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Abstract — This study investigates productivity effects to firms introducing new environmental technologies. The literature on within-firm organisational change and productivity suggests that firms can get higher productivity effects from adopting new technologies if complementary organisational changes are adopted simultaneously. Such complementarity effects may be of critical importance for the case of adoption of greenhouse gas (GHG) abatement technologies. The adoption of these technologies is often induced by public authorities to limit social costs of climate change, whereas the private returns are much less obvious. We find empirical support for complementarity between green technology adoption and organisational change for a sample of firms located in Germany. The adoption of CO_2 reducing and sustainable technologies innovations is associated with lower productivity. The simultaneous implementation of organisational innovations, however, increases the returns to the adoption of green technologies. (Keywords: Technical change, environmental innovation, organisational change, productivity)

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1. Introduction

The literature on internal 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 has mainly focused on the role of governmental regulation for abatement technology adoption and its consequences for firms' productivity and competitiveness. What this literature has not touched is the question of how abatement technologies integrate into the firms' operations and what factors determine their efficient adoption.

Only recently, Bloom et al. (2010) 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 favor of this view. However, both studies do not allow 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 within manufacturing firms. In particular, we study whether organisational change may help firms to make more efficient use from green technologies. We understand green technology adoption as any technology that reduces CO_2 emissions, taking into account that CO_2 reduction can also be achieved by using fossil fuel inputs more efficiently and is therefore related to energy-efficiency[1]. Beyond greenhouse gas (GHG) mitigation technologies we also look at sustainable innovations (i.e. material or resource saving innovations) as to provide a more comprehensive picture of green technology adoption. The selection of these two aspects of green technology is motivated by the fact that both are integrated process (no end-of-pipe, i.e. no additive) technologies.[2] Organisational change in our context comprises new business practices for organising procedures, production as well as knowledge or quality management. In addition, new methods of organising work responsibilities and decision making, decentralisation or integration may result in organisational change.

In light of the ongoing policy debate and since abatement technology provides high environmental and social returns, while private returns are unclear, the research questions ad-

[1]Improving the efficiency of fossil fuel use requires to install 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 to replace old capital (Atkeson and Kehoe, 1999). In general, the total ex-ante expected effect of abatement technology adoption on productivity remains ambiguous.

[2]Abatement technologies for local water or air emissions (such as SO_2) that often use end-of-pipe technologies are excluded. There is no reason to expect any effect of changes in firm's process or work flow organisation to affect these technologies' efficiency.

dressed here certainly deserves attention. If having to introduce CO_2 mitigation technologies or sustainable innovation would hurt firms' private returns any complementary effect from introducing organisational change that moves private returns into positive territory, would benefit the diffusion of green technologies. Understanding the underlying mechanisms through which green technology adoption—especially if introduced to cope with governmental regulation—interacts with the firms' organisation of production processes will be important to assess the impact of green technology policy on firms' incentives to adopt green technologies.

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 use and thus allow firms to achieve higher productivity gains from technology adoption. Empirical evidence for complementarity among different types of organisational change has been shown by Ichniowski et al. (1997). 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 to increase 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) provide empirical evidence that United States' (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 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 technologies). We develop an empirical framework exploring whether green technologies jointly adopted with changes in firms' organisational structure allow to improve the returns from adopting these technologies possibly even offsetting productivity losses of adopting green technology alone.

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. before 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 focused mostly on the impact of governmental regulation on firm performance and 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 in the beginning of the 1980s after the US and other highly industrialised countries introduced regulations of local water and air pollutants (like SO_2). Regulatory stringency is typically measured using data from the US Pollution Abatement Costs Expenditure (PACE) survey.

As one of the first using the PACE survey data, Gray (1987) reports a negative correlation between pollution abatement operating costs (PAOC) and total factor productivity (TFP) at the sectoral level indicating no productive use of abatement technology. The study of Gray and Shadbegian (2003) provides estimates for PAOC's impact on both TFP and output in a production function estimation. Their results based on observations for pulp and paper mills 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 process using standard inputs and investment in pollution abatement equipment to reduce pollution. They find that there is a potential for both input and pollution reduction to produce the same output. 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.

