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(In search of) The green premium: transaction level evidence of the sustainability advantage

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(In search of) The green premium: transaction level evidence of the sustainability advantage

Abstract

This paper investigates whether environmentally sustainable goods exhibit a green premium in international markets by examining the relationship between green products, patents, and export performance using transaction-level data. We integrate Italian customs data with patent information to create firm-level datasets tracking exports by firm, year, destination, and product category from 2005-2019. Patents are matched to products through probabilistic crosswalks, allowing identification of product-specific general and green patent premia. Our empirical strategy employs linear models with high-dimensional fixed effects to control for time-invariant firm characteristics, product-specific attributes, destination market conditions, and common time-varying shocks, complemented by exogenous exchange rate shocks for identification. Green classifications use OECD and WIPO taxonomies based on patent codes. We find that unpatented green products face market constraints: while they command higher unit prices, these price premia are offset by lower quantities, resulting in lower total export values. Green products also exhibit greater exchange rate pass-through, behaving like high-cost goods with limited price adjustment capacity. Patent-protected green products, however, achieve higher quantities and higher total export values relative to unpatented green products. Patent protection creates an innovation-enabled premium that shifts greenness from a price effect into a scale effect. This mechanism clarifies how firms can translate green demand into export performance by pairing environmental attributes with protectable innovation, with important implications for environmental innovation policy design.

Keywords: Intellectual Property Right, Export performance, Green innovation, Green premium

JEL classification: Q55, F14, O34, O31, Q58

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1. Introduction

The green transition poses a number of challenges, as the sustainability of its trajectory is still facing social, political, and, not least, economic feasibility barriers. Public discussion and attention in the scientific literature have benefited from the increasing availability of data to analyse and forecast the direction of the transition. However, historically, both national statistical offices and private data providers were not adequately equipped to collect data relevant to assess the green transition. In fact, standard industrial classifications were not created to assess the environmental footprint of economic activities (a first attempt in reconciling such different perspectives is proposed in Alessi et al., 2019).

The economic and business literature has long examined whether the higher cost associated with more restrictive environmental standards could be compensated—or better, more than offset—by higher rate of regulation-induced technical change in those countries adopting the regulation (see among the others, Popp, 2002). The original insight proposed by Porter (1991) and Porter and van der Linde (1995) proved prescient in anticipating a common critique: that stricter environmental regulation by a state or a group of states ultimately disadvantages domestic firms relative to foreign competitors. The so-called Porter hypothesis spurred many subsequent contributions that attempted to empirically test the conjecture; yet, to date, the evidence is ambiguous (see, among the others Jaffe and Palmer, 1997; Ambec et al., 2013; Ghisetti and Rennings, 2014; Fabrizi et al., 2018). Somewhat more recently, there have also been efforts to assess the extent to which the demand side, in terms of a higher willingness to pay for "greener" products, can contribute to reinforce the environmental transition (among the others, see Peattie, 2010; Vona et al., 2018; Besley and Persson, 2023). Our analysis contributes to this broader debate by examining whether innovation, particularly patent-protected innovation in green products, enables firms to translate environmental attributes into export performance—a key mechanism through which potential competitive disadvantages might be overcome.

Regardless of whether one adopts a demand or supply side perspective, what has been missing so far is a microfoundation of the mechanisms at work. Existing contributions have largely focused on the effects of environmental regulation (supply side) or the shift in consumer preferences at a rather aggregate level—firm, industry, or country.[1] The most original contribution of this work is to investigate the existence of a "premium" at the disaggregate level of the product (and even the transaction). This is possible thanks to detailed, product-level, data for export transactions, complemented with information on patent protection appropriately matched to the owning firms and their products.

Addressing this gap in microfoundations requires data at a much more granular level than has traditionally been available. Research on the topic has long suffered from the lack of data collection efforts explicitly aimed at assessing the environmental impact of economic activities. In contrast, green taxonomies—classification systems designed to identify environmentally sustainable economic activities—have mostly been derived and adapted from existing technological and merceological classification. Typically, the former consist of specific categories of patents (Haščič and Migotto, 2015) and the latter focus on specific product categories from the Harmonized System classification (Steenblik, 2005).

In this work, we investigate the existence of a green premium for low-emission or sustainably sourced goods by tackling some of the empirical challenges outlined above. We do this by integrating several sources of information that allow us to estimate the premium with an unprecedented level of precision. More in detail, we take advantage of highly disaggregated customs data on Italian exporters providing information on the quadruplet defined by a) company; b) year; c) country of destination of the export flow; d) Harmonized System 6-digit (HS6) product category. We complement international trade data with information on patents owned by Italian companies. The patent-to-firm match is achieved using the pairing performed by Bureau van Dijik whereas information on patent families is obtained from PATSTAT. Finally, and crucially, we use an algorithmic link with probabilities to establish a link between patent and product categories (Lybbert and Zolas, 2014).

This crosswalk, combined with detailed firm-level export data, enables investigation of patent premia while controlling for a rich set of confounding factors including firm-fixed effects, product-specific attributes, destination market conditions, and common time-varying shocks, complemented by exogenous exchange rate shocks for identification. The availability of green classifications for both patents and products allows us to investigate additional premia associated with green patents and products within patent-protected transactions. Our findings reveal that unpatented green products face market constraints: while they command higher unit prices, these price premia are offset by lower quantities, resulting in lower total export values. Patent-protected green products, however, achieve higher quantities and higher total export values relative to unpatented green products. Patent protection creates an innovation-enabled premium that shifts greenness from a price effect to a scale effect. This mechanism clarifies how firms can translate green demand into export performance by pairing environmental attributes with protectable innovation, with important implications for environmental innovation policy design.

1. Given the rising global concerns on environmental issues, there have been contributions on the topics from several fields encompassing innovation, finance, consumer behaviour, and of course, environmental economics. Clearly, it is beyond the scope of this work to provide an exhaustive list of references. Among many, we recall Starks (2023); Sautner et al. (2023); Stern and Valero (2021); Li et al. (2024); White et al. (2019); Compagnoni et al. (2025)

2. Data and methodology

2.1 Methodological framework

In this work, our objective is to isolate and estimate the green premium—our shorthand for systematic differences in unit values, quantities, and/or revenues between green and non-green products—and to assess how it varies with patent protection. We use granular export transaction data that track each firm's exports by 6-digit Harmonized System (HS6) product and destination, recording both export values and quantities that allow us to compute unit values. We combine these trade data with firm-level patent information to enable patent-to-product linkages that map technological content to traded goods.

Our methodology involves three components: identifying which traded products are green; classifying which patents are green; and linking patents to products to determine when green technologies embedded in exported goods receive patent protection in destination markets.

For the first two components, we adopt established classifications for green products and green patents from the literature (see, among others, Haščič and Migotto, 2015; Mealy and Teytelboym, 2022; Bontadini and Vona, 2023; Block et al., 2025). We provide details on these classifications in the following sections. For the third, linking patents to products, we apply the probabilistic concordance developed by Lybbert and Zolas (2014) and implemented for transaction-level trade data, among others, by De Rassenfosse et al. (2022) and Gong et al. (2025). In this work, and for the first time, we use this concordance to specifically link green patents to green products, providing additional validation of the probabilistic mapping by testing whether green technologies systematically align with green trade flows.

Next, we describe the implementation of these inputs and the construction of our dataset.

2.2 Dataset construction

We construct the dataset by combining transaction-level export data and patent data for Italy.

Export data

Export data come from the *Commercio Estero* (COE) register, which contains transaction-level information on the population of Italian exporting and importing firms from 2005 onward. Each transaction reports the HS6 product code, origin/destination country, quantity, and value. The information comes from the Single Administrative Document (SAD) for extra-EU trade and Intrastat declarations collected by the Customs Agency (*Agenzia delle Dogane*) for intra-EU trade. We retain all export transactions for firms with at least one active patent during 2005–2019. Note that while the HS unequivocally identifies a given product category, more than one variety might fall within a given HS6 class. For simplicity, we sometimes refer to HS6 as 'products', although the underlying unit is a product category. Because the HS is revised every five years (notably in 2002, 2007, 2012, 2017, and 2022), we harmonise products to a single HS vintage using the World Bank product concordances.[2] Specifically, we map observed HS codes to HS 2002, ensuring a consistent HS6 classification across years. Using HS2002 as the reference facilitates the subsequent patent–product linking, which is defined for HS 2002.

