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Spillover from private energy research

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A B S T R A C T

Technological progress is generally considered a key element in the move towards a less carbon-intensive energy use, and therefore public energy research expenditure has increased in many countries. The purpose of this paper is to investigate whether relatively high subsidies to private energy research can be justified by higher external knowledge spillovers from private energy research compared to knowledge spillovers from other private research. Estimation of spillover effects is carried out using an unbalanced panel of more than a thousand Danish private companies observed over the period 2000–2007. We reject that there are higher spillovers from private energy research compared to other types of private research. Instead the results suggest that the external knowledge spillovers from energy research may be lower than for other types of private research. This implies that high subsidies earmarked for private energy research should not be an element in a first best policy to reduce CO_2 emissions.

1. Introduction

Technological progress is generally considered an important element in the move to a more sustainable and less carbon-intensive use of energy, and proposals to reduce carbon emissions often include increased funding for energy research. In many European countries public spending on energy research accounts for an increasing share of public research expenditure. As noted by Popp and Newell (2009), this raises two concerns. First, research policies are likely to have little effect if they are not accompanied by policies requiring emission reductions, as this will often be a condition for the adoption of new sustainable and less carbon intensive technologies. Second, dramatic increases in energy research may

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come at a cost as these research efforts may draw away research from other productive sectors. Popp and Newell (2009) addressed the second concern by investigating whether energy research crowds out other types of research. In this paper we look at a closely related issue by asking whether there is a higher external benefit due to knowledge spillovers from private energy research as compared with other types of private research. If this is the case, it would justify relatively higher subsidies to private energy research than to other types of private research. On the other hand, if the external benefit of energy research is relatively low, then high subsidies to energy research that crowds out other more beneficial research may reduce growth.[1]

In recent years the interaction between technological change, regulation and CO_2-emissions has received much attention. It has been relatively well documented that higher prices of fossil fuels or regulation of emissions will lead to "induced" technological change. This means that a tax on CO_2-emissions will encourage development of sustainable and less carbon intensive energy use, see e.g. Newell et al. (1999), Popp (2002) and Johnstone et al. (2010). According to theory there are two main market failures associated with the development of technologies to support sustainable and less carbon intensive energy use. The first is the environmental market failure, i.e. consumers and producers do not fully take into account the negative environmental effects of their emissions. Without an emission tax (or similar regulation) emissions will be higher than optimal. The second market failure is that private firms do not obtain the full benefit of their investments in research as other firms may also benefit from the research due to knowledge spillovers. This yields a wedge between the private and the social return to private research, and without regulation, too little private research will be carried out, see Popp et al. (2009) and Jaffe et al. (2005a). First best policies to correct for these two market failures will require two instruments: An emission tax (or equivalent regulation) combined with subsidies to private energy research reflecting the size of the external spillovers from the particular type of private research. The intuition behind the first best combination of policies is fairly straightforward. With an optimal emissions tax the consumers and producers are provided with an incentive to adopt sustainable and less carbon intensive technologies and this also yields an incentive to potential investors in energy research. When "prices are right" the only market failure is the positive external knowledge spillovers from research, which applies to energy research as well as other types of private research.

In a growth model with a 'dirty' and a 'clean' sector Acemoglu et al. (2012) also finds that an optimal policy involves both a CO_2-tax and research subsidies in order to provide correct incentives for long run technological change. However, the research subsidies in their two sector model should only been given to the clean technologies in order to direct innovation towards development of the clean technology. In their model technology in the clean sector is initially assumed to be at a relatively low state of development compared to the dirty sector. This yields the result that without special incentives no research at all is carried out in the clean technology sector. Their results can perhaps be characterised as an "infant technology" argument, which suggest that it is necessary to subsidize research in new (beneficial) technologies.

Some studies have compared the relative efficiency of a CO_2-tax and research subsidies, when both instruments are not available. Generally, it seems that a CO_2-tax is a better (second best) instrument than a research subsidy, see Schneider and Goulder (1997), Popp (2006) and Fischer and Newell (2008). This suggests that research subsidies are a rather poor substitute for a CO_2-tax (or equivalent CO_2-regulation). The first of these studies also demonstrates that policies to address knowledge spillovers are more effective if they address all knowledge spillovers, rather than focusing only on energy research. Still, relatively high subsidies to private energy research are justified in a first best policy setting if there are higher spillover effects from energy research compared with other types of private research.

In this paper we use a panel containing information on research activities and value added for more than a thousand Danish firms from 2000 to 2007 to test whether there are higher spillover effects from

[1] The authors are grateful for comments, suggestions and help from two anonymous referee, the chairmen of the Danish Economic Councils, Lars Haagen Petersen, John Smidt, Søren Arnberg and Carter Bloch. However, any errors are solely the responsibility of the authors.

energy research compared to other types of research. Spillover effects are identified using the direct production function approach, where a spillover knowledge pool enters directly into the production function. We reject that there are higher spillovers from private energy research as compared to other types of private research. Actually, the analysis suggests that external spillover effects of energy research may be lower than for other types of private research.

Our study contributes to the literature in different ways. As already noted, a number of empirical studies regarding energy technology focus on the determinants of technological change by investigating the impact of changes in relative prices and regulation *on* the research level or innovation rate, see e.g. Newell et al. (1999), Popp (2002) and Johnstone et al. (2010). This study focuses instead on the impact *of* the energy research performed, as it investigates whether there are higher external spillovers from private energy research compared to other private research. To the best of our knowledge there are no previous empirical studies that address this issue. As noted above, in a first best setting, where a CO_2-tax is available, the size of external benefits due to knowledge spillovers should determine the level of subsidies to private energy research.

The study by Popp and Newell (2009) looks at the potential opportunity costs of increased energy research by investigating whether increased energy research crowds out other research or leads to an overall increase in total research. In this study we look at another aspect of the opportunity costs of increased energy research by investigating the size of the external benefits of the energy research. Patent citation data were used by Popp and Newell (2009) to calculate indicators of the social value of energy research. Although citation based indicators may be useful, they also have drawbacks. First, they do not capture the social value of research that is not patented. Second, it may be difficult to compare the average number of citations for patents within different technological fields, because the number of citations to a patent within a certain technology is likely to be higher if a lot of research is subsequently carried out within that field. Thus, if funding flows to energy research, the average number of citations to older energy patents will tend to go up, see OECD (2009).[2] The approach used in this paper for measuring the social value of private energy research is to measure the impact of a firm's research on other companies' productivity using methods typically employed to identify spillovers, see Hall et al. (2009).

The current study also relates to recent work by Braun et al. (2010), which also contains analyses on knowledge spillovers and energy. However, while their focus is on the effect of spillovers *on* the technological progress of two sustainable energy technologies (wind and solar energy), the focus in this paper is on the knowledge spillovers *of* energy research compared to the spillovers of other types of research. Braun et al. find that knowledge spillovers are important, but their results also suggest that spillovers are predominantly a domestic phenomenon, as international spillovers are found to have a negligible influence. Due to the nature of the data our study focuses exclusively on domestic spillovers.

The following section will briefly describe the development in Danish energy research compared to other countries. In Section 3 the empirical model for identifying knowledge spillovers is presented. The data used for the analysis are described in Section 4, while results are presented in Section 5. Section 6 concludes.

