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Vertical spillovers and the energy intensity of European industries

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ABSTRACT

The prior literature has argued that inter-sectoral supply chain links provide an important channel for technology diffusion and productivity spillovers across industries, but whether such vertical spillovers influence industrial energy use has remained unexplored thus far. This study analyzes how the energy intensity of European industries is affected by vertical technology and energy productivity spillovers along the industrial supply chain. The analysis combines international input-output tables, energy use and patent data. Panel data from 2000 to 2014 for 27 industries in 29 countries is analyzed using panel fixed effects and instrumental variable estimation methods. The findings reveal that supply-use links channel significant vertical spillovers that promote a decline in energy intensity in downstream industries. These spillovers appear to be more strongly associated with overall energy intensity changes in upstream industries and, to some degree, with patented green innovations in upstream industries.

1. Introduction

Growing alarm over the climate crisis and the central role of energy use in causing CO_2 emissions, as well as domestic energy security concerns, make energy efficiency improvements an important target for policymakers and companies. The energy intensity[1] of industrial sector decreased by 27 % in the European Union (EU) from 2000 to 2020 (Tsemekidi Tzeiranaki et al., 2022) and the trend is similar in many developed countries. This development is recognized to be mainly driven by changes within sectors rather than by the shrinking of energy intensive industrial activities (Voigt et al., 2014). Within-sector energy intensity may decline if firms substitute energy with other production inputs such as capital and labor. Prior studies also indicate that innovations in energy-saving and other green technologies significantly contribute to the reduction of industrial energy intensity (Ajayi and Reiner, 2020; Popp, 2001; Wurlod and Noailly, 2018).

Nevertheless, it is not only technological and non-technological changes within the industry itself that matter, but many important technologies and practices are initially developed in other industries and their use and impacts later diffuse to related industries. The prior literature recognizes the importance of foreign technological development for domestic innovation in energy technologies (e.g., Verdolini and Galeotti, 2011). Moreover, the energy use impacts of international trade and foreign direct investments as well as the role of spatial proximity in energy intensity convergence have been analyzed (Balado-Naves et al., 2023; Huang et al., 2017; Lee and Park, 2023; Pan et al., 2021; Sun et al., 2021). Wan et al. (2015) present an analysis perhaps the closest to the present study. They show how international trade connections contribute to the energy productivity convergence in Europe. Notwithstanding these important insights on the spatial diffusion of energy technologies, it is important to recognize that industrial energy use depends, i.a., on intermediate and investment inputs that are sourced from vertically related industries that may be domestic or foreign. A part of the technological development in upstream industries is embodied in the quality and characteristics of their products, that is, production inputs and machinery that are used by the downstream industries, as already argued by Schmookler (1966) and Griliches (1979). Such trade contacts also mediate intangible knowledge spillovers (Todo et al., 2016). Considering the technological and non-technological innovations transmitted through these supply chain links is especially important as innovation and R&D are concentrated in a few industries and the vertical spillovers can provide a more comprehensive picture of the technological development in the less R&D intensive industries (Hauknes and Knell, 2009). Nevertheless, these vertical spillovers remain unstudied in the literature analyzing energy intensity.

In line with the above arguments, the novel contribution of the

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[1] Energy intensity has been used as a proxy for energy efficiency (or its inverse) and they are sometimes used interchangeably. However, energy intensity refers to the quantity of energy divided by the value of production, such as GDP. Energy efficiency, on the other hand, can be defined as the useful output of a process divided by the energy input into a process, but there are multiple definitions of energy efficiency (Filippini and Hunt, 2015).

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present study is to analyze how spillovers from vertically related industries influence the energy intensity of downstream industries. The analysis offers further insight by probing potential spillovers from upstream green innovations as well as upstream energy productivity development. Finally, the study aims to identify the causal effect of vertical spillovers by addressing the potential endogeneity of spillovers by applying a shift-share instrumental variable approach that is a novel method in this context.

The energy productivity and technological development of industries are measured using energy intensity and patent filing data. The Y02-Y04 tagging scheme for climate change mitigation technologies and a list of energy-related patent technology codes are used to identify green patents that are likely to affect industrial energy use. In addition to the OECD REGPAT patent database, World Input Output Data (WIOD) Environmental and Socio-Economic Accounts are used to measure industrial energy intensity and other economic variables (Corsatea et al., 2019; Timmer et al., 2015). The WIOD input-output table maps vertical supply chain connections across industries. These links are hypothesized to serve as a channel of technology spillovers. This approach follows prior studies analyzing industrial emissions (Costantini et al., 2017; Jiao et al., 2020). Combining these datasets yields panel data for 27 industries in 29 European countries for the period from 2000 to 2014. In the empirical section, the impacts of vertical spillovers are analyzed using fixed-effects panel estimation and shift-share instrumental variable method. The results indicate that the vertical spillovers reduce industrial energy intensity. Specifically, a 10 % decrease in the energy intensity of upstream sectors leads to a 2.4 to 4.6 % reduction in the energy intensity of downstream sectors. Moreover, an increase in patented green technologies in upstream sectors leads to a somewhat less robust decline in the downstream energy intensity. Robustness tests confirm that these spillovers only occur from upstream to downstream but not from downstream to upstream, which assures that the observed results are not simply reflecting correlated shocks across the supply chain. Further estimations explore the industry-specific heterogeneity of results.

The rest of the study is structured as follows. The second section presents the literature review and hypotheses. The third section introduces the data, methods and discusses some econometric considerations. The fourth section presents and discusses the econometric results. The fifth section concludes.

2. Literature review and research hypotheses

2.1. Theoretical motivation and research hypotheses

The present study relates on the one hand to the extensive literature on the trends and determinants of energy intensity and on the other hand to the studies examining the industry-level impacts of technology and productivity spillovers. While energy intensity is often taken as a proxy for energy efficiency, it is also influenced by several factors other than pure energy efficiency (Filippini and Hunt, 2015). Energy intensity describes the relationship between energy use and economic activity. Thus, factors like industrial structure, behavioral changes and others can influence energy intensity while leaving efficiency unaffected.

Numerous prior studies on energy intensity have used decomposition analysis and divided the change in aggregate energy intensity into structural and efficiency effects, where the efficiency effect is argued to capture technological development (Ang, 2004; Ang and Xu, 2013; Mulder et al., 2014). In these studies, the efficiency effect typically refers to a within-industry change in energy intensity. Moreover, this approach does not yet reveal whether the changes in the efficiency effect are due to technological or non-technological development and which technology drivers, such as innovations or technology spillovers, are important. A more detailed analysis is thus called for.

A bulk of the literature, including industry-level studies, e.g., by Lescaroux (2008), Parker and Liddle (2016) and Ajayi and Reiner (2020), points to the key role of energy prices in driving a decline in industrial energy intensity. Increases in energy prices motivate input substitution away from energy use as well as induced technological and non-technological changes that may spur further reduction in energy use (Ley et al., 2016; Popp, 2002). Both mechanisms lead to a lower energy intensity. While the energy-saving potential of innovations is widely appraised, the literature on the rebound effect notes that innovations that improve energy efficiency will also lead to a rebound effect, as energy efficiency improvements decrease the real unit price of energy (Amjadi et al., 2018; Greening et al., 2000). Thus, the development of innovations may also increase energy use and the impacts of technological development on energy intensity remain technology specific.

Some studies use stochastic frontier analysis to provide estimates of energy efficiency (see, e.g., Filippini and Hunt (2015) and Lundgren et al. (2016)). However, except for a few studies like Marin and Palma (2017) and Sun et al. (2021), this strand of literature does not directly explore the role of innovations or innovation spillovers. Nevertheless, the contributions by Popp (2001), Wurlod and Noailly (2018) and Ajayi and Reiner (2020) indicate that technological innovations - commonly measured with patent counts[2] - lead to a reduction in industrial energy intensity. Country-level evidence by Sun et al. (2021) is supportive. Wurlod and Noailly (2018) show that the energy intensity changes are especially related to green technology development. Using Chinese firm-level data, Fisher-Vanden et al. (2004) and Fisher-Vanden et al. (2016) show that also research and development (R&D) expenditures, an input rather than output measure of innovation, are linked to lower energy intensity in some industries but not in all. In sum, this literature establishes that technological inventions developed within the industrial sector can reduce its energy intensity.

