Do Green Innovations stimulate Employment? – Firm-level Evidence From Germany

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Georg Licht (ZEW), Bettina Peters (ZEW)

Contribution to the Project

This research paper will use a specific set of questions on eco-innovation and its contribution to firm growth and competitiveness. This specific set of questions is only available in the German CIS. Using these data we will can more insights on the incentives to perform eco-innovation as well as the impacts on growth. Hence, this provides an empirical underpinning for modeling the growth effects of eco-innovation on the macro-level. The paper also looks at the impact of policy variables as an incentive for eco-innovation. These policy variable include various form of environmental regulation on the production but also on the demand side. Hence, the paper contributes to wwwforEurope by giving detail evidence on how innovation and environmental policy might contribute to the new growth path. This might not only contribute to CGE modelling but also to other work package which empirically deal with the growth impact of "ecological innovation".

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Executive Summary

This paper contributes to the discussion of the impact of green innovation on employment growth. In particular, we compare the employment impact of environmental and non-environmental patents as well as those of product and process innovations using data for manufacturing and service firms in Germany. It complements the analysis of Licht and Peters (2013) who analyzed the link between innovation and employment at the European level. Using German CIS data, we are able to employ more fine-grained definitions of environmental innovation and as a result we are able to better identify their employment effects. As a robustness check, we furthermore use information on patent applications for green technologies. In the empirical analysis we perform both reduced form regressions as was done in prior studies and the structural model approach suggested by Harrison et al. (2008), and we explain the major advantage of the latter approach in terms of identifying different employment effects associated with product and process innovations.

The empirical analysis shows the following key findings:

First, only a very small proportion of firms in our sample have applied for green patents, about 2% of the innovators in manufacturing and less than 1% of them in services. When we compare this with the survey-based proportion of environmental innovators, we have to ascertain that we heavily underestimate green innovation activities in both sectors using patent data. This might also be one explanation why we do not find that firms that have applied for patents protecting green technologies have grown faster, neither in manufacturing nor in services. Another explanation is that patent data do not easily allow us to identify patents related to new products and new processes though we know from theory that their employment mechanism differ quite substantially.

Second, both environmental and non-environmental product innovations are conducive to employment growth. A one-percent increase in the sales due to new products also increases *gross* employment by one percent. This elasticity tends to be lower than 1 for green product innovations in manufacturing and non-green product innovations in services, though statistically we cannot reject the null hypothesis of a unit elasticity for both types of new products in both sectors. Hence, there is no evidence that environmentally-friendly new products are produced with higher or lower efficiency than old products and thus c.p. with the same amount of labor input. A decomposition of employment growth allows us to assess the net effect of product innovation taking substitution effects on the output of old products into account. It turns out that product innovations have a positive net effect in both sectors, in manufacturing they are even the main source of employment growth. In services employment growth due to output growth in existing products exceeds that of new products. In sum, product innovations have stimulated growth by 5.6% in manufacturing and 2% in services. This is in line with results of Licht and Peters (2013) at the European level.

Third, regarding the relative importance of both types of product innovation, our findings using more detailed data on the share of sales with new products, however, suggest that still non-environmental product innovations clearly contribute more to employment growth than environmental product innovations in both sectors. This can be mainly explained by a lower engagement in green product innovation and by a relatively lower average innovation success with green product innovations, but not by differences in the transformation of a given level of innovation success to employment growth.

Fourth, the general trend in productivity has a strong negative impact of employment growth in manufacturing during the observation period but not in services.

Fifth, the displacement effect of process innovation turns out to be rather small. For non-environmental process innovators we found the effect to be about -0.3% in both sectors. The effect of environmental process innovation is negative but negligible in manufacturing and even positive in services. Adding the employment growth contribution of the change in demand for existing products for process innovators which is to a certain extent provoked by the process innovation induced reduction in prices, we find a positive net effect in both sectors.

Sixth, our results do not point towards significant differences in employment growth due to different types of process innovations. Thus, our results do not confirm prior findings of Rennings and Horbach (2013) who conclude that the employment effects of the introduction of cleaner process technologies seem to be more advantageous within a firm compared to more end-of-pipe oriented technologies.

From the perspective of generating smart and sustainable (employment) growth, we conclude that policy should stimulate product innovation and to be precise both types of product innovation. At first glance it seems to be more efficient in terms of employment growth for policy to focus on non-green product innovation since we found a larger employment contribution of non-green product innovations than of environmental product innovation. However, as noted above, this is mainly due to a lower engagement in green product innovation and a lower average innovation success with green product innovations, but not due to differences in the transformation of a given level of innovation success to employment growth. Thus, if industrial or environmental policy is able to incentivize firms to engage in green product innovation activities and also helps them to better commercialize green product innovations, environmental-friendly product innovation will most likely not have different employment impacts. The result that an industrial or environmental policy that generated more favorable conditions for environmental product innovation will not necessarily worsen the employment situation in a country holds under the assumption that there will be no structural breaks in the above mentioned transformation.

In terms of process innovation we also gained some interesting policy insights: Our results do not point towards the often feared negative employment consequences of environmental process innovation. At least for the period 2006-2008, we cannot identify a significant trade-off between more environmental-friendly production technologies and employment growth. From that result we might also infer that there is no trade-off between employment growth and stricter environmental regulations which force firms to introduce more environmental-friendly production technologies. Our findings also suggest that this would hold for stricter environmental regulations in different fields, e.g. for regulations aimed at saving material and energy or regulations aimed at reducing air, water, soil and noise pollution. Hence, there seems to be some room for industrial and environmental policies to induce the increased use of cleaner production technologies and end-of-pipe technologies in manufacturing as well as in services.

This study contributes to the Central Research Question 1 and 3 of WWWforEurope by showing that environmental innovation, e.g. induced by industrial policies to reduce environmental impact of production and consumption, will probably not weaken firms' competitiveness and destroy jobs but is able to contribute to job creation under certain conditions.

Do Green Innovations stimulate Employment? – Firm-level Evidence From Germany

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Abstract

This paper studies the impact of environmental innovation on employment growth in the period 2006-2008 using firm-level data for German manufacturing and services. It extends the model by Harrison et al (2008) in order to distinguish between employment effects of environmental and non-environmental product as well as process innovation. As a robustness check patent data on green technologies are employed. The results demonstrate that both environmental and non-environmental product innovations stimulate employment growth. We find a similar gross employment effect of both types of product innovations. That is, one-percent increases in sales stemming from new environmental and non-environmental products increase *gross* employment by one percent each. Thus, we do not find evidence that that new products with environmental benefits for consumers are produced with higher or lower efficiency than old products. Yet, the net employment contribution of non-green product innovations is 4 to 5 times larger than the net contribution of green product innovations. This is the result of differences in the average innovation engagement and innovation success of both types of new products. In contrast, environmental and non-environmental process innovation plays only a little role for employment growth. In particular, we do not identify a significant trade-off between more environmental-friendly production technologies and employment growth. This holds for both cleaner production technologies and end-of pipe technologies.

Keywords: Employment growth, environmental innovation, green patents

JEL-Codes: O33, J23, L80, C21, C23

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1. Motivation

Environmental innovations have been placed at the heart of the Europe 2020 strategy for smart, sustainable and inclusive growth and job creation. They are seen as key for Europe's economy to adjust to environmental and resource constraints. In addition to its environmental benefits, policy hopes that green innovations could provide an important contribution to strengthen the competitiveness of firms and, consequently, to the preservation or creation of *new* jobs. That's why the European Union launched its Eco-innovation Action Plan as part of its EU2020 strategy in July 2011. It complements the ambitions of the EU2020 Innovation Union and Resource Efficiency Flagship initiatives. The Eco-innovation Action Plan aims at boosting eco innovation[1] by different instruments such as implementing new environmental policy legislations, developing new standards, subsidies for research in eco innovation, mobilizing financial instruments for eco innovation, fostering international cooperation or promoting European innovation partnerships. Recent years have already seen a growth of eco industries.[2] However, it is important to note that the EU understands environmental innovation not just as being crucial for a special industry but that all firms can and should become environmental innovators by introducing new eco-innovative approaches into their operations and by launching to the market new less environmentally damaging products and services. The Eco-innovation Action Plan thus promotes the "greening of all of the sectors" and recommends the use of a broad spectrum of instruments to foster the change.

Back in 1991 Porter argued that environmental policy should not only be viewed as a restriction to a more efficient use of resources but that environmental policy might drive the long-run efficiency and induce early adjustments to upcoming price effects and hence open up opportunities to gain market shares in the future. Since then a wide variety of studies has looked at the impact of environmental policies on the adjustments of economies, industries, or firms, in particular whether it stimulates innovation. Environmental product and process innovation are supposed to be associated with positive effects by capturing two external effects. On the one hand they are supposed to reduce the negative externalities by lowering the environmental damage of production and consumption and thus contribute to climate policy goals. On the other hand, they are supposed to induce positive externalities associated with the generation and diffusion of new technologies, for instance the creation of new jobs. The possibility that environmental policy yields a "double dividend" can be seen as an important motivation also for the Eco-Innovation Action Plan. Hence, the Porter Hypothesis attracted the attention of a vast number of theoretical and empirical studies (see e.g. Porter and Linde 1995, Jaffe and Palmer 1997, Ambec and Barla 2002, Ceric 2006, Ambec and Barla 2006, Constantatos and Herman 2011, Kriechel and Ziesemar 2011, Leuuwen and Mohnen 2013, Marin 2014). This literature put forward a "weak" version of the so called Porter-Hypothesis which states that government regulations and government interventions utilizing the price mechanism affect the innovation and R&D decision of firms by putting more resources to the development and/or adoption of cleaner production and/or cleaner products. The strong version of the Porter-Hypothesis postulates that effective governmental inventions will have a positive impact on the economic performance of firms, e.g. in

[1] We use the term environmental innovation, eco innovation and green innovation interchangeably.

[2] The EU estimates a €319 billion turnover of eco industries and an employment of 3.4 million people in 2008 which has increased by 0.6 million jobs between 2004 and 2008; see EU (2011), http://ec.europa.eu/environment/ecoap/about-eco-innovation/policies-matters/eu/772_en.htm.

form of a positive effect on the productivity of firms. The majority of studies finds empirical evidence in favor of the "weak" version of the Porter-Hypothesis. The "strong" version of the Porter-Hypothesis, however, could not be confirmed by the majority of studies (see Leeuwen and Mohnen, 2013, for a short review). In addition, Marin (2014) finds the returns to eco-innovation to be substantially lower than those of non-environmental innovations. This might give rise to a crowding out of more profitable innovation by eco-innovations if firms innovation potential is limited due to the availability of financial resources or innovation capabilities. [3]

In the context of the Porter-Hypothesis this paper takes employment growth as one indicator for economic performance of firms. In order to focus on the second part of the Porter-Hypothesis we take the innovation decision as given and ask whether eco-innovation and non-eco-innovation differ in their impact on firm's employment growth. Thus, this paper contributes to the discussion of the impact of green innovation on employment growth. In particular, we compare the employment impact of environmental and non-environmental patents as well as those of product and process innovations using data for manufacturing and service firms in Germany.

The question how innovation affects employment is non-trivial since various channels exist through which different kinds of innovation may destroy existing jobs (displacement effects) or may create new jobs (compensation effects). In addition, different types of innovation such as product and process innovation influence employment via different channels. This paper studies employment effects at the firm level as the main instance where these mechanisms are more or less explicitly supposed to work (Harrison et al., 2008). Table 1 summarizes how different kinds of innovation might affect employment. Employment effects of process innovation are closely related to productivity changes. New production processes most often leads to labor productivity improvements since they allow firms to produce the same amount of output with less labor input and, ceteris paribus, lower unit costs. The size of this effect depends on the current production technology and direction of the technological change. A key open question is here whether environmental process innovations are associated with the same increase in labor productivity and thus reduction in unit costs are non-environmental process innovations. At the same time, firms can pass on lower unit costs to their product prices. In a dynamic perspective, lower prices can lead to a higher demand for the product, thus increasing output. The magnitude of this price effect depends on the price reduction, the price elasticity of demand, the degree of competition as well as on the behavior and relative strength of different agents such as managers and unions within the firm (Garcia et al., 2004). Product innovation boosts employment growth mainly via demand. Demand for the new product can either be the result of an overall market expansion, or it may come at the expense of the firm's competitors. And therefore, the size of this effect depends on the demand elasticity, the existence of substitutes and the reactions of competitors (see Garcia et al., 2004). A priori it is unclear whether and to what extent demand effects might differ for new products with and without environmental benefits for the consumer. Firm-level demand for environmental product innovations might be higher if there is less competition in the market for environmental products and services. On the other hand, eco innovations might be sold at higher prices if demand elasticity is

[3] The possibility of a crowding-out is also present in the public discussion on environmental regulation. With respect to the proposal of the EU commission on new emission goals for cars, the Wallstreet Journal comments on Chancellor Merkel's opposition to the new rule by referring to the opportunity cost of technological adjustments induced by substantially tighter standards of car emissions (see WSJ "Green Regulation and Jobs" July 1, 2013).

relatively low and this might lead to less output and thus employment. In addition, indirect demand effects on the innovative firm's existing products have to be taken into account as the new products might (partially or totally) replace the old ones. However, in the case of complementary demand relationships, the new product will cause demand for existing products to rise as well, and employment will increase further. Finally, the same amount of output of the new product may be produced at higher or lower productivity levels compared to the old product. That is, the new product may imply a change in production methods and input mix, which could either reduce or increase labor input. This effect is called productivity effect of product innovation (Harrison et al., 2008).[4]

Table 1 **Effects of product and process innovation on employment at the firm level**

	Employment-reducing effects (displacement effects)	**Employment-creating effects (compensation effects)**
Product innovation	*Productivity effect of product innovation*: New products require less (or more) labor input (-) *Indirect demand effect*: Decrease in demand of existing substitutes (-)	*Direct demand effect*: New products increase overall demand (+) *Indirect demand effect*: Increase in demand of existing complementary products (+)
Process innovation	*Productivity effect of process innovation*: Less labor input for a given output (-)	*Price effect*: Cost reduction passed on to price expands demand (+)

Source: Dachs und Peters (2014).

In a nutshell, the total effect of each type of innovation is not explicitly inferable and depends on a number of product-, technology-, firm-, sector- as well as country-specific factors. As a consequence it has to be determined empirically. In general, the majority of empirical studies finds an employment-stimulating effect of product innovation whereas the effect of process innovation is ambiguous, ranging from significantly negative to positive (for early surveys see Chennells and Van Reenen 2002 and Spieza and Vivarelli 2002, and also König et al. 1995, Van Reenen 1997, Greenan and Guellec 2000, Smolny 2002, Harrison et al. 2008, Hall et al. 2008, Lachenmeier and Rottmann 2011, Peters et al. 2013).

However, up to now empirical evidence on the employment effect of environmental innovation is still scarce, Bogliacino and Pianta (2010) at the sector level and Pfeifer and Rennings (2001), Rennings and Zwick (2002), Rennings et al. (2004), Horbach (2010), Horbach and Rennings (2013) and Licht and Peters (2013) at the firm level being an exception. Most of these studies find evidence for a positive impact of green innovation on employment. With respect to green product innovation, results are mixed. On the one hand, Horbach (2010) demonstrate that German firms belonging to the environmental sector are more likely to increase employment after they have launched new environmental products. Licht and Peters (2013) found that green and non-green product innovation similarly contribute to employment growth in Europe. Horbach and Rennings (2013), however, could not corroborate that environmental product

[4] Additional employment effects of innovations exist at a sector or macro level. Additional employment effects may occur in upstream or downstream firms, e.g. if the innovative firm is able to increase its output, its suppliers also benefit and may boost their labor demand. On the other hand, competitors which cannot keep pace with the technological progress will lose market share or even disappear, implying a deterioration of jobs in those firms.

innovators grow faster than non-environmental (product and process) innovators in Germany. Concerning environmental process innovations, they find a slightly positive impact on labor demand. They emphasize that this result is mainly driven by material and energy saving process innovations. However, process innovations aimed at reducing air and water pollution, where end-of-pipe technologies dominate, lead to labor destruction. These results corroborate prior findings of Pfeiffer and Rennings (2001) who show that cleaner production is more likely to increase employment compared to end-of-pipe technologies and Rennings and Zwick (2002) who find that end-of-pipe technologies are associated with a decrease in employment for five European countries.

