation:

$$Prob(Y_i = 1) = \frac{exp(\beta X_i)}{1 + exp(\beta X_i)} \tag{5.1}$$

Where $Prob(Y_{ij} = 1)$ is the probability that individual i is observed in green occupation. X is a vector of socio-economic characteristics of individual i including age, marital status, current job tenure, gender, skill level and so on.

Table 5.4 provides the details of logit estimates on the socio-economic characteristics of green workers in the whole sample (column (1)) and in different occupational groups (column (2) - (8)) respectively. Year fixed effects, sectoral fixed effects and regional fixed effects are included.[6] Log odds ratios are reported.[7]

To give a basic idea of the magnitudes of log odds ratio, we focus on the estimates in column (1). For example, the coefficient for *Female* is -0.818, which corresponds to the log of odds ratio between the unmarried female and unmarried male workers who have no children. Taking exponential of this value gives us the odds ratio 0.441, which means holding other factors constant, female-unmarried with no children are approximately 56% less likely to be observed in green occupations compared to male-unmarried with no children.

For simplicity, the coefficients that are reported in table 5.4 are to be interpreted as the effect of a given variable upon the likelihood of being observed in green occupations.[8] As shown in column (1) of table 5.4, workers in green occupations, *ceteris paribus*, are more likely to be male, male married, high skilled, middle skilled, non-foreign born, and are less likely to be female, especially unlikely to be female married and female with children over 12. Older workers are more likely to be found in green occupations, but the likelihood is decreasing with age, which can be indicated from the opposite signs on the square term for variable *Age2*. Green workers tend to have shorter tenure on average. What is more, green workers are more likely to be found in smaller firms that pay higher wages on average. These

[6] We have 21 macro sectors and 40 COROP regions controlled in all regressions.

[7] Summary statistics of key variables and correlation matrix tables can be found in Appendix to Chapter Five table D.1 and table D.2.

[8] The log odds ratio is the logarithm of the odds, where the odds is the probability of success over the probability of failure. If the log odds ratio equals to zero, this means the corresponding odds is 1, and hence the probability of success and the probability of failure are both 50%; if the log odds ratio is greater than zero, hence the probability of success is greater than 50%, which means the probability of failure is less than 50%, and vice versa. Therefore, if the log odds ratio is positive, this means the the effect of the give variable increase the likelihood of being found in green occupation.

findings are generally consistent with the summary statistics shown above.

To see the intra-occupation differences on the socio-economic characteristics of green workers, we perform the same regression for different occupational groups based on the first digit of the ISCO in columns (2) to (8). We show that females are less likely to be employed in green occupations across all occupational types. The female married disadvantage is found in the majority of occupational groups. Surprisingly, females with children that are at a disadvantage of being hired in green occupations are mainly found in high skilled occupational groups. By contrast, being male does not have a marriage disadvantage as males who are married tend to be found in green jobs for most of the occupational groups. Besides, males whether have children or not does not matter that much in terms of whether they are working in green occupations, this is true for nearly all the occupational groups. Apart from the gender difference, other facts worth mentioning are that green workers are more likely to be high skilled jobs in most of occupational groups except in 'Managers' and 'Elementary occupations', where more green workers are middle skilled in both these two groups.

[Table 5.4 about here]

In the next stage, we apply a multinominal logit model to examine the inter-occupational distribution of green workers more accurately. More specifically, we pay attention to gender division in green jobs by including the interaction terms of gender dummies and green dummies. Thus the probability that individual i is observed in occupation j is modelled via a multinominal logit equation as follows:

$$Prob_{ij} = \frac{exp(\beta_j X_i)}{\sum_{i=1}^{J} exp(\beta_j X_i)} \tag{5.2}$$

Where $Prob_{ij}$ is the probability that individual i is observed in occupation j; X is a vector of socio-economic characteristics of individual i, which includes green dummies indicating whether individual i is a green worker or not. Other socio-economic characteristics are also included in X such as age, marital status, current job tenure, gender, skill level and so on. $j = 1, 2, ...J$.

Table 5.5 provides detailed estimates on occupational segregation of green workers based on a multinomial logit model. The interpretation of the estimated coefficients for each occupation group are to be interpreted as the effect of a given exogenous variable upon the likelihood of being observed in a given occupation relative to the default occupational category 'Elementary occupations'. Thus, as shown in table 5.5, female green workers, *ceteris paribus*, are more likely to be found in 'Managers', and 'Professional', and less likely to be found in 'Service and sales workers', 'Craft and related traded workers' and 'Plant and machine operators and assemblers' relative to the default category. In contrast, being male green workers leads, *ceteris paribus*, to a greater likelihood of being observed in 'Managers', 'Craft and related traded workers' and 'Plant and machine operators and assemblers', but a lower likelihood of being found in other occupations relative to the default category.

In terms of other key control variables, we show being female and married decreases the likelihood of being observed in other occupations relative to 'Elementary occupations'. By contrast, being male and married increases the likelihood of being found in other occupations. Being a high skilled worker leads to a larger probability to being observed in nearly all occupations compared with the default category except the 'Plant and machine operators and assemblers', which shows no statistically significant difference to being hired to the default occupational group. Furthermore, being middle skilled workers increases the probability of being employed in all occupations relative to the default category. Finally, workers who are older and have longer tenure are more likely to be found in all the other occupations relative the the default.

[Table 5.5 about here]

5.3.3 Wage equations

Human capital wage model is used to estimate the wage equations as follows:

$$ln(W_i) = \alpha_I + \beta X_i + \epsilon_i \tag{5.3}$$

Where W_i is the hourly wage rate of individual i, X_i is a vector of individual characteristics including a green dummy indicating whether individual i is a green worker or not. Other socio-economic characteristics are also included in X such as age, marital status, current job tenure, gender, skill level and so on.

Table 5.6 provides some first results of wage equations of green jobs based on our pooled sample. Column (1) and column (2) give the estimation results for the full sample. The difference between column (1) and column (2) is whether we have included occupational dummies. The other seven columns in Table 5.6 presents the estimation results for different occupational groups in order to compare the intra-occupational wage differentials.

Without controlling for occupational dummies, we show males in green jobs, *ceteris paribus*, earn 8.42% more per hour than males in non-green jobs; and 6.01% more compared to female in green jobs. We also find females in green jobs pay 2.55% more than females in non-green jobs. We find no statistically significant wage differences between male non-green and female non-green workers, which is indicated by the insignificant coefficients on the variable *Female*. With occupational dummies included, we find the wage gap between male green workers and male non-green workers become smaller (3.35%), while the wage gap between male in green jobs and female in green jobs gets larger (9.55%). Surprisingly, female green workers are found pay 5.24% less than female non-green workers after including occupational dummies. This indicates that the average wage premium of female green workers compare to female non-green workers are mainly captured by occupational segregation. Finally, we show female non-green workers earn 0.96% less than male non-green workers. This coefficient has now become significant, though, this effect is relatively small.

Columns (3) to (9) provide detailed estimation results of wage equations for different occupational groups based on first digit ISCO code. We first focus on occupational groups that are generally considered as high skilled. In column (3), we see there is no statistically significant wage differential between male green workers and male non-green workers in 'Manager' occupational group, which can be indicated from the insignificant coefficient on *Green*. Similar results are found for female green workers and female non-green workers, where we show insignificant coefficients on both *Green* and *Female_green* indicating that there is no statistically significant wage difference between female green workers and female non-green workers who are working in managerial jobs. Besides, we show female non-green workers pay 6.39% lower salaries than male non-green workers, which can be verified by the negative coefficients on *Female*.

For male green workers who are employed in 'Professionals' occupations, we show they earn 4.54% higher wages than male non-green workers, and 5.5% more than female green workers, *ceteris paribus*. For female green workers who are working in 'Professionals' occupations, we show they earn 2.16% less than female non-green workers, and female non-green workers who are employed in 'Professionals' pay 1.20% higher than male non-green workers. Turning to 'Technicians and associate professionals', we find male green worker pay slightly higher than male non-green workers (1.33%), and 5.46% higher than female green workers, and female green workers pay 1.16% less than female non-green workers.

For the rest of the occupational groups, female green workers are found pay less than other workers in 'Service and sales workers', which can be indicated by the significantly negative coefficient on *Female_green*, while male green workers are found to be paid less than male non-green workers in 'Craft and related traded workers', which is indicated by the significantly negative coefficient on *Green*. Male green workers are found to pay more than male non-green in 'Plant and machine operators and assemblers' (9.23%). In addition, female non-green workers are found to pay less than male non-green workers in both 'Plant and machine operators and assemblers' and 'Elementary occupation'. Other coefficients are statistically insignificant.

[Table 5.6 about here]

Table 5.7 illustrates the relationship between a task-based greenness index and wage. Using a greenness index gives us a continuous measure, and can be thought of a proxy for time spending on green tasks. The estimation results are generally similar to our binary measure. For instance, in column (1) of table 5.7, we show that if a task-based greenness of a male worker increase by 0.1 units, it will lead to a 2.73% increase in the hourly wage. If a task-based greenness of a female worker increase by 0.1 units, it will result in a 1.73% increase in hourly wage rate. As above, when we control occupational dummies in column (2), the green wage premium drops to 0.78% when comparing male green workers with male non-green workers, and female workers are found to be paid less than female non-green workers when their work tasks involve more green tasks. The other columns show the relationship between a greenness index and wages for different occupational groups. The estimation results are generally similar to our binary measure.

Turning to our controls, the estimation results are consistent with the prior expectation of a human capital wage equation, where we show high/middle skilled workers earn higher wages than low skilled workers in the whole sample (with/without occupation dummies) and for different occupational groups. Workers that are older are generally found to earn more but at a decreasing rate. workers have longer tenure at the current position are paid higher. Native-born workers are found to earn more than foreign-born workers. Workers from larger households, and workers from a larger firm that pay higher average wage are found to pay higher. Besides, female workers who are married are generally paid less while surprisingly, females with children are generally paid more.

[Table 5.7 about here]

5.4 Wage differential of green jobs by gender

Statistics show that labour market disparities between men and women has been decreasing in the Netherlands. On the one side, the labour force participation rate has been increased dramatically for women in the Netherlands, from only 32% in 1977 to 75.8% in 2007 (Nientker & Alessie 2019), although most of the increase can be attribute only to an increase in part-time jobs (Wielers & Van der Meer 2003). On the other side, the educational attainment for women has increased and the difference in over-education has declined according to Van der Meer (2008). However, the wage gap between females and males remain substantial (around 20%) (Fransen et al. 2012), and this gap seems to remain surprisingly steady in the Dutch labour market (Van der Meer 2008).

Among the rather limited studies on the gender wage gap in the Dutch labour market, a small number of studies have decomposed the gender wage gap based on a human capital model. In a review of Dutch studies in Fransen et al. (2012), studies using Dutch language show that 71.5% of the gender wage gap in the Netherlands can be explained by differences in characteristics, and 28.5% remained unexplained, which could be attributed to discrimination, and this gender wage gap was largely due to unequal distribution of men and women across occupational groups, rather than the unequal pay within occupations.

From our descriptives, we find women are significantly less-represented in the green occupations, although there is not much of a wage differential between male/female green workers on average. However, from the wage equation, we show, with other characteristics controlled, female green workers are paid less than male green workers, especially when we control for occupational dummies exogenously. Given there is a substantially high share of high skilled workers in female green workers (58.05%) compared male green workers (34.97%), we consider there might be an unfair treatment towards female green workers in terms of green occupation attainment and wages. Therefore, in this section, we focus on examining the wage differential between female and male in green jobs.

5.4.1 Econometric Model

To study the wage differential by different groups, the Blinder–Oaxaca decomposition (Blinder 1973, Oaxaca 1973) is most commonly used in the labour economics. The Blinder–Oaxaca decomposition explains wage differentials based on liner regression models in a counterfactual manner. It decomposes the wage differential between two groups into an 'explained part' and an 'unexplained part', where the 'explained differential' can be explained by the productivity characteristics, such as education or work experience, while the 'unexplained part' is normally considered to be discrimination, though it also captures the effect of differences in unobservable characteristics (Jann 2008).

To further illustrate the principle of Blinder-Oaxaca decomposition method, we assume that we have two groups of workers: a group of males and a group of females. W_F stands for the wages of females, while W_M stands for wages of males. The wage level is determined by human productivity characteristics, that is:

$$ln(W_i) = X_i\beta_i + \epsilon_i \tag{5.4}$$

Where i = M or F, X is a vector of variables that include determinants of wage level, β a vector of coefficients, and ϵ is the error term, which is assumed to have a zero mean. Therefore, the difference in means of log of wages between females and males can be expressed as follows:

$$ln(\bar{W}_M) - ln(\bar{W}_F) = \bar{X}_M\beta_M - \bar{X}_F\beta_F \tag{5.5}$$

To examine the existence of potential discrimination, a non-discriminatory coefficient vector β^* is assumed to construct the counterfactual group. Hence, the wage differential can be further restructured as follows:

$$ln(\bar{W}_M) - ln(\bar{W}_F) = (\bar{X}_M - \bar{X}_F)\beta^* + \bar{X}_M(\beta_M - \beta^*) + \bar{X}_F(\beta^* - \beta_F) \tag{5.6}$$

Where the first part refers to explained part, which can explain the wage differential by human capital differences, while the second part is the unexplained part, which is normally considered as evidence of discrimination, though it also captures the effect of differences in unobservable characteristics.

This decomposition method is also known as a twofold decomposition. To determine the two components of the twofold decomposition shown in equation (3), the unknown non-discriminatory coefficient β^* needs to be estimated. Several attempts have been made in the existing literature. For example,Reimers (1983) proposed to use an average coefficients over two groups to be an estimator for β^*, while Cotton (1988) believed that using group size weighted average coefficients would be better. A more advanced proposal was suggested by Neumark (1988), who advocated the use of coefficients from a pooled model over both groups. The most commonly used is to assume there is only a positive wage discrimination towards women, and no discrimination against men. Then $\hat{\beta_M}$ can be used as an estimate for β^*, and equation (3) can be rewritten as follows:

$$ln(\bar{W}_M) - ln(\bar{W}_F) = (\bar{X}_M - \bar{X}_F)\hat{\beta_M} + \bar{X}_F(\hat{\beta_M} - \hat{\beta_F}) \tag{5.7}$$

The Blinder-Oaxaca decomposition has been criticised with the argument that it ignores the possible occupation differences and inappropriately accounts for differences in the occupational distribution of men and women. Furthermore, even though some studies have considered the effect of occupation differences by incorporating occupational category dummies in the earning regressions, these studies are likely underestimate the actual discrimination as it implicitly treats all the differences in occupation difference between men and women as justified (Brown et al. 1980). Therefore, Brown et al. (1980) proposed a method that extends the traditional Blinder-Oaxaca decomposition wage differential between male and female by incorporating the difference between inter-occupational and intra-occupational difference and measures wage differences within and between occupations more sensitively.

