Clean and Productive?

Evidence from the German Manufacturing Industry

Christoph Böhringer♣, Ulf Moslener♦, Ulrich Oberndorfer*, Andreas Ziegler#

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Abstract: In this paper, we analyze the productivity effects of environment- and energy-related expenditure and investment activities. For this purpose, we follow a production function approach accounting for environmental investment as well as environmental and energy expenditures as capital inputs, and making use a panel dataset of the German manufacturing industry between 1996 and 2002. Our estimations show only week evidence for a significant contribution of both environmental and energy expenditures for production growth. In contrast, environmental investment positively impacts on productivity. Our results therefore suggest that environmental performance, measured with environmental investment, may be a productivity driver. Given this, environmental regulation does not necessarily slow down production growth. In order to be compatible with economic goals such as productivity, however, it should stimulate investment.

Keywords: environmental performance, environmental regulation, productivity

JEL classification: Q28, Q58, D24

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♣ Carl von Ossietzky University Oldenburg, Germany, christoph.boehringer@uni-oldenburg.de
♦ Centre for European Economic Research (ZEW), Germany, moslener@zew.de
* Corresponding author. Centre for European Economic Research (ZEW), P.O. Box 103443, 68034 Mannheim, Germany, oberndorfer@zew.de
# University of Zurich, Switzerland, andreas.ziegler@ccrs.unizh.ch

I. Introduction

Are "greening" industries gaining or loosing in terms of productivity? This question is crucial not only for managerial, but also for political decision-making if the political agenda includes both economic and environmental goals. Due to its relevance, this question has also been tackled from very different points of view in the past. It is, on the one hand, related to the discussion on the economic impacts of environmental regulation: Traditional economic theory suggests negative economic effects of such regulation (Palmer et al., 1995), while the so-called Porter Hypothesis suggests economic gains from regulation due to innovation offsets in the regulated country (Porter and van der Linde, 1995). On the other hand, besides regulatory pressure, successful environmental management ("environmental performance") may lead to cleaner production.

There is a substantial literature on possible "innovation offsets" of environmental expenditures and regulation. In one of the most cited contributions, Brunnermeier and Cohen (2003) find that pollution abatement and control expenditures (PACE) have a positive impact on environmental innovation at the U.S. industry level. Other studies such as Lanjouw and Mody (1996) and Pickman (1998) corroborate this result. In contrast, Jaffe and Palmer (1997) do not receive empirical evidence for a positive effect of pollution abatement and control expenditures on – total – innovations at the U.S. industry level. Moreover, there are only few empirical contributions that tackle the impact of environmental regulation on economic performance or "competitiveness" based on more narrow competitiveness indicators. The findings of Ederington and Minier (2003) who also make use of U.S. industry panel data suggest that net imports are positively affected by the level of abatement costs which they see directly linked to the stringency of environmental regulation. More similar to our approach, Gray (1987) uses productivity growth as a competitiveness indicator. However, he does not find a significant impact of pollution abatement costs on TFP growth in his cross-sectional analysis for U.S. industries. In contrast, a recent study undertaken by Hamamoto (2006) suggests that pollution control expenditures measured at the industry level for Japan positively affect TFP growth via a stimulation of R&D investment. Our study is most closely related to Shadbegian and Gray (2005) that introduce PACE data into a production function approach at the U.S. plant level for pulp and paper mills, oil refineries, and steel mills. The authors find that pollution abatement expenditures contribute very little to production and negatively affect non-abatement inputs.

All in all, there is no clear empirical answer to the question on economic effects of environmental expenditures, regulation and performance yet. Furthermore, even if positive effects of those phenomena on special types of innovation (such as environmental innovation) are found, the general economic impacts remain unclear. E.g. a stimulating effect of *environmental expenditures* on *environmental innovation* could be accompanied by a crowding out of *conventional*, i.e. *non-environmental innovation* (cp. Jaffe et al., 1995). Moreover, innovation itself is often considered to be rather a weak indicator for economic performance: Innovation gives only few insights into success of a sector. This critique also holds for most of the studies assessing the interrelationship between environmental and economic performance, where innovation is often used as indicator of economic performance. Here, a positive effect of environmental management on environmental innovations at the firm level is generally found (e.g. Rennings et al. (2006) for Germany or Frondel et al. (2007) for a set of seven OECD countries). Recently, however, the causal relation between environmental management and economic performance is questioned (Seijas-Nogareda and Ziegler, 2007).