In contrast to the latter studies which have estimated reduced form equations (mainly on a dummy variable indicating the change in employment), we employ and estimate a more structural approach by using the model recently proposed by Harrison et al (2008) and extended by Licht and Peters (2013). This enables us to identify different theoretical employment channels of product and process innovations. This multi-product model was originally used to estimate the effect of product and process innovation on employment growth and was extended by additionally distinguishing between environmental and non-environmental product as well as process innovation. In contrast to Licht and Peters (2013) who analyzed the link between innovation and employment at the European level, we make use of the German CIS2008 data spanning the period 2006-2008. This allows us to employ more fine-grained definitions of environmental innovation and as a result we are able to better identify their employment effects. In addition we use the structural approach to investigate whether different types of green process innovation impact employment differently. As a robustness check, we furthermore use information on patent applications for green technologies.

The outline of this paper is as follows: In section 2, we sketch the theoretical and econometric model used in the empirical part of the paper. Section 3 presents the data set, and we explain the empirical implementation of the econometric model in section 4. Descriptive statistics on environmental and non-environmental innovation and employment growth in Germany are shown in section 5. The subsequent section 6 presents the econometric evidence on the employment effects of environmental and non-environmental innovations in German firms. Finally, section 7 summarizes our key findings and draws some policy conclusions.

2. Theoretical and Econometric Model

Our empirical analysis is based on the model developed by Harrison et al. (2008). It establishes a theoretical relationship between employment growth and different kinds of innovation output at the firm level. The main virtue of the model is that we can disentangle some of the theoretical employment effects explained above. Moreover, it is particularly suited for examining firm-level employment impacts of innovation using the specific information provided by CIS data. In the original model, employment effects of product innovation (sales growth rate due to new products which can be calculated from CIS data) and process innovation (yes/no) have been studied for four European countries, the UK, Spain, France and Germany (Harrison et al 2008). Since its release, the model has already been used to assess employment effects in other countries like Chile (Benavente and Lauterbach 2007), Italy (Hall et al. 2008), China (Mairesse et al. 2011), Latin America (Crespi and Tacsir 2011, Crespi and Zuniga 2012) or European services (Peters et al.

2013). It has also been used to investigate employment effects of different types of innovations (Peters 2008) and to compare whether employment creation due to innovation differs between domestic and foreign-owned firms (Dachs and Peters 2014). Licht and Peters (2013) extended the model to investigate employment impacts of green and non-green product and process innovation and we follow their approach. We briefly explain their model. For more details, we refer to Harrison et al. (2008).

The model employs a simple multi-product framework. That is, it is assumed that a firm can produce different products.[5] A firm j is observed at two points in time t (= 1, 2). In t=1 the firm produces one or more products which are aggregated to one product and which are labelled as the "old product" or "existing product". Between t=1 and t=2, the firm can decide to introduce one or more new or significantly improved products, either with or without environmental benefits to the consumers. But let's first summarize them as just the "new product". The new product can (partially or totally) replace the old one if they are substitutes or enhance the demand of the old product in case of complementarity. In order to produce the different outputs, we assume the following production function for product *i* in time *t*:

$$(1) \qquad Y_{it} = \theta_{it} F\left(C_{it}, L_{it}, M_{it}\right) e^{\eta + \omega_{it}} \quad i = 1,2;\ t = 1,2$$

The conventional production function F is linear homogeneous in the conventional inputs labor L, capital C and material M. Moreover, the output depends on specific efficiencies for the production process of both goods at each point of time θ_{it}. It is driven by the knowledge capital of the firm which is assumed to be a non-rival input. Based on these assumptions, Harrison et al. (2008) derive the conditional labor demand functions for each product for each point in time and, as a result, the overall employment growth rate:

$$(2) \qquad l = \alpha + y_1 + \beta y_2 + u\,.$$

Equation (2) shows that employment growth l stems from three different sources in the model, that is

- from the efficiency increase in the production of the old product, which negatively affects labor demand (α).
- from the rate of change in the real output of the old product (y_1). This change in the output production of old products might be provoked by the firm's own new product to a certain degree, the induced change being negative for substitutes and positive for complements. But it also captures demand shifts due to price reductions following own process innovations, general business cycle effects, changes in consumer preferences or new products and processes that have been introduced by rivals, or in upstream or in downstream firms.[6] If we would have additional demand data, we could separate the compensation effect of process innovation and the demand

[5] In the following the term product always comprises both goods and/or services unless stated otherwise.

[6] In addition to employment effects that we observe in the innovating firm, additional employment effects of innovations may occur in rival firms or upstream and downstream firms. If, e.g., the innovative firm is able to increase its output, its suppliers also benefit and they may boost their labor demand. On the other hand, competitors which cannot keep pace with the technological progress will lose market share or even disappear, implying a deterioration of jobs in those firms. With the exception of firm exiting the market due to own unsuccessful innovation or rivals' innovation and innovative firms entering the market, our estimation accounts for these effects. However, due to data constraints, we cannot further disentangle these effects.

effect of product innovation on existing products which are both captured by y_1. However, with the data at hand we are unable to do it.

- from starting production of the new product (positive sign). The employment effect of the latter depends on the efficiency ratio between both production technologies ($\beta = \theta_{11}/\theta_{22}$) and the real output growth due to new products (y_2).

Efficiency gains in the production of the old product may for instance result from process innovation, organizational innovation, better human capital endowment, training, within-firm learning effects, spillover effects, mergers and acquisitions, and so on. Since the increase in efficiency is likely to differ for non-process innovators and process innovators, Harrison et al. (2008) suggested separating the effect of process innovation from the other sources of efficiency improvements. Licht and Peters (2013) extended this idea and estimated separately employment effects that originate from efficiency improvements in producing existing products as a result of environmental and non-environmental process innovations. In order to capture differences in employment growth due to green and non-green product innovations, we furthermore differentiate between the real output growth due to new products with and without environmental benefits for consumers, $y_{2,ENV}$ and $y_{2,NE}$, respectively. This leads to the following equation:

(3) $$l = \alpha_0 + \alpha_1 pc_{ENV} + \alpha_2 pc_{NE} + y_1 + \beta_{ENV} y_{2,ENV} + \beta_{NE} y_{2,NE} + u \ .$$

α_0 measures efficiency improvements for firms without process innovation. In the estimation this effect will be industry and size specific. α_1 and α_2 account for additional efficiency improvements in the production of the old product for firms having environmental and non-environmental process innovation, respectively. $\beta_{ENV} = \theta_{11}/\theta_{22,ENV}$ indicates the efficiency ratio of the production technologies for producing the old and new environmental product. A value of less than 1 indicates that new environmental products are produced with higher efficiency and thus less labor than the old product; similar for $\beta_{NE} = \theta_{11}/\theta_{22,NE}$.

Following Harrison et al. (2008) and substituting unobserved real output growth rates by observed nominal output growth rates, we derive the following estimation equation which describes the relationship between employment growth, efficiency gains through environmental and non-environmental process innovation and the sales growth due to new products with and without environmental benefits[7]:

(4) $$l - (g_1 - \tilde{\pi}_1) = \alpha_0 + \alpha_1 pc_{ENV} + \alpha_2 pc_{NE} + \beta_{ENV} g_{2,ENV} + \beta_{NE} g_{2,NE} + v \ .$$

g_1, $g_{2,ENV}$ and $g_{2,NE}$ denote the nominal output growth (sales growth) due to old and new products with and without environmental benefits, respectively, with $g_1 = y_1 + \pi_1$ and $g_{2,k} = y_{2,k} + \pi_{2,k} y_{2,k}$ for $k = ENV, NE$. The variable $g_{2,k}$ can be calculated using CIS data (see section 4). g_1 can be calculated by

[7] Since the coefficient of the real output growth y_1 is equal to one, it can be subtracted from *l*. y_1 is not observed in the data but proxied by $g_1 - \tilde{\pi}_1$. For more details see Harrison et al. (2008) and Peters (2008).

the total sales growth rate minus the sales growth rate due to new products. π_1 measures the (unobserved) price growth rate of old products at the firm level. Since data sets usually do not include information on firm-level price changes, π_1 is proxied by $\tilde{\pi}_1$ which is the price growth rate of old products at the industry level.[8] $\pi_{2,k}$ denotes the price difference between the new and the old product in relation to the price of the old product at the firm level. The new error term ν is

$$\nu = -E\left(\pi_1 - \tilde{\pi}_1\right) - \beta_{ENV}\pi_{2,ENV}y_{2,ENV} - \beta_{NE}\pi_{2,NE}y_{2,NE} + u \ .$$

One problem that arises in this model is the fact that the sales growth rate from new products is correlated with the error term ν. An appropriate econometric method to deal with such an endogeneity problem is to use instrumental variable techniques. The instruments should be correlated with the sales growth due to new products (i.e. innovation success), but not correlated with the error term. In particular it has to be uncorrelated with the relative price difference of new to old products. We explain in section 6.2 in more detail how we empirically address this problem by using an instrumental variable estimation approach.

3. Data

The main data set that we use in order to investigate how environmental and non-environmental innovation affects employment growth is the Mannheim Innovation Panel (MIP). The MIP is based on a written survey and it collects information about firm's innovation activities in Germany. It follows the definition of innovation and the recommendations on the survey methodology that are laid down in the Oslo manual published by OECD and Eurostat (2005, first published in 1993). Since 1993, the official German innovation surveys are conducted on a yearly base by the Centre of European Economic Research (ZEW), the Fraunhofer Institute for Systems and Innovation Research (ISI) and the Institute for Applied Social Sciences (infas) on behalf of the German Federal Ministry of Education and Research (BMBF). The MIP targets all legally independent enterprises[9] with at least 5 employees in manufacturing, mining, energy and water supply, construction and services and with headquarters in Germany. Every second year (prior to 2005: every fourth year) the data set represents the German contribution to the European-wide harmonized Community Innovation Surveys (CIS).

The MIP data collects information on innovation indicators on a yearly basis. As a distinctive feature of the 2008 survey, internationally called CIS2008, is that it includes a set of questions on the introduction of innovations with environmental benefits, its motives and impact. Up to now, these questions have only been asked in CIS2008. Hence, our analysis is restricted to one cross-section which, however, covers the three-year period 2006-2008. In contrast to Licht and Peters (2013) who employ CIS data for 16 European countries, this paper sticks to the German MIP data. As we will set out in more detail in the next section, this limitation in terms of cross-country comparability is compensated by the fact that the MIP allows a more fine-grained definition of environmental innovations and a better identification of their employment effects.

[8] If we do not properly account for firm-level price changes, we cannot identify the displacement effect of process innovation.

[9] The terms enterprise, firm and company are used interchangeably throughout the text.

The MIP is drawn as a stratified random sample samples and is representative of the corresponding target population. Firm size, industry and region serve as stratifying variables. Based on the number of employees, 8 size classes are distinguished: 5–9, 10–19, 20–49, 50–99, 100–249, 249–499, 500–999 and 1000 and more employees. With regard to the region, the sample is stratified in West and East Germany (incl. Berlin). The industry classification scheme used for stratification purposes is based on the 2–digit NACE[10] level with the exception of the service sector where the 3–digit level is applied for some industries (for more detailed information, see Peters and Rammer 2013). In the econometric analysis, we aggregate firms to 13 manufacturing and service industries each. Manufacturing industries are food (FOOD), textiles (TEXT), wood/paper/pulp (WOOD), chemicals (CHEM), plastics (PLAS), non-metallic minerals (NONM), basic metals (BASM), machinery (MACH), electrical engineering (ELEC), motor vehicles (VEHI), manufacturing n.e.c (NEC), energy and water supply (ENER) and construction (CONSTR). The service sector comprises wholesale (WHOLE), transport (TRANS), telecommunication (TELE), financial intermediation (FIN), computer and related services (COMP), technical services such as architectural and engineering activities and technical testing (TECH), legal, accounting, tax and management consultancies (CONSULT), advertising (ADV), labor recruitment and provision of personnel (RECRUIT), security services (SECUR), industrial cleaning (CLEAN), other business related services (OBRS) and media (MEDIA).

The gross sample (net of neutral losses) of the German CIS2008 consisted of 29,809 firms from which 7,644 firms responded (response rate of 25%). For estimation purposes, we excluded 482 firms from mining, R&D service firms as well as firms from service industries that do not belong to the current target population (retail, renting, real estate, hotels and restaurants and public services). As already mentioned, the German innovation survey covers firms with at least 5 employees, but to facilitate comparison of results with Licht and Peters (2013) we additionally excluded firms with 5-9 employees (1,156 firms). Furthermore, newly established firms, for which employment or sales was zero in 2006, had to be dropped. Besides that, outliers, defined as firms which employment or labor productivity growth was below the 5% or above the 95% percentile, were eliminated (440 firms). Finally, firms with incomplete data for any of the relevant variables explained in the next section were dropped. The total number of observations remaining for the empirical analysis is 3,776. We split the overall sample into manufacturing (2,372) and services (1,404) in order to investigate to what extent the link between environmental innovation and employment differs in both sectors.

Table 13 and Table 14 in the Appendix present the distribution of firms by industry and by size. In manufacturing, electrical engineering (16%), basic metal (13%) and machinery (12%) make up the largest proportions. In services, the majority of firms belong to transport (18%), technical services (13%) and computer (11.5%). Wholesale, financial intermediation and consultancies account for about 8-9.5% each. With respect to size, the majority of firms belong to the smallest size category (10-49 employees) in both manufacturing (44.3%) and services (51.3%). Only roughly 6% of firms are large, meaning that they employ 1000 and more people.

[10] This study makes use of the German CIS2008 survey in which the new European industry classification NACE 2.0 was used for stratification for the first time. However, the data set includes for all firms also an industry coding based on the prior classification NACE Rev. 1.1.

CIS data provides survey-based information on environmental and non-environmental innovation. As an alternative to the CIS-based innovation indicators, we make use of information on green and non-green technologies using information from patent documents. In order to do so, we merge the CIS2008 survey with patent application data from the European Patent Office (EPO). The next section will explain in more detail how we identify and measure environmental and non-environmental innovation using CIS and patent data.

4. Empirical Model

4.1 Dependent Variable

Based on the model proposed by Harrison et al. (2008), *EMP* is used as dependent variable. EMP is defined as $l-(g_1-\tilde{\pi}_1)$. l denotes the growth rate in employment in head counts between 2006 and 2008 (*EMPGR*).[11] Information for both years comes from the 2008 survey. The real output growth due to old products $(g_1-\tilde{\pi}_1)$ is subtracted from l since the coefficient is supposed to be one.[12] g_1 is measured by the nominal sales growth rate between 2006 and 2008 that is due to old products (*SGR_OLDPD*) which can be calculated as total sales growth rate *g* (*SGR*) minus the sales growth rate due to new products g_2 (*SGR_NEWPD*, see below). Since firm-level price information is not available in the data set, we proxy the price growth rate of old products $\tilde{\pi}_1$ by the price growth rate at the industry level for the period 2006-2008 (*PRICE_GROWTH*). Producer price indices on a 4–digit Nace level are used for manufacturing. For a few 4–digit Nace classes no indices are published and producer price indices on the corresponding 3- or 2–digit Nace level have been employed as proxy. For service firms price information had to been collected from different time series. If available we measure price growth with the development of producer prices, else with corresponding components of the consumer price index.[13] All indices are elaborated and published by the German Statistical Office (Destatis).

