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Knowledge spillovers between clean and dirty technologies: Evidence from the patent citation network

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ABSTRACT

Can dirty incumbents leverage their existing knowhow to transition to clean technologies? To address this question, we systematically measure direct and indirect knowledge spillovers between clean and dirty technologies using the patent citation network. We assume citations reflect pathways of learning and knowledge proximity. We first examine the proportion of citations in clean patents that directly refer to dirty technologies. Secondly, we investigate how clean and dirty technologies are indirectly linked in the citation network and which sectors most frequently *bridge* these two fields. We find that less than one-tenth of clean patents contain a direct citation to prior dirty patents, but nearly two-thirds are indirectly linked. Significant sectoral heterogeneity exists. Patents related to control technologies, data processing and optimization, and the management of heat and waste, frequently serve as *bridges* between clean and dirty technologies in the citation network. Our results have implications for: firm-level diversification strategies, green industrial policy, and the modelling of directed technical change, where lower knowledge spillovers between clean and dirty technologies correspond to higher path dependencies.

1. Introduction

Governments around the world have adopted net-zero emissions targets in an effort to limit the impacts of anthropogenic climate change. Achieving these targets and keeping the earth's temperature within safe bounds will require substantial amounts of innovation in clean technologies, particularly in hard-to-decarbonize sectors (Stern and Valero, 2021). However, pivoting to clean innovation comes with challenges.[1]

There are many reasons why clean innovation is likely not near its socially optimal level. Clean innovation suffers from a double externality problem, that is, environmental externalities and knowledge spillovers (Jaffe et al., 2005). The policies to address these market failures, namely carbon pricing and innovation subsidies, have been challenging to implement in full measure (Klenert et al., 2018). Furthermore, access to cost-effective financing has not been easy. Since clean sectors are relatively new, investors face uncertainty over the distribution of risks and returns, which often leads to a higher cost of capital (Egli et al., 2018). Finally, there is path dependency: firms, governments, and buyers of technology may simply continue producing, innovating and buying technology that is familiar as opposed to switching to something new (Aghion et al., 2016; Geels et al., 2016). Models of directed technical change and the sustainability transition literature state that due to path dependency and the larger market for dirty inputs, incumbents may be locked-in (Acemoglu et al., 2012; Acemoglu et al., 2016, and Geels et al., 2016).[2]

Despite substantial gains in clean innovation, such as the persistent

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[1] We define "clean technologies" as those that mitigate greenhouse gas emissions, "dirty technologies" as those that contribute to emissions and "grey technologies" as those that are energy-efficient versions of dirty technologies. While any classification scheme is subject to debate, the objective of this categorization is to draw a distinction between technologies that contribute to GHG emissions reduction and those that exacerbate the problem; acknowledging that no one technology is "perfectly clean".

[2] As this study focuses on exploring the knowledge space, the term 'incumbents' informed by our results may encompass not only firms but also inventors, regions, and countries.

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cost reductions in solar panels, wind turbines and batteries (Way et al., 2022), the direction of innovation moving forward is still uncertain. As can be seen in Fig. 1, clean patenting accelerated in the early 2000s partly due to rising energy prices (Newell et al., 1999; Popp, 2002, and Verdolini and Galeotti, 2011) but in 2010, it peaked and has subsequently fallen. This decline is linked to the burst of the clean tech bubble, challenges in venture capital as a source of finance, and the rise of hydraulic fracturing (Dechezleprêtre, 2017; Gaddy et al., 2017, and Popp et al., 2020) (see Supplementary Fig. 2). Advances in hydraulic fracturing contributed to the price of natural gas falling so much that it became the primary fuel for electricity generation in the USA and estimates suggest that it might increase long-run emissions (Popp et al., 2020; Acemoglu et al., 2019). This reversal of trends has raised concerns that current progress is insufficient for reaching net-zero emissions by 2050 (IEA, 2020).

An understudied avenue towards overcoming some of these challenges is leveraging existing knowledge and competencies to transition from dirty to clean technologies in order to reduce adjustment costs and the risk of stranded labour, skills, and assets (Dugoua and Gerarden, 2023).

Given this background, this study has two main goals. First, many existing models of directed technical change in the literature assume that clean and dirty technologies are very different and that there is limited shared knowhow (see Section 2.3). While empirical evidence indicates limited knowledge spillovers between clean and dirty areas (e.g. Aghion et al., 2016; Dugoua and Gerarden, 2023), it is crucial to better account for sectoral heterogeneity in the path dependency argument. If clean and dirty technologies do share significant overlaps in their knowledge base, pivoting to clean may not be as costly as commonly assumed or estimated. We test the assumption in the directed technical change literature by analyzing knowledge spillovers between clean and dirty technologies across various sectors, offering a better quantification of potential path dependency.

Second, this study maps out potential pathways for the diversification of carbon-intensive incumbent firms. Some examples suggest that entities working on dirty and clean technologies indeed may "learn" from each other (i.e., there are direct and indirect knowledge spillovers from dirty to clean innovation). For example, firms engaged in offshore oil have expertise in seabed engineering, floating platforms and materials that can withstand bio-fouling, which have direct applications for innovation in offshore wind or marine energy (see Box 1. Companies like British Petroleum that are deeply embedded within the dirty technology paradigm also bid for seabed rights to build out new offshore wind farms in the North Sea. More systematic empirical evidence is needed to quantify the extent to which clean technologies learn from historical progress in dirty innovation and thus the potential for such learning to reduce the costs of pivoting.

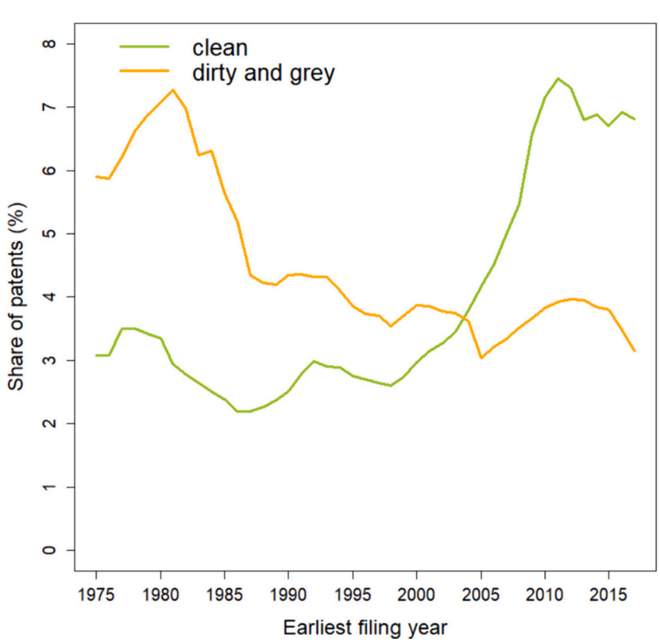

Fig. 1. Number of patents as a share of all patents.
Notes: The number of clean (green line) and sum of dirty and grey (orange line) patents as a share of all US patents by year. Patents are sorted by priority year (i.e., earliest filing year) and counted at DOCDB family-level.

