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Diffusion, Quality, and Trajectory of Technological Knowledge: Empirical Evidence from Patent Citations

Difusión, calidad y trayectoria del conocimiento tecnológico: evidencia empírica a partir de citas de patentes

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Resumen

La innovación se configura como un proceso dinámico y acumulativo en el que la recombinación y difusión del conocimiento tecnológico orientan el cambio estructural y la evolución de los sistemas productivos, condicionando la capacidad de las economías para abordar retos de largo plazo. No obstante, la literatura sobre economía de la innovación y del conocimiento ha tendido a estudiar de forma separada las distintas dimensiones de este proceso, lo que limita una comprensión integrada de la generación y utilización del conocimiento tecnológico. Esta tesis contribuye a superar esta limitación mediante la aportación de evidencia empírica sobre los determinantes de la difusión, la calidad y la trayectoria del conocimiento tecnológico en sectores de relevancia social y ambiental. Aunque cada uno de los estudios que integran la parte empírica de esta tesis aborda dimensiones específicas del proceso de innovación, la tesis permite analizar estos mecanismos de forma diferenciada dentro de un mismo marco conceptual.

Este enfoque resulta especialmente relevante en contextos donde la dirección del cambio tecnológico se vincula a objetivos de sostenibilidad, en particular en el sector energético, donde la difusión del conocimiento condiciona la transición hacia tecnologías de menor impacto ambiental. A su vez, el análisis del sector farmacéutico permite identificar el papel de la colaboración internacional en contextos caracterizados por elevada complejidad tecnológica y una fuerte dependencia de la base científica.

El marco teórico se fundamenta en los enfoques neo-schumpeterianos y evolutivos, que sitúan el conocimiento en el núcleo del cambio tecnológico y conceptualizan la innovación como un proceso acumulativo, direccional y dependiente de la trayectoria. Asimismo, incorpora aportaciones de la teoría del crecimiento endógeno, que enfatiza la generación de conocimiento y la inversión en I+D como motores internos de la innovación. Este trabajo integra además contribuciones de la literatura sobre spillovers de conocimiento, capacidad de absorción, innovación abierta y sistemas de innovación, con el objetivo de analizar los mecanismos que estructuran la difusión, la calidad y la trayectoria del conocimiento tecnológico.

El análisis empírico se desarrolla a través de tres estudios. El primero examina el efecto del conocimiento previo —interno y externo, tanto de carácter tecnológico como

científico— y de la colaboración entre empresas y universidades sobre la difusión del conocimiento tecnológico en el sector energético. El segundo analiza la dirección de los spillovers de conocimiento y su relación con la dependencia de trayectoria, incorporando la capacidad de absorción verde como mecanismo que modula la difusión y la orientación del cambio tecnológico. El tercero evalúa el efecto de la colaboración internacional y la estructura de estas redes sobre la calidad de las patentes. El análisis se basa en datos globales procedentes de PATSTAT, utilizando patentes como proxy de la actividad innovadora y las citas de patentes para medir la base de conocimiento, la difusión, la calidad y la trayectoria tecnológica, mediante la aplicación de modelos econométricos.

Los resultados muestran que la difusión del conocimiento tecnológico depende de la composición de la base de conocimiento previa, tanto tecnológica como científica, y presenta patrones diferenciados según el tipo de tecnología. Asimismo, se observa que la difusión presenta una dependencia de la trayectoria, ya que los spillovers tienden a concentrarse dentro de los mismos dominios tecnológicos, reforzando la persistencia de trayectorias. La capacidad de absorción verde modula estos efectos reduciendo la influencia de los spillovers en el caso de las tecnologías no renovables. La colaboración entre instituciones no muestra un efecto positivo sobre la difusión, mientras que la colaboración internacional se asocia con mayores niveles de calidad del conocimiento tecnológico cuando incluye participantes de países con capacidades tecnológicas elevadas.

Estos resultados aportan implicaciones relevantes para el diseño de políticas de innovación y para las estrategias empresariales. En concreto, la evidencia muestra que la intensidad de la actividad innovadora no garantiza por sí misma la reorientación del cambio tecnológico, lo que justifica el diseño de políticas que actúen sobre la dirección de los flujos de conocimiento. Asimismo, refuerza la importancia de fortalecer las capacidades de absorción y de promover estructuras de colaboración que integren capacidades complementarias, especialmente en contextos internacionales, con el fin de favorecer la generación y difusión de tecnologías de mayor impacto.

Palabras clave

Economía de la innovación, difusión del conocimiento, capacidad de absorción, calidad de las patentes, trayectoria tecnológica, spillovers de conocimiento

Abstract

Innovation is conceptualized as a dynamic and cumulative process in which the recombination and diffusion of technological knowledge shape structural change and the evolution of productive systems, thereby conditioning the capacity of economies to address long-term challenges. However, the literature in the economics of innovation and knowledge has tended to examine the different dimensions of this process separately, which constrains an integrated understanding of the generation and use of technological knowledge. This thesis contributes to overcoming this limitation by providing empirical evidence on the determinants of the diffusion, quality, and trajectory of technological knowledge in sectors of social and environmental relevance. Although each of the studies comprising the empirical part of this thesis addresses specific dimensions of the innovation process, the thesis enables these mechanisms to be analyzed in a differentiated manner within a common conceptual framework.

This approach is particularly relevant in contexts where the direction of technological change is linked to sustainability objectives, especially in the energy sector, where the diffusion of knowledge conditions the transition toward technologies with lower environmental impact. In turn, the analysis of the pharmaceutical sector allows for the identification of the role of international collaboration in contexts characterized by high technological complexity and a strong dependence on the scientific knowledge base.

The theoretical framework is grounded in neo-Schumpeterian and evolutionary approaches, which place knowledge at the core of technological change and conceptualize innovation as a cumulative, directional, and path-dependent process. It also incorporates contributions from endogenous growth theory, which emphasizes knowledge generation and investment in R&D as internal drivers of innovation. In addition, this work integrates insights from the literature on knowledge spillovers, absorptive capacity, open innovation, and innovation systems, with the aim of analyzing the mechanisms that structure the diffusion, quality, and trajectory of technological knowledge.

The empirical analysis is developed through three studies. The first examines the effect of prior knowledge—both internal and external, and of a technological and scientific nature—as well as collaboration between firms and universities on the diffusion of technological knowledge in the energy sector. The second analyzes the direction of knowledge spillovers and their relationship with path dependence, incorporating green absorptive capacity as a mechanism that modulates the diffusion and orientation of technological change. The third evaluates the effect of international collaboration and the structure of these networks on patent quality. The analysis is based on global data from PATSTAT, using patents as a proxy for innovative activity and patent citations to measure the knowledge base, diffusion, quality, and technological trajectory, through the application of econometric models.

The results show that the diffusion of technological knowledge depends on the composition of the prior knowledge base, both technological and scientific, and exhibits differentiated patterns depending on the type of technology. Furthermore, diffusion displays path dependence, as spillovers tend to concentrate within the same technological domains, reinforcing the persistence of trajectories. Green absorptive capacity modulates these effects by reducing the influence of spillovers in the case of non-renewable technologies. Institutional collaboration does not exhibit a positive effect on diffusion, whereas international collaboration is associated with higher levels of technological knowledge quality when it includes participants from countries with high technological capabilities.

These results provide relevant implications for the design of innovation policies and for firm-level strategies. In particular, the evidence indicates that the intensity of innovative activity alone does not guarantee the reorientation of technological change, which justifies the design of policies aimed at influencing the direction of knowledge flows. Moreover, it underscores the importance of strengthening absorptive capacities and promoting collaboration structures that integrate complementary capabilities, especially in international contexts, in order to foster the generation and diffusion of higher-impact technologies.

Keywords

Economics of innovation, knowledge diffusion, absorptive capacity, patent quality, technological trajectory, knowledge spillovers

CAPÍTULO 1:

INTRODUCCIÓN

1.1. Justificación y relevancia del estudio

El análisis de la generación, difusión y acumulación del conocimiento tecnológico constituye una cuestión central en la economía de la innovación (Arrow, 1962; Nelson y Winter, 1982; Dosi, 1982; Mokyr, 2002), dado su papel determinante en las dinámicas de crecimiento económico, la configuración de la competitividad empresarial y la transición hacia modelos productivos más sostenibles.

En este sentido, la literatura ha destacado el papel central del conocimiento en el cambio tecnológico, enfatizando su carácter acumulativo, su difusión entre agentes y su influencia en la configuración de trayectorias tecnológicas. Desde las perspectivas neo-schumpeterianas y evolucionistas, la innovación se concibe como un proceso dinámico y dependiente de la trayectoria, en el que las nuevas invenciones se construyen a partir de la recombinación de conocimientos previos. En este contexto, la difusión del conocimiento, los spillovers tecnológicos y la capacidad de absorción desempeñan un papel clave en la generación y orientación del cambio tecnológico. A pesar de los avances en la literatura sobre economía de la innovación, persisten limitaciones en la comprensión empírica de los factores que determinan la difusión, la calidad y la trayectoria del conocimiento tecnológico. Estos aspectos han sido analizados en gran medida de forma separada, lo que dificulta obtener una visión conjunta de los mecanismos que estructuran el proceso de innovación. Esta tesis aborda estas limitaciones mediante el análisis de estas tres dimensiones a partir de evidencia empírica basada en citas de patentes.

Con el fin de delimitar el alcance del análisis, se definen a continuación los conceptos de difusión, calidad y trayectoria del conocimiento tecnológico. En primer lugar, la difusión se entiende como el proceso mediante el cual una innovación se transmite, a lo largo del tiempo, a través de determinados canales entre los miembros de un sistema social (Rogers, 1962, p. 5). Esta concepción incluye tanto mecanismos de mercado como de no mercado. No obstante, en este trabajo se adopta una definición más restringida, centrada en los spillovers o efectos desbordamiento, entendidos como flujos de conocimiento que benefician a otros agentes sin una compensación equivalente a su valor real, o incluso sin compensación alguna (Jaffe, 1998). Desde esta perspectiva, la difusión hace referencia a la extensión y propagación del conocimiento tecnológico entre agentes, es decir, al grado en que una invención es utilizada como base para desarrollos posteriores.

Hasta aproximadamente mediados de la década de 1970, se asumía que una innovación era una cualidad invariable que no cambiaba a medida que se difundía (Rogers, 1962, p. 17). Posteriormente, la literatura incorpora el concepto de reinvención, definido como el grado en que una innovación es modificada y mejorada por los usuarios durante su proceso de difusión. Este enfoque pone de relieve que la difusión no es un proceso meramente pasivo, sino que implica transformación y adaptación del conocimiento, lo que introduce heterogeneidad en su impacto.

En este contexto, resulta necesario diferenciar la difusión de la calidad del conocimiento tecnológico, aunque ambas dimensiones se encuentren estrechamente relacionadas y se aproximen empíricamente mediante las citas recibidas de patentes. Mientras que la difusión capta la extensión del uso del conocimiento; esto es, si una invención es reutilizada y cómo se propaga en el sistema tecnológico, la calidad refleja la intensidad y relevancia de ese uso, es decir, el valor tecnológico y económico de la invención en función de su capacidad para influir en desarrollos posteriores. Aquellas innovaciones que reciben un mayor número de citas no solo están más difundidas, sino que también tienden a actuar como puntos de referencia en la generación de nuevas trayectorias tecnológicas (Trajtenberg, 1990; Popp, 2006).

De este modo, aunque ambas dimensiones comparten un mismo indicador empírico, su interpretación es conceptualmente distinta: la difusión se vincula a la propagación del conocimiento, mientras que la calidad se asocia a su impacto diferencial dentro del sistema tecnológico. Esta distinción permite evitar una interpretación redundante del análisis y abordar de forma complementaria estas dos dimensiones clave del proceso innovador.

Finalmente, la noción de trayectoria tecnológica permite integrar estas dimensiones en una perspectiva dinámica, al recoger cómo la acumulación de conocimiento y la dirección de los flujos de información configuran la evolución de las tecnologías a lo largo del tiempo (Dosi, 1982). En este sentido, la interacción entre difusión y calidad condiciona no solo la generación de nuevas invenciones, sino también la orientación del cambio tecnológico, al influir en qué líneas de desarrollo se consolidan y cuáles quedan relegadas (Arthur, 1989; Bhatt et al., 2023).

En el contexto actual, la transición hacia sistemas energéticos descarbonizados ha adquirido una dimensión estratégica a escala global, impulsada tanto por compromisos de política climática como por la necesidad de reducir la dependencia de combustibles fósiles. Los procesos inventivos en energía se articulan en torno al desarrollo y la difusión de tecnologías de bajas emisiones, lo que lo configura como un sector relevante para el análisis de la evolución tecnológica (Popp, 2011; Abulfotuh, 2007; Costantini et al., 2017; Alola y Rahko, 2024; Sun et al., 2021).

No obstante, la naturaleza acumulativa del cambio tecnológico implica que las invenciones se integran en trayectorias preexistentes, generando resultados no necesariamente alineados con los objetivos que orientaron su desarrollo inicial (Dosi, 1982; Arthur, 1989). La generación de nuevas tecnologías no garantiza por sí misma mejoras ambientales, pudiendo contribuir a la persistencia de sistemas tecnológicos dominantes, intensivos en emisiones, cuando se sustenta en trayectorias consolidadas y menos sostenibles (Unruh, 2000; Aghion et al., 2016). Esta tensión entre generación y orientación del cambio tecnológico sitúa en primer plano la necesidad de comprender los mecanismos que determinan no solo la difusión, sino también la dirección de los flujos de conocimiento (Aldieri et al., 2022).

La evidencia empírica indica que la innovación en tecnologías de bajas emisiones depende de la combinación de áreas diversas y complejas (Nemet, 2012; Garrone et al., 2014; Noailly y Smeets, 2015; Popp, 2017). Estos procesos se apoyan en la búsqueda de conocimiento externo, en las dinámicas de colaboración y en los vínculos entre ciencia y tecnología (Hötte et al., 2021; Nesta et al., 2014; Popp y Newell, 2012). Sin embargo, la evidencia no ofrece una explicación integrada de cómo estos mecanismos determinan la difusión del conocimiento, atendiendo a las particularidades del sector. Estudios previos han analizado por separado el papel de los spillovers en la difusión tecnológica (Battke et al., 2016; Noailly y Shestalova, 2017; Ardito et al., 2016) y los efectos de las políticas sobre la dirección del cambio tecnológico (Popp, 2006; Johnstone et al., 2010), pero sin integrar estos elementos en un marco analítico común.

En este sentido, el análisis de la difusión, la calidad y la trayectoria del conocimiento tecnológico resulta especialmente relevante en sectores donde la innovación y el conocimiento desempeñan un papel central en sus procesos de desarrollo.

En particular, el sector energético constituye un ámbito adecuado para analizar los factores que condicionan la difusión y la trayectoria del conocimiento, dado que la adopción de tecnologías incide en los procesos de transición hacia sistemas productivos con menor impacto ambiental.

De forma complementaria, el sector farmacéutico se selecciona por su relevancia social, su carácter intensivo en I+D y la importancia de la base científica y la colaboración internacional en sus procesos inventivos (Chen y Chang, 2010; Hall et al., 2014; Gamba, 2017; Hagedoorn, 2003; Kim y Song, 2007; Ter Wal y Boschma, 2009). No obstante, la evidencia sobre la relación entre colaboración internacional y calidad del conocimiento sigue siendo limitada (Lanjouw y Schankerman, 2004; Gay et al., 2005).

En conjunto, el análisis de ambos sectores permite examinar estos mecanismos en contextos diferentes, caracterizados por su relevancia social e intensidad inventiva, en los que la generación y utilización del conocimiento adquieren un papel clave.

Esta tesis contribuye empíricamente a la literatura sobre economía de la innovación y cambio tecnológico al analizar los determinantes de la difusión, la calidad y la trayectoria del conocimiento tecnológico dentro de un mismo marco conceptual de economía de la innovación. Asimismo, permite avanzar en la comprensión de los mecanismos asociados al conocimiento previo, interno y externo, de carácter científico y tecnológico, los spillovers tecnológicos, la capacidad de absorción y la colaboración, tanto entre instituciones como a nivel internacional.

Los resultados obtenidos permiten derivar implicaciones tanto desde la perspectiva de las políticas de innovación como desde la estrategia empresarial. En primer lugar, en el ámbito de las políticas de innovación, proporciona elementos relevantes para el diseño de instrumentos de innovación más eficaces, al poner de relieve que los incentivos generales resultan insuficientes para reorientar el cambio tecnológico en contextos caracterizados por dinámicas acumulativas. Además, aporta evidencia empírica relevante para el diseño de políticas selectivas orientadas a influir en la composición y trayectoria de los flujos de conocimiento, así como para el desarrollo de instrumentos que favorezcan la transición hacia tecnologías con mayor impacto social y ambiental. En segundo lugar, en el ámbito empresarial, aporta implicaciones para la formulación de estrategias relacionadas con la importancia de la gestión del conocimiento previo y la configuración de redes de colaboración basadas en la complementariedad de capacidades, dado su efecto sobre la calidad de los resultados tecnológicos.

1.2. Objetivos e hipótesis

El objetivo general de esta tesis es analizar los factores que influyen en la difusión, la calidad y la trayectoria del conocimiento tecnológico, considerando la base de conocimiento previa, los spillovers tecnológicos, la capacidad de absorción y la colaboración, a partir de evidencia basada en datos de invenciones patentadas. Este objetivo se desarrolla a través de tres objetivos específicos, cada uno de los cuales se aborda en un artículo empírico independiente.

Objetivo específico 1: Analizar el papel del conocimiento previo y la colaboración entre instituciones en la difusión de conocimiento tecnológico en el sector energético.

El sector de la generación de energía constituye un ámbito prioritario para el análisis de la difusión del conocimiento tecnológico, dado su papel en la transición hacia sistemas productivos más sostenibles y en la mitigación del cambio climático. La literatura sobre innovación energética ha mostrado que, a pesar del avance tecnológico, la difusión de soluciones energéticas eficientes y limpias continúa siendo lenta (Hötte, 2020). Además, comprender los procesos de generación y difusión del conocimiento en este sector resulta esencial para el diseño de políticas energéticas y ambientales eficaces (Popp, 2002; 2011).

Los estudios empíricos basados en patentes en el ámbito de las tecnologías energéticas se han centrado fundamentalmente en evaluar los efectos de las políticas de incentivos (Battke and Schmidt, 2015; Popp, 2006; Johnstone et al., 2010; Miremadi et al., 2019; Hötte, 2020) o en los flujos regionales e internacionales de conocimiento (Binz y Anadon, 2018; Gosens et al., 2015; Li et al., 2022), no adentrándose en el análisis del papel del conocimiento científico, las citas retrospectivas y la colaboración, cuyos efectos sobre la difusión tecnológica muestran resultados mixtos en otros sectores (Acosta et al., 2009; Belderbos et al., 2014; Briggs, 2015; Peeters et al., 2020).

Por ello, examinar estos factores en el ámbito energético permite comprender los mecanismos que impulsan la difusión tecnológica en un sector de alta relevancia económica y ambiental. En coherencia con este propósito, se plantean las siguientes hipótesis de investigación para el sector energético que orientan las acciones analíticas y las variables involucradas:

- H1. La intensidad en el uso del conocimiento científico afecta de forma positiva y significativa a la difusión del conocimiento tecnológico.

- H2. El grado de incorporación de conocimiento externo afecta de forma positiva y significativa a la difusión del conocimiento tecnológico.

- H3. El grado de reutilización de conocimiento propio afecta de forma positiva y significativa a la difusión del conocimiento tecnológico.

- H4. La colaboración entre empresas afecta de forma positiva y significativa a la difusión del conocimiento tecnológico.

- H5. La colaboración entre empresas y universidades afecta de forma positiva y significativa a la difusión del conocimiento tecnológico.

Objetivo específico 2: Analizar el rol de los spillovers de conocimiento y la capacidad de absorción verde en la difusión y la trayectoria del conocimiento tecnológico en tecnologías renovables y no renovables.

Este objetivo contribuye a la literatura al combinar la perspectiva de la dependencia de trayectoria con la de spillovers de conocimiento, incorporando además el efecto moderador de la capacidad de absorción verde (*Green Absorptive Capacity*).

Las tecnologías de energía ocupan un lugar estratégico en la transición hacia una economía baja en carbono, al constituir el eje sobre el cual se articulan las innovaciones en renovables y tecnologías de transición que moldean las trayectorias tecnológicas globales. Diversos estudios han evidenciado que factores como los precios de la energía, el conocimiento acumulado y los instrumentos de política condicionan la dirección del cambio tecnológico (Popp, 2002; Acemoglu, 2016), y han detectado dependencia de trayectoria en los procesos de innovación (Aghion et al., 2016). No obstante, la evidencia empírica sobre la difusión del conocimiento en este sector sigue siendo limitada. La mayor parte de las investigaciones se ha centrado en los spillovers inter e intra-sectoriales sin adoptar una perspectiva sectorial (Nemet, 2012; Nemet y Johnson, 2012), o bien en la difusión de tecnologías renovables sin considerar la base de conocimiento subyacente (Noailly y Shestalova, 2017). Asimismo, los estudios que analizan tecnologías concretas no ofrecen resultados generalizables al conjunto del sector, especialmente en el ámbito de las energías renovables (Battke et al., 2016; Stephan et al., 2019).

En este contexto, este objetivo contribuye a la literatura empírica al combinar la perspectiva de la dependencia de trayectoria con la de los spillovers de conocimiento, y permite evaluar cómo estos factores configuran la trayectoria de difusión tecnológica tanto en las energías renovables como en las no renovables, incorporando el papel moderador de la capacidad de absorción verde en la relación entre los spillovers y la difusión del conocimiento tecnológico. A partir de este objetivo, se plantean las siguientes hipótesis de investigación para el sector energético:

- H1. Los spillovers de conocimiento procedentes de tecnologías de energía renovable, incorporados en la base de conocimiento de tecnologías renovables, contribuyen de forma positiva y significativa a la difusión posterior de conocimiento tecnológico renovable.
- H2. Los spillovers de conocimiento procedentes de tecnologías de energía no renovable, incorporados en la base de conocimiento de tecnologías no renovables, contribuyen de forma positiva y significativa a la difusión posterior de conocimiento tecnológico no renovable.

- H3. La capacidad de absorción verde refuerza el efecto positivo de los spillovers renovables, adquiridos por tecnologías renovables, sobre la difusión de tecnologías de energía renovable.
- H4. La capacidad de absorción verde modera negativamente el efecto positivo de los spillovers no renovables, adquiridos por tecnologías no renovables, sobre la difusión de tecnologías de energía no renovable.

Objetivo específico 3: Evaluar el efecto de la colaboración internacional en la calidad de las invenciones farmacéuticas patentadas.

El sector farmacéutico se caracteriza por una elevada intensidad en actividades de investigación y desarrollo (I+D) y por una fuerte propensión a la generación de patentes. Estas características lo convierten en un ámbito especialmente adecuado para analizar, de manera precisa, los patrones de colaboración internacional en innovación (Hagedoorn, 2003; Ter Wal y Boschma, 2009; Loschky, 2008; Magazzini et al., 2009). Además, su fuerte dependencia de la investigación pública y de redes globales la convierte en un caso especialmente relevante (Furman et al., 2006). La relevancia del sector se evidenció especialmente durante la pandemia de la COVID-19, que puso de manifiesto su capacidad de innovación y, al mismo tiempo, las controversias en torno a la propiedad intelectual.

La literatura ha destacado que la generación de conocimiento y la innovación dependen cada vez más de la cooperación entre organizaciones y de la integración de capacidades complementarias, lo que hace relevante analizar los mecanismos que vinculan la colaboración con la calidad de los resultados tecnológicos (Hagedoorn, 2003; Kim y Song, 2007; Ter Wal y Boschma, 2009; Hall et al., 2014).

Este objetivo aborda la relación entre la colaboración tecnológica y la calidad de las invenciones, considerando la amplitud y composición de las redes de cooperación entre titulares de patentes. En este contexto, la colaboración internacional se define como la implicación de varios países en la copropiedad de la patente. Asimismo, se incorpora una dimensión novedosa al examinar la participación de empresas ubicadas en jurisdicciones de baja tributación. Este objetivo contribuye a la literatura al incorporar dimensiones poco exploradas relacionadas con la copropiedad de las patentes y la configuración de la cooperación internacional, contribuyendo a la comprensión de los factores que explican la calidad de las invenciones. Para ello, se plantean las siguientes hipótesis de investigación para el sector farmacéutico:

- H1. La colaboración internacional ejerce un efecto positivo y significativo sobre la calidad de las patentes; sin embargo, este efecto puede estar limitado a una determinada amplitud de la colaboración internacional, más allá de la cual un aumento en el número de colaboradores de distintos países implicados en el desarrollo de la patente puede dar lugar a una disminución de la calidad.
- H2. Colaborar con socios ubicados en países líderes en un determinado dominio producirá un mejor desempeño en términos de calidad de las patentes que colaborar con socios en otros países.
- H3. Las patentes en copropiedad con empresas ubicadas en paraísos fiscales presentan una mayor calidad que aquellas en copropiedad con empresas ubicadas en otras jurisdicciones.

En conjunto, los objetivos específicos de esta tesis permiten analizar tres dimensiones clave del proceso de innovación tecnológica: la difusión del conocimiento, la calidad de las invenciones y la trayectoria del cambio tecnológico. Los dos primeros objetivos se centran en los factores que condicionan la difusión y trayectoria del conocimiento en el sector energético, analizando el papel del conocimiento previo, la colaboración institucional y los spillovers en interacción con la capacidad de absorción verde. El tercer objetivo aborda la calidad del conocimiento tecnológico en contextos de alta intensidad en I+D, examinando cómo la configuración de la colaboración y la composición de los socios influyen en el impacto de las invenciones farmacéuticas.

1.3. Datos y metodología

1.3.1. Datos

Los datos de patentes constituyen una fuente ampliamente consolidada en la economía de la innovación, al proporcionar una medida observable, estandarizada y comparable de la actividad inventiva, cuya validez como proxy de la innovación está respaldada por una extensa literatura (Griliches, 1990; Hall et al., 2001; Haščič y Migotto , 2015; Squicciarini et al., 2013). Su disponibilidad a distintos niveles de agregación permite, además, rastrear los flujos de conocimiento entre tecnologías, sectores y organizaciones, facilitando el análisis de la dinámica del cambio tecnológico y la acumulación de capacidades inventivas (Jaffe et al., 1993; Breschi et al., 2003; Aghion et al., 2005).

En coherencia con estas propiedades, los tres artículos que componen esta tesis emplean datos de patentes como fuente primaria de evidencia empírica. En este marco, las citas hacia adelante se utilizan para aproximar la difusión, la calidad tecnológica de las invenciones, así como para identificar la dirección de su trayectoria (Griliches et al., 1991; Trajtenberg, 1990; Gambardella et al., 2008; Gay et al., 2005; Harhoff et al., 2009). Por su parte, las citas hacia atrás permiten reconstruir la base de conocimiento subyacente –interna y externa– y operacionalizar los spillovers de conocimiento tecnológico previo diferenciando su procedencia por dominios tecnológicos (Harhoff et al., 2003; Duguet y Macgarvie, 2005; Gay y Le Bas, 2005).

Los datos empleados en esta tesis proceden de PATSTAT (edición otoño 2017), base de datos desarrollada por la Oficina Europea de Patentes (EPO) que ofrece información global y armonizada sobre patentes con cobertura desde 1970. La unidad de análisis es la familia de patentes (en adelante, "patentes", para simplificar), definida como el conjunto de solicitudes vinculadas a una misma invención presentadas en distintas oficinas, lo que permite una mayor homogeneidad en la comparación entre jurisdicciones (Martínez, 2010; de Rassenfosse et al., 2014). El análisis se restringe a familias de patentes con al menos una solicitud protegida ante la EPO y al menos una solicitud de titularidad empresarial, mientras que la identificación tecnológica se realiza mediante los códigos de la Clasificación Internacional de Patentes (IPC).

En cuanto al horizonte temporal, se se acota un período de análisis que garantiza la cobertura y fiabilidad de los datos, ya que las observaciones más recientes de la edición de 2017 presentan un grado de consolidación incompleto, lo que podría distorsionar la actividad patentadora registrada en los últimos años.

Dado que la tesis se compone de tres artículos empíricos, se construyen tres bases de datos específicas adaptadas a cada análisis.

1.3.1.1. Base de datos I: patentes de tecnologías de energía

Los datos se componen de 54,578 familias de patentes de energía solicitadas por empresas durante el período 1990–2015, considerando como referencia la fecha de prioridad. Para el análisis descriptivo se utiliza todo el periodo, y en la ejecución del modelo econométrico se ha restringido la muestra hasta 2010 para garantizar la posibilidad de citar en una ventana de cinco años. Para identificar de manera única a los solicitantes y detectar autocitas, se aplica un proceso de armonización que combina procedimientos algorítmicos y revisión manual. Para la identificación de los dominios de energía, se aplica un esquema de clasificación basado en los códigos de la Clasificación Internacional de Patentes (IPC), siguiendo las propuestas de Johnstone et al. (2010) y Noailly y Shestalova (2017) para tecnologías renovables y fósiles, y de Albino et al. (2014) para tecnologías nucleares, abarcando ocho campos de energía.

1.3.1.2. Base de datos II: patentes de tecnologías de energía renovable y fósil

La muestra se compone de 12,966 patentes de energía renovable y 24,067 patentes de energía fósiles no renovable presentadas por empresas ante la oficina EPO durante el período 1990–2010 (según la fecha de prioridad). La identificación de las tecnologías se realizó siguiendo las clasificaciones IPC propuestas por Johnstone et al. (2010) y Noailly y Shestalova (2017) para energías renovables, y por Haščič et al. (2009) para tecnologías fósiles; tanto para la muestra, como para la distinción tecnológica de las citas recibidas. Se utiliza la armonización de nombres de solicitantes realizada en la base de datos 1 para identificar a un mismo solicitante y detectar así las autocitas.

1.3.1.3. Base de datos III: patentes de tecnologías farmacéuticas

Se compone de una muestra de 143,479 familias de patentes farmacéuticas de 30 países, considerando únicamente aquellos países con al menos 150 familias de patentes entre 1990 y 2012 (según la fecha de prioridad), con el fin de evitar casos con actividad patentadora estadísticamente poco significativa. A partir de la copropiedad de las patentes se identifican las relaciones de colaboración internacional entre países. Dado que las patentes concentran la mayor parte de sus citas en los primeros años tras su publicación (Briggs, 2015; Briggs y Wade, 2014), se realiza una prueba de robustez utilizando una ventana de tres años, obteniéndose resultados consistentes. Esta evidencia permite extender el periodo de análisis hasta 2012 sin comprometer la validez de los resultados.

1.3.2. Metodología

La tesis se compone de tres estudios empíricos independientes, cada uno con su propio diseño metodológico, basados en análisis econométricos aplicados a datos de patentes, precedidos en cada caso por un análisis descriptivo que contextualiza los datos y ofrece una primera aproximación a los patrones observados. El diseño empírico de cada estudio se fundamenta en la revisión de la literatura teórica y metodológica, que orienta la selección de variables, la construcción de indicadores y la especificación de los modelos de estimación. Aunque cada artículo responde a objetivos de investigación específicos, los tres comparten una lógica metodológica común, si bien no todos incorporan los mismos bloques analíticos ni el mismo conjunto de variables.

En términos generales, los modelos incluyen variables dependientes, que aproximan la difusión, la calidad y la dirección de la trayectoria del conocimiento tecnológico, según el objetivo de cada estudio.

Asimismo, se incorporan variables explicativas principales, vinculadas a las hipótesis de investigación, que varían entre artículos e incluyen, según el caso, la colaboración entre agentes, el uso de conocimiento previo científico y tecnológico (tanto propio como externo), los spillovers de conocimiento según el dominio tecnológico, la capacidad de absorción verde y la colaboración internacional.

Por último, los modelos consideran variables de control, que captan factores estructurales como el año de prioridad, la originalidad tecnológica, la experiencia inventiva y el dominio tecnológico, entre otros, cuya inclusión también se adapta a las características de cada estudio.

En la Tabla 1 se presenta, para cada uno de los estudios, el objetivo específico que se persigue, las variables dependientes e independientes junto a la forma en que se operacionalizan, el volumen de datos de la muestra y los modelos econométricos empleados para su estimación.

Debido a la naturaleza de los datos empleados en los tres trabajos, se emplean modelos de recuento, principalmente Poisson o binomial negativo (NB), dado que las estimaciones obtenidas mediante modelos lineales no son consistentes (Amano y Fujita, 1970; Long, 1997). El modelo Poisson constituye el punto de partida estándar en este tipo de análisis, aunque la hipótesis de igualdad entre la media y la varianza resulta restrictiva en presencia de sobredispersión, por lo que el modelo binomial negativo (NB) proporciona una representación más adecuada al permitir que la varianza dependa de manera cuadrática de la media (Cameron y Trivedi, 1986).

De forma complementaria, se emplean estimadores de cuasi-máxima o pseudo-máxima verosimilitud de Poisson (QMLE/PPML), que garantizan consistencia en la estimación de la media condicional bajo distintos supuestos de varianza (Wooldridge, 1999), y se plantean modelos inflados en ceros (ZIP y ZINB; Lambert, 1992; Heilbron, 1994). La elección de los modelos se determina atendiendo a los criterios de información de Akaike (AIC) y Bayesiano (BIC). Además, se realizan pruebas adicionales de sensibilidad temporal, estimando los modelos sobre diferentes ventanas de observación de las citas diferente a los 5 años—de 3 y 10 años—, lo que permite verificar la estabilidad de los coeficientes ante horizontes de análisis alternativos.

En cuanto a las especificaciones particulares de cada estudio, en el primer trabajo se emplean modelos binomiales negativos (NB) y se descarta el uso de modelos de ceros inflados al no existir evidencia de procesos diferenciados en las observaciones de ceros. Además, se incorporan estimaciones mediante mínimos cuadrados ordinarios sobre datos logarítmicos (Thelwall y Wilson, 2014), con el fin de contrastar la robustez de los resultados.

Tabla 1. Síntesis de objetivos, variables, datos y metodología de los tres trabajos.

Título	Objetivo	Variables	Datos y modelo econométrico
The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents	Analizar cómo el conocimiento previo y la colaboración interinstitucional influyen en la difusión del conocimiento tecnológico en el sector energético.	**Dependiente:** difusión del conocimiento tecnológico (citas recibidas). **Independientes principales:** • Conocimiento científico (citas a literatura científica). • Conocimiento tecnológico externo (citas a patentes externas). • Conocimiento tecnológico propio (citas a patentes propias). • Colaboración interempresarial (copropiedad entre empresas). • Colaboración universidad-empresa (copropiedad entre empresas y universidades).	**Datos:** 54,578 familias de patentes energéticas (1990–2015, muestra truncada a 2010). **Modelo econométrico:** Modelos binomiales negativos (NB).
Knowledge Path Dependence in Energy Innovation: The Role of Spillovers and Green Absorptive Capacity in Renewable and Non-Renewable Technology Diffusion	Analizar cómo los spillovers de conocimiento y la capacidad de absorción verde influyen en la difusión y la trayectoria del conocimiento tecnológico en patentes renovables y no renovables.	**Dependientes:** difusión y trayectoria del conocimiento tecnológico dirigida hacia renovables y hacia no renovables (citas recibidas de patentes renovables y fósiles). **Independientes principales:** • Spillovers renovables (citas a patentes renovables). • Spillovers no renovables (citas a patentes fósiles). • Spillovers externos (citas a patentes de otras tecnologías). • Capacidad de absorción verde (interacción stock acumulado en renovables y spillovers).	**Datos:** 12,966 familias de patentes renovables y 24,067 fósiles (1990–2010). **Modelo econométrico:** Modelos binomiales negativos (NB).
Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals	Evaluar el impacto de la colaboración internacional en patentes conjuntas sobre la calidad de las invenciones farmacéuticas.	**Dependiente:** calidad de la patente (citas recibidas). **Independientes principales:** • Colaboración internacional (co-patente entre solicitantes ubicados en varios países). • Amplitud de la colaboración (número de los distintos países de los solicitantes). • Amplitud geográfica (identifica la combinación de países de los solicitantes). • Países líderes (EEUU, Suiza, Japón, Alemania, Reino Unido y Francia). • Paraísos fiscales (identifica si la colaboración incluye jurisdicciones de baja tributación).	**Datos:** 143,479 familias de patentes farmacéuticas de 30 países (1990–2012). **Modelo econométrico:** Modelos binomiales negativos (NB).

El segundo trabajo también empleó modelos binomiales negativos (NB), diferenciando la variable dependiente entre energías renovables y no renovables. Para contrastar la consistencia de los resultados se utilizó el estimador Poisson de pseudo-máxima verosimilitud (PPML), adecuado frente a una alta proporción de ceros y a la falta de correspondencia entre la media y la varianza (Wooldridge, 2010). Además, como alternativa se estimaron modelos de ceros inflados—Poisson (ZIP) y binomial negativo (ZINB)— (Lambert, 1992; Heilbron, 1994).

El tercer trabajo empleó el modelo binomial negativo (NB) como especificación principal y contrastó su robustez mediante estimaciones de Poisson QMLE (Wooldridge, 1999). También se aplicaron contrastes mediante submuestras restringidas a coincidencias geográficas entre inventores y asignatarios, con el fin de controlar posibles sesgos. Finalmente, el estudio incorporó un análisis específico para evaluar posibles problemas de endogeneidad, considerando el riesgo de causalidad inversa entre la colaboración en I+D y la calidad de las patentes (Alnuaimi et al., 2012; Giuliani et al., 2016).

1.4. Estructura de la tesis

Con objeto de desarrollar la investigación propuesta, esta tesis se estructura en 7 capítulos. El capítulo 1 constituye la introducción de la tesis, e incluye su justificación, los objetivos, los datos y metodología empleados, y esta descripción de cómo se estructura la tesis.

La **Parte I** constituye el bloque de antecedentes, dedicado al desarrollo del marco teórico y a la fundamentación metodológica, agrupando los capítulos 2 y 3.

El capítulo 2 presenta el marco conceptual y teórico de la tesis y se estructura en cuatro apartados: el apartado 2.1 recoge los fundamentos de la innovación y del cambio tecnológico, el apartado 2.2 desarrolla las teorías del cambio tecnológico y el carácter acumulativo del conocimiento, el apartado 2.3 aborda los spillovers y la difusión del conocimiento en sus dimensiones tecnológica y geográfica, y el apartado 2.4 presenta la colaboración en el proceso de producción tecnológica, distinguiendo entre la colaboración entre instituciones y la colaboración internacional.

El capítulo 3 recoge los antecedentes metodológicos de la tesis en relación con la medición de la difusión, la calidad tecnológica y los flujos de conocimiento a partir de datos de patentes, y se estructura en estos apartados: el apartado 3.1 presenta la medición del proceso de innovación mediante información de patentes, el apartado 3.2 aborda las citas realizadas como indicador de spillovers, el apartado 3.3 desarrolla las citas recibidas como indicador de difusión, calidad y dirección de la trayectoria tecnológica, y el apartado 3.4 presenta las limitaciones del uso de patentes en el análisis de la innovación.

El marco conceptual desarrollado se traslada al estudio empírico en la **Parte II**, que constituye el bloque dedicado al análisis empírico de la tesis mediante tres trabajos que aportan evidencia sobre los factores que inciden en la difusión, la calidad y la dirección de la trayectoria del conocimiento tecnológico. Cada uno de estos trabajos se presenta en un capítulo independiente, correspondientes a los capítulos 4, 5 y 6, conformando el compendio de publicaciones que integra esta tesis. Los tres manuscritos han sido publicados en revistas indexadas en el *Journal Citation Reports* de *Web of Science*.

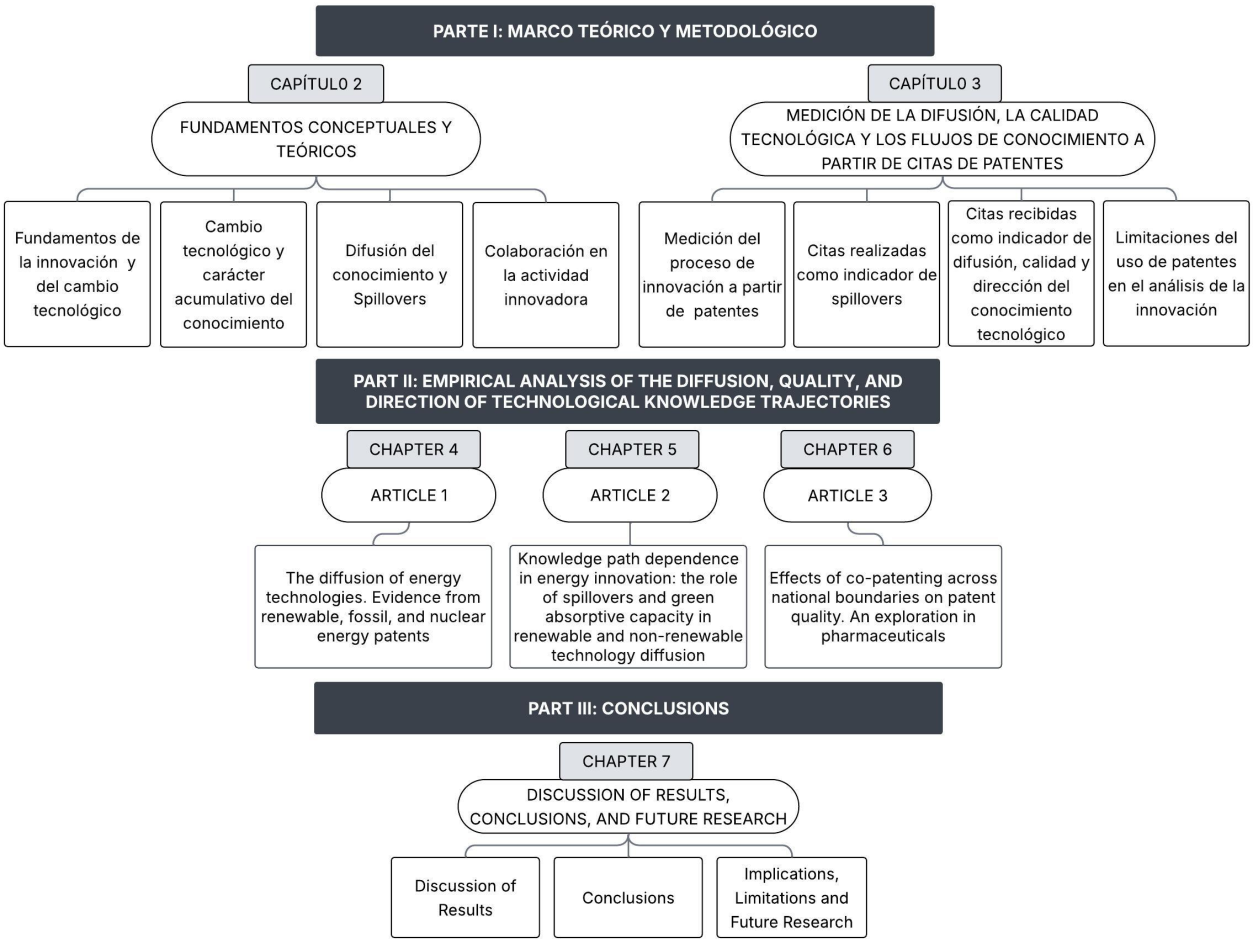
El capítulo 4 presenta el primer estudio empírico de la tesis, *The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents*, que analiza el papel del conocimiento previo, tanto interno como externo y científico, y de la colaboración institucional con empresas y universidades en la difusión del conocimiento tecnológico en el sector energético.

El capítulo 5 recoge el segundo estudio empírico, *Knowledge Path Dependence in Energy Innovation: The Role of Spillovers and Green Absorptive Capacity in Renewable and Non-Renewable Technology Diffusion*, que examina cómo los spillovers de conocimiento condicionan la difusión hacia invenciones posteriores, analizando su dirección hacia tecnologías renovables y no renovables.

El capítulo 6 desarrolla el tercer estudio empírico, *Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals*, que examina la relación entre la colaboración internacional y la calidad de las invenciones patentadas en el sector farmacéutico.

La **Parte III** articula la formulación de las conclusiones de la tesis y se materializa en el capítulo 7, que constituye su cierre. Este capítulo se estructura en tres apartados: el apartado 7.1 desarrolla la discusión conjunta de los resultados obtenidos en los distintos trabajos, el apartado 7.2 presenta las conclusiones específicas de cada uno de ellos, y el apartado 7.3 examina las implicaciones derivadas, las limitaciones del estudio y las principales líneas de investigación futura. La Parte II y la Parte III, correspondientes al análisis empírico y a las conclusiones, se desarrollan íntegramente en inglés, en coherencia con los estándares de publicación internacional y en cumplimiento de los requisitos establecidos por la Escuela de Doctorado de la Universidad de Cádiz para la obtención del Doctorado internacional.

Diagrama 1: Estructura de la tesis.



PARTE I: MARCO TEÓRICO Y METODOLÓGICO

CAPÍTULO 2:

FUNDAMENTOS CONCEPTUALES Y TEÓRICOS

2.1. Fundamentos de la innovación y del cambio tecnológico

La innovación se define como la introducción de productos o procesos nuevos o mejorados (OECD, 2005), siendo la novedad su rasgo más fundamental (Gopalakrishnan y Damanpour, 1997). En un sentido amplio, implica la utilización de nuevos conocimientos o de nuevas combinaciones del conocimiento existente con el objetivo de mejorar la capacidad competitiva y generar valor económico y social (Freeman y Soete, 2009; OECD, 2015). La innovación se orienta a facilitar la adaptación a cambios tecnológicos, regulatorios y de mercado, así como a potenciar la explotación de nuevas oportunidades y fortalecer las capacidades internas en contextos de incertidumbre y transformación constante (OCDE/Eurostat, 2018). El Manual de Oslo precisa, además, que la innovación se caracteriza por la incertidumbre respecto a sus resultados, la necesidad de inversión en activos, tanto materiales como inmateriales, y su exposición a los efectos de desbordamiento del conocimiento o spillovers (OECD, 2005). Asimismo, la innovación tecnológica no solo persigue beneficios empresariales, sino que también se vincula con el bienestar económico y social (Freeman, 1987). Constituye un componente central en la dinámica macroeconómica, al estar asociada a los procesos de crecimiento, cambios en la productividad y transformación estructural (Solow, 1957; Romer, 1990; Aghion y Howitt, 1992).

Desde una perspectiva económica, se distingue entre invención e innovación. Una invención se refiere a una idea o modelo para un producto o proceso mejorado, mientras que la innovación se produce cuando dicha invención es introducida en el mercado y se difunde (OECD, 2005). El proceso de cambio tecnológico puede organizarse en tres etapas interrelacionadas, que Schumpeter (1942) conceptualiza bajo la noción de destrucción creativa. En primer lugar, surge la invención, entendida como la generación de nuevo conocimiento. En segundo lugar, esta se transforma en una aplicación económica concreta mediante la innovación, cuando la idea se convierte en un producto o proceso comercialmente viable. Finalmente, la innovación adquiere impacto económico cuando es adoptada por otros agentes, proceso conocido como difusión.