Patent data

Patent data are drawn from ORBIS-IP Data. We extract all patent families filed by Italian firms since 2005, with current applicant information updated to November 2023, and match applicants to firms in the export data. ORBIS-IP provides bibliometric information (e.g., forward citations, family size) and technological classes via IPC/CPC codes, a unified classification system for technologies managed jointly by the European Patent Office and the U.S. Patent and Trademark Office. We complement these with indicators from the OECD Patent Quality Indicators Database covering EPO and USPTO filings.

Following De Rassenfosse et al. (2022), we (i) use patent applications (rather than only granted patents) since pending patents provide interim protection and many products are commercialized while patents remain pending; and (ii) construct a ten-year patent stock. For firm f, product p, country c, and year t, the stock counts applications with priority years in $(t - 9, t)$, aggregated at the firm–destination- product. As a preliminary validation, we replicate the core export–patent protection results for Italy, analogous to those of De Rassenfosse et al. (2022) for France. The results, reported in Appendix B, are comparable and support our empirical approach.

2.3 Linking patents to products

Matched patent export data. We first match patents to firms using common identifiers, then associate a firm's patent applications in a given given destination with the exports of that firm to that destination. To link at the firm–product level, we use the ALP crosswalk of Lybbert and Zolas (2014), extended by Goldschlag et al. (2020), which provides a probabilistic mapping between HS 2002 at 6 digits and IPC at the subclass (4-character) level.[3] Using this crosswalk, we assign to each HS6 product the set of IPC subclasses and their associated probabilities, thereby connecting firm–product export records to the firm's patent applications.

The many-to-many probabilistic link: implementation and issues

Due to the probabilistic nature of concordance and the possibility that a single IPC code is associated with multiple product categories, and vice versa, our resulting dataset exhibits many to many matches (see Figure 1).

2. https://wits.worldbank.org/product_concordance.html.

3. For a recent application of the concordance in the context of international transaction, see also Gong et al. (2025).

To indicate a firm-product or a firm-product-country match with a patent, we employ a binary indicator (0/1), where 1 represents a probabilistic weight greater than zero.

Two considerations follow:

1. **Independence of green classifications:** Green patents and green products are classified independently of the patent–product link: patents by technological content (using IPC Green Inventory), products by environmental use (using WTO, OECD, and APEC lists). See next section for more details. Because green patents and green products are classified independently, their labels do not necessarily coincide. As a result, even under perfect IPC–HS concordance, a green patent can be embodied in non-green products.

2. **Aggregation mismatch:** The concordance operates at the IPC subclass (4-character) to HS6, while green patent labels often sit at finer IPC levels (main groups or subgroups). Thus a 4-character IPC may include both green and non-green subgroups, implying that green patents can be probabilistically linked to non-green products (and vice versa) through their parent subclass.

Our empirical strategy addresses the matching uncertainty outlined above through multiple specifications. We estimate: (i) the green product premium irrespective of patent status; (ii) patent protection effects irrespective of green status; and (iii) interactions of green products with green patent protection as our strictest test of green innovation effects. By requiring both green product classification and destination-specific green patent protection in (iii), we reduce noise from classification and concordance coarseness.

2.4 Green products and green patents classifications

Green products. The definition of what makes up a green product presents both conceptual and operational challenges. Conceptually, as argued in Bontadini and Vona (2023, p. 710), one must decide whether to consider "an activity (that is, a product or a service) green in terms of the effective pollution content of its production (process approach) or in terms of its potential to minimize harmful impacts of production on the environment (output approach)." In this work, and in line with much of the previous literature, we take the perspective of the *output approach*.

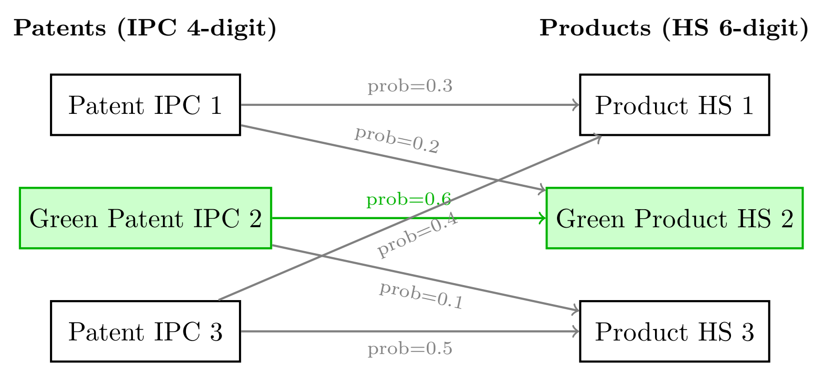


Figure 1: Many-to-many probabilistic linking between patents and products. Green patents and green products are identified independently through their classification systems. The probabilistic weights from the Lybbert and Zolas (2014) concordance create multiple matches between patents and products.

Operationally, official product classifications were not designed to identify environmental goods and this complicates measurement and comparability across studies (Steenblik, 2005; Sauvage, 2014). The classification of green products has been approached through various methodologies in the literature and by international organizations, including the WTO Core and Reference lists developed through submissions of member countries, the APEC Environmental Goods list, and the OECD/Eurostat Environmental Goods and Services Sector classifications (see, respectively, WTO, 2001; APEC, 2012; OECD, 1999; EUROSTAT, 2016). As a result, multiple classifications of green products currently coexist, creating challenges for comparing results.

Building upon Mealy and Teytelboym (2022, p. 4), in our paper we define as a green product any HS6 code included in the union of the WTO core list, the OECD lists (both the 1999 Illustrative Product List and the 2014 Custom Products List) and the APEC Environmental Goods list. This approach yields a robust set of 293 green products that have received wide expert endorsement and policy recognition across multiple international organizations. These products span various environmental categories including air pollution control, wastewater management, renewable energy technologies, and environmental monitoring equipment, all classified at the 6-digit HS2002 level. This classification ensures that each included product has either been endorsed by numerous WTO or APEC member countries, or had its environmental benefits determined through the OECD's rigorous evaluation process.