To explore this question, we empirically measure the extent of direct and indirect knowledge spillovers between clean and dirty technologies using patent citation data from U.S. Patent and Trademark office (USPTO) from 1976 to 2020. Prior work has shown that knowledge-relatedness is often a key factor in firms' diversification choices because it can reduce switching costs (Breschi et al., 2003). Notwithstanding some of the well-known issues with patent data and citations as a measure of knowledge spillovers (e.g. OECD, 2009), direct citations between clean and dirty technologies may indicate, at least on average, intuitive pathways for transition by dirty firms while indirect linkages may pinpoint skills that can bridge or better facilitate the transition (Kivimaa et al., 2020). Given the diversity of skills and knowhow in both the dirty and clean paradigms, specific pathways for transition have often been regarded as a black box (Steen and Weaver, 2017). This study addresses this gap by investigating which knowledge features connect the dirty and clean technology paradigms.

We find that less than one-tenth of clean technologies directly cite dirty patents. While the direct connection constitutes a small proportion of all clean inventions, we find that most are indirectly connected via intermediate technologies. Among clean sectors, geothermal energy, clean metals/chemicals, carbon capture and storage (CCS), and long-haul transportation have the highest direct links to dirty technologies. Further investigation to understand indirect linkages exhibits key features of bridging technologies. For example, fuel supply control technologies used in combustion have knowhow used in control technologies for temperature and power, which in turn are used for energy-efficient building technologies such as smart home appliances and smart heating.

The sectoral investigation of these areas sheds light on possible transition pathways for incumbent dirty firms. By mapping the direct and indirect linkages between clean and dirty technologies and exploring bridging solutions between these realms, we provide micro-level insights into potential diversification routes for incumbents pursuing a low-carbon transition, while acknowledging that technological aspects alone are insufficient to justify the direction of diversification. A comprehensive understanding of stranded skills and knowledge can significantly enhance firm-level decisions on the energy transition.

Our paper makes four contributions: First, we leverage the patent citation network to map out the proximity of clean and dirty technologies in aggregate in the knowledge space. By doing this, we contribute to the literature that explores how labour, scientific skills, and capital can be re-purposed or re-deployed for the low-carbon transition. Second, we provide a detailed sectoral breakdown of *which* clean technologies are most proximate to their dirty counterparts to inform views on possible transition pathways for dirty R&D incumbents by sector. Third, we move beyond direct citations and consider degrees of separation in the patent citation network to detail which technologies frequently serve as intermediaries between clean and dirty technologies. Such technologies may represent important *bridges* that could help in the pivot from dirty to clean innovation. Finally, we pool together existing classifications of "clean" and "dirty" that exist to date in the literature.

Studies that are most closely related to ours include: Dechezleprêtre et al. (2014) and Noailly and Shestalova (2017) who use patent citations to measure knowledge spillovers. They focus on how clean technology spills over to general innovation and whether clean technology spillovers exceed those of dirty technologies. They find that on aggregate, clean technologies have higher spillovers than dirty technologies,

Box 1
Offshore oil & offshore wind firm diversification

Offshore oil and offshore wind have significant technological similarities. Offshore oil industries possess knowledge of i) manufacturing and installation of electrical infrastructure ii) construction of seabed infrastructure, substation structures, and turbine foundations iii) mapping of ocean floors iv) installation of support services, maintenance and information services. This know-how has been leveraged by oil companies to diversify into offshore wind. Indeed, the first offshore wind structures were built based on offshore oil industry templates.

One of the most notable examples of diversification is Ørsted, which is today, one of the world's largest developers of offshore wind but was previously known as DONG Energy (Danish Oil and Natural Gas) and would manage such resources in the North Sea. DONG Energy undertook a wholesale transition around 2017 to move from offshore oil and become a leader in offshore wind.

Many traditional oil companies are also opening up offshore wind operations. Shell, British Petroleum and TotalEnergies are acquiring seabed rights to build their own offshore wind turbines.[1] Some oil companies are also engaging in offshore wind to power traditional assets. [2] For example, Equinor, a Norwegian petroleum company, is developing an 88 MW wind farm 140 km off the coast of Norway in the North Sea to supply energy to five oil & gas platforms.[3] Equinor is also expanding its operations in offshore wind significantly in Brazil.[4]

[1]Allan, Vicky. 2022. 'Oil Companies Are Moving into Offshore Wind. Green Transition or Green Wash?' HeraldScotland.

[2] He, Wei, Gunnar Jacobsen, Tiit Anderson, Freydar Olsen, Tor D. Hanson, Magnus Korpås, Trond Toftevaag, Jarle Eek, Kjetil Uhlen, and Emil Johansson. 2010. 'The Potential of Integrating Wind Power with Offshore Oil and Gas Platforms'. *Wind Engineering* 34 (2): 125–37. He, Wei, Kjetil Uhlen, Mahesh Hadiya, Zhe Chen, Gang Shi, and Emilio del Rio. 2013. 'Case Study of Integrating an Offshore Wind Farm with Offshore Oil and Gas Platforms and with an Onshore Electrical Grid'. *Journal of Renewable Energy* 2013 (April): e607165.

[3]Banks, Jim. 2021. 'Why Offshore Wind Is Proving so Attractive to Oil and Gas Companies'. N S Energy.

[4]Petrobras and Equinor Sign Agreement to Evaluate Seven Offshore Wind Projects in Brazil'. 2023. Equinor.

thereby making a case for larger clean tech R&D subsidies. Our work differs from theirs in two important ways: first, we consider knowledge spillovers *between* clean and dirty technologies so as to inform views on sustainability transition, and second, we focus not only on direct links but also, indirect links adapting a method used by Ahmadpoor and Jones (2017) which looks at the minimum distance in the citation network. Another closely related paper is that of Mealy and Teytelboym (2022) who use export data to document which areas of export specialization frequently coincide with having a clean product specialization. This is conceptually similar to our work as it tries to inform diversification strategies for the low-carbon transition assuming that export data can uncover manufacturing complementarities. Our work focuses on the technological domain, leveraging patent citations to trace transition opportunities for innovators. Our work differs from Mealy and Teytelboym (2022) since underlying data represents purposeful citation decisions (either by the inventor or examiner) rather than co-occurrences.

2. Literature review

2.1. Low-carbon transition and diversification

Transitioning to a net-zero economy requires innovation by new entrants and diversification by existing firms, many of whom form the base of the carbon-intensive economy. However, incumbents resist changes due to the cost of deviating from familiar cognitive routines, existing relationships, and infrastructure (Nelson and Winter, 1982). Moreover, the incentive to transition is oftentimes too low due to the absence of carbon pricing. Therefore, fossil-fuel based firms are typically described as being locked into carbon-intensive regimes (Geels et al., 2016; Aghion et al., 2016). Despite the path dependency, incumbents are increasingly required to adapt. The sustainability transition has been urged by a range of exogenous pressures including the proliferation of net zero targets, new regulations and public awareness on climate change. While these pressures can be a threat to the incumbents, they can also offer *windows of opportunity* for creating and capturing value from new markets (Geels, 2002; Farmer et al., 2019). How incumbents respond to the change through diversification can critically affect the rate and direction of change.