4.2 Environmental and Non-Environmental Innovation

Our main focus is to investigate how environmental and non-environmental innovation affects employment growth. In contrast to Licht and Peters (2013) who employ CIS data for 16 European countries, this paper makes only use of the German CIS2008 (MIP). The limitation in terms of country coverage is compensated by the fact that the German data set allows a more fine-grained definition of environmental innovations and a better identification of their employment effects.

First, in contrast to the CIS which only ask firms whether they have introduced environmental product or process innovations, the German survey additionally asked to what extent these innovations have

11 All growth rates are calculated as natural growth rates.

12 Instead of using $l-(g_1-\tilde{\pi}_1)$ as dependent variable, we would have got the same results if we had specified l as dependent variable and $(g_1-\tilde{\pi}_1)$ as additional explanatory variable where the coefficient is restricted to be 1. Therefore, we can still interpret the results in terms of employment growth.

13 Producer price indices are available for wholesale, some transport industries (Nace 2: 4920, 4941, 4942, 5224, 5210, 5020, 532, 492, 494, 521, 502), telecommunication (61) and business related services (6910, 6920, 7320, 7120, 8010, 8121, 702, 731, 812, 711, 801, 781, 782, 69, 78). For all other industries we use corresponding components of the consumer price index.

contributed to environmental protection. An environmental process innovation is the introduction of a new or significantly improved production process, distribution method, or support activity for firm's goods or services in the period 2006-2008 that has led to a reduction in material or energy use per unit of output (*_MATEN*), a slimming of the CO2 footprint and a cut-back in the air emissions (*_EMI*), water, soil, or noise pollution (*_POLL*), a replacement of dangerous materials with less polluting or hazardous substitutes or an improved recycling of waste, water and materials (*_DANGRECYC*). An environmental product innovation is the introduction of a new or significantly improved product or service with environmental benefits. Environmental benefits arise through the use of these products or services and might be related to a reduction in energy use (*ENER_CLIENT*), a reduction in air, water, soil or noise pollution (*POLL_CLIENT*), or an improved recycling of products after use (*RECYC_CLIENT*). The concept of both product and process innovation is local, that is the innovation must be new to the enterprise, but it does not need to be new to the market or the industry.[14] It thus also captures the diffusion of new (environmental) technologies and products. It turns out that for all different kinds of environmental product and process innovations, a large proportion of environmental innovators (40 to 55%) indicate only a low importance of environmental benefits. In this paper, we therefore use a stronger definition of environmental product and process innovation. A firm is counted as environmental process innovator if it has introduced at least one process innovation in the period 2006-2008 that has made a high to medium contribution to environmental protection (*PC_ENV*). A non-environmental process innovator has introduced new production technologies without any high or medium important environmental benefits (*PC_NE*). A firm that has either introduced an environmental or a non-environmental process innovation in the period 2006-2008 is called a process innovator (*PC*). Similarly, an environmental product innovator is defined as a firm that has introduced at least one product innovation in the period 2006-2008 with high to medium environmental benefits through the use of these products/services for its consumers (*PD_ENV*). In contrast, a non-environmental product innovator has introduced product innovations without high-medium important environmental benefits in the period 2006-2008 (*PD_NE*). A product innovator (*PD*) has either *PD_ENV* or *PD_NE*.

Second, the model relates employment growth not to the introduction of new products but to its innovation success measured by the sales growth rate due to new products g_2.The sales growth rate due to new products (SGR_NEWPD) can be calculated as the share of sales with new products in year 2008 related to new products introduced in the three-year period 2006-2008 times the ratio of sales in 2008 to sales in 2006. Since the CIS2008 questionnaire did not ask for the share of sales with environmental product innovations, Licht and Peters (2013) could not disentangle firm's success with environmental and non-environmental product innovation. Instead they interact *SGR_NEWPD* with *PD_ENV* and *PD_NE* to get the sales growth rate due to new products for environmental and non-environmental product innovators. This might create a bias since some of the product innovations of environmental product innovators do not have any environmental benefits. A main virtue of the German data is that is additionally asked for the share of sales with environmental product innovations. This piece of information allows us to directly measure firm's success with environmental and non-environmental product innovation and in turn the

[14] With respect to product innovation, CIS data allows to distinguish between product innovations new to market and new to the firm only. However, this distinction is only possible for product innovations in general but not separately for environmental and non-environmental product innovations. For an analysis of employment effects of different types of product innovation, see Peters (2008).

impact of each of them on employment growth. We therefore split the sales growth due to new products (g_2 =*SGR_NEWPD*) into sales growth due to new environmental ($g_{2,ENV}$ =*SGR_NEWPD_ENV)* and non-environmental products ($g_{2,NE}$ =*SGR_NEWPD_NE)*, respectively. *SGR_NEWPD_ENV* is calculated as the share of sales in year 2008 with new environmental products introduced in the three-year period 2006-2008 times the ratio of sales in 2008 to sales in 2006. *SGR_NEWPD_NE* is the difference between *SGR_NEWPD* and *SGR_NEWPD_ENV*.

Third, using CIS data, we can identify firms which have solely introduced non-environmental product innovation on the one hand and those which have introduced environmental product innovations on the other hand. However, for a firm belonging to the latter group, we cannot disentangle whether it has only introduced environmental product innovations or both types of product innovation and its relative importance. Knowledge about the share of sales with environmental and non-environmental product innovations enables us to define product innovators with only environmental product innovations (*PD_ENV_ONLY*), (*PD_NE_ONLY*) and (*PD_BOTH*).

Fourth, in the econometric model a second source of employment changes stem from efficiency increases in the production of *old* products. Efficiency improvements might arise due to process innovation or they might stem from other sources such as spillovers, organizational innovations, learning effects, mergers, acquisitions, sale of unprofitable business lines etc. While most theoretical as well as empirical studies assume that process innovations work on the supply side by reducing unit costs, the implementation of new production methods can also be a by-product of product innovations, a result of legal regulations, or process innovation are aimed at improving product quality. The fact that process innovations can also be related to the introduction of new products creates an important empirical problem in accurately disentangling the employment effects of product and process innovation. In the survey, many firms report both kinds of activities simultaneously. For process innovators, we then do not know whether (i) all process innovations are aimed at improving the efficiency of the old products, (ii) all process innovations take place in order to produce the new product(s) or (iii) a combination of both reasons is present. Prior studies have therefore defined process innovators as firms that have only introduced process innovations but no product innovation (PCONLY). In this case process innovations must be related to the old products. However, for firms that do both, the effect of process innovations with respect to an increase in efficiency in the production of old products could not be identified and was captured by the sales growth due to new products. In contrast to prior studies, we exploit another specificity of the German 2008 survey which allows us to better identify whether process innovations are related to new or old products. In 2008, all product innovators were additionally asked whether the new products in 2006-2008 demand the introduction of new or significantly improved production processes as well. Response items were all, almost all, some, none. Instead of *PC* or *PCONLY* our preferred measure for process innovation will be *PCOLD* that is 1 (i) for firms that have only introduced process innovation but no product innovation and (ii) for firms that have introduced both new products and processes but in which the launch of a new product does not involve the introduction of new processes. We furthermore split the group of process innovators related to old products into those that have introduced new processes with and without high-to medium-sized environmental benefits, *PCOLD_ENV* and *PCOLD_NE*, respectively.

Fifth, one might view it as a drawback of the CIS that information on environmental and non-environmental innovation is survey-based. As an alternative to the CIS-based innovation indicators we therefore use patent information as a robustness check. In order to do so, we merge the 2008 survey with patent application data from the European Patent Office (EPO). Environmental patents are not easy to detect in patent data since related environmental technologies do not fall under one single classification section but are scattered throughout the IPC classes. Huge efforts have been undertaken in recent years to better identify them. In 2008, EPO first introduced a tagging system (Y section) to indicate patent documents that are related to sustainable technologies. Since then, the system has been continuously updated for additional environmental technologies. Currently four sub-groups are available in the Y section: Y02B captures climate change mitigation technologies in buildings, e.g. related to lighting, heating, ventilation, air condition, construction, ICT, integrated renewables or power management. Technologies aimed at capturing and storing greenhouse gases are counted in Y02C. Y02E summarizes climate change mitigation technologies in energy generation, transmission and distribution, e.g. renewable energy, efficient combustion, biofuels or hydrogen technology. Finally, Y02T comprises climate change mitigation technologies in the transportation of goods and persons such as e-mobility, hybrid cars, efficient internal combustion engines and efficient airplanes, ship and trains.[15]

As an alternative definition, we use the IPC green inventory launched by the World Intellectual Property Office (WIPO) in 2010. The IPC green inventory tags IPC classes that are related to green technologies in a number of fields. In particular, it defines the following seven major groups of green technologies: (1) alternative energy production, (2) energy conservation, (3) transportation, (4) waste management, (5) agriculture and forestry, (6) administrative, regulatory and design aspects, and (7) nuclear power generation.

We define a set of five patent dummy variables: *PATD* equals 1 if the firm has applied for at least one patent at the EPO in the period 2006-2008. *PATD_W* and *PATD_Y* are 1 if the firm has applied for at least one environmental patent in the period 2006-2008 according to the WIPO and EPO tagging system, respectively. Accordingly, *PATD_NW* and *PATD_NY* indicate firms that have applied for at least one non-environmental patent in the period 2006-2008. We use the period 2006-2008 since this is the reference period in the CIS data.

One problem that we are confronted with using the above patent indicators is the unknown time lag between a patent application and the introduction of a new product or process, the latter being the source of employment changes. We, therefore, additionally account for past patent applications from 1999 onwards using the firm's patent stock. Using the patent stock avoids complicated lag structures of past patent applications (Czarnitzki and Kraft 2010). The patent stock (PS) of firm i in period t is calculated by the perpetual inventory method as $PS_{it}=(1-\delta)*PS_{i,t-1} + PA_{it}$, where PA is the number of patent applications in year t. We follow previous studies and set δ, the constant depreciation rate, to 15% (see Griliches and Mairesse, 1984, and Hall, 1990, for more detailed descriptions). In order to account for past patent applications at the beginning of the reference period, we specify the overall patent stock at the end of year 2005 (PATSTOCK), the environmental patent stocks (PATSTOCK_W and PATSTOCK_Y) and the non-environmental patent stocks (PATSTOCK_NW and PATSTOCK_NY).

[15] In November 2013, EPO published Y04S for smart grid technologies. Y04S has not been included in this analysis.

4.3 Control Variables

The approach by Harrison et al. (2008) derives an equation for firm's employment growth. Hence, the impact of firm-specific time-constant observable and unobservable variables on the level of employment has already been cancelled out. Still, employment changes might be influenced by many other economic factors. Besides innovation, firm size, industry structure, wages, investment in physical capital or labor supply factors like preferences for leisure or the qualification level of the labor supply may also have an influence on the employment. Due to data limitations we cannot control for the latter ones. But we control for firm size by adding four dummy variables for firms with 50-99, 100-249, 250-999 and 1000 and more employees at the beginning of the reference period in 2006. Firms with 10-49 employees present the reference category. In the past, researchers have controversially discussed whether firm size matters for employment growth. While Gibrat's law postulates that firms grow proportionally and independently of firm size (Gibrat 1934), Jovanovic (1982) argued that surviving young and small firms growth fast than older and larger ones for instance because of managerial efficiency and learning by doing. Unfortunately, we do not observe firm-level changes in wages during the reference period in the data. We therefore assume that they follow the development of wages at the industry level and can thus be captured by industry dummies. The econometric analysis includes a set of 13 industry dummies in manufacturing and services each (for a definition see Table 13 in the Appendix).

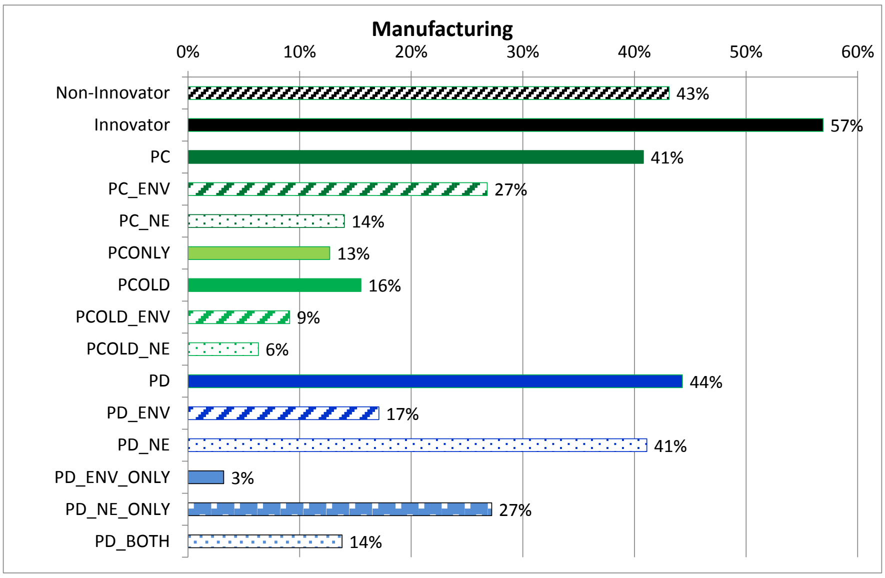
5. Descriptive Statistics

This section presents descriptive statistics on the main variables used in the empirical analysis. We start by looking at the proportion of firms with green and non-green innovations. Figure 1 and Figure 2 illustrate the innovation rates in manufacturing and services, respectively. In manufacturing, the majority of the enterprises have introduced at least one innovation in the period 2006-2008 (57%), among them are 44% product innovators and 41% have implemented new production processes. Roughly six out of ten product innovators have solely introduced new products without any environmental benefits (27% of all firms). In contrast, 14% of the manufacturing firms launched both environmental and non-environmental product innovations simultaneously. Only a small proportion of 3% reported having solely environmental product innovation. This corresponds to an overall share of firms having introduced new products with environmental benefits for their clients of about 17% whereas 41% of the firms have introduced at least one non-environmental product innovation. Interestingly, we find that the share of environmental process innovators is higher than the share of environmental product innovators. Nearly two out of three process innovators reported that among their new production processes at least one has led to major environmental benefits, either in terms of reduced material and energy use, reduction of air, water, soil and noise pollution, improved recycling or through the replacement of dangerous materials. This implies a share of 27% of all firms having environmental process innovation. In contrast, one third of the process innovators have only implemented new production technologies without environmental benefits (14%). When we focus only on those 15.5% of firms which have introduced new production technologies related to existing products we find a similar pattern. 9.2% of firms with process innovations related to old products have at least one environmental process innovation whereas 6.3% have solely invested in improved production technologies without any environmental benefits.

In services, a slightly different picture emerges. First of all, we observe a lower proportion of firms having introduced at least one innovation in the period 2006-2008, 43% compared to 57% in manufacturing. Furthermore, service firms invest more often in new processes (33%) than in new services (30%). Thirdly, both environmental process and product innovators are less frequent in absolute and relative terms in services than in manufacturing. Whereas in manufacturing two out of three process innovators reported at least one environmental process innovation, it is just the opposite in services with one out of three firms. On the contrary, two out of three process innovators have solely invested in non-environmental process innovations. This relation is similar for all process innovators and process innovators that have implemented new production technologies related to their existing products. Like in manufacturing, however, we find in services that the share of environmental process innovators is higher than the share of environmental product innovators, and we furthermore observe non-environmental product innovators to be more frequent than product innovators with environmental benefits. Roughly eight out of ten product innovators have solely introduced new services that do not create any additional environmental benefits for the consumers (22% of all firms). 8% of the services firms can be classified as environmental product innovators, among them 2% have solely introduced environmental product innovations whereas 6% of the service firms have both types of product innovations.