2. Energy and climate change mitigation research in Denmark

There has been a large increase in the share of public research expenditure allocated to energy research in Denmark as well as in several other countries, see Fig. 1. A large part of the increase in Danish public energy research expenditure has been used to subsidize energy research in the private sector.

In the empirical analysis presented it is not possible to distinguish between energy research in low CO_2 technologies and 'dirty' energy research. However, several things suggest that research in low CO_2 technologies is relatively important in Denmark. Production of wind power and

[2] It should be noted that Popp and Newell (2009) not only look at number of citations, but also a measure of generality of the patent (a patent cited by a larger range of patents in different technological areas is considered more general).

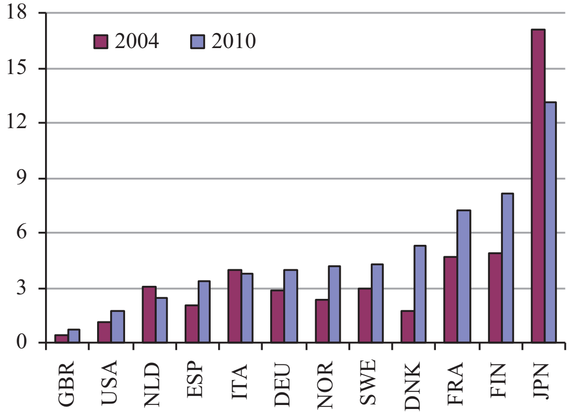

Fig. 1. Share of public research budget allocated to energy research.
Note: The figure shows the share of total government budget on research and development allocated to energy research. The most recent observation for the United Kingdom, Germany, Sweden and Japan is 2009. For the United States the most recent observation is 2008.
Source: Eurostat.

technologies to increase energy efficiency started fairly early in Denmark, probably due to ambitious CO_2 policies including high CO_2 taxation. This has resulted in a relatively high share of sustainable energy production, e.g. 29 percent of Danish electricity production was generated from renewable energy sources (mainly wind power) in 2008. It seems likely that this has directed energy research towards energy saving and sustainable energy use. In addition, the Danish public energy research programmes have focussed on supporting energy savings and sustainable energy. Finally, it also appears that Danish patent applications are relatively specialized in low CO_2 technologies and that this specialization has increased since the mid-1990s (Fig. 2). In the period 2006–2008, Denmark had one of the highest shares of climate change mitigation patents in patent applications filed with the European Patent Office (EPO).[3] An analysis presented in Danish Economic Councils (2011), shows that Danish climate change mitigation patents are generally cited more – both compared to other Danish patents and compared to other countries' climate change mitigation patents. This indicates that Danish climate change mitigation patents are of a relatively high quality.

Summing up, although the data used for estimating spillover effects does not specify the type of energy research carried out by the Danish firms, it seems likely that a large share of the observed private energy research is directed towards research in low CO_2 technologies.

3. Modelling spillover effects

The point of departure in our analysis of the social returns to energy research is the production function approach typically used when calculating the returns to research, see Hall et al. (2009) and Hall and Mairesse (1995):

$$VA_{it} = Ae^{\lambda t}K_{i,t-1}^{\alpha}L_{it}^{\beta}R_{i,t-1}^{\gamma}S_{i,t-1}^{\eta}e^{\varepsilon_{it}} \quad (1)$$

Here i denote firm i, and t is the year. VA is value added (our measure of output), A is a constant, λ is a measure of exogenous technological change, K is capital and L is labour. R is the stock of knowledge capital generated from the firm's own research, while S (spillover) measures the external stock of

[3] The picture is much the same if specialisation is determined from applications filed under the international Patent Cooperation Treaty (PCT).

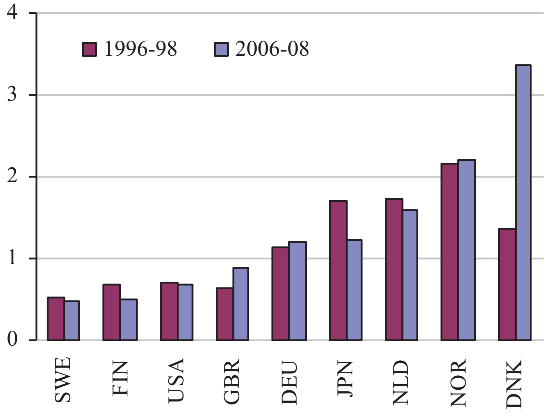

Fig. 2. Specialization in patenting of climate change mitigation technology.
Note: The figure shows patent applications filed with the EPO. Specialization indicates the relationship between the share of climate change mitigation technology patents in the country's total number of patent applications and the share of climate change mitigation patents in the total number of patent applications to the EPO.
Source: OECD, patent citations database and REGPAT database, June 2010, and Danish Economic Councils (2011).

knowledge capital generated by spillovers from other firms' knowledge. More specifically, S_i is calculated as a weighted sum of the knowledge capital of all other firms than i. The precise calculation of S_i (i.e. the choice of weights) will be discussed later. The coefficients α, β, γ and η are output elasticities with respect to K, L, R and S.

In most of the previous empirical literature the social return to research is estimated without distinguishing between different types of research, see Hall et al. (2009). The purpose of this paper is to test for differences in the private return and the spillovers from energy research compared to other types of private research. If there are no differences there is no special reason to provide higher subsidies to private energy research than to other types of research.

In order to identify a different effect of energy research on the social return to research two terms are added to Eq. (1). They measure respectively (one plus) the share of the firm's own knowledge capital that derives from energy research (R^E), and the share of the firm's external knowledge capital that derives from external energy research (S^E):

$$VA_{it} = Ae^{\lambda t}K_{i,t-1}^{\alpha}L_{it}^{\beta}(R_{i,t-1})^{\gamma}\left(\frac{R_{i,t-1}^{E}+R_{i,t-1}}{R_{i,t-1}}\right)^{\varphi}(S_{i,t-1})^{\eta}\left(\frac{S_{i,t-1}^{E}+S_{i,t-1}}{S_{i,t-1}}\right)^{\mu}e^{\varepsilon_{it}} \quad (2)$$

The value of $(S^E+S)/S$ is between 1 (no contribution from energy research to the external knowledge capital) and 2 (all external knowledge capital derives from energy research). If $S^E=0$ or $\mu=0$ then $((S^E+S)/S)^{\mu}=1$. Also, if both $\mu=0$ and $\varphi=0$, Eq. (2) is reduced to Eq. (1).

If $\mu>0$, there is an additional positive effect from external knowledge capital arising from energy research. If $\mu<0$, then energy research has lower positive spillovers compared with other research contributing to the external knowledge capital. The fraction $(R^E+R)/R$ has a similar interpretation with respect to own knowledge capital.

Note that the coefficients μ and φ have a different interpretation than the output elasticities. The interpretation of μ and φ can best be illustrated by an example. Assume that $\mu=1$ and S^E represents 10 percent of the overall external knowledge capital. In this case $((S_{i,t-1}^{E}+S_{i,t-1})/S_{i,t-1})^{\mu}=1,1^{1}$, which means that spillovers derived from energy research add 10 percent to the overall effect of the external knowledge capital on the productivity of the firms.