It is well established that diversification is easier when a firm, region or country extends its capabilities into an area which shares knowhow or preexisting capabilities. Diversification relies on the accumulated stock of capabilities, aiming to maximally leverage the existing resources (Neffke and Henning, 2013). Evolutionary economic geography has highlighted how new development pathways are achieved when agents jump from one area of expertise to another relatively proximate but different area (Frenken and Boschma, 2007; Boschma and Frenken, 2011; Hausmann and Klinger, 2007; Hidalgo et al., 2007, and Martin and Sunley, 2006). Strategy scholars have suggested that diversification into adjacent emerging areas can lead to a competent variety in not only technological but also business models and strategy dimensions (Erlinghagen and Markard, 2012; Dolata, 2009).

Since there are costs linked with searching the knowledge space to find new idea (Binswanger, 1974), understanding what is *cognitively closer* as revealed measures such as cross-citations, can give a better understanding of the available recombinant possibilities (Weitzman, 1998; Rigby, 2015). If incumbents can make novel recombination of new skills and their existing capabilities through so-called *creative accumulation*, they can competently survive under discontinuous technological changes (Bergek et al., 2013).

2.2. Measuring knowledge spillovers between clean and dirty technologies

Mapping the knowledge space in which clean and dirty technologies exist can help empirically assess how related the carbon-intensive paradigm and low-carbon innovation are, and consequently, inform our views on the ease of diversification. Measures of relatedness can be constructed on the basis of co-classifications in industrial codes (Frenken et al., 2007; Boschma and Iammarino, 2009; Boschma et al., 2009; Boschma et al., 2012, and Hartog et al., 2012), co-occurrences of products in countries' export baskets (Hidalgo et al., 2007), cross-citation patterns in patent data (Rigby, 2015), similarity of references or co-classification information in patent data (Yan and Luo, 2017), and the mobility of labour in occupational networks (Neffke and Henning, 2013; del Rio-Chanona et al., 2021), which captures resource flows.

The choice of which measure to adopt depends on the researcher's goal. For example, using the occupational network may be most appropriate for thinking about the mobility of human capital between clean and dirty sectors, while co-occurrences in the export basket may be useful in unravelling complementarities in manufacturing processes. Since our interest is in the direction of innovation, we focus on the connectivity between clean and dirty sectors in the patent citation network. Patents have the advantage that citations are active decisions made by inventors and vetted by examiners to prove the invention's novelty over existing work. This means past work is often well cited and provides a more robust measure of connectivity/relatedness than relying on factors such as co-occurrence which may be linked with more inherent randomness.

Several studies have used cross-citation patterns to infer knowledge spillovers between sectors, with a key assumption that if a citation is made, then the citing technology has learnt something from the cited technology (e.g. Dechezleprêtre et al., 2014; Noailly and Shestalova, 2017, and Andres et al., 2022). We do not need to believe *each* citation is reflective of learning, as long as we believe that *on average*, a citation link is correlated with learning between those two nodes. As Jaffe et al. (1993) state, "knowledge flows do sometimes leave a paper trail, in the form of citations in patents".

The study of knowledge spillovers between clean and dirty technologies can help determine the ease of pivoting from carbon-intensive ("dirty") innovation to low-carbon ("clean") innovation (Breschi et al., 2003). Given the path dependent and cumulative nature of knowledge (Nelson and Winter, 1982), many assume that dirty technologies will only beget more dirty innovation. Yet, since clean and dirty technologies often have the same goals such as the provision of mobility, power, and industrial growth, they may, in fact, learn from and build-upon each other. This is reflected through models which allow for spillovers between the clean and dirty paradigm (Fried, 2018). Yet this parameter requires careful calibration and the extent to which knowledge from the dirty paradigm can spill over to the clean paradigm is fundamentally an empirical question. The results of this paper will aim to bring more evidence to inform future calibrations.

2.3. Relation to models of directed technical change

In modelling terms, Acemoglu et al. (2012) assume that clean and dirty inputs (Y_c and Y_d, respectively) are made using labour and machinery (L and x respectively). Machines can be of different types, i. The share of labour and machinery in the production function is determined by $\alpha_1, \alpha_2, \alpha \in [0,1]$ and $\alpha_1 + \alpha_2 = \alpha$. R_t is the flow of exhaustible resources over time which features in the production function for Y_d. There is also knowledge or quality, A, that augments the productivity of machinery (see Eq. (1)).

$$Y_{dt} = R_t^{\alpha_2} L_{dt}^{1-\alpha_1-\alpha_2} \int_0^1 A_{dit}^{1-\alpha_1} x_{dit}^{\alpha_1} di \tag{1}$$

$$Y_{ct} = L_{ct}^{1-\alpha} \int_0^1 A_{cit}^{1-\alpha} x_{cit}^{\alpha}$$

The average productivity in a clean or dirty sector is given by the accumulation of past quality improvements (Eq. (2)) where $j \in (c,d)$. Further, as Eq. (3) shows, innovation builds on the existing quality of the machine ("standing on the shoulders of giants") where η_j represents the probability that the subsequent innovation is successful and achieves productivity increment, γ.

$$A_{ji} \equiv \int_0^1 A_{jit} di \tag{2}$$

$$A_{jt} = (1 + \gamma \eta_j) A_{jt-1} \tag{3}$$

But, crucially, in this specification, the "clean tech ladder" is distinct from the "dirty tech ladder". In other words, dirty innovation only helps future dirty innovation and clean innovation only helps future clean innovation. There are no cross-sectoral spillovers. Acemoglu et al. (2012) note in a footnote that this is an assumption and justify it with a claim that renewable energy developments do not build up from fossil fuel innovation. However, this claim is not based on systematic empirical evidence. Sectors such as offshore wind *do* build up from innovations in offshore oil, and there could be many other such examples.

A more general formulation, which takes into account the *possibility* of cross-sectoral spillovers is given by Eq. (4) where $\sim j$ denotes the other sector and ϕ_j is a linearly homogenous function.

$$A_{jt} = (1 + \gamma \eta_j) \phi_j (A_{jt-1}, A_{\sim jt-1}) \tag{4}$$

The benefit of undertaking R&D investments in a clean sector relative to a dirty one in the absence of cross-sectoral spillovers is given by Eq. (5a), which shows the relative benefit of clean vs. dirty innovation ($\frac{\pi_{ct}}{\pi_{dt}}$) depends on relative prices ($\frac{p_{ct}}{p_{dt}}$), the relative probabilities of successful follow-on innovation ($\frac{\eta_c}{\eta_d}$), the relative size of the markets ($\frac{L_{ct}}{L_{dt}}$) and relative past productivities ($\frac{A_{ct-1}}{A_{dt-1}}$).