First, Brown et al. (1980) rewrite the wage equation (1) for different groups as follows:

$$ln(\bar{W}_i) = \sum_j P_{ji}\bar{X}_{ji}\beta_{ji} \tag{5.8}$$

Where P_{ji} refers to sample proportion of group i in occupation j, $i = M/F$ and $j = 1, 2, ..., J$. Brown et al. (1980) take the β_{jM} as the reference index, which is considered as the non-discriminatory coefficient in occupation j. Then mean log wage differential between males and females can be written as follows:

$$\begin{aligned} ln(\bar{W}_M) - ln(\bar{W}_F) &= \sum_j P_{jM}\bar{X}_{jM}\beta_{jM} - \sum_j P_{jF}\bar{X}_{jF}\beta_{jF} \\ &= \sum_j P_{jM}\bar{X}_{jM}\beta_{jM} - \sum_j P_{jF}\bar{X}_{jF}\beta_{jM} \\ &+ \sum_j P_{jF}\bar{X}_{jF}\beta_{jM} - \sum_j P_{jF}\bar{X}_{jF}\beta_{jF} \\ &= \sum_j (P_{jM}\bar{X}_{jM} - P_{jF}\bar{X}_{jF})\beta_{jM} + \sum_j P_{jF}\bar{X}_{jF}(\beta_{jM} - \beta_{jF}) \end{aligned} \tag{5.9}$$

The first part $\sum_j (P_{jM}\bar{X}_{jM} - P_{jF}\bar{X}_{jF})\beta_{jM}$ can be interpreted as the explained part just as the first part in equation (4), and the second part $\sum_j P_{jF}\bar{X}_{jF}(\beta_{jM} - \beta_{jF})$ can be interpreted as the unexplained part just as the second part in equation (4). Then Brown et al. (1980) incorporate the effect of occupation segregation on the wage differential in different groups by assuming $\hat{P_{jF}}$ as the reference index which is the percentage of women in the sample who would be in occupation j if women had equal access to all occupations as men. The wage differential equation then can be further decomposed as follows:

$$
\begin{aligned}
ln(\bar{W}_M) - ln(\bar{W}_F) &= \sum_j (P_{jM}\bar{X}_{jM} - \hat{P_{jF}}\bar{X}_{jM} + \hat{P_{jF}}\bar{X}_{jM} - P_{jF}\bar{X}_{jM} \\
&\quad + P_{jF}\bar{X}_{jM} - P_{jF}\bar{X}_{jF})\beta_{jM} + \sum_j P_{jF}\bar{X}_{jF}(\beta_{jM} - \beta_{jF}) \\
&= \sum_j P_{jF}(\bar{X}_{jM} - \bar{X}_{jF})\beta_{jM} + \sum_j P_{jF}\bar{X}_{jF}(\beta_{jM} - \beta_{jF}) \\
&\quad + \sum_j (\hat{P_{jF}} - P_{jF})\bar{X}_{jM}\beta_{jM} + \sum_j (P_{jM} - \hat{P_{jF}})\bar{X}_{jM}\beta_{jM}
\end{aligned}
\tag{5.10}
$$

This is full decomposition of the Brown decomposition, where the first part on the right hand side $\sum_j P_{jF}(\bar{X}_{jM} - \bar{X}_{jF})\beta_{jM}$ denotes within occupational wage differential that can be explained by productivity characteristics, and the second part $\sum_j P_{jF}\bar{X}_{jF}(\beta_{jM} - \beta_{jF})$ refers to unexplained within occupational wage differential that can attribute to discrimination holding the occupational distribution for women constant. The third part on the right hand side $\sum_j (\hat{P_{jF}} - P_{jF})\bar{X}_{jM}\beta_{jM}$ stands for the wage differential explained by occupation distribution difference between two groups, while the last part $sum_j(P_{jM} - \hat{P_{jF}})\bar{X}_{jM}\beta_{jM}$ represents the unexplained occupational segregation holding human characteristics constant.

5.4.2 Decomposition results

Table 5.8 provides the results of the standard Blinder-Oaxaca (BO) decomposition based on equation (5) in column (1) and results of Blinder-Oaxaca-Neumark (BON) decomposition in column (2), where the non-discriminatory coefficient β^* of the latter is obtained from a pooled OLS over both gender groups. The results are rather similar using different index numbers for β^*. Controlling for the occupation dummies exogenously, we show, based on a BON decomposition, the mean of log hourly wage differential between male green workers and female green workers is -0.0490 (relatively small), of which, -0.0812 is explained by productivity difference, while 0.0322 remain unexplained. The negative value in the explained difference indicates that female green workers should have been paid even more than green male workers than they are actually paid based on the human capital difference, while the positive value in the unexplained difference refers to the unjustified wage premium of male green workers which could be attributed to discrimination or other unobservable factors.

[Table 5.8 about here]

By examining the wage differential using a BON decomposition, we show there is a wage disadvantage against female green workers after controlling occupational dummies exogenously. Next we apply a Brown decomposition to consider the occupational distribution difference between male/female green workers in contributing to the overall wage differential. To do so, we first estimate a reduced form multinomial model of occupational choice for males and females separately. Then we predict the occupational distribution of female green workers under the assumption that they are facing the same occupational choice as men in the labour market by substituting the female data into the estimated male probability model. Based on equation (8), we decompose the gender wage differential in green jobs using

Brown decomposition.

Table 5.9 presents the results of Brown decomposition that are broken down into two distinct parts: the intra-occupation difference (explained and unexplained) and inter-occupation differences (explained and unexplained). Making this distinction is important as one can clearly tell which effect is driving the overall wage differential. As we can see, the overall log of hourly wage difference between males and females is the same as above (-0.0490), of which 0.0774 can be attributed to intra-occupation differences, while -0.1264 is due to the inter-occupation effect. Clearly, the inter-occupational difference decreases the male wage premium and drives the overall wage differential between male and female green workers.

Focusing on intra-occupational difference, we show most of the wage difference within occupations is captured by differences in human capital. More specifically, only about 5% (0.0039 over 0.0774) difference remain unjustified. This is relatively small compared to previous study on gender wage gap in the Dutch labour market for all jobs (71.5% of gender wage gap is attributable to human capital difference, and 28.5% remain unexplained.)

Turning to the inter-occupational differences, both explained and unexplained inter-occupational difference lead to a decrease in the male/female wage differential in green jobs, while the unjustified difference is again, relatively small compared to justified difference, where the former accounts for 94% (-0.1190 over -0.1264) of the inter-occupational difference, and the latter only accounts for 6%. Previous studies have shown that gender wage gap is likely to be reduced due to the fact that the comparable male and female workers are distributed differently across occupations (see e.g. Kidd (1993)). Here we show this is also true in green jobs.[9]

[Table 5.9 about here]

To summarize, in the standard BO and BON decomposition that treat the occupational distribution as exogenously determined, we show that female green workers should have been paid higher than male green workers based on human capital difference, which results in an unjustified positive male wage premium that could be due to discrimination. However, when we treat occupational distribution as endogenously determined in a Brown decomposition, we show that it is the inter-occupational distribution differences which dominates the explanation of overall gender wage differential in green jobs, and the unjustified wage differences are rather small in both inter- and intra occupational decomposition results. [10]

5.5 Conclusions

Green jobs have been playing an important role in a greening economy. However, little is known on the characteristics and distribution of green workers. In this chapter, we use very detailed individual level data to examine the green workers in the Netherlands between 2001 and 2016 based on a task approach from O*NET in order to answer the questions: who are those green workers, how these green workers are distributed among occupational

[9] These results are also consistent with our previous finding that female green workers are more likely to be observed in high skill and high paid occupations like 'Professionals' in section 3.2

[10] The reason for different findings between the BO & BON decomposition and Brown decomposition is due to that fact occupational distribution is treated as exogenously and endogenously, respectively

groups, and specially what is the difference between male/female green workers in terms of occupational segregation and wages.

In line with previous literature that uses the O*NET definition of green jobs, we show green workers are dominated by males, and are high skilled and high paid jobs compared to non-green workers. Apart from the fact that females are less represented in green workers, we also show married female and female with children are even less likely to be employed in green jobs. In terms of occupational distribution, we show female green workers are more likely to be observed in high skilled occupations, such as 'Managers' and 'Professionals' ; while male green workers, *ceteris paribus*, are more likely to be found in 'Managers', 'Craft and related traded workers' and 'Plant and machine operators and assemblers' than other occupations.

Focusing on earnings, not only do we find that green workers are higher-paying jobs, but also show the wage gap between green workers and non-green workers is growing over time. Furthermore, we show that female green workers, *ceteris paribus*, are generally found to earn lower wages than male green workers. However, the Brown decomposition results show the gender wage gap between male/female green workers is relatively small. More specifically, most of the gender wage differential within occupations is explained by human capital differences. Both unjustified intra- and inter-occupational wage differences are small. Moreover, we show the occupational distribution differences decrease the gender wage gap, which drives the overall wage differential between male/female green workers.

Previous studies have shown that the gender wage gap is still substantial in the Dutch labour market, and this gap seems to decrease only slowly over time despite the enormous improvements in both women's labour participation rate and labour market attachment (Fransen et al. 2012, Van der Meer 2008). However, this is not the case in green jobs. We show women's participation rate is very low in green occupations, only 19.95% are female green workers on average during our sample period. Despite the gender disparity in representativeness, we show the gender wage gap is rather small in green jobs, and most of wage difference are justified both within and between occupations. Therefore, we suggest instead of focusing on equal pay or equal access for equal work, policy emphasis should first target at increasing women's participation rate in green jobs.

Table 5.1: Characteristics of green jobs and non-green jobs in the Dutch labour market (2001 - 2016)

	Green Jobs			Non Green Jobs			All sample		
Characteristics	Total	Female	Male	Total	Female	Male	Total	Female	Male
Female	19.95%	1	0	53.93%	1	0	48.14%	1	0
Married	62.45%	53.16%	64.76%	53.63%	53.95%	53.25%	55.13%	53.89%	56.28%
High Skill	38.90%	58.23%	34.08%	28.46%	28.69%	28.19%	30.24%	30.78%	29.74%
Middle Skill	38.87%	30.05%	41.07%	44.49%	45.59%	43.20%	43.53%	44.49%	42.64%
Low Skill	22.23%	11.72%	24.85%	27.06%	25.73%	28.61%	26.23%	24.74%	27.62%
Age	41.45	39.44	41.95	38.76	38.54	39.02	39.22	38.61	39.79
Tenure	9.14	7.61	9.51	7.75	6.99	8.63	7.98	7.04	8.86
Native	93.22%	90.90%	93.80%	91.77%	91.60%	91.98%	92.02%	91.55%	92.46%
Foreignborn	6.78%	9.10%	6.20%	8.23%	8.40%	8.02%	7.98%	8.45%	7.54%
Householdsize	3.04	2.80	3.10	3.06	3.05	3.08	3.06	3.03	3.08
Kids(under12)	33.31%	34.06%	33.13%	28.71%	29.88%	27.35%	29.50%	30.17%	28.87%
Kids(above12)	36.39%	27.10%	38.71%	43.12%	42.62%	43.71%	41.97%	41.52%	42.40%
Firmwage	30,418	28,681	30,850	23,265	20,364	26,661	24,485	20,952	27,764
Firmsize	4,879	6,386	4,504	6,427	5,951	6,983	6,163	5,982	6,331
OBS	145,674	29,059	116,615	708,563	382,156	326,407	854,237	411,215	443,022

Sources: Dutch Labour Force Survey and Tax Register Data. All monetary values are in Euros.

Table 5.2: Occupational distribution: Green jobs VS non-green jobs (2001 - 2016)

	Green Jobs			Non Green Jobs			All sample		
Occupation groups	Total	Female	Male	Total	Female	Male	Total	Female	Male
Managers	25.40%	31.15%	23.97%	0.58%	0.09%	1.15%	0.48%	0.08%	0.85%
Professionals	21.96%	35.82%	18.50%	1.79%	1.26%	2.40%	5.81%	3.37%	8.08%
Technicians and associate professionals	18.79%	19.65%	18.58%	21.63%	20.76%	22.64%	21.68%	21.83%	21.55%
Clerical support workers	0.00%	0.00%	0.00%	16.96%	18.32%	15.36%	17.27%	18.41%	16.21%
Service and sales workers	1.45%	3.51%	0.94%	14.03%	17.13%	10.41%	11.64%	15.92%	7.67%
Skilled agricultural, forestry and fishery workers	0.00%	0.00%	0.00%	22.73%	30.42%	13.72%	19.10%	28.52%	10.36%
Craft and related traded workers	12.39%	0.60%	15.33%	1.61%	0.58%	2.82%	1.33%	0.54%	2.08%
Plant and machine operators and assemblers	9.88%	0.98%	12.10%	8.17%	1.11%	16.45%	8.89%	1.07%	16.15%
Elementary occupations	10.12%	8.28%	10.58%	3.69%	1.12%	6.70%	4.74%	1.11%	8.12%
Armed forces occupations	0.00%	0.00%	0.00%	8.82%	9.22%	8.35%	9.04%	9.16%	8.93%
OBS	145,674	29,059	116,615	708,563	382,156	326,407	854,237	411,215	443,022

Sources: Dutch Labour Force Survey and Tax Register Data.

Table 5.3: Hourly wage: Green jobs VS non-green jobs (2001 - 2016)

	Green Jobs			Non Green Jobs		
Hourly wage (Euros)	Total	Female	Male	Total	Female	Male
Whole sample	25.13	26.00	24.92	22.46	23.10	21.70
2001-2004	21.25	21.43	21.21	19.69	20.34	18.99
2005-2008	24.03	24.55	23.90	21.40	22.00	20.71
2009-2012	27.39	28.13	27.18	23.92	24.51	23.20
2013-2016	28.18	28.88	27.98	24.61	25.17	23.93
Occupation groups						
Managers	31.78	27.56	33.14	28.75	28.75	33.78
Professionals	29.43	28.68	29.79	29.42	29.42	27.83
Technicians and associate professionals	23.98	24.25	23.91	24.27	24.27	23.69
Clerical support workers	N/A	N/A	N/A	21.60	21.60	20.64
Service and sales workers	18.29	17.73	18.82	20.74	20.74	19.17
Skilled agricultural, forestry and fishery workers	N/A	N/A	N/A	17.72	17.72	15.77
Craft and related traded workers	17.85	19.61	17.83	18.56	18.56	17.26
Plant and machine operators and assemblers	19.16	19.60	19.15	16.79	16.79	18.40
Elementary occupations	17.00	17.38	16.93	18.07	18.07	17.07
Armed forces occupations	N/A	N/A	N/A	19.65	16.82	19.90
OBS	145,674	29,059	116,615	708,563	382,156	326,407

Sources: Dutch Labour Force Survey and Tax Register Data.