The production function is estimated after a standard logarithm transformation:

$$\ln(VA_{it}) = a_I + \lambda_t + \alpha \ln K_{i,t-1} + \beta \ln L_{it} + \gamma \ln(R_{i,t-1}) + \varphi \ln\left(\frac{R^E_{i,t-1} + R_{i,t-1}}{R_{i,t-1}}\right) + \eta \ln(S_{i,t-1}) + \mu \ln\left(\frac{S^E_{i,t-1} + S_{i,t-1}}{S_{i,t-1}}\right) + \varepsilon_{it} \tag{3}$$

Here the exogenous technological change (not derived from own and external knowledge capital) is specified as annual dummies (λ_t).[4] The constant term a_I is allowed to vary for different industries in the economy, i.e. industry-level fixed effects. A more flexible variant of Eq. (3) is to allow the constant term to be specific for each firm in the sample (a_i). In this "firm fixed effects" variant, the firm-specific constants control for unobserved time invariant heterogeneity between firms.

One of the goals of energy research is to enhance the efficiency of the energy input, so that less energy is required in the production process. It may therefore appear surprising that energy input does not appear directly in the estimated production function (2). However, energy input (E) is included in the production function even though it does not appear explicitly. Note that the dependent variable (value added) in the estimated production function is given by $VA = P - M - E$ (by definition), where P is output and M is non-energy input. If a high level of energy research (high R^E or S^E) only has an effect on the production function by reducing E, it will also increase value added, which is the dependent variable in Eq. (2). Thus, even if the only effect of energy research is to reduce E, this will have a positive effect on productivity that is captured by the estimated production function.

The production function in Eq. (2) is one of several possible specifications to investigate whether the spillover effect of private energy research is different from the spillover effect of private research in general. As a supplement to Eq. (2) two other specifications of the production function are estimated as robustness checks:

In the first alternative specification energy input (E) is included explicitly as a factor of production.

$$VA_{it} + E_{it} = Ae^{\lambda t} K^{\alpha}_{i,t-1} L^{\beta}_{it} E^{\nu}_{it} (R_{i,t-1})^{\gamma} \left(\frac{R^E_{i,t-1} + R_{i,t-1}}{R_{i,t-1}}\right)^{\varphi} (S_{i,t-1})^{\eta} \left(\frac{S^E_{i,t-1} + S_{i,t-1}}{S_{i,t-1}}\right)^{\mu} e^{\varepsilon_{it}} \tag{4a}$$

Note that in Eq. (4a) we have added energy input to the left-side dependent variable. It would have been strange to deduct energy input from production (together with other materials) to form the dependent variable (VA) and then include energy input as a factor of production.

In the second alternative specification the overall external knowledge capital is split into two separate terms; spillover derived from energy research, S^E, and spillover derived from other research, S^O, where $S = S^E + S^O$.

$$Y_{it} = Ae^{\lambda t} K^{\alpha}_{i,t-1} L^{\beta}_{it} R^{\gamma}_{i,t-1} (S^O_{i,t-1})^{\eta} (S^E_{i,t-1})^{\mu} e^{\varepsilon_{it}} \tag{4b}$$

A potential drawback of this specification is that it does not, in practice, allow different production elasticities for own energy research capital (R).[5] In this respect Eq. (4b) is more restrictive than Eqs. (2) and (4a).

3.1. Correcting for different educational levels of labour and double counting

Our measure of L is corrected both for "double counting" and for differences in the educational level of the firms' employees, which would otherwise cause potential biases in the estimation of the output elasticities, see Hall et al. (2009).

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[4] In a small open economy such as Denmark, λ_t may capture technological progress in the form of spillovers from research in other countries (the annual dummies may also control for other unobserved time variant effects).

[5] In principle R may be split into two parts (R^E and R^O) in Eq. (4b). However, since only a small share of the firms perform both energy research and other research, such a version of Eq. (4b) can only be estimated using a small share of the observations.

The correction for double counting is carried out by deducting the number of employees engaged in research from the overall number of employees in the firm.

The correction for differences in educational levels between firms is carried out by calculating a weighted measure of the labour force, where the average wage levels for a given type of education are used as weights. The intuition behind this approach is that the higher wage of an employee with a high level of education must reflect higher productivity, see Timmer et al. (2007). More precisely, the correction for differences in educational level is calculated as:

$$L_{it} = \bar{L}_{i0t} + \sum_{f=1}^{F-1} \frac{w_{flt}}{w_{0lt}} \bar{L}_{ift} \tag{5}$$

where $\bar{L}_{ift}$ is the number of employees with educational level f in firm i in year t. The reference educational level, $\bar{L}_{i0t}$, is employees without a formal education, while w_{flt} is the average wage of employees with educational level f in industry I in year t.

Previous research suggests that it may be important to control for differences in the levels of education of the employees, see Hall et al. (2009) for a summary of three French studies on this issue. Firms with a high level of research may, in general, be firms that also have a large proportion of highly educated employees working outside the research department. If this is not accounted for, the private return to research is likely to be upward biased, because the output elasticity to own knowledge capital is likely to capture the (unaccounted for) effect on productivity of highly educated employees.

3.2. Measurement of own and external stock of knowledge (spillover)

Firms' investments in research (IR) are assumed to increase their stock of knowledge. The knowledge capital of a company can, therefore, be calculated as a function of previous investments in research using the so called "perpetual inventory method", see e.g. Hall et al. (2009):

$$R_{it} = (1-\delta)R_{i,t-1} + IR_{it} \tag{6}$$

Likewise, the stock of knowledge derived from energy research is given as:

$$R^E_{it} = (1-\delta)R^E_{i,t-1} + IR^E_{it} \tag{7}$$

Here R_{it} is the knowledge capital of firm i at the end of year t, while δ is the depreciation rate of knowledge. Following previous studies it is assumed that the depreciation rate is 15 percent.[6] The stock of knowledge in the first year the firm is observed in the data (1995 or later, see Section 4) can be calculated from their investments in research in that year subject to an assumption that the firm has had a constant real growth rate (g) in its research investments up to that year:

$$\begin{aligned} R_{i,95} &= \frac{IR_{i,95}}{g+\delta} \\ R^E_{i,95} &= \frac{IR^E_{i,95}}{g+\delta} \end{aligned} \tag{8}$$

The growth rate g is set to 7 percent, which is equal to the average real growth rate of Danish research expenditure in the private sector from 1970 to 2001.

The external (spillover) knowledge capital is calculated as the weighted sum of the knowledge capital in other firms, where the weights are given as a_{ji}:

$$S_{it} = \sum_{j \neq i} a_{ji} R_{jt} \tag{9}$$

[6] The size of the depreciation rate does not have a large effect on the estimated output elasticities of knowledge, see Hall et al. (2009).

The external knowledge capital derived from energy research is calculated in the same way (using the same weights):

$$S_{it}^{E} = \sum_{j \neq i} a_{ji} R_{jt}^{E} \tag{10}$$

In previous studies of spillover effects a number of different weight matrices have been applied, see Hall et al. (2009) and Griliches (1992).[7] Here we present results using three different weight matrices based on:

a. Geographical proximity.
b. Proximity in research profile.
c. A combination of the above.