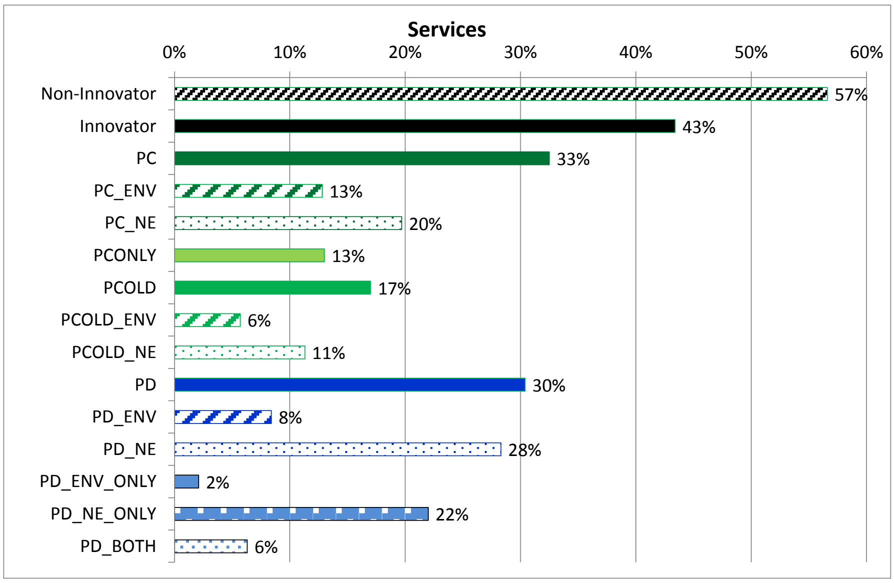
Another striking result is that among environmental innovators the majority of manufacturing and service firms in Germany focus only on environmental process innovation. That is, 15.2% of manufacturing firms have only environmental process innovation, whereas 11.6% introduce both green process and product innovations and another 6.5% focus on green product innovation. In services, 4.8% of firms introduce both kinds of environmental innovation, whereas 8.1% and 3.6% of firms have only environmental process and product innovation, respectively.

Figure 1 **Environmental Innovation in Manufacturing, 2006-2008**



Notes: For a definition of variables, see section 4.2.

Figure 2 **Environmental Innovation in Services, 2006-2008**



Notes: For a definition of variables, see section 4.2.

Table 2 illustrates the occurrence of different types of environmental process (related to old products) and product innovations by industry. A reduction of material and energy input are the most frequent environmental benefits of new processes in both manufacturing and services, followed by the reduction in water, soil and noise pollution in manufacturing and an improved recycling and replacement of dangerous materials in services. On the clients' side, energy savings most often occur as environmental benefits of new products in both sectors, followed by a reduction in pollution and improved recycling possibilities. Though industries differ in their level of environmental innovations, we observe the same pattern in many of the industries. Exceptions are plastics, electrical engineering, transport, technical services and consultancies.

As an alternative to the survey-based innovation indicators, Table 3 displays the share of firms with patent applications for environmental and non-environmental technologies. It turns out that only a rather small proportion of firms have applied for at least one patent at the EPO in the period 2006-2008: 14.6% of the innovators in manufacturing and 1.3% of them in services. However, only 2% and 0.7% of innovators in manufacturing and services have filed a patent application for green technologies according to the WIPO definition. Among environmental innovators, this proportion is only slightly higher with 2.6% and 1.7%. Employing the EPO definition, we find slightly smaller proportions of 2.1% and 1.4% of environmental innovators that have filed a patent application for climate change mitigation technologies. The share of environmental innovators with patent applications for green technologies is only little higher when we use the patent stock at the end of year 2005 instead of the patent application dummy for the period 2006-2008. The fact that we find a much smaller proportion of green innovators using patent data can be explained by two major reasons: First, innovation in the CIS does not only capture innovations that are new to the market or industry but also those that are new to the firm only. That is, it captures the diffusion of innovation as well and our results indicate that most of the firms that implement new environmental process innovations did not develop the underlying technologies themselves and seek patent protection. Second, even if the innovation is new to the market, firms might decide not patent the underlying inventions but to use other methods of protections.

Table 2 **Types of Environmental Product and Process Innovation, by Industry, 2006-2008**

	Environmental Process Innovation				Environmental Product Innovation		
	MATEN	EMI	POLL	DANGRECYC	ENER_CLIENT	POLL_CLIENT	RECYC_CLIENT
FOOD	7.3	6.7	7.3	5.2	19.7	15.0	10.4
TEXT	8.0	1.8	6.2	6.2	17.7	12.4	9.7
WOOD	7.7	6.6	5.9	7.4	15.9	12.2	12.9
CHEM	8.2	4.8	5.4	5.4	23.1	19.1	11.6
PLAS	4.7	2.3	1.6	7.0	21.1	9.4	18.0
NONM	6.5	3.3	6.5	5.4	23.9	19.6	16.3
BASM	10.6	8.7	8.7	6.8	22.9	15.2	10.7
MACH	6.3	2.4	5.9	5.2	30.7	19.2	12.2
ELEC	3.6	1.5	1.8	3.1	24.9	10.3	14.9
VEHI	5.0	3.4	3.4	4.2	23.5	20.2	18.5
NEC	11.8	8.4	11.8	9.2	16.8	16.8	14.3
ENER	3.6	3.6	4.3	3.6	17.9	17.1	4.3
CONSTR	1.6	1.6	3.1	1.6	10.9	14.1	10.9
MANUF	6.7	4.5	5.5	5.4	21.9	14.9	12.6
WHOLE	4.5	2.2	3.7	3.7	11.2	12.7	11.2
TRANS	3.6	6.0	4.0	3.2	23.9	24.7	8.8
TELE	4.3	4.3	2.2	2.2	19.6	13.0	6.5
FIN	6.4	0.8	3.2	2.4	3.2	0.8	2.4
COMP	1.2	0.6	0.6	0.6	15.5	6.2	5.0
TECH	2.7	2.2	1.6	3.2	14.5	15.1	7.5
CONSULT	2.7	0.9	0.9	3.6	8.1	6.3	8.1
ADV	0.0	0.0	0.0	0.0	3.1	0.0	0.0
RECRUIT	0.0	0.0	0.0	0.0	2.5	2.5	0.0
SECUR	2.8	2.8	2.8	0.0	13.9	5.6	11.1
CLEAN	4.2	2.8	2.8	4.2	29.2	26.4	16.7
OBRS	5.6	3.7	6.2	5.6	19.1	17.9	14.2
MEDIA	6.3	2.1	2.1	4.2	12.5	0.0	4.2
SERVICES	3.6	2.6	2.8	3.0	15.2	13.0	8.2

Notes: Displayed are proportions of firms with *environmental process innovations related to existing products*. MATEN denote the share of firms with process innovations that have reduced material and energy consumption. EMI and POLL measures share of firms with process innovations that have cut-back air emissions and reduced water, soil or noise pollution, respectively. DANGRECYC stands for the share of firms with process innovations that have replaced dangerous materials with less polluting or hazardous substitutes or have improved recycling. ENER_CLIENT, POLL_CLIENT and RECYC_CLIENT are product innovations from which clients benefit in terms of reduced energy use, reduced pollution and improved recycling, respectively.

Table 3 **Firms with EPO Patent Applications for Environmental and Non-Environmental Technologies, 2006-2008**

	Manufacturing		Services	
	(1)	(2)	(1)	(2)
Patent applications in 2006-2008 (0/1)				
PATD	14.6	14.7	1.3	3.5
PATD_W	2.0	2.6	0.7	1.7
PATD_NW	14.1	14.0	1.2	3.0
PATD_Y	1.4	2.1	0.5	1.3
PATD_NY	14.3	14.1	1.3	3.5
Positive patent stock at the end of year 2005 (0/1)				
PATSTOCK	16.8	17.2	1.6	3.0
PATSTOCK_W	2.7	3.5	0.3	0.9
PATSTOCK_NW	16.2	16.5	1.5	2.6
PATSTOCK_Y	1.0	1.6	0.2	0.4
PATSTOCK_NY	16.7	17.0	1.6	3.0

Notes: Firms with patent applications at the European patent office. Measured in percent of firms with product or process innovation (1) and with environmental product or process innovation (2).

Finally, Table 4 and Table 5 display employment, the employment growth rate (l), the overall sales growth rate (g / SGR) and its split into the sales growth that is due to old (g_1 / SGR_OLDPD) and new products (g_2 / SGR_NEWPD). The latter is further split into the sales growth rate due to environmental ($g_{2,ENV}$ / SGR_NEWPD_ENV) and non-environmental ($g_{2,NE}$ / SGR_NEWPD_NE) product innovations. The last two columns furthermore show the growth of labor productivity and prices.

The German economy boomed during the period 2006-2008 and in the data set we observe an average employment growth of about 5.5% in manufacturing. However, this figure is not directly comparable to the labor force growth rate published by the German Statistical Office. This is due to the fact that (i) we only observe surviving firms in the survey, (ii) we restrict our analysis to firms with at least 10 employees, and (iii) we average the employment growth across firms instead of taking the ratio of the sum of changes in employment for all firms to the sum of employed personnel. Due to this method, average employment growth rates are influenced more heavily by outliers although we already excluded all firms below the 5th and above the 95th percentile. The median employment growth amounts to 3.4% in manufacturing. During the same three-year period, nominal sales grew on average by 14.6% (median: 10.3%), leading to a nominal productivity growth of about 9%. Accounting for the increase in prices, real labor productivity grew by roughly 5%. The increase in sales can be mainly attributed to new products (14.4%) whereas demand for old products has stimulated sales only by 0.2%. The contribution of environmental product innovation to sales growth was much smaller than that of non-environmental product innovation: About one quarter of the rise in sales due to new products can be attributed to environmental product innovations whereas three quarters stem from the introduction of new products without any environmental benefits. In the same period prices increased on average by roughly 4%, so that growth rate in real sales was about 10.7%.

Concerning employment growth, we find that innovators exhibit a much larger increase in labor than non-innovators. However, the figures do not reveal large differences between employment growth rates of environmental and non-environmental process innovators with 6.6% and 6.7%, respectively. Likewise employment change differences seem also be small between green and non-green product innovators at first glance. However, the numbers show that firms with environmental product innovations only demonstrate a much lower employment growth rate (6.2%) than firms with only non-environmental product innovations (7.2%) or with both types of product innovation (7.8%).

In services employment and nominal sales grew on average with 5.8% and 11.3% in the period 2006-2008, implying an increase in nominal labor productivity of about 6.5%. Taking the inflation into account, real labor productivity growth was at about 1.2% in German services. Like in manufacturing, old products have contributed less to sales growth (3%) than new products (8.3%) and among the new products non-green products have been more important for sales growth. Only a little more than 10% of the increase in sales due to new products can be attributed to the introduction of environmental product innovations.

Table 4 **Growth Rates of Employment, Sales, Productivity and Prices, 2006-2008 Manufacturing**

	Employment	Employment growth (l)	Sales growth (g)	Sales growth – old products (g_1)	Sales growth – new products (g_2)	Sales growth – new env. products (g_{2ENV})	Sales growth – new non-env. products (g_{2NE})	Labor productivity growth	Price growth ($\tilde{\pi}_1$)
Total	528.58	5.53	14.60	0.24	14.36	3.21	11.15	8.99	3.89
	62.50	3.39	10.31	1.25	0.00	0.00	0.00	5.74	4.13
	8870.40	14.61	26.73	32.89	26.31	13.86	21.68	22.09	9.92
Non-Inno	111.65	3.20	12.01	12.01	0.00	0.00	0.00	9.03	4.74
	40.00	0.00	7.27	7.27	0.00	0.00	0.00	5.26	4.15
	267.78	14.41	26.48	26.48	0.00	0.00	0.00	22.92	8.22
PCOLD	224.61	6.67	16.96	12.31	4.65	0.50	4.15	9.95	3.98
	70.00	4.00	12.55	9.76	0.00	0.00	0.00	6.10	4.53
	616.64	13.64	28.37	31.59	14.92	3.17	14.25	22.77	9.85
PCOLD_ENV	233.69	6.62	15.61	12.24	3.37	0.73	2.64	9.17	4.81
	80.00	4.00	13.91	10.00	0.00	0.00	0.00	5.91	5.05
	598.59	14.12	24.49	27.60	12.10	3.76	11.03	22.37	9.65
PCOLD_NE	211.47	6.74	18.92	12.41	6.51	0.18	6.33	11.09	2.79
	59.00	3.94	11.92	9.14	0.00	0.00	0.00	7.54	4.00
	643.65	12.97	33.18	36.71	18.12	2.00	17.73	23.36	10.05
PD	1027.45	7.35	16.39	-16.02	32.41	7.24	25.17	8.74	3.03
	95.00	5.26	12.78	-12.85	22.58	0.00	15.98	5.90	3.66
	13307.19	14.68	26.03	32.20	31.27	20.11	26.61	20.92	11.46
PD_ENV	2236.37	7.55	18.35	-18.58	36.93	18.79	18.15	10.14	3.44
	129.00	5.46	13.33	-16.81	26.33	9.92	10.63	7.37	4.13
	21385.23	15.18	30.21	35.34	34.67	28.87	21.32	23.32	11.97
PD_NE	1033.72	7.44	16.07	-15.86	31.93	4.77	27.16	8.37	2.91
	95.00	5.28	12.68	-12.64	22.65	0.00	18.46	5.86	3.58
	13754.40	14.65	24.82	31.81	29.34	12.73	26.65	19.85	11.43
PD_ENV_ONLY	948.16	6.16	20.37	-18.08	38.44	38.44	0.00	13.39	4.48
	103.00	3.92	15.19	-16.67	20.83	20.83	0.00	7.26	4.25
	4946.37	15.10	38.19	36.89	49.48	49.48	0.00	31.23	11.86
PD_NE_ONLY	269.54	7.23	15.16	-14.42	29.58	0.00	29.58	7.86	2.77
	80.50	5.26	12.18	-10.85	20.10	0.00	20.10	5.25	3.50
	573.11	14.37	22.96	29.98	28.59	0.00	28.59	19.23	11.14
PD_BOTH	2538.79	7.87	17.88	-18.70	36.58	14.17	22.41	9.37	3.20
	139.50	5.66	12.93	-17.76	28.18	7.85	14.42	7.48	3.87
	23639.97	15.21	28.07	35.02	30.26	18.67	21.58	21.02	12.00

Notes: Figures reported are the mean, median and the standard deviation of the corresponding variable in the first, second and third row.

Looking at different group of service firms, we find employment growth likewise higher in innovative than in non-innovative firms and on average higher in firms with product innovation than with process innovation. In contrast to manufacturing, however, employment grew faster in service firms with environmental process innovation than in firms that focused on non-environmental process innovation. The opposite result holds for new products. Service firms which solely introduced new products without environmental benefits grew on average by 9.6%, whereas joint product innovators expand employment by 9.2% followed by green product innovators only with 9%.