Table 5.4: Characteristics of green workers: A Logit regression

	(1) All Green occupation	(2) Managers Green occupation	(3) Professionals Green occupation	(4) Technicians Green occupation	(5) Service Green occupation	(6) Trade Green occupation	(7) Machine_operator Green occupation	(8) Elementary Green occupation
Female	-0.818***	-0.166**	-0.145***	-0.693***	-0.490***	-1.822***	-1.755***	-1.395***
	(0.0128)	(0.0520)	(0.0243)	(0.0301)	(0.0824)	(0.140)	(0.110)	(0.0511)
Married	0.115***	0.0341	0.161***	0.130***	0.199*	0.0104	0.0680*	0.137***
	(0.00952)	(0.0415)	(0.0215)	(0.0234)	(0.0827)	(0.0249)	(0.0338)	(0.0410)
Kids	0.00366	-0.0319	-0.0105	0.0299	-0.00205	0.0637*	-0.0223	-0.0621
	(0.0115)	(0.0475)	(0.0264)	(0.0284)	(0.0949)	(0.0300)	(0.0414)	(0.0437)
Kids_adol	-0.0132	0.0154	-0.0521*	-0.0339	-0.0890	-0.00841	-0.0716	-0.239***
	(0.0104)	(0.0437)	(0.0246)	(0.0259)	(0.0857)	(0.0270)	(0.0368)	(0.0413)
Female_married	-0.273***	-0.0637	-0.215***	-0.349***	-0.599***	-0.0668	-0.790***	-0.656***
	(0.0151)	(0.0596)	(0.0307)	(0.0366)	(0.0968)	(0.163)	(0.134)	(0.0587)
Female_kids	-0.0216	0.0581	0.0482	0.0302	-0.114	-0.337	0.308*	-0.0399
	(0.0161)	(0.0588)	(0.0312)	(0.0380)	(0.108)	(0.194)	(0.151)	(0.0649)
Female_Kids_adol	-0.440***	-0.183**	-0.116***	-0.189***	-0.252**	-0.137	-0.233	0.00734
	(0.0160)	(0.0579)	(0.0335)	(0.0388)	(0.0951)	(0.169)	(0.137)	(0.0565)
High_skill	0.783***	-0.148**	0.315***	0.254***	0.511***	0.0941	-0.823***	0.101
	(0.00951)	(0.0541)	(0.0399)	(0.0261)	(0.0825)	(0.0543)	(0.0791)	(0.0674)
Middle_skill	0.0790***	0.156**	0.0236	-0.0320	0.460***	0.267***	-0.274***	0.291***
	(0.00819)	(0.0545)	(0.0416)	(0.0236)	(0.0549)	(0.0187)	(0.0249)	(0.0255)
Age	0.0991***	0.0195	0.0196***	0.00398	0.210***	0.00976	0.116***	0.251***
	(0.00204)	(0.0116)	(0.00553)	(0.00571)	(0.0141)	(0.00561)	(0.00775)	(0.00666)
Age2	-0.00107***	-0.000388**	-0.000198**	-0.00000836	-0.00247***	-0.000122	-0.00145***	-0.00305***
	(0.0000249)	(0.000133)	(0.0000657)	(0.0000687)	(0.000183)	(0.0000696)	(0.0000927)	(0.0000849)
Tenure	-0.00361***	0.0192***	-0.00191	-0.00405***	0.0187***	0.00000164	-0.0166***	-0.00562**
	(0.000444)	(0.00172)	(0.000981)	(0.00105)	(0.00360)	(0.00129)	(0.00174)	(0.00205)

Foreignborn	-0.186***	-0.00578	-0.0953***	-0.175***	-0.334**	-0.0751*	-0.724***	-0.130***
	(0.0125)	(0.0568)	(0.0275)	(0.0321)	(0.103)	(0.0340)	(0.0495)	(0.0384)
Householdsize	0.00871*	0.00735	-0.00637	0.00714	-0.0611*	-0.00345	0.0412*	-0.0510***
	(0.00434)	(0.0184)	(0.00987)	(0.0109)	(0.0303)	(0.0116)	(0.0164)	(0.0143)
Lnfirmwage	0.344***	-0.239***	0.379***	0.271***	-0.238***	0.390***	0.485***	0.930***
	(0.00708)	(0.0332)	(0.0201)	(0.0191)	(0.0370)	(0.0213)	(0.0299)	(0.0250)
Lnfirmsize	-0.0184***	0.0118	-0.0198***	0.0371***	-0.111***	0.0949***	-0.214***	0.0130**
	(0.00140)	(0.00624)	(0.00345)	(0.00371)	(0.00903)	(0.00449)	(0.00677)	(0.00479)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Corop	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	854237	49666	185215	147434	162934	75971	40528	77229

Technicians stand for group ‘Technicians and associate professionals’; Service stands for group ‘Service and sales workers’; Trade stands for group ‘Craft and related traded workers’;
Machine_operator stands for group ‘Plant and machine operators and assemblers’; Elementary stands for group ‘Elementary occupation’.
kids represents have children under 12; Kids_adol refers to have adolescents over 12.
Standard errors in parentheses. $^{***}p < 0.001$;$^{**}p < 0.01$;$^{*}p < 0.05$.. Constant terms are not reported

Table 5.5: Occupation segregation of green workers: A Multinomial Logit regression

	(1)	(2)	(3)	(4)	(5)	(6)
	Managers	Professional	Technicians	Service	Trade	Machine operators
Female_green	3.469***	0.612***	-0.0255	-2.271***	-1.143***	-0.918***
	(0.0379)	(0.0352)	(0.0346)	(0.0397)	(0.0830)	(0.0702)
Male_green	2.078***	-0.748***	-1.154***	-4.040***	0.541***	0.293***
	(0.0358)	(0.0280)	(0.0261)	(0.0380)	(0.0379)	(0.0384)
Male_nongreen	0.199***	-0.115***	-0.509***	-0.682***	1.655***	0.997***
	(0.0341)	(0.0241)	(0.0226)	(0.0213)	(0.0351)	(0.0360)
Married	0.986***	0.685***	0.764***	0.821***	0.590***	0.555***
	(0.0251)	(0.0218)	(0.0203)	(0.0210)	(0.0209)	(0.0232)
Kids	-0.136***	-0.181***	-0.170***	-0.139***	-0.152***	-0.127***
	(0.0280)	(0.0247)	(0.0227)	(0.0221)	(0.0232)	(0.0268)
Kids_adol	-0.597***	-0.621***	-0.535***	-0.598***	-0.384***	-0.399***
	(0.0254)	(0.0224)	(0.0204)	(0.0202)	(0.0209)	(0.0240)
Female_married	-1.411***	-1.118***	-1.155***	-1.197***	-1.116***	-0.975***
	(0.0342)	(0.0258)	(0.0237)	(0.0228)	(0.0383)	(0.0383)
Female_kids	-0.179***	0.0722**	0.0653*	0.0587*	0.00748	-0.135**
	(0.0353)	(0.0276)	(0.0256)	(0.0247)	(0.0428)	(0.0445)
Female_Kids_adol	0.0784*	0.185***	0.232***	0.557***	0.00579	0.0551
	(0.0334)	(0.0252)	(0.0229)	(0.0217)	(0.0382)	(0.0379)
High_skill	4.559***	5.238***	3.213***	1.460***	0.424***	-0.0487

	(0.0300)	(0.0271)	(0.0245)	(0.0245)	(0.0320)	(0.0377)
Middle_skill	1.909***	2.218***	1.973***	1.119***	0.884***	0.282***
	(0.0223)	(0.0188)	(0.0132)	(0.0110)	(0.0135)	(0.0156)
Age	0.381***	0.197***	0.190***	0.113***	0.150***	0.187***
	(0.00535)	(0.00372)	(0.00319)	(0.00272)	(0.00351)	(0.00405)
Age2	-0.00425***	-0.00248***	-0.00245***	-0.00155***	-0.00197***	-0.00219***
	(0.0000635)	(0.0000458)	(0.0000398)	(0.0000346)	(0.0000441)	(0.0000503)
Tenure	0.0243***	0.0246***	0.0302***	0.0162***	0.0229***	0.00403***
	(0.00109)	(0.000965)	(0.000899)	(0.000897)	(0.00103)	(0.00112)
Foreignborn	-1.384***	-1.026***	-0.943***	-0.785***	-0.459***	-0.300***
	(0.0295)	(0.0207)	(0.0186)	(0.0162)	(0.0211)	(0.0244)
Householdsize	0.0741***	0.0252**	0.00750	-0.00921	0.00180	-0.0132
	(0.00967)	(0.00776)	(0.00694)	(0.00598)	(0.00772)	(0.00954)
Lnfirmwage	0.647***	1.536***	1.382***	0.124***	0.608***	0.502***
	(0.0153)	(0.0135)	(0.0118)	(0.00919)	(0.0118)	(0.0137)
Lnfirmsize	-0.0790***	-0.0949***	-0.126***	-0.0779***	-0.243***	-0.120***
	(0.00332)	(0.00265)	(0.00238)	(0.00188)	(0.00279)	(0.00311)
Year	Yes					
Sector	Yes					
Corop	Yes					
N	739,329					

Technicians stand for group ‘Technicians and associate professionals’; Service stands for group ‘Service and sales workers’; Trade stands for group ‘Craft and related traded workers’;

Machine_operator stands for group ‘Plant and machine operators and assemblers’;

Elementary stands for group ‘Elementary occupation’.

kids represents have children under 12; Kids_adol refers to have adolescents over 12.

Robust Standard errors in parentheses. $^{***}p < 0.001;^{**}p < 0.01;^{*}p < 0.05.$; Constant terms are not reported

Table 5.6: Wage equations: green workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	All	Managers	Professionals	Technicians	Service	Trade	Machine_operator	Elementary
	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage
Green	0.0842***	0.0335***	-0.00821	0.0454***	0.0133***	-0.00796	-0.00840**	0.0923***	0.00135
	(0.00127)	(0.00130)	(0.00545)	(0.00248)	(0.00273)	(0.0114)	(0.00263)	(0.00418)	(0.00587)
Female_green	-0.0587***	-0.0859***	0.00282	-0.0670***	-0.0249***	-0.122***	-0.00741	0.0310	0.000115
	(0.00262)	(0.00262)	(0.00792)	(0.00412)	(0.00585)	(0.0175)	(0.0365)	(0.0270)	(0.0112)
Female	-0.00143	-0.00960***	-0.0639***	0.0120***	-0.0297***	0.0109*	-0.00852	-0.102***	-0.0208**
	(0.00168)	(0.00169)	(0.00894)	(0.00302)	(0.00359)	(0.00466)	(0.0122)	(0.0119)	(0.00768)
Married	0.0643***	0.0512***	0.0437***	0.0308***	0.0407***	0.0521***	0.0546***	0.0511***	0.0515***
	(0.00139)	(0.00136)	(0.00502)	(0.00265)	(0.00313)	(0.00457)	(0.00294)	(0.00458)	(0.0060)
Kids	0.00783***	0.00763***	0.00697	0.00771*	-0.00355	-0.0194***	0.0115**	0.00706	-0.0553***
	(0.00170)	(0.00166)	(0.00576)	(0.00325)	(0.00368)	(0.00545)	(0.00381)	(0.00578)	(0.00665)
Kids_adol	-0.0346***	-0.0271***	-0.0243***	-0.0549***	-0.0494***	-0.0419***	-0.0380***	-0.0234***	-0.0372***
	(0.00160)	(0.00157)	(0.00546)	(0.00316)	(0.00355)	(0.00502)	(0.00346)	(0.00536)	(0.00654)
Female_married	-0.0105***	0.00754***	-0.0399***	0.0154***	0.0205***	0.0336***	-0.0409**	-0.0228	0.00536
	(0.00187)	(0.00184)	(0.00782)	(0.00356)	(0.00414)	(0.00506)	(0.0147)	(0.0138)	(0.00744)
Female_kids	0.108***	0.109***	0.0908***	0.110***	0.143***	0.0964***	0.153***	0.158***	0.0636***
	(0.00197)	(0.00194)	(0.00758)	(0.00351)	(0.00411)	(0.00569)	(0.0170)	(0.0172)	(0.00837)
Female_Kids_adol	0.0242***	0.0171***	-0.0296***	0.0178***	0.00738	0.0128*	0.0994***	-0.000805	0.0295***
	(0.00188)	(0.00186)	(0.00786)	(0.00381)	(0.00421)	(0.00508)	(0.0152)	(0.0140)	(0.00742)
High_skill	0.377***	0.267***	0.327***	0.246***	0.225***	0.274***	0.216***	0.182***	0.285***
	(0.00140)	(0.00160)	(0.00673)	(0.00545)	(0.00340)	(0.00461)	(0.00786)	(0.0131)	(0.0114)
Middle_skill	0.146***	0.113***	0.106***	0.0980***	0.102***	0.141***	0.0650***	0.0756***	0.151***
	(0.00120)	(0.00124)	(0.00670)	(0.00568)	(0.00314)	(0.00274)	(0.00236)	(0.00364)	(0.00410)
Age	0.00707***	0.00564***	0.0432***	0.0346***	0.0262***	0.000672	0.0372***	0.00469***	-0.000179
	(0.000293)	(0.000291)	(0.00175)	(0.000754)	(0.000807)	(0.000674)	(0.000867)	(0.00132)	(0.000953)

Age2	-0.00000460	0.0000109**	-0.000343***	-0.000258***	-0.000206***	0.0000346***	-0.000364***	-0.0000306	0.0000158
	(0.00000359)	(0.00000356)	(0.0000200)	(0.00000880)	(0.00000962)	(0.00000862)	(0.0000107)	(0.0000157)	(0.0000121)
Tenure	0.00304***	0.00280***	-0.000343	0.00102***	0.00245***	0.00449***	0.000856***	0.00160***	0.000780**
	(0.0000595)	(0.0000578)	(0.000207)	(0.000117)	(0.000123)	(0.000181)	(0.000152)	(0.000227)	(0.000280)
Foreignborn	-0.105***	-0.0901***	-0.0648***	-0.0540***	-0.0934***	-0.0932***	-0.0704***	-0.0577***	-0.0954***
	(0.00171)	(0.00167)	(0.00771)	(0.00345)	(0.00393)	(0.00437)	(0.00440)	(0.00607)	(0.00512)
Householdsize	0.0304***	0.0291***	0.0292***	0.0354***	0.0362***	0.0224***	0.00400*	0.00581*	0.0137***
	(0.000669)	(0.000661)	(0.00248)	(0.00131)	(0.00147)	(0.00164)	(0.00162)	(0.00251)	(0.00224)
Lnfirmwage	0.0574***	0.0457***	0.204***	0.0688***	0.0670***	-0.0103***	0.0437***	0.0723***	0.0128***
	(0.00109)	(0.00111)	(0.00422)	(0.00308)	(0.00295)	(0.00268)	(0.00339)	(0.00463)	(0.00374)
Lnfirmsize	0.00888***	0.00799***	0.00932***	0.00628***	0.00999***	0.00585***	0.0163***	0.0200***	-0.00151*
	(0.000216)	(0.000217)	(0.000800)	(0.000472)	(0.000497)	(0.000524)	(0.000658)	(0.000964)	(0.000761)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Corop	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	No	Yes	N/A	N/A	N/A	N/A	N/A	N/A	N/A
N	854,237	854,237	49,667	185,236	147,521	163,173	75,971	40,528	77,233
R-sq	0.307	0.329	0.451	0.311	0.275	0.123	0.303	0.173	0.086

Technicians stand for group 'Technicians and associate professionals'; Service stands for group 'Service and sales workers'; Trade stands for group 'Craft and related traded workers'; Machine_operator stands for group 'Plant and machine operators and assemblers'; Elementary stands for group 'Elementary occupation'.

kids represents have children under 12; Kids_adol refers to have adolescents over 12.