Regarding a: Here it is assumed that there are knowledge spillovers between firms located in the same region, but not between firms located in different regions. A number of studies suggest that spillovers are larger for companies located close to each other, see. e.g. Autant-Bernard et al. (2007), Jaffe et al. (1993) and Jaffe et al. (2005b). Thus, it is assumed that $a_{ij} = 1$ between all firms located in the same of the five different regions in Denmark, while $a_{ij} = 0$ between all firms located in different regions. With this specification there are no spillovers between firms located in neighbouring regions. This is perhaps an extreme specification of geographical proximity, however, it is supported by results in Mairesse and Mulkay (2008), who find evidence of spillovers between firms located within a radius of 100 km, but not between firms located between 100 and 200 km away from each other.

Regarding b: Here a weight matrix is applied that reflects the proximity in research profiles between different firms. The proximity in research profiles is calculated as the pair-wise correlation in the research profiles of different firms, where research profiles are measured as shares of research spending in different technological areas (one of these being "energy" research). This approach goes back to Jaffe (1986), but is probably still "best practice", see Bloom et al. (2007).[8] More specifically, the weights are calculated as:

$$a_{ij} = \frac{\sum_{k=1}^{K} s_{ik} s_{jk}}{\left(\sum_{k=1}^{K} s_{ik} s_{ik}\right)^{1/2} \left(\sum_{k=1}^{K} s_{jk} s_{jk}\right)^{1/2}} \tag{11}$$

Here K is the number of research areas, s_{ik} is the share of firm i's research expenditure allocated to research area k. Also $0 \leq a_{ij} \leq 1$, where $a_{ij} = 0$ is the case where firms i and j have completely different research profiles, while $a_{ij} = 1$ means that the profiles are identical.

Regarding c: Here it is assumed that there are spillovers between firms with positive correlations in research profiles, but only for firms located in the same region. Thus, a_{ij} is calculated as in Eq. (11), but it is assumed that $a_{ij} = 0$ for all firms located in different regions.

In addition to the above three weight matrices, preliminary estimations were also carried out using a weight matrix based on industries' affinity (that is firms in the food industry are assumed to obtain spillovers only from other firms in the food industry).

4. Data

The data used for the empirical analysis is based on research expenditure surveys collected at firm level by the Danish Centre for Studies in Research Policy, which quantifies research performed

[7] It is not feasible to estimate the weights, so the researcher has to choose a plausible weight matrix as there is no hard evidence on the mechanism leading to spillovers. As expressed by Krugman (1991): "Knowledge flows are invisible, they leave no paper trail by which they may be measured and tracked".

[8] In Jaffe (1986) the proximity in research profiles (technology profiles) is based on firms patenting in different technology classes. Here we use the distribution of research expenditure among different research areas.

by Danish firms – both in terms of expenditure and personnel.[9] We primarily use research surveys for the years 1995, 1997, 1998, 1999, 2001, 2003, 2005, 2007 since research expenditures shares are reported for up to 15 different research areas including energy research in these years.[10] The research expenditure surveys are sent to all large Danish firms (250 or more employees), firms based in the research industry and firms that have previously reported research expenditure of at least DKK 10 million. In addition, information about research activity in medium and small sized firms is collected by means of a survey sample based on criteria relating to firm size and industry. It is voluntary to answer the research expenditure surveys.

Since the data collection is partly sample based and because it is a result of voluntary reporting, the panel containing Danish research expenditures at firm level is highly unbalanced. The highly unbalanced panel structure complicates calculating firm specific knowledge capital stock by means of the perpetual inventory method, which requires information on investments in research for consecutive year in order to calculate research knowledge stocks. In order to fill out the gaps information from research expenditure surveys for the years 2002, 2004 and 2006 was obtained. For these years the research expenditure surveys only contain information about total research expenditure, and thus no expenditure shares for energy and other research areas. Therefore, for some observations, the division of research expenditure into research area has been based on actual total research expenditure but by using interpolated research area shares. If no information on total research expenditure exists in intermediate years for firms that appear repeatedly but not continuously in the sample, both total research expenditure and research area shares have been estimated by means of linear interpolation.

Information about value added, physical capital stock and use of labour in the firms is taken from the General Firm Statistics provided by Statistics Denmark. The variable for energy input used to check the robustness of the results (Eq. (4a)) was obtained by dividing energy expenditures of each company with a general cost index for energy input.[11] As mentioned in Section 3.1, labour inputs are corrected for differences in productivity related to different levels of education. In order to make this correction, information about education and wages for each employee in each firm was obtained from the Danish Integrated Data Base for Labour Market Research. This database contains detailed information about the Danish population – including education and wages – and links it to information about their workplace. A number of observations are excluded due to missing values for value added, capital and labour use. Also, a few observations with unrealistically high or low value added per employee or research expenditure per researcher have been deleted. Further documentation of the construction of data can be found in Bjørner and Mackenhauer (2011).

Estimations are performed for the period 2000–2007 and the final sample consists of a total of 4238 observations. The sample contains information about research activity from a total of 1029 different Danish firms that, on average, appear four times. Appendix A contains descriptive statistics for the variables included in the analysis.

The estimation sample contains firms in a variety of different private industries/sectors. About 2/3 of the observations and the knowledge capital are for firms in the industrial sectors. Most of the other observations belong to firms in 'knowledge-industries' like IT-service, consulting and private research companies. In the sample used for estimation, around 75 percent of the labour is employed in industrial sectors. This corresponds to some 140,000 full-time equivalent employees each year. By comparison, total Danish employment in the industrial sector has averaged around 360,000 full-time equivalents annually over the period 2000–2007. Thus, the final sample contains research information from companies representing about 40 per cent of the industrial employment in Denmark.

[9] From 2007 and onwards this information is collected by Statistics Denmark.

[10] From these data we 'only' obtain information about the share of research related to energy research, but we do not know whether the energy research is directed towards 'dirty' energy technologies or low CO_2 technologies. However, as noted in Section 2 several things indicate that energy research in Denmark in the period observed was mainly directed towards low CO_2 technologies.

[11] We have information on the overall energy expenditures of each company, but not on the expenditures for different types of energy like electricity, oil, gas and district heating.

5. Results from the empirical analysis

Previous studies of private and external rates of return to research do not distinguish between research areas. Therefore, the first part of this section presents estimates of private and external returns to research in accordance with the standard production function approach (i.e. when no distinction is made between research areas) and compares these results with results from the literature. Subsequently, whether private and external rates of return are higher for energy research compared to other research performed by the private sector is investigated.

5.1. Estimates of returns to research using standard production function approach

Table 1 displays the estimated impact of private research and spillovers on firm productivity for each of the three methods employed to proxy knowledge spillover (see Section 3.2). Furthermore, results from both an ordinary pooled regression model (OLS) and a fixed effects model (FE) are shown.

In all models, the coefficients (or output elasticity) to the firm's own inputs to production – physical capital (K), labour (L) and research capital (R) – are significant and relatively constant. Furthermore, the sum of coefficients is close to 1 (ranging from 0.97 to 1.02 depending on model specification) indicating that there are constant returns to scale to the firm's own factors of production. The sum of the three coefficients is slightly larger in the pooled estimations compared to the fixed effects models. According to Hall et al. (2009), this is often seen when comparing pooled and fixed effects estimates of the returns to research.