Evidence is not more compelling if economic performance is proxied more directly, e.g. by financial performance. Ziegler et al. (2007) for Europe and Konar and Cohen (2001) for the U.S. find a positive effect of environmental performance on stock performance. Telle (2006),

in contrast, reports contrary results using a Norwegian plant-level panel data set, and highlights the importance of controlling for unobserved heterogeneity.
General economic impacts of environmental expenditures, regulation and performance can be identified most accurately if narrow indicators for economic performance are used as dependent variables within the empirical framework. The studies cited above are very important contributions in this respect. Against this background, the contribution of our paper is threefold. Firstly, and most importantly, we include different measures from the broad field of environmental expenditures, regulation and performance: Besides environmental expenditures, we employ environmental investment as well as energy expenditures as explanatory variables in our empirical analysis of competitiveness. Especially environmental investment may be of high relevance for indicators of economic success such as innovation or productivity, but has been neglected in empirical contributions so far. Possible endogeneity of these variables can be accounted for within an econometric framework by using an instrumental variable approach. Secondly, given that the effect of environmental expenditure or investment measures on economic performance have not been analyzed in the German context, this examination is very relevant also from this perspective. Thirdly, the literature cited above has, from a methodological perspective, been based on the application of cross-sectional and static panel data approaches. Our methodological contribution in this respect is the application of modern panel data techniques that take into account not only unobserved heterogeneity, but also state dependence, i.e. dynamic adjustment of the dependent variable. Such dynamics may be an important issue in the analysis of economic success.
The remainder of this paper is structured as follows: Section two presents the theoretical background of our analysis. In section three, we describe data and variables employed in our empirical approach. Methodological details are lined out in part four. Chapter five gives the estimation results, section six concludes.

II. Theoretical Background

One main argument to avert any kind of environmental regulation is that it will harm the regulated industry which is subject to intense international competition. Although competitiveness itself is not very well defined the reasoning behind this argument is fairly straightforward: Under simple but strong assumptions such as complete information competitive markets and profit maximizing behavior of all firms any additional restriction to the firm’s behavior (e.g., environmental regulation) tends to decrease its profits and may lead to loosing market share. Formally, restriction of the optimization procedure forces the firm to behave different from the way it would have acted without the regulation.

Although the concept of competitiveness does not seem very well defined in the literature, a less blurry question can be asked about productivity: Will environmental regulation render the economy less productive? In order to answer that question we first have a look at how production can be formulated at an aggregate level.

Assume a production function (F) for sector i (1,…,N) at time t (1,…,T) to produce a quantity (q) to depend on the actual inputs (x_k) into the production process as well as on other non-input factors (o_l) such as the macroeconomic, regulatory or market environment:

(1) $$q_{i,t} = F(x_{k,i,t}, o_{l,i,t}) .$$

If x_k are interpreted as input expenditures the question arises whether all these expenditures should (or could) be attributed directly to the productive process. If part of the expenditures are a direct consequence of environmental regulation, they may in principle be considered as non-productive (pollution abatement) input as opposed to, e.g. capital and labor used for production (Shadbegian and Gray, 2005). (In other words, pollution abatement expenditures could be considered to implicitly produce a second good, namely pollution abatement to comply with some regulation.)

The key questions would be first to identify those types of expenditures or investments that are induced by environmental regulation and second to determine how they influence productivity. In principle, cost components may leave productivity unaffected, which may suggest that they can be interpreted isolated to serve the environmental purpose. If some of the cost components show a negative impact on productivity, the result may be that they in fact are not only non-productive but that they even decrease the productivity of other inputs used for production. Such an effect may show up for a non productive abatement expenditure which decreases the energy efficiency of other capital goods uses as an input. However, if we observe a positive impact this may mean that the environmental expenditures indirectly increase the productivity of the other factors (or are themselves productive). Empirical evidence of the so-called Porter Hypothesis (Porter and van der Linde, 1995) would show up along this line.

It should be noted, however, that all the effects discussed above could in principle also be generated by different kinds of systematic data mis-reporting. If, e.g., the environmental expenditures are reported too high and the other expenditures are calculated as the remainder to mach the information on total inputs (which are then as a consequence too low) then the results would show a systematically higher productive effect of the environmental expenditures.

Assuming a simple Cobb-Douglas form of the above production function with $x_{1\ldots j}^{ENV}$ representing the non-productive inputs while $x_{1\ldots k}^{PROD}$ and $o_{1\ldots l}$ denote the other input expenditures and non-input factors, respectively, w.l.o.g. the whole production function can be formulated as follows:

(2) $$q_{i,t} = \alpha \cdot \prod_{j=1}^{J} \left(x_{j,i,t}^{ENV} \right)^{a_j} \cdot \prod_{k=1}^{K} \left(x_{k,i,t}^{PROD} \right)^{b_k} \cdot \prod_{l=1}^{L} \left(o_{l,i,t} \right)^{c_l}$$

Subsequently taking the logarithm of both sides and calculating the variation over time yields