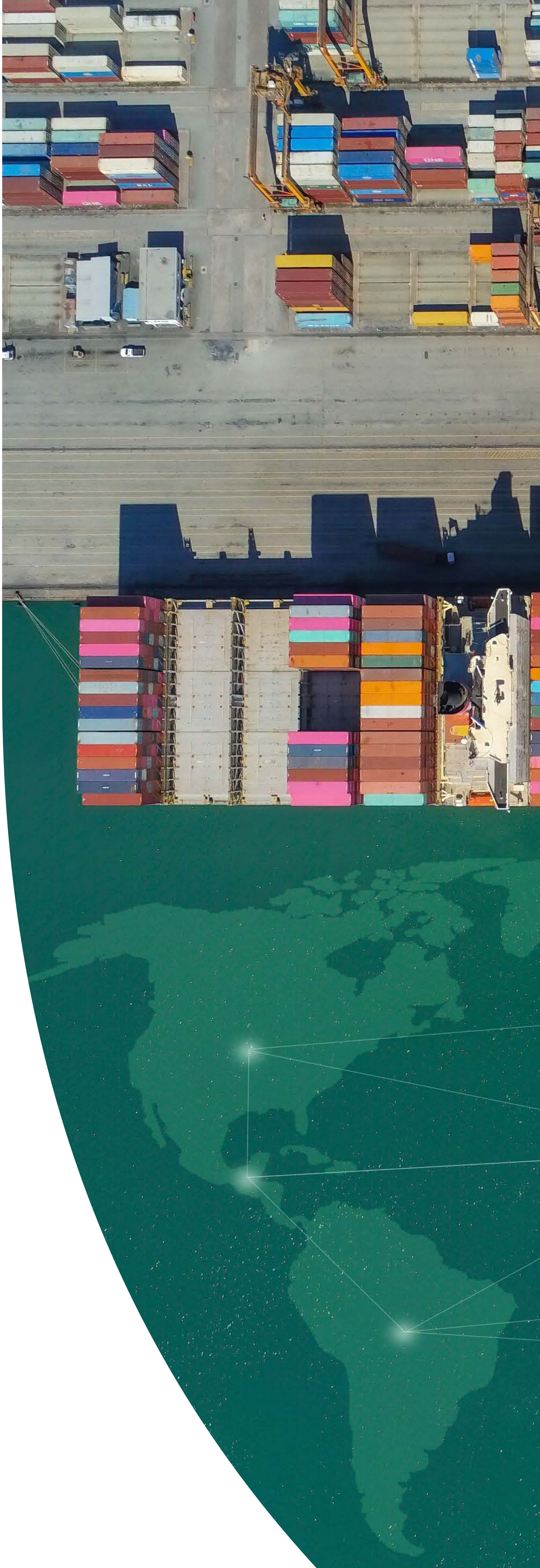
Green patents. Similar to the classification of green products, there are multiple approaches to identify green innovation using patent data. We adopt the WIPO IPC Green Inventory as our primary taxonomy. The IPC Green Inventory, developed by the IPC Committee of Experts at WIPO, facilitates searches for patent information related to

Environmentally Sound Technologies (ESTs) as listed by the United Nations Framework Convention on Climate Change (UNFCCC).[4]

The Inventory attempts to collect all such technologies in one place, providing a systematic framework that groups patents according to environmental technology categories including alternative energy production, transportation, energy conservation, waste management, and agriculture/forestry.

The classification operates at various IPC levels, from class (4- digit) down to subgroup (6+ digits), allowing precise identification of environmental technologies. Importantly, this classification is based solely on the technological content of patents, independent of their potential commercial applications or linked products (see Appendix A for a critical assessment of green patent classifications). Building on such a hierarchical system that classifies inventions into more than 70,000 technological fields, Haščič and Migotto (2015) have developed a search strategy to identify patents in environment-related technologies (ENV-tech) (for a similar application of their methodology, see, e.g., Fabrizi et al., 2018).

Our methodological contribution lies in combining three independent data sources, firm-level export transactions, patent data, and environmental classifications, through a probabilistic linking framework. While this approach introduces some uncertainty due to the many-to-many nature of patent-product links and aggregation mismatches, it enables the first comprehensive analysis of green innovation premium in international trade. By examining the intersection of green patents and green products, we identify the clearest cases of environmental innovation and their market value, while our multiple specifications allow us to assess the robustness of our findings to different definitions and linking assumptions.



4. https://www.wipo.int/classifications/ipc/green-inventory/home

3. Green innovations in international markets

This section presents descriptive evidence from a newly assembled dataset and previews three main takeaways: (i) green products are much more prevalent than green patents; (ii) patent coverage is rare in counts but disproportionately important in value; and (iii) unit prices are highest when green products are protected by green patents.

We present descriptive evidence on the original dataset that we have assembled. We analyse the universe of Italian firm–product–destination export transactions (intra- and extra-EU) from 2005–2019. For each transaction, we identify whether the product is covered by at least one patent held by the exporting firm in the destination country and whether it qualifies as a green product and/or is linked to a green patent, according to our classifications described above.

Table 1 reports four patent aggregates for Italian firms by year. Column (2) shows the total stock of active patents, while column (3) reports the subset classified as green. Columns (4) and (5) restrict the analysis to patents matched to at least one product–destination pair and, within those, the green subset. Two clear patterns emerge. First, the total stock of patents rises over time. Second, growth is faster for green patents and for transactions covered by green patents, consistent with the increasing importance of environmental technologies in both innovation and international trade.

Table 2 complements these patterns by reporting: (col. 2) the number of patenting exporters and (col. 3) the number of firm–product–destination–year transactions undertaken by those firms. Although the number of Italian firms with at least one registered patent remains relatively stable over time, the number of export transactions they generate expands. Columns (4) and (5) highlight an important asymmetry: under our definitions, export transactions involving green products are far more common than transactions linked to green patents. This gap primarily reflects the relative rarity of patenting—innovative activity remains infrequent even among exporting firms—so fewer transactions can be tied to any patent, and fewer still to a green patent. Accordingly, the intersection of these categories—transactions that both involve a green product and are covered by a green patent (col. 6)—represents a small but potentially important subset of trade flows.

Table 1: Stock of patents (and green patents) by year

Year	Patents stock (#)	Green patents stock (#)	Firm-product-country stock (#)	Firm-product-country-green stock (#)
2005	65,322	3,077	6,991	369
2006	68,735	3,404	7,785	435
2007	71,583	3,665	7,359	428
2008	73,898	4,008	7,755	457
2009	75,702	4,376	7,347	391
2010	77,312	4,723	8,450	509
2011	77,479	5,019	8,745	533
2012	77,624	5,290	9,017	573
2013	77,510	5,438	8,552	438
2014	73,814	5,261	8,659	475
2015	74,669	5,483	8,773	547
2016	74,815	5,597	9,787	616
2017	73,251	5,578	9,871	639
2018	71,541	5,580	10,005	679
2019	72,161	5,658	10,575	747

Table 2: Export transactions involving green products / patents, by year

Year	Total Firms (#)	Total Trans. (#)	Green Patent Transactions (#)	Green Product Transactions (#)	Green Patent & Product Transactions (#)
2005	6,866	304,807	648	70,750	224
2006	7,005	318,771	984	74,417	386
2007	6,949	296,377	700	68,61	279
2008	6,921	296,152	1,316	68,320	597
2009	6,856	281,197	966	58,070	352
2010	6,926	317,626	1,684	68,532	720
2011	7,005	348,928	2,321	76,037	999
2012	6,986	349,963	2,202	75,927	727
2013	6,996	355,778	1,963	76,173	721
2014	6,937	371,998	2,264	80,011	748
2015	6,873	370,708	2,375	79,683	906
2016	6,868	377,206	2,852	82,176	1,015
2017	6,756	375,266	2,178	82,555	749
2018	6,707	385,911	1,840	83,918	654
2019	6,624	368,936	1,889	83,104	679

Table 3: Green protected transactions in export markets: relative key statistics by year

Year	Protected Trans. (%)	Green Patent Trans. (%)	Green Product Trans. (%)	Green Patent & Product Transactions (% green patent)	Green Patent & Product Transactions (% green product)	Firms with Green Patent (%)	Firms with Green Product (%)
2005	2.40	9.00	23.20	34.60	0.30	1.90	72.10
2006	2.50	12.20	23.30	39.20	0.50	2.10	72.00
2007	2.40	9.70	23.20	39.90	0.40	2.10	70.30
2008	2.90	15.40	23.10	45.40	0.90	2.30	69.00
2009	3.50	9.90	20.70	36.40	0.60	2.40	66.50
2010	4.20	12.50	21.60	42.80	1.10	2.60	68.20
2011	4.20	15.80	21.80	43.00	1.30	3.00	69.10
2012	3.70	17.00	21.70	33.00	1.00	2.90	68.80
2013	4.20	13.20	21.40	36.70	0.90	2.80	68.10
2014	3.70	16.40	21.50	33.00	0.90	2.80	68.10
2015	3.90	16.30	21.50	38.10	1.10	2.90	68.10
2016	4.30	17.60	21.80	35.60	1.20	2.90	68.00
2017	3.80	15.10	22.00	34.40	0.90	3.10	69.60
2018	3.60	13.20	21.70	35.50	0.80	2.90	68.70
2019	3.80	13.40	22.50	35.90	0.80	3.00	69.00

Finally, Table 3 summarizes relative frequencies across different transaction types. Conditional on patent coverage, columns (3) and (4) provide the shares linked to green patents and to green products, respectively. Relative to transactions covered by green patents, green-product transactions account for about one third (col. 5), and this ratio is fairly stable over time. By contrast, taking green products as the reference set, the share of those transactions that are also covered by green patents (col. 6) is extremely small—on the order of, or below, 1%. The last two columns reinforce that, under our definitions, green products are far more prevalent in international trade than green patenting. Among Italy's exporting firms, only about 2–3% hold green patents, whereas roughly 70% export at least one green product.