We aim to contribute to previous research by testing whether firms may improve the productivity impact of adopting green technology when complementary organisational structures are adopted. Thereby we argue that one has to consider firms' internal behavior such as

[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 as far as saying 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 of Snyder et al. (2003) finds no significant evidence for regulation to be 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.

their implementation strategy. Antonioli et al. (2013) find that human resource management and workplace practices determine firms' decisions to adopt CO_2 abatement technologies. We look at the effects on productivity from joint adoption of new organisational structures and green technologies. Adoption of environmentally-friendly technologies is costly and may hence reduce productivity. However, if this adoption is accompanied by organisational changes that allow for more efficient use of the new technology, this productivity-reducing effect from green technology adoption can be diminished or possibly reverted if green innovation and organisational change are complementary.

3. Econometric Identification

Complementarity between any two economic activities x and x', in our case a binary choice of whether or not to adopt green respectively organisational technologies new to the firm, means that doing more of one increases the marginal benefits of doing more of the other. Athey and Stern (1998) offer an overview on the methodologies used to test for complementarities. There are, in principle, two ways to test for complementarity between firm strategies. The first one is the adoption approach, where a significant positive correlation between the adoption of two activities, conditioning on any other factors, is an indicator of complementarity (Arora and Gambardella, 1990; Arora, 1996). Section 3.1. describes our adoption approach for assessing complementarity between green and organisational technology adoption.

The adoption approach is limited in its validity, particularly when x and x' are not continuous. 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). The second approach, the productivity approach[4], does not suffer from this problem. It accounts for the effects of x and x' on a performance indicator, in our case productivity as measured by TFP. Section 3.2. sets out our productivity approach for assessing complementarity between green and organisational technology adoption.

[4]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 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. The Joint Adoption of Green and Organisational Innovations

To implement the adoption approach for assessing potential complementarity, we estimate a seemingly-unrelated discrete response model that reads as follows:

$$\begin{aligned} x_i^{gr} &= \beta_0^{gr} + \beta'^{gr}\boldsymbol{C}_i^{gr} + \varepsilon_i^{gr} \\ x_i^{or} &= \beta_0^{or} + \beta'^{or}\boldsymbol{C}_i^{or} + \varepsilon_i^{or} \end{aligned} \qquad \begin{bmatrix} \varepsilon^{gr} \\ \varepsilon^{or} \end{bmatrix} \sim N\left(0, \begin{bmatrix} \sigma_{gr}^2 & \sigma_{gr,or} \\ \sigma_{gr,or} & \sigma_{or}^2 \end{bmatrix}\right),$$

where x^{gr} (x^{or}) takes the value of one if a firm adopted green (organisational) innovation. Any unobservable factors (ε^{gr} and ε^{or}) determining adoption choices are assumed to be distributed jointly normally and are allowed to be correlated between the equations. We jointly estimate the equations system using a bivariate probit model.

As complementarity is assessed from the correlation between the error terms of both equations, other factors which could condition this correlation need to be controlled for. We control for several variables subsumed in the vectors $\boldsymbol{C}^{or}$ and $\boldsymbol{C}^{gr}$, respectively. These include controls like firm size and age, sector dummies, and competition characteristics. Beyond standard control variables, it is crucial to control for the firms' general innovative capabilities. We therefore control for whether the firm is permanently or occasionally active in R&D. Similarly, the literature stresses the importance of human capital and the skill level of employees to determine whether technological change within the firm can happen. This has been examined most explicitly for organisational change (Caroli and Van Reenen, 2001).[5]

For green innovations, following the literature, we expect firms to be more likely to introduce green technologies when induced by environmental regulations. To this end, we control for regulation-driven innovation (at the sector level). The environmental regulation variable is also included in the organisational innovation equation. As there are no direct effects from environmental regulation on organisational innovation adoption to be expected, it operates like an exclusion restriction. Finding a significant positive effect from environmental regulation on organisational innovations, can be interpreted as positive evidence for complementarity, see Athey and Stern (1998). This is because the higher probability for organisational change adoption due to environmental regulation comes from the simultaneously increased adoption of complementary green innovation.

3.2. 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

[5]This is in line with the literature that predicts technical change and organisational change to be skill-biased (Bresnahan et al., 2002). We therefore take into account firms' training and education expenditures per employee.

objective function with respect to the two variables ($\partial^2 f/\partial x \partial x'$) indicates 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), which is our case. The condition for supermodularity and complementarity reads as follows[6]:

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

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 non of both 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.