Table 5 **Growth Rates of Employment, Sales, Productivity and Prices, 2006-2008 Services**

	Employ-ment	Employ-ment growth (l)	Sales growth (g)	Sales growth – old products (g_1)	Sales growth – new products (g_2)	Sales growth – new env. products (g_{2ENV})	Sales growth – new non-env. products (g_{2NE})	Labor productivity growth	Price growth ($\tilde{\pi}_1$)
Total	518.93	5.79	11.28	3.00	8.28	0.95	7.33	6.40	4.33
	46	2.67	6.94	3.29	0.00	0.00	0.00	3.38	3.78
	6075.66	18.90	28.24	31.67	20.84	5.59	19.82	25.10	5.32
Non-Inno	188.69	3.74	9.10	9.10	0.00	0.00	0.00	6.27	4.33
	40	0.00	5.39	5.39	0.00	0.00	0.00	3.29	3.78
	702.32	18.08	28.11	28.11	0.00	0.00	0.00	25.05	5.80
PCOLD	300.74	6.77	12.16	6.55	5.61	0.51	5.10	6.65	3.91
	80	4.00	8.24	5.87	0.00	0.00	0.00	4.53	3.40
	686.39	19.59	26.55	29.55	14.51	3.59	13.54	25.40	4.22
PCOLD_ENV	401.25	7.54	8.50	4.51	3.98	0.38	3.60	2.35	3.78
	86	4.13	7.28	4.40	0.00	0.00	0.00	2.79	3.59
	1000.38	18.39	21.21	22.83	12.17	1.81	11.37	20.08	3.26
PCOLD_NE	250.16	6.38	14.00	7.57	6.43	0.58	5.85	8.81	3.97
	76	4.00	8.33	7.44	0.00	0.00	0.00	5.56	3.40
	449.02	20.22	28.76	32.42	15.52	4.22	14.49	27.49	4.63
PD	1229.25	9.50	15.15	-12.07	27.21	3.12	24.09	6.42	4.61
	40	6.25	10.00	-9.49	16.50	0.00	13.13	2.08	3.87
	10941.58	19.82	28.75	34.61	30.23	9.80	29.82	24.56	4.67
PD_ENV	3716.14	9.15	12.49	-12.11	24.60	11.30	13.30	5.61	4.64
	50	9.74	9.77	-9.38	14.68	6.54	5.93	0.00	3.78
	3716.14	9.15	12.49	-12.11	24.60	11.30	13.30	5.61	4.64
PD_NE	793.79	9.54	15.43	-12.53	27.96	2.05	25.91	6.57	4.56
	42	6.25	10.12	-9.95	17.14	0.00	14.62	2.86	4.13
	7281.79	19.75	29.10	35.48	30.68	7.27	30.15	24.66	4.75
PD_ENV_ONLY	6991.93	8.99	11.39	-5.91	17.30	17.30	0.00	4.45	5.23
	31.5	6.74	6.21	-9.05	11.34	11.34	0.00	-0.95	3.49
	31584.96	21.10	23.85	19.09	21.58	21.58	0.00	23.51	3.54
PD_NE_ONLY	279.57	9.63	16.16	-12.05	28.21	0.00	28.21	6.73	4.59
	40	6.17	10.13	-9.58	17.19	0.00	17.19	3.85	4.35
	740.87	19.96	30.49	36.69	32.00	0.00	32.00	23.54	5.00
PD_BOTH	2599.40	9.21	12.86	-14.22	27.08	9.26	17.83	6.00	4.44
	65	10.00	10.05	-10.51	16.69	5.16	10.87	0.00	3.78
	15335.34	19.09	23.53	31.00	25.64	13.16	20.66	28.38	3.79

Notes: Figures reported are the mean, median and the standard deviation of the corresponding variable in the first, second and third row.

6. Econometric Evidence

This section presents econometric evidence on the link between environmental innovation and employment growth in Germany. In section 6.1 we first perform reduced form regressions as was similarly done in previous studies. Section 6.2 provides results of the econometric model proposed by Harrison et al. (2008). Based on the econometric results of section 6.2, section 6.3 provides a decomposition of employment growth. Throughout all steps we distinguish between manufacturing and service firms.

6.1 Reduced Form Regressions

We perform reduced form regressions in which we regress employment growth l on patent variables (Table 6) and innovation indicators (Table 7). The results show that in manufacturing firms that applied for at least one patent in the period 2006-2008 exhibit an employment growth that is 2.4 percentage points higher than for firms without patents. This effect, however, is only driven by patents for non-environmental technologies. We do not find any significant impact of green patents on employment growth, neither for climate change mitigation technologies using the EPO definition nor for green technologies based on the WIPO definition. The patent stock at the beginning of the reference period, as a measure for accumulated past patent activities, does not show any significant correlation with employment growth in the period 2006-2008. The key finding for the service sector is that patent activities do not matter for employment growth.

One drawback of the patent data is that we cannot separate patents that are related to the introduction of new processes from those that are associated with the introduction of new products. CIS data allows this distinction, and Table 7 reports estimation results using innovation indicators. Partly in contrast with the previous findings, we corroborate a significantly positive impact of product innovation in both sectors.[16] The fact that we find a positive effect of product innovation but not of patents in services is probably reflecting the lower importance of patenting in services. Distinguishing between new products with and without environmental benefits, we find a similar pattern as for patents in manufacturing. That is, the results show a significant impact of non-green product innovations whereas firms with green product innovations did not grow faster. Regression (6) furthermore shows that product innovators with only green product innovations did not exhibit higher employment growth rates than non-innovators. In contrast, employment growth is roughly 3 percentage points higher for firms that introduced only non-green product innovations. Firms that focus on both types of new products grew at a similar rate implying that there are no significant additional benefits of green product innovations in terms of employment growth. The same picture emerges in the service sector.

Results for process innovations are more mixed. In manufacturing, process innovations likewise display a strong positive net impact on employment growth in the reduced form regressions. Interestingly, the effect is much smaller when we use PCOLD instead of PC, pointing towards the identification problem addressed in section 4. In contrast to the results found for patents, this finding is mainly driven by environmental process innovation whereas we do not find a significant effect for non-environmental process innovation. The same pattern emerges in services, though the overall indicator PCOLD is not significant. When we further split green process innovations into those aimed at reducing material and energy, air and water emissions, noise and soil pollution and improving recycling, we do not find any significant effects in services. In manufacturing, emission-saving process innovations tend to be associated with lower employment growth while we find a positive impact of pollution reducing process innovations. In both areas end-of-pipe technologies are dominating. On the contrary, the effect of material and energy saving process innovation is positive but not significant. Thus, our results do not fully confirm prior findings of Rennings and Horbach (2013) who conclude that the employment effects of the introduction of cleaner process technologies seem to be more advantageous within a firm compared to more end-of-pipe oriented technologies.

However, these reduced form regressions do not allow us to identify the main channels through which environmental and non-environmental product and process innovations impact employment growth and we therefore proceed with the structural approach by Harrison et al. (2008).

[16] We also find a significant positive impact of the sales growth rate due to new products both for environmental and non-environmental products, the latter one being smaller.

Table 6 **Employment Effects of Green and Non-Green Innovation Using Patent Application Data (Reduced Form Regression)**

Dependent variable: l	Manufacturing							Services						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SGR	0.254***	0.254***	0.254***	0.253***	0.254***	0.254***	0.254***	0.323***	0.323***	0.323***	0.324***	0.324***	0.324***	0.324***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
PATD	2.412***			2.448***	2.461**			-2.631			-0.221	-0.525		
	(0.872)			(0.889)	(1.019)			(3.663)			(3.427)	(4.063)		
PATD_W		-2.874				-3.986			-1.235				-0.702	
		(2.267)				(3.096)			(5.604)				(4.211)	
PATD_NW		2.967***				3.046***			-1.682				4.542	
		(0.887)				(1.015)			(5.566)				(3.526)	
PATD_Y			-1.165				-0.723			-4.488				-1.099
			(2.066)				(2.547)			(9.524)				(12.694)
PATD_NY			2.400***				2.336**			-1.151				-0.367
			(0.907)				(1.029)			(2.892)				(3.222)
PATSTOCK				-0.004							-1.086			
				(0.009)							(0.869)			
Log(PATSTOCK)					-0.051							-3.317		
					(0.516)							(4.640)		
Log(PATSTOCK_W)						1.451							-41.175***	
						(1.486)							(9.822)	
Log(PATSTOCK_NW)						-0.150							0.159	
						(0.604)							(4.574)	
Log(PATSTOCK_Y)							-0.488							7.252
							(1.380)							(24.811)
Log(PATSTOCK_NY)							0.087							-3.806
							(0.569)							(7.473)
Industry dummies	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.093	0.094	0.094	0.084	0.079	0.077	0.081
Size dummies	0.003	0.004	0.004	0.003	0.004	0.005	0.005	0.323	0.329	0.337	0.344	0.346	0.355	0.348
R2a	0.244	0.244	0.243	0.243	0.243	0.244	0.243	0.244	0.244	0.244	0.244	0.244	0.246	0.243
RMSE	12.705	12.700	12.709	12.708	12.708	12.704	12.714	16.435	16.441	16.440	16.437	16.438	16.414	16.449

Notes: PATD is a dummy variable for firms that have filed at least one patent application in the period 2006-2008. PATSTOCK measures the patent stock at the end of year 2005. Included in all regressions but not reported are the constant and industry and size dummies. Reported are the p-values of a test on joint significance of the industry and the size dummies, respectively.

Table 7 **Employment Effects of Green and Non-Green Innovation Using CIS Data (Reduced Form Regression)**

Dependent variable: *l*	Manufacturing							Services						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PD	1.755***	3.274***	2.880***					2.199*	3.443***	3.182***				
	(0.607)	(0.630)	(0.603)					(1.192)	(1.126)	(1.094)				
PD_ENV				0.474	0.376						2.092	1.958		
				(0.770)	(0.771)						(1.925)	(1.924)		
PD_NE				3.212***	2.918***						2.708**	2.564**		
				(0.636)	(0.618)						(1.203)	(1.178)		
PD_ENV_ONLY						0.877	1.030						3.733	4.071
						(1.542)	(1.540)						(3.637)	(3.689)
PD_NE_ONLY						3.011***	3.011***						2.811**	2.820**
						(0.666)	(0.665)						(1.202)	(1.203)
PD_BOTH						3.224***	3.253***						3.994*	3.961*
						(0.869)	(0.865)						(2.142)	(2.142)
PC	2.332***							2.067*						
	(0.593)							(1.110)						
PCONLY		2.761***							1.735					
		(0.852)							(1.425)					
PCOLD			1.685**							1.377				
			(0.736)							(1.263)				
PCONLY_ENV				2.891***							4.078**			
				(1.083)							(2.066)			
PCONLY_NE				2.394**							0.329			
				(1.145)							(1.773)			
PCOLD_ENV					2.223**	2.244**						3.903*	3.826*	
					(0.983)	(0.984)						(2.012)	(2.013)	
PCOLD_NE					0.924	0.936	0.961					0.194	0.158	0.102
					(0.965)	(0.965)	(0.965)					(1.524)	(1.529)	(1.530)
PCOLD_ENV_MATEN							2.287							2.309
							(1.584)							(2.848)
PCOLD_ENV_EMI							-4.742***							0.763
							(1.713)							(3.393)
PCOLD_ENV_POLL							5.392***							-3.126
							(1.757)							(3.925)
PCOLD_ENV_REC							-0.226							4.985
							(1.629)							(3.739)
Industry dummies	0.022	0.027	0.019	0.026	0.018	0.020	0.012	0.236	0.236	0.226	0.257	0.216	0.216	0.229
Size dummies	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.201	0.252	0.274	0.195	0.210	0.229	0.227
R2a	0.253	0.251	0.249	0.251	0.250	0.249	0.253	0.250	0.249	0.249	0.249	0.249	0.249	0.248
RMSE	12.631	12.643	12.658	12.644	12.656	12.658	12.623	16.368	16.380	16.382	16.382	16.378	16.381	16.397

Notes: Included in all regressions but not reported are the constant and industry and size dummies. Reported are the p-values of a test on joint significance of the industry and the size dummies, respectively.

6.2 Structural Model Approach

This subsection provides the estimation results of the econometric model proposed by Harrison et al (2008). Remember the dependent variable in the model is $EMP = l - (g_1 - \hat{\pi}_1)$. Table 8 depicts the results for employment effects of environmental and non-environmental innovation in German manufacturing. Table 10 displays service sector results. In both tables, specification (1) investigates the link between innovation and employment without distinguishing between environmental and non-environmental innovation. Specification (2) examines whether there are any employment differences between green and non-green process innovations whereas specification (3) additionally accounts for differences in the effect of new products with and without environmental benefits. Finally, specification (4) enlightens us about variations in the effect of different kinds of environmental process innovation. In both tables, our preferred measurement of process innovation, PCOLD, has been used in specifications (1) to (4). For comparison purposes, specifications (5) to (8) employ PCONLY, the variable that has been used in prior studies (e.g. Harrison et al 2008, Hall et al 2009, Dachs and Peters 2014, Licht and Peters 2013).

Before discussing our results, we first comment on the estimation strategy. As already explained one of our main variables of interest – the sales growth rate due to new (environmental and non-environmental) products – is supposed to be endogenous due to an error in variables problem with the consequence of an attenuation bias in the estimation of β. We address this endogeneity problem by using an instrumental variables approach to get consistent estimates. The instruments should be correlated with the sales growth due to new products (i.e. innovation success), but not correlated with the error term. In particular it has to be uncorrelated with the relative price difference of new to old products. We follow previous studies and use RANGE, CLIENT and R&D as instruments. RANGE measures the degree by which product innovation is aimed at increasing the product range in the period 2006-2008. It is measured on a 4 point Likert scale (3=high importance, 2=medium, 1= low and 0=not relevant). It is likely that RANGE is correlated with the expectations of new products sales and thus innovation success but enlarging the range of products doesn't imply any particular direction of the changes in prices.[17] It is also unlikely that it is correlated with unanticipated productivity shocks. We similarly argue that firms that have used clients as a high-to-medium important information source for innovation in the period 2006-2008 (CLIENTS) demonstrate higher innovation success. But using clients doesn't imply any particular direction of the changes in prices. The third instrument is a dummy variable indicating firms that continuously carry out R&D (R&D). When we split the sales growth rate due to new products into those generated by green and non-green product innovations, we employ two additional instruments that are particularly related to the introduction of environmental innovation. The two instruments are dummy variables that equal 1 if the enterprise has introduced environmental innovations in response to market demand from its customer (ENV_DEM) or as a consequence of voluntary codes or agreements for environmental good practice within its sector (ENV_AGREE). Again, we expect both variables to be correlated with the innovation success of new

[17] The CIS provides the importance of other targets such as increasing market shares or improving product quality. However, improved quality is likely to be correlated with higher prices and increased market shares with lower prices. Indeed, difference-in-Sargan C-tests reject the exogeneity of both instruments.

environmental products but to be uncorrelated with any particular direction of price changes between new green and old products.

In order to evaluate our IV strategy we have tested the validity and non-weakness of the instruments with a number of different tests. Results of the first stage regression results and diagnostics are displayed in Table 9 for manufacturing and Table 11 in services. We used the Sargan-Hansen J test on overidentifying restrictions for overall instrument validity and the difference-in-Sargan-Hansen C statistic to test for exogeneity of a single instrument.[18] It turns out that in manufacturing the null hypothesis of instrument validity cannot be rejected. Furthermore, for none of the five instruments we reject the null hypothesis of exogeneity as indicated by the C tests. For services, however, we had to reject the assumption of exogeneity of the R&D variable. We therefore left out R&D as instrument in services. For the remaining four instruments, the J statistic indicates overall instrument validity and each of the single instruments passes the test on exogeneity.