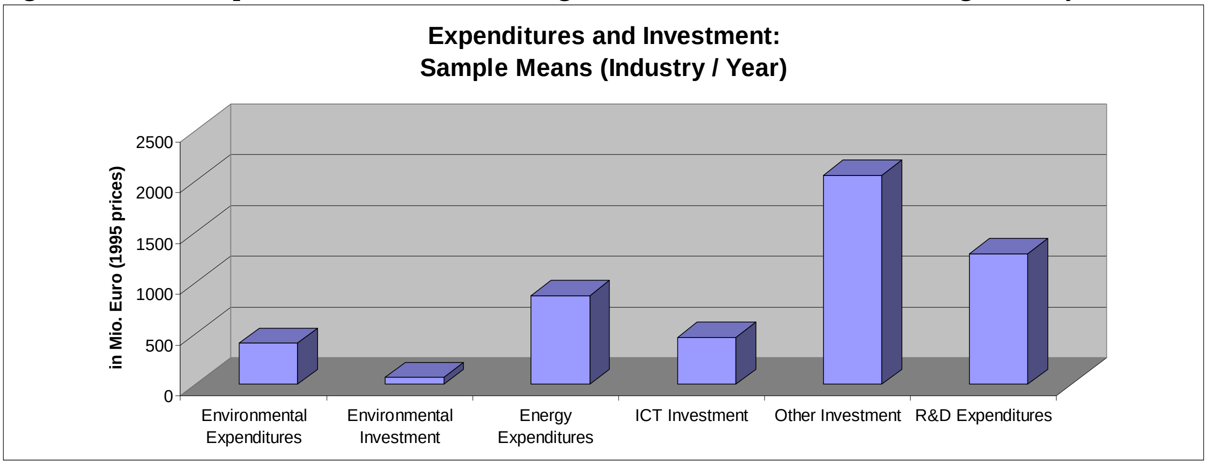
(3) $$\dot{q}_{i,t} = \sum_{j=1}^{J} a_j \dot{x}_{j,i,t}^{ENV} + \sum_{k=1}^{K} b_k \dot{x}_{k,i,t}^{PROD} + \sum_{l=1}^{L} c_l \dot{o}_{l,i,t} \ .$$

III. Data and Variables

For our empirical analysis, we employ a panel data set which includes German manufacturing industries based on the two-digit NACE codes (23 sectors) from 1996 to 2002. All monetary data is measured in prices of 1995. In our estimations, we employ log-log specifications. As the dependent variable, growth of the gross value added is employed. The dependent variable of our analysis, $\dot{q}$, is the absolute growth of gross value added (GVA), i.e. of production. This variable has a sample mean of 223.55 Mio. Euro. The explanatory variables of our major interest in this panel data analysis are those in the context of environmental regulation and performance $x_{1\ldots j}^{ENV}$. As a German “analogue” to the US Pollution Abatement Costs and Expenditures (PACE) we use the environmental expenditures – expenditures for environmental protection related to a "greener" production process – of the German manufacturing industry that are reported by the German Federal Statistical Office. This measure exclusively incorporates expenditures for the operation of "green" facilities as well as expenditures that stem from non-operational "green" measures. While product-related measures are not included, the expenditure measure incorporates e.g. fees and contributions for waste disposal and current costs for environmental protection. Examples for such expenditures are expenditures for water protection, for the restriction of air pollution as well as for other waste disposal. With a sample mean that only slightly exceeds 400 Mio. Euro per year (see Table 1), the environmental expenditures of the German manufacturing sectors reveal a modest burden driven by environmental issues compared to other expenditures (Figure 1). In the literature, environmental expenditures are often used as a proxy variable for environmental regulation (see literature review). Obviously, this is not fully unproblematic especially in our case. Besides expenditures for measures that are due to legal codes and official sanctions, the German data on environmental expenditures generally includes expenditures for voluntary pollution control measures. Such costs do not form part e.g. of PACE in the US. Furthermore, Jaffe et al. (1995) argue that even the PACE may not only give costs of compliance with environmental regulation, but include expenditures that improve the final product or at least the efficiency of the production process at the same time. Therefore, the relationship between environmental expenditures and e.g. competitiveness may only partly reflect regulatory impacts, but rather give a combination of this effect with the effect of environmental performance on competitiveness.

Furthermore, we incorporate the energy expenditures faced by the German manufacturing industry as an explanatory variable (source: German Federal Statistical Office). This measure comprises expenditures for combustibles, electricity, gas, and heating. Naturally, a large part of those energy expenditures are due to energy taxes levied by the German state, therefore partly reflecting regulatory pressure. On average, energy expenditures make up more than twice the environmental expenditures in our sample (875 Mio. Euro). Still and similarly to their environmental counterpart, they are very inhomogeneous over sectors and years, with a standard deviation of 1053. Finally, we employ the investment data on environmental protection as explanatory variable that stems from the German Federal Statistical Office as well. Those data incorporate investment that exclusively or at least predominantly provide for a less damaging environmental production impact. This encompasses investment in measures related to a "greener" production (additive investment and integrated investment), as well as in measures related to "greener" products. Analogously to the environmental expenditures, this measure does not only incorporate investment due to environmental regulation, but also voluntary "green" investment. Given the fact that environmental regulation in many cases may rather cause expenditures instead of investment, the environmental investment variable employed here may even more pronouncedly reflect environmental performance instead of regulatory pressure of the respective sector. Compared to environmental or even energy expenditures, environmental investment is small as far as its sample mean – which does not even exceed 70 Mio. Euro – is concerned (see Figure 1). There are furthermore huge differences in environmental investment especially over industries: While the sample minimum is 0.03, the maximum ranges above 540 Mio. Euro. The correlation analysis reveals that amongst the environment-related variables, environmental investment correlates most strongly (and positively) with GVA growth, with a correlation coefficient of 0.11 (see Table 2).