However, industrial energy savings are not driven only by patented technological inventions. First, not all technological inventions are patentable. E.g., many patent offices do not grant patents to software or agricultural methods, which may nevertheless bring energy efficiency benefits. Product designs are also not patentable, although they may yield energy savings (Li et al., 2019). Second, the energy-saving benefits of non-technological factors have received somewhat less attention in the literature, however, good management and energy management practices are argued to reduce industrial energy use (Backlund et al., 2012; Boyd and Curtis, 2014; Johansson and Thollander, 2018). Relatedly, Martin et al. (2012) show that climate-friendly management practices are strongly associated with higher energy efficiency and productivity in firms. Third, behavioral and organizational changes are important in enabling the adoption of energy-efficiency measures (Johansson and Thollander, 2018). Finally, a lack of information and limited skills contribute to lower energy efficiency, while information measures and energy audits can improve energy efficiency (Fresner et al., 2017). Thus, non-patentable or non-technological innovations and changes also influence industrial energy productivity.

It is also commonly understood that the social benefits of technological and non-technological improvements are higher than the private benefits to the innovator because of various rent and knowledge spillovers (Hall et al., 2010). The same logic applies also to energy-saving and environmental innovations. A related literature investigates the spillover effects of innovations on other firms, industries and countries (Hall et al., 2010). Especially relevant for the present analysis is the literature studying the effects of inter-industry R&D and technology spillovers on industrial performance such as productivity or environmental productivity. As some industries are overrepresented in innovation statistics, considering how the innovations are transmitted through supply chain links provides a more comprehensive picture of the development in less innovative industries (Hauknes and Knell,

[2] Popp (2001) measures innovation with energy technology patents, Wurlod and Noailly (2018) use green patents and Ajayi and Reiner (2020) rely on overall patent counts.

2009).

The importance of inter-industry vertical spillovers was already stressed, e.g., in the works of Schmookler (1966), Griliches (1979) and Wolff and Nadiri (1993). These and more recent studies in the same tradition recognize that it is not only the innovation and development within a specific industry that influence the economic, environmental, or, in the present case, energy intensity performance of the industry (Costantini et al., 2017; Jiao et al., 2020; Li and Bosworth, 2020; Serrano-Domingo and Cabrer-Borrás, 2017). Rather, economic performance and energy use also depend to a large degree on production inputs that are sourced from other vertically related industries. This includes inputs from both domestic and foreign origins (Costantini et al., 2017). The innovations in those upstream industries are embodied in the characteristics of their products, which in turn will be the production inputs used by the downstream industry as intermediate or investment inputs (Griliches, 1979; Hauknes and Knell, 2009). Similar arguments also apply to non-technological innovations, such as product design (Li et al., 2019), and non-patentable inventions, such as software. Vertical productivity spillovers may also be linked to changes in upstream market structures or factor market characteristics (Badinger and Egger, 2016), which are likely reflected in the characteristics of the products sold to downstream customers.

The supply-use links and related user-producer interactions also provide a channel for direct knowledge transfer and knowledge spillovers that transmit knowledge that support innovation and productivity development in firms (Todo et al., 2016). Such knowledge transfer and spillovers may mediate technological knowledge about energy-saving technologies, but they may also convey non-technological information related to energy-efficient practices, behaviors and management systems.

The existing literature on energy intensity has tended to focus on technological innovation, with patents as a common proxy for it. Yet, patents do not capture all relevant developments that influence industrial energy use, as detailed above. Wolff (2011), Badinger and Egger (2016) and Serrano-Domingo and Cabrer-Borrás (2017) have further argued that spillovers related to upstream productivity improvements can be more important than spillovers resulting from upstream R&D or technological innovations. These productivity spillovers encompass other factors that are not captured in R&D or patent data. Balado-Naves et al. (2023) and Wan et al. (2015) relied on similar arguments in their analyses of spatial and trade channels of international energy intensity convergence. In line with these arguments, we can expect the same to apply to energy productivity. Specifically, changes in energy productivity in upstream industries are expected to create spillovers and to have a parallel impact on the energy productivity of downstream industries. In the empirical approach, industrial energy intensity, i.e., the inverse of energy productivity, is analyzed. Similarly, the vertical energy productivity spillovers are empirically measured by their inverse: spillovers resulting from upstream energy intensity changes.

Based on the above discussion, the following hypotheses are formed:

H1. Green technology patents developed by upstream industries create spillovers that reduce the energy intensity of downstream industries through supply-use transactions.

H2. Changes in upstream energy intensity create spillovers that have a parallel impact on the energy intensity of downstream industries through supply-use transactions.

Hypothesis 1 suggests that the more green patents the upstream sectors develop, the more downstream energy intensity declines. Hypothesis 2 suggests that the more upstream energy intensity declines, the more downstream energy intensity will also decline.

2.2. Related empirical literature

While the consequences of vertical spillovers on energy use remain unstudied, related empirical studies have explored (1) the energy use implications of other types of spillovers, (2) vertical technology spillovers in other contexts and (3) how foreign direct investments (FDI) and international trade influence energy use.

The first set of studies recognizes the key role of spatial diffusion of energy technologies. Wan et al. (2015) study spillovers facilitated by international trade and energy productivity convergence at the sectoral level in EU countries. They find that import and export connections induce energy productivity spillovers and support energy productivity convergence. Balado-Naves et al. (2023) analyze the global energy intensity convergence and report that spatial proximity facilitates energy intensity convergence at the country level. Jiang et al. (2018) provide a spatial analysis of energy intensity convergence at the regional level in China. In the same vein, Sun et al. (2021) focus on patented energy innovations and show that the impacts of innovations spill over national borders and affect the energy efficiency of other geographically proximate countries. Regional green technology development is also shown to influence energy intensity of Chinese regions as well as the energy intensity of economically similar regions through interregional spillovers (Pan et al., 2021).

The second group of empirical studies has analyzed, e.g., how vertical green technology spillovers from upstream industries can reduce the carbon intensity and emissions in downstream industries and has shown that their impacts may even exceed those of the industries' own inventive activities (Costantini et al., 2017; Jiao et al., 2020). Relatedly, Ghisetti and Quatraro (2017) discuss emissions and how sectoral relatedness channels emission-reducing technology spillovers across sectors. Serrano-Domingo and Cabrer-Borrás (2017), Badinger and Egger (2016) and Wolff (2011) among others have analyzed general productivity improvements at the sectoral level and provided evidence of vertical productivity spillovers within the supply chain. They have also shown that spillovers resulting from upstream productivity growth are larger than spillovers resulting from upstream R&D investments. Finally, intersectoral R&D and regulatory spillovers have also been shown to influence industry level innovation and productivity outcomes (Corradini et al., 2014; Franco and Marin, 2017).

Yet other empirical studies have taken international trade or investment flows as a direct proxy for technology diffusion (e.g., Huang et al. (2017), Zhang et al. (2022) and Wu et al. (2023)). While international trade and FDI facilitate technology diffusion, they may also lead to intensified international specialization and divergence in energy intensity (Copeland and Taylor, 1999, 2004). Thus, the empirical estimates may conflate these two counteracting effects. Nevertheless, Wu et al. (2023) show that the environmental innovativeness of domestic firms increases due to FDI flows in the same industry as well as due to FDI in upstream and downstream industries. Huang et al. (2017) find that openness to FDI and imports, but not to exports, lowers energy intensity among Chinese regions. Zhao et al. Zhao et al. (2019) and Zhang et al. (2022) show that inward and outward foreign direct investments influence energy intensity and energy intensity convergence among Chinese regions.

The above-described studies explore technology and productivity spillovers transmitted through international trade flows, economic similarity or spatial proximity. The approaches are similar to the present study, but they neglect the important supply chain perspective on technology diffusion in the context of industrial energy use. In sum, the role of vertical spillovers within the supply chain remains unstudied in the context of energy intensity.

