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Organisational Change and the Productivity Effects of Green Technology Adoption*

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Abstract — This study investigates induced productivity effects of firms introducing new environmental technologies. The literature on within-firm organisational change and productivity suggests that firms can achieve higher productivity gains from adopting new technologies if they adapt their organisational structures. Such complementarity effects may be of particular importance for the adoption of greenhouse gas (GHG) abatement technologies. The adoption of these technologies is often induced by public authorities to limit the social costs of climate change, whereas the private returns are much less obvious. This study finds empirical support for complementarity between green technology adoption (either CO_2-reducing or resources and energy efficiency-enhancing technologies) and organisational change. While the sole adoption of green technologies is associated with lower productivity, the simultaneous implementation of green technologies and organisational innovations is not.

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1 Introduction

Research on firm organisation has long emphasised the importance of organisational structures for efficient technology use. Caroli and Van Reenen (2001, p. 1450), for example, make this point explicit by arguing that: “Without the organizational and skill infrastructure, technology alone is not enough.” Studies dealing with environmental technology, however, have largely ignored this stream of literature. This research focusses mainly on the role of governmental regulation for abatement technology adoption and its consequences for firms’ productivity and competitiveness. The question of how abatement technologies integrate into the firms’ operations and what factors determine their efficient adoption remained largely unexplored.

An exception is Bloom et al. (2010) who suggest that better managed firms have lower energy intensities and that advanced environmental management is associated with higher productivity. Further research by Martin et al. (2012) also offers evidence in favour of this view. However, both studies do not allow us to conclude that environmental management improves the marginal returns to environmental technology adoption in the sense that both have complementary effects on productivity.

In this study, we focus on the complementarity between green technology adoption and organisational change in manufacturing firms. In particular, we study whether firms that are open to organisational changes (i.e. firms that have introduced organisational innovations) can be more efficient in adopting new green technologies which translates into productivity gains.

Such efficiency improvements may translate into productivity gains in the adopting firms. Take the example of BASF. BASF is the world’s biggest leading chemical company and a large-scale emitter of greenhouse gases. To improve energy efficiency and to reduce greenhouse gas emissions, BASF uses environmental technologies such as combined heat and power, i.e. the technologies for the use of waste heat and the incineration of deposits from production. In addition, BASF has implemented the “Energieverbund” (energy compound) system which organises the supply of energy from these energy recovery technologies to their various plants. The “Energieverbund” “[...] therefore offers [...] a crucial competitive advantage, while also having a positive impact on the environment” (BASF, 2014). The BASF example illustrates how firms may combine an environmental innovation with new organisational designs and infrastructures to better exploit the opportunities provided by such technologies.

In the following, we consider green technology adoption as the implementation of any technology that reduces CO_2 emissions. This also includes cases in which CO_2 reduction can be achieved by using fossil fuel inputs more efficiently and are therefore related to energy-efficiency.[1] In addition to greenhouse gas (GHG) mitigation technologies we also consider sustainable innovations (i.e. material or resource-saving innovations). The se-

[1]Improving the efficiency of fossil fuel use requires the installation of new capital goods that use fossil fuels at a necessary minimum that is smaller than the levels of currently operated capital. Thus, if fossil fuel inputs and capital are used in rather fixed proportions, increasing efficiency implies the replacement of old capital (Atkeson and Kehoe, 1999).

lection of these two aspects of green technology is motivated by the fact that both are integrated process technologies, i.e. no end-of-pipe or other additive technologies.[2] Organisational change in this study's context comprises new business practices for organising procedures for production as well as for knowledge or quality management. In addition, new methods of organising work responsibilities and decision making, decentralisation or integration may result in organisational change.

From the perspective of the firm, the adoption of environmentally-friendly technologies is costly and may hence reduce productivity, especially if introduced to cope with governmental regulation. However, if this adoption is accompanied by organisational changes that allow for a more efficient use of the new technology, this productivity-reducing effect from green technology adoption may be diminished, off-set or possibly even reverted if green innovation and organisational change are complementary. Since abatement technology provides high environmental and social returns while private returns are unclear, understanding the effects on firms' productivity and therefore their incentives to adopt such technologies is crucial. If the introduction of CO_2 mitigation technologies or sustainable innovation were to hurt firms' productivity, any complementary effect from introducing an organisational change that moves private returns into positive territory would benefit the diffusion of green technologies. Thus, studying the underlying mechanisms through which green technology adoption interacts with the firms' organisation of production processes is also important for assessing the impact of green technology policy. While this paper focusses on green technologies, the general idea may also apply to other process innovations where private returns are less obvious, such as those increasing workplace safety.

In the following, we build on the literature dealing with organisational change and technology complementarity more generally. Earlier research—especially dealing with the case of information technology (IT) adoption—provides a considerable body of empirical evidence showing that adequate organisational structures complement technology adoption and thus allow firms to achieve higher productivity gains from technology adoption. Ichniowski et al. (1997) provide empirical evidence of complementarity among different types of organisational change. They find that the use of individual human resource practices complements the use of human resource management system technologies in steel producing plants, as joint adoption is identified as increasing steel finishing lines' productivity. Bresnahan et al. (2002) identify complementarity effects between organisational change and IT use on product innovation at the firm level. Most recently, Bloom et al. (2012) provided empirical evidence that US multinational enterprises located in the United Kingdom (UK) have higher returns from IT use compared to UK domestic firms. Their explanation of this phenomenon is that US firms' internal organisation allows them to make better use of IT, or in other words, the organisational form US firms have adopted is complementary to IT use.

We adopt an empirical approach in line with this literature, but focus on the productivity effects from the adoption of green technologies (GHG mitigation and sustainable

[2] This definition excludes abatement technologies for local water or air emissions (such as SO_2) that often use end-of-pipe technologies since there is no reason to expect changes in a firm's process or workflow organisation to affect these technologies' efficiencies.

technologies). We develop an empirical framework exploring whether green technologies jointly adopted with changes in firms' organisational structure improve the returns from adopting these technologies. Joint adoption may reduce or possibly even offset productivity losses from adopting green technology. We are particularly interested in "asymmetric'complementarity", i.e. where organisational change complements the use of green technologies (but not necessarily vice versa). This study provides an empirical framework to test for this asymmetric complementarity. Indeed, the results show that firms that jointly adopted both have a higher total factor productivity (TFP) compared to firms that adopted green innovations only.

The next section will discuss how our analysis adds to the literature on environmental technology adoption and firm performance. Section 3 briefly describes our estimation strategy to assess complementarity. Section 4 describes the German Community Innovation Survey (CIS) data used for the empirical analysis. Results are discussed in sections 5 and 6 and section 7 concludes.

2 Abatement Technology Adoption and Firm Performance

Over the last few decades, the effects of environmental technology adoption on firms' competitiveness has been a frequently—and at times hotly—debated topic in economic research and even more in policy. It has triggered a considerable body of empirical research at the firm level. However, previous studies focussed mostly on the impact of governmental regulation on firm performance and the productivity effects of the regulation-induced adoption of abatement technologies.[3].

A first strand in this literature looks at the impact of regulation on the adoption of environmental technology. A second strand of literature estimates the impact of regulation on firm or sector productivity. This research emerged at the beginning of the 1980s after the US and other highly industrialised countries introduced regulations for local water and air pollutants (like SO_2). In these studies, regulatory stringency is typically measured using data from the US Pollution Abatement Costs Expenditure (PACE) survey. As one of the first to use the PACE survey data, Gray (1987) reports a negative correlation between pollution abatement operating costs (PAOC) and TFP at the sectoral level, indicating no productive use of abatement technology. The study by Gray and Shadbegian (2003)

[3]For a recent survey on the impact of regulation on the adoption of environmental technologies, see Popp et al. (2010) For the early literature, the reader is referred to the review of Jaffe et al. (2002). Most of the regulation literature deals with innovation creation rather than with innovation adoption. A recent study by Johnstone et al. (2010) finds evidence for regulation-induced green innovations. They go so far as to say that "In general, policy, rather than prices, appears to be the main driver of innovation in these technologies" (Johnstone et al., 2010, p. 146). The study by Snyder et al. (2003) finds no significant evidence of regulation being a driver of technology adoption in the chlorine manufacturing industry. Another study by Kerr and Newell (2003) provides empirical evidence that market-based regulation offers greater incentives to adopt environmental technology than standard command-and-control regulation. Horbach (2008) provides further evidence from German innovation panel data regarding the drivers of environmental innovations. Veugelers (2012), using Flemish innovation panel data, finds that policy is important to stimulate private GHG mitigation innovation. Policy intervention, however, is found to be more effective if implemented in a policy mix.

provides estimates of PAOC's impact on both TFP and output in a production function estimation. Their results for pulp and paper mills also do not suggest a productive use of abatement inputs. Conversely, Shadbegian and Gray (2005) find that abatement capital inputs of pulp and paper mills significantly contribute to the production of desired outputs. However, they do not observe such effects for steel mills and oil refineries. For the latter, the study of Berman and Bui (2001) provides evidence in support of regulation-induced abatement investment's positive contribution to productivity growth. Boyd and McClelland (1999) construct measures of inefficiencies in paper mills' production processes using investment in pollution abatement equipment in addition to standard inputs. They find that there is a potential for both input and pollution reduction while keeping output constant. However, the authors weaken this statement by saying that abatement capital investment comes at the expense of otherwise productive investments and therefore may lower overall productivity. Commins et al. (2011) find that energy taxes as well as the European Emission Trading Scheme (EU-ETS) have negative impacts on TFP.