Figure 1 Selected Expenditure and Investment Figures of the German Manufacturing Industry



Source: German Federal Statistical Office and OECD

Besides these energy- and environment-related measures, we employ several control variables in our empirical analysis. These comprise especially other measures of expenditures and investment $x_{1...k}^{PROD}$. The inclusion of such variables is of particular importance in order to circumvent possible omitted variable biases in estimates of our parameters of major interest. This danger is due to the fact that correlation among different expenditure- as well as among different investment-measures is generally high. This also holds for our data set: Here, environmental investment, expenditures and energy expenditures correlate strongly with other investment and different cost measures (cp. Table 2). First, we consider investment in information and communication technologies (ICT), for which, however, only information from the OECD on its part on gross domestic product is available. Given the important role ICT investment is assigned to in recent research on competitiveness (cp. e.g. Jorgenson, 2001), we have approximated sectoral ICT investment based on this figure and the sectoral figures on gross value added from the German Federal Statistical Office. The descriptive statistics show that ICT investment is by far higher than environmental investment, with a sample mean of 465 Mio. Euro. Furthermore, we use other investment, i.e. the residual of overall investment (German Federal Statistical Office) given environmental and ICT investment. On the cost side, besides environmental and energy costs, especially gross salaries (i.e. labour costs) as the foremost cost variables of German industries (mean: 9490 Mio. Euro, source: German Federal Statistical Office) is included. What is more, we use social security contributions from the German Federal Statistical Office, i.e. the contribution of the employer to the pension fund, unemployment, health, accident, and long term care insurance. According to its magnitude (mean: 2330 Mio. Euro), those social security contributions range between gross salaries and energy expenditures. Moreover, expenditures for research and development (r&d) that are surveyed by the OECD have been included in our empirical approach. Given a sample mean of almost 1300 Mio. Euro per year, r&d expenditures is an important position on the sectors' cost side. In contrast to the other expenditure variables incorporated, r&d is ex ante supposed to be productive, spurring the development of new goods, new processes or new knowledge (Guellec and van Pottelsberghe, 2001).

Besides capital inputs such as expenditures and investment, human capital inputs are relevant for production within our theoretical framework. The quantity of labour measured with the hours worked (source: German Federal Statistical Office; sample mean: 2.7 Mio. hours per sector and year) are considered in our empirical framework. What is more, besides quantity, the quality of labour may play an important role for productivity growth (cp. e.g. Redding, 1996). Such quality of labour is captured in our model using the part of white-collar employees surveyed by the German Federal Statistical Office, which ranges between 23 and 69 per cent of total employees (mean: 38 per cent). Finally, we consider other non-input factors $o_{1...l}$, particularly competition, for productivity growth in our empirical analysis. On the one hand, competition is measured according to the Herfindahl-Hirschmann Index (HHI)[1]. On the other hand, we employ the turnover-rate in our analysis, giving the part of entering and exiting firms of the whole number of firms within an industry. Both variables have been included given the hypothesis that highly competitive industries may exhibit a higher performance than less competitive ones (Nalebuff and Stiglitz, 1983) and stem from databases of the German Federal Statistical Office.

IV. Methodology

It is a well known fact that the use of panel data has important advantages against pure time series data or cross-sectional data approaches. Besides the fact that naturally, panel data allow for the exploration of both time series and cross-sectional variation, its use is a common means in order to augment the number of observations that can be evaluated within an econometric analysis. Moreover, they generally allow for controlling for heterogeneity between the entities analyzed as well as for dynamics.[2]
Production growth may be characterized by both time and industry specific effects. While time – year – specific effects may stem from time-specific but overall economic demand factors such as business cycles, unobserved time-invariant heterogeneity over the sectors analyzed may e.g. be due to sector specific technologies. The respective setting for such case can be formulated as

(4) $$y_{i,t} - y_{i,t-1} = \beta' x_{i,t} + t_t + u_i + \varepsilon_{i,t}, \text{ with } \varepsilon_{i,t} \sim \left(0, \sigma^2\right),\ i = 1,2,...,N,\ t = 1,2,...,T,$$

where $y_{i,t}$ gives production for industry i in period t ($q_{i,t}$). In order to simplify the denotations, $x_{i,t}$ gives a vector of *all* current or lagged values of explanatory variables of the same industry, t_t is a time-specific effect common for all sectors, u_i is an unobserved industry-specific time-invariant effect, and $\varepsilon_{i,t}$ is a disturbance term that is independent and identically distributed across industries $i = 1,2,...,N$ and over time $t = 1,2,...,T$.
Here, the standard ordinary least squares (OLS) estimation of the parameter vector β without taking into account time- and industry-specific effects leads to at least inefficient results.[3] In this respect, we augment the model by dummy variables for both the time and industry dimension. The model corresponds to the Least Squares Dummy Variable estimator (LSDV; Fixed Effects or within estimator that only makes use of the time series variation within the industries) with both industry and time-specific effects. It can be shown that the use of dummy variables at the industry dimension in order to eliminate unobserved heterogeneity over industries u_i is equivalent to using mean-differentiated variables.
Still, a major problem may arise if state dependence is present in the dependent variable additional to the phenomenon of unobserved industry-specific time-invariant effects:

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[1] The HHI is calculated as $HHI_{i,t} = \frac{1000}{A_{n,t}^2} \times \sum_{k=1}^{n} a_{k,t}^2$, with $a_{k,t}$ being the market share of firm k within the respective sector i at time t, and $A_{n,t} = \sum_{k=1}^{n} a_{k,t}$.