Figure 2 pools all years and partitions transactions by patent coverage and green status. Roughly three quarters of transactions involve non-green products without patent protection. A further 21.4% are green products without any patent protection. The remaining 3.6% of transactions are covered by patents; within this small set, 14.2% are protected by green patents, and, of those, about 37% also involve a green product. Figure 3 provides the value counterpart and reveals a notable reshuffling of these shares: when weighting by values rather than transaction counts, exports covered by any patent account for 16.6% of total export value, a substantial increase from their 3.6% share of transactions. This pattern suggests that patent-protected exports command significantly higher per-transaction values.

Finally, we examine a key performance metric: unit values.[5]

5. At the transaction level, we observe total values and quantities; for each HS6 product, we define the unit price as value divided by quantity. Within categories, we use trade-weighted average unit prices across transactions.

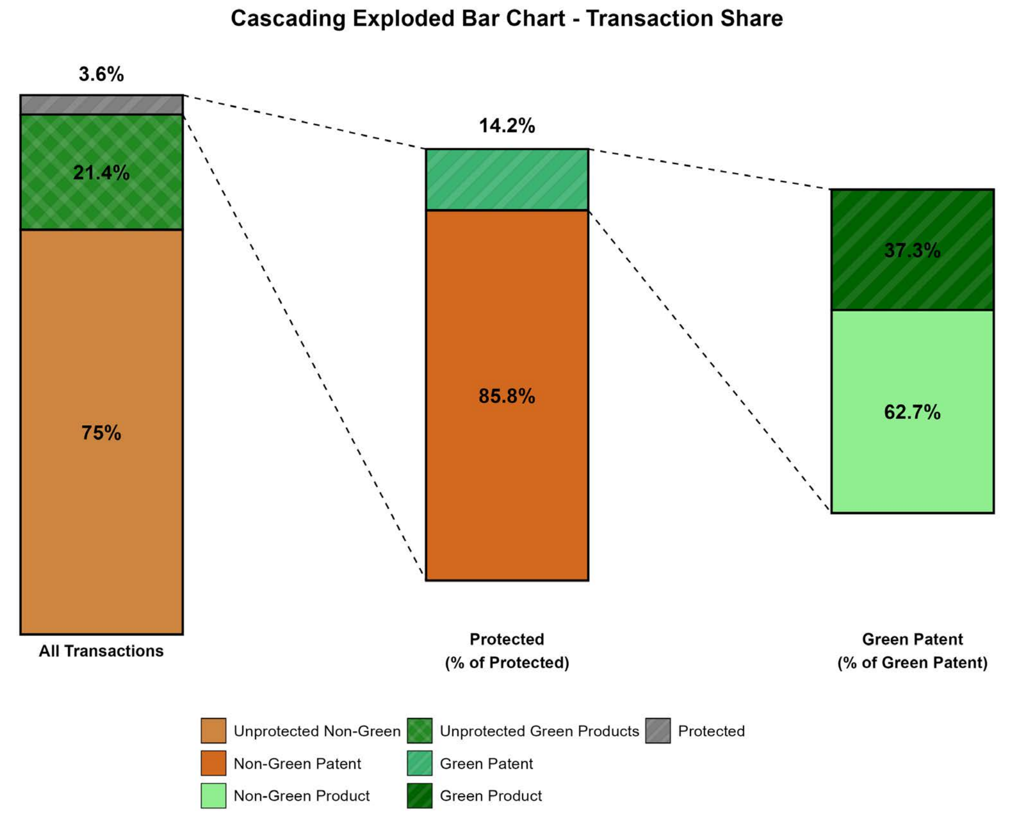


Figure 2: Share of transactions for different product and patent categories.

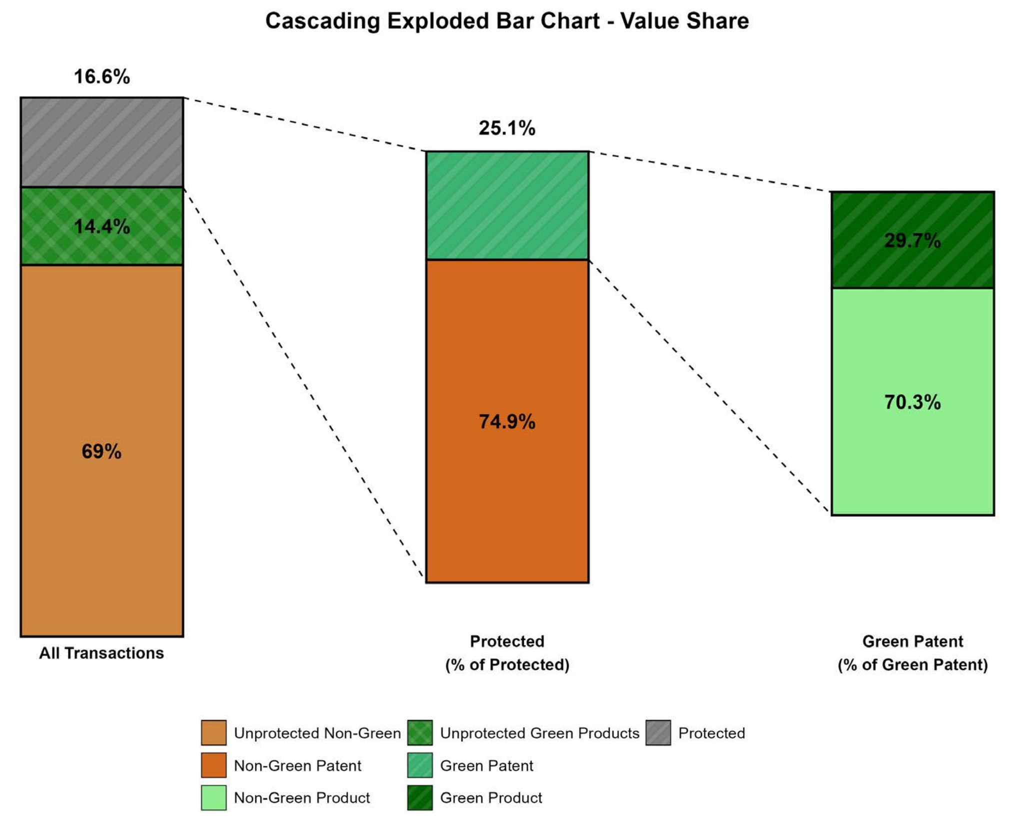


Figure 3: Exported value share of transactions for different product and patent categories.