In what follows we discuss how to obtain consistent estimates of the inequality 2. Although complementarity, as defined by inequality 2, is perfectly symmetric in the two strategies, we are particularly interested 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 to see whether additionally introduced organisational change may at least (partially) offset green technology's negative productivity effects. This could hold if the combined event results in better performing business processes or worker relationships.

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:

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

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

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

information[7]. Besides these innovation adoption choices, any further observable factors that potentially explain differences in TFP are included in the vector $\boldsymbol{C}$.

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 $\beta_{10} - \beta_{11} \geq 0$.

3.2.1. Estimating Total Factor Productivity (TFP)

TFP is—roughly speaking—a 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), causing OLS estimates 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) or the approach of Levinsohn and Petrin (2003) that builds upon the Olley and Pakes (1996) method. In the present paper, TFP is constructed using the Olley and Pakes (1996) method to obtain estimates of input elasticities:

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

where $\hat{\beta}_j, j \in \{k, l, m\}$ denote estimates of capital, labour, and material input elasticities of a 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.

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 (CIS).[8] 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 from the population of German manufacturing and service firms. For the purpose of this study, however, we focus our at-

[7] 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$_i$).

[8] 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.

tention on the manufacturing sector where CO_2 emissions are more relevant than in service sectors.

4.1. Green 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 helps to separate causality from correlation as the effects from adopted innovations (including organisational change) need time to materialise.

Information on green innovation is reported in a 4-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 where mentioned including reduced material use per unit of output, reduced energy use per unit of output, reduced CO_2 emissions. The remaining six environmental benefits concern air, water, soil and noise pollution as well replacement of hazardous substance 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 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 only new to the firm, irrespective of whether it is developed in house or acquired from elsewhere. For the case of material-saving innovations, the dummy (x^{sus}) takes the value of one if at least innovations with some impact on material (or resource) efficiency was introduced. For the case of CO_2 mitigation innovations, we make especially use of the 4-point Likert scale to rule out minor innovations. The acquisition of a hybrid firm car is an extreme example of a minor innovation new to the firm. To exclude cases of such minor green improvements, we set the dummy for CO_2-reducing technologies (x^{co2}) only to one 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 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.

4.2. Controls

For the construction of TFP, revenue data is used as output information. Sales data is highly dependent on output price so TFP is likely to account for firm-level differences in output price 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 whether the firm perceives competition to be hard due to a) entry of new firms and b) due to 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 mark ups 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[9].

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 skills and capabilities of their employees. Thus, we control for firms' logged training and education expenditures per employee. One year lagged information is used to reduce endogeneity concerns.[10] 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. Older firms are likely to replace fully depreciated capital goods for new ones. As the age-relationship is therefore unlikely to be linear, we include in addition 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 full-time equivalent number

[9]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).

[10]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.

of 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 exporting 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).

For the adoption approach model (bivariate probit), we additionally include other variables likely explaining the discrete adoption choices for green and organisational innovations. A first important one is the extent of environmental regulation in the sector. Firms were asked whether their green innovations were introduced to cope with regulations. This information from the survey, however, is only observable for green innovators. We use this information to calculate the mean at an aggregated NACE 2-digit level. This variable serves as an "exclusion restriction" in the adoption of organisational change.

We control for R&D inputs into the technology adoption by including two dummies measuring whether a firm is continuously or occasionally active R&D, the base case being firms not active in R&D[11]. Firms' (logged) capital-to-labor ratio is accounted for as the value of total fixed assets scaled by the full-time equivalent number of employees. The control for material-to-labor ratio is constructed in a similar fashion. Firms operating capital-intensive businesses are likely to have higher pollutant emissions and therefore are more likely to adopt green innovations.

Reducing environmental impacts of production activities is not always the most important criteria when introducing innovation. Instead, it can come as a "side effect" of introducing process innovation in a firm. To control for this possibility, a dummy variable is included taking the value of one if a conventional process innovation was introduced during 2006 until 2008 and zero otherwise.

4.3. Descriptive Statistics

The descriptive statistics for our sample appear in Table I below. After eliminating observations from the original data-set due to item non-response and outlier correction, the final

[11] We do not use current R&D expenditures as the need at least some lag to affect innovation. Although data for past R&D expenditures is available in the full panel version of the MIP, using this information would come at the expense of a highly reduced sample due to unbalanced panel data and non-response.