[2] Excellent overviews on panel data estimation are given by Arellano (2003) and Bond (2002).

[3] In case that the individual effects correlate with the explanatory variables, OLS is even inconsistent. Still, it has to be mentioned that production growth as the first difference GVA already excludes time-invariant industry-specific effects that could be present in GVA.

(5) $y_{i,t} - y_{i,t-1} = \gamma(y_{i,t-1} - y_{i,t-2}) + \beta' x_{i,t} + t_t + u_i + \varepsilon_{i,t}$, with $\varepsilon_{i,t} \sim (0, \sigma^2)$, $i = 1,2,...,N$, $t = 1,2,...,T$.

Here, on the one hand, even the LSDV is inconsistent in case that a lagged dependent variable has to be used as an explanatory variable. This is due to the fact that this estimator is equivalent to a demeaned OLS. For panels where the number of time periods is small (as in our case with $T = 6$), mean deviating induces correlation between the lagged dependent variable and the error term leading to biased parameter estimates (so-called "Nickell-bias", Nickell, 1981). This bias does not even vanish in samples with a high number of industries. On the other hand, neglecting existing state dependence would again result in a misspecification of the empirical model. In an analysis of production growth as it is performed here, dynamic adjustment may be an important issue. Under conditions of unobserved heterogeneity *and* state dependence, an approach that accounts for both phenomena is needed. Given this, we on the one hand make use of a (Nickell) bias corrected LSDV estimator (LSDVC; Bruno, 2005). Here, the results from a consistent estimator such supply the initial values; a bootstrap variance-covariance matrix is calculated. On the other hand, instrumental variable technique has been applied in order to solve the problem described by Nickell. In this respect, Anderson and Hsiao (1981, 1982) propose a Two Stage Least Squares estimator for the first-differenced *AR(1)* panel data model (2 SLS DIF; formulated with time effects here):

(6) $y_{i,t} - y_{i,t-1} = \beta'(x_{i,t} - x_{i,t-1}) + \gamma(y_{i,t-1} - y_{i,t-2}) + t_t + (\varepsilon_{i,t} - \varepsilon_{i,t-1})$, with $\varepsilon_{i,t} \sim (0, \sigma^2)$, $i = 1,2,...,N$, $t = 1,2,...,T$.

In contrast to industry dummies (or, alternatively, deviations from group means) used by the LSDV, first differences eliminate unobserved sector heterogeneity without introducing all realizations of the disturbance into the error term of the transformed equation for period *t* (in this setting, we restrict ourselves to the consideration of industry-specific time-invariant effects on GVA in levels). This allows for consistent parameter estimates when lagged levels $y_{i,t-2}$ are uncorrelated with $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$ and are used as an instrumental variable for equation (6). The parameter γ gives the effect of the lagged dependent variable while the parameter vector β measures the effect of the other explanatory variables. For endogenous *x*'s as well, lagged levels besides other exogenous variables are available as instruments. Environmental, ICT and other investment, environmental, energy, r&d expenditures, social security contributions, gross salaries and hours worked at the sectoral level may not only affect production growth, but may also be caused by the magnitude of production growth of the same period. Possible reverse causality problems may be avoided using instrumental variable techniques. If the panel does have more than three time series observations (as in our case), the model is overidentified as there are even more lagged levels available as instruments than only $y_{i,t-2}$. In such setting, it is beneficial to make use of the dynamic panel data estimator (GMM DIF) developed by Arellano and Bond (1991). The GMM DIF is based on the same first-difference transformation as shown in equation (6). However, asymptotically efficient parameter estimates are received from a Generalized Method of Moments (GMM) framework making use of a weighting procedure for the instrument matrix. This approach as well allows for the instrumentation of endogenous *x*'s. However, the properties of the GMM DIF hinge on the number on individuals (industries) analyzed (cp. e.g. Kiviet, 1995). According to Bruno's (2005) Monte Carlo experiments, the LSDVC should be preferred to the GMM DIF for small samples (in our case $N = 23$).

In our empirical analysis, we apply all panel techniques presented above. This underpins the choice of the "preferred" estimator, serves as an important robustness check and renders the analysis as transparent as possible.

V. Results

Given the methodological background, we apply the OLS, LSDV, LSDVC, as well as the Arellano-Bond dynamic panel data estimators to our German industry panel of production growth. The multitude of estimation techniques may serve as an important robustness check of the results. For all estimation technique, we report one specification including all explanatory variables, and another one including only the environment- and energy-related variables plus all other explanatory variables that show statistical significance at a conventional level.