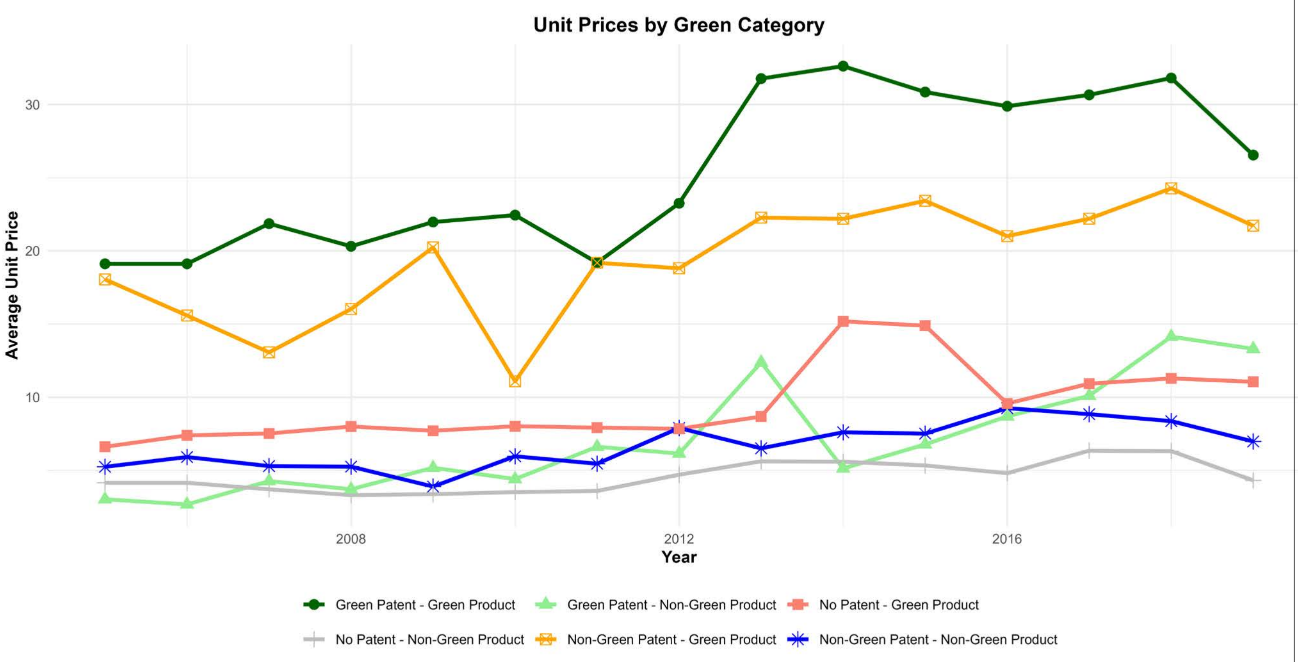


Figure 4: Unit prices timeline for different product and patent categories. Moving average 3 years

Figure 4 compares categories defined by general patent coverage, green-patent coverage, and green-product status. The highest prices are observed for transactions that combine green products with protection by green patents. The next-highest prices pertain to green products protected by non-green patents. Figure 5 confirms the same ranking when expressing prices as premia relative to a fully non-green baseline (non-green product, no patent protection). Taken together, these patterns suggest that both the characteristics of green product and patent coverage contribute independently to higher unit values, with the combination of green products and green patents commanding the highest price premium in international markets.

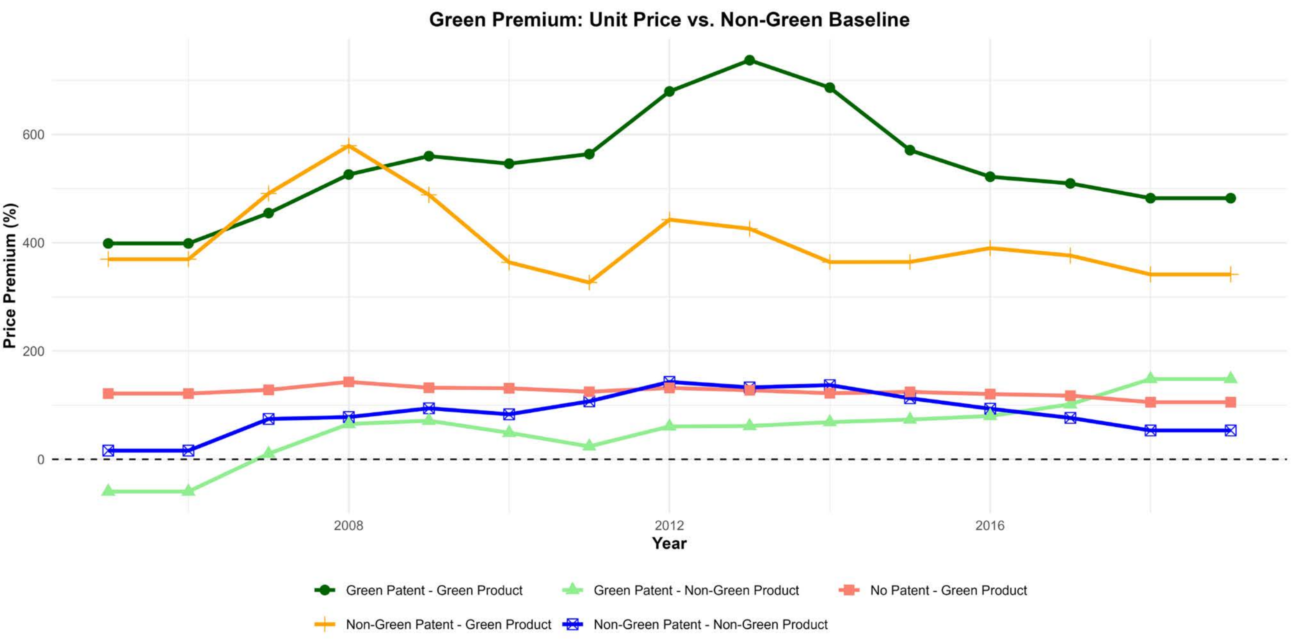


Figure 5: Green price premium timeline (computed as the ratio against unprotected transactions of non-green products). Moving average 3 year.

4. Empirical strategy and results

The descriptive evidence suggests the existence of a green premium in international trade, at least in terms of unit values, but raw comparisons cannot establish causality because they omit controls for confounding factors and may suffer from endogeneity.

We therefore move to an identification strategy based on linear models with high-dimensional fixed effects. This approach allows us to control for time-invariant firm characteristics, product-specific attributes, destination market conditions, and common time-varying shocks. We proceed in three steps: (i) estimate premia associated with green products; (ii) assess the additional role of patent coverage; and (iii) examine the interaction between green products and green patents.

To highlight the channels through which green products and innovations can create value, we follow the international trade literature (see, for instance, Bernard et al., 2007, 2011) and decompose the yearly total exports of firms in a product-country pair into extensive (quantity) and intensive margins (unit values):

$$\ln X_{fpct} = \ln \text{Quantity}_{fpct} + \ln \text{UnitValue}_{fpct}$$

where X_{fpct} is the value (in euros) of the exports of firm f of product p to country c in year t; Quantity_{fpct} is the physical quantity (in kilograms); and UnitValue_{fpct} is the corresponding unit value. Our identification strategy addresses the main concerns about endogeneity. First, we mitigate any correlation between the assignment of green status (to products and patents) and unobserved product or technology characteristics through a fixed-effects structure that absorbs time-invariant and market- specific heterogeneity. Second, we address the endogeneity of firms' green innovation and export decisions with respect to market conditions or firm capabilities by conditioning on rich firm-, product-, destination-, and time-level fixed effects. Third, we rule out reverse causality—where export success drives green innovation—by exploiting within–firm–product variation in patent protection across destination markets, following De Rassenfosse et al. (2022). We complement this design with exogenous (real) exchange rate shocks, which are not anticipated by firms, to further strengthen identification (see Berman et al., 2012; Bernard et al., 2015). This design also allows us to test whether green products—and especially those covered by (green) patents—respond differently to exchange-rate movements. If green varieties command higher markups, they may partially absorb exchange-rate fluctuations, akin to the mechanism in Berman et al. (2012) whereby more productive firms adjust markups to dampen exchange rate pass-through.

4.1 Identifying green premium with high dimensional fixed effects regression

Green Products in Export Markets We begin by testing whether green products exhibit different export performance compared to non-green counterparts. This first step focuses exclusively on product characteristics, abstracting from innovation and patent protection, to establish a baseline effect of environmental status on export outcomes.