La difusión es el proceso en el que la innovación se propaga progresivamente en el tiempo dentro de un sistema social, a través de mecanismos de comunicación que permiten la transmisión de conocimiento entre agentes (Rogers, 1962). Desde una perspectiva económica, Schumpeter (1934) señala que este proceso constituye el motor del cambio económico, en la medida en que la imitación de innovaciones impulsa la transformación estructural. En este marco, se distingue entre adopción —decisión individual de uso— y difusión —proceso colectivo de propagación— (Rogers, 1995). La literatura diferencia entre difusión de uso y transferencia de conocimiento tecnológico: mientras la primera responde a estrategias orientadas a ampliar la adopción de un producto, la segunda implica la transmisión del conocimiento subyacente que permite generar nuevas innovaciones (Stewart, 1987).

Este proceso de difusión se apoya en flujos de conocimiento entre agentes, que tienen lugar cuando se utilizan ideas o resultados generados previamente por otros (Griliches, 1979; Cohen y Levinthal, 1990). En este sentido, parte del esfuerzo innovador puede beneficiar a otros agentes, en función de cómo estos aprovechan el conocimiento disponible. El conocimiento generado en una invención pasa así a formar parte del estado del arte y sirve de base para desarrollos posteriores, reflejando la naturaleza acumulativa del cambio tecnológico, en la que las nuevas tecnologías se construyen a partir de la recombinación de conocimientos previos (Jaffe et al., 1993).

En este contexto, las invenciones no contribuyen de manera homogénea al desarrollo tecnológico, sino que presentan diferencias en su capacidad de ser incorporadas en desarrollos posteriores (Scotchmer, 1991; Hall et al., 2005). Esta heterogeneidad se vincula con el valor tecnológico y económico del conocimiento, en la medida en que aquellas invenciones con mayor utilización posterior reflejan una mayor calidad y potencial de aplicación (Hirschey y Richardson, 2004; Chen y Chang, 2010). La evidencia empírica muestra que las innovaciones más intensamente reutilizadas tienden a ocupar posiciones más centrales en la generación de nuevos desarrollos, actuando como nodos estructurantes del cambio tecnológico (Trajtenberg, 1990; Popp, 2006). En este sentido, la calidad de las invenciones se define por la intensidad en que una invención influye en desarrollos tecnológicos posteriores, constituyendo una dimensión clave para analizar el impacto diferencial del conocimiento dentro del sistema tecnológico.

Como resultado de estos procesos, el conocimiento trasciende los límites organizativos y se integra en procesos más amplios de desarrollo tecnológico, configurando trayectorias relativamente estables que orientan la dirección de la innovación (Dosi, 1982; Nelson y Winter, 1982). Este proceso condiciona la especialización tecnológica y las oportunidades futuras de innovación, en función de la base de conocimiento disponible y de los patrones de difusión previamente establecidos. Este planteamiento resulta especialmente relevante para esta tesis, al situar la difusión, la calidad y la trayectoria del conocimiento como elementos centrales del proceso innovador.

2.2. Cambio tecnológico y carácter acumulativo del conocimiento

Los modelos de Solow y Swan, desarrollados a mediados de la década de 1950, establecen el marco neoclásico que domina el análisis del crecimiento durante varias décadas. En este enfoque, la innovación tecnológica se considera un factor exógeno que explica el crecimiento económico una vez considerados los factores tradicionales como el capital y el trabajo (Solow, 1956; Swan, 1956). Este tratamiento presenta un marco estático en el que los agentes son racionales y los mercados operan bajo competencia perfecta (Alonso, 1992), concibiendo el cambio tecnológico como un elemento externo que no altera las dinámicas del sistema. La innovación fue inicialmente conceptualizada como un proceso lineal, en el que el conocimiento fluye de forma secuencial desde la investigación hasta la comercialización (Utterback, 1971; Rossegger, 1980). Esta visión fue posteriormente superada por enfoques interactivos, que conciben la innovación como un proceso no lineal y dinámico basado en la retroalimentación entre agentes y en la circulación del conocimiento (Kline y Rosenberg, 1986).

Como respuesta a las limitaciones del enfoque neoclásico, la teoría del crecimiento endógeno (Romer, 1990; Lucas, 1988; Aghion y Howitt, 1992; Grossman y Helpman, 1991) surge a mediados de los años ochenta. Supone una contribución significativa a la evolución de la economía neoclásica al considerar la tecnología como un factor endógeno. En esta teoría, las inversiones en investigación y desarrollo (I+D) realizadas por las empresas no solo mejoran el stock de conocimientos a nivel individual, sino que también generan externalidades hacia a otras empresas y sectores. Así, la innovación se considera un motor interno y activo del crecimiento, y los avances tecnológicos no son una causa exógena, sino un resultado de la actividad económica misma, especialmente impulsada por la I+D. Aghion y Howitt (1992) desarrollan un modelo de crecimiento endógeno de base schumpeteriana en el que el progreso tecnológico, impulsado por la competencia entre empresas, constituye el motor del crecimiento económico. Cada innovación introduce un insumo intermedio más eficiente que genera rentas monopólicas temporales para el innovador, pero es desplazada por la innovación siguiente, que la vuelve obsoleta. Este enfoque resulta pertinente para esta tesis al destacar el papel de las externalidades de conocimiento en la generación y difusión de innovaciones.

En contraste con los enfoques anteriores, el enfoque evolucionista (Nelson y Winter, 1982; Dosi, 1982, 1988; Freeman, 1987; Lundvall, 1992) supone una ruptura más profunda al concebir el cambio tecnológico como un proceso dinámico, histórico y acumulativo, condicionado por las capacidades organizativas e institucionales. La innovación no se dirige hacia un equilibrio óptimo, sino que evoluciona de manera continua a partir de la recombinación de conocimientos y del aprendizaje acumulado. En este marco, la heterogeneidad de capacidades entre agentes y la naturaleza tácita del conocimiento adquieren un papel central, lo que permite explicar diferencias persistentes en el desempeño innovador. Este enfoque resulta adecuado como base teórica para el análisis de esta tesis, al entender la innovación como un proceso heterogéneo y acumulativo basado en la utilización de conocimiento previo.

El enfoque evolucionista rechaza el concepto de equilibrio estático, proponiendo que los cambios en el crecimiento son impulsados por la evolución constante del cambio tecnológico, el cual está sujeto a una dinámica en la que las innovaciones compiten y se ajustan continuamente al entorno (Dosi 1988; Metcalfe, 1995). Este enfoque contrasta con la teoría neoclásica, que postula la existencia de un equilibrio estable en los mercados y asume que las empresas maximizan beneficios como su único objetivo (Solow, 1956). El enfoque evolucionista destaca el papel de los factores organizativos e institucionales como elementos interdependientes en el proceso de cambio tecnológico, y concibe a la empresa como un agente que actúa bajo racionalidad limitada y con objetivos más allá de la maximización de beneficios, incluyendo el crecimiento, la estabilidad y la adaptación (Nelson y Winter, 1982; Edquist, 1997). Enfatiza la relevancia de las capacidades tecnológicas como resultado de procesos acumulativos de aprendizaje, que integran tanto recursos tangibles como conocimiento tácito y competencias organizativas, fundamentales para la generación de innovación (Polanyi, 1966; Dosi, 1988).

Tras el enfoque evolucionista, que sentó las bases para entender la innovación como un proceso dinámico y acumulativo, surgieron otros enfoques que afinaron la comprensión de sus mecanismos y actores. El enfoque neo-schumpeteriano (Freeman y Perez, 1988; Metcalfe, 1998) amplía las ideas de Schumpeter sobre el papel de la innovación, incorporando una perspectiva dinámica, evolutiva y basada en el conocimiento, y concibe la innovación como el motor del cambio económico, integrando el análisis del progreso tecnológico en una perspectiva histórica y estructural de largo plazo. La dinámica económica se caracteriza por procesos de destrucción creativa, en los que la introducción y difusión de nuevas tecnologías, productos y formas organizativas generan cambios profundos en la estructura productiva, en la organización industrial y en la distribución del empleo y la renta (Dosi et al., 2010; Castellacci, 2008; Fagerberg et al., 2013).

El concepto de trayectorias tecnológicas, desarrollado en el marco del enfoque evolucionista, describe cómo el desarrollo tecnológico sigue patrones relativamente estables y acumulativos (Dosi, 1982; Nelson y Winter, 1982). Estas trayectorias reflejan regularidades en el proceso innovador, de modo que las mejoras tecnológicas tienden a concentrarse en determinadas líneas de desarrollo, condicionando tanto la dirección como el ritmo del cambio tecnológico (Dosi y Nelson, 2010). La innovación se desarrolla dentro de marcos tecnológicos o paradigmas que guían la búsqueda de soluciones y delimitan el espacio de posibilidades tecnológicas (Dosi et al., 1988; Freeman y Perez, 1988). En este sentido, las trayectorias tecnológicas reflejan cómo la base de conocimiento previa condiciona la dirección de la innovación y su evolución en el tiempo.

La dependencia de la trayectoria profundiza en el carácter acumulativo del cambio tecnológico, al explicar cómo las decisiones pasadas, las capacidades acumuladas y el contexto institucional generan dinámicas de auto-refuerzo que condicionan las opciones futuras. La innovación queda así vinculada a infraestructuras existentes, habilidades específicas y rutinas organizativas que dificultan la transición hacia alternativas radicalmente nuevas, incluso cuando estas son potencialmente más eficientes (Dosi, 1982; Verspagen, 2007; Liu et al., 2021). De este modo, estas dinámicas no solo orientan la dirección del cambio, sino que también tienden a consolidarse en el tiempo. El bloqueo tecnológico constituye una manifestación extrema de esta dinámica, produciéndose cuando una tecnología se consolida hasta hacer costoso el cambio hacia alternativas superiores (Arthur, 1989; Unruh, 2000). Este fenómeno se ve reforzado por la inercia organizacional, entendida como la resistencia interna al cambio derivada de rutinas establecidas, estructuras de poder y aversión al riesgo, lo que conduce a priorizar la persistencia frente a innovaciones radicales. En contraste, Christensen (1997) muestra que la innovación disruptiva puede alterar estas trayectorias cuando emergen tecnologías que no encajan en los marcos dominantes.

Junto a los enfoques anteriores, la literatura ha desarrollado otras perspectivas que contribuyen a contextualizar los procesos de producción tecnológica. El enfoque de la economía del conocimiento concibe el conocimiento como un factor productivo clave y fuente de creación de valor, destacando el papel del capital intelectual y el aprendizaje en la innovación (Drucker, 1969; Cesaroni, 2003). El enfoque institucional entiende la innovación como un proceso condicionado por el entorno normativo y organizativo, en el que las reglas formales e informales y los marcos de gobernanza configuran los incentivos y las trayectorias de desarrollo tecnológico (North, 1990; Edquist, 1997).

Desde una perspectiva colectiva y relacional, el enfoque de los sistemas de innovación sitúa el análisis en las interacciones entre actores e instituciones, considerando que la innovación resulta de redes complejas que integran empresas, universidades y organismos públicos, cuyas relaciones condicionan la generación, adopción y difusión del conocimiento (Freeman, 1987; Lundvall, 1992; Nelson, 1993). Este marco ha sido desarrollado en distintos niveles —nacional, regional y sectorial—, poniendo de relieve el carácter contextual de los procesos innovadores (Cooke et al., 1997; Malerba, 2002). A partir de esta perspectiva, los modelos sistémicos, como la Triple Hélice y sus extensiones, analizan la interacción entre los distintos actores en la producción y difusión del conocimiento (Etzkowitz y Leydesdorff, 2000; Carayannis y Campbell, 2009). Estas perspectivas complementan este análisis al situar los procesos de acumulación y difusión del conocimiento tecnológico en un contexto institucional y relacional.

En conjunto, todos estos enfoques permiten entender el cambio tecnológico como un proceso acumulativo, en el que el conocimiento previo condiciona tanto la generación de nuevas innovaciones como su difusión y trayectoria. Este marco teórico proporciona la base para analizar, en los apartados siguientes, los mecanismos mediante los cuales dicho conocimiento se transmite entre agentes y se traduce en spillovers tecnológicos, configurando los patrones de difusión y evolución del cambio tecnológico.

2.3. Difusión del conocimiento y spillovers

La naturaleza de bien público del conocimiento ha sido un concepto central en los estudios sobre innovación desde los trabajos pioneros de Nelson (1959) y Arrow (1962). Esta característica implica que el conocimiento generado por unos agentes puede ser aprovechado por otros, dando lugar a derrames de conocimiento y a cualidades de inapropiabilidad. En el contexto de la economía de la innovación, este fenómeno refleja la naturaleza no rival y parcialmente no excluible del conocimiento, lo que permite que las ideas desarrolladas por un agente impacten en la capacidad innovadora de otros. Arrow (1962) señala los fallos del mercado en la asignación de recursos a la invención, derivados de los rendimientos crecientes, la inapropiabilidad y la incertidumbre, señalando que la invención puede entenderse como la producción de conocimiento.

El conocimiento, como factor clave de la innovación, puede ser gestionado y organizado para maximizar su impacto. Mokyr (2002; 2016) subraya que el progreso tecnológico depende de la expansión del conocimiento útil y de su circulación y adopción por otros agentes. Los spillovers constituyen un mecanismo fundamental por el que el conocimiento generado por un agente se transmite a otros sin necesidad de una compensación (Jaffe, 1986; Audretsch y Feldman, 1996). Estos flujos facilitan la acumulación y recombinación del conocimiento, pero introducen una tensión: la circulación del conocimiento puede generar beneficios colectivos, al tiempo que reduce la capacidad de los agentes para apropiarse de los rendimientos de su actividad innovadora (Arrow, 1962; Jaffe, 1986). La imitación derivada de los spillovers permite a las empresas reproducir innovaciones desarrolladas por otros a un coste menor que el de generarlas mediante I+D propia. Al reducirse los costes de acceso a estas tecnologías y generarse ventajas competitivas para los imitadores, se debilitan los incentivos a invertir en innovación, en la medida en que es posible beneficiarse del conocimiento generado por terceros sin asumir plenamente sus costes (Cappelli et al., 2014; Jaffe et al., 1993).

La capacidad de absorción desempeña un papel clave en estos procesos. Cohen y Levinthal (1990) la definen como la habilidad para reconocer el valor de la información externa, asimilarla y aplicarla. Zahra y George (2002) amplían este concepto y la describen como un conjunto de rutinas organizativas que permiten adquirir, asimilar y explotar conocimiento, distinguiendo entre capacidad potencial y realizada. En un plano más amplio, la capacidad de absorción permite analizar cómo los sistemas de innovación integran conocimiento interno y externo, en un proceso de coevolución entre generación y reutilización de conocimiento (Castellacci y Natera, 2013). La absorción de spillovers está relacionada con la disponibilidad y el acceso a un acervo de conocimiento público. Aunque este conocimiento está potencialmente disponible, su aprovechamiento depende de su relevancia para las necesidades de cada empresa y de su capacidad para incorporarlo, por lo que la base de conocimiento existente y la capacidad de absorción determinan el grado en que los agentes pueden beneficiarse de los spillovers.

En consecuencia, una mayor capacidad de absorción facilita la asimilación del conocimiento y se asocia con innovaciones de mayor calidad y potencial de difusión (Moaniba et al., 2018). Además, el conocimiento absorbido se acumula y actúa como base para nuevos ciclos de aprendizaje e innovación (Cohen y Levinthal, 1990; Zahra y George, 2002), lo que explica las diferencias persistentes en desempeño tecnológico entre agentes (Karna et al., 2015). Sin embargo, la disponibilidad de conocimiento no garantiza su aprovechamiento efectivo, ya que su transmisión depende de las características de los agentes y de la relación entre ellos (Jaffe y Trajtenberg, 2002). La literatura reciente muestra que el efecto de la capacidad de absorción sobre los resultados innovadores es heterogéneo y depende del nivel de capacidades y del contexto (Kirschning y Mrożewski, 2023).

El conocimiento interno aglutina el conjunto de conocimientos acumulados por una empresa a lo largo del tiempo a través de su actividad innovadora (Dindaroğlu, 2018). Este conocimiento refuerza la ventaja tecnológica y la capacidad innovadora (Hall et al., 2005), y se asocia con una mayor calidad inventiva (Bessen, 2008; Popp et al., 2013). Además, puede proyectarse hacia fuera mediante spillovers, contribuyendo a la difusión del conocimiento. Por su parte, el conocimiento externo amplía la base cognitiva disponible y facilita la recombinación de ideas, aunque su impacto depende de la capacidad de absorción y del contexto institucional (Jaffe y de Rassenfosse, 2017). En este escenario, la proximidad cognitiva resulta clave: una mayor similitud facilita la absorción, mientras que una cierta distancia incrementa el potencial de novedad al permitir combinaciones más diversas (Nooteboom, 2000). No obstante, cuando la distancia es excesiva, la falta de comprensión limita la posibilidad de aprovechar estos flujos de conocimiento (Wuyts et al., 2005; Nooteboom et al., 2007).

La adquisición de conocimiento puede ocurrir de manera deliberada, cuando un actor obtiene conocimiento de otro a través de un intercambio pactado. Esta transacción puede darse mediante intercambio de conocimiento, en el que el conocimiento recibido se intercambia con otro, como en el modelo de Cowan y Jonard (2004), o mediante comercio de conocimiento, en el que el pago se realiza con un recurso diferente, por ejemplo, tecnologías o patentes (Gambardella et al., 2008). La difusión de conocimiento, por su parte, se refiere a un proceso en el que el conocimiento circula de manera libre y orgánica durante la interacción entre los actores, sin que haya un intercambio deliberado ni un pago recíproco. En este sentido, ambos procesos —adquisición y difusión— representan formas complementarias de transferencia de conocimiento: mientras la adquisición implica compensación, la difusión permite que la información y las experiencias se compartan, facilitando su circulación y aprovechamiento en desarrollos tecnológicos.

Desde una perspectiva económica, en el marco del crecimiento endógeno, la difusión del conocimiento a través de los spillovers constituye un eje central en la literatura (Romer, 1990; Aghion y Howitt, 1992; Grossman y Helpman, 1991, 2018; Griliches, 1991). Desde una perspectiva schumpeteriana, la difusión de la innovación activa el mecanismo de destrucción creativa, impulsando la reasignación de recursos y generando ciclos de crecimiento. Así, la velocidad y el alcance con que las innovaciones se dispersan condicionan la transformación estructural y la productividad agregada. Desde una perspectiva empírica de la difusión, Mansfield (1961, 1968) muestra que la difusión sigue un patrón sistemático en forma de curva en "S": en una primera fase, solo un número de agentes adopta la innovación; posteriormente, la adopción se acelera a medida que la información sobre sus beneficios se extiende y los costes de adopción disminuyen; finalmente, el proceso se ralentiza conforme el mercado potencial se satura.

Desde el enfoque evolutivo, la difusión se concibe como un proceso dinámico y fuera de equilibrio, caracterizado por incertidumbre, racionalidad limitada y heterogeneidad entre agentes (Nelson, 1968; Nelson y Winter, 1982; Silverberg, 1984). En este marco, la difusión genera trayectorias diferenciadas de desempeño económico, dependiendo de las capacidades de absorción y de las estrategias de adopción. En esta línea, Rogers (1962, 2002) describe la difusión como un proceso secuencial en etapas —conocimiento, persuasión, decisión, implementación y confirmación—, mientras que Mansfield (1961, 1968) destaca que los retrasos en la difusión limitan el impacto agregado de las innovaciones. Así, la velocidad de difusión condiciona la productividad y la convergencia tecnológica entre agentes, sectores y regiones.

Existen argumentos que sostienen que la expansión de difusión y combinación de tecnologías ya existentes puede tener un impacto mayor que la generación constante de nuevas innovaciones. Rogers (2002) señala que una invención solo genera impacto cuando es adoptada y se difunde, mientras que Aghion y Howitt (1992, 1998) destacan que el proceso innovador depende de la reutilización del conocimiento en sus etapas posteriores. En esta línea, Vinsel y Russell (2020) subrayan la importancia del mantenimiento y la adaptación de tecnologías existentes como fuente de impacto económico y social. En el ámbito empresarial, la comprensión de estos procesos resulta fundamental para el diseño de estrategias eficaces, en la medida en que el aprovechamiento del conocimiento tecnológico condiciona el desempeño innovador y la productividad (Baumol, 1991; Momeni y Rost, 2016).

El análisis de los spillovers permite identificar los mecanismos por los que el conocimiento se transfiere entre agentes, influyendo en sus decisiones de adopción y en la velocidad del proceso difusivo (Audretsch y Feldman, 2004). No obstante, la transferencia de conocimiento no garantiza su uso efectivo, ya que requiere su integración. En este sentido, la difusión depende tanto de los canales de transmisión como de la capacidad de absorción. Los spillovers actúan así como un canal que amplifica la difusión, actuando en su intensidad y extensión (Griliches, 1990), y explicando patrones espaciales y temporales de propagación de las invenciones (Breschi y Lissoni, 2001).

Sin embargo, la asimilación de conocimiento no se produce de forma homogénea, sino a través de spillovers que operan tanto dentro como entre sectores y regiones. La proximidad de los spillovers desempeña un papel clave en la intensidad y el aprovechamiento de estos flujos. Desde la perspectiva tecnológica, una similitud suficiente permite interpretar y asimilar conocimiento externo, mientras que una cierta distancia favorece la incorporación de elementos novedosos (Boschma, 2005; Nooteboom et al., 2007). En cuanto a la perspectiva geográfica, resulta especialmente relevante en el caso de conocimientos tácitos, cuya transmisión se ve favorecida por una interacción cercana (Jaffe, 1986; Audretsch y Feldman, 1996).

En conjunto, los spillovers introducen asimetrías en la disponibilidad y uso del conocimiento, modulando la difusión y su trayectoria (Audretsch y Belitski, 2020; Barge-Gil et al., 2020; Goya et al., 2016). Este planteamiento constituye una base conceptual relevante para la tesis. Estas dinámicas generan desigualdades en el aprovechamiento del conocimiento a nivel geográfico y entre sectores tecnológicos, dimensiones clave que se abordan con mayor detalle en los siguientes epígrafes.

2.3.1. Perspectiva tecnológica y recombinatoria

Las nuevas tecnologías se desarrollan a través de la combinación de tecnologías anteriores (Usher, 1954), incorporando conocimientos que, aunque no pertenezcan al mismo campo, interactúan de forma interdisciplinaria y complementaria para generar nuevas invenciones o mejoras. Este desarrollo sigue trayectorias condicionadas por las propiedades técnicas, las reglas y la experiencia acumulada (Aghion et al., 2016). Cada trayectoria se apoya en un paradigma tecnológico, entendido como un conjunto de conocimientos, técnicas y prácticas que sirve de base para nuevas ideas (Silverberg et al., 1984). Según Arthur (2009), las nuevas tecnologías emergen de la recombinación del conocimiento en procesos que pueden ser radicales, rompiendo barreras entre distintos campos tecnológicos y dando lugar a invenciones que abarcan múltiples dominios. Este proceso no solo refleja el carácter acumulativo del conocimiento, sino que también incluye combinaciones no incrementales (Yayavaram y Ahuja, 2008). Sin embargo, el acto de combinar conocimiento de distintas tecnologías no siempre da lugar a invenciones excepcionales, accesibles o rentables. Dado que la tecnología se basa en conocimientos existentes, comprender el conocimiento previo resulta clave para lograr avances significativos (Audretsch y Feldman, 1996; Schoenmakers et al., 2010; De Marchi, 2012; Ghisetti et al., 2015).

En este contexto, los spillovers tecnológicos facilitan la absorción de nuevas ideas y aceleran el desarrollo y la adopción de invenciones. Feldman y Audretsch (1999) muestran que la coexistencia de múltiples industrias permite acceder a una mayor variedad de ideas y combinaciones de conocimiento, aumentando la probabilidad de generar nuevas tecnologías de vanguardia. El proceso de recombinación se ve favorecido por la complementariedad entre tecnologías, influyendo en los resultados de las invenciones, especialmente en contextos como fusiones y adquisiciones de alta tecnología (Makri et al., 2009). Gallouj y Weinstein (1997) utilizan el término "innovación recombinativa" para describir la creación de nuevas configuraciones a partir de combinaciones novedosas de características existentes. Estas combinaciones pueden dar lugar a invenciones radicales basadas en ideas revolucionarias (Van den Bergh, 2008).

La distancia tecnológica se ha utilizado para caracterizar las posiciones relativas entre firmas, entendida como el grado de diferencia entre las tecnologías que actúan como fuente de conocimiento y una tecnología objetivo (Boschma, 2005; Nooteboom et al., 2007). Esta divergencia se manifiesta en la disparidad de los acervos de conocimiento y de las capacidades cognitivas. La distancia cognitiva amplía este concepto, aunque ambas están relacionadas (Wuyts et al., 2005). A medida que aumenta la distancia tecnológica, disminuye la capacidad de absorción, es decir, la habilidad para comprender y utilizar conocimiento externo (Hall et al., 2001), mientras que aumenta el potencial de novedad (Nooteboom et al., 2007). En este sentido, la proximidad en la base de conocimiento facilita la interacción y la asimilación de externalidades, mientras que una distancia excesiva puede inhibir estos flujos (Cohen y Levinthal, 1990). Por ello, una distancia tecnológica óptima resulta clave para que el conocimiento se difunda eficazmente (Nooteboom, 2000, 2007; Boschma, 2005).

En relación con estás dinámicas, distintos autores muestran que la combinación de conocimientos de tecnologías heterogéneas puede generar invenciones más avanzadas que aquellas basadas en la especialización (Nelson y Winter, 1982; Arthur, 2009; Mowery y Rosenberg, 1999). La colaboración entre dominios permite identificar soluciones integrales y optimizar recursos (Palm y Thollander, 2010). Weitzman (1998) sostiene que la innovación surge de la recombinación de ideas existentes, de modo que la diversidad del conocimiento incrementa el número de combinaciones posibles. Además, la diversidad previa incrementa la relevancia del nuevo conocimiento (Stephan et al., 2019). La radicalidad de las innovaciones se ha asociado a la distancia entre los conocimientos combinados (Guan y Yan, 2016), siendo frecuente que las invenciones más disruptivas surjan de la combinación de dominios no relacionados (Schoenmakers et al., 2010).

En este sentido, este proceso pone de relieve la importancia de capacidades recombinantes y experiencias diversas (Verhoeven, 2015). La investigación interdisciplinaria facilita esta transferencia de conocimiento entre campos y favorece innovaciones con impacto transversal (Palm y Thollander, 2010). Esto facilita a sectores como las tecnologías ambientales, que requieren de la integración de múltiples dominios debido a la complejidad de los problemas abordados (Barbieri, 2020). En estos casos, la innovación implica la combinación de diversos insumos de conocimiento interrelacionados (De Marchi, 2012; Ghisetti et al., 2015), reflejando un proceso más integrado.

No obstante, a pesar de estos beneficios, la integración de conocimiento tecnológico distante implica mayores costes, tiempo y riesgos. Las combinaciones entre dominios alejados pueden generar resultados productivos, pero suelen ser poco frecuentes y, en muchos casos, infructuosas (Vestal y Danneels, 2023). Algunos trabajos muestran que el conocimiento tecnológicamente distante puede incluso reducir el valor de invenciones posteriores en ciertos sectores (Battke et al., 2016), y su aprovechamiento depende en gran medida de la capacidad de absorción de las empresas (Todo et al., 2016; Kaplan y Vakili, 2015).

En contraste con la diversidad, el conocimiento especializado —centrado en trayectorias incrementales— se asocia con una mayor difusión tecnológica (Dosi, 1982; Lettl et al., 2009). Los procesos de aprendizaje tienden a apoyarse en conocimiento previo, facilitando la asimilación de nuevas ideas (Cohen y Levinthal, 1990; Lazear, 2004). Esto implica que los agentes tienden a innovar en áreas cercanas a las que ya dominan (Rosenkopf y Nerkar, 2001). Por tanto, la experimentación con nuevas combinaciones aumenta la incertidumbre y la variabilidad de los resultados (Fleming, 2001).

Sin embargo, una proximidad tecnológica excesiva puede llevar a la homogeneización del conocimiento y limitar el potencial de recombinación (Guan y Yan, 2016). Este fenómeno se vincula con la dependencia de la trayectoria, donde la concentración del conocimiento en áreas consolidadas favorece la persistencia tecnológica (Aghion et al., 2016). La inercia derivada de la experiencia refuerza la dependencia de la base de conocimiento existente (Wang et al., 2017), incluso cuando ello implica mantener tecnologías menos eficientes (Acemoglu et al., 2012; Jin et al., 2024).

Por último, cabe añadir, que, el análisis de los flujos de conocimiento requiere considerar no solo su intensidad, sino también la dirección de su trayectoria. Algunas invenciones generan conocimiento con un impacto amplio, que se difunde hacia campos tecnológicos diversos, mientras que otras contribuyen principalmente al avance dentro de su propio dominio (Trajtenberg et al., 1997). La evidencia muestra que la diversidad tecnológica y la centralidad del conocimiento previo influyen en la dirección de estos flujos (Stephan et al., 2019). El conocimiento especializado tiende a mantenerse dentro de su ámbito tecnológico, mientras que el conocimiento diversificado favorece flujos de conocimiento entre tecnologías (Battke et al., 2016; Cantner y Graf, 2004).

En conjunto, el énfasis en el carácter recombinatorio y acumulativo del conocimiento tecnológico fundamenta el análisis de la trayectoria del conocimiento, al permitir examinar si éste se desarrolla dentro de un mismo dominio o si se articula con otros ámbitos tecnológicos, dando lugar a nuevas combinaciones. Asimismo, este enfoque sustenta el análisis de cómo estas dinámicas condicionan la difusión del conocimiento, al influir en su reutilización y propagación en desarrollos tecnológicos posteriores.

2.3.2. Perspectiva geográfica

La capacidad de innovación y el desarrollo tecnológico están estrechamente vinculados al contexto geográfico, cuya relevancia ha sido reconocida en la economía del cambio tecnológico (Audretsch y Feldman, 1996; Audretsch, 1998; Porter, 1990). La proximidad espacial, la concentración de actores y la infraestructura institucional influyen directamente en la generación y difusión del conocimiento, en un entorno donde factores económicos, políticos y culturales interactúan y condicionan los procesos innovadores.

En este contexto geográfico, la literatura empírica muestra que los spillovers presentan un carácter localizado y dependen de la capacidad de absorción de la región receptora (Cohen y Levinthal, 1990; Griffith et al., 2004; Zahra y George, 2002). Esta capacidad condiciona la habilidad para captar, asimilar y utilizar conocimiento externo, determinando el impacto de los flujos —domésticos o internacionales— sobre la innovación y la productividad regional (Mancusi, 2008; Li, 2020).

Estas dinámicas se explican en gran medida por la naturaleza del conocimiento, que combina elementos codificados y tácitos (Dosi, 1988). El conocimiento tácito, basado en rutinas, experiencia y capacidades organizativas, resulta difícil de transferir a distancia, lo que refuerza el papel de la proximidad geográfica en la efectividad de asimilación de los spillovers (Jaffe, 1986; Audretsch y Feldman, 1996). Por el contrario, cuando el conocimiento es más codificado, la necesidad de cercanía espacial se reduce, facilitando su difusión a mayores distancias (Dosi y Nelson, 2010). Las interacciones cara a cara y la movilidad del capital humano favorece la creación de lenguajes comunes y genera confianza, elementos clave para una transferencia efectiva (Asheim y Coenen, 2005; Torre y Gilly, 2000).

La literatura ha mostrado que la proximidad geográfica condiciona los patrones de adquisición y difusión del conocimiento. Las capacidades tecnológicas presentan una distribución desigual entre regiones (Cooke et al., 1997; Fagerberg, 1994). La distancia limita la intensidad de los flujos de conocimiento y contribuye a su concentración dentro de un mismo país (Jaffe et al., 1993; Jaffe y Trajtenberg, 1999). Asimismo, el impacto de absorción de los spillovers no es homogéneo, sino que depende de su origen y de la estructura tecnológica del entorno regional (Mascarini et al., 2023). Aunque la colaboración con socios geográficamente distantes puede ampliar la diversidad cognitiva, sus beneficios se ven condicionados por mayores costes de coordinación y de integración del conocimiento (Boschma, 2005; Nooteboom et al., 2007; Boschma y Frenken, 2009).

La tendencia a la concentración geográfica del conocimiento genera dinámicas de búsqueda local que reducen la variedad de combinaciones tecnológicas (Levinthal y March, 1993; Rosenkopf y Nerkar, 2001). En contraste, la internacionalización de la I+D permite acceder a bases de conocimiento diferenciadas y ampliar el espacio de búsqueda (Cantwell, 1989; Archibugi y Pianta, 1992; Phene et al., 2006). La incorporación de conocimiento distante puede estimular la innovación y favorecer combinaciones novedosas, aunque implica mayores costes y riesgos (Gilsing et al., 2008; Guan y Chen, 2012). Asimismo, la movilidad de trabajadores cualificados y la colaboración internacional refuerzan los flujos de conocimiento y la calidad de la innovación, aunque estos beneficios coexisten con mayores costes de coordinación (Su, 2017).

Estas dinámicas se enmarcan en la literatura sobre sistemas de innovación, que enfatiza el carácter localizado e institucional del proceso innovador (Freeman, 1987; Lundvall, 1992; Nelson, 1993). En este sentido, la proximidad trasciende la dimensión geográfica e incorpora dimensiones organizativas, institucionales y sociales, incluyendo diferencias culturales, niveles de desarrollo económico y estándares tecnológicos entre países, que influyen en la capacidad de interacción y en el aprovechamiento del conocimiento (Boschma, 2005). De modo que, cuando los equipos inventivos son geográficamente heterogéneos, se integran tanto conocimientos como las propias diferencias que caracterizan a cada contexto (Simard y West, 2006; Alnuaimi et al, 2012).

Finalmente, a escala internacional, los spillovers desempeñan un papel central en el crecimiento y la convergencia económica. Los flujos de conocimiento entre países favorecen la adopción tecnológica y el aumento de la productividad (Coe y Helpman, 1995; Keller, 2010; Montobbio y Sterzi, 2011), especialmente en procesos de catching up (Fagerberg, 1994). En este contexto, la colaboración constituye un mecanismo clave para la internalización y aprovechamiento de los spillovers de conocimiento, dentro o fuera de las fronteras nacionales (Keller, 2010; Jaffe y Trajtenberg, 2007), ya que la co-creación de invenciones permite aprovechar las diferencias en las bases de conocimiento entre regiones, facilitando la absorción de conocimiento externo mediante la combinación de conocimientos especializados y complementarios (Audretsch y Lehmann, 2005; Moreno et al., 2005). Dada su relevancia en la articulación de la producción tecnológica, la colaboración se aborda de manera específica en el siguiente epígrafe.

Esta perspectiva conduce a considerar el papel del contexto geográfico en la difusión del conocimiento tecnológico, así como su posible incidencia en el valor o la calidad de la producción tecnológica, como resultado de la especialización tecnológica, la intensidad de la actividad innovadora, la experiencia acumulada y la presencia de agentes líderes en determinados entornos.

2.4. Colaboración en la actividad innovadora

En el actual entorno organizacional, caracterizado por la globalización, la limitación de recursos y la intensificación de la competencia internacional, la adopción de estrategias de colaboración se ha consolidado como un elemento central en las decisiones estratégicas de innovación. La innovación requiere recursos tanto tangibles como intangibles, especialmente conocimiento especializado y complejo, que a menudo excede la capacidad de una sola organización. La colaboración entre organizaciones facilita el acceso a recursos que trascienden las capacidades internas, especialmente conocimiento que la empresa focal no posee (Hagedoorn, 2002; Un et al., 2010). Dado que las empresas no pueden generar por sí solas todo el conocimiento necesario para sus actividades de I+D, los enfoques de innovación abierta resultan clave para incorporar conocimiento externo nuevo y complementario (Chesbrough, 2003). Las colaboraciones interorganizacionales facilitan la transferencia de conocimiento tácito y complejo, cuya transmisión resulta limitada a través de mecanismos de mercado o mediante esfuerzos individuales, y generan sinergias que permiten acceder a habilidades especializadas, economías de escala y bases de conocimiento diversificadas, factores que se asocian con una mejora en la calidad de los resultados innovadores (Simard y West, 2006; Hagedoorn, 2003). El estudio de la invención colectiva permite caracterizar la dinámica del intercambio de conocimiento en redes de innovación, donde inventores y científicos colaboran y comparten información en entornos organizativos como universidades y centros de investigación, facilitando la generación conjunta de innovaciones y conocimiento científico (Wuchty et al., 2007; Belderbos et al., 2014; Peeters et al. (2020).

En este contexto, el conocimiento, en tanto bien público, presenta una elevada capacidad de difusión transfronteriza, y su proceso de generación también se ha internacionalizado de manera significativa. Esta dinámica responde a la disminución de los costes de comunicación, que optimiza la eficiencia de las redes científicas globales, y al incremento de la especialización disciplinaria, que hace necesaria la integración de competencias altamente diferenciadas para maximizar la productividad y la calidad de los resultados de la investigación (Katz y Martin, 1997; Wuchty et al., 2007). Las alianzas estratégicas facilitan el acceso a nuevos conocimientos, tecnologías y mercados, permitiendo a las organizaciones expandir sus capacidades y desarrollar soluciones innovadoras de manera conjunta (Hagedoorn, 2002; Gulati, 1998). Estas asociaciones resultan especialmente relevantes para la entrada en mercados internacionales, tanto para grandes corporaciones como para pequeñas y medianas empresas, que encuentran en la colaboración con socios locales un mecanismo eficaz para superar barreras institucionales y reducir los costes de entrada (Kogut y Singh 1988; Dunning, 1996). En consecuencia, la probabilidad de éxito en proyectos innovadores se incrementa mediante la participación en redes de colaboración (Belderbos et al., 2010). Estas redes pueden incluir una amplia gama de actores, tales como empresas colaboradoras, proveedores, instituciones de investigación y universidades (Gulati et al., 2011; Westley y Vredenburg, 1991).

La convergencia de recursos y conocimientos a través de la colaboración favorece la recombinación de capacidades, contribuyendo a la transformación de los sistemas tecnológicos y económicos (Powell et al., 1996; Hagedoorn, 2002). La evidencia indica que la transferencia de conocimiento aumenta con la cercanía organizativa y se intensifica en contextos de interacción directa y continuada, especialmente cuando el conocimiento posee un carácter tácito basado en el know-how y la experiencia acumulada, cuya transmisión requiere mecanismos de interacción estrecha y sostenida (Gomes-Casseres et al., 2006; Teece, 1977). Asimismo, la intensidad y características de las alianzas —como su recurrencia— condicionan la magnitud de los flujos de conocimiento, lo que sugiere que las diferencias entre empresas y alianzas responden fundamentalmente al grado de implicación en la colaboración (Barzi et al., 2015). No obstante, estas relaciones generan tensiones asociadas a la apropiación, en la medida en que los socios pueden perseguir objetivos divergentes o tratar de internalizar los beneficios de la colaboración, lo que obliga a las organizaciones a equilibrar el acceso a recursos externos (Khanna et al., 1998; Pfeffer y Salancik, 2015).

Los estudios sobre formación de redes destacan la importancia de los efectos de red (Jackson y Wolinski, 1996; Bala y Goyal, 2000), ampliando la visión tradicional de la literatura sobre colaboraciones en I+D, que atribuía los beneficios de las relaciones principalmente a las características individuales de los agentes involucrados. Por un lado, la presencia de socios con conocimientos y experiencias diferentes amplía la variedad de ideas disponibles y favorece las actividades de exploración, un efecto especialmente relevante en sectores intensivos en conocimiento (Belderbos et al., 2014). Por otro lado, una elevada diversidad entre los miembros también puede dificultar la colaboración, ya que las diferencias en rutinas organizativas pueden limitar la capacidad de asimilar y aplicar nuevo conocimiento (Milliken y Martins, 1996). En el contexto de las colaboraciones que requieren altos niveles de coordinación, la diversidad no siempre se traduce en mejores resultados innovadores, ya que su impacto depende del tipo de vínculos entre los actores de la red y del grado de compatibilidad institucional entre las organizaciones participantes (Tortoriello y Krackhardt, 2010).

En términos estratégicos, la colaboración permite a las empresas explorar nuevas áreas de conocimiento con menores compromisos iniciales de inversión, generando opciones de continuidad en etapas posteriores sin asumir íntegramente el riesgo desde el inicio (Kogut, 1991). Este mecanismo resulta especialmente relevante en entornos tecnológicos caracterizados por elevada incertidumbre, donde las decisiones tempranas pueden generar ventajas competitivas, mientras que la demora en la inversión puede implicar la pérdida de oportunidades (Grant y Baden-Fuller, 2004). Asimismo, la colaboración inventiva facilita la distribución de riesgos entre los agentes participantes y amplía el acceso a recursos y capacidades complementarias, lo que adquiere particular relevancia en el caso de las PYMES, que enfrentan mayores restricciones para desarrollar estrategias innovadoras de forma independiente (Hagedoorn, 2002; Powell et al., 1996). Finalmente, la configuración de estas dinámicas de colaboración se encuentra condicionada por las características sectoriales, en la medida en que la intensidad y las formas de cooperación varían entre industrias en función de sus patrones tecnológicos (Pavitt, 1984).

En cuanto a los determinantes de la colaboración, la elección del tipo de colaboración que adopta una organización está influenciada por múltiples factores (Barzi et al., 2015), entre los que se encuentran el apoyo financiero que puede ofrecer el sector público, que a menudo actúa como un catalizador para fomentar asociaciones estratégicas. Las tecnologías de la información permiten conectar a empresas, universidades y centros de investigación de diferentes regiones, potenciando la transferencia de conocimientos y la co-creación de soluciones innovadoras (Rycroft, 2007; Kotabe et al., 2007). Este entorno dinámico promueve estrategias de innovación abierta, donde las organizaciones buscan activamente alianzas estratégicas, externalizan actividades de I+D y gestionan su propiedad intelectual para aprovechar fuentes externas de conocimiento (Chesbrough, 2003; Cano-Kollmann et al., 2016). La innovación abierta se vincula además con una visión del conocimiento como recurso distribuido y acumulativo, cuya explotación depende de la capacidad organizativa para coordinar relaciones externas complejas sin sustituir el desarrollo interno de competencias tecnológicas (Bogers et al., 2018). En este sentido, la literatura coincide en que este enfoque no implica la eliminación del esfuerzo interno, sino una reconfiguración de los procesos para articular flujos internos y externos de conocimiento (Chesbrough y Bogers, 2014). Este entrelazamiento entre colaboración global y estrategias de innovación abierta no solo fomenta la creación de nuevos conocimientos, sino que también ofrece una posible respuesta a desafíos multidimensionales y globales, como los relacionados con el desarrollo sostenible (Valdez-Juárez y Castillo-Vergara, 2020).

En este trabajo, la colaboración se entiende como la protección conjunta de un invento, en la que participan múltiples organizaciones, sin que ello implique la creación de una empresa conjunta. En los siguientes epígrafes, este concepto se aborda desde dos dimensiones—colaboración entre instituciones y colaboración internacional— que constituyen elementos centrales en la definición de las variables empíricas de esta tesis.

2.4.1. Colaboración institucional

Para entender la colaboración en I+D, es necesario considerar las diferencias entre la colaboración pública y privada, así como los distintos canales a través de los cuales el conocimiento generado en la investigación pública se difunde hacia el sector privado (Cohen et al., 2002; Bekkers y Bodas Freitas, 2008). En este contexto, las instituciones académicas y científicas desempeñan un papel central en el desarrollo de innovaciones, gracias a su capacidad para generar conocimiento avanzado y proporcionar la base científica necesaria. Estas organizaciones ofrecen servicios especializados, como el desarrollo de tecnologías, la consultoría técnica y la investigación aplicada, que resultan fundamentales para la creación de productos innovadores, especialmente en ámbitos tecnológicamente complejos (Miozzo et al., 2016; Lessard, 2014; Giuliani et al., 2016).

Según Audretsch et al. (2005), la creación de nuevas empresas de alta tecnología depende tanto de la naturaleza del conocimiento generado en las universidades como de las estructuras institucionales que regulan su acceso. El acceso a estas fuentes de conocimiento permite a las empresas beneficiarse de los spillovers derivados de la cooperación institucional en I+D (Belderbos et al., 2014). Asimismo, la capacidad de las instituciones académicas para operar en múltiples disciplinas las convierte en aliadas estratégicas para abordar problemas complejos (Bekkers y Bodas Freitas, 2008; Jaffe y Trajtenberg, 1996). Entre los mecanismos que facilitan este tipo de cooperación destacan la creación de empresas derivadas de la actividad universitaria, la implicación del sector empresarial en iniciativas de I+D, la financiación de patentes y la promoción de la investigación académica aplicada. En este contexto, las universidades desempeñan un papel relevante al incentivar a sus investigadores a registrar patentes, aprovechando el conocimiento generado en sus proyectos científicos y experimentales (Tseng et al., 2020).

Desde una perspectiva espacial y relacional, la literatura ha destacado el papel de la proximidad en la colaboración interinstitucional. Rubiralta (2004) señala que las colaboraciones entre universidades, centros tecnológicos y empresas ubicadas en áreas estratégicas constituyen un factor clave para el desarrollo de la innovación regional. En la misma línea, Jaffe (1989) muestra que la proximidad geográfica entre universidades y empresas favorece la creación de firmas de alta tecnología, al aumentar las oportunidades de interacción. Audretsch et al. (2005) encuentran que una mayor producción de conocimiento universitario, combinada con una elevada capacidad regional, atrae la localización de empresas en su entorno.

La colaboración entre universidades y empresas también enfrenta obstáculos. Bruneel et al. (2010) identifican dos principales: por un lado, las diferencias en objetivos— orientación al corto plazo en la industria frente a la generación de conocimiento en la universidad— y, por otro, las dificultades asociadas a la gestión de la propiedad intelectual, que pueden dar lugar a negociaciones complejas. Belderbos et al. (2014) no encuentran diferencias significativas en términos de citas recibidas en colaboraciones con universidades, mientras que Briggs (2015) observa que, aunque no existen diferencias en la calidad a medio plazo, sí se identifican efectos positivos en el largo plazo.

La evidencia empírica muestra que la colaboración con otros socios produce efectos diferenciados según su naturaleza. La cooperación entre empresas tiende a asociarse con una mayor difusión del conocimiento y con resultados orientados a la explotación de trayectorias existentes (Belderbos et al., 2014). La colaboración con universidades, en cambio, favorece trayectorias más exploratorias y se asocia con un mayor contenido científico de las invenciones, aunque su efecto sobre la difusión resulta menos sistemático y depende del grado de madurez del sector (Peeters et al., 2020; Briggs, 2015). La incorporación de conocimiento científico en los procesos inventivos refuerza la conveniencia de fortalecer los vínculos entre ciencia y tecnología, lo que implica fomentar la integración de perfiles científicos en los equipos de I+D y desarrollar infraestructuras de acceso abierto al conocimiento en ámbitos estratégicos como las tecnologías energéticas limpias (Narin et al., 1997; Fleming y Sorenson, 2004).