In industry panel settings only little confidence is given to simple OLS estimation results given the important sources of bias outlined in the proceeding chapter. Given the fact that production growth as the dependent variable of our setting is already the first difference of overall production (GVA), an OLS approach is less unrealistic as sector-specific differences in GVA itself are, if present, eliminated in taking first differences. However, the standard estimation procedure at least in research related to the approach followed in this paper is the application of a LSDV estimator that controls for both industry and time effects.[4] Given the fact that lagged production growth as an explanatory variable significantly enters into the estimated equation using both the LSDVC and the GMM DIF, a dynamic panel approach seems to be more adequate for our setting. In such case, 2SLS DIF yields unbiased parameter estimates, but in contrast to the GMM DIF (we apply) it is not asymptotically efficient given our time series dimension with $T = 6$. For this estimator, none of the diagnostic tests (on first- and second order serial correlation in the residuals as well as the Sargan test on overidentifying restrictions) indicates misspecification. Furthermore, in the GMM DIF we instrument all investment, expenditure and employment variables[5] in order to eliminate possible reverse causality problems from our empirical approach. Lags of both first and second order have to be applied as instruments, according to the specification tests of the first stage regressions.[6] However, in contrast to the LSDVC, the properties of GMM DIF are unknown given the small $N = 23$.

Concerning the explanatory variables of our major interest, our results show robustness over all empirical approaches used. For the expenditure figures that are related to energy and the environment, we find only weak evidence for a contribution to production growth of the respective sector. This is especially the case for energy expenditures: OLS, LSDV as well as dynamic panel data regressions using the LSDVC and GMM DIF (Table 3) consistently show very small values for the estimated coefficient of energy expenditures that, with one exemption for OLS, do not significantly differ from zero. Given this, our estimation results do not suggest a significant impact of energy expenditures on production growth in the German manufacturing industry.

The case of environmental expenditures is different to a certain extent although our estimations predominantly give very small coefficients that partly lack significance. However, especially the LSDV as well as the LSDVC give significant and positive impacts. The –

[4] The results of an F-Test for industry-specific effects in the LSDV do not suggest, however, that such effects (in contrast to time-specific effects) are already eliminated by taking first differences of GVA in order to generate GVA growth (F-statistic of 0.79 and 1.07, respectively). Therefore, both OLS with GVA growth as dependent variable and the GMM DIF should not suffer from specification problems due to omitted industry dummy variables.

[5] I.e. the variables environmental, ICT and other investment, environmental, energy, r&d, social security contributions, gross salaries and hours worked.

[6] For the respective tests of the central first stage regression results, please refer to Table 4 in the appendix.

statistically significant – difference between these LSDV/LSDVC results and the results from the GMM DIF that do not suggest statistical significance of the estimated environmental expenditures parameter could be based on endogeneity / reverse causality of the environmental expenditures in our setting. If sectors with higher production growth consequently augment their environmental expenditures, the LSDV and LSDVC (besides OLS) in contrast to the GMM DIF would yield upward biased parameter estimates for this variable. As our estimation results fit to such explanation, endogeneity of the environmental expenditures is plausible and the GMM DIF seems to give the more credible results in this respect.

Environmental investment, in contrast, is shown to be the only variable related to environment- and energy-related investment and expenditure activity that robustly shows positive implications for production growth given the analysis of our German manufacturing industry dataset. Amongst all estimation techniques, there is a positive – although not very strong –and statistically significant impact of environmental investment on production growth. In contrast to environmental expenditures, this effect does not seem to be endogenously driven by production growth itself, as GMM DIF results do not significantly differ from the results of other estimation techniques used that do not control for such possible endogeneity.

Analogously to the existing literature, we find a positive impact of ICT investment on production growth. According to our results, this effect is much – and significantly from a statistical point of view – stronger than for its environmental counterpart. Irrespective of simple OLS, such strong effect is very robust over all empirical approaches. As far as other investment is concerned, however, we receive quite robust empirical evidence for a negative, although small effect on production growth.

For expenditures that are not related to energy and the environment – such as R&D expenditures, social security contributions, and gross salaries – we do not find empirical evidence for a statistically significant impact on production growth. The same holds true for the Herfindahl-Hirschmann Index (HHI) and the turnover-rate, both employed as control variables in order to control for a possible impact of competition. In contrast, and analogously to the theoretical framework, the factor labour positively contributes to production growth at least according to the GMM DIF results. Here, the coefficients of both hours worked and quality of labour significantly enter into the estimated equation.

VI. Conclusions

In this paper, we analyze the effect of environment- and energy-related expenditure and investment measures on production growth. For this purpose, we use a panel dataset of the German manufacturing industry between 1996 and 2002. Our empirical analysis is based on a production function framework. We distinguish, as far as the capital is concerned, between different kinds of expenditures and investment, focussing on environmental investment as well as on environmental and energy expenditures.