3. Methodology and data

3.1. Model specification

The Cobb-Douglas cost function serves as a starting point in forming the equation to be estimated (Fisher-Vanden et al., 2016; Fisher-Vanden et al., 2004):

$$C(P^K, P^L, P^E) = AP_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} Q \tag{1}$$

where C is the minimum cost required to produce output Q and Ps are the prices for capital (K), labor (L) and energy (E) respectively. The α parameters denote the price elasticity of the respective input and the parameters sum to one. A is a productivity term that captures, e.g., factors influencing industrial energy efficiency. Based on Shephard's Lemma, the input demands are equal to the derivative of the cost function with respect to input price. Thus, we can derive the demand for energy input (E):

$$E = \frac{\alpha_E AP_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} Q}{P_E} \tag{2}$$

If we further assume that $P_Q = P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E}$, we can write Eq. 2 as an equation for energy intensity. Thus, the energy intensity is a function of productivity term, A, and the relative price of energy as follows:

$$\frac{E}{Q} = \frac{\alpha_E AP^Q}{P^E} \tag{3}$$

Henceforth, energy intensity, E/Q, is denoted by EI. Next, an expression for the productivity term A is needed. Productivity, A, includes technological and other factors and it is modeled as follows:

$$lnA_{ijt} = \beta_T S_{ijt}^T + \beta_{EI} S_{ijt}^{EI} + \delta X_{ijt} + \varepsilon_{ijt} \tag{4}$$

where S^T is the spillovers from upstream patented green technologies that are available for industry i in country j in year t and S^{EI} is the vertical spillovers from upstream energy intensity changes that are taken as a proxy for other than green technology-related upstream changes that create spillovers. X is a set of control variables affecting the productivity term. The controls vary across industries, countries and time. Taking a logarithm of Eq. 3 and inserting Eq. 4, we obtain an equation that we may estimate:

$$lnEI_{ijt} = \beta_0 + \beta_P ln\left(\frac{P_{ijt}^E}{P_{ijt}^Q}\right) + \beta_{EI} S_{ijt}^{EI} + \beta_T S_{ijt}^T + \delta X_{ijt} + \varepsilon_{ijt} \tag{5}$$

In the empirical estimation, control variables X include the industry's own green technology stock and country-industry and year fixed effects. To allow for differing time trends across countries or industries due to, e.g., changes in national regulation or different technological trends, the equation is also estimated using either country-year or industry-year fixed effects. Following similar studies and considering that input substitution and other factors affect energy intensity, also capital intensity, labor input and the share of imported inputs are included as control variables (Ajayi and Reiner, 2020; Matthess et al., 2023; Wang et al., 2022). Because the measures for green technology spillovers and energy intensity spillovers only cover spillovers from non-service sectors (see Section 3.2), it is also useful to control for the share of inputs sourced from the service sector.

3.2. Data and variables

The key datasets are the World Input Output Data (WIOD) 2016 release and the OECD REGPAT patent database. The WIOD input-output tables are available for the years 2000 to 2014, which sets the time span of the analysis. The years 2000 to 2002 are used as a pre-sample (see Section 3.3); thus, the estimation period is from 2003 to 2014. OECD REGPAT database covers all patents registered at the European Patent Office (EPO). Due to using EPO patent data, the sample is restricted to 29 European countries.[3] Furthermore, as the patent data is generally not suitable to analyze the service sector innovation, the service sectors are excluded from the sample. Service sectors are also excluded from the calculation of the vertical spillover variables. However, the share of inputs from service sectors is used as a control variable in the estimations. The final sample covers 27 industries in 29 countries from 2003 to 2014.

3.2.1. Patent data and variables

Patent data is used to measure the new technology development of industries. Despite the wide use of patent-based indicators, it is worth noting that they also have their limitations: e.g., patents are a better measure of inventions rather than innovations, not all inventions are patentable and not all patentable inventions are patented, the patentability requirements differ across patent offices and the value distribution of patents is highly skewed. These limitations imply that patent statistics are not suitable for measuring the technological development in, e.g., service industries, while they give a better picture of manufacturing industries. Despite these limitations, patent-based approaches are an established way to measure innovation in the literature due to the good availability of patent data and because patents are highly correlated with alternative measures of innovation and technology (Ghisetti and Quatraro, 2017; Pan et al., 2021; Popp, 2001; Wurlod and Noailly, 2018).

The empirical analysis of the present study is based on the EPO data on patent applications and their technological fields. The data is obtained from the OECD REGPAT database, while the patent filing dates are obtained from the OECD Patent Quality database. Patents are assigned a technological CPC (Cooperative Patent Classification) code, which can be linked to industries using a concordance table. In the literature, different concordance tables and linking methods have been developed (Dorner and Harhoff, 2018; Lybbert and Zolas, 2014; Van Looy et al., 2015). This study relies on the work of Lybbert and Zolas (2014) and Goldschlag et al. (2020), who use text analysis and data mining methods to calculate probability weights for industries in which a patent with a given CPC code is likely to be associated. The probability weights describe the probability that the patent is either used or produced in that industry. Combining these two types might appear to be a limitation; however, Lybbert and Zolas (2014) discuss and show that linking patents based on either use or production leads to highly similar probabilities. These probability weights are thus used to count the number of patents in each industry in each year.[4] In the case of patent applications with several CPC codes, fractional counting is used to allocate a share of the patent to industries. This approach avoids the double counting of these patents.

As Wurlod and Noailly (2018) show, the improvement in industrial energy intensity is related to green patents rather than other types of patented technologies. Specifically, they use patents in climate change mitigation and energy efficiency technologies. Following their

[3] Countries are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Switzerland and the UK.

[4] The specific concordance table is the CPC Crosswalk excluding service industries version 2209 (Goldschlag et al., 2020). While the updated version 2209 also includes links to service sectors, the authors recommend excluding services. Moreover, as argued in Section 2, the upstream technological development is especially expected to be embodied in the intermediate and investment inputs sourced from upstream sectors. This spillover mechanism appears relevant regarding upstream manufacturing sectors, but not necessarily for upstream service sectors. The concordance developed by Dorner and Harhoff (2018) provides links also to knowledge-intensive service sectors that are active in patenting. When this concordance was used as a robustness test, the main results remained valid, but only when all service sectors were excluded from the sample.

approach, the present analysis also focuses on these technologies. Green patents are identified using the Y02-Y04 tagging scheme that identifies technologies relevant to climate change mitigation. The following technologies are included: climate change mitigation technologies related to buildings (Y02B), carbon capture and storage (Y02C), information and communication technologies (Y02D), energy (Y02E), industrial production (Y02P), transportation (Y02T), waste management (Y02W) and smart grids (Y04S) (Angelucci et al., 2018).[5] However, patents related to adaptation to climate change (Y02A) are excluded. Next, this list is complemented with energy consumption related technologies following Popp (2001).[6] While these categories include many energy efficiency improving new technologies, they also include renewable energy technologies and technologies affecting pollution. While these technologies may bring indirect energy-saving benefits, this broad definition may also overestimate the energy use relevant green technology stocks (Wurlod and Noailly, 2018). The sensitivity of results to different definitions of green technologies is analyzed in Appendix A.

A further issue is whether simple patent counts should be used as in prior literature (Ajayi and Reiner, 2020; Popp, 2001; Wurlod and Noailly, 2018), or whether citation-weighted patent counts, i.e., a quality-weighted measure, would be preferable (Squicciarini et al., 2013). Following prior literature, simple patent counts are used in the baseline estimations and citation-weighted patents are analyzed in Appendix A.

The addresses of patent applicants are used to relate patent applications to specific countries. In the case of patents with several applicants from different countries, fractional counting is used. Patent priority date is used to measure the year of invention. These methods give us the number of green patents I_{ijt} in country j, in industry i in year t.

As is typical in the literature, the cumulative stock of patents is calculated using perpetual inventory model and assuming a depreciation rate of 15 %.[7] Thus, the industry's own green technology stock, T, can be calculated as follows:

$$T_{ijt} = (1-\delta)T_{ij,t-1} + I_{ijt} \tag{6}$$

Because the EPO patent data start from the 1970s, the starting values are not separately calculated.

3.2.2. Variables based on world input output data

The WIOD input-output table contains information on supply and use linkages across industries and countries (Timmer et al., 2015). The WIOD Environmental accounts contain data on industries' total energy use in TJ (terajoules) and the WIOD Socio-Economic accounts are used to obtain industrial output (Corsatea et al., 2019). Thus, the energy intensity, EI, is measured by dividing the total energy use in TJ by the industrial value added.[8] The value added is deflated to 2010 real prices using the deflator provided in the WIOD Socio-Economic Accounts.

WIOD Environmental accounts do not directly report energy expenses. However, these can be proxied using the intermediate input expenses for coke, refined petroleum, electricity, gas, steam and air conditioning supply (NACE sectors 19 and 35) both from domestic and foreign sectors following Adetutu et al. (2016) and Sharimakin et al. (2018). The energy expenditures are then divided by energy use in TJ to provide an energy price proxy. The year 2010 is used as a base year to transform the energy prices to a price index. Finally, the energy price index is divided by the price index of value added to get the relative price of energy for each industry and country.

The WIOD input-output table is also used to map supply and use linkages across industries and countries following Costantini et al. (2017) and Jiao et al. (2020). Using the input-output table, the technological spillovers are calculated as follows:

$$S^{T}_{ijt} = \sum_{c=1}^{C}\sum_{k=1}^{K} w_{ijckt} lnT_{ckt}, \forall kc \neq ij \tag{7}$$

$$S^{EI}_{ijt} = \sum_{c=1}^{C}\sum_{k=1}^{K} w_{ijckt} lnEI_{ckt}, \forall kc \neq ij \tag{8}$$

Eq. 7[9] presents technological spillovers arising from green innovations, T, in upstream sector c in country k and Eq. 8 presents vertical spillovers arising from upstream changes in energy intensity.[10] Using upstream energy intensity as a proxy for general vertical spillovers is similar to the approaches used by Balado-Naves et al. (2023), Wan et al. (2015) and Serrano-Domingo and Cabrer-Borrás (2017), who studied international energy intensity spillovers and vertical labor productivity spillovers. By including both upstream green patents and upstream energy intensity, the present analysis can uncover not just whether vertical spillovers exist, but also separate between these two causes for them.