Fixed effects models are more flexible than pooled models because they control for unobserved (time invariant) heterogeneity between observations. Consequently, the fixed effects estimates will be the focal point in the following, although the coefficients differ relatively little when comparing estimates from the pooled models with the corresponding estimates from the fixed effects models.[12]

The output elasticity of own knowledge capital lies between 0.12 and 0.14 in the estimated models, which is highly consistent with the findings of other studies. In a recent survey, Hall et al. (2009) find coefficients of own knowledge capital ranging from 0.01 to 0.25 – with 0.08 being a typical value. Bloch and Marino (2008) estimate a coefficient of 0.13 based on Danish data, while the Danish Agency for Science Technology and Innovation (2010) finds coefficients of own knowledge capital ranging from 0.05 to 0.13.

The coefficient of own knowledge capital can be used for calculating private net returns to research (ρ)[13]:

$$\rho_i = \gamma \cdot \frac{Y_i}{R_i} - \delta \tag{12}$$

In the sample, the median value of Y_i/R_i is 2.9 (see Appendix A), and research capital is calculated using an annual depreciation of knowledge (δ) of 15 percent. For research elasticities between 0.12 and 0.14, this corresponds to a private net return on investments in research ranging from 20 to 25 percent. At first glance, this may seem to be a relatively high rate of return, but according to the survey by Hall et al. (2009) several international studies suggest that the earnings could be even higher. It may also be argued that the average (ex post) return to private research has to be relatively high, given that the significant risk associated with research calls for a high risk premium. In addition, the estimated private return could be upward biased compared to the ex ante anticipated revenue. This is

[12] It can be argued that time-dependent measurement errors could be present in the computed measure of research spillover: As described in Section 3.2, S_{t-1} consists of a weighted sum of research capital in other firms. However, as the panel used for the analysis is highly unbalanced, changes in S_{t-1} could both reflect changes in firm's research activity (changes we wish to capture) and variation arising from different firms being included in the calculation of S_{-1} in different years (due to the unbalanced panel nature of the data). Such potential time-dependent measurement errors are likely to cause estimation bias that will be more profound in fixed effects models. The reason is that fixed effects estimates are identified by time-variation in the variables within individual firms whereas parameters in the pooled regressions are (mainly) identified by the variation between firms.

[13] By definition $\gamma = \rho^b(R/Y)$, where ρ^b is the marginal productivity of research. According to (Hall et al., 2009), ρ^b can interpreted as the marginal gross internal rate of return, given certain assumptions.

Table 1
Effects of private and spillover knowledge capital on value added.

Number	1		2		3		4		5		6	
Type	OLS		OLS		OLS		FE		FE		FE	
Spillover	Region		Research profile		Research profile and region		Region		Research profile		Research profile and region	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Ln (K_{t-1})	0.13**	16.4	0.13**	16.1	0.13**	16.3	0.10**	8.7	0.10**	8.5	0.10**	8.6
Ln (L_t)	0.76**	63.0	0.76**	62.9	0.76**	63.1	0.74**	36.4	0.74**	36.5	0.74**	36.5
Ln (R_{t-1})	0.12**	17.9	0.13**	18.9	0.13**	18.4	0.13**	11.5	0.14**	12.4	0.14**	12.2
Ln (S_{t-1})	0.04**	4.8	0.00	0.2	0.03**	4.3	0.05**	3.6	0.01	0.7	0.03**	2.9
Year01	0.03	1.1	0.02	0.9	0.02	0.9	0.02	1.3	0.01	0.9	0.01	0.8
Year02	0.05*	2.1	0.05*	2.1	0.05*	2.1	0.04*	2.1	0.03*	2.0	0.04*	2.0
Year03	0.04	1.6	0.04	1.5	0.03	1.4	0.03	1.6	0.03	1.3	0.02	1.2
Year04	0.05*	2.0	0.05*	2.2	0.04	1.9	0.02	1.3	0.03	1.7	0.03	1.4
Year05	0.06**	2.6	0.07**	2.7	0.06*	2.4	0.04	1.9	0.04	1.9	0.04	1.8
Year06	0.06*	2.2	0.07*	2.5	0.06*	2.2	0.05	1.9	0.05*	2.2	0.05*	2.1
Year07	0.13**	4.1	0.13**	4.0	0.13**	4.1	0.11**	4.1	0.11**	4.0	0.11**	4.1
Constant (base)	4.14**	31.5	4.66**	22.7	4.33**	40.8	4.19**	18.6	4.76**	18.0	4.55**	28.4
Constants	19 industries		19 industries		19 industries		FE		FE		FE	
N observations	4238		4238		4236		4238		4238		4236	
R^2 overall		0.9146		0.9140		0.9146		0.9096		0.9085		0.9090
R^2 within								0.2438		0.2433		0.2445
N firms							1029		1029		1028	
p (year$_i$ = 0)		0.0047		0.0032		0.0040		0.0093		0.0128		0.0073
sigma_u								0.374		0.378		0.377
sigma_e								0.294		0.294		0.294
Rho								0.618		0.624		0.622

t-Values are calculated from robust s.e.
* Significant at 5%.
** Significant at 1%.

because the sample might not include unsuccessful research investments to the full extent, since bad research investments are likely to be correlated with negative value added and therefore are excluded from the analysis as a result of the ln-transformation.

The output elasticity to spillover is significant in the models where spillover is based on geographical proximity (models 1 and 4) and in the models where spillover is based on proximity in both geographical and research profiles (models 3 and 6). The coefficient to spillover is not significant in the models where spillover is based on proximity in research profiles alone (models 2 and 5). This suggests that spillovers are geographically bounded.

In the models where the estimated knowledge spillover is significant (models 1, 3, 4, 6) the coefficients range from 0.03 to 0.05. This is largely consistent with the findings in other international analyses, where spillover coefficients are typically found to vary between 0.05 and 0.09, see Hall et al. (2009). It is, however, difficult to compare estimates of external knowledge spillover from different studies, as knowledge spillovers are defined in different ways.