Robust Standard errors in parentheses. $^{***}p < 0.001$;** $p < 0.01$;* $p < 0.05$.; Constant terms are not reported

Table 5.7: Wage equations: Greenness index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ALL	ALL	Managers	Professionals	Technicians	Service	Trade	Machine_operator	Elementary
	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage
Greenness	0.273***	0.0779***	0.00957	0.123***	0.0601***	-0.0643	-0.117***	1.367***	0.0454
	(0.00521)	(0.00495)	(0.0132)	(0.0107)	(0.0105)	(0.101)	(0.00857)	(0.0762)	(0.0254)
Female_greenness	-0.100***	-0.230***	0.0347	-0.176***	-0.200***	-1.077***	0.143	0.757	-0.0548
	(0.0123)	(0.0120)	(0.0255)	(0.0178)	(0.0330)	(0.154)	(0.0929)	(0.505)	(0.0769)
Female	-0.00944***	-0.0165***	-0.0662***	0.00610*	-0.0314***	0.0109*	-0.0145	-0.108***	-0.0186*
	(0.00166)	(0.00167)	(0.00757)	(0.00298)	(0.00348)	(0.00466)	(0.0121)	(0.0119)	(0.00751)
Married	0.0660***	0.0523***	0.0437***	0.0313***	0.0405***	0.0521***	0.0542***	0.0516***	0.0510***
	(0.00139)	(0.00136)	(0.00502)	(0.00265)	(0.00313)	(0.00457)	(0.00294)	(0.00459)	(0.00600)
Kids	0.00823***	0.00804***	0.00713	0.00815*	-0.00335	-0.0194***	0.0118**	0.00652	-0.0552***
	(0.00170)	(0.00166)	(0.00576)	(0.00325)	(0.00368)	(0.00545)	(0.00381)	(0.00580)	(0.00665)
Kids_adol	-0.0358***	-0.0279***	-0.0244***	-0.0553***	-0.0495***	-0.0418***	-0.0381***	-0.0238***	-0.0366***
	(0.00160)	(0.00157)	(0.00546)	(0.00316)	(0.00355)	(0.00502)	(0.00346)	(0.00537)	(0.00652)
Female_married	-0.0130***	0.00630***	-0.0397***	0.0153***	0.0209***	0.0336***	-0.0402**	-0.0258	0.00621
	(0.00187)	(0.00184)	(0.00781)	(0.00356)	(0.00414)	(0.00506)	(0.0147)	(0.0138)	(0.00742)
Female_kids	0.107***	0.108***	0.0904***	0.110***	0.143***	0.0964***	0.154***	0.160***	0.0634***
	(0.00198)	(0.00194)	(0.00758)	(0.00352)	(0.00411)	(0.00569)	(0.0170)	(0.0173)	(0.00837)
Female_Kids_adol	0.0257***	0.0190***	-0.0289***	0.0190***	0.00773	0.0128*	0.100***	-0.00171	0.0286***
	(0.00188)	(0.00186)	(0.00785)	(0.00381)	(0.00421)	(0.00508)	(0.0152)	(0.0140)	(0.00737)
High_skill	0.377***	0.267***	0.327***	0.247***	0.226***	0.274***	0.217***	0.175***	0.285***
	(0.00140)	(0.00160)	(0.00672)	(0.00546)	(0.00340)	(0.00461)	(0.00786)	(0.0131)	(0.0114)
Middle_skill	0.145***	0.113***	0.105***	0.0984***	0.102***	0.141***	0.0661***	0.0737***	0.152***
	(0.00120)	(0.00124)	(0.00669)	(0.00569)	(0.00314)	(0.00274)	(0.00235)	(0.00365)	(0.00410)
Age	0.00747***	0.00571***	0.0432***	0.0346***	0.0261***	0.000671	0.0371***	0.00535***	-0.000258
	(0.000293)	(0.000291)	(0.00175)	(0.000755)	(0.000807)	(0.000674)	(0.000867)	(0.00132)	(0.000942)

Age2	-0.00000915*	0.0000102**	-0.000342***	-0.000258***	-0.000206***	0.0000346***	-0.000364***	-0.0000388*	0.0000167
	(0.00000359)	(0.00000356)	(0.0000200)	(0.00000880)	(0.00000961)	(0.00000862)	(0.0000107)	(0.0000157)	(0.0000120)
Tenure	0.00300***	0.00279***	-0.000369	0.00103***	0.00244***	0.00449***	0.000892***	0.00151***	0.000781**
	(0.0000596)	(0.0000579)	(0.000207)	(0.000117)	(0.000123)	(0.000181)	(0.000152)	(0.000227)	(0.000280)
Foreignborn	-0.106***	-0.0908***	-0.0650***	-0.0546***	-0.0935***	-0.0932***	-0.0696***	-0.0617***	-0.0951***
	(0.00171)	(0.00167)	(0.00771)	(0.00345)	(0.00392)	(0.00437)	(0.00439)	(0.00609)	(0.00512)
Householdsize	0.0304***	0.0292***	0.0291***	0.0354***	0.0362***	0.0224***	0.00393*	0.00614*	0.0137***
	(0.000669)	(0.000662)	(0.00248)	(0.00131)	(0.00147)	(0.00164)	(0.00162)	(0.00251)	(0.00224)
Lnfirmwage	0.0591***	0.0462***	0.203***	0.0689***	0.0673***	-0.0103***	0.0431***	0.0743***	0.0124***
	(0.00109)	(0.00111)	(0.00421)	(0.00307)	(0.00295)	(0.00268)	(0.00339)	(0.00464)	(0.00370)
Lnfirmsize	0.00870***	0.00788***	0.00932***	0.00626***	0.0101***	0.00585***	0.0166***	0.0190***	-0.00149*
	(0.000216)	(0.000217)	(0.000800)	(0.000473)	(0.000497)	(0.000524)	(0.000655)	(0.000956)	(0.000760)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Corop	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	No	Yes	N/A	N/A	N/A	N/A	N/A	N/A	N/A
N	854,237	854,237	49,667	185,236	147,521	163,173	75,971	40,528	77,233
R-sq	0.306	0.329	0.451	0.310	0.275	0.123	0.305	0.170	0.086

Technicians stand for group ‘Technicians and associate professionals’; Service stands for group ‘Service and sales workers’; Trade stands for group ‘Craft and related traded workers’; Machine_operator stands for group ‘Plant and machine operators and assemblers’; Elementary stands for group‘Elementary occupation’. kids represents have kids under 12; Kids_adol refers to have adolescents over 12.

Robust Standard errors in parentheses. $^{***}p < 0.001$;** $p < 0.01$;* $p < 0.05$.

Table 5.8: Blinder-Oaxaca decomposition of male-female green wage differential

	(1) BO decomposition ln(hourly wage)	(2) BON decomposition ln(hourly wage)
Total wage differential	-0.0490	-0.0490
Explained	-0.0795	-0.0812
Unexplained	0.0305	0.0322
Controls	Yes	Yes
Occupation	Yes	Yes
N	145,674	145,674

Table 5.9: Brown decomposition of male-female green wage differential

	Brown Decomposition	
	ln(hourly wage)	ln(hourly wage)
Total wage differential	-0.0490	-0.0490
Intra-occupation difference		0.0774
Explained	0.0813	
Unexplained	-0.0039	
Inter-occupation difference		-0.1264
Explained	-0.1190	
Unexplained	-0.0074	
N	145,674	145,674

Chapter Six

Conclusions

This thesis includes four main empirical chapters that contribute to the environmental economics and labour economics literature. After a brief summary in Chapter one, the second chapter shows the overall trends in green jobs, and trends in green jobs by sector and occupational group in the Netherlands for the period 2000 to 2018. Taking a task-based approach, we utilise the O*NET definition of green jobs by transferring O*NET-SOC to more internationally used ISCO job classification. Our results show the share of green jobs accounts for approximately 16% of total Dutch employment. It first increased between 2000 and 2011, and stayed relatively stable from 2013 to 2018. Further results show that the share of green jobs increased in most of sectors and occupational groups in the first period, while it remained relatively stable in high-skilled occupational groups, and slightly dropped in secondary sectors and relative low-skilled occupational groups in the second period.

Based on the same task-based approach, Chapters three and four investigate how the transition towards a green economy affect total labour demand, and the demand for green jobs. More specifically, the third chapter examines how environmental taxes, which is one of the most important green growth policy tools, affected total jobs, the number of green jobs, and the share of green jobs at the sector level in the Dutch labour market for the years 2000 to 2016. Our results from 3SLS estimations show that environmental taxes have no effect on total employment, but have a positive effect on the number of green jobs, and hence the share of green jobs at the sector level. Further results suggest that the increase in green jobs in the whole economy is driven by a decrease in non-green jobs in traditional industrial sectors and a larger increase in green jobs in non-industrial sectors.

Chapter four focuses on the employment effect of eco-innovation, with special attention given to the impact of policy-driven eco-innovation at the firm level for 2006 to 2010. Eco-innovation is considered as one of the most important tools for businesses to make their product and production process more competitive and sustainable. However, how eco-innovation affects jobs is not well understood. The forth chapter therefore investigates the impact of eco-innovation on total number of workers, the number of green workers, and the percentage of green workers at the firm level. Based on the endogenous switching model, our results show that there is no statistically significant evidence of eco-innovation decreasing total jobs, but there is a significant positive effect on the number of green jobs, and hence the share of green jobs. In further results, we find policy-driven eco-innovation is positively correlated with number of green jobs, which is mainly driven by subsidies for eco-innovation activities.

The fifth chapter looks at the characteristics of green jobs, with special attention given to occupational segregation and gender wage differentials in green jobs. Using detailed individual level data, we find green jobs are male dominated, and female workers are under-represented in green jobs, especially married female and female with children. However, female green jobs are more likely to be found in high skilled occupational groups relative to male green jobs. Green jobs are paid higher wages than non-green jobs, while the wage differential between male and female green jobs is relatively small. Based on a Brown decomposition, we show that most of the gender wage differentials are justified within and between occupations, and it is inter-occupational wage difference that drives the overall wage differential between male and female green jobs.

Taken together, the empirical results of this thesis suggest several policy implications. First, the trend of green jobs shown in Chapter two illustrates the fact that green jobs might not always increase. When technologies reach maturity, the increase in green jobs might slow down or even decrease. Besides, if the green jobs are found to be less profitable than non-green jobs, they are more likely to be cut during difficult times. Hence, one could focus on the broader employment effect of transition towards a green economy rather than only focus on the type of green jobs being created.

Second, our results in Chapter three and Chapter four both suggest that the employment effect of green growth polices including environmental taxes, subsidies for eco-innovation is mainly a compositional change. That is, no effect is found on total employment, but there is a trade off between green jobs and non-green jobs. The ongoing COVID19 pandemic has evolved from a health crisis to an economic crisis and more importantly a job crisis. Hence, policy makers all around the world are eager to restore economies and save jobs by using a series of stimulus packages, including reducing or abandoning environmental taxes and fees (OECD 2020*c*). However, our results, in line with most of existing literature, show that green growth policies do not hurt total employment. More importantly, we show there is positive effect on number and share of green jobs. Therefore, reducing or abandoning environmental taxes might not be the best policy tool to support green recovery given environmental taxes are not harmful for jobs and are very effective in their environmental goals.

Third, the findings in the fifth chapter suggest that females are under represented in green jobs. However, the positive news is that the wage differential between male and female green jobs is rather small. Most of gender wage difference in green jobs are justified, which suggests that the potential wage discrimination against women is relatively small in green jobs. Therefore, we believe encouraging women participation in green jobs is a more important policy target at the moment than equal pay or equal access for equal work between male and female in green jobs.

The major limitation of this thesis is the inherent drawbacks of the crosswalk between O*NET-SOC with ISCO code. US O*NET-SOC classification categories are more detailed than the ISCO scheme. There are more than 1000 occupational categories in O*NET-SOC while only 436 occupational categories in ISCO scheme. Hence, when we transform O*NET green occupations to ISCO scheme, there will be cases where one ISCO occupation corresponds to multiple O*NET-SOC occupations, where those occupations could include both green jobs and non-green jobs. We assume workers are uniformly distributed in O*NET-SOC categories and then take the average of task-based greenness of corresponding O*NET-SOC occupations. However, it is unlikely workers are uniformly distributed in the real life, and the labour market structure in the US might not be the same as that in the Netherlands.

For future research, it would be interesting to look at the trend and distribution of green jobs in different economies, and compare them horizontally across the EU for example. The prerequisite to do so is to have a consistent and reliable measure of green jobs. This thesis provides a promising start point for such analysis by transferring O*NET green occupation to more internationally used ISCO job classification system. However, a more careful and detailed treatment are needed in the future analysis when transfer O*NET-SOC to ISCO given the inherent drawbacks mentioned above.

I would also be interested in exploring the level and trends of green jobs using different measures within the same economy. For instance, we could compare the amount of green jobs using Green sector approach and that with task-based approach. This would compare different measure of green jobs horizontally and monitor the progress in the green economy transition for one economy in different aspects.

Last but not least, there are still many unsettled questions related the the labour market consequences of green economy transition. Given the massive government spending devoted to promote green growth, understanding how green growth policies reshape the labor market is vitally important. For instance, one could also consider how such policies would affect on jobs in supply chains, i.e. induced green jobs. Apart from the labour market impacts, the environmental consequences and other economic impacts that associated with green growth policies also needed to be carefully evaluated. A systematic evaluation of green growth polices still remains a large agenda for future studies.

Bibliography

Andersson, J. J. (2019), 'Carbon Taxes and CO2 Emissions: Sweden as a Case Study', *American Economic Journal: Economic Policy* **11**(4), 1–30.

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

Bakhsh, K., Rose, S., Ali, M. F., Ahmad, N. & Shahbaz, M. (2017), 'Economic growth, CO2 emissions, renewable waste and FDI relation in Pakistan: New evidences from 3SLS', *Journal of Environmental Management* **196**, 627–632.

Barbieri, N. & Consoli, D. (2019), 'Regional diversification and green employment in US metropolitan areas', *Research Policy* **48**(3), 693–705.

Baum, C., Schaffer, M. & Stillman, S. (2010), ivreg2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression, Technical report, Statistical Software Components, Boston College Department of Economics.

Bento, A. M. & Jacobsen, M. (2007), 'Ricardian rents, environmental policy and the 'double-dividend' hypothesis', *Journal of Environmental Economics and Management* **53**(1), 17–31.