In addition to instrument validity we check for non-weakness of the instruments. The first stage regression results of specifications (1) and (2) demonstrate that RANGE, CLIENT and R&D in manufacturing are highly correlated with the endogenous variable sales growth due to new products (SGR_NEWPD). When we differentiate between sales growth due to green and non-green products, we find ENV_DEM, R&D (manufacturing) and CLIENT (services) to be highly significant in the equation for SGR_NEW_ENV whereas RANGE, CLIENT, R&D (only manufacturing) and ENV_DEM are highly correlated in the first stage regression of SGR_NEW_NE. Furthermore, the F-test of excluded instruments always yields a statistic that is clearly larger than 10, except for the first stage equation of sales growth generated by green product innovations in services where the F statistic is slightly below this threshold with about 9.8. In addition to this rule of thumb for non-weak instruments, the tables display the Kleibergen-Paap LM test on underidentification. The null hypothesis of underidentification is always rejected which likewise confirms that the excluded instruments are correlated with the endogenous regressor(s). Finally, we test for the presence of weak instruments using the F tests proposed by Cragg and Donald (1993) and Kleibergen and Paap (2006). The Cragg-Donald test assumes i.i.d. errors while the Kleibergen-Paap test is robust to heteroskedasticity. Weak instruments can lead to a large relative bias of IV compared to the bias of OLS in case of endogenous variables. The null hypothesis of weak instruments in a sense that the bias is unacceptably large, meaning that the maximal relative bias is larger than p=5%, can be rejected for specifications (1) and (2) on the basis of both tests. For specification (3) and (4) we likewise reject the null hypothesis of a bias larger than p=5% using Cragg-Donald whereas we can reject the null hypothesis only for a maximal relative bias of 10% using the Kleibergen and Paap statistic. Thus, we can conclude that our instruments are valid and non-weak.

Using the aforementioned instruments and a difference-in-Hansen C test, the results in manufacturing indeed reject the null hypothesis that the sales growth due new products variable (both total and split into its two components) is exogenous and thus confirm the endogeneity problem. As expected, the OLS estimates are downward biased leading to β coefficients of 0.851 in model (2) and 0.712 and 0.911 in

[18] We use the Hansen statistic instead of the Sargan statistic since we estimate heteroskedasticity-robust errors. In contrast to the Hansen statistic, the Sargan statistic is not consistent if heteroskedasticity is present.

model (3). In services, though, the C-test does not indicate any endogeneity problem. In the interpretation of results, we nevertheless stick to the IV results, but we additionally present OLS results in Table 10.

Table 8 **Employment Effects of Green Innovation in German Manufacturing, 2006-2008**

Dependent variable:	**PC=PCOLD**				**PC=PCONLY**			
$EMP = l - (g_1 - \hat{\pi}_1)$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Constant	-3.811***	-3.793***	-3.738***	-3.761***	-3.807***	-3.790***	-3.765***	-3.784***
	(1.431)	(1.430)	(1.442)	(1.445)	(1.431)	(1.429)	(1.442)	(1.445)
SGR_NEWPD (β)	0.978***	0.975***	-	-	0.975***	0.973***	-	-
	(0.050)	(0.050)			(0.050)	(0.050)		
SGR_NEWPD_ENV (β_{ENV})	-	-	0.769***	0.772***	-	-	0.776***	0.779***
			(0.200)	(0.200)			(0.197)	(0.197)
SGR_NEWPD_NE (β_{NE})	-	-	1.041***	1.041***	-	-	1.038***	1.037***
			(0.087)	(0.088)			(0.086)	(0.087)
PC (α)	-1.895	-	-	-	-2.147	-	-	-
	(1.592)				(1.845)			
PC_ENV (α_{ENV})	-	-0.373	-0.310	-	-	-0.677	-0.560	-
		(1.843)	(1.850)			(2.009)	(2.015)	
PC_NE (α_{NE})	-	-4.148*	-4.412*	-4.380*	-	-4.581	-4.429	-4.416
		(2.493)	(2.482)	(2.479)		(3.077)	(3.096)	(3.092)
PC_ENV_MAT	-	-	-	1.839	-	-	-	0.965
				(2.684)				(2.830)
PC_ENV_EMIS	-	-	-	-1.256	-	-	-	-2.697
				(3.082)				(3.279)
PC_ENV_POLL	-	-	-	0.101	-	-	-	1.223
				(2.979)				(3.007)
PC_ENV_REC	-	-	-	-1.392	-	-	-	-0.736
				(2.914)				(2.993)
Joint sign. (p-value)								
Industry dummies	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Size dummies	0.754	0.752	0.702	0.688	0.743	0.735	0.683	0.683
PC_ENV dummies	-	-	-	0.955	-	-	-	0.934
R2_adj	0.443	0.443	0.449	0.449	0.443	0.443	0.449	0.449
RMSE	24.437	24.419	24.282	24.278	24.430	24.414	24.281	24.277
Wald-Test: β=1	0.652	0.615	-	-	0.624	0.596	-	-
Wald-Test: β_{ENV}=1	-	-	0.248	0.255	-	-	0.255	0.262
Wald-Test: β_{NE}=1	-	-	0.634	0.643	-	-	0.663	0.673
Wald-Test: β_{ENV}=β_{NE}	-	-	0.306	0.313	-	-	0.317	0.325
Wald-Test: α_{ENV}=α_{NE}	-	0.191	0.155	-	-	0.249	0.253	-

Notes: Method: Instrumental variables estimation. Number of observations: 2372. ***, ** and * indicate significance at the 1%, 5% and 10% level. Robust standard errors are reported. Industry and size dummies are included in each regression. For each set of dummies the p-value of a test on joint significance is reported. Instruments for sales growth due to new products (SGR_NEWPD): RANGE, R&D and CLIENT. In regressions (3), (4), (7) and (8) two additional instruments have been employed: ENV_DEM and ENV_AGREE. For first stage regression results see Table 9.

Table 9 **Employment Effects of Green Innovation in German Manufacturing – First stage regression results, 2006-2008**

	PC=PCOLD				PC=PCONLY			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First stage results 1 (SGR_NEWPD / _ENV):								
RANGE	2.966***	2.979***	0.479	0.465	2.878***	2.883***	0.439	0.427
	(0.557)	(0.556)	(0.319)	(0.319)	(0.544)	(0.544)	(0.318)	(0.319)
R&D	13.631***	13.675***	3.523***	3.547***	13.270***	13.277***	3.533***	3.569***
	(1.583)	(1.582)	(0.932)	(0.935)	(1.564)	(1.565)	(0.940)	(0.941)
CLIENT	7.829***	7.846***	1.164	1.125	8.039***	8.049***	1.161	1.135
	(1.497)	(1.495)	(0.775)	(0.778)	(1.480)	(1.481)	(0.776)	(0.777)
ENV_DEM	-	-	5.786***	5.799***	-	-	5.752***	5.773***
			(1.093)	(1.095)			(1.093)	(1.096)
ENV_AGREE	-	-	0.639	0.637	-	-	0.703	0.703
			(0.781)	(0.783)			(0.786)	(0.789)
F-stat of excl. instr.	163.628	164.491	23.094	22.927	164.163	164.051	23.234	23.104
First stage results 2 (SGR_NEWPD_NE)								
RANGE	-	-	2.394***	2.345***	-	-	2.342***	2.305***
			(0.470)	(0.470)			(0.459)	(0.460)
R&D	-	-	9.911***	10.007***	-	-	9.504***	9.646***
			(1.344)	(1.348)			(1.323)	(1.328)
CLIENT	-	-	6.426***	6.329***	-	-	6.658***	6.521***
			(1.283)	(1.283)			(1.272)	(1.272)
ENV_DEM	-	-	-2.243**	-2.186*	-	-	-2.588**	-2.543**
			(1.126)	(1.127)			(1.116)	(1.119)
ENV_AGREE	-	-	-0.447	-0.415	-	-	-0.224	-0.307
			(1.099)	(1.104)			(1.097)	(1.103)
F-stat of excl. instr.	-	-	76.907	75.561	-	-	76.557	75.196
Tests on Exogeneity								
SGR_NEWPD/_ENV&_NE	0.007***	0.009***	0.029**	0.033**	0.007***	0.009***	0.028**	0.032**
Tests on instr. validity								
Sargan/Hansen J-Test	0.998	0.998	0.932	0.933	0.999	0.999	0.916	0.912
Diff-in-Sargan test								
C: RANGE	0.952	0.955	0.982	0.995	0.974	0.978	0.991	0.991
C: R&D	0.959	0.959	0.958	0.932	0.969	0.977	0.936	0.913
C: CLIENT	0.978	0.981	0.940	0.936	0.995	0.993	0.948	0.934
C: ENV_DEM	-	-	0.513	0.511	-	-	0.478	0.468
C: ENV_AGREE	-	-	0.513	0.517	-	-	0.482	0.478
Tests on underident.								
Kleibergen-Paap LM test	337.740***	339.328***	46.215***	45.832***	339.028***	339.063***	47.026***	47.037***
Test on weak inst.								
Cragg-Donald F test	166.533***	167.612***	14.339***	14.247***	165.086***	165.243***	14.811***	14.815***
Kleibergen-Paap F test	163.628***	164.491***	9.365**	9.271**	164.163***	164.051***	9.546**	9.537**
Weak instr. rob. inf.								
Anderson-R. Wald test	257.543***	256.638***	261.339***	255.432***	252.203***	250.316***	255.508***	250.071***
Stock-Wright LM test	211.144***	210.403***	212.845***	208.747***	207.487***	206.157***	208.895***	205.350***

Notes: Displayed are first stage regression results of IV estimates for models (1) to (8) of Table 8. Reported are only coefficients and standard errors of the instruments, results for the other exogenous variables in the first stage are available upon request. F reports the test statistic of an F-Test on the joint significance of the instruments in the first stage. J-Test reports the p-value of the Sargan-Hansen *test on overidentifying restrictions*. Under H0 (overall set of instruments is valid) J follows a X2(m) distribution with m as the number of overidentifying restrictions. The *difference-in-Sargan C-Test* reports the p-value of a difference-in-Sargan/Hansen test on the validity of a single instrument. A difference-in-Sargan/Hansen test statistic is likewise used for the *test on the exogeneity* of SGR_NEWPD in (1), (2), (5) and (6), and on the joint exogeneity of SGR_NEWPD_ENV and SGR_NEWPD_NE in (3), (4), (7) and (8), respectively. The test statistic is robust to violations of conditional homoskedasticity. If conditional homoskedasticity holds, it is numerically equal to a Hausman-Durbin-Wu test statistic. The test on *underidentification* tests whether the instrument matrix has full rank in the first stage. Rejection of the null hypothesis implies that the equation is identified, i.e., that the excluded instruments are relevant meaning correlated with the endogenous regressors. Reported is the heteroskedasticity-robust Kleibergen-Paap rk LM statistic (Kleibergen and Paap, 2006) which follows a X2(m+1)-distribution. *Weak instruments* can lead to a large relative bias of IV compared to the bias of OLS. The Cragg-Donald F statistic and Kleibergen-Paap Wald F statistic both test the null hypothesis that the instruments are weak, more precisely that the maximal relative bias of IV is larger than p%. Here p is chosen to be 5%, 10%, 20%, and 30%. Cragg-Donald F statistic is for i.i.d. errors whereas Kleibergen and Paap statistic is heteroskedasticity-robust. For one endogenous regressor (K=1), the test statistic is identical to the first stage F-statistic on excluded instruments. For K=1 endogenous regressor and L=3 instruments the critical values are 13.91 (p=5%,***), 9.08 (p=10%, **), 6.46 (p=20%, *) and 5.39 (p=30%, #). For K=2 endogenous regressors and L=5 instruments the corresponding critical values are 13.97, 8.78, 5.91 and 4.79. Note that these critical values are for i.i.d. errors; see Baum et al., 2007; Cragg and Donald, 1993; Stock and Yogo, 2005).

The econometric results demonstrate that higher sales growth rates due to new products are associated with significantly higher employment growth. We can thus conclude that successful product innovation significantly spurs employment growth in both manufacturing and service firms. In the structural model approach β, the coefficient of the sales growth due to new products variable, measures efficiency differences between old and new products. A value of less than one implies that new products are produced with higher efficiency and thus less labor input than old products. A value of one indicates the same efficiency of old and new products and no additional productivity effects of new products. In manufacturing, the coefficient is slightly below 1 at about 0.97. In services evidence is more in favor of additional productivity effects of new products with a coefficient of 0.86. However, the t-test does not reject the null hypothesis that the coefficient is one. Thus an increase in sales growth due to new products of 1% leads to an increase in *gross* employment by 1%. At the same time, product innovations are likely to replace existing products to a considerable extent which is captured by g_1 and which might lead to labor displacement. We present estimation results for the net employment effect of product innovation in the next subsection.

Strikingly, we find the stimulating effect of product innovation success to hold for both types of new products: environmental and non-environmental ones. In manufacturing, this impact tends to be larger for non-green than for green product innovations. For non-green product innovations we find a unity elasticity whereas the coefficient is about 0.76 for the variable sales growth due to green new products. In services we find the opposite pattern. However, using an F–test we cannot reject the null hypothesis that both coefficients are equal in both samples. Even though the coefficients are not statistically different, they reveal more variation than in Licht and Peters (2013). They find only very small differences. This is probably due to the fact that they can only measure the employment effects of the sales growth due to new products for green and non-green product innovators, knowing that some of the product innovations of green product innovators do not have any environmental benefits.

The employment effects of process innovations are mixed. We do not find any significant effect when we simply look at the process innovation dummy in specification (1), neither in manufacturing nor in services. However, when we distinguish between green and non-green process innovation, the results reveal significant productivity gains of non-green process innovation and thus displacement of labor in manufacturing. The employment growth rate is about 4.4 percentage points smaller for non-environmental process innovators than for non-innovators. In contrast, there is no downsizing involved with the introduction of new environmental production technologies in manufacturing. Even when we distinguish between different types of environmental process innovations we do not find any evidence for significant employment destruction, neither of material and energy saving process innovations nor of air, water, soil and noise pollution reducing process innovations which mainly cover end-of-pipe technologies. Hence, our results do not point towards the often feared negative employment consequences of environmental policies affecting production processes. At least for the period 2006-2008, we cannot identify a significant trade-off between stricter environmental regulation of production processes and employment growth.

Table 10 **Employment Effects of Green Innovation in German Services, 2006-2008**

Dependent variable: $EMP = l - (g_1 - \hat{\pi}_1)$	**IV: PC=PCOLD**				**IV: PC=PCONLY**				**OLS: PC=PCOLD**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Constant	-0.531	-0.447	-0.411	-0.333	-0.442	-0.372	-0.329	-0.341	-0.540
	(1.398)	(1.396)	(1.395)	(1.399)	(1.425)	(1.427)	(1.426)	(1.427)	(1.292)
SGR_NEWPD (β)	0.868***	0.862***	-	-	0.872***	0.869***	-	-	-
	(0.112)	(0.112)			(0.110)	(0.110)			
SGR_NEWPD_ENV (β_{ENV})	-	-	1.100**	1.125**	-	-	1.119**	1.097**	0.941***
			(0.496)	(0.496)			(0.496)	(0.496)	(0.143)
SGR_NEWPD_NE (β_{NE})	-	-	0.823***	0.837***	-	-	0.829***	0.845***	0.864***
			(0.144)	(0.145)			(0.141)	(0.142)	(0.050)
PC (α)	-0.738	-	-	-	-1.690	-	-	-	
	(1.803)				(2.191)				
PC_ENV (α_{ENV})	-	3.849	3.918	-	-	2.693	2.743	-	3.891
		(2.607)	(2.628)			(2.721)	(2.723)		(2.623)
PC_NE (α_{NE})	-	-3.108	-3.120	-3.198	-	-4.043	-4.116	-4.074	-3.067
		(2.250)	(2.255)	(2.253)		(2.803)	(2.822)	(2.820)	(2.238)
PC_ENV_MAT	-	-	-	4.773	-	-	-	1.354	-
				(3.847)				(3.514)	
PC_ENV_EMIS	-	-	-	0.031	-	-	-	-0.312	-
				(4.028)				(3.596)	
PC_ENV_POLL	-	-	-	-8.032	-	-	-	-8.232*	-
				(5.326)				(4.994)	
PC_ENV_REC	-	-	-	4.875	-	-	-	8.873	-
				(5.506)				(5.494)	
Joint sign. (p-value)									
Industry dummies	0.008***	0.010***	0.012**	0.010***	0.008***	0.010***	0.012**	0.010***	0.001***
Size dummies	0.541	0.516	0.519	0.467	0.541	0.530	0.533	0.508	0.523
PC_ENV dummies	-	-	-	0.565	-	-	-	0.511	-
R2_adj	0.374	0.376	0.374	0.373	0.375	0.375	0.374	0.374	0.375
RMSE	25.081	25.046	25.068	25.059	25.076	25.050	25.074	25.046	25.232
Wald-Test: β=1	0.236	0.215	-	-	0.243	0.232	-	-	
Wald-Test: β_{ENV}=1	-	-	0.841	0.800	-	-	0.810	0.845	0.683
Wald-Test: β_{NE}=1	-	-	0.220	0.261	-	-	0.223	0.274	0.007***
Wald-Test: $\beta_{ENV}=\beta_{NE}$	-	-	0.630	0.616	-	-	0.612	0.660	0.618
Wald-Test: $\alpha_{ENV}=\alpha_{NE}$	-	0.035**	0.035**	-	-	0.064*	0.060*	-	0.037**

Notes: Method: Instrumental variables estimation for models (1) to (8) and OLS for model (9). Number of observations: 1,404. ***, ** and * indicate significance at the 1%, 5% and 10% level. Robust standard errors are reported. Instruments: RANGE, CLIENT and ENV_DEM and ENV_AGR. For first stage results and diagnostics of models (1) to (8), see Table 11.