The weights, w, are the shares of inputs sector i in country j buys from upstream sector c in country k[11] in year t. Thus, the change in spillover variables S^T and S^{EI} can be interpreted as the weighted average percentage change in the upstream green patent stocks and energy intensity. It is also worth highlighting that Eqs. 7 and 8 measure vertical spillovers from both domestic and foreign upstream sectors.

Weights, w, are based on the supply chain linkages as follows:

$$w_{ijckt} = \frac{m_{ijckt}}{\sum_{c=1}^{C}\sum_{k=1}^{K} m_{ijckt}}, \forall kc \neq ij \tag{9}$$

In Eq. 9, m_{ijckt} denotes the amount of inputs industry i in country j buys from sector c in country k in year t. Thus, the higher the share of inputs, the larger the potential for input embedded spillovers and the larger the weight, w. The input use and spillovers from the own sector

[5] The Y02-Y04 tagging scheme has considerable overlap with OECD ENV-TECH search, which has also been commonly used by prior studies (Haščič and Migotto, 2015). However, OECD ENV-TECH includes also, e.g., water and waste management technologies that are expected to be less connected to energy use and more relevant for other environmental benefits.

[6] Popp (2001) lists the following patent technology codes: F01K17, F01K19, F01K23, F02G, F25B13, F25B29, F28, B22D11, C21D, C22B4, C23C, C25C, C25D, C22B21, D21C11, F02, F02B19, F23, F23L7, F23L15, F23N5, F23G5, F23G7, F03G7, F24J2, H01L25, H01L31, H01L35, H01L37, H02N6, F03D, C10J3, C10K3, C10G1 and H01M8.

[7] The depreciation rates used in the literature tend to vary between 10 % and 20 % (Verdolini and Galeotti, 2011; Wurlod and Noailly, 2018; Costantini et al., 2017; Ajayi and Reiner, 2020; Jiao et al., 2020).

[8] The WIOD Environmental accounts have a few inconsistencies in the availability of some energy sources for some countries and industries. E.g., the use of electricity, fuel oil or diesel can be zero in one year but forms a significant part of the total energy use in the next year. In case of such inconsistencies, the years with zeros are excluded from the analysis. However, if some energy source has zeros for all years, the observations are included.

[9] Spillovers from upstream green innovations also include source sectors in non-European countries and the Rest of the World group that are included in WIOD. These countries are not members of the EPO and thus the number of patents applications (as a measure of T) from these countries is likely to be lower, reflecting the home bias in patenting. However, the panel fixed effects model estimates the effect of change in upstream technology stocks and the shift-share instrumental variable estimation is based on the pre-sample input shares. Therefore, time invariant home bias in patenting does not appear to be a concern, although time varying home bias in patenting could be a source of bias.

[10] Spillovers from upstream energy intensity include source sectors in European and non-European countries that have energy use and value added available. The exception is Rest of the World group for which it is not possible to count the energy intensity.

[11] The source sectors that have zero green patents are excluded from the computation of weights, w, for Equation 7. Similarly, sectors that have missing energy intensity data are excluded from the computation of weights, w, for Equation 8.

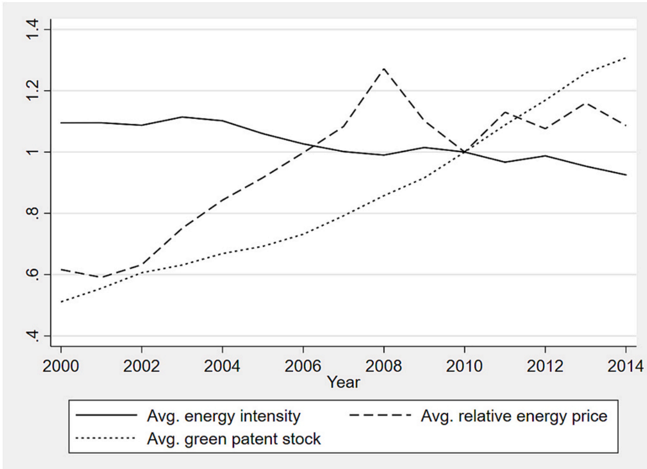

Fig. 1. Development of average energy intensity, relative energy prices and green patent stock. Notes: The variables have been averaged over industries and years and normalized (2010 = 1). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

are not allowed in Eqs. 7 and 8; however, input use and spillovers from the same sector abroad are considered. As mentioned earlier, service sectors are excluded.

Additional control variables for capital intensity, employment and share of imports are used. These variables are also based on WIOD data. Employment is measured by the number of persons engaged. As the WIOD data does not include a deflator for capital stock, capital intensity is measured as nominal capital stock divided by nominal labor compensation. The share of imports is the amount of imported inputs divided by all inputs. The final control variable is the share of inputs that are sourced from service sectors.

3.3. Econometric considerations

When estimating Eq. 5, the potential endogeneity of spillovers needs to be considered. Using industry fixed effects removes potential bias due to time-invariant unobservables. However, the industry's energy intensity may influence the amount and direction of resources devoted to innovation and technological development. This could suggest reverse causality between energy intensity and own innovation. Nevertheless, the main interest and novelty in the analysis lies in the impacts of vertical spillovers, i.e., spillover effects of new technologies and non-technological innovations developed in other sectors. The concern of reverse causality appears less marked in this case. Thus, the equation is first estimated using fixed effects panel estimation.

Remaining endogeneity concerns are that industry trends influencing energy intensity may also influence the supply-use links and that spillovers might just reflect joint trends in energy intensity. Thus, the model is also estimated using instrumental variable estimation. The underlying idea of the used instrument is to utilize the initial supply-use links as predetermined weights that describe how different industries are exposed to differing technology shocks emanating from various upstream industries. The instrumental variables are formed in line with Eqs. 7 and 8, but the weights, w, are replaced by pre-sample weights based on averages from years 2000 to 2002. Thus, the approach removes the variation of confounding factors that may affect the supply-use links over time. This instrumentation strategy follows the shift-share, or Bartik, instrumental variable approach (Bartik, 1991; Goldsmith-Pinkham et al., 2020).

Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022) show that the shift-share instruments provide valid identification of the effects when either the initial exposure weights or the technology shocks are assumed exogenous. The exogeneity of initial supply-use weights means

Table 1
Descriptive statistics.

	Mean	Median	Std. Dev.
Energy use (in TJ) (E)	119,446.2	6255.0	529,376.9
Real value added (Q)	6023.1	1395.2	15,073.3
Relative price of energy (P^E/P^Q)	1.062	1.000	0.639
Energy intensity (EI)	91.176	3.768	955.394
Spillovers from green patents (S^T)	2.150	2.248	1.640
Spillovers from energy intensity (S^{EI})	2.162	2.171	0.814
Own green patent stock (T)	45.928	1.322	242.844
Persons engaged (thousands) (L)	89.504	22.030	233.739
Capital intensity (K/L^C)	6.501	3.544	9.414
Share of service inputs	0.332	0.312	0.126
Share of imported inputs	0.384	0.355	0.184

Notes. 8334 observations. Financial variables are in millions of USD deflated to base year 2010.

that they need to be exogenous to changes in energy intensity after controlling for the control variables and industry-country fixed effects. This assumption might not hold if sectors with different initial input structures are on different energy intensity trends to begin with, which could be the case if specific countries or specific industries were driving the energy efficiency improvements. To address this concern, country-year controls or industry-year controls are used to allow for country or industry specific time trends. Further tests are conducted in Section 4.3 to support the validity of the empirical approach.

3.4. Descriptive statistics

Fig. 1 illustrates the development of industrial energy intensity, relative energy prices and green patent stock over time. Fig. 1 presents sample averages. The variables have been normalized so that the year 2010 = 1. The average energy intensity shows a moderate decline of approximately 1 % per year. During the observation period, the relative energy prices experienced a strong but uneven increase, while the accumulated green patent stock shows a steady increase of over 5 % per year.

Descriptive statistics of the variables used in the empirical analysis are presented in Table 1. A list of included industries and the number of observations by industry are provided in Appendix B. In the regression equation, most of the variables are used in logarithmic form. Thus, the sample is restricted to those observations where these variables have strictly positive values. The sample is further limited to non-service sectors as discussed earlier.