Another strand of literature deals with the so-called Porter hypothesis. Initiated by Porter (1991), this literature studies the impact of regulation on green technology innovation and its implications for firms' competitiveness. Porter and van der Linde (1995) argue that pollution is always a form of inefficiency. Properly designed regulations are seen as a way to increase firms' responsiveness so that environmentally-friendly technologies will be introduced. The crucial point in their argument is that regulations need to be properly designed. Ideally, they leave the flexibility of how to implement compliance measures with the firms, thereby allowing them to choose technologies that best fit their production techniques and organisational structures. Under this condition, firms may exploit complementarities with other technologies and processes. The Porter hypothesis has been challenged by some authors (Palmer et al., 1995, amongst others) but more recently it also received some support.[4] A recent study by Rexhäuser and Rammer (2014) using German firm-level data finds that only integrated environmentally-friendly process technologies (such as energy-, CO_2-, and material-saving innovations) can provide positive returns to adoption. However, this study does not allow the conclusion that these technologies positively affect productivity as the authors focus on financial performance.

This study aims to contribute to previous research by testing whether firms may improve the productivity impact of green technology adoption through the implementation of complementary organisational structures. We extend previous research that documented positive correlations between the joint adoption of both such as Antonioli et al. (2013) who find that human resource management (and workplace practices) predict firms' decisions to adopt CO_2 abatement technologies. We add to these insights by studying the productivity effects from sole and joint adoption of new organisational structures and green technologies, while accounting for different types of technologies and the possibility of asymmetric complementarity.

[4] See the review by Ambec et al. (2013).

3 Econometric Identification

Complementarity between any two economic activities x and x'[5] means that doing more of one increases the marginal benefits of doing more of the other. Athey and Stern (1998) offer an overview of the methodologies used to test for complementarities. There are, in principle, two ways to test for the complementarity of different firm strategies. The first one is the adoption approach, where a significant positive correlation between the adoption of two activities (conditional on any other factors) is an indicator of complementarity (Arora and Gambardella, 1990; Arora, 1996). However, the adoption approach is limited in its validity, particularly when x and x' are not continuous. The adoption approach fails to separate complementarity from correlation when there are other unobserved common determinants among x and x' leading to incoherence problems (Miravete and Pernías, 2010). More precisely, such an approach fails to separate complementarity from correlation due to other unobserved common determinants among x and x' leading to incoherence problems (Miravete and Pernías, 2010). In the context of this study, x and x' are binary indicators measuring whether one or both of the activities have occurred or not. The adoption approach is therefore not the most appropriate in this study.

The second approach, which is often referred to as the productivity approach[6]. It accounts for the effects of x and x' on a performance indicator, in our case productivity as measured by TFP. Section 3.1 sets out our productivity approach for assessing complementarity between green and organisational technology adoption in more detail.

TFP is only one performance indicator out of many. It reflects the technical efficiency of the production process. In the related literature, other performance indicators have also been used, for instance, Tobin's q, market value, or profitability (return on sales). Using financial performance indicators assess not only the technical efficiency of the production process, but will also capture higher market power or market valuations. Indeed, a better environmental performance of firms can also allow them to increase and absorb a higher customers' willingness to pay for environmentally-friendly produced goods (Arora and Cangopadhyay, 1995) and to enjoy higher market valuations (Konar and Cohen, 2001). Financial performance indicators do not allow identifying via which channel performance effects emerge, i.e. via a "reputation-demand channel" or via an efficiency-enhancing channel. Since complementarities of green innovations and organisational change in the production process are of central interest to the present study, TFP is the preferred performance indicator

[5] In this study, the two economic activities are adopting or not adopting green and organisational innovations.

[6] Another approach that is pursued at times is one that Athey and Stern (1998) label the "random practise model", which is roughly speaking a mix of the adoption and productivity approach. It is used if the adoption variables are binary and potentially correlated and if no data on an outcome variable is available. Miravete and Pernías (2006) use binary dummy variables and estimate multi-equation discrete choice models with error components for each strategy's unobservable returns and control for unobserved correlation among the different adoption equations. Similar approaches are used in Kretschmer et al. (2012), Arora et al. (2010), and Gentzkow (2007).

3.1 Productivity Effects from Green and Organisational Technology Adoption

If a performance indicator (TFP in our case) is smooth and a twice differentiable function of the arguments x and x' that are smooth as well, a positive mixed partial derivative of the objective function with respect to the two variables ($\partial^2 f/\partial x \partial x'$) indicates a complementarity of the objective function's two arguments, since increasing the value of one activity increases the returns of doing more of the other. The concept of supermodularity is directly related to complementarity (Milgrom and Roberts, 1990). As long as the set of combinations of choice variables is defined over a sublattice, the concept of supermodularity also works for binary arguments (Milgrom and Roberts, 1990, 1995). The conditions for supermodularity and complementarity read as follows[7]:

$$
\begin{aligned}
f(x) + f(x') &\leq f(x \vee x') + f(x \wedge x'), \text{or:} \quad (1)\\
f(1,0) + f(0,1) &\leq f(1,1) + f(0,0), \quad (2)
\end{aligned}
$$

where $x \vee x'$ denotes the largest element under the order (or in the sublattice), which is in our case the joint adoption of green and organisational innovations (also denoted as $(1,1)$). Likewise, $x \wedge x'$ denotes the smallest element under the order, i.e. the case where neither of the two innovations is adopted (0,0). The sublattice's elements $(1,0)$ and $(0,1)$ denote cases where only green or only organisational innovations are adopted, respectively. If both green innovation and organisational change contribute to better firm performance, we would expect productivity to increase if both forms of innovations had been adopted compared to the case in which either green or organisational innovations would have been independently introduced. Although complementarity, as defined by inequality 2, is perfectly symmetric in the two strategies, we are particularly interested in whether the adoption of organisational change improves the marginal returns of introducing green technologies, i.e. whether $f(1,1) > f(1,0)$. Particularly, when green innovations alone would decrease firms' productivity, we are interested in seeing whether additionally introduced organisational change may at least (partially) offset green technology's negative productivity effects.[8]

3.2 Estimating Complementarity

In what follows we discuss how to obtain consistent estimates for inequality 2. Since the technology choices are defined over the sublattice $\{(0,0),(1,0),(0,1),(1,1)\}$, with $f : \{0,1\}^2 \rightarrow \mathbb{R}^+$, we can test whether organisational change complements the use of green technology and how it affects TFP by analysing whether f is supermodular in its arguments. To do so, we estimate the following equation:

$$
tfp_i = \beta_0 + \beta_{10}(\text{green only}_i) + \beta_{01}(\text{orga only}_i) + \beta_{11}(\text{both}_i) + \boldsymbol{\beta}_c' \boldsymbol{C} + \varepsilon_i \quad (3)
$$

[7]See Milgrom and Roberts (1990) for a proof and further details as well as Holmstrom and Milgrom (1994).

[8]The case of asymmetric complementarity is discussed in section 3.3.

where tfp_i is our *estimate* of firm i's TFP. The term $neither_i$ is linearly dependent on the other three adoption combinations ($green\ only_i$, $orga\ only_i$, $both_i$) and thus offers no further information[9]. The important point is that the innovation adoption variables account for firms' strategic choices to introduce or not introduce innovation and are therefore unlikely to be completely exogenous. Moreover, the realisation of returns to innovation adoption (positive or negative) takes some time so that a time lag between innovation choices and TFP is needed to identify a plausible time structure and eventually a causal link. In our case, the innovation adoption choices are reported for a time period of three years and the dependent variable, TFP, is reported for the last year of this period. Endogeneity and the presence of correlation rather than causality cannot entirely be ruled out in this basic model. To address these concerns as much as possible, instrumental variables (IV) methods are applied and discussed at length in the following sections. Besides the innovation adoption choices, any further observable factors that potentially explain differences in TFP are included in the vector $\boldsymbol{C}$.