Berman, E. & Bui, L. T. (2001), 'Environmental regulation and labor demand: Evidence from the south coast air basin', *Journal of Public Economics* **79**(2), 265–295.

Bernard, J. T., Kichian, M. & Islam, M. (2018), 'Effects of BC's Carbon Tax on GDP', *USAEE Research Paper Series* pp. 18–329.

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.

Blinder, A. S. (1973), 'Wage discrimination: reduced form and structural estimates', *Journal of Human Resources* pp. 436–455.

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

Bovenberg, A. L. & De Mooij, R. A. (1994), 'Environmental levies and distortionary taxation', *The American Economic Review* **84**(4), 1085–1089.

Bowen, A. (2012), Green 'growth, 'green' jobs and labor markets, Policy Research Working Paper 5990, The World Bank.

Bowen, A. & Kuralbayeva, K. (2015), Looking for green jobs: the impact of green growth on employment, Technical report, London: London School of Economics and Political Science.

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

Bowen, W. M., Park, S. & Elvery, J. A. (2013), 'Empirical estimates of the influence of renewable energy portfolio standards on the green economies of states', *Economic Development Quarterly* **27**(4), 338–351.

Brown, R. S., Moon, M. & Zoloth, B. S. (1980), 'Incorporating occupational attainment in studies of male-female earnings differentials', *Journal of Human Resources* pp. 3–28.

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.

Carraro, C., Galeotti, M. & Gallo, M. (1996), 'Environmental taxation and unemployment: Some evidence on the 'double dividend hypothesis' in Europe', *Journal of Public Economics* **62**(1-2), 141–181.

CBS (2015), Green Growth in the Netherlands 2015, Technical report, Statistics Netherlands.

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

Cole, M. A. & Elliott, R. J. (2007), 'Do environmental regulations cost jobs? An industry-level analysis of the UK', *The BE Journal of Economic Analysis & Policy* **7**(1).

Connolly, K., Allan, G. J. & McIntyre, S. G. (2016), 'The evolution of green jobs in Scotland: A hybrid approach', *Energy Policy* **88**, 355–360.

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.

Cotton, J. (1988), 'On the decomposition of wage differentials', *The Review of Economics and Statistics* pp. 236–243.

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, IZA Policy Paper No. 62, IZA, Bonn.

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

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.

Ederington, J. & Minier, J. (2003), 'Is environmental policy a secondary trade barrier? An empirical analysis', *Canadian Journal of Economics/Revue canadienne d'économique* **36**(1), 137–154.

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

Elliott, R. J., Kuai, W., Maddison, D. & Ozgen, C. (2021), Eco-innovation and employment: A task-based analysis, IZA Discussion Paper Series 14028, IZA Institute of Labour Economics.

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.

Eppinger, P. S. (2019), 'Service offshoring and firm employment', *Journal of International Economics* **117**, 209–228.

ETAP (n.d.), '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, Luxembourg: Eurostat, European Commission.

Eurostat (2013), Environmental taxes - A statistical guide - 2013 edition, Technical report, Eurostat.

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

Federico, S. & Tosti, E. (2017), 'Exporters and importers of services: Firm-level evidence on Italy', *The World Economy* **40**(10), 2078–2096.

Fransen, E., Plantenga, J. & Vlasblom, J. D. (2012), 'Why do women still earn less than men? Decomposing the Dutch gender pay gap, 1996–2006', *Applied Economics* **44**(33), 4343–4354.

Fu, X. (2008), 'Foreign direct investment, absorptive capacity and regional innovation capabilities: Evidence from China', *Oxford Development Studies* **36**(1), 89–110.

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.

González, X., Miles-Touya, D. & Pazó, C. (2016), 'R&d, worker training and innovation: Firm-level evidence', *Industry and Innovation* **23**(8), 694–712.

Gray, W. B. & Shadbegian, R. J. (2014), Do the job effects of regulation differ with the competitive environment, *in* 'Does regulation kill jobs', University of Pennsylvania Press, Philadelphia.

Gray, W. B., Shadbegian, R. J., Wang, C. & Meral, M. (2014), 'Do EPA regulations affect labor demand? Evidence from the pulp and paper industry', *Journal of Environmental Economics and Management* **68**(1), 188–202.

Greenstone, M. (2002), 'The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures', *Journal of political economy* **110**(6), 1175–1219.

Hafstead, M. A. & Williams III, R. C. (2018), 'Unemployment and environmental regulation in general equilibrium', *Journal of Public Economics* **160**, 50–65.

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.

Harsdorff, M. & Phillips, D. (2013), *Methodologies for assessing green jobs*, ILO.

Hillage, J. & Cross, M. (2015), Exploring the value of an O* NET resource for the UK, Report from a workshop held in london.

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, Technical report, The Global Warming Policy Foundation, Report 3, London, UK.

ILO (2011), Green structural change: Sectoral analysis and policy challenges, EC-IILS joint discussion paper series, ILO, Geneva.

ILO (2012*a*), *International Standard Classification of Occupations: ISCO-08*, International Labour Organization, Geneva.

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

ILO (2018), *World Employment and Social Outlook 2018: Greening with jobs*, International Labour Organisation, Geneva.

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

Jann, B. (2008), 'The Blinder–Oaxaca decomposition for linear regression models', *The Stata Journal* **8**(4), 453–479.

Jones, V. (2009), *The green collar economy: How one solution can fix our two biggest problems*, Harper Collins.

Kahn, M. E. & Mansur, E. T. (2013), 'Do local energy prices and regulation affect the geographic concentration of employment?', *Journal of Public Economics* **101**, 105–114.

Kidd, M. P. (1993), 'Sex discrimination and occupational segregation in the Australian labour market', *Economic Record* **69**(1), 44–55.

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, WWW for Europe Working Paper No. 50.

Lin, B. & Li, X. (2011), 'The effect of carbon tax on per capita CO2 emissions', *Energy Policy* **39**(9), 5137–5146.

Liu, M., Shadbegian, R. & Zhang, B. (2017), 'Does environmental regulation affect labor demand in China? Evidence from the textile printing and dyeing industry', *Journal of Environmental Economics and Management* **86**, 277–294.

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*, Cambridge university press.

Martin, R., De Preux, L. B. & Wagner, U. J. (2014), 'The impact of a carbon tax on manufacturing: Evidence from microdata', *Journal of Public Economics* **117**, 1–14.

Metcalf, G. E. (2019), 'On the economics of a carbon tax for the United States', *Brookings Papers on Economic Activity* **2019**(1), 405–484.

Metcalf, G. E. & Stock, J. H. (2020), The macroeconomic impact of Europe's Carbon Taxes, Technical report, National Bureau of Economic Research.

Morgenstern, R. D., Pizer, W. A. & Shih, J.-S. (2002), 'Jobs versus the environment: an industry-level perspective', *Journal of Environmental Economics and Management* **43**(3), 412–436.

Neumark, D. (1988), 'Employers discriminatory behavior and the estimation of wage discrimination', *Journal of Human Resources* pp. 279–295.

Nientker, W. & Alessie, R. (2019), 'Female labor market participation across cohorts: Evidence from the Netherlands', *De Economist* **167**(4), 407–433.

Oaxaca, R. (1973), 'Male-female wage differentials in urban labour markets', *International Economic Review* pp. 693–709.

OECD (1999), *The Environmental Goods and Services Industry*, Manual for Data Collection and Analysis, Paris.

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

OECD (2011*a*), *Environmental Taxation: A Guide for Policy Makers*, Organisation for Economic Co-operation and Development, Paris.

OECD (2011*b*), *Towards Green Growth: Monitoring Progress*, Paris.

OECD (2020*a*), 'Building back better: A sustainable, resilient recovery after covid-19', https://www.oecd.org/coronavirus/policy-responses/building-back-better-a-sustainable-resilient-recovery-after-covid-19-52b869f5/.

OECD (2020*b*), 'Green growth challenge: Shifting the tax burden in favour of environmentally related taxation', https://www.oecd.org/environment/tools-evaluation/environmentaltaxation.htm.

OECD (2020*c*), 'Making the green recovery work for jobs, income and growth', https://www.oecd.org/coronavirus/policy-responses/making-the-green-recovery-work-for-jobs-income-and-growth-a505f3e7/.

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

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

Pearce, D. (1991), 'The role of carbon taxes in adjusting to global warming', *The economic journal* **101**(407), 938–948.

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

Peters, D. J., Eathington, L. & Swenson, D. (2011), An exploration of green job policies, theoretical underpinnings, measurement approaches, and job growth expectations, Technical report, Iowa State University.

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

Reimers, C. W. (1983), 'Labor market discrimination against Hispanic and black men', *The Review of Economics and Statistics* pp. 570–579.

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.

Rivers, N. & Schaufele, B. (2015), 'Salience of carbon taxes in the gasoline market', *Journal of Environmental Economics and Management* **74**, 23–36.

Rueda-Cantuche, J. M., Kerner, R., Cernat, L., Ritola, V. et al. (2016), 'Trade in services by GATS modes of supply: Statistical concepts and first EU estimates', *Chief Economist Note* (3).

Rutzer, C. (2020), Estimating the green potential of occupations: A new approach applied to the US labor market, Working Paper 2020/03.

Sheng, J., Zhou, W. & Zhang, S. (2019), 'The role of the intensity of environmental regulation and corruption in the employment of manufacturing enterprises: Evidence from China', *Journal of Cleaner Production* **219**, 244–257.

Spelman, C., Cable, V. & Huhne, C. (2011), Enabling the transition to a green economy: Government and business working together, Technical report, HMSO, London.

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

Sweeney, S. & Kubit, J. (2008), *Green jobs: Towards decent work in a sustainable, low carbon world*, Geneva: ILO.

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, Technical report, United Nations Environmental Programme, Nairobi.

Van der Meer, P. H. (2008), 'Is the gender wage gap declining in the Netherlands?', *Applied Economics* **40**(2), 149–160.

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.

Walker, W. R. (2013), 'The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce', *The Quarterly Journal of Economics* **128**(4), 1787–1835.

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 (n.d.*a*), 'Agriculture, forestry, and fishing, value added (% of GDP)', https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS. Accessed at: June 2019.

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

WB (n.d.*c*), 'Industry (including construction), value added (% of GDP)', https://data.worldbank.org/indicator/NV.IND.TOTL.ZS. Accessed at: June 2019.

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

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

Wielers, R. & Van der Meer, P. (2003), 'Lower educated workers and part-time work: The Netherlands 1973-91', *Acta Sociologica* **46**(4), 307–321.

Williams III, R. C. (2002), 'Environmental tax interactions when pollution affects health or productivity', *Journal of Environmental Economics and Management* **44**(2), 261–270.

Yamazaki, A. (2017), 'Jobs and climate policy: Evidence from British Columbia's revenue-neutral carbon tax', *Journal of Environmental Economics and Management* **83**, 197–216.

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.

Yip, C. M. (2018), 'On the labor market consequences of environmental taxes', *Journal of Environmental Economics and Management* **89**, 136–152.

Appendix One

Appendix to Chapter Two

A.1 Example of green tasks

[Table A.1 about here]

A.2 Green occupation in ISCO system by greenness

[Table A.2 about here]

A.3 Correspondence table of ISCO2008 major groups to skill levels

Table A.3 presents the cross-walk between ISCO2008 major groups and four skill levels. According to ILO (2012*a*), skill level 1 is lowest skill level, while skill Level 4 stands for the highest skill level. Occupations at different skill level means the requirements of different skills, educational level, and extensive experience and on-the-job training. Details to see ILO (2012*a*).

[Table A.3 about here]

A.4 O*NET-SOC to ISCO occupations weighted by Greenness

The O*NET-SOC classification has more than 1000 occupation categories compared to that of ISCO that has only 436 categories. Therefore, when we merge O*NET-SOC with ISCO, there will be cases when one ISCO code corresponds to multiple SOC codes see for example Table A.4.[1] Our definition of green jobs in the main text is to take the average greenness of all occupations (ISCO based) as the threshold, and a green job is therefore a dummy, when the jobs has a greenness index greater than this threshold, which could balance out the measurement error to some extent. However, we are still likely to overestimate the share of green employment. As an exmaple, '1112 senior governmental officials' in the example from Table A.4 is a green job in our definition. This will result in an over-estimation of number of green jobs in this ISCO occupation as '1112 senior governmental officials' corresponds to both green and non-green SOC occupations.

[Table A.4 about here]

Bowen et al. (2018) estimates green employment in US labour market using O*NET classification, and found green employment accounts for 19% of total employment in US based on binary approach including indirect green ID occupations. Our green jobs estimates

[1] Values in brackets are greenness indices

are more comparable to Consoli et al. (2016), who focus only on direct green occupations using the same binary approach. Their estimates ranging from 9.8% to 12.3% is lower than our estimates (16%). Alternatively, we could use continuous measure proposed by Vona et al. (2019), who reweight the employment by greenness and found about 3% total employment can be considered as green employment in the US labour market.[2]

In this subsection, we reweight the number of green jobs by their greenness index within each ISCO code by assuming ONET-SOC occupations are uniformly distributed within the corresponding ISCO occupation. Take the example above. If we observe 1,000 people in ISCO 1112 in 2018, then number of green jobs with ISCO 1112 is 1000*0.2045, which gives us 205 number of green jobs. Using this method, we calculated a new share of green jobs in Dutch economy in table A.5. Now the percentage of green jobs is very similar to Vona et al. (2019), ranging from 2.69% to 3.29%. However, we use our previous approach in the main text for consistency of the whole thesis.

[Table A.5 about here]

[2]They also exclude very small green jobs belonging to larger non-green job (details see Appendix of Vona et al. (2019)).This step is similar to our measure where we exclude jobs with greenness below the mean.