4. Results and discussion

4.1. The impacts of vertical spillovers on energy intensity

This section presents and discusses the results of econometric analysis. First, Table 2 presents the results using fixed effects panel estimation (FE models 1–3) and the results using instrumental variable estimation (IV models 4–6). The models are first estimated with year fixed effects and then with country-year fixed effects and finally with industry-year fixed effects. The estimations include both spillovers from upstream green patents and energy intensity development. Appendix A reports estimations where the spillover variables are included one at a time.

For the IV estimation to be valid, the instruments need to meet the criteria of relevance and exogeneity. The IV estimates are exactly identified, hence, there are no overidentifying restrictions to test. To assess the relevance of the instruments, underidentification and weak identification tests are conducted and reported in Table 2. The first stage Kleibergen-Paap (KP) rank Wald F-statistic is used to test potential weak identification (Kleibergen and Paap, 2006). A common rule of thumb is to interpret an F-statistic smaller than 10 as weak (Staiger and Stock, 1997; Stock and Yogo, 2005). The underidentification test using

Table 2
Baseline estimation results.

	FE			IV		
	1	2	3	4	5	6
$\ln(P^E/P^Q)$	−0.603***	−0.617***	−0.593***	−0.604***	−0.613***	−0.593***
	(0.026)	(0.029)	(0.027)	(0.025)	(0.028)	(0.026)
S^T	−0.015	0.015	−0.013	−0.079**	0.004	−0.088**
	(0.022)	(0.024)	(0.022)	(0.034)	(0.050)	(0.034)
S^{EI}	0.326***	0.326***	0.263***	0.456***	0.247***	0.305***
	(0.039)	(0.043)	(0.035)	(0.076)	(0.080)	(0.078)
ln(T)	0.004	0.011	−0.002	0.008	0.012	0.003
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
ln(L)	−0.146**	−0.149**	−0.154**	−0.135**	−0.147**	−0.146**
	(0.057)	(0.061)	(0.066)	(0.058)	(0.059)	(0.065)
$\ln(K/L^C)$	−0.087*	−0.088	−0.112**	−0.080	−0.087	−0.106**
	(0.052)	(0.055)	(0.053)	(0.052)	(0.054)	(0.052)
Share of service inputs	−1.051***	−1.024***	−0.966***	−1.048***	−1.035***	−0.946***
	(0.266)	(0.297)	(0.267)	(0.277)	(0.293)	(0.271)
Share of imported inputs	−0.395**	−0.314	−0.356*	−0.29	−0.324	−0.231
	(0.200)	(0.226)	(0.204)	(0.205)	(0.217)	(0.207)
Industry-country FE	x	x	x	x	x	x
Year FE	x			x		
Country-Year FE		x			x	
Industry-Year FE			x			x
Observations	8334	8334	8334	8334	8334	8334
Adj. R-squared	0.435	0.473	0.456	0.371	0.417	0.395
1st stage F				123.424	133.603	55.015
KP LM test				98.091	84.79	55.042
SW F S^T				516.048	274.269	530.728
SW F S^{EI}				85.696	70.017	71.249
SW Chi-squared S^T				517.865	285.822	551.568
SW Chi-squared S^{EI}				85.998	72.966	74.047
AR test p-value				0.000	0.007	0.000

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. Standard errors are clustered at the country-industry level. 1st stage F-statistic refers to the Kleibergen-Paap Wald F-statistic. LM test is the Kleibergen-Paap underidentification test statistic. SW F and SW Chi-squared refer to the Sanderson-Windmeijer tests of weak identification and underidentification, respectively, of the individual endogenous regressors. AR test refers to the Anderson-Rubin test that is robust to weak-identification.

Kleibergen-Paap LM-statistic is also reported. As there are several endogenous variables, the first stage Sanderson-Windmeijer (SW) χ^2 and Sanderson-Windmeijer F-statistic are reported for each endogenous variable (Sanderson and Windmeijer, 2016). Finally, p-value from the Anderson-Rubin test is reported to provide a weak instrument robust test of the joint significance of the endogenous variables (Anderson and Rubin, 1949). These tests support the relevance of the used instruments.

As follows from the measurement of spillover variables in Eqs. 7 and 8, hypothesis H1 suggests that the increase in the upstream green patents and related spillovers, S^T, should lead to a reduction in downstream energy intensity, hence, a negative coefficient is expected. Regarding hypothesis H2, a decrease in the upstream energy intensity is expected to lead to an energy intensity reduction in the downstream industry, thus, the variable, S^{EI}, is expected to have a positive coefficient.

The empirical results in Table 2 show that vertical spillovers lead to a statistically significant decrease in the energy intensity of downstream industries. Regarding vertical energy intensity spillovers, the coefficients are positive and in the range of 0.26–0.33 for FE estimates and in the range of 0.24–0.46 for IV estimates, which supports hypothesis H2. Thus, a 10 % decline in upstream energy intensity will result in a 2.4 to 4.6 % reduction in the energy intensity in downstream industries.

Regarding the spillovers from upstream green technologies, the results show more heterogeneity across the models. While the FE estimates show insignificant coefficients, the preferred IV specifications indicate that energy efficiency improvements also result from these spillovers. Models 4 and 6 indicate that a 10 % increase in upstream green patent stock will result in a 0.8 to 0.9 % decrease in downstream energy intensity. Nevertheless, if country-specific time trends are allowed, the coefficient is close to zero. Thus, only partial support for H1 is found. While prior studies (Costantini et al., 2017; Jiao et al., 2020) show that vertical green technology spillovers strongly affect the emission intensity of downstream industries, the results presented here indicate that the role of these spillovers is less marked in the context of industrial energy use. This finding is perhaps not surprising since green patents may reduce emissions through fuel switching, improvement in energy efficiency and other channels. Thus, their impact on emissions can be expected to be larger than their impact on energy intensity, which represents just one channel for emission reduction. Moreover, the finding that upstream energy intensity changes create more robust vertical spillovers than patented technologies can be attributed to the broader scope of S^{EI} compared to S^T, which is limited to patented green technologies. This interpretation aligns with the findings on general productivity spillovers (Badinger and Egger, 2016; Serrano-Domingo and Cabrer-Borrás, 2017). However, as shown in Fig. 1, green patenting has grown about five times faster than energy intensity has declined. Considering this difference together with the coefficient estimates in Models 4 and 6 suggests that upstream green technology and energy intensity spillovers may have contributed roughly equally to downstream energy intensity development.

A surprising result in Table 2 is that the industry's own green technology stock has statistically insignificant impact on energy intensity, which contrasts with earlier findings. The origin of this finding is explored further in Section 4.2. Other coefficients in Table 2 are in line with expectations. Higher relative price of energy leads to lower energy use. The size of coefficient is also in line with Ajayi and Reiner (2020). The negative coefficients of labor and capital intensities show a complementarity between the different production inputs. The share of inputs sourced from the service sector is associated with significantly lower energy intensity, which may reflect structural changes in industries, but it also further emphasizes the importance of suppliers for downstream energy productivity improvements. Similarly, the share of imported inputs has a negative coefficient, although it is not significant

Table 3
Industry heterogeneity.

	Energy-intensive sectors				Other sectors			
	FE	FE	IV	IV	FE	FE	IV	IV
S^T	0.025	−0.012	−0.073	−0.107**	0.020	−0.011	0.064	−0.036
	(0.031)	(0.027)	(0.063)	(0.050)	(0.041)	(0.034)	(0.066)	(0.049)
S^{EI}	0.124**	0.151***	−0.163	0.118	0.388***	0.356***	0.441***	0.542***
	(0.057)	(0.046)	(0.131)	(0.098)	(0.068)	(0.051)	(0.114)	(0.105)
ln(T)	−0.015	−0.042**	−0.016	−0.038*	0.028**	0.026**	0.027**	0.028**
	(0.021)	(0.019)	(0.020)	(0.019)	(0.013)	(0.013)	(0.012)	(0.013)
Control variables	x	x	x	x	x	x	x	x
Industry-country FE	x	x	x	x	x	x	x	x
Country-Year FE	x		x		x		x	
Industry-Year FE		x		x		x		x
Observations	3301	3301	3301	3301	5033	5033	5033	5033
Adj. R-squared	0.431	0.424	0.335	0.354	0.523	0.486	0.470	0.423
1st stage F			40.460	40.343			57.218	71.142
KP LM test			31.466	30.551			57.454	33.482
SW F S^T			143.755	186.166			136.677	312.873
SW F S^{EI}			25.401	31.315			91.366	152.514
SW Chi-squared S^T			160.077	193.691			146.466	326.134
SW Chi-squared S^{EI}			28.285	32.581			97.910	158.978
AR test p-value			0.143	0.093			0.002	0.000

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. Standard errors are clustered at the country-industry level. Control variables include the relative price of energy, number of persons engaged, capital intensity, the share of service inputs and the share of imported inputs. 1st stage F-statistic refers to the Kleibergen-Paap Wald F-statistic. LM test is the Kleibergen-Paap underidentification test statistic. SW F and SW Chi-squared refer to the Sanderson-Windmeijer tests of weak identification and underidentification, respectively, of the individual endogenous regressors. AR test refers to the Anderson-Rubin test that is robust to weak-identification.

in all estimations. The vertical spillover variables capture spillovers from both domestic and foreign upstream sectors. The negative coefficient of imports suggests that importing provides access to foreign knowledge and technologies that are not related to the characteristics of the foreign upstream sectors. The role of domestic and foreign vertical spillovers is further discussed in Appendix A.