When cross sectoral spillovers are allowed, we get Eq. (5b), where in the final term we can see how a history of dirty innovation can contribute to the relative benefit of undertaking clean innovation and vice versa. What this does to the standard result is that it attenuates the degree of path dependency and lock-in, and creates multiple equilibria i.e., dirty R&D firms can access the clean tech paradigm more easily but crucially, are looking at what other firms may be doing, resulting in a coordination problem between clean vs. dirty equilibria (see Andres et al., 2022 and Zhou and Smulders, 2023 for a more detailed explanation of coordination problems in expanded models of directed technical change). Cross-sectoral spillovers can also affect the *speed* of convergence to an equilibrium.

$$\frac{\pi_{ct}}{\pi_{dt}} = \left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{1-\alpha}} \times \frac{\eta_c}{\eta_d} \times \frac{L_{ct}}{L_{dt}} \times \frac{A_{ct-1}}{A_{dt-1}} \tag{5a}$$

$$\frac{\pi_{ct}}{\pi_{dt}} = \left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{1-\alpha}} \times \frac{\eta_c}{\eta_d} \times \frac{L_{ct}}{L_{dt}} \times \frac{\phi_c(A_{ct-1}, A_{dt-1})}{\phi_d(A_{dt-1}, A_{ct-1})} \tag{5b}$$

The issue is that the extent of spillovers between clean and dirty technologies is largely unknown and unquantified in empirical terms. Such information would allow us to more precisely specify $\phi_j(A_{jt-1}, A_{\sim jt-1})$ which can be used to empirically validate crucial assumptions made in the canonical paper by Acemoglu et al., 2012.

Lastly, in practice, diversification requires considering not only knowledge spillovers (how A_c and A_d relate to each other) but also other variables such as labour, machinery, access to raw materials, supply chains, strategic fit, etc. (Altunay et al., 2021). Yet, since knowledge is a key input into the production process and a driver of long-term growth, we pay particular attention to it. Prior literature has adopted a similar approach, with studies using patent specialisations in clean technologies as an indicator of enhanced competitiveness in a future low-carbon economy (Fankhauser et al., 2013) as well as studies looking at firms' patenting activity to proxy their position in the product/technology space to infer rivalries (Bloom et al., 2013).

3. Data

We map out the links between clean and dirty technologies in the patent citation network, using patents granted in the USPTO from 1976 to 2020.[3] Patents grant monopoly rights to inventors over inventions

[3] The United States is the largest market in the world, and its intellectual property regime is among the strongest globally. For these reasons, inventors from all over the world, particularly those whose inventions have high value, seek commercialisation of their products in the US market and relevant IP protection. In the literature, patents granted by the USPTO are often considered to represent the knowledge frontier (Granstrand, 2018).

that are novel, non-obvious, and of commercial value. The patenting also means that all of the details of the invention are released in the public domain alongside information about the inventor, their employer, and technology-class of the invention. To demonstrate novelty, inventors must cite the technological antecedents of their invention which are also reflected in citations made to prior art (Jaffe et al., 1993).

Since patents are legal instruments, there is a strict review process linked to ensuring citations are relevant and meaningful. This is arguably different from academic articles where the review process for citations is looser. The inventor has a legal duty to disclose all prior art that they consulted in the development of the invention and the patent examiner, who is a subject matter expert, vets these citations and adds their own to reflect any missed or concealed prior art (Jaffe et al., 1993; Berchicci and Van De Vrande, 2019). Jaffe et al. (2000) survey R&D managers and find that citing inventors usually have direct communication with cited inventors, and that the reasons for patent citation include using components of the cited technology and/or leveraging the cited technology to demonstrate the feasibility or use-case of the new invention.

Any study using patents, however, must acknowledge that patents represent only a subset of all innovation (Griliches, 1990) and that despite the citation-vetting process by examiners, references in patents can still contain noise (Jaffe et al., 1993; Jaffe et al., 2000). Notwithstanding various limitations including an incomplete coverage of inventive activity and a bias towards frontier technologies (e.g., OECD, 2009), patents are used extensively in the study of innovation (Griliches 1990 and Jaffe et al., 1993), and in particular clean innovation thanks to the introduction of classification codes that help identify technologies that reduce or contribute to greenhouse gas emissions (e.g., Dechezleprêtre et al., 2014, Noailly and Shestalova, 2017). In our dataset, 62% of citations in patents, are on average, added by the inventor rather than the examiner. For our results we consider all citations regardless of who added them as we are broadly interested in knowledge spillovers across technological domains, rather than specifically, the inventor's perception.

4. Method

Our data contains approximately 6 million patents and 55 million connections, from which we identify clean and dirty technologies (see Supplementary Table 1). We leverage existing classifications schemes in the literature and supplement these with our own tagging efforts to come up with these classifications (Haščič and Migotto, 2015, Aghion et al., 2016, Popp et al., 2020, Dechezleprêtre et al., 2021, and IEA (International Energy Agency), 2021). As an indicative illustration: renewable energy is "clean", oil and gas are "dirty", and energy-efficient methods of making steel are "grey". The tagging strategy gives 258,078 clean patents, 145,753 dirty patents and 98,224 grey patents which are counted at DOCDB family level to avoid double counting the same inventions.[4] There are 31,053 patents that are classified as both clean and dirty, which we exclude from our baseline analysis to focus on the cases where the technologies are obviously clean or dirty (see Supplementary Fig. 1). Supplementary Table 3 shows that the excluded patents are mostly related to the pollution abatement technologies for carbon-intensive practices, justifying our exclusion given our focus on radical transition to clean.

We measure direct knowledge spillovers between clean and dirty technologies by the proportion of backward citations in clean patents that directly refer to dirty patents. This metric has been used widely in the environmental innovation literature and we refer to it as the "intensity of connection" (Dechezleprêtre et al., 2014; Noailly and Shestalova, 2017).

However, knowledge from a dirty patent may also feed into an intermediate technology which may in turn be cited by a clean patent. These indirect links are often overlooked. To address this gap, we calculate the degrees of separation between clean and dirty patents in the citation network. We call this the "minimum distance metric (D)". The minimum distance reveals the incremental and indirect ways in which dirty knowledge has fed into clean inventions (Ahmadpoor and Jones, 2017). If our measure of minimum distance is 1 ($D_i = 1$), it means that the clean patent i directly cites a dirty patent, while if $D_i = n$, where n is larger than or equal to 2, a clean patent i must pass through at least n-1 non-dirty patents within the citation network to reach prior dirty patent(s) (see Fig. 2).[5] Clean patents that cannot be connected to dirty patents at any distance are deemed "unconnected."[6]

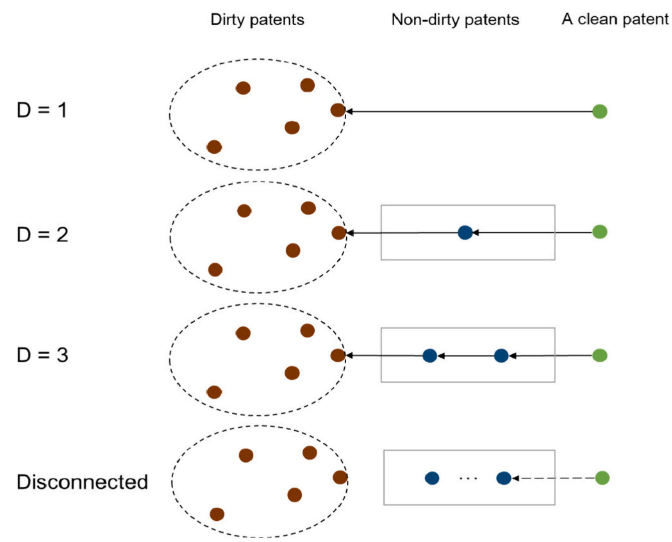

Fig. 2. A schematic diagram to explain "intellectual distance".
Notes: This figure shows how the distance from a clean patent to prior dirty patent is determined. Arrows indicate the citation direction (from citing to cited patents). Intermediary patents can also include other (i.e. different) clean patents that serve as bridges.