TFP is the residual of unexplained differences in output from a production process using several observed inputs. What complicates obtaining TFP estimates as residuals from a regression of output on inputs is that inputs cannot be considered completely exogenous (Marshak and Andrews, 1944) and that ordinary least squares (OLS) estimates of the input coefficients are likely to be biased. Different methods to obtain unbiased TFP estimates have been proposed, most importantly the Olley and Pakes (1996) method, the system GMM estimator of Blundell and Bond (2000), the GMM procedure developed by Wooldridge (2009), as well as the approach of Levinsohn and Petrin (2003) that builds upon the Olley and Pakes (1996) method. The Olley and Pakes (1996) and the Levinsohn and Petrin (2003) method have in common that they use observable proxy variables for unobservable productivity shocks (i.e. innovations). The former uses firms' investment decisions while the latter uses variable inputs (intermediates) as a proxy. That is, the Olley and Pakes (1996) method sets up a two-stage estimation procedure where estimates of the variable input's coefficients are obtained in a first stage where output is regressed on variable input and the proxy for unobserved productivity (a function of investments and capital). As this stage does not allow to identify an unbiased estimate of the capital coefficient, a second stage is needed in which the residual of unexplained output is regressed on capital and a lagged estimate of unobserved productivity. This approach, and especially the Levinsohn and Petrin (2003) method, have been subject to a discussion on identification problems Ackerberg et al. (2006). The critique by Ackerberg et al. (2006) refers to a possible collinearity of the labor inputs to the proxy of unknown productivity shock. They therefore propose a refinement where the elasticity of the labor input is also identified in the second stage. However, Ackerberg et al. (2006) argue that the Olley and Pakes (1996) method is valid if and only if the labour input decision is taken before production and the productivity change evolves *after* labour inputs decisions have been made but *before* the production takes place. In other words, labor is not a perfectly variable input and its input

[9] In other words, $f(0, 0|C) = 0$. Note that it is not necessary to restrict the effect of $neither_i$ to zero. Instead, one can omit the constant and include it. However, the interpretation of the results is more straightforward when comparing it to the case where nothing is adopted ($neither_i$).

choice depends on a past shock to productivity and not to the shock in the same period. Ackerberg et al. (2006, p.15) argue that "[...] this DGP [data generating process] seems like something that could be motivated in some empirical situations". The concern that labour is not a perfectly variable input is especially valid in European countries where there are labour market rigidities and a lot of legislations.[10]

Given these considerations and for reasons of comparability to previous productivity studies, we rely on the Olley and Pakes (1996) method to obtain estimates of input elasticities. Thus, the level of TFP of firm i is calculated as follows:

$$tfp_i \quad = \quad ln(y_i) - ln(k_i) \cdot \hat{\beta}_k - ln(l_i) \cdot \hat{\beta}_l - ln(m_i) \cdot \hat{\beta}_m, \tag{4}$$

where $\hat{\beta}_j, j \in \{k, l, m\}$ denote estimates of capital, labour, and material input elasticities in the Cobb-Douglas production function for output y_i measured by total sales. Appendix A describes the construction of TFP estimates with our data in more detail. The estimated TFP is, as previously discussed, based on the assumption that labour is a non-perfectly variable input.

3.3 Tests for Complementarity

Since TFP information is smooth and the estimates of innovation adoption combinations represent their partial effect on the objective function (TFP), supermodularity (and thus complementarity) can directly be tested for by rejecting a one-sided t-test against the null that $\beta_{10} + \beta_{01} - \beta_{11} \geq 0$. The asymmetric test for joint adoption improving green adoption only requires $\beta_{10} - \beta_{11} \geq 0$. For green innovations, this study considers two cases independently of each other. The first one is the case of CO_2 mitigation technologies because of their high policy relevance related to the argument that the adoption of such technologies (especially when policy-driven) may be associated with adverse performance effects. The second case is that of material and resource-saving innovations because of their importance in light of resource scarcity accompanied by high input prices.

Note that this study is interested not in complementarity between these two types of green technologies but in the complementarity of a green technology (be it CO_2 mitigation or material and resource efficiency innovations) and organisational change. Each of the green innovation activities and organisational change therefore form a two-dimensional lattice so that the single above mentioned inequality condition needs to be tested for each case separately. From a theoretical point of view there is no reason to expect complementarity between CO_2 mitigation innovations and resource-saving innovations.

4 Data and Variables

The data used in the analysis is mainly based on the Mannheim Innovation Panel (MIP), which is the German contribution to the European Community Innovation Survey

[10] Only recently, Griffith and Macartney (2014) showed that labour market regulations (for instance, employment protection legislations) increase firms' adjustment costs and thus likely trigger underinvestment in several activities, such as innovation activities.

(CIS).[11] German data provides a good testing ground for our research question because Germany is among the most active countries in terms of environmental technology. The MIP survey is conducted annually, allowing us to use longitudinal data for the estimation of total factor productivity. The surveyed firms are a representative sample drawn from the population of German manufacturing and service firms. For the purpose of this study, however, we focus our attention on the manufacturing sector where CO_2 emissions are more relevant than in service sectors.

4.1 TFP, Green Technologies and Organisational Innovations

The panel data covering the period 2000 until the end of 2008 is used for the estimation of firm-level TFP (see Appendix A for the details). Information on green innovation is, however, not available in the full panel. The 2009 wave of the MIP that refers to the years 2006-2008 is the first and so far only wave that provides detailed information on green innovation adoption and organisational change in addition to more general firm and innovation-related information.

Information on (completed) innovation adoption is reported as one indicator for the entire period 2006-2008. Thus, identification comes from relating the 2008 value of TFP to firms' adoption decisions in the two preceding years. This time lag is introduced as the effects from adopted innovations (including organisational change) need time to materialise.

Information on green innovation is reported in a four-point Likert scale ranging from no innovation with environmental benefits to innovation with high environmental benefits. This information is based on firms' responses to the question: "During the three years 2006 to 2008, did your enterprise introduce innovations with any of the following environmental benefits at the level of your enterprise?" Nine environmental benefits were mentioned including reduced material use per unit of output, reduced energy use per unit of output, and reduced CO_2 emissions. The remaining six environmental benefits concern air, water, soil and noise pollution as well as the replacement of hazardous substances and improved recycling possibilities. As achieving these six benefits at the firm level can be done using end-of-pipe abatement technologies, we exclude them from our study. We also exclude energy-saving technologies as these are too broad, e.g. including the installation of electricity-saving light bulbs or electricity-saving office equipment installed for the first time in a particular firm.

Green technologies do not necessarily reflect inventions by the firms due to own R&D but rather the adoption of a technology that is new to the firm, irrespective of whether it is developed in-house or is acquired from elsewhere. For the case of material-saving innovations, the dummy (x^{sus}) takes the value of one if at least innovations with at least some impact on material (or resource) efficiency was introduced. The survey includes for the case of CO_2 mitigation innovations, also minor innovations such as the acquisition of a hybrid company car. To exclude cases of such minor green improvements, we set

[11] The survey is conducted annually by the Centre for European Economic Research (ZEW), infas Institut fuer Sozialforschung and ISI Fraunhofer Institute on behalf of the German Federal Ministry of Education and Research. A detailed description of the survey data and the sampling method can be found in the background reports available at ZEW.

the dummy for CO_2-reducing technologies (x^{co2}) to one only if firms reported at least a medium impact of CO_2 mitigation.

The second key component of the innovation survey data is information on organisational changes adopted within the firms. Firms were asked to indicate whether they had introduced a) new business practices for organising procedures and/or b) new methods of organising work responsibilities and decision making during the reference period. The dummy for organisational change (x^{or}) takes the value of one if at least one of these options was introduced and zero otherwise. It is thus a rather broad indicator of organisational change that can occur in very different areas of the firm. The dummy is therefore seen to reflect firms' openness to organisational changes in general rather than to relate to specific changes in a certain area (for instance, waste management or logistics).

4.2 Controls

Sales data is used as output information for the construction of TFP. Sales data is highly dependent on output price so that TFP is likely to account for firm-level differences in output prices in addition to differences in efficiency of production. We account for this problem by controlling for likely differences in prices due to market concentration and due to technological leadership. For the former, we use information reported in the MIP survey of whether the firm perceives competition to be hard due to a) entry of new firms and b) high competitive pressure from abroad. The advantage of this information compared to the frequently used Herfindahl-Hirschman index is that it allows for firm-level variation instead of variation only at the sector level. For high markups due to technological leadership, we control for firms' (logged) patent stock per employee in 2007. To this end, we link the innovation survey data to patent information from the European Patent Office (EPO). The stock of patents as a measure of technological knowledge is constructed using the perpetual inventory method where a yearly depreciation rate of the knowledge stock of 15% is assumed.[12]

An important determinant of productivity is management quality (Bloom and Van Reenen, 2007). Since direct measures of such qualities are difficult to obtain, we derive several alternative variables that capture at least some of the differences in management practices across firms. First, good managers are expected to invest in human capital by upgrading the skills and capabilities of their employees. Thus, we control for firms' logged training and education expenditures per employee. Information lagged by one year is used to reduce endogeneity concerns.[13] Variation in management practices may also be explained by firm age. Younger firms are more likely to be managed by the founder or owner whereas older ones are more likely to be managed by contracted managers or family members of the founder. Firm age may also account for differences in capital vintage.