4.2. *Industry specific heterogeneity*

In Table 3, the industry heterogeneity of results is explored. Wurlod and Noailly (2018) found that the effects of green innovations on energy intensity tended to be stronger in energy-intensive industries. These industries are likely to have greater potential for economic gains from energy productivity improvements. Thus, the industries are classified into two categories: (1) energy-intensive sectors[12] and (2) others. In Table 3, the FE specifications 2–3 and IV specifications 5–6 are estimated separately for energy-intensive sectors and others. The table presents the coefficients for the technology variables while the coefficients of the control variables are omitted.

The results in Table 3 indicate that the industry's own green innovations indeed reduce energy intensity, but these effects appear to be concentrated in energy-intensive manufacturing and do not appear elsewhere. In other industries, green innovations tend to increase energy intensity. This could be due to, e.g., higher green innovativeness leading to higher renewable energy use. There may also be endogeneity bias and the results for the industry's own green technology stock may not be interpreted as causal.

Turning towards the findings on vertical spillovers, the results again show sectoral heterogeneity. Specifically, vertical spillovers related to energy intensity are less important in the energy-intensive sectors and stronger in the less energy-intensive sectors. In contrast, the spillovers from green patents appear more important in the energy-intensive sectors. Overall, Table 3 highlights that own green innovations and green innovation-related spillovers are an important driver for energy productivity improvements in energy-intensive industries, while in other industries general energy intensity spillovers appear more important.

4.3. *Robustness tests*

The above-used instrumental variable estimation provides valid identification of the causal effects if the instruments are exogenous. As the estimated equations in Tables 2 and 3 are exactly identified, this assumption cannot be tested. Moreover, as the spillovers appear to be linked especially to changes in upstream energy intensity, it remains a concern that the estimation results might not reflect true spillovers but some shocks that influence energy intensity and happen to be correlated across the supply chain. However, if the findings were purely due to correlated shocks, then the results should also be similar when analyzing potential spillovers from downstream to upstream. To test this, Table 4 estimates the effects of potential spillovers from both upstream and downstream. A limitation of this test is that, as argued in Section 2.1, vertical spillovers may be embodied spillovers or intangible knowledge spillovers and the latter type could also flow from downstream to upstream (Javorcik, 2004).

In Table 4, the vertical spillovers from downstream are calculated in line with Eqs. 7 and 8, but now the spillover source sectors are downstream sectors, i.e., customer sectors. Instrumental variables can also be calculated for the downstream spillovers in line with Section 3.3. Model specifications 2–3 and 5–6 of Table 2 are re-estimated with downstream spillover variables included. Table 4 presents the coefficients for the spillover and technology variables while the coefficients of the control variables are omitted.

The FE results in Table 4 show that downstream energy intensity appears to have some influence on the energy intensity of the upstream industries. However, when the initial supply-use links are used to create instruments and IV models are estimated, neither downstream green innovation nor downstream energy intensity changes create significant spillovers in the upstream sector. Thus, upstream energy intensity

[12] The energy-intensive category includes mining and quarrying; food, beverage and tobacco; wood products, paper, coke and petroleum; chemicals; rubber and plastics; other non-metallic mineral products; basic metals; electricity, gas, steam and air conditioning. The rest of industries are included in the other group.

Table 4
Vertical spillovers from upstream and downstream.

	FE		IV	
	1	2	3	4
S^T	0.011	−0.022	−0.013	−0.099**
	(0.025)	(0.025)	(0.053)	(0.041)
S^{EI}	0.314***	0.248***	0.259**	0.263**
	(0.042)	(0.035)	(0.103)	(0.116)
Downstream S^T	0.039	0.033	0.032	0.016
	(0.024)	(0.023)	(0.036)	(0.036)
Downstream S^{EI}	0.061*	0.076**	−0.033	0.053
	(0.033)	(0.032)	(0.095)	(0.107)
ln(T)	0.010	−0.004	0.011	0.003
	(0.012)	(0.011)	(0.012)	(0.012)
Control variables	x	x	x	x
Industry-country FE	x	x	x	x
Country-Year FE	x		x	
Industry-Year FE		x		x
Observations	8334	8334	8334	8334
Adj. R-squared	0.476	0.460	0.417	0.397
1st stage F			36.177	22.723
KP LM test			82.394	53.351
SW F S^T			227.685	285.546
SW F S^{EI}			113.248	107.082
SW F Downstream S^T			174.152	174.590
SW F Downstream S^{EI}			88.846	105.844
SW Chi-squared S^T			237.335	296.833
SW Chi-squared S^{EI}			118.047	111.314
SW Chi-squared Downstream S^T			181.533	181.491
SW Chi-squared Downstream S^{EI}			92.611	110.028
AR test p-value			0.036	0.000

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. Standard errors are clustered at the country-industry level. Control variables include the number of persons engaged, capital intensity, the share of service inputs and the share of imported inputs. 1st stage F-statistic refers to the Kleibergen-Paap Wald F-statistic. LM test is the Kleibergen-Paap under-identification test statistic. SW F and SW Chi-squared refer to the Sanderson-Windmeijer tests of weak identification and underidentification, respectively, of the individual endogenous regressors. AR test refers to the Anderson-Rubin test that is robust to weak-identification.

changes and, to a weaker extent, green technology innovations create vertical spillovers that influence the downstream energy intensity, and this finding cannot be explained by purely correlated shocks. Instead, the argument that the spillovers are embodied in the inputs sourced from the upstream sectors gains support.

A further concern regarding the presented empirical results may be that it may take time before technological innovations and related spillovers can be adopted and applied in the downstream industries. Thus, the estimations were repeated using one-year lagged values of the spillover variables as independent variables. The baseline results were confirmed using the lagged variables. These estimates are not reported to save space.

Moreover, while some observations with inconsistencies in the energy use data are dropped from the sample, inconsistencies in real value added may also lead to large jumps or drops in energy intensity. Thus, as a further test to check the robustness of results, the change in real value added was included as a control variable. Moreover, additional sectors that show large changes in energy intensity were also dropped from the sample. This robustness check again confirmed the baseline results.

Finally, it was checked whether individual countries, sectors, input source countries or source sectors are driving the results. Leave-one-out regressions were run by dropping each country and industry from the sample in turn. Next, each input source country was picked in turn and the time trend was allowed to vary depending on the pre-sample share of inputs from that country. Lastly, each source sector was picked in turn and the time trend was allowed to vary depending on the pre-sample share of inputs from that sector. These estimates are not reported to save space. Nevertheless, these estimations do not reveal that any individual country or sector is driving the results in Table 2. Similarly, the results remain robust in regressions that control for a time trend that is allowed to depend on pre-sample source sector input shares. However, when the time trend is allowed to depend on pre-sample source country input shares, the results show somewhat more heterogeneity. Moreover, the statistical significance of results is sometimes weaker if country-year time trends are simultaneously allowed. Overall, the findings remain in line with Table 2, but the observed heterogeneity indicates that some countries are more important sources for spillovers than others.

5. Conclusions

This study has analyzed the determinants of energy intensity among European industries. As a novel contribution to the existing literature, the study has examined the impacts of vertical green technology and energy intensity spillovers along the industrial supply chain. Besides creating intangible knowledge spillovers, the technological innovations developed by upstream industries are also embodied in the quality of their products that are used by the downstream industries as production inputs. As energy use related innovations are not evenly distributed among industries, the analysis of vertical spillovers complements our understanding of the industry-level drivers of technological change.