Patent bibliography lengths are growing over time (Supplementary Fig. 6), which could theoretically increase the chance of citing old hydrocarbon knowledge and consequently, decrease D_i mechanically. However, this does not happen. Despite the increasing lengths of bibliography, we see the opposite: values of D_i rise over time as the composition of clean innovation shifts towards technologies that are more distant from the hydrocarbon paradigm (Supplementary Fig. 7). From the 1970s to the present day, the composition of clean patenting has changed, with the share of patenting in electric/hybrid vehicles, clean ICT and solar PV rising, and the share of patenting in nuclear energy declining.

[4] DOCDB families are a cluster of patents that represent the same invention.

[5] Measures of distance based on patents have been used to study various questions. For example, Ahmadpoor and Jones (2017) use minimum distance to assess the extent to which scientific knowledge feeds into patented technologies. Bloom et al. (2013) use a patent-based distance metric to assess competition and product market rivalries across firms.

[6] The D metric is adapted to conduct additional analyses reported in supplementary material. Supplementary Fig. 3 shows connectivity from dirty to prior clean patents, and Supplementary Fig. 4 shows connectivity from clean to prior dirty patents (Applicant citation only) and Supplementary Fig. 5 shows connectivity from clean to grey patents. Supplementary Fig. 5 shows that grey has a slightly higher proportion of direct connections to dirty, compared to clean's direct connection to dirty, which is an intuitive result. Since whether dirty incumbents should diversify into grey technologies as a steppingstone for the ultimate transition to clean is a controversial agenda (Stern and Valero, 2021), we have focused on radical transition to clean instead of discussing diversification routes to grey areas.

D_i aims to measure the proximity of fields of knowledge. All else equal, if D_i is systematically very high between patents of two different technology classes, then the "intellectual distance" between these fields is large and there is less of a common language that can help facilitate the diffusion of ideas. By the same token, weak ties at 2 degrees of separation may represent a particularly fruitful direction for ideas exchange as they are not too similar to lead to cognitive lock-in and yet not too different such that there is no practical room for knowledge exchange (Granovetter, 1973).

Fig. 2 illustrates our minimum distance calculation schematically. Intermediate technologies in our analysis can be classified into two cases. First, intermediate technologies can be non-dirty and non-clean i.e., belonging to some third category. Second, the intermediate technologies can be clean technologies that feed into *other* clean technologies. For sectors where the intermediate technologies are mostly other clean inventions, we can speculate that D = 2 represents an intuitively closer link than in cases where the intermediate technology belongs to some third category. Some of this may just be driven by the boundary of clean classifications since boundaries have to be drawn.

5. Results

5.1. Aggregate and sectoral results

We find that nearly one in every ten clean patents contains some reference to a dirty technology. The mode of clean patents' distance to a dirty patent is 3 and 53% of clean patents are within three degrees of separation from dirty patents (Fig. 3). By comparison, the average distance between *any* two randomly selected patents in USPTO is 8.5 (Mostafavi et al., 2012). The relative proximity between clean and dirty patents is partly attributable to the fact that many have common goals such as generating electricity, mobility, etc. Yet the limited proportion of direct connections (7.5%) and the relatively high proportion of unconnected patents (27%) highlight that they are different technologies, that often stem from cognitively dissimilar paradigms. However, these aggregate results conceal significant heterogeneity at the sectoral level.

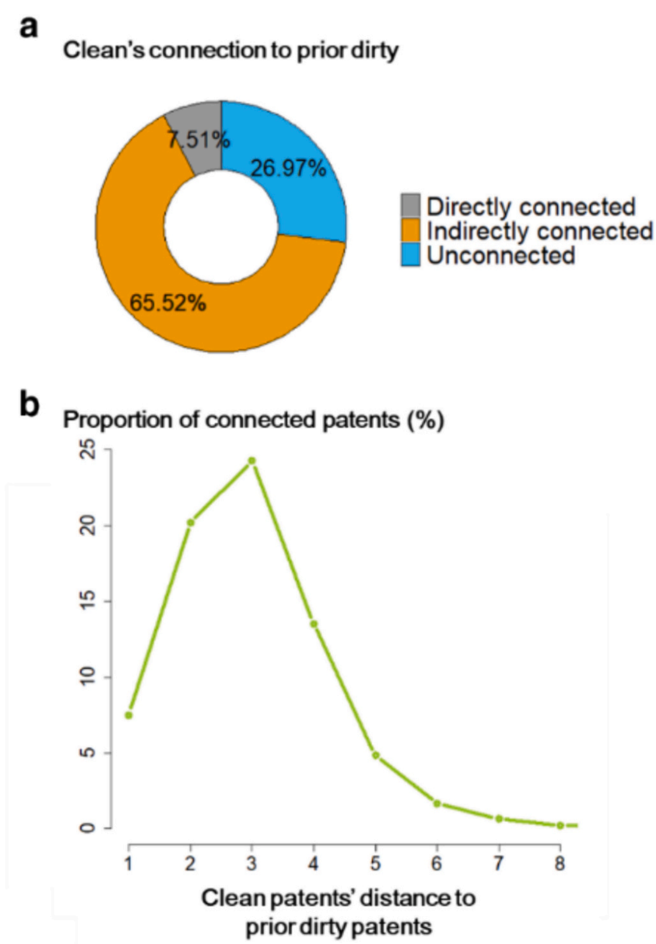

Fig. 3. Connectivity from clean to prior dirty patents.
Notes: Figures are made based on the directed graph of citation network from clean to previous dirty patents.

The average clean patent has 9 references in its bibliography (at the DOCDB family-level, which clusters patents that cover a single invention), while the number varies across sectors and time (Supplementary Fig. 6). Geothermal energy, clean metals and CCS patents have the highest proportion of direct references to dirty inventions (Figs. 4, 5, and Supplementary Fig. 8). Geothermal energy relies on geological surveying, drilling techniques, field development, and the construction of wells, pipelines, and other infrastructure, which requires knowledge inputs that are commonly used by fossil fuel firms. Clean innovation in metals is largely incremental in nature and consequently, still closely connected to the dirty production paradigm.[7] CCS is a complement to coal-fired power plants, gas stations and other point-sources of carbon emissions and has to be fitted to these.

Clean ICT and solar PV have negligible direct links to dirty technologies. In the case of solar PV, this may be reflective of just how different the photovoltaic paradigm is from the hydrocarbon paradigm. The former is based on the photovoltaic effect while the latter relies on spinning a coil around a magnet to generate power (i.e., turbines). This may explain why turbine-based technologies such as hydroelectric power, wind energy, and some types of marine energy have more citations to dirty technologies than solar PV.