Our estimations show only week evidence for a significant impact of both environmental and energy expenditures on production growth of German sectors. In contrast, environmental investment exhibits a positive impact that is stronger than the – inexistent – effect of conventional (“other”) investment, but substantially lower than ICT investment. Our results are based on the application of modern panel data techniques that especially allow for lagged adjustment of the dependent variable. Furthermore, we take into account possible endogeneity of the explanatory variables making use of their lagged values as instrumental variables. This proves to be useful especially concerning the contribution of environmental expenditures for production growth: Our estimation results suggest that environmental expenditures are endogenous for our setting; techniques not taking into account such endogeneity indicate a positive effect that in reality may stem from a – reverse – positive effect of production growth on such expenditures.

Our result that environmental expenditures do not affect production (growth) of the respective sector of the German manufacturing industry is largely in line with the existing literature, e.g. with Shadbegian and Gray (2005). If we abstain from the possible explanation of misreporting, our results suggest that environmental expenditures are, economically speaking, not productive at all. The same holds true for energy expenditures. In contrast, the positive impact of environmental investment suggests that environmentally oriented activities of firms or sectors – in our case of the German manufacturing industries – may be productive in contributing to output. Such finding, however, is no clear support of the Porter hypothesis, stating that environmental regulation spurs competitiveness of the regulated countries. Environmental investment may not necessarily be driven by regulation, but is in any case an indicator of environmental performance of the respective entity. In this respect, our results indicate that the sectors that increase their environmental performance via investment instead of expenditure activities profit in economic terms via productivity growth. Although our analysis is no direct evaluation of economic or environmental policy, our empirical examination does contribute to the assessment of economic consequences of environmental policy. In this light, we find that environmental regulation does not necessarily slow down production growth. In order to be compatible with economic goals such as the stimulation of productivity, however, it should encourage investment instead of purely creating costs. According to economic theory, this is the case for market based policy instruments that provide more incentives for investment and technological change than command and control measures (Requate, 2005).

In order to complement our findings, it would be interesting to analyse whether these results also hold for countries other than Germany. Furthermore, an analysis at the micro level could be very promising. No data on environment- and energy-related investment and expenditure activities at the firm instead of industry level was available to us. The exploitation of such dataset could offer new insights into the research question tackled in this paper.

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Appendix

Table 1 Descriptive Statistics Dataset

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
Environmental Expenditures	399.92	630.59	6.67	3450.28	161
Environmental Investment	66.65	92.86	0.03	544.02	161
Energy Expenditures	874.43	1052.88	24.36	4101.92	161
ICT Investment	464.58	427.58	6.26	1916.18	161
Other Investment	2058.89	2204.23	56.47	11143.12	161
R&D Expenditures	1288.44	2194.17	2.82	10823.03	161
Gross Salaries	9491.03	9707.89	183.73	37619.31	161
Social Security Contributions	2328.93	2425.38	41.95	10508.29	161
HHI	50.01	72.21	1.44	266.48	161
Turnover	0.18	0.11	0.05	0.92	161
Hours Worked	267189.70	252448.10	10151.00	943605.00	161
Quality of Labor	0.38	0.12	0.23	0.69	161
Gross Value Added	17046.89	15316.99	490.00	57510.00	161
Gross Value Added Growth	223.55	1527.92	-4600.00	8060.00	138

Note: All monetary data is given in Mio. Euro and is measured in 1995 prices.

Table 2 Correlations

	Environ-mental Expenditures	Environ-mental Investment	Energy Expenditures	ICT Investment	Other Investment	R&D Spending	Gross Salaries	Social Sec. Contributions	HHI	Turnover	Hours Worked	Quality of Labour	Gross Value Added	Gross Value Added Growth
Environmental Expenditures	1.00													
Environmental Investment	0.94	1.00												
Energy Expenditures	0.87	0.79	1.00											
ICT Investment	0.49	0.54	0.50	1.00										
Other Investment	0.59	0.61	0.63	0.83	1.00									
R&D Spending	0.46	0.47	0.38	0.65	0.84	1.00								
Gross Salaries	0.39	0.40	0.48	0.91	0.88	0.72	1.00							
Social Security Contributions	0.45	0.46	0.52	0.91	0.91	0.77	0.99	1.00						
HHI	-0.38	-0.05	-0.25	0.03	-0.09	0.05	-0.12	-0.09	1.00					
Turnover	-0.22	-0.12	-0.20	-0.17	-0.20	-0.15	-0.16	-0.16	-0.08	1.00				
Hours Worked	0.92	0.31	0.47	0.83	0.81	0.54	0.94	0.91	-0.25	-0.17	1.00			
Quality of Labour	0.13	0.10	-0.14	0.09	-0.07	0.10	-0.06	-0.05	0.41	-0.09	-0.27	1.00		
Gross Value Added	0.68	0.68	0.82	0.87	0.95	0.75	0.98	0.98	-0.38	-0.22	0.92	0.05	1.00	
Gross Value Added Growth	0.07	0.11	-0.06	-0.04	-0.10	-0.02	-0.15	-0.13	0.23	0.13	-0.19	0.09	-0.07	1.00

Notes: 138 observations. All variables are in logs.