The main method of analysis relies on fixed effects instrumental variable estimation, where the initial supply-use links are used to form instrumental variables in line with the shift-share instrumental variable approach. The empirical results reveal that the supply-use connections mediate spillovers that have an impact on downstream energy intensity. These spillovers are more robustly linked to upstream energy intensity changes and, to some extent, also to upstream green patents. General energy intensity spillovers aggregate several factors, and they are, thus, somewhat uninformative about exact underlying mechanisms for vertical spillovers. Nevertheless, spillovers due to upstream green technological innovations form just a part of vertical spillovers and further research should explore the other mechanisms for vertical spillovers that have an evidently strong influence on industrial energy use.

Moreover, industries' own green patents and the spillovers from upstream green patents appear important for the energy efficiency improvements in energy-intensive manufacturing sectors, whereas in other sectors only general energy intensity spillovers appear to matter. Further estimations revealed no significant spillovers from downstream to upstream. This emphasizes that the observed vertical spillovers from upstream to downstream are specifically linked to the supply of intermediate and investment inputs and that the findings are not merely reflecting correlated shocks.

On the policy side, the empirical findings highlight that reaching energy efficiency targets, such as those set by the European Union, depends not only on the investments and innovations made by individual companies or industries, but on improvements made through the whole supply chain and the successful integration of these actions. From a managerial perspective, this emphasizes the effective management of the supply chain and the importance of user-producer interactions. Moreover, the results suggest that policies that stimulate demand for energy efficiency technologies can also contribute to lower energy intensity. While the economic benefits from green innovations through increased revenues appear to be especially linked to consumer market exposure (Antweiler and Harrison, 2003), policies that increase the transparency of energy use and the environmental impacts of supply chains can strengthen similar motives and revenue generation also in business to business transactions. Such policies could thus support the demand for green and energy efficiency innovations.

The findings also show that industries' own green innovations do not always reduce energy intensity but may even increase energy intensity. Thus, if policymakers wish to use R&D support policies to support further reductions in energy intensity, it appears more effective to target the funding to energy-intensive industries, where the green innovations and related spillovers are likely to have the most impact on energy use.

While this study has provided a novel analysis of the drivers of industrial energy intensity, the study is also subject to some limitations and leaves room for extensions. First, the analysis could be extended to cover horizontal technology spillovers. Second, as mentioned above the exact causes of spillovers, besides green technological innovations, call for further study. Moreover, as Probst et al. (2021) showed, the global green patenting activity increased strongly until 2012, but has decreased since then, likely due to a decline in fuel prices. As the WIOD data set ends in 2014, novel data would be needed to analyze the energy use impacts of green technologies in the context of fewer green innovations and lower fuel prices. Finally, the service sector was not analyzed in this study. As the determinants of energy use in the service sector are likely to differ and patent data is not well suited for the analysis of the service sector, these questions could be analyzed with different methods.

CRediT authorship contribution statement

Jaana Rahko: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

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Appendix A. Appendix

The estimations in Tables 2–4 include both spillovers from upstream green patents and energy intensity development. However, as green patents may also influence upstream energy intensity development, the coefficient for upstream energy-intensity-related spillovers might also capture a part of the effect of upstream green patenting. To clarify this aspect, Table A1 analyzes the roles of these two spillover sources individually. The IV estimate of the effect of upstream green patents is now somewhat larger at −0.109, compared to −0.079 in Table 2. Otherwise, the results are very close to those in Table 2. These results suggest that a part of the effect of green patents in Table 2 may be mediated through changes in upstream energy intensity.

Table A1
One-by-one analysis of vertical spillover variables.

	FE	IV	FE	IV
S^T	0.002	−0.109***		
	(0.022)	(0.036)		
S^{EI}			0.324***	0.474***
			(0.039)	(0.079)
ln(T)	0.002	0.010	0.002	0.002
	(0.011)	(0.012)	(0.011)	(0.011)
Industry-country FE	x	x	x	x
Year FE	x	x	x	x
Observations	8334	8334	8334	8334
Adj. R-squared	0.403	0.332	0.434	0.372
1st stage F		515.701		74.949
KP LM test		108.872		63.803
SW F S		515.701		74.949
SW Chi-squared S		517.455		75.203
AR test p-value		0.003		0.000

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Standard errors are clustered at country-industry level. 1st stage F-statistictic refers to Kleibergen-Paap Wald F-statistic. LM test is the Kleibergen-Paap underidentification test statistic. SW F and SW Chi-squared refer to Sanderson-Windmeijer tests of weak identification and underidentification, respectively, of the individual endogenous regressors. AR test refers to the Anderson-Rubin test that is robust to weak-identification.

Next, the robustness of results concerning the definition of green technologies is explored. Section 3.2.1 outlines the baseline approach to form patent-based variables. This approach focuses on climate change mitigation and energy-efficiency-related patents, which aligns with prior literature, e.g., Wurlod and Noailly (2018). However, different sub-sections of the Y02-Y04 tagging scheme may have different energy use implications, and some energy-use-related patents might not be included in the scheme. For instance, carbon capture and storage (Y02C) and waste (Y02W) related technologies might appear less relevant for energy savings. Therefore, the sensitivity of results to different definitions of green technologies is explored. Each sub-section of Y02-Y04 scheme is considered separately as a proxy for green technologies. The model is also re-estimated using only the energy efficiency technology patents following the list provided in Popp (2001). Moreover, as some sub-sections of the Y02-Y04 scheme appear more closely related to energy savings, the model is re-estimated focusing on those sub-sections. The selected energy-efficiency-related sub-sections are: Y02B except Y02B10, Y02D, Y02E20/12–30, Y02E40, Y02P10/25, Y02P40/121, Y02P60/121, Y02P60/14, Y02P70/10, Y02P80/10–15, Y02P90/82, Y02T except for Y02T10/30, Y02T10/60–72, Y02T50/678, Y02T70/52, Y02T90, and lastly Y04S. The excluded categories relate to, e.g., renewable energy generation, carbon capture, waste management and electric transportation, which may have only indirect energy-saving potential. Finally, the WIPO (World Intellectual Property Organization) Green Inventory also includes a list of technology codes related to energy conservation inventions that have been analyzed in the literature (Rexhäuser and Löschel, 2015). Thus, the model is also re-estimated considering only these technologies, although this list includes fewer technologies than the other approaches. To retain the same sample as in Table 2, ln(T) now refers to the logarithm of 1 + industry's own patent stock in each of the above described technology groups.

The results of these additional estimations are presented in Tables A2 and A3. The tables report both fixed effects and instrumental variable estimation results. However, due to the large number of estimations only results with year fixed effects are presented. For comparison, the tables also reproduce the results of FE model 1 and IV model 4 from Table 2.

The results in Tables A2 and A3 indicate heterogeneity across the different Y02-Y04 sub-sections. The coefficient of green technology spillovers is positive for Y02B and Y02C but mostly negative and insignificant for the other sub-sections. The only technology spillovers that appear negative and significant in both FE and IV estimation are spillovers from Y04S, i.e., smart grid, technologies. The other exception is the energy conservation technology category following the WIPO list, which is significantly positive in the IV results. This result is, however, not robust to the inclusion of industry-specific time controls (not reported in the tables). Overall, focusing on the energy-efficiency-related sub-sections of the Y02-Y04 scheme appears to reproduce the results of the baseline model. This holds true also when country-specific or industry-specific time controls are included (not reported in the tables). Thus, the analysis of both broader climate- and energy-related technologies and narrower energy-efficiency-related climate technologies leads to the same conclusions. Finally, it should be noted that the formation of sub-section-specific variables relies on fewer patents than the variables on aggregate green technology and related spillovers. Thus, sub-section-specific variables may be less precise measures of green technology stocks and spillovers, which may cause attenuation bias in the estimation.

Table A2
Alternative definitions of green technologies. Fixed effect estimation results.

	Baseline	Y02B	Y02C	Y02D	Y02E	Y02P	Y02T	Y02W	Y04S	Popp (2001)	Selected Y02-Y04	WIPO
S^T	−0.015	0.017	0.024	−0.051***	−0.001	0.018	−0.012	−0.012	−0.031**	−0.012	−0.009	0.016
	(0.022)	(0.015)	(0.016)	(0.016)	(0.018)	(0.019)	(0.018)	(0.018)	(0.015)	(0.020)	(0.019)	(0.017)
S^{EI}	0.326***	0.319***	0.312***	0.315***	0.321***	0.309***	0.326***	0.318***	0.321***	0.328***	0.325***	0.322***
	(0.039)	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)	(0.039)
ln(T)	0.004	−0.006	0.112***	−0.066	0.037	0.110***	0.020	0.134***	−0.034	0.001	0.030	0.011
	(0.011)	(0.032)	(0.043)	(0.055)	(0.026)	(0.040)	(0.034)	(0.050)	(0.029)	(0.033)	(0.031)	(0.029)
Control variables	x	x	x	x	x	x	x	x	x	x	x	x
Industry-country FE	x	x	x	x	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x	x	x	x	x
Observations	8334	8334	8334	8334	8334	8334	8334	8334	8334	8334	8334	8334
Adj. R-squared	0.435	0.435	0.437	0.438	0.435	0.437	0.435	0.436	0.436	0.434	0.435	0.435

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Standard errors are clustered at country-industry level. Control variables include the relative price of energy, number of persons engaged, capital intensity, share of service inputs and share of imported inputs.