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 I, 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 of green innovation seem more relevant to the broader range of firms, especially in our sample of mainly small and medium-sized firms. Organisational changes had been introduced by 46.5% of the firms during the survey period. Further descriptive statistics are provided for the pairwise adoption of the potentially complementary innovation variables, see Table II.

Table I: 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 (sector means)	[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 expenditures 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
world wide sales markets	[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 market entrants	[2006-2008]	0.348	0.477	0	1

Table II 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 frequency reported in parentheses that reflect the estimated frequency that would have been observed, had the two adoption decisions been independent. If both choices had been independent, we would have observed only 9.00% of the firms having jointly adopted green and organisational change if both choices had been independent, while we actually observe that 11.98% of the firms jointly adopted both innovations. Having introduced both forms of innovation jointly is more frequently observed in case of sustainable technology as compared to the case of CO_2 abatement technology, showing a stronger correlation (or complementarity) in this case. This correlation is a first piece of evidence in favor of complementarity but needs to be singled out from other non-random factors affecting these correlations.

Table II: 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.

Case: CO_2 abatement technology: Pearson chi^2(1) = 38.80 Pr = 0.00; Kendall's tau-b = 0.15, P > z = 0.00

Case: sustainable technology: Pearson chi^2(1) = 137.89 Pr = 0.00; Kendall's tau-b = 0.29 , P > z = 0.00

5. Econometric Results

5.1. Correlations and Complementarity Between Adoption Decisions

Table III below presents estimation results from a bivariate probit model. The important result from Table III is the (conditional) correlation of the equations' error terms, which is 0.16 and 0.28, respectively. Both are highly significant. The adoption approach thus provides significant evidence in favor of complementarity, particularly between sustainable technology adoption and organisational change. A significant determinant of green innovation is (sectoral) environmental regulation. This holds for both CO_2 abatement and sustainable technology. More surprisingly, the adoption of organisational change is also affected by environmental regulation significant at $<10\%$ for CO_2 abatement technology and marginally above 10% for sustainable technology. As there is no obvious reason why environmental regulation should directly affect organisational change, this positive coefficient is consistent with an indirect effect coming from a complementary relationship of green technologies and new organisational structures. The exclusion restriction approach therefore provides an additional piece of evidence in favor of complementarity.

What the results in Table III do not allow to conclude is whether and how complementarity affects overall economic performance of firms. We address this issue in the following section where the productivity approach is used to quantify this effect.

Table III: Results from the Bivariate Discrete Response Model

Cases:	CO_2 abatement technology		Sustainable technology	
Dependent Variables:	x^{co2}	x^{or}	x^{sus}	x^{or}
	Coef. (Std. Err.)	*Coef. (Std. Err.)*	*Coef. (Std. Err.)*	*Coef. (Std. Err.)*
regulation driven green innovation	0.82*** (0.32)	0.50* (0.30)	0.68*** (0.25)	0.47 (0.29)
ln(number of employees)	0.08** (0.04)	0.15*** (0.03)	0.11*** (0.03)	0.15*** (0.02)
ln(capital intensity)	0.10*** (0.03)	-0.07** (0.03)	0.04 (0.03)	-0.07** (0.03)
ln(material intensity)	0.01 (0.04)	-0.03 (0.05)	-0.04 (0.04)	-0.03 (0.05)
ln(patent stock per employee)	-0.51 (2.04)	-0.77 (1.71)	-2.84* (1.66)	-0.77 (1.70)
ln(age)	0.11 (0.17)	0.20 (0.19)	-0.00 (0.16)	0.20 (0.19)
$\ln(\text{age})^2$	-0.03 (0.03)	-0.03 (0.03)	-0.01 (0.03)	-0.03 (0.03)
process innovation introduced	0.28*** (0.08)	0.66*** (0.07)	0.50*** (0.07)	0.66*** (0.07)
location in East Germany	-0.20* (0.10)	0.02 (0.09)	-0.08 (0.08)	0.01 (0.09)
ln(education expenditures per employee)	0.33*** (0.11)	0.50*** (0.13)	0.49*** (0.11)	0.50*** (0.13)
dummy for continuous R&D activities	0.15 (0.12)	0.26*** (0.09)	0.36*** (0.09)	0.26*** (0.09)
dummy for occasional R&D activities	0.28** (0.11)	0.25*** (0.08)	0.48*** (0.08)	0.25*** (0.08)
perceived high competition from abroad	-0.13 (0.08)	0.04 (0.07)	0.10 (0.07)	0.04 (0.07)
perceived high competition from entrants	0.17** (0.07)	0.03 (0.07)	0.15** (0.07)	0.03 (0.07)
firm is part of a group	0.05 (0.10)	0.02 (0.08)	0.08 (0.09)	0.02 (0.08)
sector dummies	yes	yes	yes	yes
constant	-1.43*** (0.42)	-1.81*** (0.44)	-1.00*** (0.38)	-1.79*** (0.44)
correlation coefficient	0.16*** (0.05)		0.28*** (0.04)	