[12] Typically, scholars have measured the technology knowledge stock of firms by the discounted sum of prior R&D investments and/or patents (see e.g. Bloom and Van Reenen (2002)). We use a 15% depreciation rate as suggested by Griliches and Mairesse (1984).

[13] For a few firms, sales and training information in 2007 were missing. To avoid possible sample selection due to non-response, we used 2008 information in these cases instead. The results are not sensitive to this adjustment.

Older firms are likely to replace fully depreciated capital goods for new ones. As the age relationship is therefore unlikely to be linear, we also include a squared term of firm age. Management quality may differ according to firm size which is, in addition, a control for scale economies in productivity (see Appendix A). Size is measured with the logarithm of the equivalent number of full-time employees. Firms that are part of an enterprise group may have access to advanced production technologies and management practices. A group-dummy variable is included to capture these effects.

Another control variable is firms' (logged) ratio of exports to total sales. This control addresses the recent literature's findings that export and productivity are positively related. Firms can enjoy higher returns from investing in productivity-enhancing technologies when operating in larger (export) markets (e.g. Yan Aw et al., 2008; Lileeva and Trefler, 2010). As causality can also run from higher productivity to the amount of exports, we use the one-year lagged value. To address the market size effect of exports, we include a dummy that takes the value of one if firms export to worldwide destinations and zero otherwise. Finally, we include 17 sector dummies based on the aggregated two-digit NACE (Rev. 2.0) level for the manufacturing sectors to account for productivity dispersion acrosss sectors; see e.g. Syverson (2004).

4.3 Descriptive Statistics

Table 1 provides descriptive statistics for the pairwise adoption of the potentially complementary innovation variables. This table clearly shows that jointly adopting green technologies (either a CO_2 abatement or a sustainable technology) with organisational change appears more frequently in our sample than the case that green technology is adopted only. In other words, the adoption decisions do not seem to be randomly allocated in the sample, which indicates that there is an underlying correlation among the strategies. This correlation becomes more obvious if we look at the expected frequencies that would have been observed if the two adoption decisions were independent (reported in parentheses). In that case we would have observed only 9% of the firms having jointly adopted green and organisational change instead of 11.98%. Joint adoption is more frequent in case of sustainable technology as compared to the case of CO_2 abatement technology, indicating a stronger correlation of both activities for this case.

Table 1: Relative Frequencies for Adoption Decision in Percent

Case: CO_2 abatement technology				**Case: sustainable technology**			
	x^{or}				x^{or}		
x^{co2}	**0**	**1**	**Total**	x^{sus}	**0**	**1**	**Total**
0	45.30 (42.32)	35.89 (38.87)	81.19	**0**	34.99 (27.83)	18.39 (25.55)	53.38
1	6.83 (9.81)	11.98 (9.00)	18.81	**1**	17.14 (24.30)	29.48 (22.32)	46.62
Total	52.13	47.87	100	**Total**	52.13	47.87	100

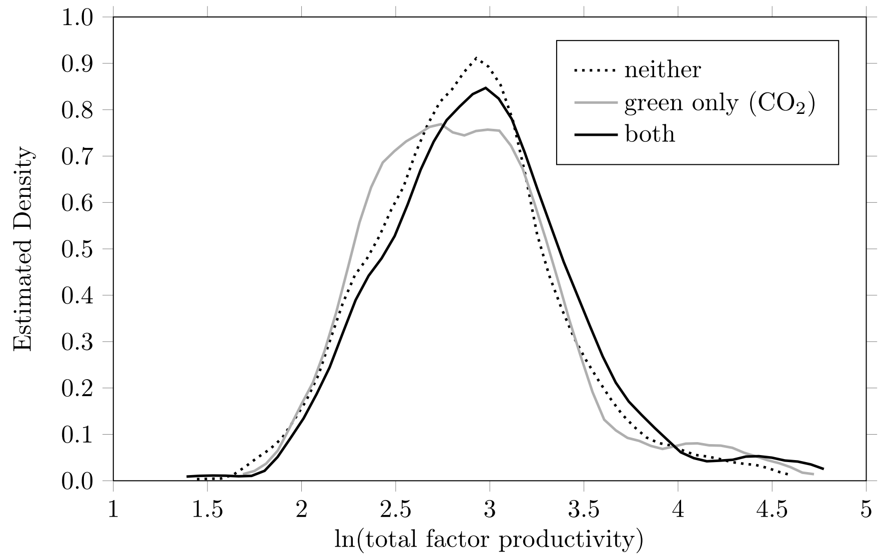
Expected frequencies appear in parentheses.

Pearson $chi^2(1) = 38.80$ Pr = 0.00 — Pearson $chi^2(1) = 137.89$ Pr = 0.00

Kendall's tau-b = 0.15, P > z = 0.00 — Kendall's tau-b = 0.29 , P > z = 0.00

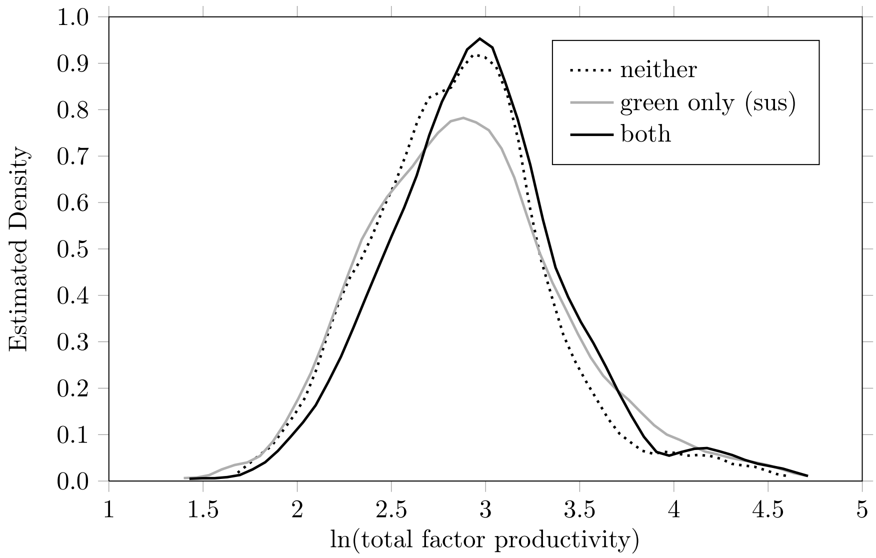
In light of the effects of technology adoption on TFP, we would expect that firms that introduced green innovation jointly with organisational changes can make more efficient, i.e. more productive use of green technology than innovators that did not introduce organisational changes. The data provides descriptive support of this hypothesis as shown in Figure 1 and Figure 2.

Figure 1: Kernel Density Estimates for Total Factor Productivity
Case: CO_2 abatement technology



These figures plot Kernel density estimates for firm-level (logged) total factor productivity by innovation adoption choices. Figure 1 shows the case of CO_2 abatement technology. The probability density mass for firms that only introduced green (CO_2 abatement technology) innovation without organisational changes is located left of the respective plot for firms that introduced both jointly for almost the whole range of the observed productivity. In other words, the probability of observing adopters of green technology only at lower productivity levels is higher the probability of observing firms that jointly adopted both innovation types. Compared to the probability of observing adopters of green technology only at higher productivity levels is lower compared to the probability of observing firms adopted both innovations jointly. Figure 2 below presents the respective plots for the case of sustainable innovation, i.e. material-saving innovations.

Figure 2: Kernel Density Estimates for Total Factor Productivity
Case: Sustainable Innovation



Finally, the summary statistics for all variables used in the econometric approach are presented in Table 2. After eliminating observations from the original data set due to item non-response and outlier correction, the final sample contains 1,669 firm-level observations. The average firm in our sample is relatively small. The mean firm has 276.8 employees (median is 54). As seen in Table 2, only 18.8% of the firms in our sample introduced a CO_2 abatement technology (x^{co2}) as compared to 47.9% that implemented a material-saving innovation (x^{sus}). The latter type seems more relevant to the broader range of firms, especially in our sample of mainly small and medium-sized firms. Organisational changes were introduced by 46.5% of the firms during the survey period.