En coherencia con estos planteamientos teóricos, la tesis incorpora la colaboración entre empresas y con universidades como parte del proceso innovador, considerando la solicitud conjunta de la protección de una invención como una manifestación de estas interacciones. Asimismo, se integra el papel del conocimiento científico y la dimensión colectiva del proceso inventivo, en línea con la relevancia atribuida en la literatura a la interacción entre distintos agentes y fuentes de conocimiento.

2.4.2. Colaboración internacional

La colaboración internacional se ha convertido en un pilar clave para la generación de innovación, habilitada por los avances en telecomunicaciones y transporte, que facilitan la coordinación entre actores globales y reducen los costes organizacionales asociados (Kotabe et al., 2007; Criscuolo et al., 2005). Esto hace que la distancia geográfica tenga un impacto cada vez menor en las colaboraciones tecnológicas y los proyectos de investigación internacionales. El fortalecimiento de la colaboración internacional es fundamental para una producción tecnológica de calidad, ya que permite a las organizaciones acceder a recursos y conocimientos especializados que no están disponibles internamente en sus respectivos países. Aunque la tecnología digital ha avanzado considerablemente y ha reducido los costes de compartir conocimiento a distancia, la literatura sobre innovación sigue considerando que la ubicación geográfica de los socios de colaboración continúa siendo un elemento relevante de análisis (Balland et al., 2015; Boschma, 2005).

La actividad de I+D internacional puede centrarse en adaptar productos o procesos a las condiciones del mercado local, facilitando la entrada en nuevos mercados y apoyando la producción de las filiales locales. En este enfoque, la internacionalización de la innovación tiene como objetivo principal explotar la ventaja tecnológica desarrollada en el país de origen, actuando como una extensión del trabajo de I+D previamente realizado (Kuemmerle, 1997). Más allá de esta lógica de explotación, las empresas innovadoras también pueden expandirse al extranjero para acceder a desarrollos tecnológicos internacionales, mejorar sus activos, compensar debilidades tecnológicas y aprovechar conocimientos disponibles en otros contextos. Desde esta perspectiva, el objetivo es ampliar la base de conocimiento mediante la combinación de capacidades internas con nuevas competencias tecnológicas adquiridas en el exterior, accediendo a activos estratégicos complementarios (Dunning y Narula, 1995).

Las investigaciones sobre flujos internacionales de conocimiento muestran que las colaboraciones funcionan como canales más eficaces que las transacciones de mercado, ya que permiten transferir tanto conocimiento codificado como conocimiento tácito, difícil de formalizar. En este contexto, un uso intencional de los flujos de conocimiento, recursos y vías de comercialización implica que las organizaciones pueden gestionar deliberadamente estos flujos a través de sus fronteras para mejorar el desarrollo interno de innovaciones y comercializar sus resultados mediante una adecuada gestión de la propiedad intelectual (Chesbrough, 2003). Phene et al. (2006) muestran que el conocimiento internacional puede favorecer la innovación radical cuando mantiene afinidad con la base tecnológica de la empresa, mientras que una elevada distancia tecnológica limita su aprovechamiento, un patrón que se explica por la diversidad geográfica del conocimiento, derivada de la especialización tecnológica de los países (Cantwell, 1989).

Una cuestión clave es si el efecto de la colaboración internacional sobre la calidad de las patentes es más positivo que el de formas de colaboración más cercanas, como la colaboración nacional o regional. La proximidad geográfica ha sido ampliamente reconocida como un factor que facilita el intercambio de conocimiento y mejora el rendimiento innovador, debido a la mayor facilidad de interacción directa (Jaffe et al., 1993; Audretsch y Feldman, 1996). Sin embargo, la colaboración internacional amplía la diversidad de conocimiento disponible. La evidencia muestra que la amplitud de la colaboración con socios regionales, nacionales e internacionales influye directamente en la innovación, aunque este efecto depende de la ubicación del socio, del tipo de socio y de la capacidad de absorción (Belitski et al., 2024). Entre las principales ventajas de la colaboración internacional se encuentran el acceso a distintos sistemas nacionales de innovación, una mayor diversidad tecnológica, flujos más variados de ideas y entornos regulatorios diferenciados (Kotabe et al., 2007), lo que permite acceder a conocimientos menos redundantes que los disponibles en entornos locales (Mascia et al., 2017; van Beers y Zand, 2014; Molina-Morales y Expósito-Langa, 2013).

Desde un punto de vista empírico, diversos estudios muestran que la capacidad de aprendizaje en colaboraciones internacionales puede ser superior a la observada en colaboraciones de proximidad, debido al acceso a una mayor variedad de conocimientos, lo que se traduce en innovaciones de mayor calidad (Su, 2021; van Beers y Zand, 2014). No obstante, la evidencia también indica que el conocimiento mantiene un componente espacial significativo: la tendencia a concentrarse geográficamente, lo que sugiere que el conocimiento local se utiliza con mayor facilidad que el procedente de regiones distantes, especialmente en las primeras fases de la invención (Jaffe et al., 1993; Jaffe y Trajtenberg, 1996). Asimismo, el impacto de la distancia geográfica y de las condiciones institucionales varía según el tipo de empresa, afectando de forma distinta a economías emergentes y a filiales multinacionales (Montobbio, 2013).

A pesar de sus ventajas, la colaboración internacional también puede presentar efectos negativos. El aumento del número de socios y de la diversidad geográfica incrementa los costes de coordinación y dificulta la integración del conocimiento (Furman et al., 2002; Singh, 2008). Además, para que la colaboración sea efectiva, es necesaria la existencia de confianza y disposición para compartir información (Broekel y Brachert, 2015). Un obstáculo relevante es el riesgo de fuga de conocimiento, que puede reducir la calidad de los resultados cuando las empresas son reticentes a compartir información estratégica (Laursen y Salter, 2014; Easterby-Smith et al., 2008). En consecuencia, aunque la colaboración internacional permite acceder a conocimiento diverso y complementario, también introduce costes y riesgos que condicionan su impacto (Blind et al., 2006; Bessen, 2008; Yang et al., 2010).

En coherencia con los planteamientos teóricos expuestos sobre la colaboración como mecanismo de acceso a conocimiento diverso y de recombinación de capacidades, el presente trabajo considera la participación conjunta en la protección de una invención por solicitantes procedentes de distintos países como evidencia de colaboración internacional, con el fin de analizar su influencia sobre el impacto de las invenciones en desarrollos tecnológicos posteriores.

CAPITULO 3:

MEDICIÓN DE LA DIFUSIÓN, LA CALIDAD TECNOLÓGICA Y LOS FLUJOS DE CONOCIMIENTO A PARTIR DE DATOS DE PATENTES

3.1. Medición del proceso de innovación a partir de datos de patentes

Comprender y medir los procesos de innovación es esencial tanto para las empresas en la definición de sus estrategias competitivas como para los gobiernos en el diseño, implementación y evaluación de políticas públicas destinadas a fomentar la innovación. No existe una única medida perfecta, por lo que los investigadores suelen recurrir a una variedad de indicadores que capturan diferentes aspectos del proceso innovador.

Desde el lado de los recursos (inputs), se emplean indicadores que cuantifican los insumos destinados a actividades innovadoras, entre los que se incluyen los gastos en I+D, el personal dedicado a I+D, la adquisición externa de conocimiento —como I+D contratada, licencias o know-how— y otros gastos vinculados a actividades innovadoras no estrictamente de I+D (OECD y Eurostat, 2018). Estos indicadores permiten aproximar el esfuerzo innovador de las organizaciones, aunque no garantizan la obtención de resultados observables en el corto plazo, dado el carácter incierto y acumulativo del proceso innovador (Crépon et al., 1998; Hall et al., 2010). Desde el lado de los resultados (outputs), los indicadores captan las manifestaciones observables de la actividad innovadora, tales como las patentes y la introducción de nuevos productos al mercado, así como indicadores de desempeño como la productividad, que reflejan los efectos económicos indirectos asociados a la innovación (OECD y Eurostat, 2018; Griliches, 1990; Hall et al., 2010).

No obstante, la capacidad para medir la innovación de manera precisa es objeto de debate. La literatura muestra consenso en el uso de la inversión en I+D y las estadísticas de patentes como proxies principales de la actividad innovadora (Griliches, 1990; Hall et al., 2005; OECD/Eurostat, 2018; WIPO, 2022; de Rassenfosse et al., 2013), ya que cada uno captura una etapa o dimensión diferente del proceso.

La inversión en I+D se considera una medida del input del proceso innovador. Representa los recursos financieros que las organizaciones invierten en la creación de conocimiento y en el desarrollo de nuevas tecnologías, productos y procesos. El gasto en I+D puede medirse como un porcentaje de las ventas, lo que permite comparaciones entre empresas de distinto tamaño. No obstante, la inversión en I+D no garantiza el éxito inventivo ni la patentabilidad de los resultados. Diversos autores han señalado sus limitaciones como indicador del proceso innovador, al tratarse de una medida agregada que dificulta comparaciones precisas y puede incluir gastos no estrictamente vinculados a la invención (Chakrabarti, 1991; Griliches, 1990). Asimismo, este indicador presenta sesgos en favor de determinadas tecnologías, sectores industriales y grandes empresas con mayor capacidad de inversión (Cockburn, 1989; Scherer, 1983; Griliches, 1991; Keith, 1992).

Para que la inversión privada en I+D sea rentable y motive a las empresas a innovar, la propiedad intelectual se protege mediante derechos de apropiación exclusiva. Las patentes son títulos de propiedad industrial concedidos por el Estado que otorgan derechos exclusivos de explotación comercial por un período limitado, a cambio de la divulgación pública del contenido de la invención. La concesión de una patente constituye una validación legal de que la invención cumple con los criterios de novedad, y aplicabilidad industrial. Tradicionalmente, los economistas han recurrido al recuento de patentes como variable proxy para medir los resultados de la innovación (Griliches, 1990; Schmookler, 1962; Narin et al. 1987). Las estadísticas de patentes se han consolidado como un indicador ampliamente aceptado en el estudio del cambio tecnológico y las capacidades innovadoras (Hall et al., 2001; Jaffe y Rassenfosse, 2019; Jaffe y Trajtenberg, 2002), ya que representan una manifestación estandarizada de nuevas ideas tecnológicas cuya validez es evaluada por examinadores (Alcácer et al., 2009).

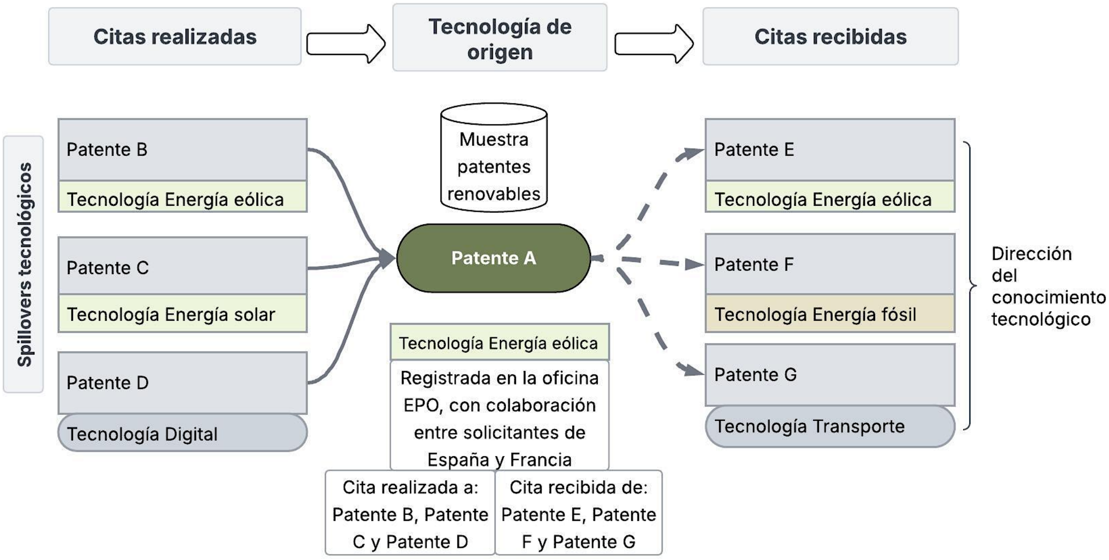
Las patentes pueden considerarse un producto tangible de la I+D, en tanto reflejan cómo se materializa la innovación tecnológica (Kang y Tarasconi, 2015). En este sentido, los recuentos de patentes funcionan tanto como medida del resultado innovador como indicador de la intensidad de la actividad innovadora (Popp, 2005; Jaffe y Trajtenberg, 2002). Además, los documentos de patentes constituyen una fuente valiosa sobre las características técnicas de las invenciones, facilitando la comparación entre tecnologías y sectores (Hall et al., 2001;2005; OECD, 2015).

Si bien el gasto en I+D constituye un input y las patentes un output del proceso innovador (Acs y Audretsch, 1989), el análisis conjunto de ambos permite una visión más completa. Existe una correlación positiva entre el gasto en I+D y las solicitudes de patentes, generalmente con un desfase temporal (Griliches, 1990), aunque esta relación varía según el tamaño de la empresa y el sector. Al mismo tiempo, la literatura reciente enfatiza la naturaleza multidimensional de la innovación y la necesidad de complementar estos indicadores tradicionales con nuevas métricas y fuentes de información, como datos digitales, indicadores compuestos y medidas alternativas del rendimiento innovador (Dziallas y Blind, 2019; Stundziene et al., 2024; Todorov et al., 2024).

El análisis de la información contenida en los documentos de patentes permite examinar cómo se produce y en qué deriva la innovación tecnológica (Hall et al., 2005; Kang y Tarasconi, 2016). Más allá del número de patentes, existe consenso en que las citas de patentes reflejan el uso y flujo del conocimiento (Griliches et al., 1990; Jaffe et al., 2000; Squicciarini et al, 2013). En particular, las citas hacia atrás permiten identificar la base de conocimiento previa y aproximar los spillovers tecnológicos que alimentan la actividad inventiva (Jaffe et al., 1993; Hall et al., 2005), mientras que las citas hacia adelante capturan la difusión del conocimiento (Jaffe y de Rassenfosse, 2017), permiten aproximar la calidad tecnológica a partir de su utilización posterior (Trajtenberg, 1990; Gambardella et al., 2008) y contribuyen a identificar la dirección de la trayectoria (Jaffe et al., 2000; Trajtenberg; 1997).

De este modo, la estructura de citas se integra de forma directa en la estrategia empírica de la tesis, al constituir el instrumento principal para la ejecución de los objetivos de investigación, por lo que sus fundamentos y antecedentes metodológicos se abordan con mayor detalle en los siguientes epígrafes.

Diagrama 2. Esquema ilustrativo del uso de citas de patentes. Ejemplo de una patente de tecnología renovable.



Fuente: elaboración propia.

3.2. Citas realizadas como indicador de spillovers

El uso de las citas realizadas de patentes tiene como función identificar el *estado del arte*, es decir, el conjunto de conocimientos existentes en un determinado ámbito tecnológico, así como delimitar el alcance de los derechos de propiedad que confiere una patente. Dado que toda patente debe demostrar novedad, durante el proceso de evaluación se recopila el estado previo de la técnica y se consigna en el documento de patente. En este contexto, la interpretación más directa de la información transmitida por el proceso de citación es que, si la patente B cita a la patente A, ello implica que la patente A representa conocimiento previamente existente sobre el cual se apoya la patente B y respecto del cual esta última no puede reivindicar derechos exclusivos (Hall et al., 2001; Jaffe y Trajtenberg, 2002).

Las citas hacia atrás corresponden al deber legal de referenciar las patentes previas en las que se basa la invención, y pueden ser incorporadas no solo por los propios solicitantes, sino también por los examinadores o por terceros (Azagra-Caro y Tur, 2018). Las citas introducidas por los examinadores responden a la necesidad legal de identificar el estado del arte relevante para evaluar la patentabilidad, por lo que tienden a ofrecer una referencia más sistemática del conocimiento previo pertinente. En este sentido, las citas de examinadores capturan vínculos de conocimiento que podrían no haber sido reconocidos o declarados por los inventores, aportando información adicional sobre la relevancia y reutilización del conocimiento en el proceso innovador (Cotropia et al., 2013; Alcácer y Gittelman, 2006).

Las citas realizadas constituyen una herramienta útil para rastrear la influencia de invenciones pasadas a lo largo del tiempo, ya que permiten medir el origen y la intensidad de los spillovers de conocimiento (Jaffe et al., 2000; Duguet y MacGarvie, 2005). En este marco, el estudio de citas de patentes ha cobrado relevancia como herramienta para mapear la base de conocimiento tecnológico, constituyendo un rastro documental de conocimiento explícito (Jaffe et al., 1993; Jaffe et al., 2000). Asimismo, las citas revelan patrones de spillovers intersectoriales, transferencias entre empresas y universidades, así como la incorporación de avances científicos en aplicaciones industriales (Hu y Jaffe, 2003; Nelson, 2009; Narin y Olivastro, 1988), lo que permite identificar la influencia de ciertas invenciones no solo sobre sectores específicos, sino también sobre la economía.

Desde una perspectiva espacial, el análisis de las citas realizadas se ha utilizado para estudiar los patrones de localización geográfica, mostrando que los spillovers tienden a concentrarse en determinados territorios y a verse influenciados por la proximidad geográfica (Hu y Jaffe, 2003). Por su parte, desde una perspectiva tecnológica, las citas de patentes pueden entenderse como spillovers a través del espacio tecnológico (Benner y Waldfogel, 2008), bajo el supuesto de que una cita entre clases de patentes refleja transferencias de conocimiento entre distintos dominios tecnológicos (Nemet, 2012; Moaniba et al., 2018).

Las autocitas realizadas por las organizaciones a sus propias patentes constituyen una evidencia de procesos de aprendizaje intraorganizacional, ya que reflejan la reutilización y aplicación de conocimiento previamente generado dentro de la misma organización (Dindaroğlu, 2018). Este tipo de citas permite observar la acumulación y continuidad del conocimiento tecnológico a lo largo del tiempo (Gay et al., 2005), al indicar que la invención actual se apoya en desarrollos previos. Esto reduce la necesidad de recurrir a fuentes externas de conocimiento y los costes de transacción asociados a su búsqueda, adquisición y adaptación (Hall et al., 2005; Popp et al., 2013). Además, cuando los inventores se basan en sus propios desarrollos, suelen contar con un mayor conocimiento tácito, lo que facilita su comprensión y aumenta las probabilidades de éxito en nuevas invenciones (Zucker et al., 2002).

Por su parte, las citas dirigidas a patentes pertenecientes a otros agentes se utilizan como una medida aproximada del uso de conocimiento externo. Estas citas reflejan en qué medida una invención se apoya en desarrollos tecnológicos previos generados fuera de la organización y permiten aproximar el grado de dependencia tecnológica de la empresa respecto de fuentes externas de conocimiento (Jaffe y de Rassenfosse, 2017).

3.3. Citas recibidas como indicador de difusión, calidad y dirección del conocimiento tecnológico

El uso de las citas recibidas se fundamenta en su capacidad para representar de forma observable las interrelaciones entre invenciones, al configurar vínculos direccionales que permiten rastrear las trayectorias de reutilización del conocimiento (Jaffe y de Rassenfosse, 2017). Asimismo, el análisis de los patrones de citas facilita la identificación de diferencias entre áreas tecnológicas, instituciones y regiones, así como la heterogeneidad en los procesos de absorción y recombinación cognitiva (Jaffe et al., 2000; Hall y Helmers, 2013).

Cada cita refleja la incorporación de conocimiento previo en un nuevo desarrollo, lo que permite aproximar empíricamente los procesos de transmisión al identificar vínculos observables entre invenciones a lo largo del tiempo. Desde la perspectiva de la difusión, las citas recibidas indican que una patente ha sido utilizada en desarrollos posteriores, reflejando la reutilización efectiva del conocimiento codificado (Jaffe et al., 1993; Caballero y Jaffe, 1993). En este sentido, la probabilidad de ser citada puede interpretarse como un indicador de la capacidad de una invención para difundirse, mientras que la frecuencia de citas captura la intensidad y el alcance de dicha difusión (Jaffe y Trajtenberg, 2007). Este enfoque permite evaluar cómo el conocimiento se propaga dentro del sistema tecnológico y cómo se articula su incorporación en nuevas combinaciones inventivas.

Desde la perspectiva de la calidad, las citas hacia adelante se han empleado de forma recurrente como indicador del valor tecnológico y económico de las patentes, en la medida en que una mayor frecuencia de citas refleja una mayor recurrencia del conocimiento en invenciones posteriores (Trajtenberg, 1990; Hall et al., 2001, 2005). La evidencia empírica muestra que las patentes más citadas tienden a integrarse en trayectorias tecnológicas más influyentes, lo que se asocia con una mayor calidad del conocimiento incorporado (Trajtenberg, 1990). Además, presentan una mayor probabilidad de ser renovadas hasta el final de su vigencia legal, lo que indica la existencia de beneficios suficientes para cubrir los costes de mantenimiento (Harhoff et al., 1999; Thomas, 1999). Estas patentes actúan con mayor frecuencia como insumos cognitivos en desarrollos posteriores, ampliando su contribución social (Lanjouw y Schankerman, 2004), y se asocian, a nivel de empresa, con incrementos en el valor de mercado (Briggs, 2015).

El análisis de las citas recibidas permite también identificar la dirección de las trayectorias tecnológicas posteriores, en la medida en que la estructura y composición de las citas hacia adelante revelan qué líneas de conocimiento son retomadas y desarrolladas con mayor frecuencia en invenciones siguientes (Trajtenberg, 1990; 1997). La concentración de citas en determinados campos o dominios tecnológicos indica patrones de continuidad y especialización, mientras que la aparición de citas provenientes de áreas distintas sugiere desplazamientos o recombinaciones en la orientación de los desarrollos posteriores (Jaffe et al., 1993, 2000). Asimismo, la distribución intercampo de las citas permite observar cómo ciertos conocimientos actúan como puntos de referencia en la evolución de trayectorias técnicas, contribuyendo a delinear la dirección de los desarrollos subsecuentes más allá del ámbito de origen de la patente citada (Hall et al., 2001; Hall y Helmers, 2013; Jaffe y de Rassenfosse, 2017).

La interpretación de las citas recibidas requiere considerar su dimensión temporal, ya que existe un desfase entre la concesión y la aparición de sus primeras citas (Hall et al., 2001).

Como consecuencia, las patentes más recientes se encuentran truncadas por construcción y presentan una menor probabilidad observada de ser citadas. La evidencia empírica muestra que las distribuciones de los retardos en las citas siguen patrones regulares, en los que la probabilidad de recibir una cita aumenta tras la concesión, alcanza un máximo y posteriormente disminuye, reflejando procesos de obsolescencia del conocimiento (Bacchiocchi y Montobbio, 2010). La obsolescencia constituye un elemento central en el análisis de las citas recibidas, ya que las patentes no mantienen indefinidamente su capacidad de influir en desarrollos posteriores. La disminución progresiva en la frecuencia de cita se interpreta como una pérdida relativa de relevancia cognitiva, un patrón identificado de manera consistente entre distintos campos tecnológicos y oficinas de patentes (Bacchiocchi y Montobbio, 2010).

En comparación con otras variables, como licencias, adopción comercial o datos de mercado, las citas de patentes presentan ventajas empíricas bien documentadas. Ofrecen una cobertura amplia y sistemática en el tiempo y entre países, a diferencia de los datos contractuales o empresariales, que suelen ser incompletos o no observables (Hall et al., 2001). Además, permiten observar fases tempranas de reutilización cognitiva, antes de que se materialicen otros resultados observables, lo que resulta particularmente relevante en el análisis de trayectorias incipientes (Hegde et al., 2023).

3.4. Limitaciones del uso de datos de patentes en el análisis de la innovación

Si bien las patentes constituyen un indicador ampliamente utilizado en el análisis del proceso innovador, su uso presenta una serie de limitaciones que es necesario tener en cuenta en la interpretación de los resultados. En primer lugar, no todas las invenciones se patentan, por lo que este indicador solo captura una parte de la actividad innovadora (Jaffe y Trajtenberg, 2002). Además, las patentes difieren en calidad y valor, aunque con frecuencia se tratan de forma homogénea en los análisis empíricos. A ello se suman comportamientos estratégicos de patentamiento que pueden distorsionar la información observada, como el uso defensivo de patentes o su acumulación con fines competitivos

(Bessen, 2005; Harhoff et al., 1999). Asimismo, la clasificación tecnológica puede no reflejar plenamente la naturaleza interdisciplinaria de algunas invenciones, y la existencia de una patente no implica necesariamente su adopción o utilización efectiva (Popp, 2005).

Estas limitaciones se extienden al análisis de las citas de patentes como indicador de flujos de conocimiento. Su interpretación requiere considerar que las citas reflejan distintos tipos de conocimiento y no capturan de forma completa los flujos de conocimiento entre invenciones (Marx y Fuegi, 2020). El proceso de citación está influido tanto por los solicitantes como por los examinadores: mientras que los primeros pueden omitir antecedentes relevantes, los segundos pueden incorporar referencias que el inventor no conocía (Alcácer y Gittelman, 2006; Jaffe et al., 1997). Como resultado, las citas constituyen un indicador útil pero imperfecto de los flujos de conocimiento, al no reflejar necesariamente de forma completa ni directa las relaciones cognitivas subyacentes.

La propensión a citar varía según el periodo, la región, el sector y el tipo de institución, lo que introduce diferencias sistemáticas en los datos (Lampe, 2012; Cotropia et al., 2013). Además, no todas las citas responden a flujos cognitivos efectivos, ya que algunas derivan de requisitos legales o de estrategias defensivas. La inclusión de referencias depende en parte de las estrategias del solicitante y de los requisitos formales del proceso de examen, lo que implica que no todo el conocimiento efectivamente utilizado queda reflejado en las citas declaradas (Lampe, 2012). La evidencia muestra que estas citas pueden ser incompletas o estar influidas por incentivos estratégicos, ya que los solicitantes pueden omitir antecedentes cercanos que debiliten la novedad de sus reivindicaciones (Hegde y Sampat, 2009; Lampe, 2012; Cotropia et al., 2013).

En consecuencia, las citas capturan de forma parcial el conjunto de antecedentes cognitivos relevantes, aunque siguen aportando información útil sobre el conocimiento explícitamente reconocido. No obstante, la literatura coincide en que, una vez controlados estos factores —por ejemplo, mediante efectos fijos o el tratamiento de las autocitas—, las citas recibidas conservan información empírica relevante sobre los patrones de uso del conocimiento (Bacchiocchi y Montobbio, 2010; Jaffe y de Rassenfosse, 2017).

PART II: EMPIRICAL ANALYSIS OF THE DIFFUSION, QUALITY, AND DIRECTION OF TECHNOLOGICAL KNOWLEDGE TRAJECTORIES

CHAPTER 4:

The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents (Article 1)

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The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents

Abstract

Technology innovation is widely recognised as a critical means in tackling climate change and fulfilling energy policy objectives. The objective of this paper is twofold: first, to provide a descriptive analysis of innovation in energy technology across countries and sectors and over time; and second, to explore the determining factors of patented knowledge diffusion of energy technologies by distinguishing between renewables and other energy patents, i.e., fossil and nuclear patents) thorough a regression analysis. The data employed in this paper consists of an original database on renewables and other energy patents applied by firms in the period 1990-2015 and contained in PATSTAT. By drawing on patent citations as an indicator of knowledge diffusion and focusing on characteristics extracted from patent documents, a set of econometric models is estimated. Our results show that those patents containing more citations to previous scientific literature and patents attain greater diffusion. Joint patents with other firms or universities exert a negligible effect on technology regarding renewables. Co-ownership with universities has a negative effect on the diffusion of other types of energy technology. Several policy implications can be determined from our results: for example, the justification for policies oriented towards enhancing the incorporation of scientific knowledge and co-inventorship in energy innovation.

Keywords

Patent quality, renewable energy technologies, fossil technologies, nuclear technologies, co-ownership, forward citations.

1. Introduction

Technology innovation is widely recognised as a critical means in tackling climate change and attaining energy policy objectives, including those of increasing energy access and reducing air pollution (IEA, 2020). Mitigating the harmful effects of climate change involves working towards the best use of clean energy and encouraging the transition of the world energy system towards electricity generation from low-carbon sources and other gases (IEA, 2017). Due to increasing concerns over the environmental consequences of greenhouse gas emissions from fossil fuels, renewable energy has emerged as a substitute energy source, since the reduction of CO_2 emissions and the control of climate change must include the reorganisation of the energy sector (Abulfotuh, 2007; Apergis & Payne, 2012; Balsalobre-Lorente et al., 2018). It is clear that the energy sector will only reach net-zero emissions through a global effort for innovation (IEA, 2020). Furthermore, investing in renewable energy sources can contribute towards other public-policy objectives, such as greater energy security, in the face of the uncertain markets of fossil fuels (Johnstone et al., 2010). Furthermore, this sector constitutes a driving force for innovation, since it exerts a significant impact on other sectors that are indirectly affected, such as transport and waste management (Schmidt et al., 2012).

Previous research has revealed the importance of external knowledge sourcing and knowledge diffusion across sectors (Nemet, 2012; Duch-Brown & Costa-Campi, 2015), and geography (Binz & Anadon, 2018; Gosens et al., 2015; Li et al., 2021). It has also shown the relevance of collaboration for green innovation (Ghisetti et al., 2015; Araújo & Franco, 2021) and in general for innovation, which is in line with the open innovation paradigm. Additionally, there is an observed increase towards the incorporation of science into energy patents, especially in renewables (Hötte et al., 2021; Perrons et al., 2021).

This paper addresses two limitations of the extant literature. First, previous contributions on the diffusion of energy technology using patent data have focused on the effect of policy incentives in inducing innovation (Battke & Schmidt, 2015; Noailly & Shestalova, 2017; Popp, 2006; Johnstone et al., 2010; Miremadi et al., 2019; Hötte, 2020) or in the international or regional knowledge flows (Binz & Anadon, 2018; Gosens et al., 2015; Li et al., 2021). Second, the literature exploring the effect of in-text patent indicators on knowledge diffusion has not focused on the energy sector and extant non-specific energy sector reserch provides mixed evidence on the effect of scientific linkages, backward citations, and co-ownership on the diffusion of technology (e.g., see Acosta et al. (2009) for environmental technologies; Schmid (2018) for military technologies; and Belderbos et al. (2014), Briggs (2015), and Peeters et al. (2020) for general evidence).

This paper aims to fill these gaps by providing a comprehensive analysis of patented energy technology generation and of the factors affecting its diffusion based on patent data. Firstly, a description is provided of the temporal evolution of patented energy technology over the period 1990-2015, and of its distribution across technological fields. Light is also shed on which countries lead the process of patented technology in the energy sector. Additionally, descriptive statistics enable comparisons between renewables and other energy technologies. Secondly, a set of econometric models is estimated to identify the factors that determine the diffusion of renewable energy technologies and other energy technologies, which includes scientific linkages, backward citations, and co-ownership of patents. For this purpose, two technological sectors are distinguished: renewable technologies, and other technologies producing energy. Renewable energy technologies include *Wind*, *Solar*, *Geothermal*, *Marine*, *Hydro*, *Biomass*, *Waste,* and *Storage* technologies. Other technologies producing energy include *Fossil Fuels* and *Nuclear* technologies. Our analysis is based on the number of citations a patent receives in subsequent patents, that is, forward citations, as a proxy for knowledge diffusion.

The consequences of patent diffusion make this research relevant both from the firms' and policy-makers' perspectives. At the firm level, empirical literature has shown a strong relationship between patent diffusion (e.g., the impact of a patent on subsequent patented inventions) and several indicators of firm performance (Chen & Chang, 2010; Hall & MacGarvie, 2010; Hall et al., 2005; Harrigan et al., 2018; Hirschey & Richardson, 2004; Patel & Ward, 2011): for example, stock prices (Hall & MacGarvie, 2010), market value (Hall et al., 2005; Kim et al., 2018 for the renewables sector), and reputation for technological innovation, which in turn correlate with the firm's competitive advantage (Henard & Dacin, 2010; Höflinger et al., 2018). Furthermore, patent diffusion promotes innovation by reducing transaction costs and coordinating R&D efforts between rivals (Sag & Rohde, 2007; Thomas, 2002). From the policy-makers' perspective, understanding innovation and diffusion of energy technologies become essential for efficient energy and environmental policy design, and may contribute towards explaining why certain existing technological solutions in the market diffuse slowly, even when they are technologically superior (Hötte, 2020). These crucial consequences of patent quality for the firm and for society trigger political and academic interest in understanding the factors affecting patent diffusion in the energy sector.

2. Theoretical background

Broadly speaking, comprehension of the mechanisms underlying knowledge creation and diffusion is essential for economic growth to be understood (Silverberg et al., 1998; Klarl, 2014; Andergassen et al., 2017). In one of the seminal contributions of knowledge diffusion, Rogers (1962, p. 5) defined diffusion as "a process by which an innovation is communicated through certain channels over time among the members of a social system". This concept of diffusion conveys both market and non-market channels. However, in this paper, a more constrained concept of diffusion is adopted, which is centred on knowledge spillovers. These can be defined as external knowledge sources upon which organisations are built and in which there is no compensation, or said compensation lies below the actual value of the knowledge (Jaffe, 1998; Korres, 2012). From a macroeconomic viewpoint, knowledge diffusion through spillovers plays a key role in the literature on endogenous economic growth (Grossman & Helpman, 1991, 2018; Griliches, 1992; Aghion & Howitt, 1992; Acemoglu & Akcigit, 2012). From a microeconomic viewpoint, technological diffusion provides a key factor for productivity growth (Baumol, 1991). Furthermore, the identification and understanding of the processes of technological knowledge diffusion and acquisition is essential in the design of successful business strategies (Bonesso et al. 2011; Momeni & Rost, 2016). However, the process of knowledge diffusion is not automatic, as shown by a large set of studies initiated by Jaffe et al. (1993), but instead depends on agents' absorptive capacity (Cohen & Levinthal, 1990; Lane et al., 2006).

2.1. The diffusion of technology in the energy sector

Although not precisely focused on the factors affecting knowledge diffusion, a growing number of studies rely on patent data to examine innovation and knowledge sourcing in the energy sector and provide relevant clues for this research.

Motivated by the fact that technological change is considered a cumulative process in which new technologies result from the recombination of existing knowledge in innovative ways (Arthur, 2007), several papers have provided evidence on knowledge flows through the analysis of backward patent citations within/across technological sectors (Nemet, 2012; Duch-Brown & Costa-Campi, 2015) or geography (Binz & Anadon, 2018; Gosens et al., 2015; Li et al., 2021). In the case of renewables, evidence has revealed that energy innovation depends on a broad range of knowledge sources since it usually involves the combination of diversified and complex knowledge areas (Nemet, 2012; Garrone et al., 2014; Noailly & Smeets, 2015; Popp, 2017). This highlights the importance of external knowledge sourcing to foster innovation and diffusion. However, the rate of diffusion depends on the type of technology. For example, green technologies exert a higher impact on future inventions (Barbieri et al., 2020). Overall, patents in wind, storage, and solar technologies tend to be more frequently cited than other renewable technologies (Noailly & Shestalova, 2017).

Additionally, previous research has found that energy innovation increasingly relies on science (Hötte et al., 2021; Perrons et al., 2021), particularly in the case of renewable energies (Perrons et al., 2021; Persoon et al., 2020), which may indicate an increasing dependence of invention on scientific research over time.

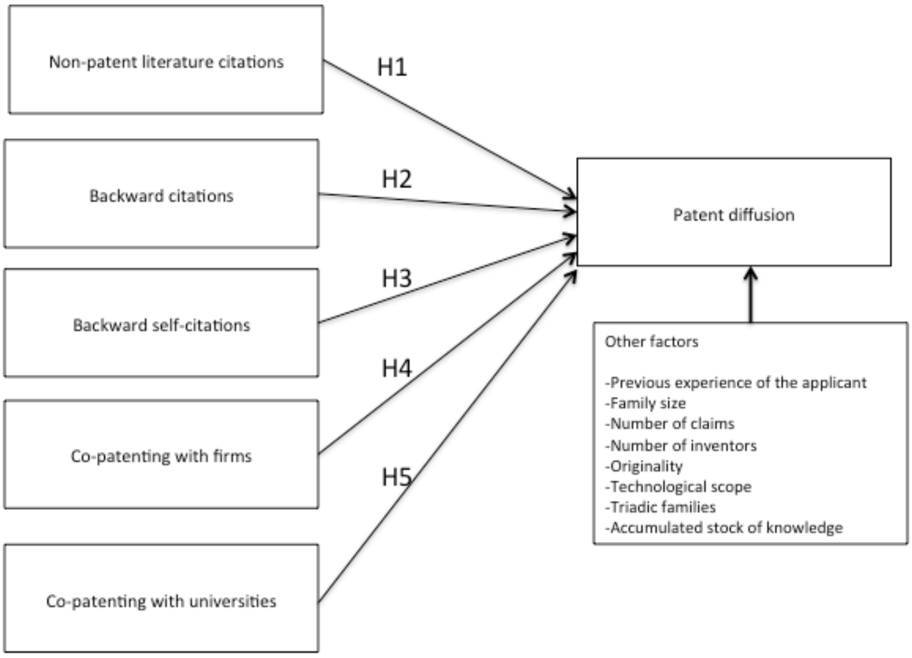
From an institutional point of view, open innovation becomes a relevant paradigm (see Lacerda & Van den Bergh, 2020 for renewable technologies). The open innovation perspective stresses the value of external knowledge by arguing it is a necessary strategy to increase R&D productivity in the face of growing competition and faster technology development cycles. Nevertheless, successful environmental innovations are highly dependent on the participation of different stakeholders in their development/uptake, that is, they are likely to result from the cooperation between the public sector, academia, and business (Carrillo-Hermosilla et al., 2010). However, it has been found that universities play a less important role in wind research than they do for solar and biofuels, which the authors interpret as being wind energy research at a more applied stage where commercialisation and final product development has become more important than basic research (Hötte et al., 2021). In particular, green energy innovations rely on technologies developed outside the field of power generation (Noailly & Ryfish, 2015) and often require the combination of various items of knowledge developed by different actors in different countries (Corrocher & Mancussi, 2021), which exemplifies the relevance of open innovation.

Despite the importance of building upon previous extant technological, scientific knowledge and cooperation for energy innovation, their effect on diffusion has yet to be explored. Therefore, in the subsequent section, the non-specific energy empirical evidence on the determinants of patent diffusion is reviewed.

2.2. Determinants of patent diffusion

The cumulative nature of knowledge and path dependancy make it crucial to rely on previous knowledge for innovation. Two prominent sources of knowledge are those of previous codified knowledge (either in patent or non-patent literature), and R&D cooperation (either with universities or firms). In this section, our hypotheses are derived, as summarised in Figure 1.

Figure 1. Research model and hypotheses



2.2.1. Citations to non-patent literature

Scientific research has been largely discussed as being relevant for technological innovation (e.g., Bush, 1945; Brooks, 1994; Godin, 2006; Balconi et al., 2010; Ribeiro et al., 2014; Fleming et al., 2019). Fleming & Sorenson (2004) suggested that science functions as a map of the technological landscapes that can guide private research towards useful combinations, thereby avoiding dead-end research efforts. Furthermore, the growth of markets for technology including those from academia, implies that firms have access to a larger scientific pool than ever (Marx & Fuegui, 2020).

Several papers have found a close relationship between scientific citations and the value of patented inventions (e.g., Sorenson & Fleming, 2004; Branstetter, 2005; Gambardella et al., 2005; Ahmadpoor & Jones, 2017; Poege et al., 2019 provide non-specific sector evidence; see, Harhoff et al. (2003), for pharmaceutical and chemical patents). However, the empirical evidence remains mixed. For example, Harhoff et al. (2003) found a positive effect of citations to the non-patent literature and the value of pharmaceutical and chemical patents, but not in other technical fields. Cassiman et al. (2008) found that references to scientific publications are not relevant in explaining forward citations in patents from a set of technological classes, which they justify because patents citing science may be uncovering knowledge of a more complex and fundamental nature, which is less readily diffused or remains far from market applications. Petruzzelli et al. (2015), using a sample of biotechnology patents, found that the use of scientific knowledge varies in its impact depending on the level of analysis of knowledge diffusion. According to their results, non-patent citations do not affect the number of forward citations, nor do patent citations from the same technology domain, nor the number of citations from other assignees. However, they did find a negative effect of scientific citations on a patent's impact on subsequent patents outside the biotechnology industry, and they found a positive effect of the technological relevance of the patent for the assignee's future inventions.

On the whole, the empirical evidence on the effect of scientific linkages of technological innovations remains largely unclear, although it does seem to remain dependent on the technological sector under analysis, whereby it has greater relevance in technologically complex sectors. The widely discussed relationship between science and technology, and the increasing importance of science for energy innovations (Hötte et al., 2021; Perrons et al., 2021), motivates the following hypothesis:

H1. More scientific knowledge sourcing exerts a positive effect on energy patent diffusion.

2.2.2. Backward patent citations

Backward citations have been used in other studies as a proxy for spillover effects and show a positive effect on the market value of firms (e.g., non-specific sector evidence available in Harhoff et al., 2003; Duguet & Macgarvie, 2005; Gay & Le Bas, 2005).

Backward citations can be directed towards patents owned by others or to self-owned patents. In the specific case of self-citations, these are a measure of path-*dependent technologies* (Sørensen & Stuart, 2000 for high-tech industry; Song et al., 2003 for non-specific sector evidence). Interestingly, Hall et al. (2005) provided general empirical evidence that self-citations have an even stronger effect on market value than do other citations. Liu et al. (2008) found that US pharmaceutical and biotechnology patents that are part of sequential inventions show increased technological value. Thus, the higher the number of self-citations included in a patent, the higher the expected number of forward citations, since it signals that the firm maintains greater accumulated technological knowledge (Gay et al., 2005).

In consideration of the positive effect of citations and self-citations on innovation performance and diffusion, we advance the following hypothesis:

H2. More citations to the patents of others exerts a positive effect on the diffusion of energy patents.

H3. More citations to one’s own patents exerts a positive effect on the diffusion of energy patents.

2.2.3. R&D collaboration and co-patenting

Collaboration with external organisations is generally viewed as positive for the firm’s innovation because it provides access to resources, especially knowledge, that the focal firm lacks (Un et al., 2010). In the particular case of industry-university collaboration, universities can provide the scientific basis for technological progress and basic research (Peeters et al., 2020). Co-patenting implies the joint ownership of collaborative outcomes and has been used as an instrument to analyse the effect on value creation and appropiation (Belderbos et al., 2014). However, co-patenting creates uncertainty over the control that each co-owner possesses of the co-owned patent (Hagedoorn, 2003).

Empirical evidence on the effect of co-ownership reveals mixed results. Belderbos et al. (2014) find that co-ownership between firms receives more forward citations than do single-owned patents, while co-ownership with a university yields no statistical difference in the number of forward citations received compared to single-owned patents. With respect to the latter, Briggs (2015) obtained similar results when using forward patent citations within three years, but found a positive effect of co-ownership with universities on quality when using the total number of forward citations over the whole life of the patent. Recently, Peeters et al. (2020) found a positive effect of co-ownership with universities in exploratory trajectories, but a negative effect on forward citations for exploitative trajectories. They justify this result by stating that the more ‘certain’ exploitative trajectories are developed in-house, whereas the more uncertain types are more likely to be outsourced.

Given the distinct benefits of collaborating with different types of partners, we consider that in-depth studies are needed into the effect of co-ownership with universities and firms on patent diffusion in the “era of open innovation” (Enkel et al., 2009). This leads us to advance the following hypotheses:

H4. Co-patenting with other firms has a positive effect on the diffusion of energy patents.

H5. Co-patenting with universities has a positive effect on the diffusion of energy patents.

3. Methods and data

3.1. Measuring knowledge diffusion through the forward citations of patents

This paper relies on patent citations as an indicator of technological diffusion. Patent applicants are required to cite all “prior art” related to the invention (Criscuolo & Verspagen, 2008; Jaffe et al., 2000). Thus, patent citations are added to the patent documents if the knowledge in the cited patent is relevant to the citing patent. In other words, if patent B cites patent A, then it may be indicative of a knowledge flow from patent A to B (Hall et al., 2001). Following this reasoning, there is a large body of research using citation indicators of technological relations between the citing and cited patents (see, for example, Jaffe et al., 1993; Jaffe & Trajtemberg, 1999; Hall et al., 2001; Hu & Jaffe, 2003; Maurseth, 2005; Gay et al., 2005; Liu & Roseau, 2010; Schmid, 2018). However, patent citations fail to constitute a perfect measure of technological diffusion for two basic reasons (Verspagen, 2000). First, they depend on the consideration of patents as a reliable indicator of innovation. Thus, in sectors where inventions are less prone to be patented, patent citations provide a limited indicator of diffusion. Second, patent citations serve a legal purpose by limiting the claims that can be made on the invention: on recognising previous technology, they narrow the innovativeness of the invention. For this reason, it is the ultimate responsibility of the patent examiner to determine which references should be included. It can happen, therefore, that the inventor remains unaware of the cited patent[1] (Alcácer & Gittelman, 2006; Cockburn et al., 2002). Several studies have focused on the validation of patent citations as indicators of knowledge flows (for a review, see Jaffe & de Rassenfosse, 2017). The overall conclusion of these studies is that patent citations are an accurate, though noisy, indicator of actual knowledge flows. Nevertheless, they constitute "the most widely employed measure of knowledge flows in the economics, management, and policy literatures" (Roach & Cohen, 2013).

From this literature, a number of studies have built upon the use of forward citations to measure technological diffusion (Sorenson & Fleming, 2004; Hoetker & Agarwal, 2007; Schmid, 2018). In addition, forward patent citations can be considered a measure of patent quality and hence a proxy for the economic value of a patent and its diffusion. An increased count of forward citations (citation of a patent in subsequent patents) means that the patent contributes with relevant knowledge to other inventions (e.g., Trajtenberg, 1990; Gambardella et al., 2008; Fischer & Leidinger, 2014; Briggs & Wade, 2014; Abrams et al., 2018). The relationship between forward patent citations and economic value suggests that patents related to a significant new technical knowledge receive more citations than other patents, which in turn reveals a close association between citations and the socio-economic value of innovations (Carpenter et al., 1981; Albert et al., 1991; Harhoff et al., 2003; Lanjouw & Schankerman, 2004; Gay et al., 2005).

[1] An analysis of the influence of citations included by the inventor and by the examiner, and the deviation generated in the determination of technological flows can be found in Alcácer & Gittelman (2006) and Thompson (2006).