Marine energy, for example, requires knowledge inputs that are common to dirty technologies such as offshore oil. This includes seabed engineering, constructing offshore platforms, placing under-sea cables, under-sea robots and materials that can withstand biofouling. This may explain why offshore oil companies like British Petroleum put in bids for seabed rights in the North Sea to develop offshore wind farms, as they can leverage existing knowhow (King, 2021). For electric/hybrid vehicles, some elements of innovation such as car design and a more efficient internal combustion engine rely on dirty knowledge, while other elements, such as batteries are different.

5.2. Indirect connections and identifying the "bridging technologies"

The majority of the connections between clean and dirty technologies are indirect. The minimum distance at which clean patents are connected to dirty patents differs largely by technology, as plotted in Fig. 6. Nuclear has the largest share of completely disconnected patents illustrating how distinct the nuclear paradigm is from dirty technologies. Other relatively disconnected fields include solar thermal and clean agriculture, where the share of direct connections is also on the lower side.

For many sectors, there are a substantial proportion of patents that are connected at D = 2. To give a sectoral understanding of the bridging technologies, we extract features of intermediates that frequently connect the clean to dirty technologies when D = 2. These intermediates highlight how there may still be indirect pathways for diversification for dirty sectors where there is no direct link to clean technologies. Literature has emphasized the importance of these indirect routes, which are

[7] There are some radical strands zero-carbon innovation in metals such as zero-carbon steel made from hydrogen (e.g., the HYBRIT project). Such innovation effort is still so nascent and rare that it is not reflected in patent databases. As such, it is possible that future analyses find that clean metals rely less on dirty knowledge because radical clean innovation becomes more commonplace and better documented.

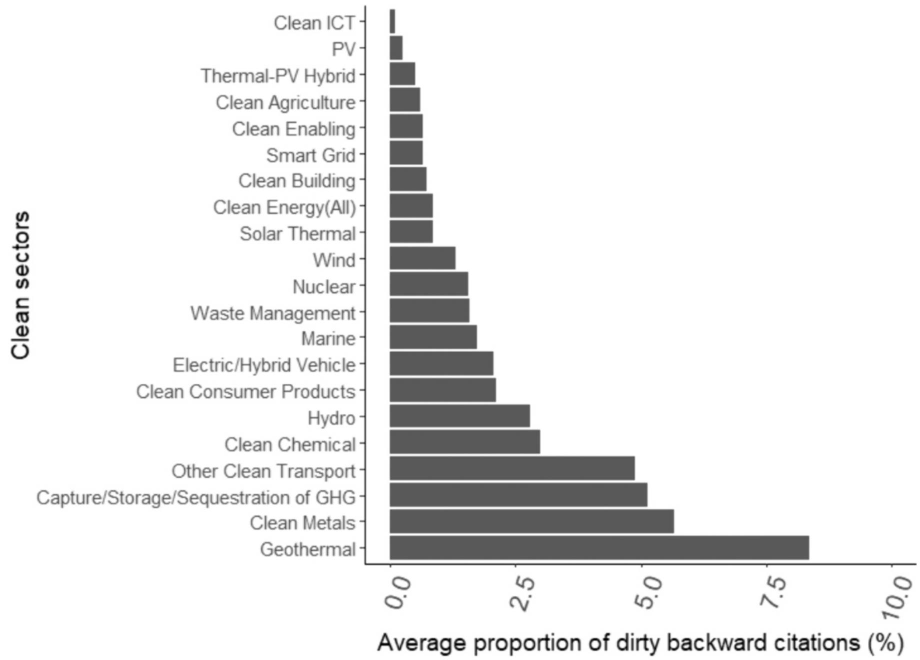

Fig. 4. The average proportion of dirty backward citations by clean technology (D = 1).

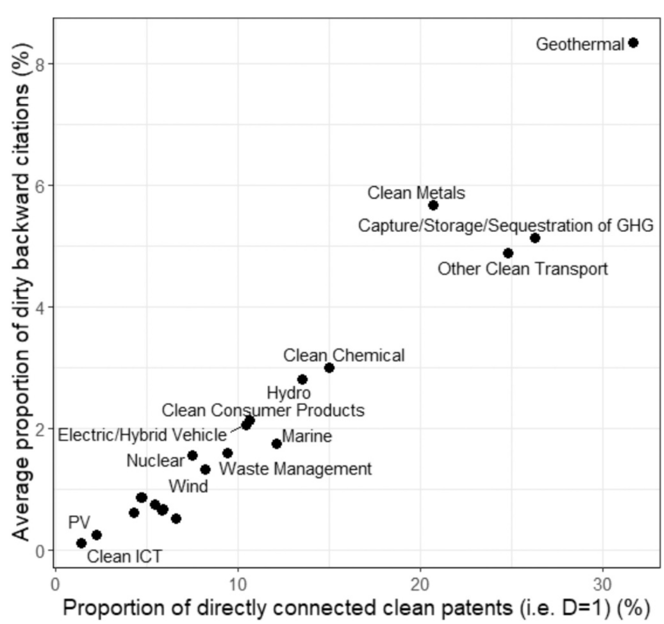

Fig. 5. Sectoral mapping of range and intensity of direct connections.
Notes. X-axis indicates the proportion of clean patents that are directly connected to prior dirty patents among the clean patents in each sector (Range of direct connection). Y-axis is the average of the proportion of dirty backward citations among the total backward citations (Sectoral average of intensity metric). Overall, the figure shows that the range and intensity of direct connection tend to be positively correlated, confirming that our D metric well represents the connectivity between clean and dirty technologies.

promising as they are different enough to be novel yet close enough to still be accessible (Noteboom 2000). In addition, bridging technologies can be understood as gatekeepers forming weak ties between the two heterogeneous areas of clean and dirty (Granovetter, 1973).

As described in Section 4, there are two different types of intermediate technologies in D = 2: (1) one has weak relevance to clean or dirty technologies but bridges the two areas and (2) another indicates clean technologies themselves that inform other clean technologies. As the former case is more relevant to our intention of understanding bridge technologies, we present the results of the former case in Table 1 and the latter case in the Supplementary Table 4.

Table 1 describes the most frequent intermediate technologies at D = 2 in each clean sector.[8] Box 2 describes some archetypical examples using specific patents while Table 1 reviews all major clean sectors and describes the high frequency indirect linkages these sectors have to dirty sectors.[9] Table 1 is the outcome of analysis which examines patent documentation and indirect links to establish the scientific basis of the connection.[10] Sectoral description of representative bridging technologies reveals the routes via which dirty incumbents can jump to relevant clean areas by understanding key bridging knowledge. The key bridging technologies in each sector present the potential directions for dirty incumbents to develop or acquire skills relatively easily to move towards cleaner production, provided such a transition is also feasible in other critical aspects, such as the difficulty of sourcing the required skills.