Table 2: Descriptive Statistics (1669 Observations)

Variables	**Timing**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent variables					
x^{co2}	[2006-2008]	0.188	0.391	0	1
x^{sus}	[2006-2008]	0.466	0.499	0	1
x^{or}	[2006-2008]	0.479	0.500	0	1
tfp (in logs)	[2008]	2.900	0.479	1.538	4.627
Covariates					
regulation driven green innovation*	[2006-2008]	0.280	0.130	0.053	0.750
ln(number of employees)	[2008]	4.029	1.554	0	>10.000
ln(capital intensity)	[2008]	-3.746	1.231	-10.229	>0.600
ln(material intensity)	[2008]	4.109	1.035	0.193	8.471
process innovation introduced	[2006-2008]	0.461	0.499	0	1
ln(age)	[2008]	3.158	0.914	0	6.190
ln(age)^2	[2008]	10.809	5.953	0	38.320
ln(patent stock per employee)	[2007]	0.006	0.019	0	0.298
Continuous R&D activities	[2006-2008]	0.163	0.369	0	1
Occasional R&D activities	[2006-2008]	0.365	0.482	0	1
ln(education expend. per employee)	[2007]	0.289	0.323	0	2.398
location in East Germany	[2006-2008]	0.294	0.456	0	1
firm is part of a group	[2006-2008]	0.348	0.477	0	1
worldwide market sales	[2006-2008]	0.510	0.500	0	1
ln(ratio of exports to total sales)	[2007]	0.192	0.201	0	0.693
perceived high competition from abroad	[2006-2008]	0.515	0.500	0	1
perceived high competition from entrants	[2006-2008]	0.348	0.477	0	1

* This variable represents means by sectors.

5 Econometric Results

In order to assess complementarity, we test to which extent the joint adoption of green technology and organisational change translates into performance (i.e. productivity). To do so, we regress[14] adoption decisions defined over a lattice on total factor productivity (see Table 3). The results show that adopting green innovation without adopting organisational innovations is associated with a significant negative impact on TFP. A firm that introduced CO_2-reducing (material-saving) technologies without organisational change is observed to have a 5.9% (4.6%) lower productivity compared to the control group, i.e. firms that neither introduced green innovations nor organisational change. The coefficients of green only and joint adoption differ significantly from each other in both model variants.[15] We can reject a one-sided t-test against the null that (green only) + (orga only) − (both) ≥ 0 in both models, supporting complementarity. Note that organisational change alone has no significant impact on productivity. However, introducing it jointly with green innovations is associated with an offset of green technology's negative productivity effects. In this sense, complementarity seems to be asymmetric, meaning that organisational changes enhance

[14] As the Breusch-Pagan test strongly rejects the Null of constant variance of the (unobserved) error term, conditional on all covariances, we use heteroscedasticity robust standard errors in what follows.

[15] A version of Model 1a estimated without a constant so that all four mutually exclusive innovation adoption combinations are included leads to exactly the same results for the complementarity test.

the efficiency of green technology but not the other way round. An asymmetric test for complementarity would only require a rejection of the null that (green only) $\geq$ (both). This null is rejected in the case for CO_2 abatement technology as well as in the case of sustainable technology.

Most of the controls have the expected signs. The (logged) ratio of export to total sales is strongly significant and is one of the most important covariates of productivity. Firms that export to worldwide destinations have a significant 3.5% higher productivity than firms that either export to European destinations or do not export at all. Firms belonging to a group also have significantly higher productivity than independent ventures. Possible explanations are that these firms have access to more sophisticated production technologies or are managed in a different, i.e. more efficient, way. Moreover, firms that invest higher amounts in the eduction and training of their employees also produce more efficiently, which comes at no surprise. Neither firms' patent stock (per employee) nor the two dummies for competition are statistically different from zero.

Table 3: Results from the Productivity Approach

Dependent Variable: TFP	**Model 1a**		**Model 1b**	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
Innovation Adoption Combinations				
green only (CO_2 abatement technology)	-0.059**	(0.029)	-	
orga only	-0.024	(0.018)	-	
both	0.027	(0.028)	-	
green only (sustainable technology)	-		-0.046**	(0.022)
orga only	-		-0.038*	(0.022)
both	-		-0.008	(0.022)
Controls				
ln(number of employees)	0.026***	(0.007)	0.027***	(0.008)
ln(age)	0.047	(0.043)	0.047	(0.043)
ln(age)^2	-0.005	(0.007)	-0.006	(0.007)
ln(patent stock per employee)	0.333	(0.660)	0.327	(0.664)
ln(education expenditures per employee)	0.191***	(0.028)	0.193***	(0.029)
location in East Germany	-0.136***	(0.019)	-0.136***	(0.019)
firm is part of a group	0.080***	(0.020)	0.082***	(0.020)
worldwide market sales	0.035*	(0.019)	0.036*	(0.019)
ln(ratio of exports to total sales)	0.147**	(0.059)	0.141**	(0.060)
perceived high competition from abroad	-0.025	(0.017)	-0.023	(0.017)
perceived high competition from entrants	-0.023	(0.017)	-0.022	(0.017)
sector dummies†	yes		yes	
constant	2.417***	(0.081)	2.421***	(0.081)
Observations [R^2]	1669	[0.590]	1669	[0.589]
Test for Complementarity:	*Test Stat.*	*p-value*	*Test Stat.*	*p-value*
H_0 (full test):				
(green only) + (orga only) - (both) ≥ 0	7.741	0.003	6.025	0.007
H_0 (asymmetric test):				
(green only) $\geq$ (both)	5.785	0.008	2.846	0.046

† The model includes 14 jointly significant sector dummies based on NACE 2-digit level.
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

6 Extensions and Robustness Checks

In the following, extensions and robustness checks are carried out to further explore the (asymmetric) complementarity between green and organisational innovation adoption and to test for the potential endogeneity of the choice variables.

6.1 Direction of Complementarity: The Effect of Organisational Change on Adoption of Green Technologies

To assess asymmetric complementarity more directly, we split the sample in green innovators and non-adopters of green innovations. In this split setup, by including the dummy for organisational change (x^{or}) in the regression on TFP and comparing its effects for green innovators versus non-green innovators, we can focus on the one side of complementarity that interests us most, i.e. whether organisational innovations may help to improve the productivity effect of green innovations (or reduce their negative impact). The results for the case of CO_2 reducing innovations appear in Table 4.

Table 4: Case of CO_2 Abatement Innovation only

Dependent Variable: TFP	$x^{gr}=1$		$x^{gr}=0$	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
Organisational Innovation Adoption				
x^{or}	0.080**	(0.035)	-0.021	(0.018)
Controls				
ln(number of employees)	0.035**	(0.014)	0.023***	(0.009)
ln(age)	0.109	(0.100)	0.033	(0.049)
ln(age)^2	-0.008	(0.016)	-0.005	(0.008)
ln(patent stock per employee)	-0.943	(1.361)	0.407	(0.716)
ln(education expenditures per employee)	0.233***	(0.063)	0.179***	(0.032)
location in East Germany	-0.081	(0.053)	-0.149***	(0.020)
firm is part of a group	0.029	(0.039)	0.097***	(0.022)
world wide sales markets	0.039	(0.045)	0.029	(0.022)
ln(ratio of exports to total sales)	0.159	(0.169)	0.147**	(0.060)
perceived high competition from abroad	-0.019	(0.041)	-0.027	(0.018)
perceived high competition from entrants	-0.023	(0.041)	-0.024	(0.018)
sector dummies†	yes		yes	
constant	2.174***	(0.189)	2.458***	(0.091)
Observations [R^2]	314	[0.626]	1355	[0.590]

† The model includes 14 jointly significant sector dummies based on NACE 2-digit level.
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

For the group of CO_2-reducing innovators, having introduced organisational change is associated with significantly higher productivity. Adopters of green technologies enjoy an 8% higher productivity if new forms of business practices for organisational procedures or new forms of organising work responsibilities or decision making are introduced. Simulateneously, we do not observe any significant effect of organisational change for the sample of non-adopters of CO_2-reducing innovations. The sample split model therefore confirms the findings from the productivity approach (Table 3). Table 5 below presents the results for the case of sustainable, i.e. material-saving, innovations.