Table A3
Alternative definitions of green technologies. Instrumental variable estimation results.

	Baseline	Y02B	Y02C	Y02D	Y02E	Y02P	Y02T	Y02W	Y04S	Popp (2001)	Selected Y02-Y04	WIPO
S^T	−0.079**	0.063	0.037	−0.012	−0.025	−0.016	0.043	−0.052	−0.049*	−0.046	−0.067*	0.073***
	(0.034)	(0.047)	(0.036)	(0.032)	(0.032)	(0.038)	(0.030)	(0.040)	(0.027)	(0.039)	(0.036)	(0.025)
S^{EI}	0.456***	0.420***	0.446***	0.460***	0.471***	0.461***	0.481***	0.468***	0.457***	0.485***	0.480***	0.465***
	(0.076)	(0.082)	(0.078)	(0.080)	(0.081)	(0.079)	(0.077)	(0.079)	(0.076)	(0.080)	(0.080)	(0.078)
ln(T)	0.008	−0.035	0.094**	−0.057	0.033	0.103**	−0.002	0.113**	−0.022	0.005	0.040	−0.003
	(0.011)	(0.042)	(0.044)	(0.058)	(0.027)	(0.041)	(0.037)	(0.054)	(0.031)	(0.035)	(0.032)	(0.030)
Control variables	x	x	x	x	x	x	x	x	x	x	x	x
Industry-country FE	x	x	x	x	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x	x	x	x	x
Observations	8334	8334	8334	8334	8334	8334	8334	8334	8334	8334	8334	8334
Adj. R-squared	0.371	0.371	0.376	0.374	0.372	0.375	0.366	0.373	0.374	0.371	0.368	0.368
1st stage F	123.424	105.741	84.188	71.848	39.675	141.933	122.576	100.874	37.434	54.885	152.346	37.547
KP LM test	98.091	83.507	106.201	73.116	66.563	65.842	114.613	85.543	63.042	17.573	107.759	63.812
SW F S^T	516.048	226.088	307.224	364.526	564.546	292.300	392.737	313.353	604.047	109.931	417.475	1151.538
SW F S^{EI}	85.696	148.033	69.488	106.886	76.606	73.451	122.553	84.444	75.540	64.937	74.008	75.858
SW Chi-squared S^T	517.865	226.884	308.306	365.809	566.534	293.329	394.120	314.457	606.173	110.318	418.945	1155.592
SW Chi-squared S^{EI}	85.998	148.554	69.733	107.262	76.876	73.710	122.985	84.742	75.806	65.166	74.269	76.125
AR test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Standard errors are clustered at country-industry level. Control variables include number of persons engaged, capital intensity, share of service inputs and share of imported inputs. 1st stage F-statistictic refers to Kleibergen-Paap Wald F-statistic. LM test is the Kleibergen-Paap underidentification test statistic. SW F and SW Chi-squared refer to Sanderson-Windmeijer tests of weak identification and underidentification, respectively, of the individual endogenous regressors. AR test refers to the Anderson-Rubin test that is robust to weak-identification.

Another critique of using patent-based technology indicators is that the value of a patent varies significantly from one patent to another. This could mean that simple patent counts are a poor measure of industries' green technology stocks. There are various patent indicators that aim to correct this and measure the value of patents (Squicciarini et al., 2013). Perhaps the most common method is to use forward citation-weighted patent counts. As a robustness test, Eq. 5 is re-estimated using citation-weighted green patents as a measure of industry's own green technology stock and as a source of upstream green technology spillovers. The OECD Patent Quality Indicators database is used to obtain data on forward citations received within 7 years after application (Squicciarini et al., 2013). The estimation results are reported in Table A3. To retain the same sample as in Table 2, ln(T) again refers to the logarithm of 1 + industry's citation-weighted green patent stock.

Lastly, Table A3 also presents estimations that separate domestic and foreign upstream sectors as spillover source sectors. While international knowledge diffusion receives much attention (Sun et al., 2021; Wan et al., 2015), the literature also argues that geographic proximity promotes spillovers (Jaffe et al., 1993). Thus, both domestic and foreign vertical spillovers appear important. To separately compute domestic and foreign spillovers, Eq. 7 is replaced by Eq. A1 for domestic spillovers (*DS*) and Eq. A2 for foreign spillovers (*FS*). Eq. 8 for energy intensity spillovers is replaced by two analogous equations that are not presented here.

$$DS_{ijt}^{T} = \sum_{c=1}^{C}\sum_{k=1}^{K} w_{ijckt} lnT_{ckt}, \forall k \neq i \text{ and} \forall c = j \tag{A1}$$

$$FS_{ijt}^{T} = \sum_{c=1}^{C}\sum_{k=1}^{K} w_{ijckt} lnT_{ckt}, \forall c \neq j \tag{A2}$$

Results in Table A4 indicate that using citation-weighted green patent stocks does not alter the findings. The coefficient estimates have similar magnitude and statistical significance as those in Table 2. Furthermore, the coefficients for domestic and foreign vertical spillovers indicate that both sources provide energy productivity spillovers. However, fixed effects and instrumental variable estimations produce somewhat different results regarding the relative importance of these two sources. Thus, it is not possible to offer a definite answer as to which of the two sources is more important. With respect to green technology spillovers, only domestic spillovers have a significant coefficient in the IV model.

Table A4
Additional estimations.

	Citation-weighted		Domestic and foreign spillovers	
	FE	IV	FE	IV
Citation-weighted S^T	−0.010	−0.087***		
	(0.018)	(0.029)		
DS^T			0.003	−0.101***
			(0.022)	(0.035)
FS^T			−0.037	0.027
			(0.038)	(0.136)
S^{EI}	0.325***	0.472***		
	(0.039)	(0.079)		
DS^{EI}			0.372***	0.426***
			(0.046)	(0.080)
FS^{EI}			0.275***	0.691***
			(0.050)	(0.144)
ln(T)	0.016	0.026	0.003	0.007
	(0.024)	(0.024)	(0.011)	(0.011)
Control variables	x	x	x	x
Industry-country FE	x	x	x	x
Year FE	x	x	x	x
Observations	8334	8334	8334	8334
Adj. R-squared	0.434	0.365	0.436	0.340
1st stage F		45.158		11.068
KP LM test		67.723		42.314
SW F S^T		457.715		
SW F S^{EI}		75.247		
SW F DS^T				647.399
SW F FS^T				69.106
SW F DS^{EI}				81.757
SW F FS^{EI}				59.935
SW Chi-squared S^T		459.326		
SW Chi-squared S^{EI}		75.511		
SW Chi-squared DS^T				649.834
SW Chi-squared FS^{EI}				69.366
SW Chi-squared DS^{EI}				82.064
SW Chi-squared FS^{EI}				60.161
AR test p-value		0.000		0.000

Notes. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. Standard errors are clustered at the country-industry level. Control variables include the number of persons engaged, capital intensity, the share of service inputs and the share of imported inputs. ln(T) refers to the logarithm of 1 + industry's own citation-weighted green technology stock (models 1–2) or baseline green technology stock (models 3–4). 1st stage F-statistic refers to the Kleibergen-Paap Wald F-statistic. LM test is the Kleibergen-Paap underidentification test statistic. SW F and SW Chi-squared refer to the Sanderson-Windmeijer tests of weak identification and underidentification, respectively, of the individual endogenous regressors. AR test refers to the Anderson-Rubin test that is robust to weak-identification.

Table B1
List of sectors.

Sector	Observations
Agriculture	293
Forestry and logging	228
Fishing and aquaculture	135
Mining and quarrying	313
Food, beverage and tobacco	338
Textiles, textile products and leather	327
Wood products	320
Paper	303
Printing	163
Coke and petroleum	308
Chemicals	348
Pharmaceuticals	294
Rubber and plastics	336
Other non-metallic mineral products	342
Basic metals	348
Metal products	339
Computers, electronic and optical products	337
Electrical equipment	337
Machinery nec	333
Motor vehicles	319
Other transport equipment	309
Other manufacturing	324
Repair and installation of machinery	313
Electricity, gas, steam and air conditioning	345
Water	342
Sewerage and waste	322
Construction	318
Total	8334

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108053.

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