The same result is valid for the German service sector. We cannot detect a significant employment effect of process innovation in general. When we distinguish between the introduction of green and non-green production technologies, results demonstrate a negative employment impact of non-green process innovation. This effect is only little smaller than in manufacturing (-3.1 percentage points) though it slightly failed significance at conventional levels (p-value of 0.14). The effect of green process innovation on employment growth is positive and significantly larger than the effect of non-green process innovation. This result differs from Licht and Peters (2013) who did not find any significant differences between both types of process innovation at the European level.

Table 11 **Employment Effects of Green Innovation in German Services – First Stage Regression Results, 2006-2008**

	PC=PCOLD				PC=PCONLY			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First stage results 1 (SGR_NEWPD / _ENV):								
RANGE	3.307***	3.302***	0.323	0.314	3.223***	3.203***	0.310	0.300
	(0.635)	(0.636)	(0.197)	(0.197)	(0.626)	(0.627)	(0.193)	(0.193)
CLIENT	7.482***	7.488***	0.888	0.894	7.712***	7.749***	0.910	0.926*
	(1.746)	(1.748)	(0.553)	(0.556)	(1.740)	(1.744)	(0.553)	(0.557)
ENV_DEM	-	-	3.083***	3.093***	-	-	3.034***	3.050***
			(0.921)	(0.929)			(0.911)	(0.916)
ENV_AGREE	-	-	1.159	1.187	-	-	1.171	1.189
			(0.777)	(0.785)			(0.779)	(0.785)
F-stat of excl. instr.	93.932	93.943	9.742	9.770	102.668	102.396	10.003	9.978
First stage results 2 (SGR_NEWPD_NE)								
RANGE	-	-	2.984***	2.943***	-	-	2.905***	2.873***
			(0.595)	(0.597)			(0.589)	(0.592)
CLIENT	-	-	6.608***	6.716***	-	-	6.869***	6.908***
			(1.654)	(1.663)			(1.653)	(1.670)
ENV_DEM	-	-	-2.834**	-2.884**	-	-	-3.141**	-3.125**
			(1.407)	(1.394)			(1.383)	(1.391)
ENV_AGREE	-	-	-1.695	-1.612	-	-	-1.654	-1.649
			(1.369)	(1.380)			(1.360)	(1.371)
F-stat of excl. instr.	-	-	40.392	40.194	-	-	44.043	43.538
Tests on Exogeneity								
SGR_NEWPD/_ENV&_NE	0.971	0.935	0.946	0.941	0.972	0.982	0.940	0.952
Tests on instr. validity								
Sargan/Hansen J-Test	0.712	0.760	0.950	0.950	0.723	0.771	0.954	0.970
Diff-in-Sargan test								
C: RANGE	0.712	0.760	0.750	0.756	0.723	0.771	0.761	0.810
C: CLIENT	0.712	0.760	0.750	0.755	0.723	0.771	0.760	0.809
C: ENV_DEM	-	-	0.970	0.948	-	-	0.965	0.967
C: ENV_AGREE	-	-	0.982	0.958	-	-	0.976	0.977
Tests on underident.								
Kleibergen-Paap LM test	149.388***	149.113***	33.714***	33.592***	160.723***	160.170***	33.679***	33.802***
Test on weak inst.								
Cragg-Donald F test	103.333***	103.073***	16.640***	16.681***	109.019***	108.711***	16.846***	16.908***
Kleibergen-Paap F test	93.932***	93.943***	8.899**	8.856**	102.668***	102.396***	8.843**	8.866**
Weak instr. rob. inf.								
Anderson-R. Wald test	45.011***	44.388***	46.137***	48.355***	47.909***	47.506***	48.962***	49.771***
Stock-Wright LM test	42.206***	41.581***	42.824***	44.826***	44.759***	44.345***	45.440***	46.206***

Notes: Displayed are first stage regression results of IV estimates for models (1) to (8) of Table 10. Instruments: RANGE, CLIENT and ENV_DEM and ENV_AGR. R&D is not a valid instrument in services according to the Sargan-Hansen C-test and it has therefore been left out. With one endogenous regressor and two excluded instruments, the critical value for the Cragg–Donald statistic for 10% (***) maximal size distortion is 16.87 (see regressions 1, 2, 5 and 6). With two endogenous regressors and four excluded instruments, the critical values for the Cragg–Donald statistic for a p% maximal relative bias of IV are 11.04 (p=5%,***), 7.56 (p=10%, **), 5.57 (p=20%, *) and 4.73 (p=30%, #).

6.3 Contribution of Innovation to Employment Growth

We finish our empirical investigation with a decomposition analysis. The decomposition allows us to identify the contribution of several sources to employment growth for different types of firms. In particular, we are able to separate the employment effects of green and non-green product and process innovation from effects originating from general demand and productivity trends. We extend the decomposition of employment growth proposed by Harrison et al. (2008) in the following way:

$$l = \underbrace{\hat{\alpha}_{0,CIS}}_{1} + \underbrace{\hat{\alpha}_1 pc_{ENV}}_{2a} + \underbrace{\hat{\alpha}_2 pc_{NE}}_{2b} + \underbrace{\left[1 - I\left(g_{2,ENV} > 0 \cup g_{2,NE} > 0\right)\right]\left(g_1 - \tilde{\pi}_1\right)}_{3}$$

(5)

$$+ \underbrace{I\left(g_{2,ENV} > 0 \cup g_{2,NE} > 0\right)\left(g_1 - \tilde{\pi}_1\right)}_{4.1a} + \underbrace{I\left(g_{2,ENV} > 0\right)\hat{\beta}_{ENV} g_{2,ENV}}_{4.1b} + \underbrace{I\left(g_{2,NE} > 0\right)\hat{\beta}_{NE} g_{2,NE}}_{4.1c} + \hat{v}$$

1. The first term $\hat{\alpha}_{0,\,CIS}$, measures the contribution of the *general trend in productivity* in the production of *old products* to employment growth. Note that $\hat{\alpha}_{0,\,CIS}$ captures the estimated effect of the constant, industry and size dummies. The general productivity trend is thus industry and size specific. It accounts for all changes in efficiency and in turn in employment that are not attributable to firm's own process or product innovation. That is, it captures employment effects of training, improvements in the human capital endowment, corporate restructuring, acquisitions of firms, organizational innovation, productivity effects from spillovers, wages etc. It is measured as the average effect across innovators and non-innovators.

2. Term 2a and 2b capture changes in employment due to additional changes in efficiency that result from the introduction of *process innovation* applied in the production of *old* products. Term 2a measure the displacement effect (gross effect) of process innovation related to old products for environmental process innovators. Term 2b presents the contribution of process innovations for non-green process innovators. The sum of 2a and 2b make up the gross effect of process innovation.

3. In equation (6) $I(.)$ denotes the indicator function. It is 1 if the condition in brackets is fulfilled and 0 otherwise. $1 - I\left(g_{2,ENV} > 0 \cup g_{2,NE} > 0\right)$ therefore indicates non-product innovators. This implies that the third component captures shifts in employment which originate from the real *growth of output in old products* for firms that do *not* introduce any new products. Changes in output for existing products might occur because of changes in demand, consumers' preferences, price reductions, and business cycle impacts but also because of rivals' product innovations. This term therefore also comprises the (positive or negative) externalities that arise from product innovation of other firms. The occurrence of negative externalities is known as 'business stealing' effect. Substitution between sales from old and from new products within the same firm, however, is included in terms 4.1a.

4. Components 4.1a to 4.1c summarize the *net* contribution of *green and non-green product innovation* to employment growth for product innovators. The net effect of product innovation results from (i) increases in the demand for new products with and without environmental benefits, $I\left(g_{2,ENV} > 0\right)\hat{\beta}_{ENV} g_{2,ENV}$ and $I\left(g_{2,NE} > 0\right)\hat{\beta}_{NE} g_{2,NE}$, respectively, and (ii) possible (positive or negative) shifts in demand for the old product $\left(I\left(g_{2,ENV} > 0 \cup g_{2,NE} > 0\right)\left(g_1 - \tilde{\pi}_1\right)\right)$.

   The net contribution of product innovation can be represented in an alternative way using the following decomposition:

$$l = \underbrace{\hat{\alpha}_0}_{1} + \underbrace{\hat{\alpha}_1 pc_{ENV}}_{2a} + \underbrace{\hat{\alpha}_2 pc_{NE}}_{2b} + \underbrace{\left[1 - I\left(g_{2,ENV} > 0 \cup g_{2,NE} > 0\right)\right](g_1 - \tilde{\pi}_1)}_{3}$$

$$+ \underbrace{I\left(g_{2,ENV} > 0 \cap g_{2,NE} = 0\right)\left(g_1 - \tilde{\pi}_1 + \hat{\beta}_{ENV} g_{2,ENV}\right)}_{4.2a}$$

(6)
$$+ \underbrace{I\left(g_{2,ENV} = 0 \cap g_{2,NE} > 0\right)\left(g_1 - \tilde{\pi}_1 + \hat{\beta}_{NE} g_{2,NE}\right)}_{4.2b}$$

$$+ \underbrace{I\left(g_{2,ENV} > 0 \cap g_{2,NE} > 0\right)\left(g_1 - \tilde{\pi}_1 + \hat{\beta}_{ENV} g_{2,ENV} + \hat{\beta}_{NE} g_{2,NE}\right)}_{4.2c} + \hat{v}$$

In equation (6) term 4.2a measures the net contribution of product innovation for product innovators with green product innovation only. It consists of the output reduction in old products and the output increase in new environmental products for this group of firms. Similarly, 4.2b accounts for the net contribution of product innovation for product innovators with non-environmental product innovation only. Finally, 4.2c records the net contribution of product innovation for product innovators which simultaneously introduce both types of product innovation.

We can obtain an estimate of the decomposition of the average employment growth by inserting into the equation the

- estimated coefficients $\hat{\alpha}_{0,\,CIS}, \hat{\alpha}_1, \hat{\alpha}_2, \hat{\beta}_{ENV}$ and $\hat{\beta}_{NE}$ (from the preferred specification 3 of Table 8 and 10),
- average shares of non-innovators, green and non-green process and product innovators (Figure 1 and 2) and
- employment, price and sales growth rates (either total or for the corresponding group of firms, see Table 4 and 5).

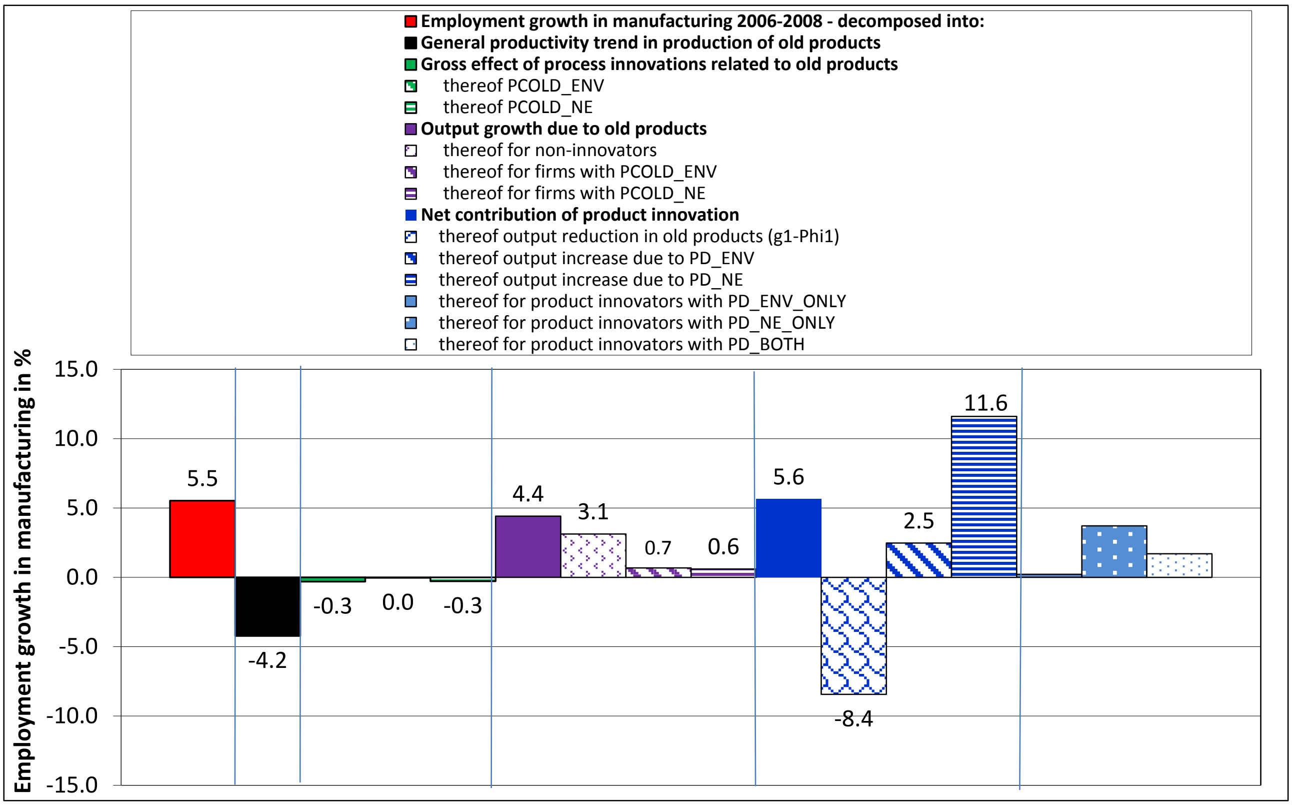
The residual is zero by definition. Table 12 depicts the results of the employment growth decomposition and Figure 3 and Figure 4 additionally provide a graphic illustration for manufacturing and services, respectively.