For example, geothermal collection and geothermal energy generation technologies draw on intermediary knowledge related to heat exchange or compression which in turn cite patents in the sub-field of upstream fossil fuels, such as bore-holing. Hence, oil and gas companies equipped with earth drilling technologies can intuitively build (or, already have) capabilities related to heat pumps and exchanges, which help them acquire clean skills needed for geothermal energy generation. Wind energy supply and distribution technologies cite technologies related to controlling electric motors, which connect back to dirty technologies used to turn on motors in combustion engines. Therefore, dirty incumbents that have used motors for combustion engines can expand their electric motor-related technologies to leverage their

[8] We found that a similar analysis for D = 3 (which should go through two other bridging technologies) is less intuitive to interpret and difficult to be translated into action in many cases. Given this, we interpret that D $\geq$ 3 is distant enough in absolute term.

[9] Supplementary Fig. 8 provides an overview of the patterns of sectoral connections between clean and dirty technologies, with varying distances. This figure comprehensively maps out the potential directions of diversification for the dirty incumbents.

[10] Supplementary data will be provided upon request.

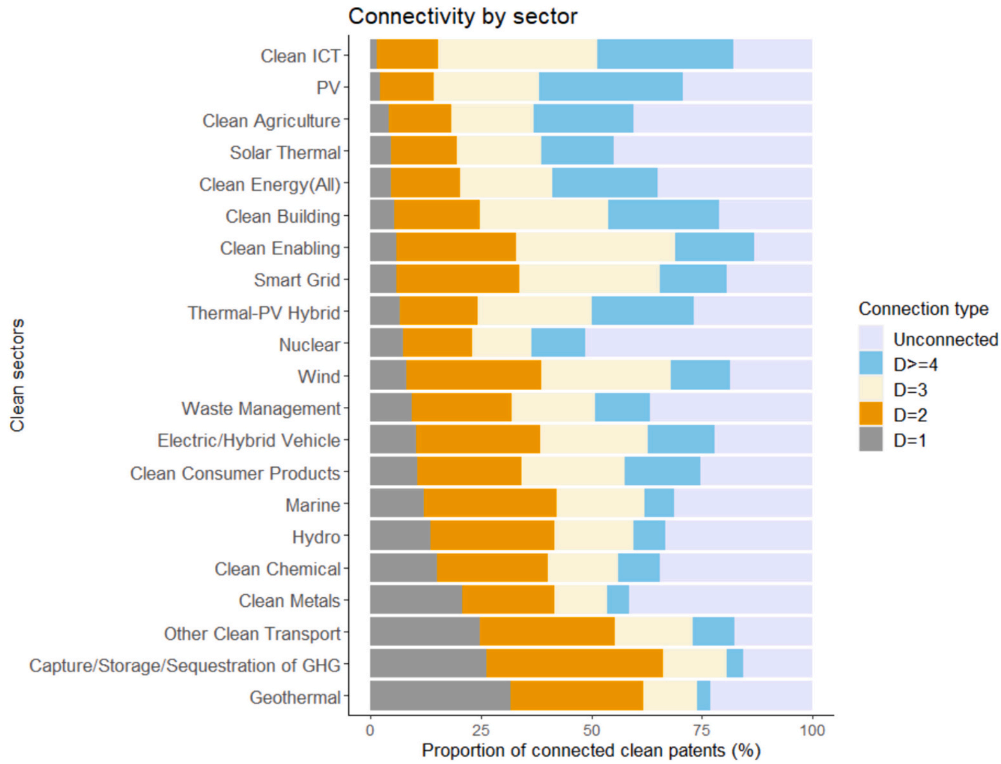

Fig. 6. Sectoral details of direct and indirect connections.
Notes: Each clean sector's direct and indirect connections to prior dirty technologies.

existing capabilities to perform new business in wind energy generation. Smart grid technologies frequently rely on control technologies used in power distribution, air conditioning, and temperature, which connect back to combustion control technologies for fuel or air supply. Therefore, if dirty incumbents with combustion control capabilities invest in further development of a broader set of control technologies for air conditioning, temperature and power control, they will be in a good position to engage in smart grid or smart home-related new businesses. Government interventions to encourage dirty incumbents' investment in such targeted bridging areas of each clean sector can facilitate sustainability transition across the economy.

6. Discussion

Economic activity has an imperative to transition to a low-carbon paradigm to limit the impacts of climate change. For carbon-intensive ("dirty") firms, the pivot towards clean industries is not only a matter of honoring climate pledges but also of mitigating transitional risks since regulation is expected to move in the direction of higher carbon prices, mandatory disclosure of climate-related risks, and border carbon adjustments.

As the fracking revolution revealed, the overall direction of innovation is still uncertain and can move in directions that do not support the clean energy transition. The target of net zero emissions by 2050 necessitates control over the amount, direction, and speed of innovation (Stern and Valero, 2021), and in this regard, it is important to understand areas where dirty knowledge spills over into clean technologies.

To what extent does society's large history of dirty R&D lock it into further dirty R&D? Models of directed technical change argue that there is hysteresis in the innovation system (Acemoglu et al., 2012; Aghion et al., 2016). Such models arrive at this conclusion by implicitly assuming that clean and dirty technologies do not learn from each other.

We test this assumption empirically and find that 7.5% of clean patents have a direct connection to dirty technologies. Around 27% of clean patents cannot be connected to dirty patents at any distance in the citation network. The remaining are indirectly linked (65%), with the mode of connection being 3 degrees. We interpret this as indicative that the pivot from dirty to clean, in many cases, may not be straightforward, especially for the cases in which D$\geq$3.

However, aggregate results conceal significant areas of relative proximity, particularly at the sectoral level. In reality, the degree to which clean technology learns from dirty technology is nuanced, sector-specific and sometimes indirect. Clean sectors that draw significantly from the hydrocarbon knowledge paradigm include geothermal, clean metals, CCS, long-haul transport and clean chemicals. Others include marine and wind energy where the learning largely is indirect rather than direct. Our mapping of sector-level linkages between clean and dirty technologies provides potential routes for diversification that dirty incumbents could consider. This is an optimistic message that is often ignored in studies that only focus on direct knowledge spillovers. Our sectoral-level findings also align with previous studies that have demonstrated a widespread interaction of technological knowledge across seemingly distinct domains (e.g. Benson and Magee, 2015).

There is a rich literature on how external factors such as location matter for innovation due to agglomeration benefits, complementarities, and access to resources (Porter and Stern, 2001). We build upon the thinking that even location in the knowledge space has a bearing on innovation strategy. Insofar as technological capital has complementarities with labour, we can also infer that similar types of skilled labour and scientists would be deployed. Proximity in the knowledge space likely correlates with similarity across other dimensions.

The pivot to clean innovation is fundamental to the concept of "green growth", the idea that it is possible to respect planetary boundaries and have an economically prosperous future (Ekins, 2002; Bowen et al., 2016, and Bowen and Hepburn, 2014). Since innovation is a long-term driver of growth, our investigation of how distinct the clean innovation paradigm is from the dirty one is useful in terms conceptualizing how difficult this shift may be. This in turn, may be useful for policymakers contemplating green industrial policy or firms deciding on resource allocation to become net zero compliant (Hafner et al., 2020).

Table 1
Most frequent indirect links between clean and dirty technologies.