Table A.1: Examples of green tasks

O*NET-SOC Code	Occupation Title	Green tasks/Total tasks	Example of Green tasks (Important score /Normalised importance score)	Greenness
17-2081.00	Environmental Engineers	28/28	Design, or supervise the design of, systems, processes, or equipment for control, management, or remediation of water, air, or soil quality (4.24/0.0428); Write reports or articles for Web sites or newsletters related to environmental engineering issues (2.15/0.0217).	1
19-1013.00	Soil and Plant Scientists	17/27	Investigate soil problems or poor water quality to determine sources and effects (3.7/0.0407); Study ways to improve agricultural sustainability, such as the use of new methods of composting (3.52/0.0387).	0.6218
17-2051.00	Civil Engineers	8/17	Prepare or present public reports on topics such as bid proposals, deeds, environmental impact statements, or property and right-of-way descriptions (3.53/ 0.0575); Design energy efficient or environmentally sound civil structures (3.53/ 0.0575).	0.4516
13-2051.00	Financial Analysts	6/18	Conduct financial analyses related to investments in green construction or green retrofitting projects (2.46/ 0.0407); Forecast or analyze financial costs associated with climate change or other environmental factors, such as clean water supply and demand (2.14/0.0354).	0.2961
17-2051.01	Transportation Engineers	6/25	Design or engineer drainage, erosion, or sedimentation control systems for transportation projects (3.95/0.0442) ; Analyze environmental impact statements for transportation projects (2.83/0.0317).	0.1794

Table A.2: Green occupation in ISCO system by task-based greenness

ISCO08	Occupation title	Task-based Greeness
2143	Environmental engineers	1
9612	Refuse sorters	1
1321	Manufacturing managers	0.5714
7119	Building frame and related trades workers not elsewhere classified	0.5333
7411	Building and related electricians	0.5000
3123	Construction supervisors	0.5000
2631	Economists	0.5000
3141	Life science technicians (excluding medical)	0.5000
9611	Garbage and recycling collectors	0.5000
2112	Meteorologists	0.4624
1223	Research and development managers	0.4612
2164	Town and traffic planners	0.3604
1322	Mining managers	0.3268
1439	Services managers not elsewhere classified	0.3268
1349	Professional services managers not elsewhere classified	0.3268
1213	Policy and planning managers	0.3268
1120	Managing directors and chief executives	0.3067
2422	Policy administration professionals	0.2857
2433	Technical and medical sales professionals (excluding ICT)	0.2781
2161	Building architects	0.2683
2162	Landscape architects	0.2601
7111	House builders	0.2510
1323	Construction managers	0.2510
1113	Traditional chiefs and heads of villages	0.2500
2132	Farming, forestry and fisheries advisers	0.2073
1112	Senior government officials	0.2045
2434	Information and communications technology sales professionals	0.1854

1324	Supply, distribution and related managers	0.1662
1431	Sports, recreation and cultural centre managers	0.1634
2151	Electrical engineers	0.1607
2412	Financial and investment advisers	0.1593
8114	Cement, stone and other mineral products machine operators	0.1500
3132	Incinerator and water treatment plant operators	0.1500
3119	Physical and engineering science technicians not elsewhere classified	0.1477
1114	Senior officials of special-interest organizations	0.1467
2149	Engineering professionals not elsewhere classified	0.1308
9333	Freight handlers	0.1250
9329	Manufacturing labourers not elsewhere classified	0.1250
3131	Power production plant operators	0.1195
1420	Retail and wholesale trade managers	0.1134
5221	Shopkeepers	0.1134
7233	Agricultural and industrial machinery mechanics and repairers	0.1111
3257	Environmental and occupational health inspectors and associates	0.1107
2153	Telecommunications engineers	0.0984
1221	Sales and marketing managers	0.0860
3323	Buyers	0.0828
2421	Management and organization analysts	0.0823
7126	Plumbers and pipe fitters	0.0804
3116	Chemical engineering technicians	0.0797
7213	Sheet-metal workers	0.0714
3522	Telecommunications engineering technicians	0.0668
3155	Air traffic safety electronics technicians	0.0668
3114	Electronics engineering technicians	0.0668
8211	Mechanical machinery assemblers	0.0648
3117	Mining and metallurgical technicians	0.0638
3115	Mechanical engineering technicians	0.0628
2131	Biologists, botanists, zoologists and related professionals	0.0622

2114	Geologists and geophysicists	0.0581
1346	Financial and insurance services branch managers	0.0567
1343	Aged care services managers	0.0567
1219	Business services and administration managers not elsewhere classified	0.0545
3113	Electrical engineering technicians	0.0531
3112	Civil engineering technicians	0.0528
8332	Heavy truck and lorry drivers	0.0428
3111	Chemical and physical science technicians	0.0410
3339	Business services agents not elsewhere classified	0.0390
211	Physical and earth science professionals	0.0389
3142	Agricultural technicians	0.0367
1312	Aquaculture and fisheries production managers	0.0361
1311	Agricultural and forestry production managers	0.0361
2619	Legal professionals not elsewhere classified	0.0281
7513	Dairy-products makers	0.0270
2633	Philosophers, historians and political scientists	0.0225
2642	Journalists	0.0193
8131	Chemical products plant and machine operators	0.0180
9313	Building construction labourers	0.0172
8111	Miners and quarriers	0.0153
7231	Motor vehicle mechanics and repairers	0.0151
8113	Well drillers and borers and related workers	0.0083
2519	Software and applications developers and analysts not elsewhere classified	0.0057
7223	Metal working machine tool setters and operators	0.0055
3311	Securities and finance dealers and brokers	0.0050
3324	Trade brokers	0.0033
2529	Database and network professionals not elsewhere classified	0.0028

Table A.3: Correspondence table of ISCO-08 major groups to skill levels

ISCO-08 major groups	Skill level
Managers	3 + 4
Professionals	4
Technicians and Associate Professionals	3
Services and Sales Workers	2
Craft and Related Trades Workers	2
Plant and Machine Operators, and Assemblers	2
Elementary Occupations	1

Source: ILO (2012*a*)

SOC	SOC-title	ONET-SOC	ONET-SOC title
111011	Chief Executives (0.5)	111011.03	Chief Sustainability officer (1)
		111011.00	Chief Executives (0)
111021	General and Operations Managers (0.1134)	111021.00	General and Operations Managers (0.1134)
119161	Emergency Management Directors (0)	119161.00	Emergency Management Directors (0)

(a) O*NET-SOC to SOC

ISCO	SOC	SOC-title
	111011	Chief Executives (0.5)
1112	111021	General and Operations Managers (0.1134)
Senior government officials (0.2045)	119161	Emergency Management Directors (0)

(b) SOC to ISCO

Table A.4: An example of O*NET-SOC occupation to ISCO occupation

Table A.5: Share of green jobs weighted by greenness (2000 - 2018)

Year	Obs.	Share of green jobs
2000	23,926	3.10%
2001	68,597	3.21%
2002	50,678	3.18%
2003	51,574	3.20%
2004	58,326	3.01%
2005	55,717	3.09%
2006	51,495	3.01%
2007	51,256	3.16%
2008	53,617	3.29%
2009	46,265	3.15%
2010	69,610	3.16%
2011	51,127	3.14%
2012	85,115	2.92%
2013	61,861	2.88%
2014	58,133	2.79%
2015	61,546	2.83%
2016	58,814	2.84%
2017	58,901	2.69%
2018	70,406	2.75%

Appendix Two

Appendix to Chapter Three

B.1 Data description

B.1.1 Variable description and source

Table B.1 gives description and source of variables in this paper. Share of green jobs and share of high skilled workers are obtained from confidential individual data of Labour Force Survey(LFS). Most variables at sector level are readily available from Eurostat or StatLine except data on trade. Data on export and import is extracted from UN Comtrade. To aggregate trade data to sectoral level, we make use of two data sources: trade in goods and trade in service in Netherlands between year 2000 to 2016.

[Table B.1 about here]

Trade in goods data is available for the research period based on the Standard international trade classification (SITC Rev.3) at 5-digit product level. [1] In order to aggregate

[1]The SITC REV3 is the best version we could use which covers the study period, otherwise data is not available for more recent years using latest code classification

to our sectoral level, we make use of the correspondence table between ISIC REV. 3 and SITC REV.3.[2] Our target industrial activities codes is ISIC REV4 as the first digit of which is consistent with Dutch SBI 2008. Unfortunately, there is no direct correspondence table between ISIC REV3 and ISIC REV4. Therefore, we make use of the correspondence table between ISIC REV3 and ISIC REV3.1, and ISIC REV3.1 to ISIC REV4. [3]

Trade in service data is available during the study period using the Extended Balance of Payments Services (EBOPS 2002) classification. However, trade in service information is largely missing at more disaggregated levels after 2010, we therefore choose service data based on the first level of EBOPS 2002 classification, and then matched it roughly to industry activities classification (ISIC REV.4) following Eppinger (2019), Federico & Tosti (2017), Rueda-Cantuche et al. (2016). The correspondence table can be found in tableB.2.

[Table B.2 about here]

[2]The number of type of import and export products are almost consistent each year with slight difference. For instance, the number of type of products imported in the Netherlands is 2610 in 2015 while 2618 in 2016. Ideally, we would expect all the products type can be transformed into industrial activities, however, there are always some unmatched product left each year. For instance, the unmatched amount of product type is 49 for import in 2015 while 48 in 2016. These number of unmatched product codes are consistent as well for both import and export for each year with number ranging from 46 to 52

[3]All the correspondence tables are downloaded from ROMAN of Eurostat. Matching all these codes is not easy. There are certain concerns. Like in the correspondence table between SITC REV3 and ISIC REV3, there are cases that one SITC code matches two ISIC codes. For instance, SITC "05791" is corresponded to ISIC "0112" and "0113". We tackled this problem by giving ratios to repeated source code. In the example, SITC "05791" will have two ratios, 0.5 for ISIC "0112" and 0.5 for "0113". Consequently, the trade values under code SITC "05791" will be divided half to half for ISIC "0112" and "0113" respectively. I apply the same method when match ISIC REV3 to ISIC REV4. As we are examining at very aggregated industry level, these approximation at very detailed level should not be a big problem as they will be added together eventually

B.1.2 Sample consistency

Figure B.1 shows the sample distribution by sectors for the year 2011 to 2013. As we can see in figure (b), there are more number of observations in year 2012. This is because we are not able to dropped those duplicated observations that exist both in the last wave of 2011 and first wave of 2012. However, this will not affect the sample distribution. We see the sample distribution by sectors in all three years remain the same.

[Figure B.1 about here]

B.1.3 Summary statistics and correlation matrix

[Table B.3 about here]

[Table B.4 about here]

B.2 Environmental tax classification

According to Eurostat (2013), environmental taxes can be broken down into four main categories: energy taxes (including tax on fuel for transport), transport taxes (excluding fuel for transport), pollution taxes and resources taxes. Table B.5 presents the breakdown of environmental tax in this paper, and it also gives the subcategories of each broad category and examples of each subcategory.

[Table B.5 about here]

The categories that are used on Statline is different from the Eurostat categories. There are two main categories in Statline: environmental taxes and environmental fees. Environmental taxes are also further divided into taxes on products, mobility tax and manure surplus tax. Table B.6 below shows for each tax of Dutch categories and the corresponding Eurostat category (Energy / Transport / Resources / Pollution).

[Table B.6 about here]

B.3 Environmental tax and employment: Fixed effect model

To ensure that our results are robust we further run our estimations again treating environmental taxes as exogenous and estimate Equation (2) using a fixed effects model.[4] Table B.7 presents the fixed effect estimation results for the whole sample, industrial and non-industrial sectors respectively. For the whole sample there is still no statistically significant effect of environmental taxes on total employment at the sector level. However, environmental tax are significantly and positively correlated with the number of green jobs and the share of green jobs at the sector level matching the findings from the 3SLS results in Table 3.1. More specifically, a 10% increase in the environmental tax take will lead to a 0.728% increase in number of green jobs (equivalent to 451 green workers), approximately equal to 0.178% increase in the share of green workers at the sector level. The magnitudes are just a little smaller than those found in Table 3.1.

Column (4) to (9) of table B.7 present the Fixed effect model results for industrial

[4] A Hausman test suggests that a fixed effects model is more appropriate than a random effects model

and non-industrial sectors respectively. Environmental taxes are found to be statistically and negatively correlated with total employment in the industrial sector, but positively correlated with the number of green workers in the non-industrial sector. Finally, we show that environmental taxes are positively correlated with the share of green workers in both sectors. These results are broadly consistent with our 3SLS results.

[Table B.7 about here]

Finally. the results from a fixed effects model that examine the relationship between energy taxes and employment for the whole sample, and the industrial and non industrial samples are presented in Table B.8. Results are broadly consistent with those found in Table 3.2. For the whole sample, energy taxes are found to have a significant and positive effect on the number of green workers and the share of green workers but no impact on total employment (compared to a marginally significant positive impact in Table 3.2). When we split the sample into industrial and non-industrial sectors, we find that energy taxes have a negative impact on industrial sector total employment, but a positive and significant impact on the number of green workers in non-industrial sectors. A positive and significant effect on the share of green jobs is found in both sectoral groupings. The results suggest that energy taxes are driving the sectoral differences found in Table B.7 when energy taxes are treated exogenously.

[Table B.8 about here]

Table B.1: Variable description and source

Variable	Description	Source
Total employment	Number of employees(excluding self-employed*1000)	StatLine Database
Share of green jobs	Share of green workers	Labour Force Survey
Entax	Total Environmental Tax (million euros)	StatLine Database
Wage	Hourly wage rate	StatLine Database
GVA	Gross Value Added (million euros)	Eurostat Database
Wagegrowth	Growth in wage	StatLine Database
GVAgrowth	Growth in GVA	Eurostat Database
Surplus	Net operating surplus(million euros)	StatLine Database
Openness	Imports plus exports as a share of GVA	UN Comtrade
Netexport	Net export as a share of GVA	Eurostat Database
Capitalstock	Capital stock(million euros)	StatLine Database
GHG	GHG emission	StatLine
Highskill	Share of high skilled workers	Labour Force Survey

Note: all variables are reported by industry and by year

Green employment is calculated by total employment multiply by share of green jobs

Table B.2: Correspondence table for trade in service

EBOPS 2002	Commodity	SBI code
205	1 Transportation	H
236	2 Travel	I
245	3 Communications services	J
249	4 Construction services	F
253	5 Insurance services	K
260	6 Financial services	K
262	7 Computer and information services	J
266	8 Royalties and license fees	J
268	9 Other business services	M
287	10 Personal, cultural, and recreational services	R
291	11 Government services, n.i.e.	O

Table B.3: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Total employment	255	5.138	1.268	2.079	6.799
Green employment	255	3.496	1.247	1.099	5.377
Share of green jobs	255	0.234	0.125	0.017	0.636
Entax	255	5.503	1.103	2.197	7.650
Wage	255	24.925	7.883	13.1	48
GVA	255	9.741	0.882	7.877	11.250
Wagegrowth	255	2.482	1.981	-5.2	8
GVAgrowth	255	0.032	0.078	-0.370	0.420
Openness	255	1.237	1.650	0.001	8.438
Netexport	255	0.096	0.246	-0.115	1.048
Surplus	255	8.611	2.490	0	11.023
Capitalstock	255	1.061	1.105	-0.930	3.475
GHG	255	8.065	1.725	5.485	11.008
Highskill	255	0.282	0.156	0.040	0.594

Table B.4: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1.Total employment	1											
2.Green employment	0.8453*	1										
3.Share of green jobs	-0.4563*	0.0461	1									
4.Entax	0.7333*	0.7240*	-0.1355	1								
5.Wage	-0.3994*	-0.1077	0.4452*	-0.4768*	1							
6.GVA	0.7035*	0.7732*	-0.1105	0.4587*	0.2492*	1						
7.Wagegrowth	0.0034	0.0605	0.0581	-0.1296	-0.0402	0.0317	1					
8.GVAgrowth	-0.0106	-0.0042	0.0418	-0.0865	-0.0925	0.0095	0.1855*	1				
9.Capitalstock	0.2533*	0.4770*	0.2482*	0.3142*	0.2955*	0.6366*	0.0566	-0.0483	1			
10.Surplus	-0.0443	-0.0734	-0.0487	0.0395	0.1029	0.1080	-0.0539	0.0145	-0.3157*	1		
11.Netexport	0.0453	-0.0084	-0.1009	0.2959*	-0.2681*	0.0381	-0.1158	-0.0770	0.2990*	0.1334	1	
12.Openness	0.3545*	0.2500*	-0.1972*	0.3670*	-0.1708*	0.3588*	-0.1176	-0.0786	0.2836*	0.3063*	0.6421*	1