Table 3 Estimation Results

Gross Value Added Growth	**OLS**	**OLS**	**LSDV with time (year) dummies**	**LSDV with time (year) dummies**	**LSDVC with time (year) dummies**	**LSDVC with time (year) dummies**	**GMM DIF with time (year) dummies**	**GMM DIF with time (year) dummies**
Environmental Expenditures	0.04 (0.03)	0.06 (0.05)	0.23** (0.11)	0.31*** (0.09)	0.20 (0.13)	0.24** (0.11)	0.00 (0.10)	0.02 (0.12)
Environmental Investment	0.06 (0.04)	0.03** (0.02)	0.07* (0.04)	0.07** (0.03)	0.05 (0.04)	0.05* (0.03)	0.06** (0.02)	0.06** (0.03)
Energy Expenditures	-0.04 (0.03)	-0.11** (0.05)	-0.02 (0.12)	-0.07 (0.11)	0.03 (0.14)	0.01 (0.12)	0.05 (0.08)	0.03 (0.08)
ICT Investment	0.12 (0.08)	-	0.52** (0.24)	-	1.08*** (0.29)	1.08*** (0.27)	1.36*** (0.37)	1.29*** (0.33)
Other Investment	-0.12 (0.12)	-	-0.20** (0.08)	-0.18*** (0.07)	-0.20** (0.09)	-0.16** (0.08)	-0.23*** (0.08)	-0.23* (0.09)
R&D Expenditures	0.02** (0.01)	-	-0.00 (0.10)	-	-0.01 (0.11)	-	-	-
Gross Salaries	0.56* (0.31)	-	-0.22 (0.57)	-	-0.57 (0.73)	-1.02** (0.50)	-0.42 (0.43)	-
Social Security Contributions	-0.50* (0.29)	-	-0.59* (0.36)	-	-0.49 (0.37)	-	-0.55 (0.45)	-0.63* (0.37)
HHI	0.02 (0.01)	-	0.06 (0.09)	-	-0.01 (0.09)	-	0.08 (0.08)	-
Turnover	0.06* (0.03)	-	0.10 (0.12)	-	-67.48** (31.55)	-	0.02 (0.09)	-
Hours Worked	-0.04 (0.07)	-	0.38 (0.46)	-	-0.07 (0.15)	-	0.66** (0.30)	0.42* (0.22)
Quality of Labour	-0.04 (0.07)	-	0.49 (0.70)	-	0.37 (0.73)	-	0.91** (0.44)	0.69* (0.38)
Gross Value Added Growth (t-1)	-	-	-	-	-0.43*** (0.08)	-0.45*** (0.08)	0.21** (0.11)	0.21** (0.10)
Constant Term	-0.02 (0.51)	0.26*** (0.08)	-0.56 (3.25)	-0.08 (0.75)	-	-	1.27 (1.88)	1.59 (2.03)
No. Obs.	**138**	**138**	**138**	**138**	**115**	**115**	**115**	**115**
R-sq.	**0.24**	**0.22**	**0.31**	**0.25**	**-**	**-**	**-**	**-**
F-Test	**1.51**	**2.40****	**2.64*****	**4.34*****	**-**	**-**	**-**	**-**
Wald-Test	**-**	**-**	**-**	**-**	**-**	**-**	**15132.94*****	**2631.96*****
m1	**-1.35**	**-1.13**	**-**	**-**	**-**	**-**	**-2.16****	**-2.16****
m2	**-0.67**	**-0.70**	**-**	**-**	**-**	**-**	**-0.49**	**0.01**
Sargan	**-**	**-**	**-**	**-**	**-**	**-**	**91.85**	**94.13**

Notes: Huber-White robust standard errors in brackets (std. errors of LSDVC based on bootstrapping procedure). *, ** and *** show significance at the 10%-, 5%-, and 1%-level, respectively. All estimations include time (year) dummies in the regression equations (parameter estimates not reported). m1 and m2 show the z-statistics for first- and second-order serial correlation, respectively. Sargan refers to the Sargan test for overidentifying restrictions. For GMM DIF, Hours Worked, Quality of Labour, Environmental Expenditures, Environmental Investment, ICT Investment, Other Investment, Gross Salaries, Social Security Contributions, and Energy Expenditures are treated instrumented with lagged levels.

Table 4 First Stage Regressions

Dep. Var.	**Environmental Expenditures**	**Environmental Investment**	**Energy Expenditures**
F-Test	3.37***	2.68***	3.46***

Notes: Regressions using the first, or first and second lags of Hours Worked, Quality of Labour, Environmental Expenditures, Environmental Investment, ICT Investment, R&D Spending, Other Investment, Gross Salaries, Social Security Contributions, and Energy Expenditures (besides the regular alternative explanatory variables of the second stage regressions) as explanatory variables. *, ** and *** show significance at the 10%-, 5%-, and 1%-level, respectively. The respective complete first stage regression results for all instrumented variables are available on request from the authors.