Clean Technology	Intermediate Technology	Dirty Technology	Description of the Indirect Link (Dirty ➔ Intermediate ➔ Clean)
Clean ICT	Data processing (Program control, memory systems and architecture)	Technologies used to control and optimise the performance of internal combustion engines	Technologies used to control and optimise the performance of internal combustion engines (e.g. fuel injection, ignition timing) feed into data processing technologies related to the program control, memory systems and architecture, which are subsequently linked to the development of energy-efficient computing (e.g. low power processors, power management and thermal management).
PV	Control and regulation of electric motors	Technologies used to start combustion engines	Technologies used to start combustion engines feed into control and regulation technologies for electric motors (i.e. arrangements of electric generators for optimum output), which subsequently inform PV circuit arrangements for electric supply and distribution.
Clean Agriculture	Material investigation (chemical or physical properties)	Earth drilling technologies used to test the nature of borehole walls	Earth drilling technologies used to test the nature of borehole walls (e.g. obtain samples of soil) feed into technologies for investigating materials (chemical or physical properties), which inform cleaner production technologies related to agriculture or livestock.
Solar Thermal	Power generation from renewables	Using waste heat of combustion engines	Technologies for using waste heat of combustion engines inform technologies for energy generation from renewable sources (e.g. devices for producing mechanical power from solar energy), which subsequently feed into various types of solar heat collectors.
Clean Building	Other general control technologies	Control technologies used in combustion (e.g. fuel or air supply control)	Technologies used to control the combustion process (e.g. fuel or air supply control) feed into other control technologies (e.g. air condition control, temperature control and power control), which are referenced by clean building technologies such as energy-efficient heating of buildings, ventilation or air conditioning of buildings, and end users' power consumption management technologies used in buildings (e.g. home appliances and smart grid).
Clean Enabling	Program control (monitoring and testing)	Controlling or regulating the internal combustion piston engines	Technologies for controlling or regulating the internal combustion piston engines feed into technologies for program control (monitoring and testing), which are used in sensors for clean enabling manufacturing (e.g. sensors in EV charging stations).
Smart Grid	Other general control technologies	Combustion process control technologies (e.g. fuel or air supply control)	Combustion process control technologies (e.g. fuel or air supply control) feed into other control technologies such as power distribution control, air conditioning control, and temperature control, which can be used to develop smart grid technologies.
Thermal-PV Hybrid	Semiconductors used in water-intensive sectors	Distillation technologies used in the oil and gas sector	Distillation technologies used in the oil and gas sector are linked to semiconductor technologies used in water-intensive sectors, which in turn informs power generation from solar energy and boilers (e.g. devices sensitive to infra-red radiation).
Wind	Control of electric motors	Technologies used to start combustion engines	Technologies used to start combustion engines inform technologies on control of electric motors, which feed into optimal circuit arrangements for supply and distribution of wind energy and controlling and adaptation of wind motors.
Clean Consumer Products	Machines for liquids and control/ regulation of electric motors	Control technologies used in hot gas engine plants	Control technologies used in hot gas engine plants (e.g. temperature or air supply control) inform machines for liquids and control/regulation of electric motors, which inform arrangements for measuring electric/ magnetic variables related to clean manufacturing of consumer products.
Marine	Adaptation of engines for special use	Stirling type engines used in hot gas or combustion plants	Stirling type engines used in hot gas or combustion plants inform the adaptation of engines for special use, which feed into clean technologies on energy generation through marine renewables sources such as ocean waves and tides.
Hydro	Indexing scheme technologies	Hydraulic engineering technologies	Hydraulic engineering technologies such as construction methods for floating platforms inform indexing scheme technologies used for various purposes, that feed into energy generation through hydropower.
	Gravitational measurement techniques	Earth drilling technologies	Earth drilling technologies, such as mining and quarrying, feed into gravitational measurement techniques (e.g. acoustic prospecting or detecting), which then inform machines for energy generation through hydropower.
Geothermal	Technologies related to heat pumps and heat exchange	Earth drilling technologies used in the oil and gas sector	Earth drilling technologies used in the oil and gas sector frequently inform technologies related to heat pumps and heat exchange, which in turn are relevant for subsequent innovation in the geothermal collection and geothermal energy generation.
Waste Management	Compositions of mortars, concrete, or artificial stone	Material technologies used in compositions for drilling/treating of wells	Material technologies used in compositions for drilling/treating of wells inform compositions of mortars, concrete, or artificial stone, which then feed into technologies for solid waste management.

In terms of limitations, we are constrained to a large extent by existing classifications of clean and dirty patents. Future work could use machine learning to better discern categories using information contained within patents' abstract, title, and claims. Additionally, while patents represent a well-codified and accessible dataset for researchers, not all forms of technological knowledge are captured in patents. Tacit knowledge, including skills, knowhow, and systemic aspects of products and systems, is often unpatentable and hard to document. Some knowledge remains undisclosed, such as trade secrets (Roach and Wesley, 2013). One could also use data on scientific publications, categorise them as clean, dirty, or grey, and measure spillovers using this dataset, and compare it to the results of this paper.

Box 2
Indirect learning between clean and dirty technologies through bridge technologies

Case 1: Solar Panels & Glass

Clean patent #36933371 (DOCDB family id), which is about solar cells using high transmission glass cites intermediate patent #22076423 which is about infrared absorbing glass, which in turn cites dirty patent #24632438, which is about inductively heating molten glass.

Case 2: Smart Grids & Monitoring

Clean patent #49382706, which is related to programmable electrical devices (used in clean buildings & smart grids) cites intermediary patent #11418031 related to monitoring technologies, which in turn builds upon technologies used in patent #23474906, which is about automatic safety checks in thermal powerplants.

Case 3: Wind Turbines & Optimization

Clean patent #72944505, which is about software to determine the orientation of a wind turbine nacelle, cites intermediary patent #36694399 which is about model-based, multi-objective asset optimization, which in turn cites dirty patent #29272616 which is about models to detect heat exchanger tube failures to optimise the operations of a thermal powerplant.

Case 4: Indoor Pollution Abatement & Filtration

Clean patent #50731728 which is about reducing indoor air pollution cites intermediate patent #36590829 which is about filtration/removing contaminants, which in turn cites dirty patent #23777699 which is about particulate traps used in the exhaust system of a diesel engine.

An avenue for future research is to explore knowledge flows between clean technologies and other general sectors of the economy. Furthermore, it would be interesting to more systematically test if knowledge spillovers, as measured by patent citations, are positively correlated with the use of similar types of capital and labour (e.g., seabed engineers, floating platforms, and robots that work at sea, etc.). While this is implicit from the contents of the patents, formal testing, which is beyond the scope of this paper, would be valuable. Lastly, other measures of technological distance (e.g. Yan and Luo, 2017) could be considered in future studies to further extend and deepen the findings of this study.

Ethics approval and consent to participate

This research does not include human participants and/or animals.

Consent for publication

This research does not include human participants and/or animals.

CRediT authorship contribution statement

Su Jung Jee and Sugandha Srivastav have contributed equally to the study. **Su Jung Jee:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sugandha Srivastav:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author upon request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108310.

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