Our baseline specification takes the following form:

$$\ln Y_{fcpy} = \beta \cdot \text{GreenProduct}_p + \alpha_{fcp} + \gamma_{fpy} + \delta_{cy} + \varepsilon_{fcpy} \quad (1)$$

where Y_{fcpy} represents either export value (X_{fcpy}), quantity, or unit price for firm f exporting product p to country c in year y. Our variable of interest, GreenProduct_p, is an indicator equal to one if the product is classified as environmentally friendly according to the HS 6-digits green product classifications described in Section 3.

The specification employs high-dimensional fixed effects to address various sources of unobserved heterogeneity. We note that firms may self-select into greener product markets based on pre-existing ties to destinations with stricter environmental standards or stronger demand for green products. Moreover, better firms may be more likely to sort into green products, creating a correlation between green status and unobserved firm quality. Our first set of fixed effects absorbs this time-invariant selection mechanism. In our baseline specification (Panel A), firm-country-product category fixed effects (α_{fcp}) absorb all time-invariant characteristics of firm-destination pairs within 4-digit HS product categories. We do not include HS6 fixed effects because the green indicator is defined at HS6 and would be absorbed. Instead, HS4 fixed effects ensure comparisons are made between green and non-green products within the same broader technological class. In our refined specification (Panel B), we replace the 4-digit product categories with technological similarity classes constructed from product descriptions, yielding tighter comparisons than the standard HS-based categories while still preserving variation in the green product indicator.

Across both specifications, firm-product-year fixed effects (γ_{fpy}) control for time-varying shocks at the firm-product category level affecting all destinations equally, such as productivity improvements in specific product lines, technology upgrades, or common input-cost shifts. In Panel A, these are defined at the firm-4-digit-year level; in Panel B, at the firm-technological similarity group-year level. Country-year fixed effects (δ_{cy}) capture destination-specific time-varying factors including environmental regulations, exchange rate fluctuations, and aggregate demand shocks that might differentially affect green versus non-green products. Thus, the coefficient β identifies the green premium by comparing export outcomes of green versus non-green products within the same firm-country-product category-year cell, conditioning on firm-product category-year and destination-year fixed effects.

A key challenge in interpreting these results is that green products may differ from non-green products in both demand and costs. Green technologies often require more expensive materials, specialized manufacturing processes, stringent quality controls, and environmental certifications—all of which may increase unit costs. Since our green product indicator is defined at the 6-digit HS level, we cannot include 6-digit product fixed effects without absorbing all the variation we seek to exploit. Instead, we control for product categories at the 4-digit HS level through firm-country-product category fixed effects (a_{fcp}), limiting comparisons to technologically similar products that share core production technologies, input requirements, and functional characteristics.

To further refine the comparison, we implement a narrower matching approach based on functional and technological similarity (Panel B of Table 4). For each green 6-digit product in our sample, we manually identify comparable non-green products using three criteria: (i) belonging to the same 4-digit HS category; (ii) sharing similar technological characteristics, material composition, or end-use applications; and (iii) serving as plausible consumer substitutes. For example, bio-based polyethylene film (HS 392020) is matched with conventional polyethylene and polypropylene films (e.g. HS 392043, and related codes within HS 3920), ensuring comparison between functionally equivalent plastic films that differ primarily in their bio-based versus petroleum-based composition. Similarly, energy-efficient LED lighting fixtures are matched with other lighting products in the same functional category. This approach creates tighter comparison groups than standard 4-digit HS categories by identifying products that are close substitutes in both production methods and applications. This helps address the cost identification challenge by comparing green products to conventional alternatives that share similar baseline production cost structures, isolating the incremental effects of environmental attributes.

The technological similarity matching approach, combined with our fixed effects structure, reduces the regression sample from 4.2 million to 1.25 million observations. While the matching successfully identifies comparable green and non-green products, our empirical specification requires that matched product pairs both appear within the same firm-country-year combination to be included in the regression. Many matched pairs are excluded because: (i) firms often export only green or only non-green variants to specific markets in a given year; (ii) some green products lack conventional substitutes within the firm's export portfolio for particular destinations; and (iii) some 4-digit categories contain predominantly green or non-green products, limiting within-firm variation. This sample reduction may limit generalizability, as the regression sample likely over represents mature green technologies where firms export both green and conventional variants to the same markets. Table 4 presents the estimation results. Panel A shows the baseline specification controlling for 4-digit product categories, while Panel B presents results using the refined technological similarity matching.

Panel A shows that green products command significantly higher unit prices — 24.3% above comparable non-green products ($e^{0.2177} - 1 = 0.243$).[6] However, this price differential coincides with lower export quantities, — 40.6%. The quantity penalty dominates the price premium, resulting in 26.1% lower total export values for green products. This pattern is consistent with several non-mutually exclusive interpretations. First, it may reflect niche market demand: green products serve a smaller customer base willing to pay premium prices, but this segment is limited in size. Second, higher production costs may necessitate higher prices, which in turn reduces demand and quantities through standard price elasticity mechanisms. Third, supply constraints—limited production capacity for newer green technologies or higher marginal costs—may restrict quantities even when demand exists. Without direct production cost data, we cannot definitively separate these mechanisms.

Panel B, using the technological similarity matching, reveals quantitatively similar but slightly larger effects. Green products show a 24.3% price premium, a 40.6% quantity penalty, and a 26.1% reduction in total export values. The larger coefficients in the matched sample suggest that when we compare green products to their closest technological substitutes—products plausibly with more similar production costs, serving overlapping market niches—the green performance differential becomes more pronounced.

6. Throughout this paper, we report percentage effects from log-linear specifications using the exact formula ($e^{\beta} - 1$) × 100 rather than the approximation β × 100, which is only valid for small coefficients. This is particularly important for our results as several coefficients are above the threshold where the approximation error becomes substantial.

Table 4: Export performance of green products: Value, quantity, and unit prices

Panel A			
Dependent Variables:	ln X_{fpcy}	ln $Quantity_{fpcy}$	ln $UnitValue_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
Green Product	-0.1875**	-0.3669***	0.1809***
	(0.0805)	(0.1197)	(0.0423)
Fixed-effects			
Firm-Country-Product Cat. (4-digit)	Yes	Yes	Yes
Firm-Product Cat. (4-digit)-Year	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes
Fit statistics			
Observations	4,191,388	4,167,881	4,167,881
R^2	0.68009	0.76274	0.88200
Within R^2	0.00056	0.00159	0.00214

Clustered (Product Cat. (6-digit)-Year) standard-errors in parentheses

Panel B			
Dependent Variables:	ln X_{fpcy}	ln $Quantity_{fpcy}$	ln $UnitValue_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
Green Product	-0.3029***	-0.5191***	0.2177***
	(0.0834)	(0.1336)	(0.0517)
Fixed-effects			
Firm-Country-TechSim Product	Yes	Yes	Yes
Firm-TechSim Product-Year	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes
Fit statistics			
Observations	1,251,388	1,244,330	1,244,330
R^2	0.67903	0.73748	0.83297
Within R^2	0.00394	0.00774	0.00665

*Clustered (TechSim Product-Year) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table presents the performances of green products in export transactions. The dependent variables are the natural logarithm of export value (ln X_{fpcy}), quantity (ln $Quantity_{fpcy}$), and unit value (ln $UnitValue_{fpcy}$) at the firm-product-country-year level. The main explanatory variable is a green product indicator that equals one if the transaction involves a product classified as environmentally friendly. The specifications include firm-country (α_{fc}), firm-year (γ_{fy}), and country-year (δ_{cy}) fixed effects to control for time-invariant bilateral relationships between firms and destination markets, firm-specific shocks over time, and country-specific macroeconomic conditions in each year, respectively. Standard errors are clustered at the product-year level to account for potential correlation in the errors within product categories over time.

In the sections that follow, we explore whether these patterns vary systematically when firms face exogenous shocks, particularly exchange rate fluctuations, which may help distinguish demand-side from supply-side interpretations. We also investigate whether patent protection—which could both signal innovation to buyers and provide market power to sustain price premia even with higher costs—affects these relationships.