Table 5: Case of Sustainable Innovation only

Dependent Variable: TFP	$x^{gr}=1$		$x^{gr}=0$	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
Organisational Innovation Adoption				
x^{or}	0.034	(0.023)	-0.041*	(0.022)
Controls				
ln(number of employees)	0.031***	(0.009)	0.021*	(0.012)
ln(age)	0.086	(0.058)	-0.003	(0.067)
ln(age)^2	-0.012	(0.009)	0.001	(0.011)
ln(patent stock per employee)	0.487	(0.520)	0.141	(0.971)
ln(education expenditures per employee)	0.176***	(0.033)	0.223***	(0.048)
location in East Germany	-0.130***	(0.029)	-0.149***	(0.026)
firm is part of a group	0.076***	(0.026)	0.083***	(0.031)
worldwide market sales	0.029	(0.027)	0.046*	(0.027)
ln(ratio of exports to total sales)	0.184**	(0.078)	0.107	(0.091)
perceived high competition from abroad	-0.022	(0.024)	-0.024	(0.024)
perceived high competition from entrants	-0.011	(0.024)	-0.040	(0.024)
sector dummies†	yes		yes	
constant	2.273***	(0.114)	2.552***	(0.121)
Observations [R^2]	778	[0.657]	892	[0.534]

† The model includes 14 jointly significant sector dummies based on NACE 2-digit level.
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

Although these results are similar to the findings presented in Table 4 with respect to the signs of the coefficient estimates, they differ in their significance. The most important difference is that organisational innovation adoption does not generate a significant effect for the sample of sustainable innovations. This robustness check confirms the results found in Table 3 that although there is also asymmetric complementarity between sustainable innovation and organisational change, it holds less strongly than in the case of CO_2-reducing innovations.

6.2 Potential Endogeneity of Innovation Adoption Choices

The error term of equation 3 is still likely to account for productivity differences across firms which remain unexplained after all available covariates determining productivity have been controlled for. In particular, as no direct control for management quality is available, the core variables of interest—green and organisational innovation—may suffer from omitted variable bias. That is, clever managers of highly productive firms may be aware of complementary effects. Our complementarity may therefore be picking up management quality rather than any supermodularity.

To account for potential endogeneity in green and organisational innovation adoption, we construct several instrumental variables (for $green\ only_i$, $orga\ only_i$, $both_i$) to estimate two-stage least squares (2SLS) regressions for the case of CO_2 abatement technology.

Finding proper instruments is in general very challenging, and particularly in this study as all variables in the CIS survey are self-reported and many are likely to be endogenous themselves, influenced by management quality. A first instrumental variable exercise is to construct the means of the variables *green only*, *orga only*, and *both* by sector and firm size classes.[16] The stringency of environmental regulation may differ largely between sectors as may their level of pollutant emissions. In addition, larger firms are more likely to be affected by regulatory constraints or may emit more pollutants. The sectors used for constructing the means are the same as for the TFP estimates (see Appendix A) and the same as controlled for by the dummies in the regressions. After sector affiliation and firm size have been controlled for in the structural equation, means by sector and size class are expected only to affect productivity via their impact on the endogenous variables, so that they can be correctly excluded from the structural equation. A regression of TFP on these instruments supports this view as the three means-variables by sector and size class have no significant partial effect on TFP once all other covariates have been controlled for. However, it is not unlikely that certain sectors are more productive and are more likely to adopt green innovations at the same time. If this relationship would not vary between firms of different size in these sectors, exogeneity of the instruments is not satisfied and the exclusion restriction may not hold. To cope with this concern, we use the Hansen J-test statistic to confirm for the exogeneity of the excluded instruments.

Beyond the sector and size class means, more instruments for the innovation strategies are needed to directly test exogeneity using overidentification restrictions. In addition, more instruments increase the first stages' R^2 and thus the precisions of the instrumental variable regressions. A further instrument comes directly from the MIP and is derived from the survey question responses on the objectives for introducing innovations. Although any objective is likely to be correlated with productivity, and thus also with the error term of the regression of productivity on all covariates, we find that this was not the case for the objective related to increasing market share. This variable turned out to have no partial effect on productivity once all covariates have been controlled for. Moreover, this particular objective is highly relevant to innovating firms. It may matter particularly in the case of organisational change since an increase in market share via firm growth may require new forms of work organisation to fit to new structures.

The results of the 2SLS regressions for the case of CO_2 abatement technology are reported in Table 6.[17]

[16] We define seven size classes by defining firms as very small ($\leq$10 employees), rather small ($>$10, $\leq$25 employees), small ($>$25, $\leq$50 employees), medium ($>$25, $\leq$50 employees), medium-large ($>$50, $\leq$100 employees), large ($>$100, $\leq$250 employees), and very large ($>$250 employees). Note that this definition is simply based on the fact that our representative sample mainly includes small and very small firms (see section 4).

[17] As already seen in the OLS case, we rejected the Null of constant errors so that a heteroscedasticity robust estimation procedure is carried out.

Table 6: 2SLS Regression Results and Test for Endogeneity

Dependent Variable: TFP	**2SLS**‡		**Endo. Test (OLS)**	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
Innovation Adoption Combinations				
green only (CO_2 abatement technology)	-0.284*	(0.166)	-0.284*	(0.159)
orga only	-0.074	(0.070)	-0.074	(0.069)
both	0.229	(0.142)	0.229	(0.141)
Controls				
ln(number of employees)	0.020**	(0.010)	0.020**	(0.010)
ln(age)	0.043	(0.045)	0.043	(0.044)
ln(age)^2	-0.004	(0.007)	-0.004	(0.007)
ln(patent stock per employee)	0.365	(0.668)	0.365	(0.663)
ln(education expenditures per employee)	0.184***	(0.033)	0.184***	(0.033)
location in East Germany	-0.139***	(0.020)	-0.139***	(0.019)
firm is part of a group	0.078***	(0.021)	0.078***	(0.020)
worldwide market sales	0.037*	(0.020)	0.037*	(0.019)
ln(ratio of exports to total sales)	0.150**	(0.060)	0.150**	(0.060)
perceived high competition from abroad	-0.031*	(0.018)	-0.031*	(0.017)
perceived high competition from entrants	-0.031*	(0.018)	-0.031*	(0.017)
sector dummies†	yes		yes	
residuals green only			0.234	(0.163)
residuals orga only			0.052	(0.070)
residuals both			-0.209	(0.137)
constant	2.450***	(0.084)	2.450***	(0.082)
Observations [R^2]	1669	[0.551]	1669	[0.591]
Tests for Complementarity and Exogeneity of Instruments:	*Test Stat.*	*p-value*	*Test Stat.*	*p-value*
H_0 (full test):				
(green only) + (orga only) - (both) ≥ 0	6.620	0.005	6.861	0.004
H_0 (asymmetric test):				
(green only) $\geq$ (both)	5.925	0.007	6.296	0.006
Hansen J-test	0.050	0.823	-	-

† The model includes 14 jointly significant sector dummies based on NACE 2-digit level.
‡ The 2SLS model uses means by sector and size class
as well the goal to increase market share as instruments (four instruments).
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

The Hansen J-test statistic is far away from the rejected area, providing statistical support for the exogeneity of our instruments. Moreover, as a rule of thumb, Staiger and Stock (1997) argue that F-statistics for the joint significance of the excluded instruments in the first stage, that are larger than ten suggest that the instruments are not weak. This requirement is fulfilled in any first stage regressions, see Table 9 in Appendix B. Provided the instruments are exogenous and that the instruments are non-weak, we can test for endogeneity using a regression-based test. That is, we regress all potential endogenous variables on the set of instruments and all covariates and predict the residuals for each of these three regressions. As these residuals are the source of endogeneity bias in the second stage, they should have a significant partial effect on TFP if our three variables of interest were indeed endogenous. However, as indicated in Table 6, this is not the case.

Our central results of complementarity are confirmed in the instrumental variables regression. The test for complementarity is highly significant. The same holds true for the asymmetric test. That is, we clearly reject the null that (green only) $\geq$ (both). Directly comparing the OLS results (Table 3) with the 2SLS results points to much higher estimates of the variables of interest in the 2SLS case associated with stronger complementary.[18]

Table 7 below provides the results for the case of sustainable, i.e. material-saving innovations. The instruments used are constructed in the same fashion as used in the exercise for CO_2 abatement technology. The Hansen J-test provides support for the exogeneity of the instruments. Moreover, the first stage F-statistics of the excluded instruments are all above the critical value, see Table 10 in Appendix B.

[18]Although the instruments are not weak, they are also not very strong so that the differences between OLS and 2SLS may be—at least in part—caused by an instrumental variable bias that tends to be larger the smaller the sample is. Support for this view comes from the first stage F-statistics for the excluded instruments. The respective values in the case of *green only* and *both* are much smaller than the those for *orga only* but are nevertheless in acceptable territory (larger than ten). This may explain the higher deviation of these two variables between the 2SLS and the OLS regressions than in the case of the *orga only* estimates.