3.2. Variables, model, and data

3.2.1. Variables

A regression analysis of patent families (hereinafter referred to as "patents") is conducted.

Table 1 summarises variables and definitions. Our dependent variable (***forward_citations_5years***) is the count of citations that an invention (i.e., patent family) receives within a 5-year window from the first publication date (for more details, see de Rassenfosse et al., 2014; Squicciarini et al., 2013).

The mechanisms generating applicant and examiner citations differ widely (see discussions regarding the role of the examiner in Alcácer et al., 2009; Chen, 2017; Azagra-Caro & Tur, 2018). Examiner citations are excluded since the inventor might remain unaware of the cited patents and may fail to utilise them for the creation of inventions and therefore may fail to truly indicate knowledge diffusion (Jaffe et al., 2000)[2]. Self-citations (i.e., citations made by an assignee to their own previous patents[3]) have also been excluded from the dependent variable (see, for example, Acosta et al., 2012).

Further to factors mentioned in Section 2.2, other factors have also been identified as determinants of forward patent citations:

- *Previous experience of the applicant.* Given the path dependancy nature of knowledge creation, it is assumed that inventors that have previously innovated are more

[2] Following the recommendation of one anonoymous reviewer, we replicated our mainstream models using examiner citations as the dependent variable. Similar conclusions are reached regarding our hypotheses testing, except for Hypothesis 5. For brevity, the results are not displayed here but they are available from the authors upon request.

[3] To identify self-citations, we first harmonise companies' names. To this end, we consider two applicants as being the same applicant if they have the same name (even if they have different legal forms) and belong to the same country (Callaert et al., 2011).

likely to develop relevant patents than inventors with no experience (Gambardella et al., 2005).

- *Family size.* The number of different jurisdictions where the same invention has been filed positively affects forward citations (e.g., Duch-Brown & Costa-Campi, 2015 for the oil and gas industries). The main argument explaining this relationship is that applying for protection is costly, therefore applicants are more likely to apply for protection in multiple countries for their most valuable inventions (Harhoff et al., 2003; Lanjouw & Schankerman, 2004 for manufacturing firms; Sampat, 2005).

- *Number of claims.* Each claim represents a distinct inventive contribution (Tong & Frame, 1992). Patents with more claims delimit broader property rights and thus are expected to be more frequently cited (see Bessen, 2008 for a set of technological sectors; Nemet, 2012 for energy technologies).

- *Number of inventors.* Increased team size increases richness of the knowledge involved in the patent and the access to a wider and more heterogeneous network (for non-energy specific evidence, see: Guellec & Van Pottelsberghe de la Potterie, 2001; Lee et al., 2007; Singh, 2008; Cassiman et al., 2008; Sun et al., 2020).

- *Originality.* Patent originality refers to the breadth of the fields of technology upon which a patent relies (Squicciarini et al., 2013). It is expected that the most original patents receive, on average, more citations since a broader search is the base for a broader range of subsequent innovations (Petruzelli et al., 2015 provide evidence for biotechnology). However, it has also been argued that searching widely is a risky process that conveys uncertainty regarding the outcomes (Petruzelli et al., 2015).

- *Technological scope.* A higher frequency of citations is expected when the patent family is assigned to a broader range of technological fields (Trajtenberg et al., 1997).

- *Triadic families.* It has been shown that EP patents simultaneously applied to US and Japan receive, on average, a higher number of citations than EP-only patents (Criscuolo, 2006 for a set of technological sectors, but not specific to energy).

- *Accumulated stock of knowledge.* The number of citations also depends on the number of opportunities to be cited: a large number of patents in a given technological domain indicate more inventors working on related technologies and thus the increased propensity of a given patent to be diffused (Acosta et al., 2013, and Schmid, 2018, for military technologies).

Table 1. Variables and definitions

Variable	**Definition**
Dependent variable	
Forward_citations_5years	No. of forward citations within the window of 5 years
Independent variables	
Non_patent_literature	No. of citations to non-patent literature
Backward_others_citations	No. of backward citations
Backward_self_citations	No. of backward self-citations
Collaboration_firm	Dummy: 1 indicates collaboration with a firm, 0 otherwise
Collaboration_university	Dummy: 1 indicates collaboration with a university, 0 otherwise
Previous_experience	No. of total inventions in energy technologies of the firms owning the patent in the previous ten years before the application date of the patent (as a logarithm)
Family_size	No. of different patent jurisdictions in the patent family
Claims	No. of claims in the patent family
Inventors	Maximum number of inventors in the patent family
Original	Originality index based on Trajtenberg et al. (1997). If all cited patents belong to exactly the same set of technologies, then the originality index is 0. A large "originality" value indicates broader technological roots of the invention
Scope	No. of different 4-digit IPC subclasses
US_JP	Dummy: 1 indicates protection in the US and JP, 0 otherwise
Stock	No. of inventions that already exist in the particular technological field over the last 10 years (as a logarithm)
Control variables	
Year dummies	Year effects: Dummy variable from 1990 to 2005, taking 2006 as base category
Field dummies	Field effects: Dummy variable. Renewables (*Wind*, *Solar*, *Geothermal*, *Marine*, *Hydro*, *Biomass*, *Waste* and *Storage*) and other technologies (*Fossil* and *Nuclear*)

Source: Author's own based on Patstat data.

All regressions control for year and field effects by including dummies. The year's fixed effects capture differences in the quality of patents relative to the last year in the sample. Similarly, several dummies capture possible differences between technological subcategories in the energy sector, both in renewables (*Wind*, *Solar*, *Geothermal*, *Marine*, *Hydro*, *Biomass*, *Waste,* and *Storage*) and other technologies (*Fossil* and *Nuclear*) (see Noailly & Shestalova, 2017, and Albino et al., 2014 for the list of IPC codes identifying each category). Each variable takes the value of 1 if the corresponding technological field appears in the group of IPC classification assigned to the patent family, and 0 otherwise.

Table 2 shows the frequencies of citations over 5 years for the whole sample. Our data shows that 74.45% of the patents in our sample do not receive citations in a 5-year window and 8.16% receive only one citation.

Table 2. Frequency of 5-year forward citations (1990-2015)

No. of forward citations	No. of patents	Cumulative count	% of patents over total	Cumulative %
0	40632	40632	74.45	74.45
1	4451	45083	8.16	82.60
2	2566	47649	4.70	87.30
3	1681	49330	3.08	90.38
4	1138	50468	2.09	92.47
5	864	51332	1.58	94.05
6	673	52005	1.23	95.29
7	460	52465	0.84	96.13
8	375	52840	0.69	96.82
9	284	53124	0.52	97.34
10	220	53344	0.40	97.74
>10	1234	54578	2.26	100

Source: Author's own based on Patstat data.

3.2.2. Model specification

As mentioned above, in order to estimate the influence of the various factors on the diffusion of knowledge in the energy sector, we estimate a model using the count data of forward citations over a 5-year window as a dependent variable (***forward_citations_5years***). The nature of the data implies the formulation and estimation of a counting model (Poisson or Negative Binomial), since estimates obtained from linear regression can be inconsistent, inefficient, and biased (Amano & Fujita, 1970; Long, 1997). Similar to many other studies, a baseline specification is assumed following a Poisson distribution with non-linear form. However, one restriction of the Poisson model is that it assumes the mean and variance of the dependent variable to be equal. When the dependent variable shows over-dispersion, (i.e., when the variance of the dependent variable is greater than the mean), then negative binomial models are preferred (for details, see Cameron & Trivedi, 1986). Given the large number of zeros in our sample (as shown in Table 2, almost 75% of the patents in our sample fail to receive citations in a 5-year window), zero-inflated negative binomial regression models could be considered. However, these models assume that there is a mixed distribution composed of the two processes, one representing the count (Poisson or NB) and the other the excess of zeros (e.g., a logistic function). Following Bornmann & Leydesdorff (2015), since there is no known difference in the mechanism for the first citation and the later citations, zero-inflated negative binomial models are not used in this paper. Thelwall & Wilson (2014) recommended the use of the generalised linear model with lognormal residuals for scientific citation data, although they recognise limitations to their study that probably provoke the overestimation of the unreliability of negative binomial regression for citations. Despite these limitations, and given the similarities in the distribution of patent and scientific citations, ordinary least squares models based on logarithmised citation data were additionally calculated to test the robustness of our results[4].

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[4] Whereby 1 is added to the citation data, the logarithm is taken, and ordinary least squares regression is used.

3.2.3. Data

The empirical data consists of 54,578 energy patent families applied for by firms and which includes at least one application to the European Patent Office (EPO) in the period 1990-2015, considering the earliest filing year of the family, that is, the priority date. The source of data is the *EPO Worldwide Patent Statistical Database (Patstat, autumn 2017 edition)*. In order to uniquely identify patent applicants, the OECD HAN database is employed together with manual harmonisation. The OECD HAN database provides harmonised patent applicants' names, but it is only available for patent applicants at the EPO. Hence, our sample is limited to families of patents that include at least one application at the EPO. We follow the classification scheme based on the International Patent Classification Codes (IPC) as proposed in Noailly & Shestalova (2017) for renewables and fossil technologies, and in Albino et al. (2014) for nuclear technologies.

The DOCDB simple patent family concept is employed to build families, that is, a collection of patent documents that share identical technical content and are considered to protect a single invention. Our data is obtained from patent families instead of individual patents for several reasons (see Martínez, 2011, for a discussion on patent families). Since the same invention can be patented in multiple offices (Popp, 2005), in order to avoid duplication, patent families are used as an inventive integral unit, instead of using the individual counting of applications (Martínez, 2011). Furthermore, patent families can be associated to a unique priority filing (i.e., the earliest priority date), which should be that closest to the invention (Bastianin et al. 2021). From the side of citations, the focus on families prevents the multiple counting of citations (Fischer & Leidinger, 2014; Nesta et al., 2014). Moreover, if an application of the family receives a citation, it is just as valid as that received directly to the initial application (Bakker et al., 2016). Given these benefits of patent families, it is not unusual that they are increasingly used as the unit for counting patents (e.g., Baruffaldi & Shimeth, 2020; Bastianin et al., 2021), and examining knowledge diffusion across sectors (Nemet, 2012; Duch-Brown & Costa-Campi, 2015) or geographical areas (e.g., Li et al., 2021, for energy technologies).

Since citations can continue accumulating over a patent's life, the count of patent citations presents a truncation problem. Additionally, since older patents have had more time to be cited, they are expected to have received more citations. In accordance with previous contributions, we deal with these issues by using citations within a five-year time window (Petruzzelli et al., 2015) subsequent to when the invention was first published (Hall & Helmers, 2013; Moaniba et al., 2018).

However, our data is still truncated for two reasons. First, there is a publication delay: an application takes 18 months to be published after the initial filing date. Second, many EP applications are increasingly based on earlier PCT applications. For PCT applications, the applicant has 31 months to decide whether or not the application becomes a European application. In this paper, families with at least one EP application with priority date between 1990 and 2015 are considered, and hence the analysis of the data beyond 2011, which is the latest comprehensive year in our sample, should be approached with caution. In order to deal with these data truncation issues in regression analysis, the time frame of our sample is limited to enable the citation window to be completed. For example, the main set of econometric models is estimated using data for 1990-2006 patents to have complete information for the 5-year citation window.

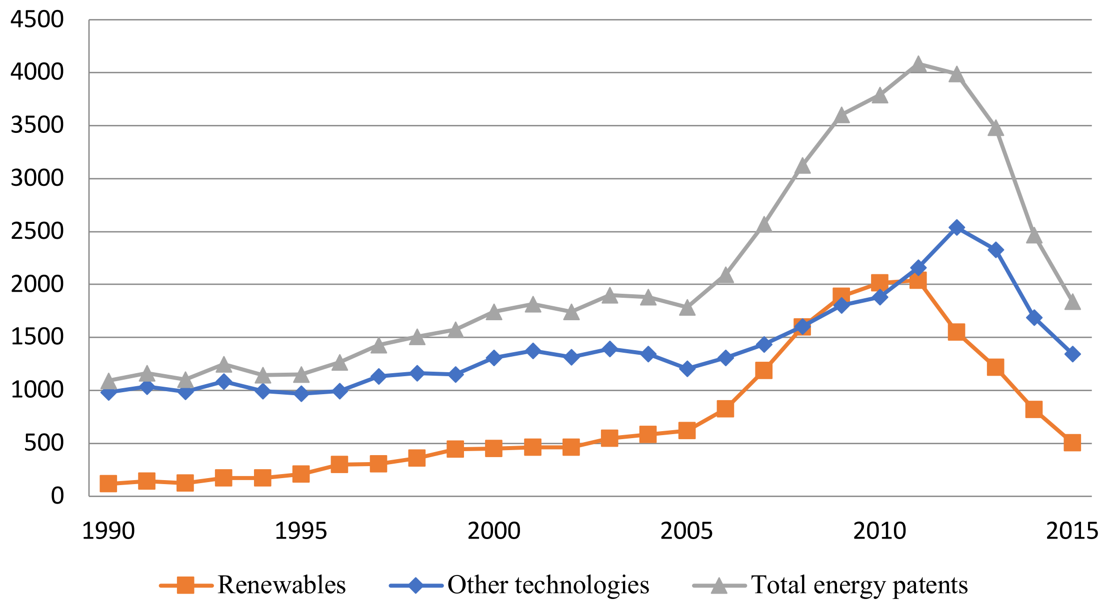
4. Results

In this section, the results of our descriptive analysis are provided together with the estimation of an econometric model to identify the factors affecting forward citations of patented energy technology. Separate models for renewables and other technologies are estimated. In so doing, allowances are made for differences in the factors that encourage the diffusion of renewables and other technologies.

4.1. Descriptive analysis

For the purpose of contextualisation, a brief description is presented of patent families in our sample to provide insights into innovation in energy over time and its distribution across technological fields. Regarding the temporal evolution, Figure 2 shows the number of patents related to renewable energy, related to other types of energy, and the total number of energy patents. For the joint series of renewables and other types of technologies, a consistent increase in the number of patents is observed from 1990 to 2011, and a decay from 2012 onwards. With the focus on renewables, the data reveals the catching up of innovation in renewable energies rising from 117 in 1990 to 2,040 in 2011 (a 1,643.59% increase), while other technologies rise from 984 in 1990 to 2,160 in 2011 (119.51%). In 2011, renewable patents represented 49.95% of the total number of patented energy technologies. As in Haščič et al. (2015), the drop in recent years is likely to be due to a temporary phenomenon whereby certain batches of new data are included with a time lag.

Figure 2. Number of inventions per type of energy technology (1990-2015)



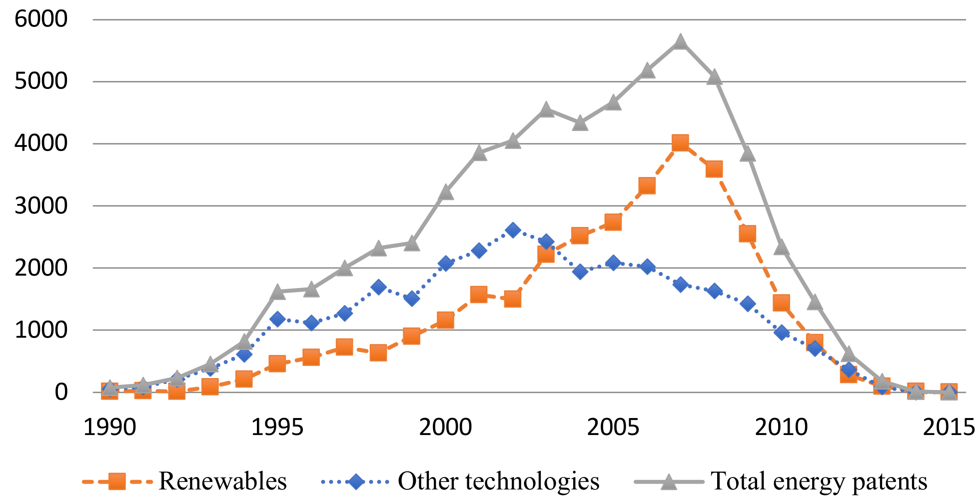
Source: Authors' own based on Patstat data.

Figure 3 depicts the number of 5-year forward citations to energy patents, which shows an increasing trend from 1990 to 2007, but a notable decrease from 2008. This result can be explained: since citations are computed at the family level, and recent patent families might still be incomplete in that further applications might be expected to be added to the family. Moreover, it is worth mentioning that the number of citations that an invention receives becomes 0 in 2015, because these patents have not had enough time to be cited

(5-year window not completed). Comparing these two types of energy technologies, Figure 3 confirms the relevance of renewable energy technologies as having inventions that are more frequently cited for the generation of electricity since 2004.

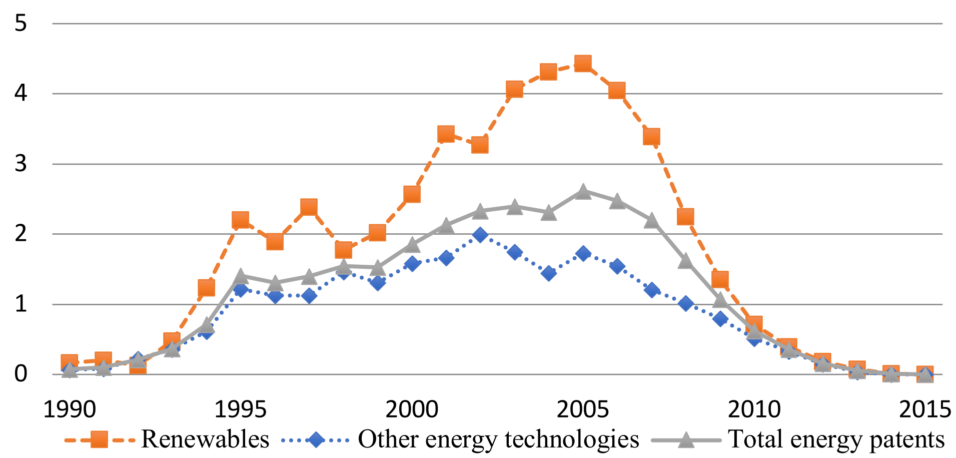
Finally, by focusing on 5-year forward citations per patent over time, Figure 4 shows a major increase in renewable energies, which surpass other technologies.

Figure 3. Number of 5-year-window forward citations (1990-2015)



Source: Authors' own based on Patstat data.

Figure 4. Number of 5-year forward citations per patent (1990-2015)



Source: Authors' own based on Patstat data.

Table 3 reports the distribution of patent families and forward citations per technological field. Our results show that other technologies account for the largest share of total patents in the energy sector (65.25%). However, renewable energy technologies are cited more often than other traditional technologies for the generation of electricity (the former accounts for 51.58% of 5-year forward citations in the energy sector). Focusing on technological fields, our results also reveal that *Solar* (12.22%), *Wind* (11.63%), and *Storage* (6.37%) technologies account for the largest number of patents among the renewable energy technologies. These are also the fields with the largest share of citations in the energy sector. Furthermore, the minor importance of nuclear technologies in terms of patents and citations can be observed in comparison to fossil fuel technologies. The last column in Table 3 depicts information regarding citations over 5 years per patent family, once again revealing a higher impact of renewable energies (1.67) than for other technologies (0.84). *Wind*, *Biomass,* and *Storage* are the fields that receive more citations per patent family.

Table 3. Distribution of patent families and forward citation per technological field (1990-2015)

Technological field	A. No. of patent families	No. of patent families per field /total no. of energy patents (%)	B. No. of 5-year forward citations	No. of 5-year forward citations per field/ total no. of energy 5-year forward citations	B/A 5-year forward citations per patent family
Wind	6,565	11.63	11,445	18.00	1.74
Solar	6,901	12.22	10,357	16.28	1.50
Geothermal	274	0.49	300	0.47	1.09
Marine	878	1.55	1,049	1.65	1.19
Hydro	522	0.92	792	1.25	1.52
Biomass	310	0.55	540	0.85	1.74
Waste	573	1.01	489	0.77	0.85
Storage	3,597	6.37	7,834	12.32	2.18
Renewables	19,620	34.75	32,806	51.58	1.67
Fossil	33,493	59.31	29,465	46.33	0.88
Nuclear	3,355	5.94	1,330	2.09	0.40
Other technologies	36,848	65.25	30,795	48.42	0.84
Total energy	56,468	100	63,601	100	1.13

Note that a patent family may be related to more than one technological sector. For this reason, the sum of patent families is greater than the total sample.
Source: Authors' own based on Patstat data.

In order to shed light on which countries lead the process of knowledge generation in the energy sector, Table 4 presents the top ten countries with the highest number of energy inventions in the European Patent Office. Our data shows that 60.31% of the inventions in total energy originate from the United States, Germany, and Japan, with a high concentration in a few countries. This value falls to 57.19% in renewables, led by Germany, and rises to 62.07% in other technologies, led by the US. Regarding citations over 5 years per invention, Table 4 also shows the importance of the US as the leader of 5-year forward citations and 5-year citations per patent in renewables, other technologies, and total energy. Our data confirms the concentration of innovation activity in energy (for evidence on renewable technologies, see Garrone et al., 2014; Haščič & Migotto, 2015; Noailly & Ryfisch, 2015). When focusing on 5-year citations per patent, the best performing countries are Spain (1.39) and Republic of Korea (1.32) in renewable energy technologies, Japan in other technologies (0.73), and Denmark in total energy (1.06).

Table 4. Top 10 countries with the highest number of patent families and their 5-year forward citations (1990-2015)

	Renewables					Other technologies					Total energy				
Rank	Country	Patent families	% Patent families over total	5-year forward Citations	5-year forward citations/patents	Country	Patent families	% Patent families over total	5-year forward Citations	5-year forward citations/patents	Country	Patent families	% Patent families over total	5-year forward Citations	5-year forward citations/patents
1	DE	5240	23.38	5041	0.96	US	11707	29.50	11727	1.00	US	15882	25.57	20369	1.28
2	US	4175	18.63	8933	2.14	DE	8591	21.65	3101	0.36	DE	13831	22.27	8117	0.59
3	JP	3405	15.19	3915	1.15	JP	4334	10.92	3153	0.73	JP	7739	12.46	7067	0.91
4	DK	1528	6.82	1825	1.19	FR	3201	8.07	1672	0.52	FR	4142	6.67	2552	0.62
5	FR	941	4.20	884	0.94	CH	2187	5.51	1314	0.6	CH	2820	4.54	1819	0.65
6	GB	885	3.95	1240	1.4	GB	1775	4.47	977	0.55	GB	2660	4.28	2212	0.83
7	ES	673	3.00	936	1.39	IT	1423	3.59	428	0.3	IT	1995	3.21	763	0.38
8	CH	633	2.82	517	0.82	SE	769	1.94	273	0.36	DK	1804	2.90	1920	1.06
9	IT	572	2.55	335	0.59	NL	760	1.91	465	0.61	NL	1303	2.10	1277	0.98
10	KR	569	2.54	749	1.32	AT	708	1.78	230	0.32	SE	1109	1.79	502	0.45
	Others	3795	16.93	5434	1.43	Others	4232	10.66	2568	0.61	Others	8818	14.20	8756	0.99
	Total	22416	100	29809	1.33	Total	39687	100.00	25908	0.65	Total	62103	100	55354	0.89

AT: Austria CH: Switzerland DE: Germany DK: Denmark ES: Spain FR: France GB: United Kingdom IT: Italy JP: Japan KR: Republic of Korea NL: Netherlands SE: Sweden US: United States

* Note that one invention may be counted in two or more countries. For this reason, the number of inventions is greater than the total sample.

4.2. Main estimation results

Table 5 reports the descriptive statistics for all the explanatory variables, including patents from renewable energy technologies and other technologies. Renewable energy patents receive more citations on average than do other technologies (3.0573 vs. 1.1864). Several of the most notable differences are subsequently highlighted. Renewable energy patents are more prone to cite previous patents (*Backward_others_citations* and *Backward_self_citations*). The mean number of inventors and claims is also higher for renewable energy patents than for other technologies. On the other hand, average previous experience and scope is larger for other technologies than for renewables. Interestingly, co-ownership with other firms is more usual for other technologies than for renewable energy patents (0.3259 vs. 0.3080, respectively), while co-ownership with universities is more frequent in renewable energy technologies than in other technologies (0.0102 vs. 0.0018, respectively).

Table 5. Descriptive statistics (1990-2006)

	RENEWABLES				OTHER TECHNOLOGIES			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Forward_citations_5years	3.0573	6.1617	0	99	1.1864	3.6416	0	186
Non_patent_literature	2.5193	12.2941	0	300	0.9785	7.5843	0	374
Backward_others_citations	6.4541	14.6875	0	176	3.6455	10.4930	0	197
Backward_self_citations	0.8803	2.8636	0	65	0.6937	2.3606	0	88
Collaboration_firm	0.3080	0.4617	0	1	0.3259	0.4687	0	1
Collaboration_university	0.0102	0.1003	0	1	0.0018	0.0419	0	1
Previous_experience	2.7610	2.3586	0	9.5613	3.8262	2.5453	0	10.0459
Family_size	5.4917	3.0381	1	30	5.4201	3.3320	1	33
Claims	16.8781	15.5567	0	199	14.1813	11.3574	0	373
Inventors	2.7742	1.9072	0	20	2.5751	1.7979	0	26
Original	0.6177	0.2443	0	0.9731	0.6990	0.2019	0	0.9750
Scope	2.3607	1.6393	1	23	2.9768	1.5925	1	26
US_JP	0.4583	0.4983	0	1	0.4487	0.4974	0	1
Stock	8.7658	0.5643	5.8579	10.0685	11.1509	0.4754	9.3248	11.6006
No. Obs. (year<=2006)	5900				19343			

As explained above, the dependent variable is the number of times that a patent family is cited as being the relevant state of the art in subsequent patent families filed within 5 years after the first publication of the patent family, excluding examiner citations and self-citations (*Forward_citations_5years*). According to Table 5, the variance (square of standard deviation) is greater than the mean. This difference suggests that over-dispersion is present and that a Negative Binomial model would be appropriate.

Table 6 shows the main econometric results using Negative Binomial models. Models 1, 3, and 5 explain knowledge diffusion in the renewable sector and include binary variables for each field. Models 2, 4, and 6 are estimated for other technologies and include two binary variables to control for nuclear and fossil energy innovations. In all the regressions, we also control for temporal effects. Patents that share codes from both renewables and other technologies are excluded. Furthermore, since *Backward_self_citations* and *Backward_others_citations* are components of the total backward citations, and despite not showing high linear correlations to each other and the fact that the VIFs are low, we estimate our Negative Binomial model by including *Backward_others_citations* and omitting *Backward_self_citations* (and vice versa). Given the space limitations herein, only the results of Negative Binomial regressions for these separated regressions are included in Table 6, which are the preferred models, given the over-dispersion of citations.

The results show certain similarities in the variables in the explanation of the diffusion of renewables and other technologies. In all models, backward citations to other patents show a positive and significant coefficient, which emphasises the importance of knowledge sourcing for knowledge diffusion. Backward self-citations are also significant in all models, thus supporting the cumulative nature of knowledge. Co-ownership with other firms is not relevant in any model. The number of inventors, claims, scope, originality, and previous experience in the development of innovations exert a positive and significant effect on enhancing knowledge diffusion. Non-patent literature citations are only relevant for renewable energy technologies, but theyt also become significant for other technologies when omitting *Backward_self_citations* or *Backward_others_citations* from the main regression (see Models 4 and 6). While being wary of encountering a possible multicollinearity problem, we conclude that scientific knowledge is relevant for innovations in the energy sector, both in renewables and other technologies.

Table 6. Negative binomial estimations. Dependent variable: 5-year forward citations (1990-2006)

	Negative Binomial		Negative Binomial *Backward_self_citations* omitted		Negative Binomial *Backward_others_citations* omitted	
	Renew. (1)	Other (2)	Renew. (3)	Other (4)	Renew. (5)	Other (6)
Non_patent_literature	0.0047** (0.0021)	0.0024 (0.0016)	0.0055*** (0.0021)	0.0032* (0.0017)	0.0126*** (0.0023)	0.0092*** (0.0019)
Backward_others_citations	0.0111*** (0.0018)	0.0152*** (0.0020)	0.0123*** (0.0018)	0.0170*** (0.0019)		
Backward_self_citations	0.0231*** (0.0060)	0.0445*** (0.0079)			0.0318*** (0.0065)	0.0568*** (0.0080)
Ccollaboration_firm	0.0720 (0.0570)	-0.0860 (0.0568)	0.0725 (0.0567)	-0.0879 (0.0569)	0.0731 (0.0567)	-0.0778 (0.0565)
Collaboration_university	0.3676* (0.2207)	-0.8377** (0.3957)	0.3651* (0.2175)	-0.8840** (0.3964)	0.3041 (0.2104)	-0.7812** (0.3945)
Previous_experience	0.0511*** (0.0109)	0.0686*** (0.0096)	0.0569*** (0.0107)	0.0791*** (0.0093)	0.0468*** (0.0109)	0.0602*** (0.0093)
Family_size	0.0468*** (0.0092)	-0.0004 (0.0088)	0.0469*** (0.0092)	0.0005 (0.0088)	0.0517*** (0.0092)	0.0009 (0.0088)
Claims	0.0187*** (0.0019)	0.0320*** (0.0022)	0.0189*** (0.0019)	0.0329*** (0.0021)	0.0204*** (0.0019)	0.0353*** (0.0021)
Inventors	0.0449*** (0.0145)	0.0503*** (0.0119)	0.0451*** (0.0145)	0.0511*** (0.0119)	0.0490*** (0.0145)	0.0524*** (0.0116)
Original	0.5039*** (0.1289)	1.0320*** (0.1462)	0.5201*** (0.1283)	1.0376*** (0.1465)	0.5170*** (0.1284)	1.0979*** (0.1457)
Scope	0.0490*** (0.0153)	0.0625*** (0.0160)	0.0501*** (0.0153)	0.0613*** (0.0160)	0.0515*** (0.0152)	0.0704*** (0.0157)
US_JP	0.0809 (0.0933)	0.6745*** (0.0731)	0.0741 (0.0931)	0.6801*** (0.0730)	0.1012 (0.0936)	0.6904*** (0.0735)
Stock	0.0340 (0.2117)	-2.7247*** (0.6258)	0.0404 (0.2117)	-2.7627*** (0.6260)	-0.0127 (0.2126)	-2.6944*** (0.6173)
_cons	-1.4396 (1.6464)	23.1848*** (5.9100)	-1.4969 (1.6457)	23.5537*** (5.9110)	-1.0962 (1.6491)	22.8783*** (5.8284)
Time dummies	YES	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES	YES
lnalpha	1.2641*** (-0.0302)	1.6633*** (-0.0243)	1.2667*** (-0.0301)	1.6672*** (-0.0243)	1.2723*** (-0.0301)	1.6734*** (-0.0241)
No. obs.	5900	19343	5900	19343	5900	19343
pseudo R^2	0.044	0.058	0.043	0.058	0.043	0.057
Log-likelihood	-10825.3080	-21385.0997	-10828.4833	-21396.5387	-10836.3758	-21409.9299
Wald chi2	1147.9718***	1759.5052***	1136.2801***	1695.8557***	1079.6083***	1705.5769***

Standard errors are given in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Additionally, several differences across renewables and other technologies are also observed. There is a negative effect of co-ownership with universities and a positive effect of triadic families on knowledge diffusion within 5 years for other energy technologies, but this effect does not hold for renewable energy technologies. The stock of knowledge in the energy sector is only relevant in fossil and nuclear technologies, which exerts a negative effect on the number of citations thus suggesting that the competition effect for citations is greater than the size effect. In contrast, family size only increases the impact of renewable patented technologies since it is not relevant for the diffusion of other energy technologies.

4.3. Robustness checks

In addition to the sensitivity analysis provided in the previous section, we estimate the models using the number of 3-year forward patent citations as a dependent variable (Table 7). Given the shorter 3-year citation window, we extend the period of the sample used in the estimations until 2009.

The results of the alternative specifications included in Table 7 largely mirror the results from the main models in Table 6 regarding the principal conclusions. However, one notable result can be observed: the coefficient of coownership (either with universities or firms) is negative and significant in other energy patents, which strongly supports the conclusion that co-patenting with other companies or universities significantly hinders the diffusion of knowledge in the 3-year shorter run for fossil and nuclear technologies. The effect of co-ownership on the diffusion of renewable patented technologies remains insignificant.

Table 7. Negative binomial estimations. Dependent variable: 3-year forward citations (1990-2008)

	Negative Binomial		Negative Binomial *Backward_self_citations* omitted		Negative Binomial *Backward_others_citations* omitted	
	Renew. (7)	Other (8)	Renew. (9)	Other (10)	Renew. (11)	Other (12)
Non_patent_literature	0.0051**	0.0044*	0.0056**	0.0053**	0.0151***	0.0111***
	(0.0021)	(0.0023)	(0.0022)	(0.0023)	(0.0023)	(0.0023)
Backward_others_citations	0.0119***	0.0164***	0.0135***	0.0185***		
	(0.0020)	(0.0028)	(0.0020)	(0.0027)		
Backward_self_citations	0.0265***	0.0497***			0.0388***	0.0645***
	(0.0086)	(0.0117)			(0.0086)	(0.0116)
Collaboration_firm	0.0848	-0.2808***	0.0767	-0.2738***	0.0960	-0.2683***
	(0.0724)	(0.0902)	(0.0721)	(0.0903)	(0.0722)	(0.0897)
Collaboration_university	0.4288	-1.5744***	0.4162	-1.6640***	0.3765	-1.4455**
	(0.3205)	(0.6093)	(0.3203)	(0.5993)	(0.3137)	(0.6225)
Previous_experience	0.0248*	0.0576***	0.0306**	0.0698***	0.0202	0.0468***
	(0.0134)	(0.0146)	(0.0133)	(0.0140)	(0.0134)	(0.0140)
Family_size	0.0441***	0.0088	0.0446***	0.0086	0.0474***	0.0090
	(0.0114)	(0.0169)	(0.0114)	(0.0169)	(0.0114)	(0.0169)
Claims	0.0186***	0.0310***	0.0189***	0.0319***	0.0209***	0.0355***
	(0.0024)	(0.0032)	(0.0023)	(0.0032)	(0.0024)	(0.0031)
Inventors	0.0613***	0.0828***	0.0608***	0.0831***	0.0650***	0.0847***
	(0.0186)	(0.0172)	(0.0186)	(0.0173)	(0.0185)	(0.0170)
Original	0.5433***	1.3965***	0.5511***	1.3878***	0.5694***	1.4685***
	(0.1632)	(0.2392)	(0.1624)	(0.2401)	(0.1629)	(0.2381)
Scope	0.0766***	0.0986***	0.0786***	0.0975***	0.0810***	0.1040***
	(0.0188)	(0.0236)	(0.0188)	(0.0235)	(0.0186)	(0.0233)
US_JP	-0.0313	0.5014***	-0.0405	0.5074***	-0.0082	0.5247***
	(0.0967)	(0.1096)	(0.0972)	(0.1097)	(0.0961)	(0.1096)
Stock	-0.1859	-2.0636**	-0.1752	-2.0957**	-0.2129	-2.0958**
	(0.1975)	(0.9137)	(0.1967)	(0.9206)	(0.1969)	(0.8987)
_cons	-0.1174	16.0783*	-0.2027	16.4102*	0.0608	16.2942*
	(1.5700)	(8.5704)	(1.5639)	(8.6335)	(1.5655)	(8.4271)
Time dummies	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
lnalpha	2.0534***	2.7004***	2.0552***	2.7031***	2.0605***	2.7096***
	(0.0297)	(0.0308)	(0.0296)	(0.0308)	(0.0296)	(0.0304)
No. obs.	8559	22256	8559	22256	8559	22256
pseudo R^2	0.0371	0.0460	0.0368	0.0456	0.0363	0.0451
Log-likelihood	-10496.1332	-13775.3583	-10498.5317	-13781.0434	-10504.6038	-13789.0086
Wald chi2	37333.4499***	936.0816***	34582.4743***	890.6581***	37490.0924***	916.8443***

Robust standard errors are given in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8 presents ordinary least squares regression models based on logarithmised citations, both for 5-year forward citations and 3-year forward citations. Due to the limited space, only the re-calculation of models 1, 2, 7, and 8 are presented (those including *Backward_self_citations* and *Backward_others_citations*). The comparison of the results of these models with those of the negative binomial regression models largely confirms the robustness of our results.

Table 8. Ordinary least squares regression models based on logarithmised citation data

	Dependent variable: 5-year forward citation		Dependent variable: 3-year forward citation	
	Renew. (13)	Other (14)	Renew. (15)	Other (16)
Non_patent_Literature	0.0040^{**} (0.0017)	0.0038^{***} (0.0009)	0.0048^{***} (0.0018)	0.0033^{***} (0.0010)
Backward_others_citations	0.0089^{***} (0.0013)	0.0081^{***} (0.0009)	0.0062^{***} (0.0012)	0.0045^{***} (0.0007)
Backward_self_citations	0.0264^{***} (0.0050)	0.0187^{***} (0.0047)	0.0134^{**} (0.0054)	0.0092^{***} (0.0028)
Collaboration_firm	0.0007 (0.0269)	-0.0166 (0.0107)	-0.0251 (0.0204)	-0.0260^{***} (0.0077)
Collaboration_university	0.0987 (0.1542)	-0.2105^{*} (0.1098)	-0.0170 (0.1148)	-0.1285^{*} (0.0703)
Previous_experience	0.0332^{***} (0.0056)	0.0272^{***} (0.0022)	0.0153^{***} (0.0039)	0.0111^{***} (0.0016)
Family_size	0.0187^{***} (0.0045)	-0.0059^{***} (0.0016)	0.0106^{***} (0.0035)	-0.0033^{***} (0.0011)
Claims	0.0082^{***} (0.0010)	0.0091^{***} (0.0008)	0.0048^{***} (0.0009)	0.0047^{***} (0.0006)
Inventors	0.0165^{**} (0.0071)	0.0146^{***} (0.0031)	0.0171^{***} (0.0055)	0.0120^{***} (0.0024)
Original	0.1201^{**} (0.0511)	0.0974^{***} (0.0205)	0.0781^{**} (0.0377)	0.0552^{***} (0.0142)
Scope	0.0415^{***} (0.0094)	0.0217^{***} (0.0040)	0.0289^{***} (0.0074)	0.0141^{***} (0.0029)
US_JP	0.0513 (0.0364)	0.1244^{***} (0.0112)	-0.0088 (0.0260)	0.0503^{***} (0.0080)
Stock	0.1724^{**} (0.0819)	0.2482^{***} (0.0487)	0.1165^{**} (0.0524)	0.1414^{***} (0.0286)
_cons	-1.8292^{***} (0.5577)	-2.4501^{***} (0.4736)	-1.0180^{***} (0.3607)	-1.4699^{***} (0.2788)
Time dummies	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES
No. obs.	5900	19343	8559	22256
R2	0.2165	0.1593	0.1302	0.0803
F test	54.53***	126.14***	39.78***	52.25***

Robust standard errors are given in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Discussion

In this section, we focus on the implications of the effects found for the main variables of our study, namely those related to external knowledge sourcing, which have been the focus of our hypotheses: scientific citations, patent citations and co-ownership with other firms and universities.

Non-patent literature citation exerts a positive effect on knowledge diffusion of renewables and other energy technologies, which confirms Hypothesis 1 and is in line with the literature that signals the increasing importance of science for energy innovations, specially in the renewables sector (Hötte et al., 2021; Perrons et al., 2021). These findings are consistent with the "linear model" of innovation, which argues that scientists work to advance understanding, but that such advances may underlie practical applications, often in indirect or unexpected ways (Ahmadpoor & Jones, 2017).

We found a positive effect of backward patent citations both to self-owned patents and other companies in knowledge diffusion, thus supporting Hypothesis 2 and Hypothesis 3. This result confirms the path dependancy and cumulative nature of knowledge and supports the reasoning that a large number of backward citations indicates a strong technological base, which is associated with patents of a more valuable nature (Harhoff et al., 2003; Harhoff & Wagner, 2009; Lee & Sohn, 2017).

Hypothesis 4 and Hypothesis 5 on the positive effect of co-ownership on diffusion are rejected in all models. However, our results are sector- and/or time-dependant. For renewable energy patents, the effect of co-ownership with other firms and universities is not significant. This is in line with the general evidence provided by Belderbos et al. (2014) and partially in line with Briggs (2015), who obtained similar results when using forward patent citations within three years, but found a positive effect of co-ownership with universities on quality when using total forward citations over the whole life of the patent. In contrast, for other technologies, the effect of co-ownership with universities and other firms is significant in the 3-year diffusion window, which indicates that co-patenting hinders the diffusion of other energy technologies in the shorter run. Co-patenting with universities also has a negative effect on 5-year forward citations received by other technologies. Although our data provides no clues as to the underlying mechanisms motivating these results, the contribution of Peeters et al. (2020) is relevant here. They found a negative effect of co-patenting with universities on forward citations for exploitative trajectories, which they justify because riskier trajectories are more likely to be outsourced. Although the exploitative or exploratory nature of each individual patent remains unexamined, it is well known that fossil and nuclear technologies are in a more mature stage than are renewables, which remain in a more exploitative phase: this could explain the negative effect of co-patenting for this sector.

6. Conclusions and policy implications

Innovation in energy technologies is required for the reduction of the enviromental impact of power production. Therefore, ascertaining the factors that affect the diffusion of technology is essential. This paper contributes towards identifying the factors that affect the diffusion of patented technology in the energy sector. The empirical analysis is based on forward patent citations.

Our descriptive analysis shows an increasing trend towards innovation in renewable energy technologies from 1990 to 2011, the latest full year of our sample. Our data also confirms the relevance of renewable technologies in terms of the number of forward citations. Since inventions from renewable energy technologies are more frequently cited than other technologies, their knowledge is better distributed and environmental improvement is therefore encouraged.

The objective of our econometric model is to determine the factors affecting knowledge diffusion in the energy sector, by focusing on the role of non-patent literature citations, backward patent citations, and co-ownership of patents. Certain similarities are found in the factors affecting forward citations between renewables and other patented technologies: backward citations to other patents, backward self-citations, co-inventorship, claims, scope, originality, previous experience of the applicant in energy technologies, and non-patent literature all exert a positive effect on knowledge diffusion. However, certain differences across sectors can also be found. Family size is a significant variable in enabling the diffusion of renewable energy technologies, while triadic families exert a positive effect only in the diffusion of other technologies. An accumulated stock of knowledge negatively affects the number of forward citations of patented inventions in fossil and nuclear technologies. Interestingly, we find that co-ownership with other firms or universities is not significant for the diffusion of renewable energy technologies. In contrast, when focusing on other technologies, co-ownership with universities hinders the diffusion of innovations. It is also found that co-ownership with other firms negatively affects the diffusion of other energy technologies but only in the shorter 3-year term.

The analysis offered several practical implications for policy-makers and firms. Our results show that patents more extensively based on scientific knowledge diffuse more readily, thereby enhancing the development of future innovations. For firms, this result highlights the importance of strengthening their scientific base through, for example, the incorporation of scientists into their research teams. Innovation policies could therefore be oriented towards creating incentives for this incorporation. Furthermore, this result, together with the positive effect of backward citations to other patents, justify initiatives oriented towards the creation of knowledge pools of patents and scientific papers related to research on energy technologies in order to enhance knowledge accessibility and the retrieval of potentially interesting information in this line of research. For example, the IPC Green Inventory, which facilitates searches for patent information relating to Environmentally Sound Technologies (ESTs), constitutes a well-justified initiative according to our results. Similar initiatives could also be addressed for the creation of a pool of publicly available scientific papers that would provide a scientific base for the development of further clean technologies.

Our results also show that co-ownership with other firms or universities may hinder the diffusion of fossil and nuclear patented technologies, while it exerts a negligible effect on the diffusion of renewable energy technologies. From the perspective of the firm, this finding is relevant because technological impact of the research is related to firm performance (e.g., Kim et al., 2018). Additionally, our results do not provide support for public or firm initiatives supporting co-patenting strategies if the objective involves theenhancement of the diffusion of patented technologies. In contrast, the role of co-inventorship is clear both in renewables and other technologies, and hence company strategies and policies oriented towards the formation of research teams are preferred over the facilitation of the R&D co-patenting strategies.

This paper presents several limitations. First, despite the widespread use of patent citations as indicators of knowledge diffusion, its use is not without limitations since knowledge diffusion is a complex proccess that can be measured through a variety of indicators. Second, not all collaborative efforts result in the co-ownership of a patent, and hence the conclusions cannot be extended to include all collaboration in R&D. Third, the geographical or sectoral profile of the co-assignee remains to be analysed, which could shed light on the characteristics of collaborations of a more successful nature. Fourth, data on knowledge diffusion is truncated (citations are measured at a point in time) and diffusion in longer time windows has yet to be explored. These limitations could be addressed in further research.

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CHAPTER 5:

Knowledge path dependence in energy innovation: the role of spillovers and green absorptive capacity in renewable and non-renewable technology (Article 2)

Coronado, D., Ferrándiz, E., & Medina, J. (2026). Knowledge path dependence in energy innovation: the role of spillovers and green absorptive capacity in renewable and non-renewable technology diffusion. *Eurasian Business Review*, 1-35.

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Knowledge Path Dependence in Energy Innovation: The Role of Spillovers and Green Absorptive Capacity in Renewable and Non-Renewable Technology Diffusion

Abstract

The innovation and diffusion of renewable energy technologies are critical to advancing the energy transition. This study investigates how knowledge acquisition through spillovers from renewable and non-renewable patented technologies affects the subsequent diffusion of these technologies. Using a dataset comprising 12,966 renewable energy patent families and 24,067 non-renewable (fossil fuel-based) patents owned by firms between 1990 and 2010, we analyse backward citations as indicators of knowledge spillovers and forward citations to trace knowledge diffusion. We classify spillovers into three types: clean spillovers, dirty spillovers, and external spillovers (originating from non-energy fields). Our results show that, for renewable technologies, clean spillovers have a positive and significant effect on diffusion, while dirty spillovers hinder it, indicating a clean knowledge path dependence. In contrast, for non-renewable technologies, dirty spillovers significantly promote diffusion toward other non-renewable technologies, confirming a dirty knowledge path dependence. Green absorptive capacity does not moderate spillovers in the case of renewables, but it does reduce the influence of non-renewable spillovers on the diffusion of dirty technologies. These findings have important implications for innovation policy and knowledge transfer mechanisms aimed at accelerating the energy transition.

Keywords

Knowledge path dependence, green absorptive capacity, renewable and non-renewable energy patents, knowledge spillovers, knowledge diffusion.