According to Hall et al. (2009) a measure of the social rate of return to research from an individual firm can be obtained by adding its private rate of return to the sum of the returns to external research for all recipients of spillovers from that firm:

$$\frac{\partial Y_i}{\partial R_i} + \sum_{j \neq i} a_{ij} \frac{\partial Y_j}{\partial S_j} - \delta = \gamma \cdot \frac{Y_i}{R_i} + \eta \cdot \sum_{j \neq i} a_{ij} \frac{Y_j}{S_j} - \delta \tag{13}$$

In the models where spillover is based on both research profiles and geographical proximity (models 3 and 6) the social rate of return is in the range of 25–28 percent, when calculated from median values.[14] Approximately 4 percentage points of the social rate of return can be attributed to external spillover, which is equivalent to between one sixth and one seventh of the social rate of return to research. In the two models based solely on geographical proximity, a slightly higher rate of return to external spillover is found, ranging between one fifth and one quarter of the total social return.[15] The external rate of return (and thus the social rate of return) found in this analysis is slightly smaller than what is typically found in international studies. According to Hall et al. (2009) large variation is also found in estimates of external rates of return.[16]

Another measure of the economic implications of the estimated spillover effects can be found by comparing the size of S^{η} for different levels of spillover (S). In model 6 the estimated value of η is 0.0255, and according to Appendix A, the 10th and 90th percentiles of S are 676,575 and 12,716,634, respectively. This is equivalent to a value of S^{η} of between 1.409 and 1.519 which corresponds to a difference in value added of 8 percent between firms that benefit from a "very high" level of external knowledge (the 90th percentile) and firms that receive relatively little spillover (the 10th percentile). This difference can be related to the findings of a Danish analysis of cluster effects on productivity, which finds a positive effect on productivity from belonging to a cluster equal to 9 percent, see Madsen et al. (2003). Consequently, since cluster effects on productivity are often attributed to local knowledge spillovers, the differences in value added between firms with high and low research spillovers found in our study appear to be quite reasonable.[17]

[14] Among the firms in the sample some of the larger perform very little research. For these firms Y_i/R_i will be very high and contribute to making the average value of Y/R – and hence the average private and ultimately the social rate of return – unrealistically high. Therefore, median values have been used for calculating the private and social rates of return.

[15] In the models where spillover is based on geographical proximity, i.e. models 1 and 4, the social rates of return are 26 and 29 percent, respectively. Of these social rates of return, 5 and 7 percentage points can be accredited external rates of return.

[16] The estimated external rates of return are likely to be rather conservative, as firms that do not carry out research themselves, but would potentially benefit from other firm's research, are not included in the analysis.

[17] The difference between spillover effects on value added for the 10th and the 90th percentile in models 1, 3 and 4 is 10.7 percent, 8.4 percent and 14.0 percent, respectively. Hence, when spillover is based solely on geographical proximity (models 1 and 4) differences in spillover effects on value added between firms receiving high and low spillovers are relatively large. Therefore, the smaller (and in our view more plausible) difference in productivity gains between firms with high and low research spillovers suggests that the models where research spillover is based on geographical proximity and proximity in research profiles are to be preferred.

5.2. The relative significance of energy research on research spillovers

Table 2 demonstrates the consequences of including in the estimated model the two terms measuring the share of the firm's own knowledge capital that arises from energy research $(R^E + R)/R$ and the share of the firm's external knowledge capital (spillover) that arises from energy research $(S^E + S)/S$. The coefficient of $(R^E + R)/R$ is insignificant in all models, which implies that a large proportion of energy in a firm's own knowledge capital does not give rise to additional effects on private returns. The result is consistent with the assumption that firms are fully capable of assessing the returns to their research investments, as this would, in principle, imply that no additional productivity gains can be achieved from investing in different types of research.

The estimated coefficient of $(S^E + S)/S$ is negative in all models but only significant in two (models 1 and 6). Hence, although the models do not give rise to a strong conclusion, there is nothing to suggest that energy research gives rise to additional spillovers compared to private research in general.

The interpretation of the parameter $(S^E + S)/S$ differs from the interpretation of the output elasticities. In the sample the 90th percentile of $(S^E + S)/S$ is 1.076 (see Appendix A) and the numerically highest (significant) coefficient for energy spillover is around −0.9 (taken from model 1). This yields $1.076^{-0.9} = 0.96$, which implies that a very high proportion of energy research in total spillover capital of a firm reduces overall effect of spillover for the firm by around 4 percent. Thus, the seemingly large parameter value represents a relatively small effect.

In sum, the results demonstrated in Table 2 indicate that energy research does not lead to higher private returns or spillovers compared to other research. In fact, the analysis indicates that energy research has a slightly negative impact on the general spillovers from research.

5.3. Robustness of the results

As a test of the robustness of the findings that the external spillover from energy research is not higher than the spillover from other private research, a number of supplementary estimations have been performed. Results from these estimations are shown in Appendix B and will be summarized briefly below.

In the first test of robustness of the results energy input is included explicitly in the production function, see Eq. (4a) in Section 3. Results using this specification are reported in Table B1 in Appendix B. Focussing on the parameter to spillover from energy research, it appears that very similar parameters are estimated compared to the results for the same parameter found in Table 2. This supports the conclusions drawn from Table 2 that there is no sign of relatively high spillover form energy research compared to other types of private research.

The second test of the robustness of the results involves an alternative specification of the production function where external knowledge capital is divided into two separate terms: Spillover from energy research (S^E) and spillover from other research (S^O), see Eq. (4b) in Section 3. The general result from this estimation, demonstrated in Table B2 in Appendix B, is that the coefficients of spillover capital from other research are positive and generally significant, while negative and generally insignificant coefficients are obtained for the energy spillover variable. This also suggests that spillover from other research is higher than spillover from energy research.

Finally, an alternative specification of spillover has been tested, where spillover is based on a combination of geographical proximity and industry. The assumption is that spillovers are restricted to firms within the same industry and region. The results are shown in Table B3 in Appendix B, and the general insight is that the coefficients for energy spillover are negative – but insignificant. Again, the results confirm that there is no indication of a positive contribution to spillover from energy research. Another interesting result from this model is that the coefficients of the spillover variable (S) are insignificant in both the pooled and the fixed effects model, and in the latter, the coefficient of the spillover variable is negative. Although it is typically assumed that spillovers from research affect firm productivity positively, it cannot be

Table 2
Impact of energy research on the effect of private and spillover knowledge capital.

Number	1		2		3		4		5		6	
Type	OLS		OLS		OLS		FE		FE		FE	
Spillover	Region		Research profile		Research profile and region		Region		Research profile		Research profile and region	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Ln (K_{t-1})	0.13^{**}	16.4	0.13^{**}	16.1	0.13^{**}	16.3	0.10^{**}	8.7	0.10^{**}	8.6	0.10^{**}	8.6
Ln (L_t)	0.76^{**}	63.0	0.76^{**}	63.0	0.76^{**}	63.3	0.74^{**}	36.4	0.74^{**}	36.2	0.74^{**}	36.5
Ln (R_{t-1})	0.12^{**}	17.5	0.13^{**}	18.7	0.12^{**}	18.2	0.13^{**}	11.5	0.14^{**}	12.0	0.13^{**}	12.1
Ln (($R^E_{t-1}+R_{t-1})/R_{t-1}$)	−0.01	−0.1	−0.01	−0.1	0.05	0.7	−0.12	−0.8	−0.08	−0.5	−0.02	−0.2
Ln (S_{t-1})	0.03^{**}	3.5	0.00	0.0	0.03^{**}	3.9	0.04^{**}	2.9	0.00	0.2	0.02^{**}	2.3
Ln (($S^E_{t-1}+S_{t-1})/S_{t-1}$)	-0.87^{*}	−2.4	−0.08	−0.3	−0.19	−1.2	−0.66	−1.4	−0.29	−0.8	-0.34^{*}	−2.0
Year01	0.03	1.1	0.02	0.9	0.02	0.9	0.02	1.2	0.02	1.0	0.01	0.9
Year02	0.05^{*}	2.3	0.05^{*}	2.1	0.05^{*}	2.2	0.04^{*}	2.2	0.04^{*}	2.0	0.04^{*}	2.1
Year03	0.05^{*}	2.0	0.04	1.5	0.04	1.4	0.04^{*}	2.0	0.03	1.5	0.03	1.4
Year04	0.05^{*}	2.3	0.05^{*}	2.3	0.04	1.9	0.03	1.6	0.03	1.8	0.03	1.5
Year05	0.06^{*}	2.6	0.07^{**}	2.7	0.06^{*}	2.4	0.04	1.9	0.04^{*}	2.0	0.04	1.9
Year06	0.06^{*}	2.3	0.07^{*}	2.5	0.06^{*}	2.3	0.05^{*}	2.0	0.06^{*}	2.3	0.05^{*}	2.2
Year07	0.14^{**}	4.3	0.13^{**}	4.0	0.13^{**}	4.2	0.12^{**}	4.2	0.11^{**}	4.1	0.11^{**}	4.2
Constant (base)	4.32^{**}	29.6	4.70^{**}	18.1	4.35^{**}	39.2	4.35^{**}	18.7	4.89^{**}	16.0	4.63^{**}	27.3
Constants	19 industries		19 industries		19 industries		FE		FE		FE	
N observations	4238		4238		4236		4238		4238		4236	
R^2 overall	0.9147		0.9140		0.9146		0.9098		0.9087		0.9092	
R^2 within							0.2442		0.2434		0.2452	
N firms							1029		1029		1028	
p (year$_i$ = 0)	0.0024		0.0034		0.0035		0.0071		0.0105		0.0057	
sigma_u							0.374		0.376		0.376	
sigma_e							0.294		0.294		0.294	
Rho							0.618		0.621		0.621	