* p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered by sector and size class (see footnote 11) and appear in parentheses.

5.2. *Results from the Productivity Approach*

In a further step 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[12] adoption decisions defined over a lattice on total factor productivity (see Table IV). The results show that adopting green innovation without adapting the organisational infrastructure 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 having neither introduced green innovations nor organisational change. The coefficients of green only and joint adoption differ significantly from each other in both model variants[13]. We can reject a one-sided t-test against the null that $(\text{green only}) + (\text{orga only}) - (\text{both}) \geq 0$ in both models, supporting complementarity. Note that organisational change alone has no significant impact on productivity. However, introducing it jointly with green innovations helps to offset green technology's negative productivity effects. In this sense, complemen-

[12]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.

[13]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.

tarity seems to be asymmetric meaning that organisational change enhances the efficiency of green technology but not the other way round. Note that an asymmetric test for complementarity would only require to reject the null that (green only) $\geq$ (both). The null is rejected in the case for CO_2 abatement technology and in the case of sustainable technology.

Most of the controls have the expected sign. The (logged) ratio of export to total sales is strongly significant and one of the most important covariates of productivity. Firms that export to world wide destinations have a significant 3.5% higher productivity than firms that either export to European destinations or do not export at all.

Table IV: 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)
world wide sales markets	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 market 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.

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 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.

In the following step, extensions and robustness checks are carried out to further explore the (asymmetric) complementarity between green and organisational innovation adoption and to test for potential endogeneity of the choice variables. As the case of CO_2 reducing technologies is much more hotly debated in the policy discussion, we focus in what follows on this case.

6. Extensions and Robustness Checks

6.1. Direction of Complementarity: The effect of Organizational Change on Adoption of Green Technologies

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 V.

Table V: Sample Split Models, Case of CO_2 Abatement Innovation only

Dependent Variable: TFP	$x^{gr}=1$		$x^{gr}=0$	
	Coef.	*(Std. Err.)*	*Coef.*	*(Std. Err.)*
Organizational 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)
$\ln(\text{age})^2$	-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 market 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. Conversely, 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 IV).

6.2. Potential Endogeneity of Innovation Adoption Choices

The error term of equation 3 is likely to still 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 maybe 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 to estimate two-stage least squares (2SLS) regressions for the case of CO_2 abatement technology. Note that in general, it is very challenging to derive valid instruments from the CIS survey data as all variables are self-reported and many are likely to be endogenous themselves, influenced by management quality. We therefore calculate the means of the variables *green only*, *orga only*, and *both* by sector and firm size classes[14]. The stringency of environmental regulation may differ largely between sectors as well as 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 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 by sector and size class have no significant partial effect on TFP once all other covariates have been controlled for.

As this is no sufficient proof for exogeneity of the instruments, more instruments 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 motives for introducing innovations. Although any objective

[14]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.

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 goal 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[15] appear in Table VI[16].

Table VI: 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)
$\ln(\text{age})^2$	-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)
world wide sales markets	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 and the goal to increase market share as instruments (four instruments).
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

[15] We applied the same instrumental variables for the case of sustainable technologies. The results also strongly support previous OLS estimates and are available from the authors upon request.