1. Introduction

Clean-energy technologies are not only a strategy for climate change mitigation (Abbas et al., 2022; Probst et al., 2021), but also a driver of sustainable economic growth (Hou et al., 2023; Dzwigol et al., 2023). Furthermore, the decarbonisation of economic activities is a key objective, particularly in the European Union, and it involves renewable energy technologies and efficiency improvements (Tian et al., 2022; Montresor and Vezzani, 2023). Thus, it becomes clear that the development and global diffusion of clean technologies is crucial to reducing environmental impact and achieving sustainable economic growth. However, the diffusion process of clean technologies is complex. This complexity extends to knowledge search and knowledge acquisition activities, which involve combining knowledge components to produce clean technologies with the potential to diffuse. Since a large part of knowledge acquisition occurs through spillovers, a key question in the diffusion process of clean-energy technology is whether the acquisition of technological knowledge from clean or dirty technology influences the diffusion of new clean technologies. But to what extent does knowledge path dependence exist in the production of energy technology? In this paper, we explore the relationship between knowledge acquisition from clean and dirty energy technologies via spillovers and its diffusion. Specifically, we assess whether spillovers confined to clean energy or dirty energy technologies impact the diffusion of renewable and non-renewable technologies, respectively. Furthermore, we consider the role of green absorptive capacity (GAC) as a moderating variable in the effect of spillovers on the diffusion of energy technology.

To identify the influence of spillovers on renewable technology diffusion, our theoretical framework builds on two key concepts: knowledge path dependence and spillovers. Knowledge path dependence of technological progress could explain the slow diffusion of green technology (Hötte, 2020). In a broad sense, the reason is probably that the dirty network infrastructure is already established, whereas clean infrastructure is still lacking. As a result, investing in improved methods for utilizing dirty technologies offers more and immediate and direct economic benefits than using clean technologies (Aghion et al., 2019). Furthermore, knowledge acquired through spillovers that occur within a same field reinforces the existing technological trajectories (Dosi, 1982). Thus, acquiring knowledge through spillovers on dirty technology creates knowledge path dependence that favours subsequent innovation in dirty technologies.

Building on these ideas, we propose that two distinct forms of path dependence may arise, depending on whether technologies rely on knowledge from clean or dirty energy fields and whether their diffusion occurs within renewable or non-renewable domains. Furthermore, we introduce the role of GAC as a moderating variable of spillovers to enhance technology diffusion in the energy field. To test these hypotheses, we analyse a dataset comprising 12,966 renewable energy patent families and 24,067 non-renewable (fossil-fuel energy) patents owned by firms during the period 1990–2010. We proxy knowledge spillovers through backward patent citations and the diffusion of technologies through forward patent citations. GAC is measured by the accumulated number of renewable energy patents filed by each firm. This metric provides insight into a firm's capacity to integrate and utilize renewable energy knowledge from spillovers.

This research makes two relevant contributions. First, we contribute to the literature on path dependence in economics. For instance, Popp (2002) highlights the substantial influence of energy prices and past knowledge stocks on the direction of innovation. Acemoglu (2016) explores the transition to clean technology both theoretically and empirically, emphasizing the impact of carbon taxes and research subsidies. Similarly, Aghion et al. (2016) provide empirical evidence on how carbon taxes shape the direction of technological change, identifying path dependence in the auto industry through the types of innovation (clean versus dirty) driven by aggregate spillovers. Our contribution to this literature lies in adopting a bibliometric approach to assess the degree of path dependence in renewable and non-renewable technologies.

Second, our paper contributes to the limited empirical literature addressing the role of knowledge spillovers in technological diffusion. Previous studies, such as Nemet (2012) and Nemet and Johnson (2012), have investigated the effects of inter-sectoral and intra-sectoral knowledge spillovers but do not adopt a sector-specific perspective on diffusion within the energy sector. Noailly and Shestalova (2017) examined the sectoral diffusion of renewable energy technologies to subsequent inventions, but did not explore the role of the knowledge base. Zhang et al. (2023) recently analysed the role of path dependence in radical innovation, finding that knowledge path dependence in public research institutes negatively affects radical innovation. However, their focus was on the radicalness of innovation rather than its diffusion. Finally, Battke et al. (2016) and Stephan et al. (2019) emphasized the critical role of spillovers in technological diffusion of battery patents, but the findings may not be generalized to the energy sector. In contrast, our paper examines the effect of spillovers on the trajectory of technological diffusion and explores the moderating role of GAC.

The remainder of the paper is structured as follows. Section 2 reviews the literature on the sources of knowledge for the energy transition. Section 3 presents the data and sources. Section 4 describes the variables and the model. The empirical estimation results are presented in Section 5. A discussion on these findings is presented in Section 6. Our main conclusions and policy implications are summarised in Section 7.

2. Literature review

2.1. Knowledge path dependence: from spillovers to the diffusion of renewable knowledge

Path dependence theory underscores the significant influence of historical choices and established capabilities on the trajectory of industries (David, 1997; Liu et al., 2024). In the innovation field, the path-dependent nature of innovative technologies can lead to the persistence of environmentally harmful technologies (Acemoglu et al., 2012), particularly when the stock of dirty technologies is high (Jin et al., 2024). As a consequence, path dependence may explain the slow diffusion and continued use of less efficient green technologies (Hötte, 2020; Jin et al., 2024). Fouquet (2016) claims that energy systems are highly path-dependent due to technological, infrastructural, institutional, and behavioural lock-ins. He illustrates with several examples the effects of path dependence.

For instance, it accounts for 60% of coal-fired power plant capacity in some US counties. Aghion et al. (2019) argue that path dependence occurs because knowledge production often concentrates in well-funded areas with established research communities, leading to a bias toward traditional, less sustainable technologies. Consequently, firms with a strong knowledge base in environmentally harmful technologies are more likely to continue innovating along these lines, rather than pursuing groundbreaking green technologies. Path dependence towards dirty technologies is further reinforced by the perceived risks associated with radical green innovation, which demands a distinct set of competencies compared to incremental green innovation (Chadha, 2011; Cecere et al., 2014).

In this paper we focus on knowledge path dependence. This concept is closely tied to the idea that effective learning occurs when new ideas are connected to existing knowledge (Cohen and Levinthal, 1990). As a result, inventors with a deep understanding of a specific technological field are better equipped to recognize, interpret, and assimilate related information (Cohen and Levinthal, 1990; Lazear, 2004). Knowledge spillovers play a crucial role in the diffusion and assimilation of knowledge, expanding the available sources of ideas for innovation. By drawing upon an enriched knowledge base, researchers and innovators can recombine existing ideas to produce novel solutions with a greater likelihood of diffusion. Consequently, a significant portion of the inventive output of a given period can be attributed to the recombination of knowledge from different periods and various sources. In this context, knowledge path dependence emerges as a process in which the acquisition of specialized knowledge in the development of innovative technologies fosters the diffusion of related knowledge.

According to the above arguments, path dependence can hinder the development of clean technologies, which relates to what David (1997) includes within a concept of path dependence related to an (environmental) inefficient outcome, especially for firms with a strong background in dirty technologies. In this context, knowledge spillovers arising from clean and dirty technologies play a significant role in shaping the trajectory towards clean technological innovation. The reason is that the public stock of knowledge accumulated through knowledge spillovers from past inventions constitutes a crucial input to generate new ideas (Caballero and Jaffe, 1993). Thus, knowledge path dependence suggests that firms, relying on a robust knowledge base in fossil fuels, are more likely to develop further dirty technologies. Conversely, a greater reliance on clean technologies can stimulate innovation in cleaner energy solutions.

Knowledge spillovers can be decomposed into three types: dirty spillovers, clean spillovers, and non-energy spillovers. Dirty spillovers take place when firms recombine knowledge related to fossil fuel technologies, whereas clean spillovers occur when firms use knowledge on renewable technologies to generate a renewable invention. Non-energy spillovers refer to the incorporation of external knowledge not related to any energy-technology field.

Building on the reasoning above, we define two types of knowledge path dependence: clean and dirty knowledge path dependence. The first emerges when the creation of clean technologies (renewables) depends on previous clean knowledge spillovers, which is then diffused to other renewable technologies. The second occurs when the development of dirty technologies (fossil-fuel technologies) relies on related dirty knowledge spillovers (from other fossil technologies), which is subsequently disseminated to other dirty technologies. These ideas are outlined in the following hypotheses:

H1. Technological knowledge spillovers from renewable energy technologies incorporated in renewable technology positively and significantly contribute to the diffusion of subsequent renewable energy knowledge.

H2. Technological knowledge spillovers from non-renewable technology absorbed by non-renewable patents positively and significantly influence the diffusion of non-renewable energy knowledge.

By testing H1 and H2, we can assess whether acquiring knowledge through spillovers generates knowledge path dependence within the energy sector. H1 corresponds to what we term clean knowledge path dependence (i.e., from renewable knowledge acquisition through spillovers to renewable technology diffusion), while H2 represents dirty knowledge path dependence (i.e., from non-renewable knowledge acquisition through spillovers to non-renewable technology diffusion).

2.2. The moderating role of green absorptive capacity on knowledge acquisition through renewable and non-renewable spillovers

In this section, we discuss whether absorptive capacity serves as a significant moderator in knowledge acquisition through renewable and non-renewable spillovers, and why this moderating role alters the intensity of knowledge diffusion. In other words, we explore the extent to which the firm's absorptive capacity can mitigate the knowledge path dependence for both clean and dirty technologies

According to the pioneering work of Cohen and Levinthal (1989), absorptive capacity is defined as the "firm's ability to identify, assimilate, and exploit knowledge from external sources", which "represents an important part of a firm's ability to create new knowledge" (Cohen and Levinthal, 1989). This ability to identify the relevance of new information, integrate it, and utilize it is heavily influenced by a firm's existing related knowledge (Cohen and Levinthal, 1990). Within this framework, the widely cited work by Zahra and George (2002) makes a distinction between potential and realized absorptive capacities: "Potential capacity comprises knowledge acquisition and assimilation capabilities, and realized capacity centres on knowledge transformation and exploitation" (Zahra and George, 2002). Our paper focuses on the realized capacity. If realized capacity affects the ability to recombine acquired knowledge, it is reasonable to assume that this capacity might also moderate the role of knowledge spillovers in facilitating knowledge diffusion. This is feasible since absorptive capacity offers a broader range of recombination options (Belenzon, 2012), which can, in turn, enhance the novelty of inventions and promote greater knowledge diffusion.

Applying these ideas to the recombination of spillovers from renewable and non-renewable technologies, we examine the moderating effect of absorptive capacity on knowledge diffusion in clean energy technologies. For this purpose, we use the concept of green absorptive capacity (Chen et al., 2014; Pacheco et al., 2018; Qu et al., 2022), which retains the original meaning of absorptive capacity but focuses on environmental domains (i.e., renewable energy production). The mechanism through which GAC may intensify the effect of spillovers on renewable energy diffusion is straightforward: firms with greater renewable absorptive capacity can more effectively assimilate and recombine renewable energy knowledge stemming from external sources. Since innovation is fundamentally a process of knowledge recombination, a greater ability to transform renewable knowledge from various origins should result in high-quality innovations (Moaniba et al., 2018) with stronger diffusion potential.

In other words, a strong absorptive capacity focused on renewable technologies amplifies the impact of spillovers from both clean and dirty technology. This ability is critical for leveraging technology from spillovers to develop breakthrough renewable energy technologies with great potential to be diffused. In contrast, GAC may weaken the influence of dirty spillovers on the diffusion of fossil technologies to other dirty technologies. This is because the recombination of knowledge from GAC and dirty spillovers could lead to the development of hybrid technologies (primarily dirty but incorporating renewable elements), which would have a reduced ability to diffuse into other fossil technologies.

These considerations lead us to the following hypotheses:

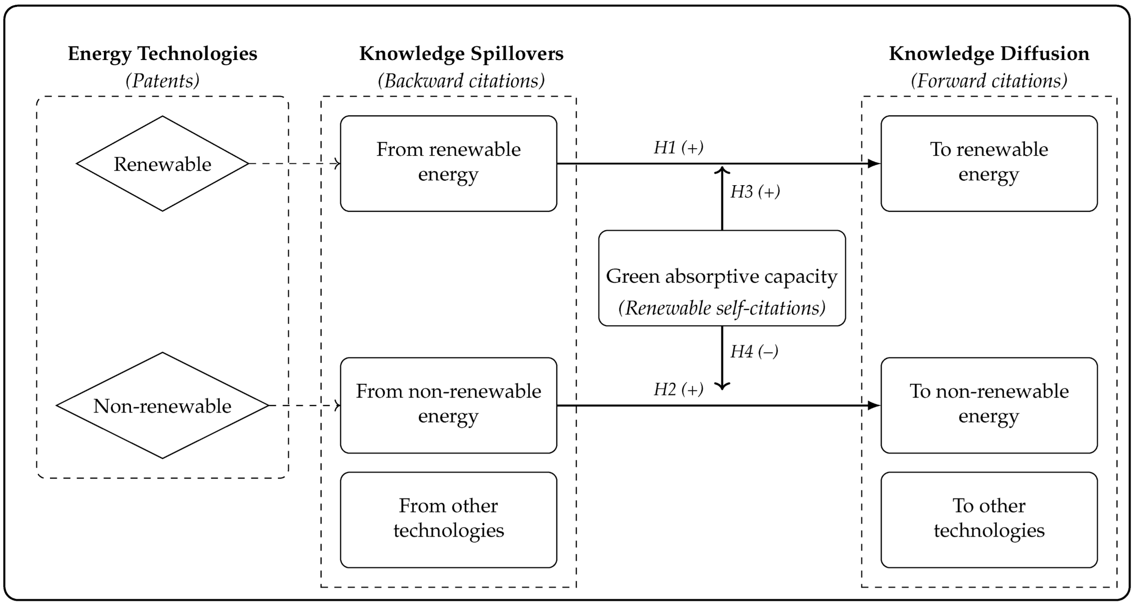
H3. Green absorptive capacity enhances the positive effect of renewable spillovers absorbed by renewable technologies towards the diffusion of renewable energy technologies.

H4. Green absorptive capacity negatively moderates the positive effect of non-renewable spillovers acquired by non-renewable technologies towards the diffusion of non-renewable energy technologies.

These two hypotheses extend and refine **H1** and **H2** by integrating the concept of GAC, defined as a firm's capability to identify, assimilate, and utilize renewable energy knowledge from external sources.

Figure 1 presents the conceptual framework, which examines how knowledge spillovers embedded in energy patents influence their diffusion, depending on the technological domain (renewable or non-renewable). Spillovers from renewable domains are expected to enhance the diffusion of renewable patents into subsequent renewable technologies (H1), while spillovers from non-renewable domains are hypothesized to facilitate the diffusion of non-renewable patents into other non-renewable technologies (H2). These effects reflect the technological path dependence of innovation processes. The model also incorporates the moderating role of GAC in shaping the impact of spillovers on the diffusion of renewable (H3) and non-renewable (H4) energy technologies. We limit our hypotheses to spillover effects within the same energy domain, in line with the path dependence perspective. However, spillovers across technological domains are included in the econometric models to account for all potential spillover effects. Diffusion beyond the energy sector is not analysed, as it falls outside the scope of this study.

Figure 1. Conceptual framework linking knowledge spillovers, green absorptive capacity (GAC), and technology diffusion under a path-dependence perspective.



Source: Own elaboration.

3. Data

To evaluate our hypotheses, we need a sample of energy patents (renewable and non-renewable), a measure of spillovers (from both renewable and non-renewable knowledge), and a metric for knowledge diffusion (towards both renewable and non-renewable energy). Additionally, it is essential to create an indicator of GAC, which serves as a moderating variable for spillovers.

To build our sample of energy patents, we use the DOCDB patent family as the unit of observation (for clarity, we refer to patent families simply as patents in subsequent sections), defined as the set of patents filed in several countries that are related to each other by one or more common priority filings (Albrecht et al., 2010). These simple families comprise all documents related to the same invention, but include only patent documents formally published as family members (Martínez, 2010). The technical content of these family applications is considered nearly identical; hence, their publications are sometimes referred to as equivalents (EPO Data Catalogue, 2017 Autumn Edition). By treating the patent family as the unit of analysis, we avoid multiple counting of applications for the same underlying invention (Fischer and Leidinger, 2014; Nesta et al., 2014). Our focus is on patent families with at least one protected application in the European Patent Office (EPO), as this helps filter the potentially most valuable inventions (Sapsalis et al., 2006).

The search for energy patents is based on the International Patent Classification (IPC) codes and enables renewable energy technologies to be distinguished from those that are non-renewable (fossil technologies). The IPC code is used instead of the Y02E code for renewable fields. This makes it possible to include inventions that, even if they do not have a climate change mitigation purpose, can contribute to the energy transition. To this end, several classification schemes are combined. For renewable energy technologies, we follow Noailly and Shestalova (2017) and rely on the identification of IPC codes related to renewable energy proposed by Johnstone et al. (2010). This allows us to classify renewable energy patents into eight distinct fields: wind, solar, geothermal, marine, hydroelectric, biomass, energy utilisation of solid waste, and energy storage. We followed Haščič et al. (2009) to identify fossil technologies. We will refer to these technologies as non-renewable energy technologies. Following this method, our database finally included detailed information on 12,966 renewable and 24,067 non-renewable energy patents worldwide applied for firms to the European Patent Office (EPO) during the period 1990-2010 (based on the priority date).

To capture knowledge spillovers from renewable and non-renewable energy sources, we rely on backward citations, which serve as indicators of reliance on prior knowledge (Jaffe and de Rassenfosse, 2017). The OECD Patent Statistics Manual (Zuniga et al., 2009, p. 109) defines backward patent citations as follows: "If a patent B cites patent A, it means that patent A represents a piece of previously existing knowledge upon which patent B builds or to which patent B relates, and over which B cannot have a claim." Thus, citations highlight knowledge that has played a meaningful role in the development of a patented invention.

Our measure of knowledge diffusion is the number of forward citations, defined as the citations a focal patent receives in subsequent patent applications. Although patent citations are an imperfect measure of information diffusion—since it can be difficult to distinguish between actual externalities and strategic knowledge transmission (Peri, 2003)—they are widely used in the literature to capture micro-level knowledge flows (Jaffe and Trajtenberg, 2002; Singh, 2004). Many authors have employed forward citations in environmental and energy technology studies as proxies for knowledge diffusion (Lovely and Popp, 2008; Popp, 2006; Acosta et al., 2009; Costantini et al., 2015; Verdolini and Galeotti, 2011).

A number of forward citations take place within the same family of patents, or to previous inventions of the same entity. Specifically, we identify self-citations as those citations made by a firm to their own previous inventions. In the count of citations, self-citations have been excluded to ensure an unbiased evaluation of technology diffusion (Hall et al., 2001; Hohberger, 2014). Our decision of excluding self-citations is based on the fact that citations between patents owned by the same assignee are typically considered less indicative of the broader dissemination of knowledge (Hall et al., 2001). Moreover, self-citations tend to follow different diffusion dynamics (Messeni-Petruzzelli et al., 2015; Hohberger, 2016).

To identify self-citations, we harmonized entity names following Eurostat (2011) guidelines: we group name variants that share the same legal form within a country, while maintaining separation across countries. To ensure citation comparability across patents and to focus on immediate knowledge diffusion, we count citations received within a 5-year window following the first publication date (as in Messeni-Petruzzelli et al., 2015; Hall and Helmers, 2013; Moaniba et al., 2018). This date reflects when knowledge enters the public domain (Hohberger, 2016) (for further methodological details, see De Rassenfosse et al., 2014; Squicciarini et al., 2013).

Using citations as a proxy for knowledge flows involves some limitations (Roach and Cohen, 2013; Jaffe and de Rassenfosse, 2017; Corsino et al., 2019). First, some citations are added by examiners rather than applicants, which may misrepresent true spillovers if the inventor was unaware of the cited work (Alcácer et al., 2009; Azagra-Caro and Tur, 2018). Second, citations to patents by the same applicant reflect internal knowledge accumulation, whereas non-self-citations better capture external spillovers. These issues are partly mitigated by excluding self-citations and examiner-added citations. Third, applicants may include or omit citations for strategic reasons (Corsino et al., 2019; Schuster and Valentine, 2022), potentially to increase their chances of patent approval. Unfortunately, our dataset does not include metadata to control for such strategic behaviour. Despite these limitations, validation studies conclude that while citations contain noise, they remain the most widely accepted measure of knowledge flows in economics, management, and policy research (Roach and Cohen, 2013).

Finally, to capture GAC, we draw on Cohen and Levinthal's (1989) foundational definition of absorptive capacity as “the development of a stock of prior knowledge”, in this case, related to renewable energy. Several proxies have been proposed (see Sancho-Zamora et al., 2021), including single-indicator and multidimensional approaches. In this paper, we adopt the self-citation-based measure introduced by Mancusi (2008) and used by subsequent studies (Aldieri et al., 2018; Li et al., 2020; Nicotra et al., 2014; de Almeida et al., 2021). This proxy is appropriate because self-citations reflect a firm's internal knowledge accumulation and its capacity to build on prior innovation. A higher cumulative number of self-citations per patent in a sector is interpreted as a sign of greater absorptive capacity.

To specifically measure GAC, we consider only backward self-citations to renewable energy patents, consistent with the methodology used by Li et al. (2020). The indicator is calculated as the cumulative number of self-citations made by a firm to its own renewable patents between 1990 and the priority year. If multiple companies are listed in a patent family, the measure includes the self-citations of each. We rely on self-citations because, as noted above, they align well with the concept of absorptive capacity and effectively capture the cumulative and path-dependent nature of innovation. Unlike broader indicators such as R&D expenditures, which reflect input efforts, self-citations directly indicate how a firm integrates previously developed internal knowledge into new innovations. Moreover, the use of patent self-citations as a proxy for absorptive capacity is well grounded in prior literature, as self-citations are strongly related to other key indicators such as internal R&D efforts. Mancusi (2008), for example, shows that self-citations effectively capture knowledge accumulation resulting from internal R&D, arguing that they reflect a firm’s ability to build upon and integrate its prior inventive activities, which is an essential dimension of absorptive capacity. This view is reinforced by Harris and Yan (2019), whose survey highlights that a firm’s ability to recognise, assimilate, transform, and apply external knowledge fundamentally depends on the level of its prior stock of knowledge, which in turn presupposes sustained investment in internal R&D and human capital. Consistently, Pereira de Almeida et al. (2021) argue that self-citations can serve as an indirect measure of the appropriability of R&D investment returns, thereby signalling the extent to which firms retain and reuse internally generated knowledge. From this perspective, self-citations not only align conceptually with absorptive capacity but also offer a practical and empirically validated indicator for large-scale patent-based analyses. Nevertheless, this measure captures only the internal and cumulative component of absorptive capacity and does not reflect other aspects such as the acquisition of external knowledge. As a result, one limitation of this measure is that it does not capture the multiple dimensions of absorptive capacity as do survey-based multidimensional indicators (Jiménez-Barrionuevo et al., 2011; Kastelli et al., 2024; Knoppen et al., 2022). However, survey-based data are generally limited in terms of sample size and time coverage, making them less suitable for the large-scale longitudinal analysis of technological innovation conducted in this study.

In addition, the construction of more comprehensive, multidimensional indicators of absorptive capacity is not feasible within the empirical framework of this study. Our analysis relies on disaggregated patent-level data covering thousands of firms over a long historical period (1990–2010). While this level of granularity is essential for tracing technological trajectories and knowledge spillovers over time, it also means that we do not observe complementary firm-level variables such as R&D expenditure, R&D intensity, human capital indicators, or collaboration patterns for the same sample, time span, or level of technological detail. Firm-level R&D datasets typically have limited coverage, shorter time horizons, and inconsistencies in firm identifiers, which makes it impossible to merge them reliably with global patent family data across multiple decades. Similarly, survey-based indicators of absorptive capacity are only available for small samples and short periods, and therefore cannot be integrated into a longitudinal panel of this scale. These data constraints make patent self-citations the only consistently available, standardised, and comparable indicator that can be constructed for all firms and technologies in our dataset, enabling a robust and coherent analysis of knowledge accumulation and absorptive capacity over time.

4. Variables and model

4.1. Variables

4.1.1. Dependent variables

We define two dependent variables to account for the path dependence of both renewable and non-renewable knowledge:

- *f_ren*. This variable captures knowledge diffusion within the renewable domain (diffusion to renewables from renewable energy patents). It is defined as the number of forward citations to renewable patents within five years after the first publication of the focal renewable patent family.
- *f_nren*. This variable captures knowledge diffusion within the non-renewable domain (to non-renewables from non-renewable energy patents). It is defined as the number of forward citations to non-renewable patents within five years after the first application of the focal non-renewable patent family.

4.1.2. Independent variables

4.1.2.1. Technological spillovers

In line with our theoretical framework, which categorizes spillovers based on their origin (renewables, non-renewables, and external sources from non-energy fields), we define three key independent variables:

- *b_ren*. This variable represents spillovers originating from prior renewable patents and is quantified by counting backward citations to renewable patents.
- *b_nren*. This variable reflects spillovers from earlier non-renewable patents, measured as the number of backward citations to non-renewable patents.
- *b_ext*. This variable accounts for spillovers from external fields unrelated to energy. It is measured by the number of backward citations to non-energy patents.

4.1.2.2. The moderating role of green absorptive capacity

The variable green absorptive capacity (gac) is constructed as the accumulated number of self-citations to a firm's own-renewable patents. For each renewable patent being analysed, we tally how many times the same firm that filed that patent has cited its own previous renewable patents. This cumulative count over time serves as a metric for the internal knowledge base and experience a firm has developed specifically in green technologies. We hypothesize that the variable ***gac*** will positively or negatively moderate these effects, depending on how the firm's established path dependence influences its ability to effectively leverage knowledge for technological diffusion. To capture this fact, we construct three interaction terms:

- *gac*b_ren.* Interaction between *gac* and *b_ren*.
- *gac*b_nren*. Interaction between *gac* and *b_nren*.
- *gac*b_ext.* Interaction between *gac* and *b_ext*.

4.1.2.3. Control variables

Along with the variables discussed earlier, it is essential to account for a set of control factors that may influence patent diffusion measured by forward citations. The type and number of such additional determinants can vary across studies depending on the goals of each study and the data accessibility. In our models, the following factors are considered:

- Institutional collaboration between applicants. To account for this type of collaboration, we include three dummy variables: *univ* (if a university appears among the applicants along with a firm); *gov* (if a government institution is listed among the applicants along with a firm); and *firm* (when at least two firms are listed as applicants, but there is no university or government institution). Networks enable access to complementary capabilities and support the creation of a more extensive knowledge base, leading to greater knowledge diffusion compared to innovations developed by isolated inventors. Belderbos et al. (2014) and Acosta et al. (2024) find that collaboration increases the number of forward citations.
- Firm experience (*exper*). Past experience in energy-related patenting is expected to be associated with greater knowledge diffusion. This assumption is based on the idea that teams with prior invention experience are likely to possess a robust knowledge base and refined practices that enhance diffusion. For example, according to Plank and Doblinger (2018), firms in the German renewable energy sector with strong technological capabilities and large patent portfolios tend to receive a higher number of follow-up citations.

- Number of claims (*claims*). The number of claims indicates the breadth of intellectual property protection. An invention with a greater range of claims is expected to receive more citations (Bessen, 2008; Nemet, 2012). We use the maximum number of claims in the patent family.
- Number of inventors (*ninv*). This is an indicator of collaborative effort and potentially the depth of expertise involved in the innovation process (Ma and Lee, 2008). Due to the synergies arising from diverse backgrounds, enhanced problem-solving capabilities, and complementary skills, inventions involving more inventors are expected to be more substantial and more frequently cited. We use the maximum number of inventors in the patent family.
- Number of countries of applicants' residence (*countries*). This variable proxies for international collaboration among assignees. Several studies show that international collaborations provide access to more diverse knowledge, leading to greater innovation impact (Su, 2022; Lino et al., 2021).
- Triadic patents (*eu_us_jp*). This is a dummy variable that captures whether the invention is protected in the European, US, and Japanese patent offices. Some studies suggest that patents filed in these major offices have greater impact (Moaniba et al., 2018).
- Family size (*size*). Patents are often filed in multiple jurisdictions to enhance protection. Family size refers to the number of different jurisdictions in which the same invention has been filed. Since only the most valuable inventions tend to be filed in multiple countries due to the high cost of protection, family size is a widely accepted proxy for patent impact (Fischer and Leidinger, 2014; Nesta et al., 2014). Therefore, a larger family size is associated with more citations.
- Technological scope (*scope*). This variable captures the number of distinct 4-digit IPC classes assigned to a patent. Broader technological scope is typically associated with more frequent citation, as such patents are relevant across multiple fields (Trajtenberg et al., 1997).

– Non-patent literature citations (*npl*). The number of references to non-patent literature reflects the degree to which scientific knowledge is used in the invention process (Ardito et al., 2016). Several studies suggest that citations to scientific literature may serve as indicators of science-based spillovers (Kim et al., 2018). However, the empirical literature reports mixed findings on how *npl* influences forward citations (Acosta et al., 2024).

Finally, our model also controls for year effects and sector effects, which for renewables include dummies for wind, solar, geothermal, marine, hydroelectric, biomass energy, energy utilization of solid waste, and energy storage.

4.2. Model

In order to specify and estimate the models, both the count nature of the dependent variable and the prevalence of zeros must be taken into account. A Poisson specification often provides the baseline regression for the modelling of a count variable:

$$\begin{aligned} f\_ren_i = \exp\Bigg(& \beta_0 + \beta_1 b\_ren_i + \beta_2 b\_nren_i + \beta_3 b\_ext_i + \beta_4 gac * b\_ren_i \\ & + \beta_5 gac * b\_nren_i + \beta_6 gac * b\_ext_i \\ & + \beta_4 univ_i + \beta_5 gov_i + \beta_6 firm_i + \beta_7 exper_i + \beta_8 claims_i \\ & + \beta_9 ninv_i + \beta_5 countries_i + \beta_6 eu\_us\_jp_i + \beta_7 fsize_i + \beta_8 scope_i \\ & + \beta_9 npl_i + \sum_{k=1}^{K-1} \lambda_k\, sector_{ik} + \sum_{t=1}^{T-1} \varphi_t\, year_{it} + \varepsilon_i \Bigg) \end{aligned}$$

where the dependent variable *f_ren* is the indicator of diffusion (forward patent citations to renewables within a 5-year window, excluding examiner and self-citations) and 'i' refers to the unit of analysis (patent family). The same model is specified for *f_nren* (non-renewables). We estimate regression models using both dependent variables.

When the data exhibit overdispersion, the Poisson model's standard errors become downward biased, leading to artificially inflated t-statistics (Cameron and Trivedi, 1986). The negative binomial (NB) model is the most commonly used approach to address overdispersion, as it assumes that the variance is a quadratic function of the mean (for a detailed explanation of the estimation process, see Cameron and Trivedi, 1998). As an alternative estimation strategy to ensure robustness, we also employ Poisson pseudo-maximum likelihood (PPML) estimators and zero-inflated models.

5. Results

5.1 Baseline results

Table 1 presents the variable definitions along with their descriptive statistics. The results show that renewable energy technologies receive an average of 1.4 forward citations from subsequent renewable patents, whereas non-renewable energy patents receive, on average, 0.66 forward citations from other non-renewable patents. Thus, renewable patents exhibit a higher degree of diffusion within their technological domain compared to the diffusion observed among non-renewable patents.

Furthermore, it is observed that both renewable and non-renewable energy patents rely significantly on external knowledge acquired through spillovers, though the patterns differ considerably. For renewable energy patents, the average value of *b_ren* (spillovers from renewables captured by backward citations) is 2.85, while the value of *b_nren* (spillovers from non-renewables) is only 0.21. Additionally, other external sectors contribute an average of 3.6 backward citations to the development of renewable patents. In contrast, for non-renewable energy patents, the average value of *b_ren* is only 0.10 citations per patent, whereas *b_nren* reaches 2.26. Other external sectors provide an average of 2.15 backward citations. These early descriptive results suggest the presence of knowledge path dependence: renewable patents draw heavily from renewable knowledge, whereas non-renewable patents rely primarily on non-renewable knowledge.

Tables 2 and 3 present the correlation matrices for the variables in the renewable and non-renewable models, respectively. The correlations between the key variables representing spillovers and the moderating effect of GAC are relatively low, indicating that multicollinearity is not a concern in our models.

Table 1. Summary of variable definitions and descriptive statistics.

Variable	Definition	Renewables (1)				Non-renewables (fossil) (2)			
Dependent variable		***Mean***	***Std. Dev.***	***Min.***	***Max.***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
f_ren	Diffusion to renewables. Number of forward citations to renewable energy patents within five years after the first application of the focal renewable patent family.	1.40	3.27	0	56				
f_nren	Diffusion to non-renewables (fossil). Number of forward citations to non-renewable energy patents within five years after the first application of the focal non-renewable patent family.					0.66	1.99	0	55
Independent variables ***Variables capturing spillovers***									
b_ren	Spillovers from renewables. Number of backward citations to renewable energy patents.	2.85	6.88	0	108	0.10	1.23	0	76
b_nren	Spillovers from non-renewables (fossil). Number of backward citations to non-renewable energy patents.	0.21	2.12	0	106	2.26	6.12	0	122
b_ext	Spillovers from other external fields. Number of backward citations to non-energy patents.	3.63	10.16	0	167	2.15	7.75	0	167
Interaction between spillovers and green absorptive capacity (GAC)									
*gac*b_ren*	Interaction between *gac* and *b_ren*	36.93	174.2	0	5,329	0.43	10.49	0	990
*gac*b_nren*	Interaction between *gac* and *b_nren*	0.80	11.13	0	656	13.30	140.29	0	6,566
*gac*b_ext*	Interaction between *gac* and *b_ext*	28.82	186.4	0	8,556	8.41	103.18	0	5,148
Other determinants of patent diffusion (patent characteristics)									
univ	Dummy=1 if the patent was co-applied for by a university.	0.01	0.10	0	1	0.01	0.05	0	1
gov	Dummy=1 if the patent was co-applied for by a government institution.	0.01	0.10	0	1	0.01	0.08	0	1
firm	Dummy=1 if the patent was co-applied for by another firm.	0.25	0.43	0	1	0.31	0.46	0	1
exper	Number of patents in the energy field that each firm had applied for before the focal patent.	956.3	2,535	1	16,417	1,503	3,119	1	19,516
claims	Maximum number of claims in the focal patent family.	14.19	12.77	0	199	13.60	10.83	0	373
ninv	Maximum number of inventors in the focal patent family.	2.63	1.82	0	21	2.62	1.79	0	26
countries	Number of countries of the applicants' residence.	1.19	0.46	1	5	1.14	0.42	1	8
eu_us_jp	Dummy if the patent is triadic.	0.85	0.36	0	1	0.84	0.37	0	1
fsize	Number of patents in the family.	5.09	2.97	1	30	5.25	3.34	1	33
scope	Number of different 4-digit subclasses of the IPC.	2.67	1.81	1	29	3.24	1.69	1	29
npl	Number of citations to non-patent literature.	3.40	11.21	0	301	1.91	8.22	0	389
Other control variables: *sector dummies, year dummies.*									

N. observations (renewable energy patent families): 12,966
N. observations (non-renewable energy patent families): 24,067
Source: PATSTAT and own elaboration.

Table 2. Correlations (variables included in renewable models)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. f_ren	1.000																	
2. b_ren	0.259	1.000																
3. b_nren	-0.006	0.114	1.000															
4. b_ext	0.105	0.487	0.151	1.000														
5. gac*b_ren	0.082	0.319	-0.003	0.107	1.000													
6. gac*b_nren	0.003	0.060	0.264	0.036	0.151	1.000												
7. gac*b_ext	0.053	0.188	0.001	0.297	0.509	0.106	1.000											
8. univ	0.009	0.033	0.000	0.048	-0.014	-0.007	-0.002	1.000										
9. gov	0.014	0.011	-0.001	0.028	-0.015	0.008	0.001	0.164	1.000									
10. firm	0.022	0.043	0.041	0.051	-0.052	-0.003	-0.014	0.004	0.021	1.000								
11. exper	0.066	-0.026	-0.006	-0.061	0.249	0.142	0.128	-0.028	-0.025	-0.094	1.000							
12. claims	0.149	0.234	0.090	0.278	0.091	0.024	0.097	0.037	0.017	0.041	0.002	1.000						
13. ninv	0.004	0.035	0.026	0.112	0.004	0.032	0.022	0.071	0.082	0.050	0.055	0.109	1.000					
14. countries	0.044	0.059	0.011	0.030	0.155	0.044	0.061	0.018	0.051	0.108	0.157	0.002	0.061	1.000				
15. eu_us_jp	0.018	0.050	0.019	0.082	0.005	0.011	0.015	0.013	0.007	0.043	0.045	0.074	0.079	-0.016	1.000			
16. fsize	0.116	0.151	0.053	0.142	0.011	0.018	0.036	0.013	0.043	0.237	-0.046	0.168	0.024	0.065	0.201	1.000		
17. scope	0.080	0.113	0.179	0.186	0.047	0.062	0.055	0.029	0.049	0.044	0.009	0.120	0.019	0.062	0.056	0.211	1.000	
18. npl	0.155	0.420	0.154	0.591	0.081	0.042	0.148	0.093	0.036	0.044	-0.046	0.289	0.097	0.020	0.061	0.115	0.169	1.000
N. observations (renewable energy patent families): 12,966																		

Table 3. Correlations (variables included in non-renewable models)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. f_nren	1.000																	
2. b_ren	0.076	1.000																
3. b_nren	0.209	0.232	1.000															
4. b_ext	0.079	0.182	0.371	1.000														
5. gac*b_ren	0.026	0.218	0.060	0.045	1.000													
6. gac*b_nren	0.013	0.020	0.157	0.028	0.298	1.000												
7. gac*b_ext	0.015	0.030	0.064	0.120	0.347	0.475	1.000											
8. univ	-0.005	0.022	0.014	0.020	-0.002	-0.004	-0.001	1.000										
9. gov	0.005	0.015	-0.009	-0.009	-0.002	-0.001	0.001	0.050	1.000									
10. firm	-0.008	0.008	0.019	0.019	-0.006	-0.029	-0.013	0.003	0.028	1.000								
11. exper	0.088	-0.019	0.004	-0.019	0.078	0.217	0.181	-0.004	-0.016	-0.156	1.000							
12. claims	0.160	0.077	0.232	0.237	0.023	0.025	0.033	-0.004	-0.009	0.040	0.013	1.000						
13. ninv	0.066	0.012	0.058	0.060	0.015	0.042	0.039	0.043	0.064	0.038	0.156	0.103	1.000					
14. countries	0.012	0.014	0.059	0.022	0.021	0.018	0.016	0.030	0.033	0.158	-0.055	-0.006	0.074	1.000				
15. eu_us_jp	0.068	0.014	0.059	0.063	-0.004	0.027	0.023	0.010	0.012	0.063	0.137	0.105	0.063	0.006	1.000			
16. fsize	0.019	0.025	0.076	0.077	-0.010	-0.024	-0.016	0.004	0.037	0.305	-0.075	0.157	0.050	0.116	0.209	1.000		
17. scope	0.058	0.108	0.152	0.261	0.021	0.042	0.068	0.026	0.020	0.075	0.033	0.173	0.098	0.063	0.154	0.231	1.000	
18. npl	0.089	0.185	0.224	0.412	0.043	0.026	0.033	0.008	-0.002	0.015	0.064	0.148	0.059	0.004	0.046	0.077	0.159	1.000
N. observations (non-renewable energy patent families): 24,067																		

Table 4 presents the negative binomial estimation results. The significant coefficient of *lnalpha* suggests overdispersion in the Poisson models, supporting the choice of the negative binomial model over the Poisson model. Furthermore, the variance inflation factors (VIFs) calculated across all models are below the conventional threshold, confirming that multicollinearity is not an issue. Models 1–4 show the results for the renewable[5] models, and Models 5–8 present the results for the non-renewable (fossil) models. To check the sensitivity of the coefficients, we report base models with only the key variables, followed by full models that include all control variables.

Focusing first on Models 1–4, Model 1 presents the estimation results for the key spillover variables, while Model 2 adds all control variables. Both models indicate that clean spillovers (from renewable energy technologies) exert a positive and significant effect on the diffusion of renewable technologies toward other renewables. In contrast, dirty spillovers (knowledge derived from fossil fuel technologies) have a negative and significant influence on the diffusion of renewable technologies. The signs and significance of these two coefficients suggest a pattern of clean path dependence in renewable energy. Green knowledge acquisition by renewable energy technologies promotes their diffusion, whereas the acquisition of dirty knowledge hinders it. This finding supports **H1**. Models 3 and 4 introduce the moderating effect of GAC. As shown in these models, the interaction terms are not statistically significant, indicating that GAC does not moderate the effect of spillovers on the diffusion of renewables. Consequently, our results do not provide support for **H3**.

Examining the specific effect of the variable *b_ren*, its coefficient in the complete model for renewables (Model 4) is 0.035. This value indicates that, on average, each additional backward citation to renewable energy patents within renewable patents increases the expected number of forward citations to renewables by approximately 3.5%. Conversely,

[5] Renewables include wind, solar, geothermal, marine, hydroelectric, biomass, energy utilization of solid waste, and energy storage. Non-renewables include only fossil technologies.

the coefficient for *b_nren* is –0.033, suggesting that each additional backward citation to non-renewable energy patents within renewable patents decreases forward citations to renewables by approximately 3.3%. This implies that while backward citations to renewables reinforce path dependence within renewable energy technologies, backward citations to non-renewables act as a barrier to clean energy diffusion. Given the similar magnitude but opposite signs of these two coefficients, relying equally on spillovers from renewable and non-renewable sources would result in a net-zero effect on the diffusion of renewable energy technologies.

Turning to the non-renewable models (Models 5–8), we apply the same structure as for the renewable models. Model 5 reports the estimation results for the key spillover variables, and Model 6 includes the control variables. The coefficient of *b_ren* is not statistically significant, indicating that spillovers from renewables do not contribute to the diffusion of non-renewable technologies. In contrast, the coefficient of *b_nren* is highly significant, showing that spillovers from non-renewables promote diffusion toward subsequent non-renewable technologies. This finding supports the knowledge path dependence of dirty technologies and aligns with **H2**. Models 7 and 8 introduce the moderating effect of GAC. In the complete Model 8, the interaction term between GAC and non-renewable spillovers (*gac*b_nren*) is negative and statistically significant. This result provides evidence of a moderating effect: GAC mitigates the positive impact of non-renewable spillovers on the diffusion of dirty technologies. This finding is consistent with the theoretical expectation of **H4**.

For both renewable and non-renewable technologies, the negative coefficient for *b_ext* suggests that an excessive reliance on knowledge from distant, non-energy fields can hinder diffusion within the same technological trajectory.

Table 4. Technology path dependence and the moderating role of green absorptive capacity. Negative binomial regressions.

	Renewables				Non-renewables (fossil)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
b_ren	0.0673***	0.0359***	0.0655***	0.0353***	0.0154	0.0047	0.0095	-0.0002
	(0.0042)	(0.0033)	(0.0044)	(0.0034)	(0.0114)	(0.0117)	(0.0122)	(0.0121)
b_nren	-0.0353***	-0.0366***	-0.0328***	-0.0335***	0.0753***	0.0496***	0.0761***	0.0510***
	(0.0105)	(0.0103)	(0.0111)	(0.0108)	(0.0045)	(0.0039)	(0.0045)	(0.0039)
b_ext	-0.0035*	-0.0058***	-0.0040*	-0.0063***	0.0028	-0.0075***	0.0024	-0.0076***
	(0.0020)	(0.0022)	(0.0022)	(0.0023)	(0.0026)	(0.0025)	(0.0026)	(0.0025)
*gac*b_ren*			0.0001	0.0001			0.0029	0.0029
			(0.0002)	(0.0001)			(0.0025)	(0.0020)
*gac*b_nren*			-0.0009	-0.0014			-0.0003	-0.0004***
			(0.0023)	(0.0019)			(0.0002)	(0.0001)
*gac*b_ext*			0.0001	0.0001			0.0002	0.0000
			(0.0002)	(0.0001)			(0.0002)	(0.0002)
univ		0.0228		0.0204		-0.7086*		-0.7077*
		(0.1870)		(0.1870)		(0.4224)		(0.4222)
gov		0.4577**		0.4590**		0.2657		0.2685
		(0.1817)		(0.1815)		(0.2110)		(0.2108)
firm		-0.0069		-0.0049		-0.0088		-0.0090
		(0.0424)		(0.0424)		(0.0423)		(0.0423)
exper		0.0001***		0.0001***		0.0001***		0.0001***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
claims		0.0157***		0.0157***		0.0269***		0.0269***
		(0.0016)		(0.0016)		(0.0019)		(0.0019)
ninv		0.0480***		0.0480***		0.0441***		0.0437***
		(0.0104)		(0.0104)		(0.0101)		(0.0101)
countries		0.0729*		0.0702*		0.0367		0.0394
		(0.0387)		(0.0389)		(0.0450)		(0.0450)
eu_us_jp		-0.0371		-0.0362		0.5060***		0.5058***
		(0.0516)		(0.0516)		(0.0535)		(0.0535)
fsize		0.0421***		0.0423***		0.0052		0.0052
		(0.0068)		(0.0068)		(0.0062)		(0.0062)
scope		0.0111		0.0110		-0.0184		-0.0179
		(0.0109)		(0.0109)		(0.0117)		(0.0117)
npl		0.0083***		0.0083***		0.0031		0.0030
		(0.0020)		(0.0020)		(0.0024)		(0.0024)
_cons	0.0766***	-2.5109***	0.0739***	-2.5131***	-0.6882***	-2.1588***	-0.6884***	-2.1466***
	(0.0226)	(0.1618)	(0.0226)	(0.1618)	(0.0214)	(0.1072)	(0.0214)	(0.1074)
Sector dummies	No	Yes	No	Yes	No	Yes	No	Yes
Year dummies	No	Yes	No	Yes	No	Yes	No	Yes
lnalpha	1.3985***	0.9910***	1.3979***	0.9907***	1.8580***	1.6493***	1.8573***	1.6476***
	(0.0215)	(0.0241)	(0.0215)	(0.0241)	(0.0206)	(0.0215)	(0.0206)	(0.0215)
Observations	12966	12966	12966	12966	24067	24067	24067	24067
Max. VIF	1.33	1.77	1.53	1.93	1.20	1.42	1.40	1.44
R^2_Adj	0.0134	0.0686	0.0135	0.0687	0.0129	0.0430	0.0130	0.0432
AIC				34803.53				43132.07
BIC				35154.62				43512.23
Log likelihood	-18383.93	-17355.75	-18382.44	-17354.76	-22201.29	-21523.48	-22199.31	-21519.03
LR chi2	500.55***	2556.92***	503.54***	2558.89***	579.31***	1934.93***	583.27***	1943.82***
Chi2_c	26451.1***	16564.7***	26439.1***	16557.3***	27475.2***	23045.7***	27453.2***	23009.3***

Dependent variables: f_ren: forward citation to renewables (5-year citation window), examiners' citations excluded (Models 1-4); fnon_ren: forward citation to non-renewables (5-year citation window), examiners' citations excluded (Models 5-8).
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

With respect to coefficient interpretation, the value of *b_nren* in the full non-renewable model (8) is 0.051. In the absence of GAC, this indicates that each additional backward citation to non-renewables within non-renewable patents is associated with an approximate 5.1% increase in expected forward citations. However, when GAC is taken into account, this estimate must be adjusted. Given the significant interaction coefficient between GAC and non-renewable spillovers (–0.0004), the marginal effect of non-renewable spillovers must be recalculated. Using the average value of *gac* among firms producing non-renewable energy technologies (3.21, measured as accumulated self-citations to renewables), the marginal effect of *b_nren* decreases slightly to approximately 4.9%.[6]

5.2 Robustness analysis

Our main findings are based on a negative binomial regression, which is particularly appropriate for overdispersed count data, where the variance exceeds the mean. To ensure the robustness of our results, we explored alternative model specifications. Given the characteristics of our dependent variable (the count of forward patent citations in both renewable and non-renewable energy) and the high proportion of zero values in the sample (ranging from 64% to 78%, depending on the energy type), we estimated three types of models for each patent group.