Exchange Rate Pass-Through and Green Products. To probe whether the observed price premium for green products reflects demand-side willingness to pay or supply-side cost differentials, we examine how green versus non-green products respond to exchange-rate fluctuations. Berman et al. (2012) show that higher-productivity firms exhibit lower exchange-rate pass-through into export prices, while Chatterjee et al. (2013) extend this logic within multiproduct firms: products closer to a firm's core competency—those with lower marginal costs—display lower pass-through than higher-cost peripheral products. Following an appreciation, this framework predicts that low-cost, high-margin products display greater exporter price flexibility (larger price cuts, smaller quantity adjustments) because firms can pass through less of the exchange-rate shock to destination prices. High-cost, thin-margin products show greater price rigidity (smaller price cuts, larger quantity adjustments) because they have less scope to adjust prices without eroding margins.

If green products face higher production costs (e.g., expensive materials, specialized processes, certifications), we expect them to behave like peripheral products: under appreciation, they should exhibit smaller price cuts and larger quantity declines relative to comparable non-green products. Conversely, if green products benefit from a demand-side premium that effectively raises margins, they should resemble core products: larger price cuts and smaller quantity responses under appreciation.

We augment our baseline specification with PPP-adjusted bilateral real exchange rates:

$$\ln Y_{fpcy} = \beta_1 \cdot \text{GreenProduct}_p + \beta_2\, \text{Real}FX_{cy} + \beta_3 \cdot (\text{GreenProduct}_p \times \text{Real}FX_{cy}) + a_{fcp} + \gamma_{fpy} + \tau_y + \varepsilon_{fpcy} \quad (2)$$

Here, RealFX_{cy} captures the bilateral real exchange rate (home currency per foreign currency), with increases indicating appreciation of the exporter's currency (loss of competitiveness). The coefficient β_2 measures the baseline exchange rate elasticity for non-green products, while β_3 captures the differential elasticity for green products. Crucially, we replace country-year fixed effects with year fixed effects to preserve variation in bilateral exchange rates while still controlling for global shocks. All other fixed effects (a_{fcp} and γ_{fpy}) remain as in the baseline specification.

Table 5 presents the results in two panels. Panel A shows results for the full sample of export destinations. Panel B restricts the sample to non-Euro area destinations, excluding countries sharing a common currency with Italy.[7]

This restriction addresses the concern that within a monetary union, PPP-adjusted real exchange rates largely capture structural price levels, wage differentials, and productivity gaps rather than movements in nominal exchange rates, thereby confounding identification of exchange rate effects. The baseline exchange rate elasticity (β_2) shows the expected negative signs across both panels: in Panel A, a 10% appreciation reduces export values by 1.43%, split between a 1.13% quantity decline and a 0.30% price reduction (in Euro terms). In Panel B (excluding the Euro area), the magnitudes are nearly identical—1.38% for values, 1.07% for quantities, and 0.31% for unit values—confirming that the inclusion of Euro area destinations does not materially affect our estimates. The observed magnitudes are in line with the pricing-to-market literature, which typically finds that firms make modest pricing adjustments across different markets, leading to high rates of exchange rate transmission to destination prices (Berman et al., 2012; Chatterjee et al., 2013; Bernard et al., 2015). The interaction terms reveal striking differential responses for green products. In Panel A, the Green Product × Real FX rate coefficient on unit values is positive and significant (0.0360), indicating that green products reduce their prices less than non-green products when facing appreciation. This price rigidity comes at a cost: the interaction term on quantities is negative and larger in magnitude (-0.0867), implying that green products experience substantially larger volume losses. The net effect on total export values is negative (-0.0521), indicating that the limited price adjustment fails to prevent disproportionate declines in export value. Panel B confirms these patterns in the sample excluding Euro area destinations. The interaction coefficient on unit values remains positive (0.0329), the quantity response remains negative (-0.0709), and the overall value effect remains negative (-0.0394).

This pattern aligns with the Berman–Chatterjee prediction for high-cost, peripheral products. Green varieties appear margin-constrained: firms cut their prices only modestly under appreciation while quantities contract sharply. By contrast, non-green products exhibit larger price cuts and smaller quantity responses, consistent with lower-cost core products that permit greater markup adjustment. These exchange-rate responses suggest that green products face higher marginal costs relative to conventional alternatives. While this does not exclude demand-side premia for green attributes, it points to supply-side cost differentials as a key driver of the observed price–quantity dynamics.

4.2 Identifying green innovations: the role of patent protection

We have established that green products command a unit value green premium but do not achieve an export value green premium, with higher prices more than offset by larger quantity penalties, and that they behave like high-cost products in their exchange rate responses. We now examine whether patent protection can provide green products with a competitive advantage in international markets. Patent protection may offer legal security that enables firms to expand their exports (De Rassenfosse et al., 2022), or act as a signal of product quality (Gong et al., 2025).

Patent protection and green product performance We extend our baseline specification to distinguish between three types of green products: those without patent protection, those protected by non-green patents, and those protected by green patents.

Our specification takes the form:

$$\ln Y_{fpcy} = \beta_1 \cdot \text{GreenProd}_p + \beta_2 \cdot (\text{Patent}_{fpcy} \times \text{GreenProd}_p) + \beta_3 \cdot (\text{Patent}_{pcy} \times \text{GreenPat}_{pcy} \times \text{GreenProd}_p) + a_{fc} + \gamma_{fy} + \delta_{cy} + \varepsilon_{fpcy} \quad (3)$$

where Patent$_{fpcy}$ indicates whether the firm holds any patent protection linked to the transaction, and GreenPat$_{fpcy}$ further identifies whether the protecting patent is classified as environmentally friendly. The coefficient β_1 captures the baseline performance of unpatented green products. The coefficient β_2 identifies how non-green patent protection modifies green product performance. Finally, β_3 isolates the incremental effect when green products are protected by green patents.

This specification maintains our high-dimensional fixed effects structure: firm-country-product category (4-digit) fixed effects (a_{fcp}), firm-product category-year fixed effects (γ_{fpy}), and country-year fixed effects (δ_{cy}). Standard errors are clustered at the product (6-digit)-year level.

Table 6 shows that patent protection changes the market performance of green products. In the absence of protection, green products display the familiar disadvantage from the baseline: higher unit values, but lower quantity and export value. Patent protection reverses this pattern. When a green product is covered by a non-green patent, the quantity penalty disappears and becomes an

7. The excluded Euro area countries are: Austria (AT), Belgium (BE), Cyprus (CY), Germany (DE), Estonia (EE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Lithuania (LT), Luxembourg (LU), Latvia (LV), Malta (MT), Netherlands (NL), Portugal (PT), Slovenia (SI), and Slovakia (SK).

advantage. The patent–green interaction coefficient of 0.6172 implies that, relative to unpatented green products in the destination where protection applies, patented green products sell about 85.0% more. Combining this with the baseline green effect, patented green products, in countries and years where protection is active, sell 25% more than the firm's non-green products.

This quantity expansion more than compensates for a reduction in the unit value advantage: the interaction coefficient on unit values (-0.0949) indicates that patent protection reduces the green price advantage by 9 percentage points, bringing it to approximately 9%. The net result is that patent-protected green products achieve 69% higher total export values relative to unpatented green products, and 37% higher values than non-green products.

When green products are protected by green patents, performance gains intensify further. The triple interaction coefficients (0.0960 on quantities, 0.0555 on values) are positive, although they are not significant. They are estimated very imprecisely, probably due to the small number of observations in this specific cell.