Table 7: 2SLS Regression Results and Test for Endogeneity

Dependent Variable: TFP	**2SLS**‡		**Endo. Test (OLS)**	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
Innovation Adoption Combinations				
green only (sustainable technology)	-0.144	(0.097)	-0.144	(0.094)
orga only	-0.161	(0.106)	-0.161	(0.103)
both	0.093	(0.071)	0.093	(0.070)
Controls				
ln(number of employees)	0.020**	(0.010)	0.020**	(0.009)
ln(age)	0.048	(0.044)	0.048	(0.043)
$\ln(\text{age})^2$	-0.005	(0.007)	-0.005	(0.007)
ln(patent stock per employee)	0.377	(0.700)	0.377	(0.675)
ln(education expenditures per employee)	0.175***	(0.034)	0.175***	(0.032)
location in East Germany	-0.141***	(0.019)	-0.141***	(0.019)
firm is part of a group	0.083***	(0.021)	0.083***	(0.020)
worldwide market sales	0.042**	(0.020)	0.042**	(0.020)
ln(ratio of exports to total sales)	0.114*	(0.064)	0.114*	(0.063)
perceived high competition from abroad	-0.026	(0.018)	-0.026	(0.017)
perceived high competition from entrants	-0.027	(0.017)	-0.027	(0.017)
sector dummies†	yes		yes	
residuals green only			0.100	(0.097)
residuals orga only			0.127	(0.106)
residuals both			-0.105	(0.071)
constant	2.458***	(0.085)	2.458***	(0.083)
Observations [R^2]	1669	[0.559]	1669	[0.591]
Tests for Complementarity and Exogeneity of Instruments:	*Test Stat.*	*p-value*	*Test Stat.*	*p-value*
H_0 (full test):				
(green only) + (orga only) - (both) ≥ 0	6.161	0.007	6.515	0.005
H_0 (asymmetric test):				
(green only) $\geq$ (both)	4.454	0.017	4.788	0.014
Hansen J-test	0.068	0.794	-	-

† The model includes 14 jointly significant sector dummies based on NACE 2-digit level.
‡ The 2SLS model uses means by sector and size class
as well as the goal to increase market share as instruments (four instruments).
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

Although the coefficient estimates of interest are not statistically different from zero, at least not at conventional levels, the joint test for complementarily reveals a significant complementary relationship between organisational change and sustainable technology adoption. In this sense, the results from the basic model in Table 3 survive the IV regressions. Although the tests do not support the concern that organisational change adoption is endogeneous, we apply the same test for the the sample split models. However, as the split sample exercise runs on a very small sample sizes, the efficiency of the 2SLS estimator becomes an issue. Although we find similar signed coefficients, they are not significantly different from zero.

7 Concluding Remarks

The literature on within-firm organisational change and productivity suggests that firms can make more efficient use of certain technologies if complementary forms of organisational structure are adopted. Such complementarities may be of even greater importance for the case of the adaption of green technologies for which the returns to the firms are not necessarily positive or even hamper firms' competitiveness. Any complementarity effects may therefore be crucial for lifting the private returns from adopting green technologies in positive territory.

Using German firm-level data on environmental technology adoption, we examined the relationship between the adoption of green technologies (either CO_2-mitigation or sustainable technologies) and the introduction of organisational change. To assess complementarity between the two, we performed a productivity analysis in which we were particularly interested in whether the adoption of organisational change positively affects the returns to adopting green innovations. The results supports the hypothesis that organisational change is positively correlated with higher returns to the use of CO_2-reducing or material-saving technologies, which partially offsets negative effects on productivity. In other words, firms that adopt green technologies jointly with changes to their organisational structure can make better use of green technologies and hence offset productivity losses compared to those firms that only adopted green technology. These results suggest that regulators may want to better understand how firms implement pollution control technologies, in order to adjust policy designs that allow firms to exploit complementary effects that eventually boost the private incentives for adopting green innovations.

However, complementarities are not automatic. Although this study suggests that organisational structures matter, we cannot conclude that green technology adoption is, per-se, beneficial to a firm if it simply introduces the right organisational structure. There is still a lot of covered heterogeneity in the sample in how firms can exploit this source of complementarity. Similarly, we can also not simply conclude that policy makers can introduce stringent environmental regulations without side effects. Such a naive view would ignore the possibility that a firm could have adopted an even more productivity-increasing technology in the absence of regulatory pressure to adopt green technology. Gray and Shadbegian (1998) and Hottenrott and Rexhauser (2015), for instance, document such crowding out effects.

Despite all efforts, this study has some limitations. Most importantly, the result do not necessarily prove causality. The short time lag of innovation adoption and the measure of performance (TFP) does not allow to test long-term implications for firms and the environment. Thus, the results reflect the short-term effects that may largely differ from long-term consequences. In addition, our study lacks direct controls for management quality which is only one source of unobserved heterogeneity. Better managed firms may not only have higher levels of productivity, they may also be more environmentally responsible and more open to organisational change. With the limitations of the present study in mind, we encourage further research on the integration of environmental technologies. In the long run, the concerns raised above may be addressed through the continuous expansion of the

CIS data and the repetition of the survey questions that generated our main variables in this study.

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Appendix A: Applying the Olley and Pakes (1996) Approach

In what follows, we briefly describe the estimation procedure of Olley and Pakes (1996), where firm-level panel data on output and inputs as well as investments are needed.[19] Assume that firms produce total sales y using variable inputs labor (l) and intermediate (m) and fixed inputs of capital (k), where lowercase letters denote natural logarithms. Following Olley and Pakes (1996), we assume that firms know their productivity (ω_{it}) at the beginning of each period so that the production functions reads as:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it}, \tag{5}$$

where η_{it} accounts for any other random productivity shock or measurement errors of firm i in year t. Since ω_{it} is known by the firm, it can enjoy higher returns to productivity by using variable inputs more intensively or put otherwise: variable inputs are endogenously related to ω_{it} which is known to the firm but unobservable to the econometrician. Estimates of labour and intermediates are therefore expected to be biased. Remember that capital is fixed so that high productivity may motivate a firm to invest in new capital to enjoy higher returns to high productivity in the next period. In this sense, investments (inv_{it}) of firms are assumed to enter capital stock in the following period, so that $k_{it+1} = (1-\delta)k_{it} + inv_{it}$.[20] Investment is therefore a function of productivity and the current capital stock, i.e. $inv_{it} = inv(\omega_{it}, k_{it})$. If $inv > 0$, this function is strictly increasing in ω_{it}, see Pakes (1994), and invertible leading to $\omega_{it} = h_{it}(inv_{it}, k_{it})$.[21] So as to correct the bias in variable inputs, Olley and Pakes (1996) suggest estimating equation 5 using OLS, and including an approximation of the unknown function h_{it} using a polynomial expansion. We thus estimate the partially linear regression model:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \phi_{it}(inv_{it}, k_{it}) + \eta_{it}, \tag{6}$$

which identifies the (unbiased) coefficients of the variable inputs labour and intermediates (hereinafter $\hat{\beta}_l$ and $\hat{\beta}_m$, respectively). The reason is that the term $\phi_{it}(inv_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + h_{it}(inv_{it}, k_{it})$ includes productivity (approximated by the unknown function $h(.)$) and therefore eliminates the (likely upward) bias in variable inputs. Olley and Pakes

[19] We therefore use a time period of ten years of the full panel of the MIP including yearly observations for output (total sales), capital (total fixed assets), materials (material and energy expenditures), labour (number of full-time employees), and investments. We use sector-level deflators provided by the World Input Output Database (WIOD, www.wiod.org) and deflate capital and investment values to 2008 prices using the value-added deflator. Sales and intermediate inputs are deflated in the same fashion using the gross output and intermediate input deflators, respectively.

[20] We assume a depreciation rate δ to be 0.1. The estimation results are strongly robust to changes in δ.

[21] Therefore, all observations with $inv_{it} = 0$ are dropped from our sample, which is the case for almost 12% of the observations.