First, we employed the Pseudo Poisson pseudo-maximum likelihood (PPML) estimator, which is well-suited to our data structure. PPML consistently estimates the parameters of the conditional mean function, regardless of the actual form of the conditional distribution or the relationship between the conditional variance and mean (Wooldridge, 1999; Gourieroux et al., 1984). In other words, the PPML estimator performs reliably even when

[6]As an additional analysis, we re-estimated our models including forward self-citations. The results differ from those of our main models, confirming previous findings that self-citations follow distinct diffusion dynamics and do not reflect external knowledge flows (Hall et al., 2001; Messeni-Petruzzelli et al., 2015; Hohberger, 2016). Given our focus on inter-organizational diffusion, these results are not reported here but are available upon request.

the conditional variance does not closely track the conditional mean. Moreover, it is not adversely affected by the large proportion of zero observations in the dependent variable (Silva and Tenreyro, 2011).

Second, to account for the high number of zeros in the sample, we estimated zero-inflated models, specifically, the zero-inflated Poisson (ZIP) model (Lambert, 1992) and the zero-inflated negative binomial (ZINB) model (Heilbron, 1994). In these models, the zero-inflated distribution is interpreted as a finite mixture incorporating two sources of overdispersion: one due to excess zeros and another arising from unobserved heterogeneity among observations with positive counts.

The three alternative specifications for renewable energy patents are reported in Table 5 (Models 1–3). Model 1 presents the PPML estimates, while Models 2 and 3 correspond to the ZIP and ZINB models, respectively. In the zero-inflated models, we assume two distinct sources of overdispersion. The first captures individual heterogeneity among patents with positive citations, for which all explanatory variables are included. The second explains the excess zeros, modelled using patent-specific characteristics and the technological field within renewable energy.

The results from these alternative specifications (Models 1–3) consistently indicate that clean spillovers (knowledge flows originating from renewable energy technologies) have a positive and significant effect on the diffusion of renewable technologies to other renewable domains. In contrast, dirty spillovers (derived from fossil fuel technologies) have a negative and significant effect on diffusion. The signs and statistical significance of these coefficients confirm the existence of a clean path dependence in renewable energy technologies: the acquisition of green knowledge facilitates further diffusion within the renewable sector, whereas exposure to dirty knowledge constrains it.

Table 5. Technology path dependence and the moderating role of green absorptive capacity. Alternative specifications.

	Renewables					Non-renewables (fossil)				
		ZIP		ZINB		(4) PPML	ZIP		ZINB	
	(1) PPML	(2) Count (Poisson)	Inflate (Logit)	(3) Count (NegBin)	Inflate (Logit)		(5) Count (Poisson)	Inflate (Logit)	(6) Count (NegBin)	Inflate (Logit)
b_ren	0.0266***	0.0206***		0.0327***		0.0065	0.0038		0.0048	
	(0.0020)	(0.0018)		(0.0028)		(0.0151)	(0.0125)		(0.0107)	
b_nren	-0.0242**	-0.0235*		-0.0402***		0.0280***	0.0145***		0.0511***	
	(0.0118)	(0.0126)		(0.0100)		(0.0020)	(0.0018)		(0.0039)	
b_ext	-0.0041*	-0.0041*		-0.0050**		-0.0037*	-0.0040**		-0.0043*	
	(0.0023)	(0.0023)		(0.0020)		(0.0022)	(0.0019)		(0.0023)	
*gac*b_ren*	-0.0001	-0.0003***		-0.0002*		0.0025***	0.0013*		0.0027	
	(0.0001)	(0.0001)		(0.0001)		(0.0008)	(0.0007)		(0.0017)	
*gac*b_nren*	-0.0026	-0.0028*		-0.0028*		-0.0003***	-0.0004***		-0.0006***	
	(0.0016)	(0.0014)		(0.0017)		(0.0001)	(0.0001)		(0.0001)	
*gac*b_ext*	0.0000	0.0002**		0.0001		0.0000	-0.0000		0.0000	
	(0.0001)	(0.0001)		(0.0001)		(0.0002)	(0.0001)		(0.0002)	
univ	-0.1521	-0.1287	-0.2496	-0.1953	-0.7797	-0.6398*	-0.2876	0.3729	-0.5794	0.1992
	(0.2122)	(0.1808)	(0.2351)	(0.1984)	(0.5813)	(0.3798)	(0.2931)	(0.4568)	(0.4866)	(1.1024)
gov	0.5007***	0.4214***	-0.1099	0.5100***	0.2472	0.2146	0.3047	0.1144	0.2563	0.2120
	(0.1627)	(0.1242)	(0.2003)	(0.1958)	(0.3142)	(0.2390)	(0.1895)	(0.2017)	(0.2587)	(0.5277)
firm	-0.0241	0.0459	0.1435***	0.0939**	0.2950***	0.0058	0.0365	0.1017**	0.0192	0.1610
	(0.0477)	(0.0428)	(0.0494)	(0.0455)	(0.0768)	(0.0441)	(0.0438)	(0.0401)	(0.0521)	(0.1101)
exper	0.0001***	0.0001*	-0.0001***	0.0001**	-0.0001***	0.0001***	0.0001***	-0.0001***	0.0001***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
claims	0.0102***	0.0050***	-0.0157***	0.0083***	-0.0143***	0.0126***	0.0098***	-0.0229***	0.0147***	-0.0438***
	(0.0013)	(0.0011)	(0.0018)	(0.0016)	(0.0033)	(0.0020)	(0.0014)	(0.0018)	(0.0022)	(0.0077)
ninv	0.0344***	0.0164*	-0.0438***	0.0136	-0.0818***	0.0433***	0.0192*	-0.0409***	0.0036	-0.1461***
	(0.0096)	(0.0093)	(0.0120)	(0.0111)	(0.0228)	(0.0100)	(0.0103)	(0.0093)	(0.0137)	(0.0430)
countries	0.0495	-0.0353	-0.1743***	-0.0502	-0.3899***	0.0468	0.0197	-0.0814**	0.0191	-0.1204
	(0.0353)	(0.0336)	(0.0460)	(0.0379)	(0.0931)	(0.0455)	(0.0457)	(0.0408)	(0.0642)	(0.1634)
eu_us_jp	0.0048	0.0000	-0.0496	-0.0082	-0.0748	0.5005***	0.2890***	-0.2553***	0.3537***	-0.2502*
	(0.0525)	(0.0481)	(0.0592)	(0.0544)	(0.0997)	(0.0637)	(0.0681)	(0.0578)	(0.0738)	(0.1283)
fsize	0.0400***	0.0330***	-0.0300***	0.0485***	0.0021	-0.0036	-0.0031	0.0115**	-0.0123	-0.0023
	(0.0058)	(0.0056)	(0.0074)	(0.0074)	(0.0125)	(0.0061)	(0.0060)	(0.0057)	(0.0086)	(0.0206)
scope	0.0179	0.0242**	0.0029	0.0186	-0.0268	-0.0107	-0.0244**	-0.0605***	-0.0298**	-0.1457***
	(0.0111)	(0.0094)	(0.0126)	(0.0115)	(0.0227)	(0.0114)	(0.0098)	(0.0108)	(0.0134)	(0.0305)
npl	0.0057***	0.0043***	-0.0187***	0.0034**	-0.0485***	0.0039***	0.0022*	-0.0067***	0.0009	-0.0849***
	(0.0012)	(0.0011)	(0.0032)	(0.0014)	(0.0106)	(0.0013)	(0.0013)	(0.0020)	(0.0020)	(0.0270)
cons	-2.0549***	155.5404***		183.0600***		-1.9568***	1.1163		-0.4311	
	(0.1258)	(8.4547)		(13.9488)		(0.1065)	(8.0745)		(8.2121)	
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No
lnalpha				0.3316***					1.2733***	
				(0.0639)					(0.0723)	
Obs.	12966	12966		12966		24067	24067		24067	
Zero obs.	8,312 (64%)	8,312 (64%)		8,312 (64%)		18,837 (78%)	18,837 (78%)		18,837 (78%)	
AIC	51358.87	41071.65		35282.56		66137.35	48937.92		43575.05	
BIC	51702.5	41422.75		35641.13		66501.33	49309.99		43955.22	
Log likelih.	-25633.44	-20488.83		-17593.28		-33023.67	-24422.96		-21740.53	
LR chi2	2991.23***	922.64***		891.79***		2286.98***	287.15***		544.47***	

Dependent variables: f_ren: forward citation to renewables (5-year citation window), examiners' citations excluded (Models 1-3); fnon_ren: forward citation to non-renewables (5-year citation window), examiners' citations excluded (Models 4 - 6).
∗ p < 0.10; ∗∗ p < 0.05; ∗∗∗ p < 0.01.

Turning to the non-renewable energy models (Models 4–6 in Table 5), we apply the same estimation strategy as for renewable energy patents. These results show that the coefficient for *b_ren* is not statistically significant, indicating that spillovers from renewable technologies do not support the diffusion of non-renewable (dirty) technologies. By contrast, the coefficient for *b_nren* is highly significant, highlighting the strong effect of knowledge spillovers from non-renewable technologies in promoting diffusion within the non-renewable sector. These findings reinforce the presence of knowledge path dependence in dirty technologies. Furthermore, as in Model 8 of Table 4, the interaction term *gac*b_nren* remains negative and significant across the alternative specifications, confirming the moderating role of GAC in weakening the positive influence of non-renewable spillovers on the diffusion of dirty technologies.

While Tables 4 and 5 report the estimated coefficients from different count-data models, they are not directly comparable as these rely on different distributional assumptions and operate in different scales. For this reason, we do not interpret differences in their magnitudes across models. Instead, we use the alternative specifications in Table 5 solely as robustness checks, focusing on the stability of the signs and statistical significance of the key spillover and interaction terms. The consistency of these signs and significance levels across models confirms the robustness of our main findings in Table 4. Nonetheless, we retain the negative binomial regression as our preferred specification, given its theoretical appropriateness for overdispersed count data and its superior empirical fit (it presents the lowest AIC and BIC among all model alternatives).

Although backward citations necessarily refer to earlier inventions and therefore cannot be influenced by subsequent forward citations, endogeneity may still arise through omitted technological characteristics. High-quality, broad, or strategically significant patents tend to cite a larger body of prior art, reflecting the wider knowledge base on which they build, and they also tend to receive more forward citations because of their greater technological relevance. Thus, backward and forward citations may be correlated through unobserved dimensions of patent quality rather than purely through knowledge spillovers. To mitigate this concern, our spillover variables already exclude self-citations, and our models incorporate detailed controls for patent quality such as family size, number of claims, applicant category, technological field fixed effects, and application-year fixed effects, commonly used in the patent literature to absorb latent heterogeneity. Additionally, we consider firm patenting experience as a potential source of variation in backward citation behaviour, since more experienced applicants often cite more extensively due to greater legal and technological expertise. As firm experience may also directly influence patent quality –and thus forward citations– we include it as a control variable rather than as an instrument, in order to avoid violating the exclusion restriction.

While these measures substantially reduce potential bias, we acknowledge that fully identified causal strategies (e.g., instrumental variables or panel-data estimators) are not implementable with patent-level data of this scale. Patent datasets do not include firm-level variables such as R&D shocks, organisational changes, or policy-induced variation, which are typically required to construct valid instruments that satisfy the exclusion restriction. In addition, each patent appears only once in the dataset, which prevents the use of dynamic panel models or within–patent variation. Moreover, instruments constructed solely from patent characteristics would risk violating the exclusion restriction by directly affecting forward citations. For these reasons, causal identification designs are not feasible in this context, and our approach follows the reduced-form empirical tradition widely established in the innovation and patent-citation literature.

6. Discussion

This study explores the effect of technological spillovers and the moderating role of green absorptive capacity (GAC) on knowledge diffusion of energy technologies, from a path dependence perspective.

First, the findings provide evidence of path dependence in innovation (David, 1997; Liu et al., 2024), supporting **H1** and **H2**. We find that clean spillovers enhance the diffusion of renewable technologies into subsequent renewable innovations. Similarly, dirty spillovers promote the diffusion of non-renewable technologies within their own domain.

Furthermore, the negative effect of dirty spillovers on the diffusion of clean technologies supports prior findings that an established base in fossil fuel innovation creates carbon lock-ins that hinder the clean transition (Acemoglu et al., 2012; Jin et al., 2024). This partially aligns with the work of Noailly and Shestalova (2017), who observed a concentration of knowledge within energy technologies, with approximately two-thirds of renewable forward citations being intra-technological. Similarly, Battke et al. (2016) showed that specialized knowledge is more likely to contribute to intra-technology knowledge flows. While their estimated coefficient (0.094) is not directly comparable to ours (0.035) due to methodological differences, both results underscore the role of knowledge specialization in shaping diffusion patterns within the same technological domain.

Regarding cross-domain energy spillovers, our results show mixed effects for near and external knowledge. For renewable technologies, both non-renewable and external knowledge spillovers have negative effects on diffusion (–0.0335 and –0.0063, respectively). For non-renewable technologies, the influence of renewable knowledge spillovers is not statistically significant, while external knowledge has a negative and significant effect. Our findings are consistent with Battke et al. (2016), who found that an increase in peripheral knowledge was associated with a statistically significant decrease of 0.116 units in intra-technology knowledge flows. Interestingly, Nemet (2012) reported a contrasting result, finding that “near citations” had a negative effect on forward citations for energy patents, while “far citations” had a positive effect, suggesting that knowledge from more distant domains can enhance technological impact. However, in a broader study across various technologies, Nemet and Johnson (2012) found that “near” knowledge had a more pronounced and positive effect (0.0517) on the number of citations received, compared to external knowledge. This divergence may be explained by the idea that excessive technological proximity can lead to knowledge homogenization, reducing the potential for novel recombination (Guan & Yan, 2016). Likewise, although a greater "prior sectoral distance" may increase knowledge diversity, it does not always translate into higher innovation impact (Stephan et al., 2019), likely due to the difficulty of effectively applying highly distant knowledge. Moreover, “experience inertia” (Wang et al., 2017) may lead inventors to rely on existing knowledge, limiting the diffusion and integration of external knowledge, and potentially explaining the lack of significant cross-domain diffusion effects.

Second, we examined the moderating role of GAC on the relationship between technological spillovers and diffusion (**H3** and **H4**), and found mixed results. For renewable technologies, GAC does not moderate the effect of clean spillovers on renewable technology diffusion (**H3** not supported). That is, the diffusion of green technologies drawing on renewable knowledge appears to follow a consistent path, regardless of firms' GAC levels. For non-renewable technologies, GAC negatively moderates the effect of dirty spillovers on dirty technology diffusion (**H4** supported). This partially contrasts with the expectations of Chen et al. (2014) and Qu et al. (2022), who suggest that absorptive capacity typically amplifies the benefits of external knowledge. We argue that the key mechanism lies in technological alignment. In the case of clean spillovers, the trajectory of renewable innovation is already aligned with the knowledge base, reducing the need for additional GAC. This interpretation is consistent with previous findings that absorptive capacity is most critical when external knowledge diverges from a firm's internal knowledge base (Cohen & Levinthal, 1990; Zahra & George, 2002). In contrast, for non-renewable technologies, firms with high GAC may be able to recombine dirty knowledge with their own clean knowledge, thereby disrupting the dirty innovation trajectory and reducing the likelihood of further diffusion within that domain. This interpretation is consistent with the arguments of Pacheco et al. (2018) and Belenzon (2012), who contend that absorptive capacity expands the firm's recombination space and can influence the direction of innovation. In this context, absorptive capacity may act as a constraint on the diffusion of non-renewable technologies. Therefore, our results suggest that green absorptive capacity does not amplify the effect of green spillovers but does weaken the effect of dirty knowledge spillovers.

7. Conclusions

This paper aimed to investigate whether technological spillovers influence the diffusion of clean and dirty energy technologies and to what extent green absorptive capacity moderates this process within the context of path dependence. Given the growing concern to mitigate climate change and achieve sustainability goals, understanding the mechanisms that drive the production and diffusion of clean and dirty technologies in the energy sector is essential. Using a dataset comprising 12,966 renewable and 24,067 non-renewable energy patent families, this study analyses whether the type of knowledge employed in the development of energy technologies shapes diffusion pathways toward renewable or non-renewable domains. Additionally, we examine the moderating role of green absorptive capacity in this process. By drawing on a unique dataset of over 37,000 patent families across two decades, this study provides robust evidence on the long-term dynamics of knowledge diffusion in the energy sector.

Theoretically, our findings contribute to the literature on path dependence by discussing how spillover origins shape technological trajectories in energy innovation. Additionally, the differentiated role of green absorptive capacity provides new insights into how internal capabilities interact with external knowledge in clean and dirty innovation contexts. In line with theoretical expectations, we identify two key empirical findings. First, the results confirm the existence of knowledge path dependence in both renewable and non-renewable energy technologies. Specifically, a strong reliance on clean spillovers within renewable technologies significantly enhances their diffusion to subsequent renewable innovations. Conversely, non-renewable technologies that depend predominantly on dirty spillovers exhibit a marked tendency to diffuse toward other non-renewable technologies. These findings highlight how spillovers help shape the trajectories along which technologies evolve.

Second, our results reveal that green absorptive capacity (GAC) plays a differentiated role depending on its technological alignment with the knowledge spillovers. For renewable technologies, GAC does not amplify the effect of clean spillovers on diffusion toward other renewables. This may be due to the close cognitive and strategic alignment between the external spillovers and the renewable innovation trajectory, which reduces the need for firms to rely on internal capabilities to interpret or assimilate this knowledge. Importantly, the absence of a moderating effect does not imply that GAC is irrelevant in the context of renewable innovation. Rather, GAC may still play a crucial role in enabling firms to generate green innovations and identify and assimilate external knowledge. In contrast, for non-renewable technologies, we find that higher levels of GAC weaken the extent to which dirty spillovers contribute to further diffusion. This suggests that GAC may act as a barrier, reducing the influence of non-renewable spillovers on the persistence of dirty technologies.

Relevant policy implications derive from our results. Given the diversity of global energy policies, and the need to situate policy recommendations within a coherent governance framework, we focus our discussion on the European Union, whose integrated clean-energy strategy provides a consistent and relevant context for interpreting our results. The EU combines regulatory instruments, long-term strategic planning, and coordinated research and innovation (R&I) agendas, offering a policy environment in which the spillover-driven mechanisms identified in this study can be meaningfully connected to specific instruments and ongoing initiatives.

We find that spillovers from renewable inventions foster further diffusion within renewable domains, whereas spillovers from fossil technologies hinder it. This pattern strongly supports the non-neutral orientation of current EU strategies, including the European Green Deal, which seeks to accelerate the deployment of renewables while reducing dependence on fossil fuels. The revised Strategic Energy Technology (SET) Plan explicitly seeks to make the EU “world number one” in renewables, objective pursued through coordinated clean-energy research and innovation (R&I) agendas and joint programming via instruments such as the Clean Energy Transition Partnership. Our results provide an additional rationale for this policy architecture: concentrating R&I support on renewable and enabling technologies not only yields direct technological and emissions benefits, but also expands the underlying stock of green knowledge that generates self-reinforcing clean spillovers, making subsequent renewable diffusion progressively easier. At the same time, REPowerEU's emphasis on avoiding new fossil-fuel lock-ins and limiting additional gas and oil infrastructure to what is strictly necessary is consistent with our finding that exposure to dirty knowledge strengthens fossil innovation trajectories and crowds out clean diffusion. These insights also point to areas where future policy could evolve, for example by tailoring R&I funding criteria to reward projects with demonstrable potential to generate strong clean spillovers, by screening publicly funded research for the risk of reinforcing fossil innovation paths, or by establishing EU "clean knowledge hubs" that intentionally channel expertise and data across renewable sectors to amplify positive spillover dynamics.

The moderating role of green absorptive capacity (GAC) has further implications for capability-building policies within the EU. Since GAC does not amplify the effect of clean spillovers, but does weaken the reinforcing effect of dirty spillovers in fossil-based technologies, capability-building measures should prioritise firms and sectors still embedded in carbon-intensive trajectories. This orientation is strongly reflected in current EU initiatives. The revised SET Plan places major emphasis on upskilling and reskilling, including large-scale green-skills partnerships that aim to create deep-tech talent and strengthen firms' ability to integrate and apply green knowledge. REPowerEU similarly calls for dedicated skills partnerships in renewable technologies and new training programmes to build the competencies needed for the hydrogen economy. Together, these measures expand firms' and workers' capacity to adopt and recombine renewable knowledge, thereby helping incumbent fossil-intensive sectors pivot away from dirty innovation paths. From our findings, capability-building policies could be further enhanced by introducing diagnostic tools that help firms assess their internal green knowledge base, by providing targeted support for incumbents that commit to strengthening their clean R&D capabilities, and by creating opportunities for temporary placements or exchanges that allow engineers and researchers from fossil-intensive sectors to work directly with leading clean-technology teams.

Our results also point to the relevance of the patent system and broader intellectual-property governance for guiding the direction and diffusion of clean technologies in the EU. Because our findings indicate that clean spillovers accelerate renewable diffusion, IP frameworks that facilitate access to green knowledge can amplify these positive effects, while defensive patenting in fossil-based technologies risks perpetuating lock-ins. The implementation of the new Unitary Patent system and the emerging debate on essential-IP frameworks for net-zero technologies offer valuable opportunities to align IP governance with transition objectives. Looking ahead, the EU could explore the creation of a voluntary clean-technology patent commons to promote wider licensing of strategic renewable inventions, ensure that publicly funded R&I outputs include favourable licensing conditions for clean-energy applications, and strengthen monitoring mechanisms within the European Patent Office to identify patent clusters that may hinder the diffusion of renewable solutions. A patent system that facilitates clean knowledge spillovers while limiting the persistence of fossil-based knowledge would help accelerate the diffusion of renewable technologies.

These policy mechanisms also translate into some strategic considerations for firms. Our findings highlight the importance of actively managing their technological knowledge base. Strengthening the ability to identify and integrate clean external knowledge, while reducing dependence on legacy fossil-related knowledge, can help firms reposition themselves on cleaner technological trajectories and accelerate their transition toward renewable innovation.

This study presents some limitations that suggest directions for future research. First, our analysis is confined to knowledge spillovers and diffusion within the energy sector. Future studies could extend this analysis to other sectors closely linked to carbon emissions to determine whether similar diffusion dynamics hold. Second, we do not explore how different types of spillovers interact or under which conditions they influence technological diffusion. Further research could examine these interactions by incorporating sectoral or geographical characteristics such as technological maturity or the complexity of the innovation systems in which firms operate. Third, measuring Green

Absorptive Capacity solely through self-citations to renewable patents is conceptually grounded and widely used to reflect firms' accumulated internal knowledge, however, this indicator does not capture the full multidimensional nature of absorptive capacity. Future research could address this limitation by combining patent data with more detailed firm-level datasets or survey-based measures, enabling the development of multidimensional indicators of green absorptive capacity. A fourth limitation concerns potential endogeneity arising from unobserved technological characteristics that may jointly influence a patent's backward and forward citations. Although our empirical design excludes self-citations and incorporates extensive controls for patent quality and technological heterogeneity, residual endogeneity may not be fully eliminated in citation-based analyses. Future research could overcome this limitation by integrating patent data with detailed firm-level R&D information or by exploiting exogenous policy shocks or other sources of quasi-experimental variation to implement instrumental-variable or natural-experiment approaches that enable stronger causal inference.

Finally, our analysis relies exclusively on patent citations, which provide a detailed and internationally comparable source of information for tracing technological knowledge flows over long- time horizons. This focus is consistent with the objective of constructing a large-scale and longitudinal dataset, but it inevitably leaves aside other relevant channels of knowledge transfer, such as scientific publications, R&D collaborations, or market-driven mechanisms. Because these alternative sources of information are not systematically available at the global scale or over extended periods comparable to our patent data, they fall outside the scope of the present study. Nevertheless, future research could build upon our findings by integrating patent-based indicators with complementary data such as collaboration networks, publication records, or firm-level innovation surveys, to provide a more comprehensive picture of how different forms of knowledge exchange interact in shaping technology diffusion.

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CHAPTER 6:

Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals (Article 3)

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Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals

Abstract

This paper explores three novel research questions. First, is an increase in the number of countries involved in ownership of a co-patent an effective way to enhance patent quality? Second, if the objective is to raise patent quality, which are the right countries to collaborate with? And third, does cooperation with partners located in a tax haven affect patent quality? The empirical methodology relies on forward citations as an indicator of quality, and patent co-ownership as a measure of international collaboration. We estimated several count models with a sample of 143,479 pharmaceutical patents (patent families). Our econometric findings show that, first, the average effect of international collaboration is a 4.9% increase in patent quality compared with those patents for which the assignees come from a single country (once we controlled for patent characteristics). When the number of countries in which the assignees are based increases, the effect of this wider collaboration on patent quality is also greater, though only for up to a maximum of five countries. Second, to produce patents of better quality, the most suitable countries with which to collaborate were found to be the United States, Switzerland, Japan, Germany and the United Kingdom. Finally, collaboration with firms located in a country categorized as a tax haven does not have any significant impact on patent quality.

Key words

Patent quality, collaborative patent, international collaboration, pharmaceutical industry.

1. Introduction

The interest of firms in patent quality results from both the positive relationship between patent quality and firm performance (Hirschey and Richardson, 2004; Hall et al., 2005; Chen and Chang, 2010; Patel and Ward, 2011; Harrigan et al., 2018), and the effects of patent quality on a firm's reputation for technological innovation (Henard and Dacin, 2010; Höflinger et al., 2018). Patent quality can also benefit the whole patent system in accomplishing one of its main objectives, which is to confer a net benefit on society by encouraging follow-on inventions. Providing high quality patents on which subsequent inventors can build without infringement serves this purpose (Scotchmer, 1991; Higham et al., 2021). Among the factors affecting patent quality, one key issue that we study in this paper is whether international collaboration in producing joint patents improves patent quality. Joint patents, collaborative patents (co-patents) or co-assigned patents refers to the situation where two or more patent-holders (e.g., companies) own property rights to a registered invention (Hagedoorn et al., 2003; Kim and Song, 2007). A co-patent is international when at least one assignee (owner) is located outside of country A, and at least one other assignee is located within country A.

The need for strengthening international collaboration to produce high-quality patents is particularly relevant because through collaboration in research and development (R&D) activities, organizations may gain access to other countries' resources that firms cannot generate internally, and which help in coping with the increased complexity of innovation (Penner-Hahn and Shaver, 2005; De Beule and Van Beveren, 2019). When firms collaborate with other firms, they are exposed to a larger amount of knowledge and thus higher patent quality is expected. Furthermore, international collaboration can be a more effective strategy to produce quality patents than national or regional collaboration between firms. The main reason for this is that firms located close to one another sometimes use similar knowledge that can overlap. Thus, collaboration across national boundaries is likely to involve a greater variety of knowledge, thus enhancing learning (Molina-Morales and Expósito-Langa, 2013; Mascia et al., 2017).

There are two main methods used to study international collaboration in producing patents. One consists of identifying the location of the patents' inventors, and the other is based on the location of patent owners (assignees). These methods capture two (different) dimensions of geographical technological collaboration. The former reflects the collaboration on inventive activity. The latter represents the economic collaboration produced by innovation (Ma et al., 2009; Lei et al., 2013), and it is also a relevant strategy for companies developing technology jointly (Belderbos et al., 2014). The main advantage of patent co-ownership for firms is that it allows them to overcome individual limitations, in terms of technical or market innovation capabilities (Ponta et al., 2022). However, the analysis of the effect of joint patent ownership on producing quality patents has been neglected. To our knowledge, only Belderbos et al. (2014), Briggs and Wade (2014), Briggs (2015) and Lino et al. (2021) have studied the link between collaboration using patent ownership and patent quality, but only the latter two papers focus on international co-patents. These studies show that quality seems to be higher in joint patents with co-owners in multiple countries. We build on these empirical papers on the effect of co-ownership on patent quality to answer three questions that this literature does not disentangle. In particular, this paper sheds light on the following research questions: first, does an increase in the number of collaborations with partners in different countries, with different regulations, norms and national innovation systems, produce benefits for or have a detrimental impact on patent quality? Second, if the objective is to produce the best performance in terms of patent quality, what are the best countries to engage with in collaboration? And third, patent co-ownership might not be the result of effective collaboration, but simply of patent co-ownership with subsidiaries located in tax havens for fiscal reasons. Thus, to what extent does this affect patent quality?

We address these three main research questions by focusing on patented pharmaceutical technologies. We rely on detailed information for 143,479 pharmaceutical patents (patent families, excluding cosmetics) with assignees from 30 countries between the years 1990-2012. The pharmaceutical industry is characterized by a strong resort to patents because of the high uncertainty, and the high R&D costs of producing technologies, making patents a relevant indicator of firms' technological activities (Chen and Chang, 2010; Hall et al., 2014; Gamba, 2017). Furthermore, pharmaceuticals is one of the sectors where the use of patent co-ownership is more meaningful. Modern pharmaceutical R&D is increasingly complex and requires bringing together a wide range of skills. This can be achieved through co-patents and the collaborations that precede them (Kim and Song, 2007). The pharmaceutical sector is characterized by a great intensity of patent co-ownership because it is more difficult to split inventions into a set of independent components that can be separately patented (Hagedoorn, 2003; Ter Wal and Boschma, 2009).

Findings from the current study are expected to make several contributions. First, rather than focusing on the binary choice of whether or not to collaborate internationally, we analyse the extent to which the breadth of collaboration between patent owners from different countries has a decisive effect on patent quality. Furthermore, we identify whether co-patenting with leading countries in the pharmaceutical industry contributes to obtaining patents of better quality. Second, we investigate these issues in the pharmaceutical sector, a field characterized as being high intensity in R&D, but where the relationship between international collaboration in patent ownership and patent quality remains unexplored. Third, the effect on patent quality of co-ownership with firms located in tax havens is unknown. Finally, by including the variable international collaboration in patent ownership along with other variables, our study contributes to the growing empirical literature on the factors explaining patent quality. Among those factors considered by previous studies are, for example, the use of scientific and technological knowledge developed by other firms and institutions, the breadth of the technological base, the number of patent claims, and the size of the team that developed the patent, (Lanjouw and Schankerman, 2004; Gay et al. 2005; Popp, 2006; Sapsalis et al. 2006; Lahiri, 2010; Nemet and Johnson, 2012; Chang et al., 2018; Acosta et al., 2021).

The paper unfolds as follows. Section 2 reviews the literature on the effect of international collaboration on patent quality. Section 3 presents the data sources and a descriptive analysis of international collaborative patents in the pharmaceutical sector. Section 4 deals with the method, including a brief discussion of patent citations as an indicator of patent quality. This section also describes the variables and the model. The core empirical estimation is presented in Section 5, and we summarize our main conclusions in Section 6.

2. Patent quality and the role of international collaboration

2.1 Patent quality and its measurement

We define the quality of a patent as its impact on subsequent patented inventions. In this respect we follow the same definition as in Argyres & Silverman (2004), Gay et al. (2005), Popp (2006), Sapsalis et al. (2006), Lahiri (2010), Nemet and Johnson (2012), Schmid and Fajebe (2019), and Acosta et al. (2021). Thus, a patent that has an impact in many subsequent patents, in the sense that is used to support other inventions, is considered to have greater quality than others with less impact. This view deals with the technological and economic aspects of patents, for example the underlying capacity of knowledge embedded in patents to promote innovation, encourage the diffusion of technology, and affect economic performance. A related concept used in the literature is patent value, which is a term linked to the extent to which the impact of the patent correlates with any indicator of firm performance and market value (for discussions see, for example, Barberá-Tomás et al. 2011; and de Rassenfosse and Jaffe, 2018). There are clear differences between these concepts, however, there is strong evidence in the literature that indicators of the technological quality of patents are correlated with their economic value (see references in surveys by Hall and Harhoff, 2012; and de Rassenfosse and Jaffe, 2018).

A crucial consideration about patent quality is the issue of how to measure it. Although there are several ways to measure the quality of a patent (for a review, see Squicciarini et al., 2013), in this paper we use the number of forward patent citations. The logic behind the use of forward citations to capture the importance of patents is based on the idea that patents cited by subsequent patents in their 'state of the art' section (or forward citations) include bits of knowledge on which the underlying inventions rely. Therefore, if a patent is cited in many subsequent patents, this means that this particular patent has had a greater technological impact on future inventions, or it is more important than other patents that are less cited. Forward citations may also capture the economic value, as several validation studies have proved. Validation studies have found correlations between forward citations and different measures of patent value, such as social value (e.g., Trajtenberg 1990), values that R&D managers and experts give to patents (e.g., Albert et al. 1991; Harhoff et al. 1999), variation in the stock market value of firms (Hall et al. 2005), the decision to pay renewal fees (Thomas, 1999; Bessen, 2008; Harhoff and Wagner, 2009), measures of performance (Moser et al., 2017), and licensing revenue (Abrams et al., 2018). Some studies, however, cast doubt on forward citations as an indicator of economic value, because the authors did not find such a clear relationship (e.g., Gambardella et al., 2008; Azagra-Caro et al., 2017).

Overall, the use of citations may be justified as a measure of technological impact/value, but it should be acknowledged that this indicator carries significant 'noise' (Hall et al., 2005; Gambardella et al., 2008). This problem can arise from three main sources related to the role of examiners, self-citations, and time truncation. For example, Azagra-Caro and Tur (2018) show that for European Patent Office (EPO) patents, there are different patterns of examiner citations, depending on the examiner's country of residence. Moser et al. (2017) indicates that examiner-added citations are typically unrelated to improvements in performance or a follow-on invention. This study suggests that citations by examiners should be excluded from the number of forward citations. Self-citations might be the most direct procedure to observe follow-on innovations, but as with Higham et al. (2021), we will exclude self-citations in order to isolate the more informative citations. Finally, the truncation problem (the fact that patents continue to be cited over long periods and more recent patents have a lower probability of being cited) can be addressed by considering patents within a window of at least five years from their application date (Lanjouw and Schankerman, 2004; Mariani and Romanelli, 2007; Lahiri, 2010).

2.2 Does a greater number of collaborations between partners from different countries lead to patents of better quality?

Co-patenting across national boundaries indicates some degree of research collaboration, and a joint patent is the result of such collaborative efforts (Kim and Song, 2007). Patent co-ownership shows a strong commitment to the collaborative work from the parties involved, and suggests that the proportion of shared knowledge is relatively high

(Hagedoorn et al., 2003; Belderbos et al., 2014; Elvers and Song, 2014). Furthermore, co-owned patents may assume an important role in industries with a strong regime of appropriability, such as the pharmaceutical sector (Hagedoorn, 2003), which is the sector that we analyse in this paper. However, co-patents only reflect a fraction of the firm's collaboration environment, which means that joint patents do not account for all collaborative R&D efforts (Belderbos et al., 2014; Briggs, 2015; Elvers and Song, 2014; Fritsch et al., 2020). Despite this drawback, the analysis of joint patents can provide new insight into the relationship between the cooperation intensity between agents and innovation success measured as patent quality, as the empirical literature has shown (Belderbos et al., 2014; Briggs and Wade, 2014; Briggs, 2015; and Lino et al., 2021).

When collaborative efforts at international level take place, part of which is captured by joint patenting, the theoretical argument explaining why international collaboration in R&D may produce innovative outputs of better quality is straightforward. Through research collaboration, partners can have access to specific knowledge available in other countries, which increases the quality of the research output (Su, 2017; Lee et al., 2020). Network ties positively influence firm innovation by facilitating access to complementary skills, by scale benefits, and by forming a broader knowledge base among the partners that agree on complementary aims (Simar and West, 2006; Knell and Srholec, 2008). Furthermore, collaboration can affect the output by increasing the probability of successful realization (Belderbos et al., 2010).

A key question in our analysis is whether the effect of international collaboration on patent quality could be more positive than for other forms of collaboration at closer geographical distance (e.g., national or regional). It has been widely documented that inter-organizational exchange of flows of knowledge is strongly influenced by the geographical proximity between partners, positively affecting technological and firm performance (e.g., Jaffe et al., 1993; Audretsch and Feldman, 1996). Geographical proximity is beneficial in promoting innovation since learning and knowledge acquisition is facilitated by face-to-face interaction, which is easier at short distances. However, there are several arguments suggesting that collaboration between innovators at larger distances could offer greater benefits than the collaboration between partners at closer geographical distances. First, Boschma (2005) proposed a multidimensional view of proximity. He argued that although geographical proximity facilitates interaction and cooperation for the acquisition of knowledge, other forms of proximity may act as a substitute for geographical proximity. Some empirical papers point in this direction (e.g. Maggioni et al.; 2007; Basile et al.; 2012; Marrocu et al., 2013). Second, Kotabe et al. (2007), based on an extensive literature review, suggest a number of advantages of international collaboration, such as tapping into different national systems of innovation, gaining access to new lines of technological diversification reflected in local markets, obtaining a more varied flow of ideas, products, processes and technologies, and potential benefits from positive regulatory environments and favourable foreign government incentives. These advantages suggest that firms may reap more benefits in terms of diverse knowledge acquisition from geographically disperse structures (Mascia et al., 2017; van Beers and Zand, 2014). Thus, engaging in inter-organizational relations with geographically distant partners may entail advantages by overcoming the problem of knowledge overlap between two or more actors collaborating at close proximity (Molina-Morales and Expósito-Langa, 2013), which is produced, for example, because the knowledge sources may be the same. Several empirical papers have shown that the capacity for learning when collaborating across international boundaries can be greater than when collaborating over smaller distances because of the access to a greater variety of knowledge, leading to greater quality of innovation (Su, 2021; van Beers and Zand, 2014).

Despite the expected positive effect of international collaboration on patent quality, increasing the number of partners in different countries could have a detrimental impact. The explanation for this is that the potential gains from access to a pool of knowledge from different locations are lessened or neutralized by the difficulty in achieving integration of knowledge across multiple locations (Furman et al., 2006; Singh, 2008), and this problem is aggravated when the number of partners increases. Moreover, collaboration configurations differ in their potential to generate value, meaning that the successful effects of collaborative R&D cannot be generated with just any partner. There should be trust, commitment, and willingness to exchange information between partners

(Geum et al., 2013; Broekel and Brachert, 2015). One of the underlying obstacles to knowledge integration with many countries is associated with leakages of knowledge. To obtain knowledge, organizations have to share some parts of their own knowledge with external firms, which motivates the source firm to proceed with caution to prevent the disclosure of crucial knowledge which can then be copied. Laursen and Salter (2014) coined the term "paradox of openness" to describe this problem. Collaborative patents across countries, as a way of formal international collaboration to obtain an innovative output, confront a similar "paradox of openness". On the one hand, firms may obtain advantages from sharing knowledge with other companies and institutions located in different countries, but on the other hand, leakage of knowledge to a potential rival located in a different country might weaken the competitive position of the company (Easterby-Smith et al., 2008; Frishammar et al., 2015). Several papers have warned of the need to proceed with caution in international collaboration, to prevent the risk of opportunistic behaviour, that in turns increases transaction costs and can affect the results of an alliance or lead to failure to achieve its objectives (Delanghe et al., 2009; Santamaría et al., 2021). Although the risk of leakage and opportunistic behaviour is increased in geographically-close firms competing in the same product market (Oxley and Sampson, 2004, and Reuer and Lahiri, 2014), such risk is less, but still remains, when the collaboration is at an international level, particularly between firms which share a similar product market. As a result, in the process of developing a patent, firm A in one country shares its knowledge with another firm B, located in another country, but the latter may use the knowledge of firm A to produce subsequent inventions that compete with those of firm A, the firm that provided the original and crucial knowledge. This fact may prompt firms to only share non-crucial or irrelevant knowledge and this may lead to a co-patent of lower quality than if the patent were produced without collaboration, particularly when the number of collaborators is large and so the probability of knowledge leakage is greater.

If firms are capable of optimally determining the knowledge delivered to other companies, and rationally capturing technological knowledge in the process of developing the collaborative patent, the effect should be an increase in their gains in terms of better patent quality. When there are few countries involved in the collaboration, it is expected that the resulting patent will be of better quality than if the patent were produced alone. In other words, the benefits of collaboration would outweigh the drawbacks of coordination and leakage of relevant knowledge. However, if the number of collaborators from different countries rises, so does the probability of leakage (along with an increase in the cost of coordination), since knowledge is exposed to more firms from different countries. In a context of collaboration with many countries, the firm may still want to collaborate in order to produce a patent for protecting and blocking motives, reputational gains, and the formation of a recombined pool of complementary knowledge to produce follow-on innovations (Blind et al., 2006; Bessen and Maskin 2009; Yang et al. 2010). However, the firm might keep crucial knowledge for itself, rather than openly sharing sensitive information across borders. If all firms involved in the patent adopt a strategy of releasing only non-crucial knowledge, the result will be a decline in patent quality compared to a collaboration in which the firms share all knowledge resources (this is the case analysed, for example, by Acosta et al., 2021).

The above theoretical arguments lead to our first hypothesis:

Hypothesis 1: *Cross-border collaboration exerts a positive and significant effect on patent quality; however, this effect may be limited to a certain breadth of international collaboration, beyond which an increase in the number of collaborators from different countries involved in developing the patent can lead to a decline in quality.*

2.3 Are the leaders in a particular technological domain the right countries with which to establish collaborative relationships to produce patents of better quality?

The number of links between different countries involved in a particular invention captures the breadth of international collaboration, but not the type and quality of knowledge from which firms can benefit by collaborating. Since not all foreign locations have all the specific skills, types of employees and knowledge required for successful collaboration, firms must choose the best countries with which to establish relationships with their inventors. Thus, along with the uncertainty about the effect of the number of countries involved in developing a co-patent, another relevant issue is the choice of the best international partners to produce the greatest result in terms of patent quality.

Developing countries seem to benefit, in terms of obtaining better outputs, from collaborating with developed countries (e.g., Giuliani et al., 2016). This fact seems to confirm the intuitive idea that the most benefit is obtained from partners located in countries that have specialized workers and leading institutions, forming a strong innovation system. Thus, there are two main reasons to collaborate with specific partners. The first is the level of specialization of the partner. To qualify as an attractive partner, apart from the willingness of the firms to collaborate and share knowledge, the partner in the target country should have obvious technological advantages and should offer better knowledge capabilities (Su, 2017; Lee et al., 2020). Thus, the 'supply-oriented' factors that enhance the efficiency of R&D, such as favourable access to skilled technical expertise, could be one of the keys in choosing the right partner to produce patents of better quality. In other words, firms share their knowledge with a partner with higher knowledge capabilities to acquire useful knowledge in return (Guellec and van Pottelsberghe, 2004; Knell and Srholec, 2008).

The second reason is that firms might want to take advantage of different national and sectoral systems of innovation, gaining access to new lines of technological diversification, capturing foreign university knowledge, obtaining more varied flow of ideas and technologies, or even enjoying favourable foreign government incentives (Criscuolo et al., 2005; Kotabe, 2007; Picci and Savorelli, 2018). Lee et al. (2020) claim that to qualify as an attractive partner, a country should have obvious market or technological advantages, and its firms should be willing to collaborate with those in other countries. From this idea and the above discussion, we put forward our second hypothesis:

Hypothesis 2. *Collaborating with partners located in leading countries in a particular domain will produce better performance in terms of patent quality than collaborating with partners in other countries.*

2.4 To what extent can co-ownership with firms located in tax havens affect patent quality?

The fact that patent ownership is assigned to partners in different countries can be the result of effective collaboration, but it may also be that some firms co-locate the legal ownership of patents both in the country where the invention was developed and in tax havens. In these cases, the co-ownership of a patent is not necessarily the result of collaboration in the inventive activity. Tax havens are countries and territories that offer low tax rates and favourable regulatory policies to foreign investors (Hines, 2010). Sharing the ownership of patents with subsidiaries or other collaborating firms located in low corporate tax jurisdictions is apparently an attractive strategy to reduce corporate tax burdens (Karkinsky & Riedel, 2012; Baumann et al., 2020). With a sample that links information on patent applications to European multinationals (more than nine thousand firms), Karkinsky & Riedel (2012) found that multinationals tend to distort the location of their corporate patents in favour of low-tax affiliates. Bauman et al. (2020) reached a similar conclusion using data on multinational entities (MNEs) in Europe. However, some European countries levy tax on the net present value of the expected revenue stream on a patent when it is moved out of the country, and this means it is not worthwhile to relocate to a lower tax jurisdiction (Griffith et al., 2014). Another issue that plays against tax havens as potential locations of patent ownership for inventions developed elsewhere is the implementation in a number of countries of policies allowing special taxation rates for corporate income derived from the ownership of patents. Such tax regimes are also known as “patent boxes” (Bradley et al., 2015; Gaessler et al., 2021).

Given that the lower taxes in tax havens will affect patent income, it is expected that ownership or co-ownership of high-quality patents is more likely to be located in these countries. Thus, low corporate tax jurisdictions could affect not only the location of the co-ownership in these countries, but also patent quality. The scarce empirical research available points in this direction. The results by Baumann et al. (2020) found that the propensity to assign patent ownership to a haven economy and separate it from the location of the inventor increases with the value of the patent. Ernst et al. (2014) provide evidence that patent income taxation exerts a significantly negative effect on average patent quality. In line with the previous arguments, we expect that choosing a tax haven as location of patent ownership has a positive and significant impact on patent quality, which leads to the third hypothesis:

Hypothesis 3. *Patents co-owned with firms located in tax havens have greater quality than those co-owned with firms located in other jurisdictions.*

3. Data

3.1 The international context of the pharmaceutical industry

To find answers to our research questions, we investigated international cooperation in pharmaceutical patents for the period 1990–2012. The pharmaceutical industry is a particularly interesting context in which to explore our research questions. It was chosen for the analysis of international collaboration in patents for several reasons. First, the pharmaceutical industry is an industry with high research and development (R&D) intensity (Loschky, 2008). Recent figures show that total R&D costs worldwide per employee are more than twice as high in pharmaceuticals than in any other industry, while in terms of aggregate R&D, the pharmaceutical industry is the second sector in value after the computer and electronic products industry (Lakdawalla, 2018). Second, there is a high likelihood that firms patent their inventions in the pharmaceutical industry (Cohen et al., 2000; Kotabe et al., 2007; Magazzini et al., 2009; Gamba, 2017), thus the study of patent collaboration in this sector can show, better than in any other sector, the international R&D collaboration. Finally, the trade-off between the desire to locate all research in a single location or in multiple countries across the world to take advantage of local spillovers is crucial for multinational pharmaceutical firms, because of their dependence on public research (Furman et al., 2006).