t-Values are calculated from robust s.e.

* Significant at 5%.

** Significant at 1%.

rejected that research spillovers may have a negative effect on firm productivity. According to Bloom et al. (2007), this could be the case if, for example, a firm's research leads to product innovations that outperform products from other firms producing similar products. This could potentially be the reason why a significant positive spillover is not found for firms in the same industry and region – given that these, to a larger degree, compete in the same product markets.

6. Summary and conclusion

In this paper the external benefits of private research derived from knowledge spillovers have been estimated using an unbalanced panel of more than a thousand Danish firms over the period 2000–2007. The purpose was to test whether there are higher external benefits from private energy research compared to other private research. First, we estimated a standard production function without distinguishing between different types of research. This gave output elasticities to own and external (spillover) knowledge as well as private and social rates of return to research that were in line with results from previous studies. Next, an extended model that allowed us to test for higher external benefits of private energy research was estimated. It was rejected that there are higher spillovers from private energy research compared to other private research. Instead the results suggest that the external knowledge spillovers from energy research may be lower than for other types of private research. This finding was robust to different definitions of the spillover mechanism and to different model specifications.

It should be noted that the analysis is based on data on private energy research, which do not allow us to distinguish between research in 'dirty' energy technologies and research in low CO_2 technologies. Thus, in principle the results could reflect that there is a high spillover from research in low CO_2 technologies and a low spillover from research in dirty energy technologies (or visa versa). However, other indicators suggest that Danish private energy research in the period analysed was directed towards research in low CO_2 technologies.

The implication of the empirical analysis and the conjecture that the results also apply to research in low energy technologies is that relatively high subsidies to private energy research should not be an element in an optimal policy to reduce CO_2 emissions, when it is possible to tax CO_2 emissions.

It should also be emphasised that the study focuses on the positive benefits of private research and the conclusions cannot be generalized to more fundamental research carried out at universities or in public research institutions. Others have argued that it is necessary to invest more in more fundamental research in order to make a move towards more sustainable and less carbon intensive use of energy. This may be correct, but it is important to consider the opportunity costs of the forgone research in other areas if a larger share of the public research budgets is allocated to more basic energy research.

A potential argument against the conclusion regarding subsidies to private energy research could be that sustainable energy use is a new and rather undeveloped technology, and therefore research in this new technology cannot (yet) be expected to yield spillovers similar to other more mature and developed technologies. Once research in sustainable and low carbon energy use advances to a higher level the spillovers from the research may be at least as high as spillovers from other types of research. This could be true, but it should also be recalled that research in sustainable energy use and low carbon energy use in Denmark is not new. Due to an ambitious Danish policy towards sustainable energy and energy conservation there has been a fairly long tradition for this type of research in Denmark. Relatively large shares of international patents in these technologies are Danish and the number of citations to the Danish energy patents also suggests that these patents are of a high quality. Thus, the above argument for larger future spillovers from energy research, due to the infant state of the research, appears less valid in the Danish case.

Appendix A. Descriptive Statistics

See Table A1.

Table A1
Descriptive statistics.

Variables	No. obs.	Mean	Median	10th percentile	90th percentile
Value added[a], Y_t	4238	181,598	57,565	7504	350,610
Physical capital[a], K_{t-1}	4238	155,006	24,453	1364	279,421
Knowledge capital[a], R_{t-1}	4238	120,222	17,735	2817	186,916
Energy contribution to knowledge capital, $(R^E_{t-1}+R_{t-1})/R_{t-1}$	4238	1.035	1	1	1.094
Labour[b], L_t	4238	368	149	17	770
Value added per employee[a], Y_t/L_t	4238	497	391	254	794
Value added per knowledge capital, Y_t/R_{t-1}	4238	8.5	2.9	0.4	17.8
Spillover (region)[a], S_{t-1}	4238	25,761,738	10,424,181	3,750,240	63,176,244
Spillover (research profile)[a], S_{t-1}	4238	17,949,661	18,299,675	6,718,390	27,643,712
Spillover (region and research profile)[a], S_{t-1}	4238	5,532,691	3,994,844	676,575	12,716,634
Spillover contribution from energy (region), $(S^E_{t-1}+S_{t-1})/S_{t-1}$	4238	1.043	1.041	1.022	1.076
Spillover contribution from energy (research profile), $(S^E_{t-1}+S_{t-1})/S_{t-1}$	4238	1.044	1.036	1.010	1.094
Spillover contribution from energy (region and research profile), $(S^E_{t-1}+S_{t-1})/S_{t-1}$	4236	1.047	1.037	1.005	1.097

[a] 1000 DKK, deflated (2000-prices).
[b] Number of full-time equivalent employees, corrected for double counting and differences in productivity related to different levels of education.

Appendix B. Robustness estimations

See Tables B1–B3.

Table B1
Including energy as a factor of production.