(1996) show that the results do not differ much between a third-order approximation to the unknown function $h(.)$ or one of the fourth order so that we use the third-order polynomial approximation. Because equation 6 does not identify the coefficient of capital separately from that of investments, a further step is needed that makes use of the estimates of $\hat{\beta}_l$, $\hat{\beta}_m$, and $\hat{\phi}_{it}$. To identify β_k, Olley and Pakes (1996) rearrange equation 6 and consider the expectation:

$$E[y_{it+1} - \hat{\beta}_l l_{it+1} - \hat{\beta}_m m_{it+1}] = \beta_0 + \beta_k k_{it+1} + E[\omega_{it+1}|\omega_{it}]. \tag{7}$$

Assuming that ω_{it+1} is a function of ω_{it} only, i.e. $g(\omega_{it})$, and that ξ_{it+1} is the innovation in ω_{it+1}, where $\xi_{it+1} = \omega_{it+1} - E[\omega_{it+1}|\omega_{it}]$ leads to the following equation:

$$y_{it+1} - \hat{\beta}_l l_{it+1} - \hat{\beta}_m m_{it+1} = \beta_k k_{it+1} + g(\hat{\phi}_{it} - \beta_k k_{it}) + \xi_{it+1} + \eta_{it+1}. \tag{8}$$

ξ_{it+1} is independent of k_{it+1}, simply because we assume that capital is fixed and only changes depending on ω_{it}. What is not independent of ξ_{it+1} are the variable inputs labour and materials. This is exactly why Olley and Pakes (1996) propose a two-step procedure to estimate these coefficients in the first step and exclude variable inputs in the second one. Again, the unknown function $g(.)$ is approximated using a third-order polynomial expansion. Recall that $\hat{\phi}_{it}$ was the estimate of the unknown productivity function $h(.)$ in t and $\beta_k k_{it}$ (which is therefore subtracted from $\hat{\phi}_{it}$ in $g(.)$). The function $g(.)$ is thus the source of the bias in k_{it+1} so that estimating equation 8 using non-linearly least squares (because β_k is included twice) eliminates the bias and identifies the coefficient of capital, $\hat{\beta}_k$.

We apply this procedure separately to 15 manufacturing sectors. A grid search routine revealed that several local optima existed. We therefore used start values for capital from an OLS regression of logged output on logged inputs for each sector. This routine worked well for all sector apart from "other non-metallic mineral products", where the OLS estimate of capital was about 0.1 whereas the grid search identified the estimate of -0.055 as global optimum, which is also the solution when using the OLS start values. Table 8 provides the estimates for the Olley and Pakes (1996) method. Unlike Olley and Pakes (1996) who focus on the telecommunication sector which is characterized by high capital requirements, this paper focusses on cross-sectoral firm-level data including also service firms. Furthermore, the typical firm's capital intensity is rather low. This may also be a result of the fact that information on fixed asset serves as the measure for capital. Thus, low fixed assets in our case does not necessarily imply a low amount of capital input because fixed assets represent the book value and not the real economic value of these capital goods. For these two reasons, the input elasticity estimates presented in Table 8 are not directly comparable to other studies focussing on larger firms in capital-intensive sectors. Javorcik (2004), for instance, also uses firm-level data from various sectors and reports in several cases non-significant or even significantly negative capital input coefficient estimates that are similar to ours.

Table 8: Estimated Elasticities of the Production Function by Sector

NACE	Description	Obs.	Capital		Labor		Intermediates	
		(Stage 1)	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Manufacturing								
10-12	Food, beverages, and tobacco	783	0.144*	(0.074)	0.291***	(0.025)	0.502***	(0.015)
13-15	Textiles, wearing apparel, leather	519	0.036	(0.039)	0.529***	(0.026)	0.447***	(0.016)
16, 31	Wood and cork products, and furniture	501	0.036**	(0.017)	0.438***	(0.020)	0.547***	(0.016)
17-18	Pulp, paper, and printing	734	0.025	(0.041)	0.485***	(0.020)	0.492***	(0.013)
19-21	Coke and petroleum, chemicals, basic pharmaceutical products	831	0.097***	(0.021)	0.430***	(0.022)	0.540***	(0.013)
22	Rubber and plastic products	728	0.041	(0.027)	0.413***	(0.020)	0.488***	(0.013)
23	Other non-metallic mineral products	516	-0.055	(0.059)	0.341***	(0.018)	0.555	(0.013)
24	Basic metals	385	0.053	(0.050)	0.212***	(0.023)	0.669***	(0.015)
25	Fabricated metal products, except machinery and equipment	1201	0.012	(0.023)	0.492***	(0.015)	0.462***	(0.009)
26	Computer, electronic and optical products	1039	0.076***	(0.012)	0.431***	(0.020)	0.496***	(0.013)
27	Electrical equipment	603	0.018	(0.038)	0.424***	(0.021)	0.544***	(0.014)
28	Machinery and equipment	1404	0.024	(0.028)	0.475***	(0.016)	0.475***	(0.010)
29-30	Motor vehicles and other transport equipment	635	-0.016	(0.063)	0.461***	(0.021)	0.525***	(0.013)
32	Other manufacturing	398	-0.017	(0.158)	0.429***	(0.037)	0.380***	(0.021)
33	Repair and installation of machinery and equipment	348	0.009	(0.025)	0.625***	(0.025)	0.423***	(0.017)

* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix B: First Stage Regression Results

Table 9: First Stages for Model 2SLS-3 (1669 Obs.)
Case: CO_2 Reducing Innovation

Dependent Variables:	**green only**		**orga only**		**both**	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
ln(number of employees)	>0.00	(0.01)	>0.00	(0.01)	0.02**	(0.01)
ln(age)	0.02	(0.03)	<0.00	(0.06)	0.03	(0.04)
ln(age)^2	<0.00	(0.01)	>0.00	(0.01)	-0.01	(0.01)
ln(patent stock per employee)	0.09	(0.28)	-0.09	(0.67)	0.06	(0.37)
ln(education expenditures per employee)	0.03	(0.02)	0.10***	(0.04)	0.08***	(0.03)
location in East Germany	-0.03**	(0.01)	0.01	(0.03)	-0.01	(0.02)
firm is part of a group	0.01	(0.02)	-0.01	(0.03)	0.01	(0.02)
worldwide market sales	<0.00	(0.02)	0.02	(0.03)	-0.01	(0.02)
ln(ratio of exports to total sales)	<0.00	(0.04)	-0.11	(0.08)	-0.06	(0.06)
perceived high competition from abroad	-0.02*	(0.01)	0.02	(0.02)	0.01	(0.02)
perceived high competition from entrants	<0.00	(0.01)	-0.03	(0.02)	0.03*	(0.02)
sector dummies†	yes					
mean of green only by sector and size class	0.93***	(0.14)	<0.00	(0.22)	-0.07	(0.14)
mean of orga only by sector and size class	-0.02	(0.07)	0.87***	(0.13)	-0.14	(0.09)
mean of both by sector and size class	-0.04	(0.10)	-0.12	(0.18)	0.75***	(0.14)
innovation goal: increase of market share	0.02	(0.01)	0.16***	(0.03)	0.07***	(0.02)
constant	-0.03	(0.06)	-0.10	(0.11)	-0.08	(0.08)
F-Statistics of joint significance and Partial R^2 of excluded instrum.	13.91	[0.04]	25.38	[0.05]	12.83	[0.04]

† The model includes 14 sector dummies based on NACE 2-digit level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors in parentheses.

Table 10: First Stages for Model 2SLS-3 (1669 Obs.)
Case: Sustainable Innovation

Dependent Variables:	**green only**		**orga only**		**both**	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
ln(number of employees)	>0.00	(0.01)	>0.00	(0.01)	0.03***	(0.01)
ln(age)	-0.01	(0.05)	0.01	(0.05)	0.02	(0.06)
ln(age)^2	0.00	(0.01)	0.00	(0.01)	-0.01	(0.01)
ln(patent stock per employee)	-0.22	(0.40)	0.29	(0.60)	-0.31	(0.54)
ln(education expenditures per employee)	0.01	(0.03)	>0.00	(0.03)	0.19***	(0.04)
location in East Germany	-0.03	(0.02)	-0.01	(0.02)	0.01	(0.02)
firm is part of a group	0.02	(0.02)	0.01	(0.06)	-0.01	(0.02)
worldwide market sales	>0.00	(0.03)	0.03	(0.03)	-0.03	(0.03)
ln(ratio of exports to total sales)	-0.05	(0.06)	-0.15**	(0.06)	-0.02	(0.07)
perceived high competition from abroad	0.01	(0.02)	>0.00	(0.02)	0.03	(0.02)
perceived high competition from entrants	0.01	(0.02)	-0.02	(0.02)	0.02	(0.02)
sector dummies†	yes		yes		yes	
mean of green only by sector and size class	0.92***	(0.14)	-0.02	(0.14)	-0.18	(0.15)
mean of orga only by sector and size class	>0.00	(0.14)	0.96***	(0.14)	-0.23	(0.16)
mean of both by sector and size class	-0.05	(0.11)	-0.01	(0.10)	0.61***	(0.13)
innovation goal: increase of market share	0.08***	(0.02)	0.05**	(0.02)	0.18***	(0.02)
constant	0.00	(0.10)	-0.06	(0.10)	-0.96	(0.11)
F-Statistics of joint significance and Partial R^2 of excluded instrum.	18.43	[0.04]	16.02	[0.04]	30.51	[0.06]

† The model includes 14 sector dummies based on NACE 2-digit level.
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

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