Some figures help to identify the leading countries in the pharmaceutical domain. Table 1 presents the data for countries with the largest firms in the pharmaceutical industry, as obtained from the EU R&D Scoreboard (Hernández et al., 2020)[7]. Note that six countries account for more than 90% of the total R&D expenditure. The United States is at the top, with almost half of the total R&D in pharmaceuticals, followed by Switzerland and the UK. According to the information in the EU R&D Scoreboard, these countries are at the top when using other indicators such as net sales and employees. Although we do not have access to data from before that period, the figures are quite stable, which suggests that firms in those countries have been leaders in R&D expenditure for a long period of time.

Table 1. R&D expenditure. Top countries in the pharmaceutical industry

Country	2005		2008		2010		2012	
	€M	%	€M	%	€M	%	€M	%
United States	28,150	47.77	30,175	43.16	30,628	39.17	41,992	43.04
United Kingdom	7,904	13.41	8,005	11.45	8,260	10.56	8,631	8.85
Switzerland	7,888	13.38	11,426	16.34	13,709	17.53	14,555	14.92
France	4,425	7.51	4,924	7.04	4,761	6.09	6,397	6.56
Germany	3,893	6.61	3,501	5.01	4,089	5.23	8,005	8.20
Japan	3,816	6.47	7,563	10.82	11,837	15.14	11,031	11.31
Top-6 countries	56,076	95.15	65,594	93.82	73,284	93.72	90,611	92.88
Others	2,857	4.85	4,315	6.17	4,917	6.29	6,965	7.14
Total	58,933	100	69,909	100	78,201	100	97,575	100
Source: Own elaboration from the EU Scoreboard, available at https://iri.jrc.ec.europa.eu/scoreboard/								

3.2 Pharmaceutical patents. Data and sources

Our unit of measurement is the patent family, which can be defined as the set of patents filed in several countries that are related to each other by one or several common priority filings (Organisation for Economic Co-operation and Development, OECD, 2009; for a detailed discussion, see also Martínez, 2010, 2011; Bakker et al., 2016). In other words,

[7] The EU R&D Scoreboard analyses the 2500 companies that invested the largest sums in R&D worldwide. These companies have headquarters in 43 countries. The Scoreboard total R&D is equivalent to approximately 90% of the total expenditure on R&D financed by the business sector worldwide. The whole set of primary data is available at: https://iri.jrc.ec.europa.eu/scoreboard/2019-eu-industrial-rd-investment-scoreboard.

a patent family comprises all patent documents covering the same invention. To ensure that the patent family has a certain quality standard, we retrieved the most important and valuable inventions, following the criterion of patents applied for at least at USPTO and EPO. One of the main advantages of using patent families is the avoidance of duplications in the information contained in patents that cover the same invention in different countries (Martínez 2011; de Rassenfosse et al., 2014). Moreover, the calculated citation indicators may differ substantially depending on the procedures of the patent office where the patent application was submitted. Therefore, patent families reveal the most uniform results, and can be used as a comprehensive measure of inventiveness compared to the simple count of patents (Bakker et al., 2016; van Raan 2017; Tahmooresnejad and Beaudry, 2019).

As patent families contain different dates, and as we considered a window of five years, it is important to clarify the dates. Following de Rassenfosse et al. (2014), to account for time, patent families were sorted by the priority year (when the first application for the family was filed). In order to search the patent families in the pharmaceutical sector, we have used the International Patent Classification (IPC) codes. Pharmaceutical patents are clearly identified by the codes A61K (Preparations for medical purposes) and A61P (Specific therapeutic activity of chemical compounds or medicinal preparations). From the A61K we have excluded the subclass A61K 8/00 (Cosmetics or similar toiletry preparations) because inventions in this subclass do not serve the same purpose as pharmaceuticals. We also dropped the pharmaceutical patents from countries where the number of patents produced may be statistically meaningless, keeping them only for countries with more than 150 patent families over the selected period.

The information was retrieved from the EPO Worldwide Patent Statistical Database (PATSTAT), resulting in a sample of 143,479 pharmaceutical patent families from 30 countries with more than 150 patent families between the years 1990-2012 (see Table A.1 in the Appendix). To identify the international collaboration in generating a collaborative patent, we have classified all the patent families by the country of the assignee. Table 2 presents the number of patent families distributed by the number of countries of the applicants. From the total sample, about 75% are single-owned patents (patent families for which assignees are from a single country, independently of whether there is only one assignee, or the patent includes several assignees from the same country) and 25% are international co-patents: patent families co-owned by assignees from two or more different countries.[8] Note that counting collaboration in this way may include collaboration not only between different companies, but also between parent firms located in one country and subsidiaries in other countries. Regarding the countries of residence of the assignees, the number of pharmaceutical patent families is rather concentrated. The United States accounts for 47.5% of all patent families, followed by Japan (9.3%), Germany (8.1%), the United Kingdom (5.9%) and France (4.8%) (Table 3).

Table 2. Number of patent families according to the number of countries of the assignees (1990-2012)

No. different countries of inventors	No. patent families	No. forward patent citations	No. forward citations per patent familiy
Single-owned	107,941	103,012	0.95
Co-patents	35,538	44,689	1.26
2 Countries	27,468	32,479	1.18
3 Countries	6,467	9,024	1.40
4 Countries	1,328	2,410	1.81
5 Countries	234	643	2.75
6 Countries	27	90	3.33
7 Countries	12	33	2.75
8 Countries	2	10	5.00
Total patent families	143,479	147,701	1.03

Single-owned: patent families owned by one or several partners from a single country. Co-patents: sum of patent families with partners from between two and 8 different countries. Source: Patstat and own elaboration.

For each patent family, we tracked the forward patent citations in a five-year window, which is our indicator of quality. Note that the number of citations per patent increases as the number of countries involved in the ownership grows (Table 2).

From Table 3, it can be observed that the average number of citations for single-owned patents is 0.95 citations per patent, and 1.26 for co-patents. We have also retrieved the

[8] This high intensity in co-patenting is a characteristic of the pharmaceutical industry. Hagerdorm (2003) suggested the following reasons for this fact. First, having a large proportion of co-patents is a characteristic in industries with strong regimes of appropriability such as chemicals and pharmaceuticals. Hagedoorn (2003) found for US patents that chemicals and pharmaceuticals "are found to have a disproportionate share of joint patenting activities", because in pharmaceuticals it is more difficult to claim for different patents since there are many interdependencies between the various components of a process leading to a product. A second reason pointed out by Hagedoorn (2003) is the experience of applicants with the legal complexities of joint patenting in the pharmaceutical industry.

other variables that capture the characteristics of the families, which, according to the literature discussed above, include the backward-cited patents (excluding citations made by examiners), the number of non-patent citations, the number of claims, and the number of different IPC classes to capture the breadth of collaboration involved in a technology.

Table 3. Distribution of pharmaceutical inventions by countries of the assignees (1990-2012)

ISO	Country	Patent families (1)					Forward patent citations (5-year window) (2)					
		no.	%	Single-owned	In coll.	% coll.	no.	Single-owned	In coll.	Aver.	Aver. Single	Aver. in coll.
us	United States	68,164	47.51	57,887	10,277	15.08	83,657	69,991	13,666	1.23	1.21	1.33
jp	Japan	13,371	9.32	12,281	1,090	8.16	10,031	8,506	1,525	0.75	0.69	1.40
de	Germany	11,752	8.19	8,395	3,357	28.56	10,566	6,061	4,505	0.9	0.72	1.34
uk	United King.	8,491	5.92	4,806	3,685	43.4	7,679	3,414	4,265	0.9	0.71	1.16
fr	France	6,883	4.8	4,724	2,159	31.37	4,757	2,286	2,471	0.69	0.48	1.14
ch	Switzerland	4,799	3.34	1,144	3,655	76.16	5,900	929	4,971	1.23	0.81	1.36
ca	Canada	3,295	2.3	1,978	1,317	39.97	3,771	1,886	1,885	1.14	0.95	1.43
it	Italy	3,208	2.24	2,333	875	27.27	1,987	1,045	942	0.62	0.45	1.08
se	Sweden	2,605	1.82	1,349	1,256	48.21	2,322	811	1,511	0.89	0.6	1.20
nl	Netherlands	2,263	1.58	1,291	972	42.95	1,897	999	898	0.84	0.77	0.92
il	Israel	1,969	1.37	1,373	596	30.25	1,317	764	553	0.67	0.56	0.93
be	Belgium	1,879	1.31	887	992	52.8	1,981	650	1,331	1.05	0.73	1.34
dk	Denmark	1,826	1.27	1,215	611	33.45	2,099	1,201	898	1.15	0.99	1.47
kr	Korea	1,818	1.27	1,638	180	9.89	1,116	914	202	0.61	0.56	1.12
in_	India	1,775	1.24	1,253	522	29.4	1,915	1,119	796	1.08	0.89	1.53
au	Australia	1,705	1.19	1,235	470	27.56	802	455	347	0.47	0.37	0.74
cn	China	1,621	1.13	1,031	590	36.38	1,403	495	908	0.87	0.48	1.54
es	Spain	1,449	1.01	1,061	388	26.77	1,137	736	401	0.79	0.69	1.04
at	Austria	1,071	0.75	336	735	68.64	952	119	833	0.89	0.35	1.13
ie	Ireland	644	0.45	214	430	66.75	662	127	535	1.03	0.59	1.24
no	Norway	464	0.32	224	240	51.68	235	85	150	0.51	0.38	0.63
fi	Finland	446	0.31	331	115	25.83	153	90	63	0.34	0.27	0.55
sg	Singapore	329	0.23	189	140	42.49	237	103	134	0.72	0.54	0.96
hu	Hungary	313	0.22	198	115	36.8	100	34	66	0.32	0.17	0.57
nz	New Zealand	299	0.21	172	127	42.4	161	83	78	0.54	0.48	0.62
tw	Taiwan	252	0.18	98	154	61.12	167	46	121	0.66	0.47	0.79
ru	Russia	239	0.17	110	129	54.06	131	12	119	0.55	0.11	0.92
br	Brazil	202	0.14	156	46	22.92	63	42	21	0.31	0.27	0.45
lu	Luxembourg	184	0.13	31	153	83.18	110	6	104	0.6	0.19	0.68
bm	Bermuda	164	0.11	1	163	99.39	394	3	391	2.4	3	2.40
Total		143,479	100	107,941	35,538	24.77	147,701	103,012	44,689	1.03	0.95	1.26

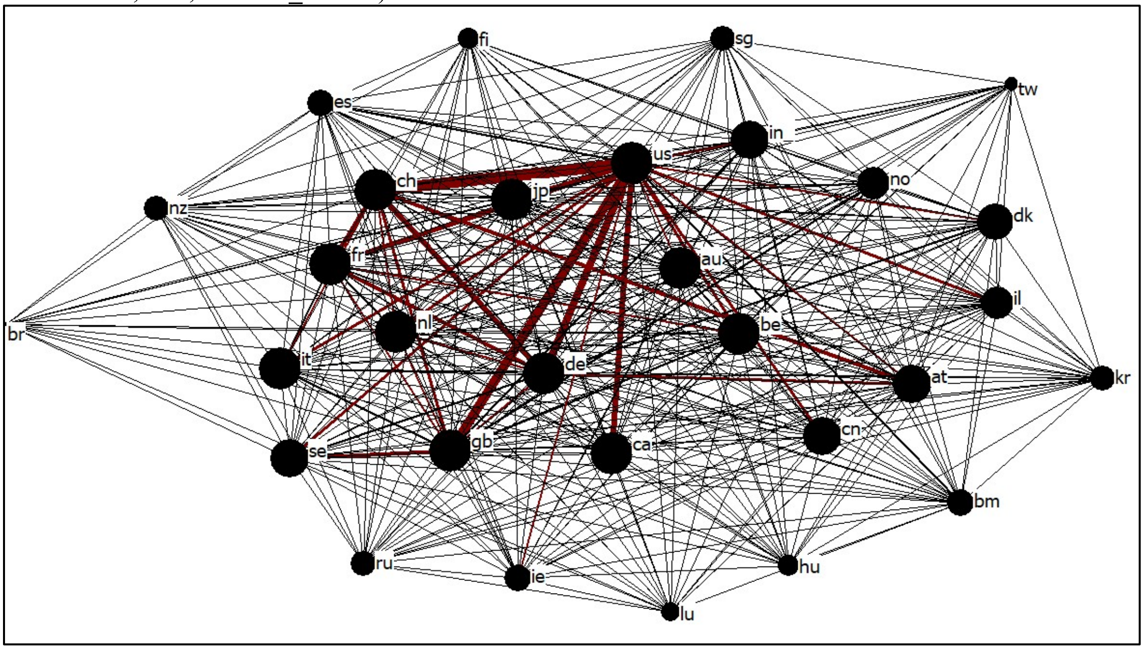
(1) Number of patent families by countries.
Single-owned means that the owner of a patent is from one single country. In coll. includes the patents in collaboration with two or more countries, and % coll. is the percentage of co-patents (patents in collaboration) over the total patents of the country.
(2) The last three columns of the table present the average forward citations (number of forward citations divided by the number of patents of each country) for the total number of patents of the country, those applied for by a single country, and those applied for in collaboration with other countries.
Source: Patstat and own elaboration.

3.3 International patent collaboration

Although a detailed network analysis is beyond the scope of this paper (the unit of our analysis is the patent family, not the country), some preliminary network indicators help to clarify the extent of the international cross-border relationships between different international partners in the pharmaceutical sector. In this respect, Graph 1 shows the degree centrality, which is a relative measure of the number of direct links between nodes divided by the total number of links. A connection implies that there is a collaborative patent, which means that the patent includes two or more assignees. If the patent includes, for example, the United States and other assignees from 5 countries, the number of connections for each of the assignee countries is 5. In our sample, the number of connections between different countries ranges from 16 to 30 in the net of 30 countries. Countries such as the United States, Germany, Japan and the United Kingdom, for example (those in the middle of the graph), have had connections with all the other 29 countries in the network. However, others such as Taiwan, Russia, Luxembourg and Brazil have collaborated with a lower number of countries. The sizes of the nodes are determined by the degree centrality. The country with the highest degree centrality is the United States with 36.13%, which means that this country accounts for 36.13% of all the countries' connections. The United States is followed by Germany (9.17%), the UK (8.04%) and Switzerland (7.92%).

Going back to Table 3, the percentages of collaboration (patent families with applicants from at least two countries) range from 8.2% for Japan, which is the country with the least collaborative patent families, to 99.4% for Bermuda, the country with the highest degree of collaboration. Note that there are substantial differences between countries and, on average, the percentage of cross-border collaborative patents is 24.8%. In this respect, it is necessary to bear in mind that, as we explained in Section 2.3, part of patent ownership is the result of international R&D collaboration, but firms can also use partners in tax havens to reduce corporate tax burdens. Thus, our sample contains six countries considered low-tax jurisdictions by the EU, IMF and Oxfam: Bermuda, the Netherlands, Switzerland, Singapore, Ireland and Luxembourg. All of these countries present percentages of patent co-ownership well above the average.

Graph 1. Network of international collaborative patents in the pharmaceutical sector (degree centrality. Max US: 36,13%; Min BR_ 0.13%)



Source: Patstat and own elaboration.

Regarding quality of patent families by countries, in terms of patent impact, several observations can be drawn from the right part of Table 3. First, on average, the quality of patent families produced through international collaboration is higher than that of patent families produced by teams in a single country: 1.3 forward citations of international co-patents compared to 0.9 forward citations of those applied for by assignees based in one single country. Second, Russia is the country which obtains the most substantial benefit from collaboration in terms of quality (0.11 citations per patent family when there is no collaboration, compared to 0.92 in international collaborative patents). Thus, assuming that forward citations is a good proxy for quality, the collaborative patents involving Russia have a quality that is about seven times higher than for patent families in which the assignees are only from Russia. The same table shows that other countries such as Hungary, Luxembourg, Austria, and China greatly benefit from international collaboration; the average quality of their collaborative patents is more than twice that of those obtained without collaboration.

Third, patent families from the United States present similar values for the indicator of quality when the patent family is owned by partners only from the US or from multiple countries (1.2 forward citations compared to 1.3). In any case, the indicator of quality is always greater for collaborative patents for all countries (Bermuda is the only exception in which the quality of a non-collaborative patent is greater than its collaborative patents, but this country is a rare case as it has only one non-collaborative patent out of 164 total patents).

4. Variables and model

4.1 Dependent variable

Following previous studies, our dependent variable to capture patent quality was the number of forward patent citations (as in, for example, Lerner, 1994; Hall et al., 2005; Sapsalis and van Pottelsberghe, 2007; Sterzi, 2013; Giuliani et al., 2016; Acosta et al., 2009, 2021). As explained in Section 2.1, the main argument for considering the number of forward citations as proxy for quality is based on the idea that patents that are cited by subsequent patents in their 'state of the art' section (or forward citations), include small pieces of knowledge on which the underlying inventions rely. Therefore, if a patent is cited in many subsequent patents, this means that this particular patent has a greater technological impact on future inventions, or that it is more important than other patents which are less cited.

Considering the previous remarks, the dependent variable in this work was the number of times that a focal patent family was cited as relevant state of the art in subsequent patent families filed within a 5-year time window after the first application of the focal patent family. Note that, as we consider patent families as subsequent patents that cite the focal patents, duplicate citations are eliminated from the count. For example, when a subsequent patent family cites two different patents of the same focal family, this counts as one citation. The forward citations in our sample exclude self-citations and examiner citations (*fpc5years*). The most common spans in forward citations to avoid truncation are 5-year (Lanjouw & Schankerman, 2004; Mariani & Romanelli, 2007; Schettino et al., 2013) and 3-year spans (e.g. Briggs, 2015; Briggs and Wade, 2014). Less frequent is using 10-year spans (Lahiri, 2010; Higham 2021), which requires working with samples too far from the year of the analysis to give time for the latest focal patents in the sample to be cited (within the 10-year span). Squicciarini et al (2013) recommend 5-7 years in the cohort, although they also comment that “almost no gain would be obtained by extending the window of observation for two additional years” (Squicciarini et al., 2013, p. 39). We use a 5-year cohort (and a 3-year to check for robustness) in our main models for two reasons. First, 5-year (and 3-year) spans are the more frequently used in empirical analysis of patent quality. Second, we should not use 7 or 10-year cohorts because our sample consists of patent applications in the period 1990-2012, and there is a risk that, if considering a cohort of 7 or 10 years, the number of forward citations in the final years would decline simply because not all citations have been incorporated into databases yet.

4.2 Independent variables

4.2.1 International collaboration

Our key independent variable is international collaboration. International technological collaboration on patents implies that the invention, the teams generating this invention, and the ownership tend to cross national borders in order to create and share knowledge (Maggioni et al., 2007; Lin et al., 2012; Mazzola et al., 2016; Su, 2017). Thus, there are different ways to measure collaboration on patents. The majority are based on the country of residence of the inventor (Guan and Chen, 2012; von Proff and Dettman, 2013; De Pratto and Nepelski, 2014), the country of residence of the assignee (Briggs, 2015; Su, 2017; Alonso-Martínez et al., 2021), or on both, with a different combination of inventorship and ownership (Ma et al., 2009; Montobbio and Sterzi, 2013; Picci, 2010; Danguy, 2017). Using any of these indicators has advantages and disadvantages (see, for example, Section 7.3 in OECD, 2009, and Bergek and Bruzelius, 2010, for a detailed discussion), but overall, the result will tend to converge because a patent with co-assignees in two countries very often involves inventors from these two countries (de Rassenfosse and Seliger, 2020).

In this paper we use cross-border ownership of the patent (or cross-border co-patent), which means that the organization units (assignees or owners) are located in different countries. Joint patenting or co-patents assume that co-owned patents are the result of inter-firm R&D collaboration and ownership is shared (Hagedoorn, 2003; Belderbos et al., 2014; Briggs, 2015; Alonso-Martínez et al., 2021). Furthermore, co-owned patents are disproportionately important in industries with strong regimes of appropriability such as chemicals and pharmaceuticals (Hagedoorn, 2003).

It should be noted that not all research collaborations will be captured with a co-patent indicator. As is well known, not all collaborative R&D efforts will result in an application for a patent. Even if R&D collaboration does yield a patent application, specific IP arrangements can mean that finally only one partner applies for the patent (Lecocq and Van Looy, 2009), or there may be a division of the invention so that each partner applies for a patent only for the part of the invention that they contributed to producing (Hagedoorn, 2003). Thus, joint patents should be considered a conservative indicator of collaboration since not all collaborative research efforts and subsequent innovation from such efforts are captured by such an indicator (Van Looy, 2009; Briggs, 2015). Besides, as explain above, the co-ownership of a patent might be the result of strategic decisions by firms, such as attempting to reduce the tax burden.

Following this criterion, we have considered different variables to capture whether a patent family was developed in collaboration with partners from different countries:

- Cooperation (*coop*) is a dummy variable that takes value 1 if the assignees of a patent are located in two or more countries, and 0 if the assignees are from a single country. This variable captures the presence of a co-patent owned by assignees in at least two different countries.
- Number of countries (*country*). This is a count variable that captures the number of different countries in which the assignees are based. For example, if a patent was applied for by assignees from a single country, its value is 1. If it was applied for by assignees from, for example, the United States, Germany and the United Kingdom, the value of the variable is 3.
- Dummies for the number of collaborating countries in a patent family (*country2* to *country8*). This is a set of 7 dummy variables to capture whether the patent was owned by two, three, or up to eight countries. The base category is a single country (patent developed without collaboration). We have also considered this way as an

alternative to the previous count variable because, considering several dummy variables rather than the count variable *country*, the marginal effect can be compared with the base category (patents developed in a single country) and it varies according to the dummy variable (from two to eight countries). However, in the previous count variable *country*, the marginal effect would be constant, independently of the number of countries. It provides, for example, the increase in quality when the number of countries increases by one unit, independently of the number of countries involved.

- Dummies for the countries involved in collaboration (us-ch-jp-de-uk-fr). In order to identify those countries which are worth collaborating with to enhance patent quality, we have considered a set of dummies for countries with the greatest potential in the pharmaceutical industry. Each variable takes value 1 when the collaborative patent includes the United States (us), Switzerland (ch), Japan (jp), Germany (de), the United Kingdom (uk), or France (fr), and 0 otherwise.
- Location in a tax haven. To capture whether collaboration with partners located in tax havens affects patent quality, we have created a dummy variable when a co-patentee is located in a country considered a low-tax jurisdiction by the European Union (EU), the International Monetary Fund (IMF), or Oxfam.

4.2.2 Other determinants of patent quality

Along with collaboration, it is necessary to control for other factors affecting patent quality. The type and number of patent quality determinants vary widely across studies. These determinants depend on the objectives of each study, and the availability of data. We control in our models for the following factors:

- Number of inventors (inventors). This is a rough variable that may increase the cost of an invention, the richness of the knowledge involved in the patent, and the access to a wider and more heterogeneous external network (Guellec and van Pottelsberghe, 2001; Singh 2008; Sun et al., 2020). Some papers confirm that the number of inventors is positively associated with patent quality when the sample is composed mostly of corporate patents (Guellec and van Pottelsberghe, 2001; Singh, 2008), whereas the coefficient is found to be negative or not significant for academic patents (Sapsalis and van Pottelsberghe, 2007; Sterzi, 2013). Our analysis involved corporate patents; thus, a significant and positive sign was expected for the coefficient of this variable.

- Backward patent citations (*back*). This variable includes citations to companies, universities and research centres, capturing the extent to which a patent relies on previous technological knowledge developed in patents owned by these agents (See Jaffe and de Rassenfosse, 2017; and, Aristodemou and Tietze, 2018, for detail reviews). This variable is rather common in studies of patent quality, although its effect is not clear (Jaffe and de Rassenfosse, 2017). Harhoff et al. (2003) and Moaniba et al. (2018) found a positive and significant effect on patent quality. Michelino et al. (2016) also found that patents that do not have backward citations typically have a lower technological and market impact. However, Nemet and Johnson (2012) found positive and negative effects, depending on the type of backward citation.
- Number of claims (*claims*). Claims are the list of 'inventive things' for which the applicant is claiming exclusive rights. The number of claims can be considered a proxy for the patent size (see Rodriguez, 2010, and van Zeebroeck and van Pottelsberghe, 2011, for a discussion). Studies have found a positive correlation between the number of claims and quality for two main reasons. First, the number and content of the claims determine the breadth of the rights conferred by a patent (Lanjouw and Schankerman, 2004). The total number of claims corresponds to the number of variations in the core inventive ideas of the patent. The second reason to expect that patents with more claims are of better quality is the cost; the number of claims is one of the factors that determines the total cost of a patent (Zuniga et al., 2009). The number of claims is frequently correlated with patent quality and value (Gambardella et al., 2008; Chang et al., 2018; Moaniba et al., 2018).
- Citations to non-patent literature (*npl*). The antecedents of a patent include not only citations to other patents (backward citations), but also non-patent citations. Usually known as citation to non-patent literature, this variable encompasses scientific publications, other relevant scientific literature, and firm reports. The rationale for

including scientific citations as a determinant of patent quality relies on capturing the complexity and science intensity of the current patent (Cassiman et al., 2008; Squicciarini, 2013; van Raan, 2017). The empirical literature draws mixed conclusions about the effect of *npl* on the number of forward patent citations. For example, Branstetter (2005), and Sorenson and Fleming (2004) found a positive relationship. In contrast, Gittelman and Kogut (2003) demonstrated that important scientific papers are negatively associated with high-impact innovations. Cassiman et al. (2008) found no-relationship, and Harhoff et al. (2003) found a positive effect in some particular sectors but not in other technical fields.

- Scope of the patent (*ipc4*). The scope of a patent captures its technological breadth. Apparently, the larger the number of technologies embedded in a patent, the more the opportunities to be cited. However, the patent scope can be the response to a strategy designed to achieve the exclusion of competitors (Harhoff and Reitzig, 2004). This means that if the number of fields that can be covered by a patent is large, then the possibility of infringement rises, which may reduce the subsequent citations of the patent for risk of infringement. As in Lerner (1994) and Lanjouw and Schankerman (2001), we measured the scope using the number of distinct 4-digit IPC subclasses of a patent family. The the extent to which scope reflects patent quality is ambiguous in empirical analyses. For example, Messeni Petruzzelli et al. (2015) found that patents with a broader scope exert a stronger influence (measured by forward patent citations) on the technological developments outside biotechnology. Other authors, however, have reached different conclusions, although using other indicators of quality. For example, in Harhoff and Reitzig (2004) the coefficient of scope to explain opposition to biotechnology and pharmaceutical patents is non-significant. Lanjouw and Schankerman (2001) found that the effect of the scope variable (number of different four-digit codes of the Standard Industrial Classification) to explain litigation (‘the narrower patents tend to be litigated more often’) is negative.

4.3 Model

To specify and estimate the model, both the count nature of the dependent variable, and the number of zeros that it might contain have to be considered. A Poisson specification is often the starting point for modelling a count variable following the non-linear form:

$$fpc5years_i = \exp\left(\alpha + \beta_1 international\ collaboration_i + \beta_2 inventors_i + \beta_3 back_i + \beta_4 claims_i + \beta_4 npl_i + \beta_5 ipc4_i + \sum_{j=1}^{t} \lambda_j\, year_{ij} + \varepsilon_i\right),$$

where ‘i’ is our unit of analysis (patent family). Note that according to Section 3.2.1, international collaboration to produce a patent is measured by several types of explanatory variables. Thus, the variable *international collaboration* can be a dummy variable (*coop*), a count variable (*country*), a set of dummies to account for the number of collaborative countries in the patent family (country2 to country8), a set of dummies to capture the countries of residence of the inventors, and the co-ownership with a firm located in a tax haven. As all of these variables capture international collaboration, sometimes they are highly correlated and are included separately in the empirical models to test the hypotheses and provide answers to our empirical questions.

Once the model is specified, if the data display overdispersion, the standard error of the Poisson model will be biased toward the lower end, resulting in spuriously high values of the t-statistic (Cameron and Trivedi, 1986; Wooldridge, 1999). The most common formulation for considering overdispersion is the negative binomial (NB) model, as it assumes that the variance is a quadratic function of the mean (for a comprehensive discussion of the estimation procedure, see Cameron and Trivedi, 1998). The proposal of the density function, the logarithmic likelihood function and the first-order conditions, etc., are discussed comprehensively in Cameron and Trivedi (1998). An alternative to the NB is applying the Poisson quasi-maximum likelihood estimator (QMLE) (Wooldridge, 1999). When the sample contains many zeros, other usual models are the zero-inflated models (zero-inflated Poisson [ZIP], Lambert, 1992; and zero-inflated negative binomial [ZINB], Heilbron, 1994). In these cases, the zero-inflated distribution can be interpreted as a finite mixture with a distribution whose mass is concentrated at zero. This model contains two sources of overdispersion, one that allows several extra zeros, and another that introduces the individual heterogeneity of the set with positive values. As there are no clear theoretical reasons to think of a mixture of distributions in our data, we have opted to estimate NB models and Poisson QMLE.

5. Results

5.1 The effect of international collaboration on patent quality

Our first empirical analysis focuses on the relationship between international collaboration and the quality of family patents, and particularly on whether the increase in the number of countries has a positive effect on quality. Table 4 provides a brief description of all variables. Tables 5 and 6 present the descriptive statistics and the correlation matrix for the dependent variable (forward patent citation in a 5-year window) and the independent variables. The number of forward citations in each patent family ranges between 0 and a maximum of 174. The mean number of forward citations was 1.02, with a standard deviation 2.77 (variance, 7.70). The correlation matrix shows, on the one hand, that the linear correlation between the dependent variable and those explanatory factors capturing international collaboration is positive, although rather low. On the other hand, variables such as *coop* and *country*, and *coop* and some of the dummy variables capturing the number of countries in collaboration, are highly correlated. This is expected, as these variables measure collaboration in different ways. To avoid collinearity problems, they will be included in separate models.

Table 4. Variables and definitions

Variable	Definition
Dependent variable	
fpc5years	No. forward citations within five years after the first application of the focal patent family.
Independent variables ***Variables capturing international collaboration***	
coop	Dummy variable that takes value 1 if the assignees are located in two or more countries, and 0 if the assignees are from a single country.
country	Number of different countries of the assignees.
country2 to country8	Set of 7 dummy variables to capture whether the patent was owned by a single country or by two, three, or up to eight countries. Each variable takes value 1 for collaborative patents with the number of specified countries, and 0 otherwise (patents with owners from a single country).
us-ch-jp-de-uk-fr	Set of dummy variables that take value 1 when the collaborative patent includes the countries with the greatest potential in the pharmaceutical domain: United States (us), Switzerland (ch), Japan (jp), Germany (de), United Kingdom (uk), France (fr), and 0 for other collaborative patents.
haven	Dummy variable that takes value 1 when the collaborative patent includes the countries considered tax havens by the EU, IMF and Oxfam. The countries in our sample that match with the criteria of these institutions are: Bermuda, the Netherlands, Switzerland, Singapore, Ireland and Luxembourg. As Switzerland is one of the countries with the greatest potential in pharmaceuticals, it is excluded from this dummy.
Other determinants of patent quality (patent characteristics)	
Inventors	No. of inventors in the patent family
claims	No. of claims in the focal patent family.
back	No. of backward patent citations
npl	No. of citations to non-patent literature.
ipc4	No. of different 4-digit subclasses of the IPC (Lerner, 1994).
Control for time	
Year dummies	22 dummies (years 1990 to 2012)
Source: Patstat and own elaboration.	

Table 7 presents the estimations of negative binomial (NB) models to identify both the extent to which international collaboration affects the quality of patent families and the role of the number of countries in collaboration. We first estimated Poisson MLE (maximum likelihood estimator) (not presented) and then, due to overdispersion, NB models with all the independent variables described in section 3.2 (see short description in Table 4). The models also account for year dummies (22 dummies). To select the best models between Poisson and NB, a likelihood ratio (LR) test of the overdispersion parameter alpha was performed (see the row LR-alpha in Table 5). The null hypothesis alpha=0 is rejected, providing evidence that the NB models are always preferred over the Poisson MLE models.

Table 5. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
fpc-5years	1.02942	2.77493	0	174	143,479
coop	0.24769	0.43167	0	1	143,479
country	1.31742	0.62352	1	8	143,479
country2	0.19144	0.39344	0	1	143,479
country3	0.04507	0.20746	0	1	143,479
country4	0.00926	0.09576	0	1	143,479
country5	0.00163	0.04035	0	1	143,479
country6	0.00019	0.01372	0	1	143,479
country7	0.00008	0.00914	0	1	143,479
country8	0.00001	0.00373	0	1	143,479
us	0.56109	0.49626	0	1	143,479
ch	0.06959	0.25445	0	1	143,479
jp	0.10196	0.30260	0	1	143,479
de	0.11301	0.31661	0	1	143,479
uk	0.09127	0.28800	0	1	143,479
fr	0.06902	0.25349	0	1	143,479
haven	0.04215	0.20092	0	1	143,479
inventors	3.92743	2.84431	1	56	143,479
claim	15.4628	16.2968	0	383	143,479
back	12.8682	31.1088	0	1,807	143,479
npl	23.0678	54.4426	0	1,861	143,479
ipc4	3.91566	1.74426	1	33	143,479

Source: Patstat and own elaboration.

Table 6. Correlations

	fpc-5years	coop	country	country 2	country3	country 4	country 5	country 6	country 7	country 8	haven	Inven-tors	claim	back	npl	ipc4
fpc-5years	1.000															
coop	0.047***	1.000														
country	0.057***	0.887***	1.000													
country2	0.027***	0.848***	0.533***	1.000												
country3	0.029***	0.379***	0.586***	-0.106***	1.000											
country4	0.027***	0.168***	0.416***	-0.047***	-0.021***	1.000										
country5	0.025***	0.070***	0.239***	-0.020***	-0.009***	-0.004	1.000									
country6	0.011***	0.024***	0.103***	-0.007*	-0.003	-0.001	-0.001	1.000								
country7	0.006*	0.016***	0.083***	-0.004	-0.002	-0.001	-0.000	-0.000	1.000							
country8	0.005*	0.007*	0.040***	-0.002	-0.001	-0.000	-0.000	-0.000	-0.000	1.000						
haven	0.001	0.227***	0.264***	0.126***	0.165***	0.113***	0.063***	0.030***	0.021***	0.018***	1.000					
inventors	0.153***	0.116***	0.140***	0.065***	0.074***	0.068***	0.051***	0.030***	0.024***	0.012***	-0.005*	1.000				
claim	0.086***	0.020***	0.023***	0.013***	0.007*	0.015***	0.012***	0.002	0.001	0.004	-0.003	0.074***	1.000			
back	0.147***	0.054***	0.057***	0.036***	0.031***	0.016***	0.016***	0.005	0.009***	0.005	0.004	0.086***	0.237***	1.000		
npl	0.123***	0.042***	0.050***	0.023***	0.030***	0.016***	0.020***	0.012***	0.009**	0.006*	0.007*	0.062***	0.272***	0.571***	1.000	
ipc4	0.035***	0.000	0.003	-0.003	0.005*	-0.001	0.004	0.004	-0.003	0.002	0.002	0.067***	0.146***	0.132***	0.237***	1.000

Source: Patstat and own elaboration.
$* p < 0.10$; $** p < 0.05$; $*** p < 0.01$.

Models 1 and 2 in Table 7 include the dummy variable *coop,* which captures whether a patent was assigned to partners from at least two countries. Model 1 is a base model that does not control for patent characteristics, and Model 2 includes the control variables. The coefficient of *coop* is positive and statistically significant. On average, when we control for other factors affecting quality such as the size of the patent (variables *claim* and *ipc4*), the size of the team (*inventors*) and the extent to which the patent uses previous technological and scientific citations (variables *back* and *npl*), the effect of international collaboration is, on average, a 4.9% increase in patent quality compared with patent families for which the assignees are from a single country[9].

Models 3 and 4 in Table 7 present the results of the NB estimations when the count variable *country* (number of countries in collaboration) instead of *coop* was included as explanatory factor. When we control for the characteristics of the patent families (Model 4), the results show that when there are assignees from an additional country, the quality increases on average by 4.8%. Finally, Models 5 and 6 present the results using 7 dummies capturing the collaboration between from two to eight countries. These models allow us to identify the effect of international collaboration when partners from different countries are involved in the ownership of the patent family (patent families with assignees from a single country is the base category). Once we control for the patent characteristics (Model 6), the results show that the quality of the patent rises dramatically when the number of countries increases, for up to five countries in collaboration (dummies *country2* until *country5* are positive and statistically significant). However, we did not find significant differences in quality, compared to patenting by assignees from a single country, when there are more than five countries involved in the ownership of a patent. These results provide support for Hypothesis 1, that international collaboration exerts a positive and significant effect on patent quality, but that this effect is limited to a

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[9] Note that the generic interpretation is that the response has a log-count increase of the dependent variable for a one-unit increase in the value of the predictor, other predictors held at their mean value. As the "log-count increase" is not a very intuitive way to understand the importance of the estimated coefficients, we apply $100x(e^{\beta}-1)$, which provides the exact percentage change in the expected count for a unit change in x (Cameron and Trivedi, 2009, p. 336; Long and Freese, 2001, p. 232).

maximum of five countries in collaboration. When there are co-owners from more than five countries involved in patenting, there is no observed benefit from collaborating in the pharmaceutical sector. Note, however, that the number of patents in which there are more than five co-assignees is a small fraction of the sample (only 41 co-patents), which suggests a need to be cautious about this finding.

Table 7. Effects of international collaboration on patent quality. Negative binomial estimations

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
coop	0.1620***	0.0481***				
	(0.0130)	(0.0127)				
country			0.1347***	0.0477***		
			(0.0087)	(0.0085)		
country2					0.1143***	0.0282**
					(0.0143)	(0.0140)
country3					0.2320***	0.0758***
					(0.0264)	(0.0257)
country4					0.4617***	0.2020***
					(0.0552)	(0.0534)
country5					0.9318***	0.4458***
					(0.1273)	(0.1223)
country6					1.0642***	0.4873
					(0.3695)	(0.3517)
country7					1.0129*	0.2538
					(0.5589)	(0.5410)
country8					1.2332	0.6547
					(1.3365)	(1.2625)
inventors		0.0947***		0.0939***		0.0938***
		(0.0020)		(0.0020)		(0.0020)
claim		0.0082***		0.0082***		0.0082***
		(0.0004)		(0.0004)		(0.0004)
back		0.0077***		0.0077***		0.0077***
		(0.0003)		(0.0003)		(0.0003)
npl		0.0003**		0.0003**		0.0003**
		(0.0001)		(0.0001)		(0.0001)
ipc4		-0.0034		-0.0033		-0.0034
		(0.0034)		(0.0034)		(0.0034)
_cons	-0.4527***	-1.1159***	-0.5911***	-1.1634***	-0.4559***	-1.1135***
	(0.0273)	(0.0303)	(0.0293)	(0.0318)	(0.0273)	(0.0304)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,479	143,479	143,479	143,479	143,479	143,479
LR alpha=0	198,236.37***	176,032.88***	197,740.71***	175,927.98***	197,653.73***	175,902.21***
Log likelihood	-179,034.53	-175,859.31	-178,988.14	-175,850.77	-178,979.48	-175,846.16
LR chi2	8,636.86***	14,987.30***	8,729.63***	15,004.38***	8,746.96***	15,013.60***

Dependent variable: Forward citation (5-year citation window), examiners' citations and self-citations excluded. Standard errors in parentheses.
∗ $p < 0.10$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.

Our results showing the positive and significant effect of international collaboration on patent quality are in line with other previous studies (such as Briggs, 2015; and Lino et al., 2021), although the final impact is different. Other studies on a similar topic that used inventors rather than owners also point out a positive and significant effect of cross-border inventions on forward patent citations (e.g., Alnuaimi et al., 2012; Branstetter et al., 2015; Giuliani et al., 2015), but the contexts are so different that their results are hardly comparable to ours.

5.2 What countries should be the best to engage with in collaboration?

According to theory, to benefit from collaboration, the country of a partner in a co-patent should have obvious technological advantages and should offer better knowledge capabilities. The six countries with the greatest potential in the pharmaceutical industry, both in R&D and in other economic variables such as net sales and number of employees, are those presented in Table 1: the United States, Switzerland, Japan, Germany, the United Kingdom and France. This means that, according to the arguments supporting our second hypothesis, collaborating with these countries would allow the harnessing of a more varied flow of ideas and technological knowledge, which would contribute to improving patent quality.

To identify whether collaborating with these countries has a greater impact on patent quality than collaboration with other countries, we have estimated several negative binomial models using the patent families in collaboration as unit of observation (Table 8). The key variables are dummies capturing the collaboration with the United States (us), Switzerland (ch), Japan (jp), Germany (de), the United Kingdom (uk) and France (fr). For example, the dummy *us* takes value 1 if the co-patent includes assignees from the United States (along with partners from other countries), and 0 otherwise. This same criterion is used to construct the other dummies. Thus, the base category is collaborating with countries other than those specified in these models. As in Table 7, all models include control variables.

Model 1 in Table 8 presents the results of collaborating with the top six countries in pharmaceuticals when the assignees are located in two or more countries. The coefficients of the United States, Switzerland, Japan, Germany and the United Kingdom are all positive and statistically significant. This means that if the patent includes any of these countries in a collaborative patent, the impact of this patent is greater compared to co-patents in which none of these countries is the location of at least one of the assignees. For example, when the co-patent between two countries includes the United States as the location of one of the assignees of the co-patent, the quality in terms of impact in subsequent patents is almost 21.5% greater compared to the base category. Note also that the values of the coefficients become smaller as the potential in terms of R&D of the country decreases. Thus, when one of the partners in the co-patent is located in the US, the coefficient is 0.194. The coefficient of Switzerland is a little smaller (0.187), followed by Japan (0.153), and so on, until the coefficient of France, which is not statistically significant (the co-patents that include these countries –and exclude the other five countries– have similar technological quality as the base category, which is the collaboration with countries other than those included as explanatory variables).

Models 2, 3, 4 and 5 in Table 8 are estimated with co-patents in which there are partners from two, three, four and five countries, respectively. For example, according to Model 2 (results when there are partners from just two countries), those co-patents including the US as location of one of the assignees have on average 21.1% higher quality than those patent families of the base category. Note from Models 3, 4 and 5 that when the number of countries increases, the number of countries from which obtaining benefits in terms of quality becomes fewer. For example, if we look at Models 4 and 5, the only partners that are worth collaborating with when there are assignees from four or five different countries are those located in the United States and Germany, respectively. These results support Hypothesis 2, that collaborating with partners located in leading countries in a particular domain, pharmaceuticals in this case, will produce better performance in terms of patent quality than collaborating with other countries.

5.3 Collaborative patents with firms located in tax havens

As co-patents could be, at least partially, the result of sharing the ownership of patents with subsidiaries located in tax havens to reduce corporate tax burdens, we have constructed a dummy variable for those countries that, according to the EU, IMF and Oxfam, are considered low tax jurisdictions: Bermuda, the Netherlands, Switzerland, Singapore, Ireland and Luxembourg. From this group of countries, Switzerland is, at the same time, one of the countries with the greatest potential in pharmaceuticals, and thus a patent co-ownership with partners in Switzerland can be the result of effective R&D collaboration to benefit from its sectoral innovation system in pharmaceuticals, rather than a mechanism to benefit from lower tax burdens. Thus, Switzerland is excluded from the dummy *haven*.

As shown in Table 8, the coefficient of the dummy variable "haven" is not significant in any model. The correlation coefficients between this variable and the dummies capturing the top leading countries in pharmaceuticals are quite low (between -0.11 and 0.02). Furthermore, the variance inflation factors (VIFs) range between 1.02 and 1.59, which are well below the usual cut-offs, suggesting that the non-significant coefficient of "haven" is not caused by multicollinearity problems. This result suggests that patents co-owned with firms located in tax havens do not have greater quality than patents co-owned with firms located in other jurisdictions, in contrast to what we stated in Hypothesis 3.

Finally, we discuss the other variables used as determinants of the quality of patent families in both analyses (Tables 7 and 8). Overall, the effect of these variables (patent characteristics) that we included as control is similar to that obtained in the previous literature. The number of inventors (inventors) is statistically significant in all models, pointing to the fact that an increase in the number of inventors significantly affects patent quality, in line with other studies such as Sapsalis et al. (2006), Guellec and van Pottelsberghe (2000, 2002), and Singh (2008). These empirical papers suggest that larger teams are associated with strategic research projects with high expected profits, and consequently higher quality. The variable *claim* is relevant, indicating –as in other papers (Gambardella et al., 2008; Chang et al., 2018; Moaniba et al 2018)– a significant relationship between the size of the patent (proxied for the number of claims) and quality.

Table 8. Effects of collaborating with the top countries in pharmaceuticals on patent quality. Negative binomial estimations

	Model (1) More than one	Model (2) Two countries	Model (3) Three countries	Model (4) Four countries	Model (5) Five countries
us	0.1947***	0.1919***	0.2019***	0.3969***	-0.4684
	(0.0238)	(0.0294)	(0.0567)	(0.1302)	(0.3576)
ch	0.1872***	0.1720***	0.2693***	-0.0209	0.0718
	(0.0248)	(0.0343)	(0.0527)	(0.1304)	(0.3285)
jp	0.1533***	0.1592***	0.1770*	0.0772	0.2477
	(0.0422)	(0.0482)	(0.1021)	(0.2423)	(0.4812)
de	0.0865***	0.0814**	0.0485	0.0809	0.6213**
	(0.0262)	(0.0341)	(0.0555)	(0.1206)	(0.2831)
uk	0.0709***	0.1187***	0.0270	-0.2905**	0.2668
	(0.0269)	(0.0342)	(0.0587)	(0.1276)	(0.2782)
fr	0.0411	-0.0724*	0.1759***	0.1556	0.3318
	(0.0305)	(0.0423)	(0.0610)	(0.1203)	(0.3181)
haven	-0.0260	0.0331	-0.1146*	0.0206	-0.1909
	(0.0330)	(0.0440)	(0.0664)	(0.1306)	(0.3044)
inventors	0.0987***	0.0994***	0.0962***	0.1034***	0.0571*
	(0.0035)	(0.0041)	(0.0076)	(0.0155)	(0.0309)
claim	0.0079***	0.0080***	0.0065***	0.0111***	0.0116
	(0.0007)	(0.0008)	(0.0017)	(0.0034)	(0.0090)
back	0.0066***	0.0070***	0.0072***	0.0012	0.0076*
	(0.0005)	(0.0006)	(0.0010)	(0.0022)	(0.0042)
npl	0.0002	0.0001	0.0002	0.0006	-0.0006
	(0.0002)	(0.0003)	(0.0004)	(0.0010)	(0.0021)
ipc4	-0.0269***	-0.0330***	-0.0091	0.0166	0.1220
	(0.0068)	(0.0079)	(0.0147)	(0.0366)	(0.0845)
_cons	-1.1502***	-1.2005***	-1.3091***	-1.4593***	1.6208
	(0.0715)	(0.0829)	(0.1899)	(0.4888)	(1.3104)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	35,538	27,468	6,467	1,328	234
LR alpha=0	49,516.66***	35,896.10***	8,929.07***	2,581.83***	475.73***
Log likelihood	-48,607.27	-36,491.49	-9,374.66	-2,121.26	-403.75
LR chi2	3,961.11***	2,948.31***	801.28***	204.24***	95.95***

Model 1 includes patents applied for by partners from two or more different countries. Model 2 includes patents applied for by partners from just two countries, Model 3 from just three countries, Model 4 from just four countries, and Model 5 from just five countries.
Dependent variable: Forward citation (5-year citation window), examiners' citations and self-citations excluded. Standard errors in parentheses.
∗ $p < 0.10$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.