Number	1		2		3		4		5		6	
Type	OLS		OLS		OLS		FE		FE		FE	
Spillover	Region		Research profile		Research profile and region		Region		Research profile		Research profile and region	
	Coef.	t	Coef.	T	Coef.	t	Coef.	t	Coef.	t	Coef.	t
Ln (K_{t-1})	0.10**	12.9	0.10**	12.6	0.10**	12.8	0.07**	6.9	0.07**	6.8	0.07**	6.8
Ln (L_t)	0.67**	46.9	0.67**	46.9	0.67**	47.0	0.66**	28.6	0.66**	28.5	0.66**	28.7
Ln (E_t)	0.12**	12.6	0.12**	12.2	0.12**	12.3	0.10**	8.3	0.10**	8.1	0.10**	8.1
Ln (R_{t-1})	0.11**	17.3	0.12**	18.5	0.12**	18.0	0.13**	11.8	0.13**	12.3	0.13**	12.5
Ln ($R^E_{t-1}+R_{t-1})/R_{t-1}$	−0.04	−0.6	−0.01	−0.1	0.02	0.3	−0.08	−0.5	−0.04	−0.3	−0.01	0.0
Ln (S_{t-1})	0.03**	4.0	−0.01	−0.4	0.02**	4.0	0.04**	3.5	0.00	0.0	0.02*	2.2
Ln ($S^E_{t-1}+S_{t-1})/S_{t-1}$	−0.82*	−2.4	−0.31	−1.0	−0.24	−1.6	−0.51	−1.1	−0.28	−0.8	−0.29	−1.7
Year01	0.02	0.8	0.02	0.7	0.01	0.6	0.01	0.8	0.01	0.5	0.01	0.4
Year02	0.04	1.9	0.04	1.7	0.04	1.8	0.03	1.7	0.03	1.6	0.03	1.6
Year03	0.03	1.2	0.02	0.8	0.02	0.7	0.02	1.0	0.01	0.6	0.01	0.5
Year04	0.04	2.0	0.05*	2.1	0.04	1.6	0.02	1.1	0.03	1.4	0.02	1.1
Year05	0.06*	2.4	0.06**	2.7	0.05*	2.3	0.03	1.6	0.04	1.8	0.03	1.6
Year06	0.06*	2.2	0.07*	2.5	0.06*	2.2	0.04	1.7	0.05*	2.2	0.05*	2.0
Year07	0.14**	4.5	0.14**	4.3	0.14**	4.4	0.12**	4.4	0.11**	4.3	0.11**	4.4
Constant (base)	4.21**	30.9	4.75**	19.3	4.31**	41.4	4.28**	19.2	4.96**	16.7	4.67**	28.7
Constants	19 industries		19 industries		19 industries		FE		FE		FE	
N observations	4214		4214		4212		4214		4214		4212	
R^2 overall	0.9227		0.9221		0.9226		0.9172		0.9160		0.917	
R^2 within							0.2665		0.265		0.267	
N firms							1025		1025		1024	
p (year$_i$ = 0)	0.0019		0.0007		0.0009		0.0021		0.002		0.0010	
sigma_u							0.3631		0.3650		0.3657	
sigma_e							0.2793		0.2794		0.2793	
Rho							0.6285		0.6305		0.6316	

The variable E_t is calculated from the overall energy expenditures of each company divided by an energy cost index. In the estimations in table.
B2.2 the dependent variable is $\ln(VA_{it}+E_{it})$. In the other presented estimations the dependent variable is $\ln(VA_{it})$.

* Significant at 5%.

** Significant at 1%.

Table B2
Model with spillovers divided into two separate terms – energy and other spillovers.

Number	1		2		3		4		5		6	
Type	OLS		OLS		OLS		FE		FE		FE	
Spillover	Region		Research profile		Research profile and region		Region		Research profile		Research profile and region	
	Coef.	t	Coef.	t	Coef.	t	Coef.	T	Coef.	t	Coef.	T
Ln (K_{t-1})	0.13**	16.4	0.13**	16.1	0.13**	16.2	0.10**	8.7	0.10**	8.6	0.10**	8.6
Ln (L_t)	0.76**	62.9	0.76**	62.9	0.76**	62.5	0.74**	36.4	0.74**	35.8	0.75**	36.8
Ln (R_{t-1})	0.12**	17.6	0.13**	18.4	0.12**	18.0	0.13**	11.4	0.13**	11.7	0.13**	12.0
Ln (S^O_{t-1})	0.06**	4.2	0.01	0.7	0.03**	3.7	0.06**	3.0	0.03	1.5	0.04**	3.7
Ln (S^E_{t-1})	−0.03*	−2.0	−0.01	−1.0	0.00	−0.6	−0.03	−1.2	−0.02	−1.7	−0.02*	−2.1
Year01	0.03	1.1	0.02	1.0	0.02	1.0	0.02	1.2	0.02	1.2	0.02	1.0
Year02	0.05*	2.2	0.05*	2.2	0.05*	2.2	0.04*	2.2	0.04*	2.3	0.04*	2.2
Year03	0.05	1.8	0.42	1.6	0.04	1.5	0.04	1.9	0.04	1.8	0.03	1.6
Year04	0.05*	2.1	0.06*	2.3	0.05	2.0	0.03	1.6	0.04	1.9	0.03	1.5
Year05	0.06*	2.5	0.07**	2.8	0.06*	2.5	0.04	1.9	0.05*	2.3	0.04	1.9
Year06	0.06*	2.2	0.07*	2.6	0.07*	2.3	0.05	1.9	0.06*	2.5	0.05*	2.2
Year07	0.13**	4.2	0.13**	4.1	0.14**	4.2	0.11**	4.1	0.12**	4.3	0.12**	4.3
Constant (base)	4.18**	32.2	4.68**	23.5	4.31**	39.9	4.25**	19.4	4.77**	18.5	4.54**	28.4
Constants	19 industries		19 industries		19 industries		FE		FE		FE	
N observations	4238		4238		4208		4238		4238		4208	
R^2 overall	0.9146		0.9140		0.9143		0.9097		0.9089		0.9090	
R^2 within							0.2439		0.2436		0.2469	
N firms							1029		1029		1025	
p (year$_i$ = 0)	0.0038		0.0025		0.0029		0.0085		0.0045		0.0046	
sigma_u							0.374		0.376		0.376	
sigma_e							0.294		0.294		0.294	
Rho							0.618		0.620		0.621	

t-Values are calculated from robust s.e.

* Significant at 5%.

** Significant at 1%.

Table B3
Model where spillover is based on industry and geographical proximity.

Number	1		2	
Type	OLS		FE	
Spillover	Industry and region		Industry and region	
	Coef.	t	Coef.	t
Ln (K_{t-1})	0.13**	15.9	0.10**	8.5
Ln (L_t)	0.76**	63.0	0.74**	35.9
Ln (R_{t-1})	0.13**	18.7	0.14**	12.3
Ln ($R^E_{t-1} + R_{t-1})/R_{t-1}$	−0.02	−0.4	−0.12	−0.9
Ln (S_{t-1})	0.00	0.8	−0.01	−1.6
Ln ($S^E_{t-1} + S_{t-1})/S_{t-1}$	−0.15	−1.5	−0.17	−1.5
Year01	0.03	1.5	0.02	1.1
Year02	0.05*	2.0	0.03	1.8
Year03	0.04	1.6	0.02	1.1
Year04	0.05*	2.2	0.04	1.9
Year05	0.07**	2.8	0.05*	2.1
Year06	0.07*	2.5	0.05*	2.3
Year07	0.13**	4.0	0.11**	3.7
Constant (base)	4.65**	48.9	5.02**	41.7

Constants	19 industries	FE
N observations	4163	4163
R^2	0.916	
R^2 within		0.250
N firms		1019
p (year$_i$ = 0)	0.004	0.030
sigma_u		0.377
sigma_e		0.292
Rho		0.624

t-Values are calculated from robust s.e.
* Significant at 5%.
** Significant at 1%.

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