In manufacturing, employment grew on average by 5.5% which resulted from the following sources: General improvements in productivity in isolation have led to a destruction of jobs by 4.2%. This shows that the general productivity trend has a strong negative impact on employment. It is much larger than the labor destruction that results from process innovation induced efficiency gains. For non-environmental process innovation these efficiency gains lead to an additional 0.3% reduction in employment. The contribution of environmental process innovation to employment growth is negative but negligible (-0.03%). These negative impacts on employment have been more than offset by the growth in output (demand) of old and new products. It turns out that the growth in new products was the main contributor to employment growth fostering it by about 5.6%. An additional 4.4% employment growth originates from the output growth in old products for non-product innovators, split into 3.1% for non-innovators and 1.3% for process innovators. This also implies that in sum we end up with a net effect for process innovators of about 1%. Interestingly, this is very close to the reduced form regression results. When we disentangle the net contribution of product innovation, we find that non-environmental product innovations have contributed to a much larger extent (+11.6%) to employment growth than environmental product innovations (+2.5%). At the same time, product innovators have been faced with a decline in the output of their old products which dampened the positive employment effect by about 8.4%. The fact that we find a smaller employment impact of environmental product innovation can be explained by larger productivity gains associated with the production of new green products (indicated by the lower β coefficient), by a lower innovation success (indicated by a lower average $g_{2,ENV}$ for green product innovators than $g_{2,NE}$ for non-green product innovators), and by a lower engagement in green product innovation (indicated by the lower proportion of green product innovators). The finding that non-green product innovation creates more employment than green product innovation points towards the fact that Licht and Peters (2013) overestimate the effect of green product innovation at the European level. The reason is that European CIS data only allows identifying green and non-green product innovators but not sales growth that stems from both types of new products. Using the alternative representation of the decomposition we find that product innovations from product innovators with non-environmental product innovation only contributed the most to employment growth (+3.7%), followed by joint product innovators (+1.7%) and product innovators having only green product innovations (+0.2%).

Table 12 **Employment Growth Decomposition, 2006-2008**

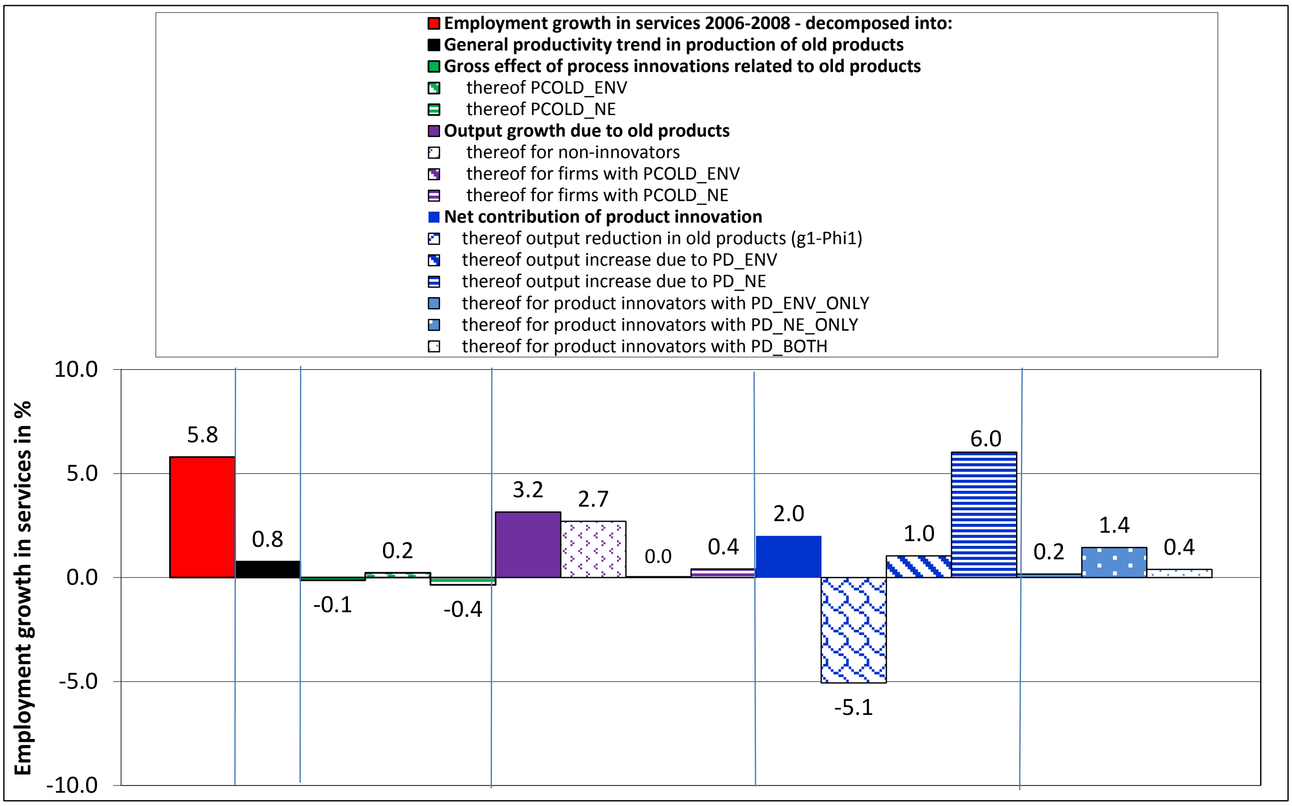
	Manuf.	**Services**
Employment growth	**5.52**	**5.79**
Decomposed into		
(1) General productivity trend in production of old products	**-4.23**	**0.77**
(2) Gross effect of process innovations related to old products	**-0.31**	**-0.13**
(2a) Thereof environmental process innovations	-0.03	0.22
(2b) Thereof non-environmental process innovation	-0.28	-0.35
(3) Output growth of old products for non-product innovators	**4.42**	**3.15**
(3a) Thereof for non-innovators	3.13	2.70
(3b) Thereof for environmental process innovators	0.68	0.04
(3c) Thereof for non-environmental process innovators	0.61	0.41
(4) Net contribution of product innovations	**5.64**	**2.00**
Decomposition 1:		
(4.1a) Thereof output reduction in old products	-8.44	-5.07
(4.1b) Thereof output increase in new environmental products	2.47	1.04
(4.1c) Thereof output increase in new non-environmental products	11.61	6.03
Decomposition 2:		
(4.2a) ***Net contribution of product innovation for product innovators with environmental pd only***	***0.23***	***0.17***
- Output reduction in old products	-0.73	-0.24
- Output increase in new environmental products	0.96	0.41
(4.2b) ***Net contribution of product innovation for product innovators with non-environmental pd only***	***3.71***	***1.45***
- Output reduction in old products	-4.68	-3.66
- Output increase in new non-environmental products	8.39	5.11
(4.2c) ***Net contribution of product innov. for product innovators with both types of product innov.***	***1.71***	***0.39***
- Output reduction in old products	-3.03	-1.17
- Output increase in new products	4.73	1.56

Figure 3 **Decomposition of Employment Growth in German Manufacturing, 2006-2008**



In German services we find some interesting similarities and dissimilarities compared to manufacturing. Average employment growth was similar in magnitude (+5.8%). However, results do not point towards major efficiency gains due to general productivity improvements that have led to a reduction in employment. In contrast, the general productivity trend has led to an increase in employment by 0.8%. Like in manufacturing the labor displacement effect of process innovation was rather small in services (-0.1%). While the effect of non-green process innovation was similar in both sectors (-0.3%), non-environmental process innovations even spurred employment growth (+0.2%). Also like in manufacturing employment growth in services was mainly the result of the growth in output (demand) of old and new products. The demand growth in old products for non-product innovators fostered employment by 3.1%. But even though its contribution was smaller than in manufacturing, it has been the main contributor to the increase in labor demand in services. The introduction of new products stimulated employment by 2%. Like in manufacturing we observe that non-environmental product innovations have contributed more to employment growth than environmental product innovations, though at a lower level with 6.0% and 1.0%. At the same time the positive employment effect for product innovators was weakened by 5% due to the decline in the demand for their old products. Given the fact that the estimated coefficient is similar for both types of product innovation, the lower contribution is mainly the result of a lower engagement in environmental product innovations and a lower innovation success of environmental product innovations.

Figure 4 **Decomposition of Employment Growth in German Services, 2006-2008**



7. Conclusions

This paper contributes to the discussion of the impact of green innovation on employment growth. In particular, we compare the employment impact of environmental and non-environmental patent as well as those of product and process innovations using data for manufacturing and service firms in Germany. In the following we will first summarize the key findings followed by some policy conclusions that can be drawn from the analysis.

First, only a very small proportion of firms in our sample have applied for green patents, about 2% of the innovators in manufacturing and less than 1% of them in services. When we compare this with the survey-based proportion of environmental innovators, we have to ascertain that we heavily underestimate green innovation activities in both sectors using patent data. This might also be one explanation why we do not find that firms that have applied for patents protecting green technologies have grown faster, neither in manufacturing nor in services. Another explanation is that patent data do not easily allow us to identify patents related to new products and new processes though we know from theory that their employment mechanism differ quite substantially.

Second, both environmental and non-environmental product innovations are conducive to employment growth. A one-percent increase in the sales due to new products also increases *gross* employment by one percent. This elasticity tends to be lower than 1 for green product innovations in manufacturing and non-green product innovations in services, though statistically we cannot reject the null hypothesis of a unit elasticity for both types of new products in both sectors. Hence, there is no evidence that environmentally-friendly new products are produced with higher or lower efficiency than old products and thus c.p. with the same amount of labor input. The decomposition of employment growth allows us to assess the net effect of product innovation taking substitution effects on the output of old products into account. It turns out that product innovations have a positive net effect in both sectors, in manufacturing they are even the main source of employment growth. In services employment growth due to output growth in existing products exceeds that of new products. In sum, product innovations have stimulated growth by 5.6% in manufacturing and 2% in services. This is in line with results of Licht and Peters (2013) at the European level.

Third, regarding the relative importance of both types of product innovation, our findings using more detailed data on the share of sales with new products, however, suggest that still non-environmental product innovations clearly contribute more to employment growth than environmental product innovations in both sectors. This can be mainly explained by a lower engagement in green product innovation and by a relatively lower average innovation success with green product innovations, but not by differences in the transformation of a given level of innovation success to employment growth.

Fourth, the general trend in productivity has a strong negative impact of employment growth in manufacturing during the observation period but not in services.

Fifth, the displacement effect of process innovation turns out to be rather small. For non-environmental process innovators we found the effect to be about -0.3% in both sectors. The effect of environmental process innovation is negative but negligible in manufacturing and even positive in services. Adding the employment growth contribution of the change in demand for existing products for process innovators which is to a certain extent provoked by the process innovation induced reduction in prices, we find a positive net effect in both sectors.

Sixth, our results do not point towards significant differences in employment growth due to different types of process innovations. Thus, our results do not confirm prior findings of Rennings and Horbach (2013) who conclude that the employment effects of the introduction of cleaner process technologies seem to be more advantageous within a firm compared to more end-of-pipe oriented technologies.

In a nutshell, our results highlight the importance of green and non-green innovation activities in stimulating employment in Germany. It is even likely that we underestimate the size of the total employment effect of product and process innovation since we only investigate a three-year period. Due to data constraints we cannot employ a panel data analysis and examine long-term impacts of new products and processes. While it is sensible to assume that displacement effects of process or product innovations won't be lagging much to the time of their introduction, compensation effects especially of process innovations may appear with a certain delay implying an underestimation of the employment effect. An underestimation of positive employment effects might apply, of course, to both green and non-green innovations. However, it is hard to assess whether both types of innovations would be affected differently.

From the perspective of generating smart and sustainable (employment) growth, we conclude that policy should stimulate product innovation and to be precise both types of product innovation. At first glance it seems to be more efficient in terms of employment growth for policy to focus on non-green product innovation since we found a larger employment contribution of non-green product innovations than of environmental product innovation. However, as noted above, this is mainly due to a lower engagement in green product innovation and a lower average innovation success with green product innovations, but not due to differences in the transformation of a given level of innovation success to employment growth. Thus, if industrial or environmental policy is able to incentivize firms to engage in green product innovation activities and also helps them to better commercialize green product innovations, environmental-friendly product innovation will most likely not have different employment impacts. The result that an industrial or environmental policy that generated more favorable conditions for environmental product innovation will not necessarily worsen the employment situation in a country holds under the assumption that there will be no structural breaks in the above mentioned transformation.

In terms of process innovation we also gained some interesting policy insights: Our results do not point towards the often feared negative employment consequences of environmental process innovation. At least for the period 2006-2008, we cannot identify a significant trade-off between more environmental-friendly production technologies and employment growth. From that result we might also infer that there is no trade-off between employment growth and stricter environmental regulations which force firms to introduce more environmental-friendly production technologies. Our findings also suggest that this would hold for stricter environmental regulations in different fields, e.g. for regulations aimed at saving material and energy or regulations aimed at reducing air, water, soil and noise pollution. Hence, there seems to be some room for industrial and environmental policies to induce the increased use of cleaner production technologies and end-of-pipe technologies in manufacturing as well as in services.

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Annex

9. Tables

Table 13 **Distribution by Industry**

Manufacturing					Services				
Industry	Nace 1.1	N	%	Cum	Industry	Nace 1.1	N	%	Cum
FOOD	15-16	193	8.1	8.1	WHOLE	51	134	9.5	9.5
TEXT	17-19	113	4.8	12.9	TRANS	60-63	251	17.9	27.4
WOOD	20-22	271	11.4	24.3	TELE	64	46	3.3	30.7
CHEM	23-24	147	6.2	30.5	FIN	65-67	125	8.9	39.6
PLAS	25	128	5.4	35.9	COMP	72	161	11.5	51.1
NONM	26	92	3.9	39.8	TECH	74.2-74.3	186	13.2	64.3
BASM	27-28	310	13.1	52.9	CONSULT	74.1	111	7.9	72.2
MACH	29	287	12.1	65.0	ADV	74.4	32	2.3	74.5
ELEC	30-33	389	16.4	81.4	RECRUIT	74.5	40	2.8	77.3
VEHI	34-35	119	5.0	86.4	SECUR	74.6	36	2.6	79.9
NEC	36-27	119	5.0	91.4	CLEAN	74.7	72	5.1	85.0
ENER	40-41	140	5.9	97.3	OBRS	74.8, 90	162	11.5	96.5
CONSTR	45	64	2.7	100.0	MEDIA	92.1-92.2	48	3.4	100.0
Total		2,372	100.0		Total		1,404	100.00	

Table 14 **Size Distribution**

	Manufacturing			Services		
Size	N	%	Cum	N	%	Cum
<50	1028	44.3	44.3	720	51.3	51.3
50-99	448	18.9	63.2	247	17.6	68.9
100-249	447	18.8	82.0	201	14.3	83.2
250-999	317	13.4	95.4	154	11	94.2
1000+	132	5.6	100.0	82	5.8	100.0
Total	2,372	100.0		1,404	100.0	

Notes: Size is measured by the number of employees in 2008.

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Project Information

Welfare, Wealth and Work for Europe

A European research consortium is working on the analytical foundations for a socio-ecological transition

Abstract

Europe needs change. The financial crisis has exposed long-neglected deficiencies in the present growth path, most visibly in the areas of unemployment and public debt. At the same time, Europe has to cope with new challenges, ranging from globalisation and demographic shifts to new technologies and ecological challenges. Under the title of Welfare, Wealth and Work for Europe – WWWforEurope – a European research consortium is laying the analytical foundation for a new development strategy that will enable a socio-ecological transition to high levels of employment, social inclusion, gender equity and environmental sustainability. The four-year research project within the 7th Framework Programme funded by the European Commission was launched in April 2012. The consortium brings together researchers from 33 scientific institutions in 12 European countries and is coordinated by the Austrian Institute of Economic Research (WIFO). The project coordinator is Karl Aiginger, director of WIFO.

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	Ratio	Ratio	Sweden
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