The variable *back* (citations to other patents) is highly significant in the majority of our models. The literature, however, is unclear with respect to the effect of this variable on patent quality, as we explained in Section 3.2.2. The reason is probably the difference in origin of the backward citations, which may include citations from university patents, citations to patents from firms in the same and different sectors to the focal patent, etc. This difference in the background of citations would require a disaggregation of citations to further analyse the extent to which backward citations correlate with patent quality.

As for the variable *npl* (citations to non-patent literature), we obtained positive values for the coefficients, but mixed results regarding significance (statistically significant at the 5% level in the models in Table 7 and non-significant in the models in Table 8). Obtaining positive relationships between this variable and patent quality in sectors such as pharmaceuticals, chemistry and biotechnology is quite frequent, due to these sectors' high reliance on science (Harhoff et al., 2003; Arts et al., 2013), but again, the literature offers mixed results on the significance of this variable (see references in Section 3.2.2). The coefficient of the *ipc4* variable points to a non-significant and even negative effect in some models, implying that the number of technologies in patents (measured by the number of IPC codes) is not correlated with quality, or that the relationship could even be negative. This result may be explained by the possibility that a patent with a large number of different codes may not be the result of greater innovativeness, but strategic choices (that might not be correlated with patent quality).

5.4 Robustness checks

In order to check the robustness of our results, we have carried out further analyses. Firstly, as an alternative way to cope with overdispersion, we have estimated the same models as presented in Tables 7 and 8, but applying a Poisson QMLE (quasi-maximum likelihood estimation), which has compelling robustness properties to model overdispersed count data (see for example, Wooldridge, 1999). Note that the negative binomial estimations (Tables 7 and 8) and the Poisson QML estimations (Tables A.2 and A.3 in the Appendix) lead to practically the same results in terms of significance of the coefficients, although there are slight differences in the values.

Secondly, to check whether our results hold using a different cohort for the forward patent citations of each family, we have estimated the same models as in Tables 7 and 8 but using a 3-year window rather than a 5-year cohort. The results of these models are in Tables A.4 and A.5 (Appendix). Again, the results are rather similar in terms of the significance of our key variables, although there are slight differences in values (usually greater when using a 3-year window).

Thirdly, note that the information from the EU R&D Scoreboard, from which we identified the leading countries in pharmaceuticals, refers to the period 2005-2012. To analyse whether considering this period (compared to the period 1990-2012) means any change in the results, we estimated the models in Tables 7 and 8 using this subsample, and no substantial changes in terms of significance of the coefficients were observed.

Fourthly, although international R&D collaboration can be captured by using co-assignees as an indicator, an important part of such collaboration is international cooperation between inventors. In order to check the extent to which our results hold when the countries of the co-inventors are the same as the countries of the co-assignees, we gathered new information about the inventors of each patent and their country of location. Then, we ruled out all patents in which the countries of residence of the assignees do not match the countries of the residence of the inventors. This resulted in a sample of 109,442 patent families. This sample is substantially smaller than our main sample (143,479 patent families). The reason for such a difference is that the new sample is an exact match; this means that all patent families that do not meet the criteria of the same country for all assignees and inventors are excluded. Using this subsample, we estimated the same models as we did with the original sample that included collaboration between assignees (presented in Tables 7 and 8). The new models show that the significant coefficients capturing international collaboration (coop, country and the dummies country2-country8) in Models 1 to 6 in Table 7 (with only assignees) are the same in the new models, which provides (robust) support to the first part of hypothesis 1. The new models also provide support to the second part of hypothesis 1, although this finding must be taken with caution due to the reduced number of patent families in collaboration with more than five inventors/assignees from different countries. The results from the new estimation to test hypothesis 2 are also rather similar in terms of significance of coefficients to those obtained with the original sample, supporting the hypothesis that collaborating with partners located in leading countries in pharmaceuticals results in greater patent quality than collaborating with other countries.

As in Models 3, 4, and 5 in Table 8, the results of the new models show that when the number of collaborating countries increases, the number of countries from which obtaining benefits in terms of patent quality becomes fewer.[10]

Finally, it is important to mention that some papers have raised endogeneity issues on the relationship between collaboration and patent quality. Alnuaimi et al. (2012) point out the risk of reverse causality in the estimations, since teams involved in international collaborations may be assigned to the most promising and valuable projects. Giuliani et al. (2016) argue that their sample can suffer from this same endogeneity problem due to potentially more inventive projects possibly being preassigned to international rather than domestic teams of inventors. This potential endogeneity problem is mitigated in our analysis. First, note the time-related sequence in our models. The dependent variable (patent quality) is measured by the number of forward citations, and the patent can only have citations at the end of the project, once the invention has been developed (with or without R&D collaboration) and the patent has been applied for and published. Second, there is usually a great deal of uncertainty about the results of a project and whether it can lead to a patent of good quality. The number of claims and the scope of the patent can give some idea about the technological impact (number of forward citations) that a patent might have in the future, but our models already controlled for these variables. Third, we focus neither on MNC (as for example in Alnuaimi et al, 2012) nor on firms that have patented repeatedly (as in Giuliani et al., 2016). We gathered information on patent families by filtering by pharmaceuticals IPC codes and institutional applicants. This means that our sample is composed of patent families applied for by a variety of firms with different characteristics and size. In other words, the number of firms which applied for patents is considerably greater and more diverse in their characteristics compared to the sample of large firms used in the cited previous works.

[10] The models estimated in the third and fourth sections of the robustness check are not presented, but they are available upon request.

6. Conclusions

The main rationale for collaborating internationally in producing patents relies on the idea that collaborative efforts give access to partners' resources, along with the opportunity to benefit from the innovation environment of the country in which the partners are located. Thus, collaboration may result in better innovation performance, for example, in an increase in patent quality when the co-patent involves partners from several countries. Although an increasing body of empirical literature has stressed the positive role of international collaboration in improving patent quality, there is still research that points in the opposite direction. The reason why international collaboration could reduce patent quality is not only the difficulty in achieving integration of knowledge across multiple locations, but also the fear of leaking knowledge to a potential rival. This paper contributes to this literature by addressing three novel questions. First, to what extent does increasing the number of collaborations with partners in different countries produce benefits in terms of increased patent quality? Second, what are the right countries with which to collaborate when the objective is to achieve patents of better quality? And third, since the co-patents can be the result of sharing the co-ownership of such patents with partners in territories that offer low tax rates, to what extent does this fact affect patent quality? To answer these empirical questions and test three respective hypotheses, we gathered a sample of 143,479 pharmaceutical patent families for the period 1990-2012, from which 24.7% are patents with assignees from two or more countries (co-patents). With such a sample, the estimation of several count models leads to the conclusions presented in the following paragraphs.

First, the results show that, controlling for factors affecting quality such as the size of the patent, the size of the team, and the use of previous technological and scientific knowledge, the impact of international collaboration is, on average, a 4.9% increase in patent quality compared with patents with assignees from a single country. When the number of countries in which the assignees are based increases, the effect of a wider collaboration on patent quality is also greater, but we did not find any difference when the number of countries involved is above five (note, however, that this finding must be taken with caution, due to the small number of collaborative patents with more than five assignees). These results provide some evidence for the hypothesis that the effect of collaboration is limited to a certain breadth of cross-border collaboration.

Second, to produce patents of better quality, the appropriate countries with which to collaborate are the United States, Switzerland, Japan, Germany and the United Kingdom. The quality of patents involving one or more of these five countries is substantially higher than that of patents that do not include any of these countries as locations of the assignees. On average, the quality was found to be around 21% higher (compared to patents belonging to partners from a single country) if the co-patent includes the US, 20% for Switzerland, 17% for Japan, 8% for Germany, and 7% higher for the United Kingdom. The significance and values of the coefficients of each country vary depending on the number of countries involved in the co-patent. For example, when there are assignees from four different countries, the only country that is worth collaborating with to get patents of better quality is the US. These results provide evidence for our second hypothesis, that collaborating with countries with greater potential in pharmaceuticals leads to the production of patents of better quality.

Third, according to our findings, there is no effect of co-owning patents with partners in tax havens. Thus, our results do not support the hypothesis that collaborating with partners located in tax havens has a positive effect on patent quality. A plausible explanation for this result is that the tax levied on the expected revenues from patents moved out of the country, and the special treatment by many countries of the taxation of corporate income derived from patent ownership, could offset the benefits of co-assigning patents with partners located in low-tax jurisdictions.

Our results offer some policy implications from both a managerial and a social perspective. From a managerial point of view, the main message of this paper is that international collaboration, apart from providing advantages such as the benefits of collective and organizational learning, can improve the quality of the innovative output (patents) in a technology domain such as pharmaceuticals. However, in order to prevent leakages of knowledge that can result in a co-patent of lower quality than expected, it is recommended that the number of countries in which the assignees are based be maintained at a low number. From a social perspective, it is well known that one of the objectives of the patent system is to encourage innovation by conferring a monopoly over an invention. The other is to achieve greater diffusion of innovation to facilitate follow-on innovations through patent disclosure. Thus, any financial and organizational innovation measure that contributes to encouraging international collaboration with a selected group of leading countries in specific domains can address both perspectives, and contribute to reducing uncertainty around patent quality.

A few caveats must be borne in mind in our study that may give rise to future research. First, our main indicator to capture international collaboration in producing a patent is the country of the assignee. Others have used the country of the inventor, or a combination between the countries of the owner of the patent (assignee) and the inventor. In this paper, we included a robustness check to identify differences between the use of co-assignees and coinventors. In this respect, the analysis of some case studies that allow interviews with patent owners and inventors may shed light on which indicator is the best to capture international collaboration on patents in the pharmaceutical sector. Second, the analysis of more refined indicators of patent quality (for example, using the different codes of relevance of the patent citations) may contribute to improving the measurement of quality. Another relevant factor to take into account in future research is whether our results hold in a more general context. Thus, similar analyses could be carried out for other R&D-intensive sectors, such as aerospace and electronics, and other more traditional industries (e.g., the food sector). Finally, our study focuses on the benefits in terms of patent quality from collaborating with countries with technological advantages in the field of pharmaceuticals, but we do not take into account the level of development of the countries of residence of the co-assignees. Thus, in line with the scarce research on this topic (Alnuaimi et al., 2012; Branstetter et al., 2013; Giuliani et al., 2016; and Herman and Xiang, 2022), analysing the extent to which international patent co-ownership increases opportunities for developing countries is another topic that it is worth exploring.

Appendix

Table A.1. IPC codes used to identify patent families in the pharmaceutical industry (1990-2012).

<table>
<tr><th>IPC</th><th colspan="2">Description</th><th>Inventions (1)</th></tr>
<tr><td>A61P</td><td colspan="2">Specific therapeutic activity of chemical compounds or medicinal preparations</td><td>113,218</td></tr>
<tr><td>A61P_1</td><td colspan="2">Drugs for disorders of the alimentary tract or the digestive system</td><td>23,400</td></tr>
<tr><td>A61P_3</td><td colspan="2">Drugs for disorders of the metabolism</td><td>25,135</td></tr>
<tr><td>A61P_5</td><td colspan="2">Drugs for disorders of the endocrine system</td><td>7,824</td></tr>
<tr><td>A61P_7</td><td colspan="2">Drugs for disorders of the blood or the extracellular fluid</td><td>14,045</td></tr>
<tr><td>A61P_9</td><td colspan="2">Drugs for disorders of the cardiovascular system</td><td>30,486</td></tr>
<tr><td>A61P_11</td><td colspan="2">Drugs for disorders of the respiratory system</td><td>17,847</td></tr>
<tr><td>A61P_13</td><td colspan="2">Drugs for disorders of the urinary system</td><td>14,475</td></tr>
<tr><td>A61P_15</td><td colspan="2">Drugs for genital or sexual disorders and contraceptives</td><td>10,338</td></tr>
<tr><td>A61P_17</td><td colspan="2">Drugs for dermatological disorders</td><td>18,293</td></tr>
<tr><td>A61P_19</td><td colspan="2">Drugs for skeletal disorders</td><td>18,697</td></tr>
<tr><td>A61P_21</td><td colspan="2">Drugs for disorders of the muscular or neuromuscular system</td><td>8,114</td></tr>
<tr><td>A61P_23</td><td colspan="2">Anaesthetics</td><td>833</td></tr>
<tr><td>A61P_25</td><td colspan="2">Drugs for disorders of the nervous system</td><td>34,809</td></tr>
<tr><td>A61P_27</td><td colspan="2">Drugs for disorders of the senses</td><td>13,630</td></tr>
<tr><td>A61P_29</td><td colspan="2">Non-central analgesic, antipyretic or anti-inflammatory agents</td><td>26,091</td></tr>
<tr><td>A61P_31</td><td colspan="2">Anti-infectives, i,e, antibiotics, antiseptics, chemotherapeutics</td><td>28,379</td></tr>
<tr><td>A61P_33</td><td colspan="2">Antiparasitic agents</td><td>4,355</td></tr>
<tr><td>A61P_35</td><td colspan="2">Antineoplastic agents</td><td>39,028</td></tr>
<tr><td>A61P_37</td><td colspan="2">Drugs for immunological or allergic disorders</td><td>25,483</td></tr>
<tr><td>A61P_39</td><td colspan="2">General protective or antinoxious agents</td><td>2,725</td></tr>
<tr><td>A61P_41</td><td colspan="2">Drugs used in surgical methods</td><td>944</td></tr>
<tr><td>A61P_43</td><td colspan="2">Drugs for specific purposes, not provided for in groups</td><td>46,435</td></tr>
<tr><td>A61K</td><td colspan="2">Preparations for medical, dental, or toilet purposes</td><td>143,479</td></tr>
<tr><td>A61K_6</td><td colspan="2">Preparations for dentistry</td><td>1,953</td></tr>
<tr><td>A61K_9</td><td colspan="2">Medicinal preparations characterised by special physical form</td><td>31,689</td></tr>
<tr><td>A61K_31</td><td rowspan="13">Medicinal preparations characterised by active ingredients:</td><td>Organic active ingredients</td><td>93,677</td></tr>
<tr><td>A61K_33</td><td>Inorganic active ingredients</td><td>5,177</td></tr>
<tr><td>A61K_35</td><td>Materials or reaction products with undetermined constitution</td><td>12,800</td></tr>
<tr><td>A61K_36</td><td>Material from algae, lichens, fungi or plants</td><td>4,257</td></tr>
<tr><td>A61K_38</td><td>Peptides</td><td>42,040</td></tr>
<tr><td>A61K_39</td><td>Antigens or antibodies</td><td>26,729</td></tr>
<tr><td>A61K_41</td><td>Obtained by treating material with wave energy or particle radiation</td><td>1,369</td></tr>
<tr><td>A61K_45</td><td>Active ingredients not provided for in groups</td><td>29,305</td></tr>
<tr><td>A61K_47</td><td>Non-active ingredients used</td><td>27,259</td></tr>
<tr><td>A61K_48</td><td>Medicinal preparations with genetic material, gene therapy</td><td>14,749</td></tr>
<tr><td>A61K_49</td><td>Genetic material to treat genetic diseases or gene therapy</td><td>6,258</td></tr>
<tr><td>A61K_50</td><td>Electrically conductive preparations for therapy or testing in vivo</td><td>16</td></tr>
<tr><td>A61K_51</td><td>Radioactive substances for use in therapy or testing in vivo</td><td>4,209</td></tr>
<tr><td colspan="4">(1) Number of patent families that include the respective IPC class. The total number of patent families in the sample is 143,479, but note that the sum by subclass in (1) is not the total number of patent families (an invention can be classified into several subclasses).
Source: Patstat and own elaboration.</td></tr>
</table>

Table A.2. Effects of international collaboration on patent quality. Poisson QMLE

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
coop	0.1742***	0.0720***				
	(0.0154)	(0.0151)				
country			0.1460***	0.0617***		
			(0.0110)	(0.0107)		
country2					0.1239***	0.0484***
					(0.0170)	(0.0167)
country3					0.2482***	0.0995***
					(0.0286)	(0.0286)
country4					0.4838***	0.2419***
					(0.0613)	(0.0594)
country5					0.9035***	0.3992**
					(0.1726)	(0.1764)
country6					1.0839***	0.3266
					(0.2542)	(0.3083)
country7					0.9198**	0.0673
					(0.4619)	(0.4886)
country8					1.3728**	0.3054
					(0.5962)	(0.9678)
inventors		0.0815***		0.0810***		0.0809***
		(0.0020)		(0.0020)		(0.0020)
claim		0.0081***		0.0080***		0.0080***
		(0.0003)		(0.0003)		(0.0003)
back		0.0022***		0.0022***		0.0022***
		(0.0003)		(0.0003)		(0.0003)
npl		0.0013***		0.0013***		0.0013***
		(0.0001)		(0.0001)		(0.0001)
ipc4		-0.0080*		-0.0078		-0.0078
		(0.0048)		(0.0048)		(0.0048)
_cons	-0.4518***	-0.9620***	-0.5979***	-1.0216***	-0.4476***	-0.9569***
	(0.0427)	(0.0456)	(0.0430)	(0.0456)	(0.0428)	(0.0458)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,479	143,479	143,479	143,479	143,479	143,479
Log likelihood	-278,152.72	-263,875.75	-277,858.50	-263,814.76	-277,806.34	-263,797.27
LR chi2	4,309.35***	7,688.36***	4,383.71***	7,722.09***	4,422.31***	7,748.18***

Dependent variable: Forward citation (5-year citation window), examiners' citations excluded. Robust standard errors in parentheses.
$*$ $p < 0.10$; $**$ $p < 0.05$; $***$ $p < 0.01$.

Table A.3 Effects of collaborating with the top countries in pharmaceuticals on patent quality. Poisson QMLE

	Model (1) More than one	Model (2) Two countries	Model (3) Three countries	Model (4) Four countries	Model (5) Five countries
us	0.2018***	0.1708***	0.2540***	0.3425**	-0.4291
	(0.0290)	(0.0334)	(0.0669)	(0.1689)	(0.3785)
ch	0.2035***	0.1752***	0.2799***	-0.0556	0.0607
	(0.0291)	(0.0393)	(0.0598)	(0.1448)	(0.3669)
jp	0.1831***	0.1735***	0.2296**	0.0453	-0.2723
	(0.0502)	(0.0582)	(0.1166)	(0.3007)	(0.4503)
de	0.0811***	0.0478	0.1038*	0.0491	0.6390*
	(0.0314)	(0.0399)	(0.0609)	(0.1328)	(0.3365)
uk	0.0685**	0.1094***	0.0781	-0.3980***	0.0821
	(0.0307)	(0.0393)	(0.0643)	(0.1467)	(0.3094)
fr	-0.0139	-0.1642***	0.1015	0.1494	0.3454
	(0.0384)	(0.0506)	(0.0642)	(0.1207)	(0.3079)
haven	-0.0156	-0.0325	-0.0180	0.1524	-0.2547
	(0.0414)	(0.0546)	(0.0712)	(0.1540)	(0.2600)
inventors	0.0825***	0.0879***	0.0772***	0.0950***	0.0797***
	(0.0038)	(0.0036)	(0.0063)	(0.0163)	(0.0309)
claim	0.0072***	0.0071***	0.0067***	0.0104***	0.0018
	(0.0006)	(0.0007)	(0.0012)	(0.0023)	(0.0057)
back	0.0025***	0.0025***	0.0028***	-0.0001	0.0027
	(0.0002)	(0.0002)	(0.0008)	(0.0017)	(0.0034)
npl	0.0008***	0.0008***	0.0008***	0.0007	0.0019
	(0.0002)	(0.0003)	(0.0003)	(0.0007)	(0.0020)
ipc4	-0.0213***	-0.0322***	0.0096	-0.0078	0.1504*
	(0.0071)	(0.0076)	(0.0186)	(0.0377)	(0.0831)
_cons	-1.0054***	-1.0284***	-1.3513***	-1.2461**	1.7180*
	(0.1083)	(0.0951)	(0.2539)	(0.5673)	(0.9037)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	35,538	27,468	6,467	1,328	234
Log likelihood	-73,365.60	-54,439.54	-13,839.20	-3,412.17	-641.61
LR chi2	2,536.58***	2,070.26***	702.19***	5,001.70***	2,722.88***

Model 1 includes patents applied for by partners from two or more different countries. Model 2 includes patents applied for by partners from just two countries, Model 3 from just three countries, Model 4 from just four countries, and Model 5 from just five countries.

Dependent variable: Forward citation (5-year citation window), examiners' citations excluded. Robust standard errors in parentheses.
∗ p < 0.10; ∗∗ p < 0.05; ∗∗∗ p < 0.01.

Table A.4. Effects of international collaboration on patent quality. Forward citations with a 3-year window (Negative binomial estimations)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
coop	0.1988***	0.0639***				
	(0.0195)	(0.0190)				
country			0.1628***	0.0615***		
			(0.0131)	(0.0128)		
country2					0.1390***	0.0369*
					(0.0216)	(0.0209)
country3					0.2851***	0.1076***
					(0.0398)	(0.0385)
country4					0.5734***	0.2737***
					(0.0836)	(0.0804)
country5					1.0283***	0.4365**
					(0.1947)	(0.1858)
country6					1.1749**	0.5607
					(0.5700)	(0.5396)
country7					1.2765	0.3911
					(0.8526)	(0.8133)
country8					1.4267	0.7525
					(2.0670)	(1.9464)
inventors		0.1169***		0.1158***		0.1157***
		(0.0031)		(0.0031)		(0.0031)
claim		0.0099***		0.0099***		0.0098***
		(0.0006)		(0.0006)		(0.0006)
back		0.0101***		0.0101***		0.0101***
		(0.0004)		(0.0004)		(0.0004)
npl		0.0002		0.0002		0.0002
		(0.0002)		(0.0002)		(0.0002)
ipc4		-0.0022		-0.0019		-0.0021
		(0.0053)		(0.0053)		(0.0053)
_cons	-0.5195***	-1.3350***	-0.6864***	-1.3961***	-0.5227***	-1.3312***
	(0.0389)	(0.0436)	(0.0420)	(0.0458)	(0.0389)	(0.0436)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,479	143,479	143,479	143,479	143,479	143,479
Log likelihood	-128,632.75	-126,505.07	-128,603.00	-126,498.97	-128,598.88	-126,496.79
LR chi2	6,368.51***	10,623.86***	6,428.01***	10,636.05***	6,436.24***	10,640.41***

Dependent variable: Forward citation (3-year citation window), examiners' citations excluded. Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A.5 Effects of collaborating with the top countries in pharmaceuticals on patent quality. Forward citations with a 3-year window (negative binomial estimations)

	Model (1) More than one	Model (2) Two countries	Model (3) Three countries	Model (4) Four countries	Model (5) Five countries
us	0.2222***	0.2173***	0.2149***	0.6029***	-0.8940*
	(0.0345)	(0.0433)	(0.0812)	(0.1796)	(0.5394)
ch	0.2242***	0.2120***	0.2995***	-0.1282	-0.0795
	(0.0360)	(0.0502)	(0.0748)	(0.1849)	(0.4671)
jp	0.2360***	0.2573***	0.2161	0.1787	-0.0051
	(0.0617)	(0.0710)	(0.1475)	(0.3384)	(0.6774)
de	0.1415***	0.1504***	0.0844	-0.0110	0.6397
	(0.0382)	(0.0502)	(0.0790)	(0.1690)	(0.4119)
uk	0.0495	0.1027**	0.0175	-0.4343**	0.2939
	(0.0392)	(0.0504)	(0.0835)	(0.1774)	(0.3836)
fr	0.0491	-0.1223**	0.2586***	0.2516	0.0781
	(0.0443)	(0.0624)	(0.0880)	(0.1675)	(0.4726)
haven	-0.0198	0.0556	-0.1621*	-0.1324	-0.1289
	(0.0481)	(0.0646)	(0.0953)	(0.1855)	(0.4403)
inventors	0.1152***	0.1152***	0.1114***	0.1272***	0.0731*
	(0.0051)	(0.0061)	(0.0111)	(0.0222)	(0.0430)
claim	0.0093***	0.0094***	0.0075***	0.0123**	0.0331**
	(0.0010)	(0.0012)	(0.0025)	(0.0051)	(0.0146)
back	0.0087***	0.0095***	0.0088***	0.0008	0.0054
	(0.0007)	(0.0009)	(0.0016)	(0.0032)	(0.0066)
npl	0.0002	-0.0001	0.0006	0.0015	-0.0026
	(0.0003)	(0.0004)	(0.0007)	(0.0014)	(0.0028)
ipc4	-0.0339***	-0.0400***	-0.0105	0.0121	0.1370
	(0.0102)	(0.0121)	(0.0213)	(0.0530)	(0.1278)
_cons	-1.3833***	-1.4193***	-1.5749***	-1.6847***	1.9950
	(0.1004)	(0.1177)	(0.2602)	(0.6535)	(1.8364)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	35,538	27,468	6,467	1,328	234
Log likelihood	-36,888.44	-27,288.33	-7,359.46	-1,716.42	-338.36
LR chi2	2,936.74***	2,182.55***	590.22***	169.66***	72.78***

Model 1 includes patents applied for by partners from two or more different countries. Model 2 includes patents applied for by partners from just two countries, Model 3 from just three countries, Model 4 from just four countries, and Model 5 from just 5 countries.

Dependent variable: Forward citation (3-year citation window), examiners' citations and self-citations excluded. Standard errors in parentheses.
∗ $p < 0.10$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$.

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PART III: CONCLUSIONS

CHAPTER 7:

DISCUSSION OF RESULTS, CONCLUSIONS AND FUTURE RESEARCH

7.1. Discussion of Results

This section presents the results in an integrated manner, with the aim of jointly addressing the research objectives of the thesis, in line with the existing literature and previous studies.

Regarding prior knowledge, the results show that patents incorporating a higher number of backward citations exhibit greater diffusion in the energy sample. Consistently, in the case of pharmaceutical patents, backward citations to prior knowledge have a positive effect on quality. Self-citations show a positive and significant effect on diffusion in energy patents, reflecting the cumulative nature of knowledge. This indicates that prior knowledge affects diffusion both through the incorporation of externally generated knowledge and through the use of internal knowledge. The accumulated stock of knowledge, which reflects the volume of inventive activity within the technological domain, has a negative and significant effect on diffusion in fossil and nuclear technologies, while it is not statistically significant in renewables. This suggests possible saturation effects in more mature technological domains. Regarding prior experience in patent development, the results show a positive effect on diffusion in the energy sector, reflecting the cumulative nature of knowledge and the importance of learning processes. A key result across the energy-related analyses is the systematic heterogeneity between renewable and non-renewable technologies, indicating that the role of prior knowledge differs depending on the maturity and structure of the technological domain.

In this context, the disaggregation of this knowledge base by technological origin allows the impact of technological spillovers on diffusion and trajectory to be identified. In renewable technologies, spillovers from renewable knowledge are associated with greater diffusion directed towards technologies within the same domain, while spillovers from non-renewable knowledge are associated with lower diffusion towards renewable technologies. In non-renewable technologies, spillovers from non-renewable knowledge are associated with greater diffusion directed towards their own domain, while spillovers from renewable knowledge do not show a statistically significant effect. This pattern is consistent with empirical evidence on knowledge concentration (Noailly and Shestalova, 2017; Battke et al., 2016) and aligns with the notion of technological path dependence (Acemoglu et al., 2012). This result further highlights the importance of distinguishing between technological domains, as spillovers tend to reinforce existing knowledge structures rather than promoting cross-domain recombination.

Building on these knowledge spillovers, defined according to their technological origin as part of the knowledge base, the results allow the interaction with green absorptive capacity to be examined in terms of its effect on diffusion and trajectory. The results show that green absorptive capacity does not moderate the relationship between spillovers and diffusion in renewable technologies. In contrast, it reduces the influence of spillovers from non-renewable technologies on diffusion, with a significant and negative effect, limiting the reinforcement of carbon-intensive technological trajectories. This result indicates that green absorptive capacity affects the direction of technological trajectories by constraining the continuation of those associated with non-renewable technologies.

In addition to the technological knowledge base derived from patented inventions, non-patented knowledge incorporated through citations to scientific literature is also considered. The results show that citations to non-patent literature are positively associated with diffusion in the energy sector, particularly for renewable technologies. In the pharmaceutical sector, the linkage to science is associated with higher levels of patent quality. These results are consistent with the literature highlighting the role of science as a guide in the exploration of the technological space (Fleming and Sorenson, 2004; Ahmadpoor and Jones, 2017), although its intensity varies across sectors.

The role of collaboration is examined from two perspectives: institutional collaboration and international collaboration, with effects observed on diffusion and quality. From the perspective of institutional collaboration, collaboration between firms does not show a significant effect on diffusion in energy technologies. Co-ownership with universities does not have a significant effect on diffusion in renewable technologies and shows a negative effect in fossil and nuclear technologies. However, the number of inventors involved in developing a patent shows a positive and significant effect on diffusion. Similarly, in pharmaceutical technologies, a higher number of inventors is associated with a positive effect on quality.

From the perspective of international collaboration, defined as pharmaceutical patents co-owned by applicants from different countries, there is an increase in quality compared to patents developed within a single country. This effect increases with the number of participating countries up to a maximum of five, after which it becomes non-significant. Countries with lower technological capabilities experience greater relative improvements in patent quality when engaging in international collaboration. Co-ownership with entities located in jurisdictions classified as tax havens does not show a statistically significant effect on quality. These results indicate that the effects of collaboration depend on the configuration of partners and the technological context, in line with previous evidence on international collaboration (Belderbos et al., 2014; Briggs and Wade, 2014).

The results also show geographical heterogeneity in the diffusion and quality of patented knowledge. Innovative activity is concentrated in a limited number of leading countries in the energy sector, mainly the United States, Germany, and Japan. Furthermore, when considering international collaboration, the quality of pharmaceutical patents varies depending on the partner country, with the United States, Germany, Japan, Switzerland, and the United Kingdom being associated with higher levels of quality.

Overall, the results show that the diffusion, quality, and trajectory of technological knowledge are shaped by the knowledge base and its composition, the technological origin of spillovers, their interaction with absorptive capacity, the incorporation of scientific knowledge, the configuration of collaboration, and the geographical dimension.

7.2. Conclusions

The following conclusions synthesize the main contributions derived from each of the three empirical studies, developed and published independently, which jointly address the general objective of the research. Taken together, the results highlight that technological change is shaped by cumulative knowledge dynamics, the direction of knowledge flows, and the structure of collaboration networks, with implications for both the innovation economics literature and policy design in strategically relevant sectors.

The first study shows that the diffusion of technological knowledge exhibits differentiated patterns depending on the type of technology, with distinct dynamics between renewable and non-renewable technologies in both knowledge generation and diffusion. This differentiation allows for the identification of heterogeneous technological trajectories, whose consideration is necessary for analyzing technological change in the energy sector.

Knowledge diffusion operates as a cumulative process based on the recombination of prior knowledge, in which both internal and external knowledge sources condition the likelihood of incorporation into subsequent developments and their orientation within specific technological trajectories. The greater presence of references to scientific literature in renewable technologies is associated with a knowledge base more closely linked to science, corresponding to stronger interactions between scientific knowledge and technological development in these trajectories. Both components shape the knowledge base of inventions and are associated with their diffusion, indicating that a higher degree of knowledge integration increases the probability that inventions will be used in subsequent technological developments.

Differences across technological domains are reflected in the role of accumulated knowledge through inventive experience in shaping diffusion. Technologies with more established trajectories exhibit dynamics in which prior inventive experience is associated with lower incorporation of new inventions into subsequent developments, whereas in renewable technologies, the accumulation of prior knowledge favors its incorporation into later developments.

Regarding collaboration, the results show that its effect on knowledge diffusion is not homogeneous but depends on both the type of technology and the organizational form it takes. In particular, patent co-ownership is not associated with higher levels of diffusion and may even have a negative effect in certain technological contexts. The evidence does not confirm the expected positive role of inter-organizational collaboration in diffusion. In contrast, internal knowledge generation dynamics, proxied by the size of inventor teams, are systematically associated with greater diffusion capacity, suggesting a more prominent role for internal knowledge production mechanisms relative to inter-organizational collaboration.

The second study reinforces the idea that technological innovation follows path-dependent trajectories, showing that the direction of technological change is conditioned by the nature of the knowledge flows that feed the innovation process. In this sense, the origin of knowledge affects not only the intensity of diffusion but also its orientation, contributing to the persistence of specific technological trajectories.

These results indicate that the transition towards more sustainable technologies depends not only on the generation of new inventions but also on the ability to redirect existing knowledge flows. The predominance of spillovers within the same technological domain reinforces the continuity of trajectories, which may hinder processes of structural change in the absence of mechanisms that promote technological diversification.

The role of absorptive capacity emerges as contingent on the degree of alignment between external knowledge and the existing technological base. The evidence shows that the impact of incorporating external knowledge varies depending on its compatibility with the technological trajectory, influencing both the intensity and direction of knowledge diffusion.

The third study shows that the quality of technological knowledge is closely linked to the structure of international collaboration and that the effectiveness of collaboration depends on both its configuration and the characteristics of the partners involved.

In particular, the quality of technological knowledge is associated with the ability to integrate heterogeneous knowledge and manage the complexity arising from interactions within international innovation networks. The global innovation network exhibits a hierarchical structure, in which certain countries concentrate a greater capacity to generate and articulate high-impact knowledge. In this context, collaboration with countries possessing stronger technological capabilities is associated with higher levels of quality in inventions.

At the same time, the results indicate that the relationship between the breadth of collaboration and quality follows a non-linear pattern, whereby the benefits of collaboration increase up to a certain threshold and stabilize beyond that point. Furthermore, countries with lower technological capabilities experience greater relative improvements in patent quality when engaging in international collaboration. International collaboration thus acts as a mechanism for accessing external knowledge, particularly relevant for countries with lower technological capabilities, which experience relative improvements in the quality of their patents.

Finally, co-ownership with entities located in jurisdictions classified as tax havens is not associated with improvements in patent quality, indicating that such structures do not correspond to effective processes of knowledge integration.

7.3. Implications, Limitations and Future Research

In light of the conclusions presented above, it is necessary to examine in an integrated manner the implications derived from these studies, as well as their limitations and the research avenues they open. The evidence allows implications to be drawn for public policy design, firm strategies, and inventors' decisions, considering the interaction between knowledge bases, collaboration structures, and outcomes in terms of diffusion and patent quality.

The empirical evidence confirms that the subsequent impact of an invention depends on its articulation with existing knowledge and on the channels through which this knowledge is diffused, in line with the view of technological change as a cumulative process (Nelson and Winter, 1982; Dosi, 1982; Jaffe et al., 1993). Moreover, forms of collaboration influence both the direction and scope of diffusion and the quality of the knowledge generated, reinforcing the idea that innovation emerges from interactions among agents with heterogeneous capabilities (Cohen and Levinthal, 1990; Audretsch and Feldman, 1996; Chesbrough, 2003).

From a public policy perspective, the results indicate that general innovation support instruments increase the intensity of innovative activity but have a limited capacity to influence the orientation of knowledge flows that determine the direction of technological change. The persistence of trajectories associated with non-renewable technologies is explained by the historical accumulation of knowledge and by the presence of intra-sectoral spillovers that reinforce these trajectories, thereby limiting the effectiveness of environmental policies.

Diffusion is mainly concentrated within the technological domain in which knowledge is generated, reinforcing the continuity of specialized trajectories. This dynamic, grounded in accumulated knowledge bases, encourages the reuse of proximate knowledge and reduces the likelihood of incorporating knowledge from alternative domains. Although external knowledge expands recombination opportunities, its effective contribution depends on its compatibility with the existing cognitive base, introducing constraints on knowledge openness in path-dependent contexts. These results highlight the need to design selective policies capable of influencing the composition of knowledge underlying innovation processes. In particular, the evidence that spillovers from non-renewable technologies reduce the subsequent diffusion of clean technologies supports the adoption of instruments that modify relative incentives across trajectories, such as carbon taxes or differentiated R&D subsidies (Aghion et al., 2016).

The positive effect of incorporating scientific knowledge into inventive processes further supports the need to strengthen linkages between science and technology. This involves promoting the integration of scientific profiles within corporate R&D teams and developing open-access infrastructures for technological and scientific knowledge in strategic areas such as clean energy technologies.

Regarding collaboration, the results show that its effectiveness depends on both its configuration and the technological context. Patent co-ownership is not associated with higher levels of diffusion and may generate frictions in certain environments, whereas larger inventor teams are consistently associated with greater diffusion capacity. In addition, international collaboration exhibits non-linear returns, implying that the expansion of collaborative networks should be evaluated in relation to the ability to coordinate and integrate knowledge. These findings support open innovation approaches based on effective access to and use of knowledge, rather than on the formalization of collaboration agreements alone.

From a firm-level perspective, the results highlight the strategic importance of strengthening the internal scientific base as a means to increase the impact of inventions.

At the same time, collaboration decisions require careful partner selection, as the technological and institutional quality of collaborators conditions outcomes in terms of knowledge quality. In this regard, collaboration with agents located in well-developed innovation systems is associated with higher levels of impact.

Evidence on co-ownership with universities indicates that its effects on diffusion depend on the type of technological trajectory and on the degree of alignment between scientific objectives and knowledge exploitation. This reinforces the need to tailor collaboration strategies to the technological context and the development stage of inventions.

From the perspective of inventors, the results imply that decisions related to knowledge search, selection, and recombination directly shape the impact of inventions. Specialization within a given technological domain increases the likelihood of generating relevant outcomes while orienting inventive effort toward established trajectories. In this context, the incorporation of more diverse knowledge from different domains emerges as a strategy to expand technological exploration opportunities, although it may require additional capabilities for effective integration.

The results should be interpreted considering a set of methodological and empirical limitations that also open avenues for future research. The use of patent citations as an indicator of knowledge diffusion and quality is widely accepted but does not capture the full range of knowledge transmission mechanisms. Technological diffusion is a complex process that includes dimensions not observable in patent data, and citations may contain noise derived from strategic practices, affecting their interpretation as precise measures of technological impact. The measurement of diffusion through forward citations is subject to truncation issues, limiting the ability to capture long-term effects. Similarly, the measurement of patent quality could be improved through more refined indicators that account not only for the number of citations but also for their relevance and technological context.

The measurement of collaboration through patent co-ownership also introduces limitations. This indicator captures only part of R&D interactions, as not all collaborations result in joint patents. Consequently, the results are not directly generalizable to all forms of collaborative strategies. In addition, in the analysis of the international dimension, the use of the applicant's country as a proxy for collaboration captures only one aspect of technological cooperation and could be complemented with information on inventors or other more detailed indicators.

Future research should move towards the use of complementary indicators that better capture the complexity of diffusion and technological quality, extend the temporal scope of analysis, and deepen the study of collaboration by incorporating broader measures of R&D interaction. Extending the analysis to other sectors would allow for the assessment of the external validity of the results, while considering countries' levels of development and their innovation systems would contribute to a better understanding of the heterogeneous effects of international collaboration.

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ANEXO I: INFORMES DE PUBLICACIONES DEL COMPENDIO DE TESIS

INFORME SOBRE LA CONTRIBUCIÓN DEL DOCTORANDO EN LAS PUBLICACIONES QUE CONFORMAN LA TESIS DOCTORAL POR COMPENDIO DE PUBLICACIONES

En cumplimiento de lo previsto en el artículo 23.4 del Reglamento de Doctorado de la Universidad de Cádiz, se emite el presente informe con el fin de describir y justificar la contribución realizada por la doctoranda Jennifer Medina Zamora en las siguientes publicaciones que conforman la tesis doctoral presentada bajo la modalidad de compendio de publicaciones:

- The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents, publicado en: *Technological Forecasting & Social Change.*
- Knowledge path dependence in energy innovation: the role of spillovers and green absorptive capacity in renewable and non-renewable technology diffusion, publicado en: *Eurasian Business Review.*
- Effects of co-patenting across national boundaries on patent quality. An exploration in pharmaceuticals, publicado en: *Economics of Innovation and New Technology.*

La doctoranda ha participado de forma directa y sustancial en el desarrollo de las investigaciones que dieron lugar a las publicaciones incluidas en la tesis. Su contribución ha abarcado las distintas fases del proceso investigador, incluyendo la definición de los objetivos científicos, la revisión y análisis de la literatura especializada, el diseño metodológico de los estudios, la recopilación, depuración y tratamiento de los datos, la aplicación de las técnicas de análisis, la interpretación de los resultados obtenidos y la redacción de los manuscritos científicos.

Por todo ello, se hace constar que la participación en las publicaciones que conforman la tesis doctoral por compendio de publicaciones reúne la relevancia y el alcance requeridos para su valoración por la Escuela de Doctorado de la Universidad de Cádiz.

En Cádiz a 3 de junio de 2026

Firmado por la doctoranda: Jennifer Medina Zamora

Universidad de Cádiz

Tesis por compendio de publicaciones
Documento de conformidad y renuncia de coautores

D.ª Ana Fernández Pérez, con DNI o Pasaporte: 32859562Z, coautor de la publicación que se identifica a continuación: *The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents,* publicado en: Technological Forecasting & Social Change

de acuerdo con lo establecido en el **Artículo 23.4** del **Reglamento UCA/CG12/2023, de 29 de septiembre, de Doctorado de la Universidad de Cádiz (BOUCA nº 394).**

Manifiesta su conformidad para la presentación de la citada publicación como parte de la tesis doctoral de D./Dª. Jennifer Medina Zamora, titulada:

Diffusion, Quality, and Trajectory of Technological Knowledge: Empirical Evidence from Patent Citations. (Difusión, calidad y trayectoria del conocimiento tecnológico: evidencia empírica a partir de citas de patentes)

Y expresa su renuncia a presentar la citada publicación como parte de otra tesis doctoral en cualquier otra universidad.

En Cádiz, a 1 de junio de 2026

Fdo.: ______________________________________

Tesis por compendio de publicaciones
Documento de conformidad y renuncia de coautores

D.ª Esther Ferrándiz León, con DNI o Pasaporte: 48900811M, coautor de la publicación que se identifica a continuación: *The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents,* publicado en: Technological Forecasting & Social Change

de acuerdo con lo establecido en el **Artículo 23.4** del **Reglamento UCA/CG12/2023, de 29 de septiembre, de Doctorado de la Universidad de Cádiz (BOUCA nº 394).**

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Tesis por compendio de publicaciones
Documento de conformidad y renuncia de coautores

D. Daniel Coronado Guerrero, con DNI o Pasaporte: 52301434D, coautor de la publicación que se identifica a continuación: *Knowledge path dependence in energy innovation: the role of spillovers and green absorptive capacity in renewable and non-renewable technology diffusion*, publicado en: Eurasian Business Review

de acuerdo con lo establecido en el **Artículo 23.4** del **Reglamento UCA/CG12/2023, de 29 de septiembre, de Doctorado de la Universidad de Cádiz (BOUCA nº 394).**

Manifiesta su conformidad para la presentación de la citada publicación como parte de la tesis doctoral de D./Dª. Jennifer Medina Zamora, titulada:

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INFORME SOBRE EL ORDEN DE AUTORÍA EN PUBLICACIONES CIENTÍFICAS

(A efectos de lo dispuesto en el art. 23.5 del Reglamento UCA/CG12/2023, de 29 de septiembre, de Doctorado)

DANIEL CORONADO GUERRERO, en calidad de **director del Grupo de Investigación PAIDI SEJ-295**, adscrito a la Universidad de Cádiz,

INFORMA

Que, por acuerdo del Grupo de Investigación PAIDI SEJ-295, adoptado hace más de **diez años** y mantenido de forma continuada hasta la actualidad, se estableció como **criterio general para la firma de publicaciones científicas** la **ordenación alfabética de los autores**, con independencia del grado de contribución individual de cada uno de ellos.

Este criterio responde a una **convención ampliamente aceptada en determinadas disciplinas del ámbito de las Ciencias Sociales**, en las que el orden de autoría no refleja jerarquía académica ni nivel de aportación, sino un principio de igualdad entre los miembros del equipo investigador. Dicha práctica es conocida, pública y sistemática en las publicaciones del citado grupo, y ha sido aplicada de manera uniforme en todos los trabajos colectivos derivados de su actividad investigadora.

En consecuencia, el hecho de que **D.ª JENNIFER MEDINA ZAMORA** no figure en primer o segundo lugar en el orden de firma de los artículos que conforman su tesis doctoral que será presentada en la modalidad de **compendio de publicaciones, no obedece a una menor relevancia de su contribución**, sino exclusivamente a la aplicación estricta del citado **criterio alfabético previamente acordado**, conforme a los usos y prácticas de la disciplina.

Por todo ello, y a los efectos oportunos, se emite el presente informe para que sea tenido en cuenta por la **Escuela de Doctorado de la Universidad de Cádiz**, al amparo de lo previsto en el **artículo 23.5 del Reglamento de Doctorado**, en relación con la valoración de órdenes de autoría distintos del preferente cuando así lo justifique la especialidad científica correspondiente.

Y para que así conste, firmo el presente informe en **Cádiz**, a **30 de enero de 2026**

Fdo.: DANIEL CORONADO GUERRERO

Director del Grupo de Investigación PAIDI SEJ-295

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Cádiz, 23 de marzo de 2026

Luis Escoriza Morera, director de las escuelas doctorales, EDUCA y EIDEMAR, de la Universidad de Cádiz, en función de lo establecido en el *Reglamento UCA/CG12/2023, de 29 de septiembre, de Doctorado de la Universidad de Cádiz* en lo que respecta a las tesis como compendio de publicaciones, recogidas en el artículo 23, en el que se dice que "la persona responsable de la dirección de la escuela doctoral que corresponda podrá emitir un informe valorando la relevancia y la eventual equivalencia de un orden de autores distinto del expresado, atendiendo a las especialidades de la disciplina de que se trate", INFORMA favorablemente sobre la presentación de publicaciones científicas para la modalidad de compendio en las que no se cumpla el orden de autoría reflejado en el reglamento en aquellos casos en los que dicho orden obedezca a criterios exclusivamente alfabéticos y dicho criterio quede acreditado por el responsable del Grupo de investigación al que pertenezcan los autores de las publicaciones implicadas.

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