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

The Hansen J test statistic is very far away from the rejected area so we can be very sure, at least from a statistical point of view, that the instruments are exogenous. Moreover, as a rule of thumb, Staiger and Stock (1997) argue that a F-statistics for joint significance of the excluded instruments in the first stages larger than 10 ensure that the instruments are not weak. This requirement is fulfilled in any first stage regressions, see Table VIII in Appendix B. Provided that 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 for each of these three regressions the residuals. 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 would be indeed endogenous. However, as indicated in Table VI, this is not the case.

Our central results of complementarity also survive 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 $(\text{green only}) \geq (\text{both})$. Directly comparing the OLS results (Table IV) with the 2SLS results points to much higher estimates of the variables of interest in the 2SLS case associated with stronger complementary[17].

For the sample split models[18], the same test were applied which do not support the concern that organisational change adoption is endogenous. However, the effect of organisational change for the group of green innovators was not significantly different from zero, which could be due to the very small sample size of 314 observations, combined with the inefficiency of the 2SLS estimator.

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 green technologies for which the returns to the firms are not necessarily positive. Any complementarity effects may therefore be crucial to lift the private returns from adopting green technologies in positive territory. Previous research on the effects of green technologies, however, had largely neglected complementarities from adopting other firm strategies.

Using German firm-level data on technology adoption, we examined the relationship between the introduction of two types of green technologies, CO_2 mitigation and sustainable

[17] 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 is the 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 one for *orga only* but nevertheless in acceptable territory (larger than 10). This may explain the higher deviation of these two variables between the 2SLS and the OLS regressions than it is the case for the estimates of *orga only*.

[18] The results are available by the authors upon request.

technologies on the one hand and the introduction of organisational innovations on the other hand. To assess complementarity we employed both an adoption and a productivity analysis, the latter measured by TFP. We are particularly interested in whether the adoption of organisational change improves the returns to adopting green innovations, for both CO_2-mitigating and materials-saving green innovations. Our analysis supports the hypothesis that organisational change increases the returns to the use of CO_2-reducing and material-saving technologies which partially offsets negative effects on productivity. The results from different estimation procedures suggest that the introduction of green technologies and organisational innovations are indeed complementary. In other words, firms that adopted green technologies jointly with changes to their organisational structure can make better use of green technologies and hence offset productivity losses compared to firms having only adopted green technology.

Although the evidence suggests that organisational structure matters, a conclusion our results do not allow to draw at this stage is that green technology adoption per se is beneficial to a firm if it simply introduces the right organisational structure and that—as a consequence—policy makers can introduce stringent environmental regulations without side-effects. Such a naive view would ignore the possibility that a firm could have had adopted an even more productivity increasing technology in absence of regulatory pressure to adopt green technology. Gray and Shadbegian (1998) for instance, document such a crowding out effect. Moreover, this naive view also neglects that complementarities are not automatic.

Despite all efforts, this study has some limitations. In particular, we were not able to test long-term implications for firms and the environment. In this sense, our results reflect rather short-term effects that may differ largely from long term consequences. We therefore strongly encourage further research addressed at better understanding how, when and for whom these complementarities can be realised.

Given these limitations, this paper can only be a first step to better understand how firms implement new pollution control technologies. Our research clearly signals that regulators should better understand how firms implement pollution control technologies. Policy should look at the appropriate framework needed for firms to exploit complementary effects, which can critically boost the private incentives for adopting green innovations.

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 lower case letters denote natural logarithms. Following Olley and Pakes (1996), we assume that firms know there 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 it otherwise: variable inputs are endogenously related to ω_{it} which is know 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] As to correct the bias in variable inputs, Olley and Pakes (1996) suggest to estimate equation 5 using OLS and include 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 labor 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 (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 approxima-

[19]We therefore use a time period of 10 years of the full panel of the MIP including yearly observations for output (total sales), capital (total fixed assets), materials (material and energy expenditures), labor (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.

tion. Because equation 6 does not identify the coefficient of capital separately from the one 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 labor and materials. This is exactly why Olley and Pakes (1996) propose a two-step procedure as 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 exited. We therefore used start values for capital form an OLS regression of logged output on logged inputs for each sector. This routine worked well for all sector but 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 VII provides the estimates for the Olley and Pakes (1996) method.

Table VII: 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 VIII: First Stages for Model 2SLS-3 (1669 Obs.)

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)
$\ln(\text{age})^2$	<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)
world wide sales markets	<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 [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.

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