Table B.5: Environmental tax categories

Energy tax:
— Energy products for transport purposes
— Energy products for stationary purposes
— Greenhouse gases emission
Pollution tax:
— Measured or estimated emissions to air or water
— Waste management
Resource tax:
— Water abstraction
Environmental tax on transport
— Motor vehicles import or sale (one off taxes)
— Registration or use of motor vehicles, recurrent (e.g. yearly taxes)
— Road use (e.g. motorway taxes)
— Congestion charges and city tolls (if taxes in national accounts)
— Other means of transport (ships, airplanes, railways, etc.)
— Vehicle insurance (excludes general insurance taxes)

Note: source: Eurostat (2013)

Table B.6: Environmental tax categories corresponding table

StatLine main categories	StatLine sub-categories		Eursotat category
Environmental taxes	Environmental taxes on products	Waste tax	Pollution
		Fuel tax	Energy
		Tax on electricity and gas use	Energy
		Tap water and groundwater taxes	Resource
		Tax on packaging	Pollution
		Flight tax	Transport
	Mobility tax	Excise duties	Energy
		Tax on passenger cars and motercycles	Transport
		Motor vehicle tax	Transport
	Manure surplus tax		Pollution
Environmental fees	Waste collection fee		Pollution
	Noise tax civil aviation		Pollution
	Fees on groundwater ans refuse dumps		Pollution
	Sewerage charges		Pollution
	Fees on water pollution		Pollution

Table B.7: Environmental tax and employment: Fixed Effect Model

	Whole sample			Industrial sectors			Non-industrial sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs
Entax	0.00184	0.0728***	0.0178***	-0.0188**	0.0247	0.0153**	0.0359	0.150***	0.0211**
	(0.0121)	(0.0225)	(0.00449)	(0.00730)	(0.0177)	(0.00641)	(0.0275)	(0.0556)	(0.0107)
$Wage_{t-1}$	-0.0242***	-0.00819	0.00185	-0.0108	0.0380**	0.0229***	-0.0250***	-0.00954	0.000361
	(0.00358)	(0.00665)	(0.00133)	(0.00718)	(0.0175)	(0.00631)	(0.00377)	(0.00761)	(0.00146)
GVA_{t-1}	0.631***	0.352*	-0.00445	1.329***	1.311***	-0.0446	0.387***	0.252	0.0533
	(0.100)	(0.186)	(0.0372)	(0.123)	(0.299)	(0.108)	(0.126)	(0.254)	(0.0488)
$Wagegrowth_{t-1}$	0.00338	-0.00510	-0.00146	0.00382	-0.00429	-0.00398	-0.00209	-0.00931	-0.0000733
	(0.00283)	(0.00525)	(0.00105)	(0.00289)	(0.00702)	(0.00254)	(0.00321)	(0.00647)	(0.00124)
$GVAgrowth_{t-1}$	-0.107*	0.0240	0.0333	-0.0668	-0.00996	0.0271	-0.114	-0.00990	0.0268
	(0.0642)	(0.119)	(0.0238)	(0.0673)	(0.164)	(0.0592)	(0.0722)	(0.146)	(0.0280)
$Surplus_{t-1}$	-0.181***	-0.153*	-0.00733	-0.314***	-0.410***	-0.0316	-0.175***	-0.136	-0.0176
	(0.0423)	(0.0786)	(0.0157)	(0.0530)	(0.129)	(0.0466)	(0.0555)	(0.112)	(0.0215)
$Openness_{t-1}$	0.00221	-0.0240	-0.00319	-0.0155	0.0236	0.0115	-0.00945	0.00186	-0.000139
	(0.0119)	(0.0220)	(0.00441)	(0.0146)	(0.0354)	(0.0128)	(0.0143)	(0.0288)	(0.00553)
$Netexport_{t-1}$	-0.163**	0.149	0.0298	0.131	0.0351	-0.000852	-0.311***	0.285*	0.0621*
	(0.0740)	(0.137)	(0.0275)	(0.0865)	(0.210)	(0.0760)	(0.0835)	(0.169)	(0.0323)
$Capital_{t-1}$	-0.00481	0.00763	0.00216	0.00170	-0.0945	-0.0393*	-0.00630	0.0106	0.00219
	(0.00391)	(0.00726)	(0.00145)	(0.0246)	(0.0598)	(0.0216)	(0.00394)	(0.00795)	(0.00153)
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	64	64	64	176	176	176

* p<0.10 ** p<0.05 *** p<0.01; Standard errors in parentheses; Constants are not reported

All the variables are logged except ratios; All the control variables are lagged for one period

Column (1) to (3) for whole sample

Column (4) to (6) for industrial sample, and column (7) to (9) for non-industrial sample

Table B.8: Energy taxes and employment: Fixed Effect Model

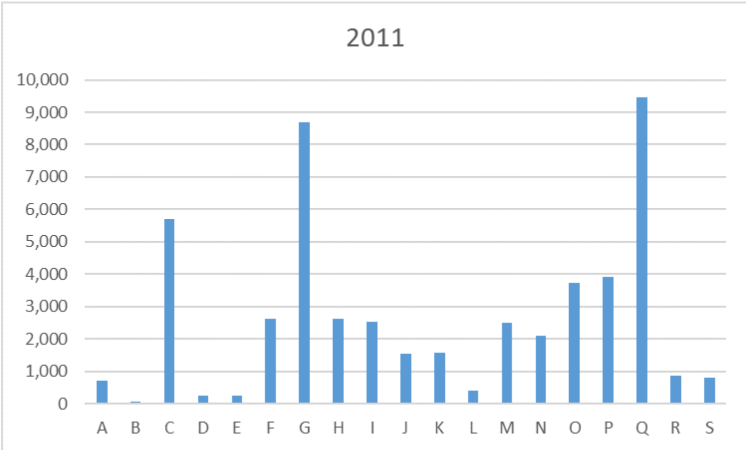
	Whole sample			Industrial sectors			Non-industrial sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs
$Energytax$	-0.00638	0.0589***	0.0126***	-0.0167***	0.0229	0.0131**	0.0396	0.182***	0.0217**
	(0.0104)	(0.0193)	(0.00391)	(0.00576)	(0.0142)	(0.00511)	(0.0255)	(0.0508)	(0.00989)
$Wage_{t-1}$	-0.0246***	-0.00531	0.00244*	-0.0147*	0.0435**	0.0259***	-0.0235***	-0.00243	0.00117
	(0.00363)	(0.00677)	(0.00137)	(0.00734)	(0.0180)	(0.00651)	(0.00395)	(0.00784)	(0.00153)
GVA_{t-1}	0.637***	0.314*	-0.0121	1.381***	1.244***	-0.0873	0.358***	0.130	0.0365
	(0.101)	(0.187)	(0.0378)	(0.118)	(0.290)	(0.105)	(0.124)	(0.247)	(0.0482)
$Wagegrowth_{t-1}$	0.00322	-0.00590	-0.00169	0.00400	-0.00450	-0.00415	-0.00236	-0.0105	-0.000223
	(0.00282)	(0.00525)	(0.00106)	(0.00282)	(0.00694)	(0.00250)	(0.00320)	(0.00636)	(0.00124)
$GVAgrowth_{t-1}$	-0.117*	0.0367	0.0340	-0.0796	0.0112	0.0355	-0.106	0.0283	0.0310
	(0.0647)	(0.121)	(0.0243)	(0.0668)	(0.164)	(0.0593)	(0.0724)	(0.144)	(0.0280)
$Surplus_{t-1}$	-0.185***	-0.148*	-0.00706	-0.324***	-0.398***	-0.0228	-0.166***	-0.0933	-0.0126
	(0.0424)	(0.0790)	(0.0160)	(0.0509)	(0.125)	(0.0452)	(0.0558)	(0.111)	(0.0216)
$Openness_{t-1}$	0.00304	-0.0200	-0.00205	-0.0182	0.0274	0.0135	-0.0122	-0.0119	-0.00156
	(0.0118)	(0.0220)	(0.00444)	(0.0144)	(0.0353)	(0.0127)	(0.0145)	(0.0288)	(0.00562)
$Netexport_{t-1}$	-0.166**	0.118	0.0220	0.152*	0.00709	-0.0177	-0.302***	0.328*	0.0669**
	(0.0736)	(0.137)	(0.0277)	(0.0846)	(0.208)	(0.0751)	(0.0837)	(0.166)	(0.0324)
$Capital_{t-1}$	-0.00495	0.00799	0.00221	-0.00158	-0.0913	-0.0361*	-0.00645	0.0103	0.00208
	(0.00391)	(0.00728)	(0.00147)	(0.0235)	(0.0577)	(0.0209)	(0.00390)	(0.00776)	(0.00151)
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	64	64	64	176	176	176

* p<0.10 ** p<0.05 *** p<0.01; Standard errors in parentheses; Constants are not reported

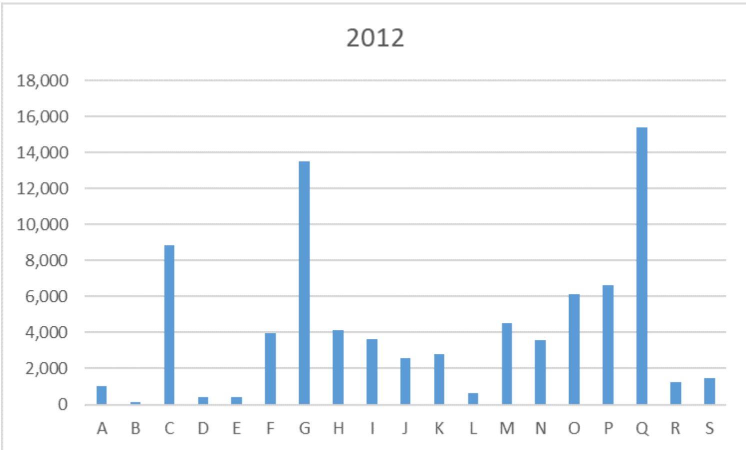
All the variables are logged except ratios; All the control variables are lagged for one period

Column (1) to (3) for whole sample

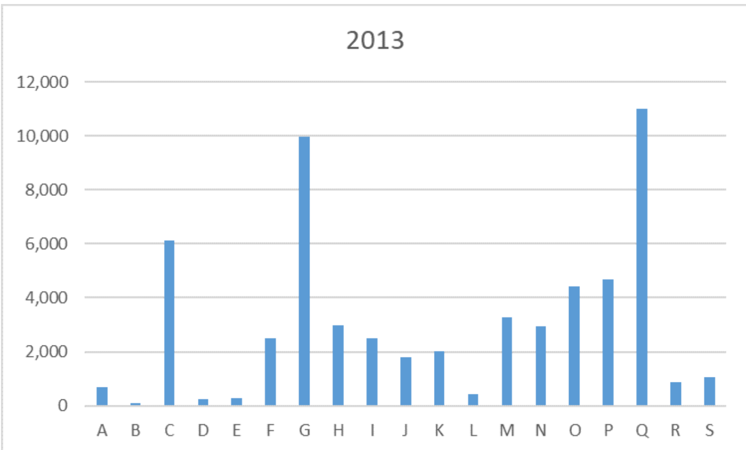
Column (4) to (6) for industrial sample, and column (7) to (9) for non-industrial sample



(a) 2011



(b) 2012



(c) 2013

Figure B.1: Sample distribution by sectors (2011 - 2013)

Appendix Three

Appendix to Chapter Four

C.1 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.[1] 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

[1]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.

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.[2] 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)). [3] The importance value for each task come directly from O*NET based on reports from both O*NET analysts and those employees that are doing the jobs (incumbents).[4] 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.

To identify green jobs in the Dutch Labour Force Survey (LFS), we compile a green

[2]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.

[3]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.

[4]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.

occupation list based on ISCO. This means we match O*NET-SOC with SOC, and then transfer SOC with ISCO. Our solution is to again calculate the average greenness of each ISCO code based on the greenness value of each SOC code, same as in Chapter Tow. 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 in Table C.1.

[Table C.1 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. [5] Based on these three different definitions of a green occupation, Table C.3 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 C.3, 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 “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 C.2 about here]

[Table C.3 about here]

C.2 Green jobs in the LFS

Figures C.1 and C.2 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

[5] Details see tableC.2

for core green occupations is steeper than that of broad green occupations. Figure C.3 and C.4 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 C.1 about here]

[Figure C.2 about here]

[Figure C.3 about here]

[Figure C.4 about here]

C.3 Firm distribution by size and industries

Figure C.5 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 C.5 about here]

Figure C.6 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 C.6 about here]

C.4 Descriptive statistics and correlation coefficients

[Table C.4 about here]

[Table C.5 about here]

C.5 Additional regression tables

[Table C.6 about here]

C.6 Test for validity of IVs

C.6.1 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.[6] 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 C.7 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 C.7, the Hansen

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

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 C.7 about here]

C.6.2 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 C.8. 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 C.8. 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), 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 C.8, 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 C.8 about here]

C.6.3 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 C.9. 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 C.9 about here]

Table C.1: 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 C.2: 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 C.3: 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

Table C.4: 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 C.5: 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

Table C.6: 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; $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table C.7: 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 C.8: 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 C.9: 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

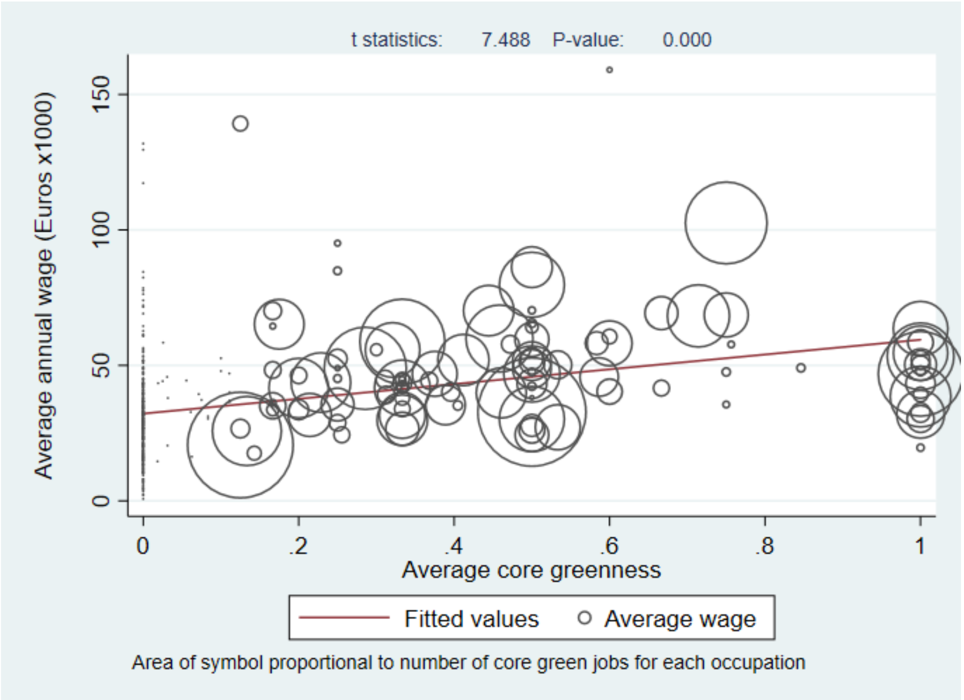


Figure C.1: Wage and core greenness

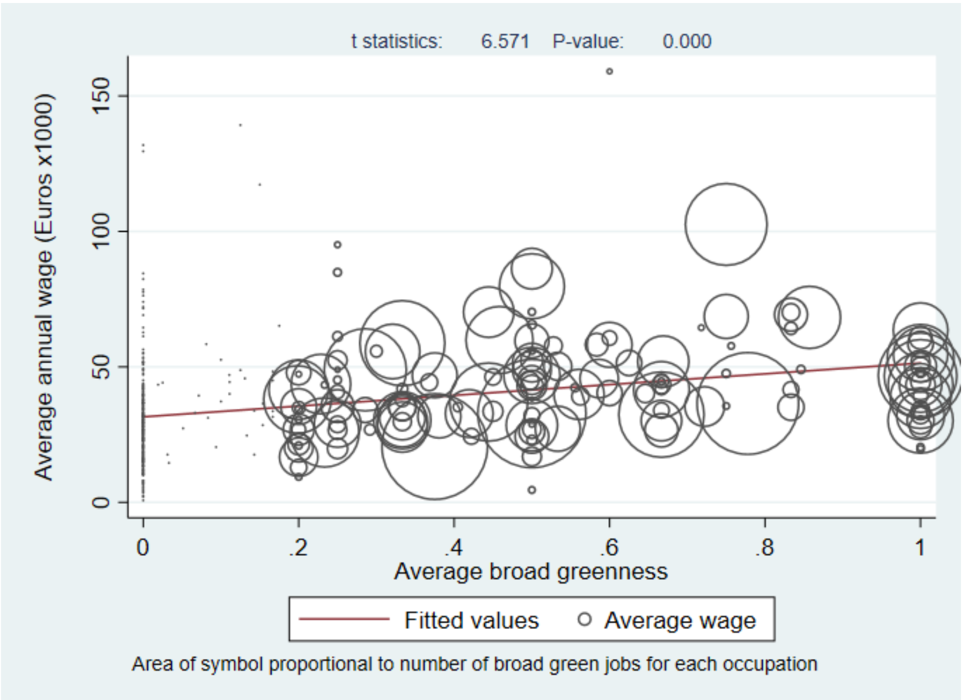


Figure C.2: Wage and broad greenness

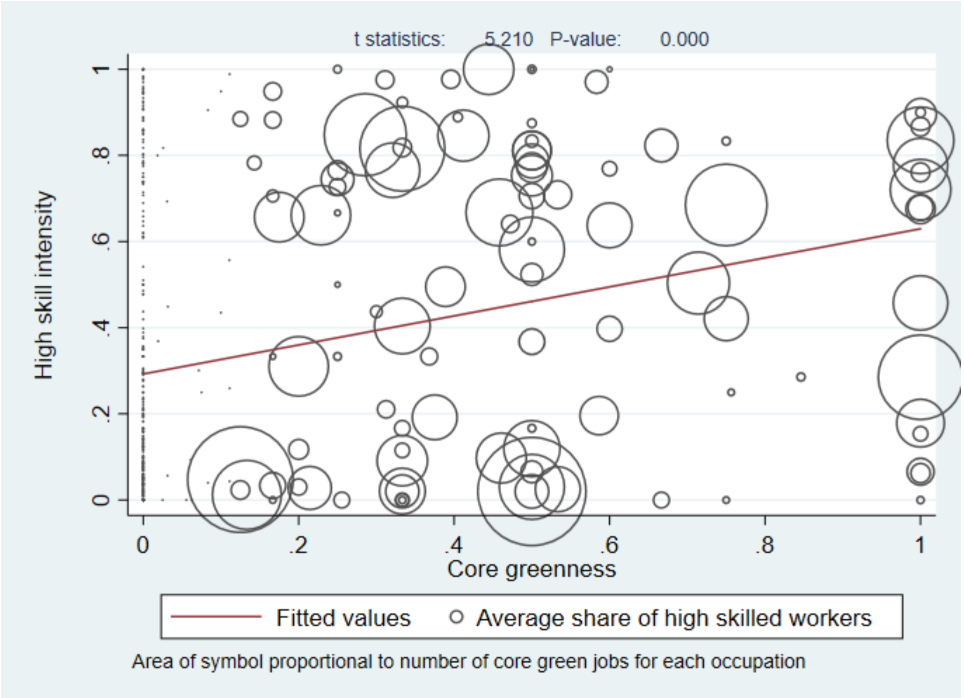


Figure C.3: High skill intensity and core greenness

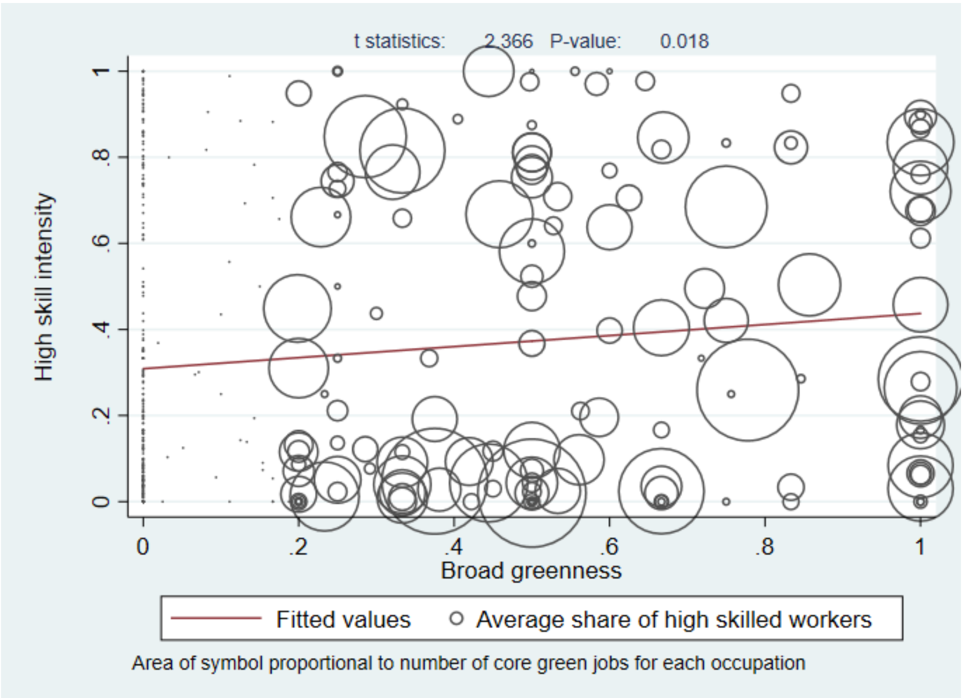


Figure C.4: High skill intensity and broad greenness

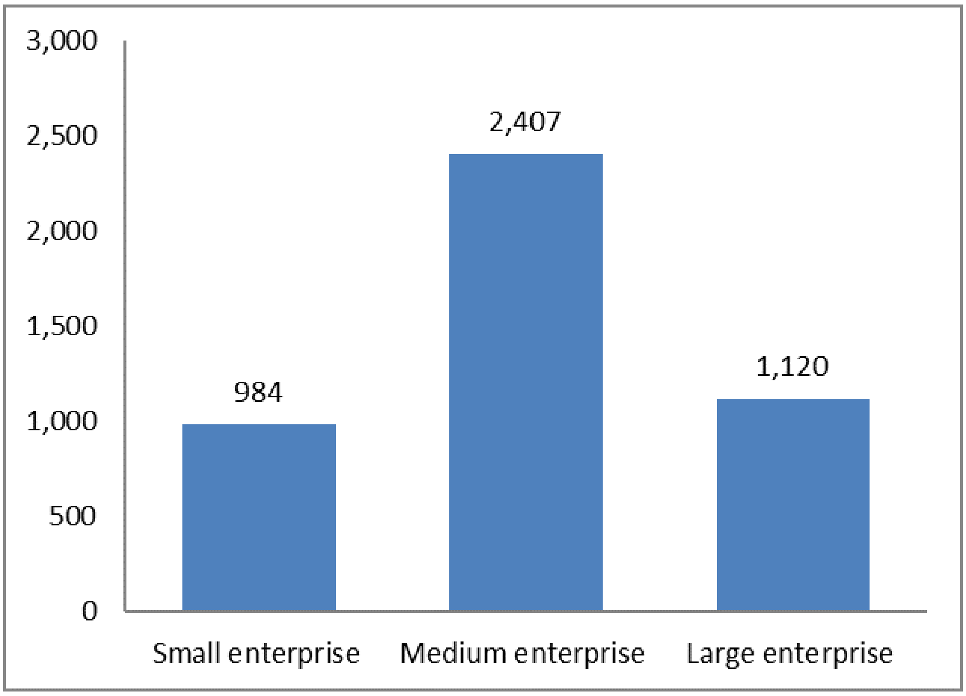


Figure C.5: Firm size distribution

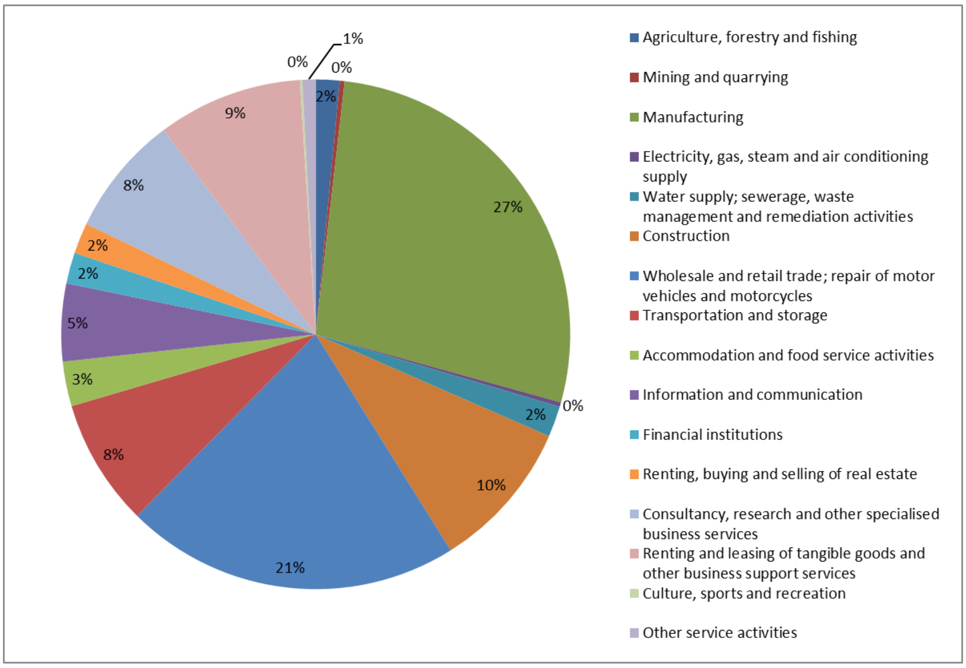


Figure C.6: Sector distribution

Appendix Four

Appendix to Chapter Five

D.1 Summary statistics and correlation matrix

[Table D.1 about here]

[Table D.2 about here]

Table D.1: Summary statistics and variable description

Varaible	Descriptions	Obs.	Mean	S.D.
Green	Dummy =1 if individual is a green job	854,237	0.171	0.376
lnwage	Log of hourly wage	854,237	3.009	0.488
Female	Dummy =1 if individual is female	854,237	0.481	0.500
Married	Dummy =1 if individual is married	854,237	0.551	0.497
Kids	Dummy =1 if individual has kids under 12	854,237	0.295	0.456
Kids_adol	Dummy =1 if individual has adolescents above 12	854,237	0.420	0.494
High skill	Dummy =1 if individual is high skilled	854,237	0.302	0.459
Middle skill	Dummy =1 if individual is middle skilled	854,237	0.435	0.496
Age	Years of age	854,237	39.220	12.891
Tenure	Years of tenure in the current position	854,237	7.983	8.347
Foreignborn	Dummy =1 if individual is foreign born	854,237	0.080	0.271
Householdsize	Total number of people in the family	854,237	3.059	1.312
Lnfirmwage	Log of average wage at firm level	854,237	9.912	0.684
Lnfirmsize	Log of total number of emploees at firm level	854,237	6.115	2.563

Note: minimum and maximum values are not reported due to output control of Dutch microdata

Table D.2: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Green	1													
2. lnwage	0.0951*	1												
3. Female	-0.2558*	0.0185*	1											
4. Married	0.0667*	0.2361*	-0.0240*	1										
5. Kids	0.0379*	0.1108*	0.0143*	0.2549*	1									
6. Kids_adol	-0.0513*	-0.1018*	-0.0099*	-0.0513*	-0.1877*	1								
7. High skill	0.0855*	0.3603*	0.0113*	0.0551*	0.0609*	-0.1657*	1							
8. Middle skill	-0.0426*	-0.0720*	0.0186*	0.0122*	0.0091*	-0.0032*	-0.5780*	1						
9. Age	0.0785*	0.2993*	-0.0458*	0.5134*	-0.1015*	-0.0918*	0.1074*	-0.0196*	1					
10.Tenure	0.0626*	0.2119*	-0.1094*	0.2923*	-0.0584*	-0.0424*	0.0266*	0.0279*	0.5297*	1				
11. Foreignborn	-0.0201*	-0.0581*	0.0167*	0.0055*	0.0502*	-0.0134*	-0.0184*	-0.0097*	0.0092*	-0.0547*	1			
12. Householdsize	-0.0071*	0.0272*	-0.0183*	0.2520*	0.4766*	0.5374*	-0.0794*	-0.0039*	-0.1800*	-0.0805*	0.0016	1		
13. Lnfirmwage	0.1871*	0.3076*	-0.2257*	0.2381*	0.0788*	-0.1980*	0.2851*	-0.0321*	0.3660*	0.3395*	-0.0258*	-0.1076*	1	
14. Lnfirmsize	-0.0414*	0.1044*	0.0719*	0.0017	-0.0176*	-0.0030*	0.0958*	-0.0393*	0.0442*	0.1777*	0.0308*	-0.0297*	0.0579*	1