Two mechanisms could explain these results. First, De Rassenfosse et al. (2022) find that firms value foreign patent protection primarily for legal security rather than monopoly pricing opportunities, which may explain why patents enable market expansion for green products. This legal security may be particularly crucial given their innovation-intensive nature and the substantial investments required to build market acceptance for environmentally differentiated offerings. Patent protection allows firms to pursue volume strategies and invest in market development without fear that competitors will appropriate their innovations, enabling the quantity expansions we observe without the price premia typically associated with monopoly power. Second, patents may signal quality and technological credibility (Gong et al., 2025), particularly valuable for green products where environmental performance claims are difficult to verify ex ante. The formal examination process and public disclosure requirements provide independent validation of technological merit, reducing information asymmetries that otherwise confine green products to buyers with specialized knowledge or strong environmental preferences.

The reduction in unit value advantages for patent-protected green products (-10% for any patent, with no additional reduction for green patents) does not necessarily indicate reduced pricing power but likely reflects compositional and strategic factors. As De Rassenfosse et al. (2022) note, new patented products entering markets may initially reduce average prices within product categories even while expanding total value. Additionally, our probabilistic patent-product matching necessarily includes process patents alongside product patents. Process innovations could entail cost reductions that lower prices while expanding quantities.

Exchange rate sensitivity of green innovations Our final analysis examines whether patent protection changes the way in which green products react to exchange rate fluctuations.

We extend our innovation specification to include exchange rate interactions:

$$\begin{aligned}\ln \boldsymbol{Y}_{fpcy} = {} & \beta_1 \cdot \mathrm{Real}\boldsymbol{FX}_{cy} + \beta_2 \cdot \mathrm{GreenProd}_p + \beta_3 \cdot (\mathrm{GreenProd}_p \times \mathrm{Real}\boldsymbol{FX}_{cy}) \\ & + \beta_4 \cdot (\mathrm{Patent}_{fpct} \times \mathrm{GreenProd}_p) + \beta_5 \cdot (\mathrm{Patent}_{fpct} \times \mathrm{GreenProd}_p \times \mathrm{Real}\boldsymbol{FX}_{cy}) \\ & + \beta_6 \cdot (\mathrm{Patent}_{fpct} \times \mathrm{GreenPat}_{fpct} \times \mathrm{GreenProd}_p) \\ & + \beta_7 \cdot (\mathrm{Patent}_{fpct} \times \mathrm{GreenPat}_{fpct}\ \mathrm{GreenProd}_p \times \mathrm{Real}\boldsymbol{FX}_{cy}) \\ & + a_{fcp} + \gamma_{fpy} + \tau_y + \varepsilon_{fpcy} \qquad (4)\end{aligned}$$

As in the exchange rate analysis presented before, we exclude Euro area destinations to ensure genuine currency variation and replace country-year fixed effects with year fixed effects to enable identification of exchange rate effects. The coefficients on the various exchange rate interactions (β_3, β_5, β_7) reveal whether and how innovation protection moderates exchange rate transmission for green products.

Table 7 presents the results. The baseline exchange rate elasticity for non-green products confirms standard patterns: exchange rate appreciation reduces export values, quantities, and prices. Unpatented green products experience additional value losses following appreciation, driven by more pronounced quantity responses. Combined with greater price rigidity, this pattern reinforces our earlier interpretation: unpatented green products behave like high-cost goods with thin margins, unable to absorb competitive shocks through pricing adjustments and consequently suffering larger demand losses. Patent protection appears to change this pattern. The triple interaction coefficient (β_5 = 0.0713 on values, 0.0539 on quantities) reveals that patent-protected green products show significantly reduced exchange rate sensitivity. For each 10% appreciation, patent protection offsets approximately 0.74 percentage points of the amplified green product value response, operating primarily through the quantity channel. Patent-protected green products maintain similar price responses to exchange rates as their unpatented counterparts (the coefficient of 0.0193 on unit values is statistically insignificant), but their quantity elasticity decreases substantially, even if also this coefficient is not statistically significant. Interestingly, the additional effect of green patents on exchange rate sensitivity (the quadruple interaction, β_7) is statistically insignificant across all outcomes, consistent with the previous table. Green-patent-protected green products do not show meaningfully different exchange rate responses compared to green products protected by conventional patents. This null result probably reflects substantial loss of statistical power as the number of transactions meeting these conditions is very small. However, it may suggest that the innovation insurance effect operates through patent protection itself rather than the specific environmental content of the innovation.

Table 5: Exchange rate pass-through for green products

Panel A: All destinations			
Dependent Variables:	ln X_{fpcy}	ln Quantity$_{fpcy}$	ln UnitValue$_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
Green Product	-0.0462	-0.1329***	0.0854***
	(0.0480)	(0.0614)	(0.0195)
RealFX rate	-0.1427***	-0.1127***	-0.0301***
	(0.0064)	(0.0077)	(0.0030)
Green Product × RealFX rate	-0.0521***	-0.0867***	0.0360***
	(0.0112)	(0.0155)	(0.0061)
Fixed-effects			
Firm-Country-Product Cat. (4-digit)	Yes	Yes	Yes
Firm-Product Cat. (4-digit)-Year	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,649,483	2,634,132	2,634,132
R^2	0.70034	0.76474	0.88063
Within R^2	0.00078	0.00132	0.00166

Clustered (Product Cat. (6-digit)-Year) standard-errors in parentheses

Panel B: Excluding euro area destinations			
Dependent Variables:	ln X_{fpcy}	ln Quantity$_{fpcy}$	ln UnitValue$_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
Green Product	-0.1007**	-0.2004***	0.0983***
	(0.0466)	(0.0648)	(0.0218)
RealFX rate	-0.1379***	-0.1068***	-0.0311 ***
	(0.0063)	(0.0076)	(0.0030)
Green Product × RealFX rate	-0.0394***	-0.0709***	0.0329 ***
	(0.0101)	(0.0141)	(0.0055)
Fixed-effects			
Firm-Country-Product Cat. (4-digit)	Yes	Yes	Yes
Firm-Product Cat. (4-digit)-Year	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,256,433	2,241,079	2,241,079
R^2	0.66326	0.75452	0.88435
Within R^2	0.00103	0.00168	0.00196

*Clustered (Product (6-digit)-Year) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table examines the differential exchange rate elasticity of green products in export transactions. The dependent variables are log of export value (ln X_{fpcy}), quantity (ln Quantity$_{fpcy}$), and unit value (ln UnitValue$_{fpcy}$) at the firm-product-country-year level. The specification includes a green product index, the PPP-adjusted real exchange rate, and their interaction to capture differential exchange rate sensitivities. Panel A includes all export destinations. Panel B excludes Euro area countries (Austria, Belgium, Cyprus, Germany, Estonia, Spain, Finland, France, Greece, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Portugal, Slovenia, and Slovakia) where Italy shares a common currency, ensuring that PPP adjustments reflect genuine currency risk rather than structural price differences within EU. All specifications include firm-country-product category, firm-product category-year, and year fixed effects. Standard errors are clustered at the product-year level.

Table 6: Green premium for green innovations

Panel A: All destinations			
Dependent Variables:	ln X_{fpcy}	ln $Quantity_{fpcy}$	ln $UnitValue_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
Green Product	-0.2073***	-0.3907***	-0.1849***
	(0.0508)	(0.0765)	(0.0276)
$DPat_{fpct}$	0.0635***	0.0833***	-0.0197**
	(0.0231)	(0.0249)	(0.0078)
Green Product × $DPat_{fpct}$	0.5229***	0.6172***	-0.0949***
	(0.0588)	(0.0626)	(0.0182)
$DPat_{fpct}$ × Green Patent	0.2158***	0.2226***	-0.0080
	(0.0664)	(0.0725)	(0.0225)
Green Product × $DPat_{fpct}$ × Green Patent	0.0555	0.0960	-0.0373
	(0.1079)	(0.1183)	(0.0349)
Fixed-effects			
Firm-Country-Product Cat. (4-digit)	Yes	Yes	Yes
Firm-Product Cat. (4-digit)-Year	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes
Fit statistics			
Observations	4,191,388	4,167,881	4,167,881
R^2	0.68031	0.76292	0.88201
Within R^2	0.00123	0.00232	0.00224

*Clustered (Product (6-digit)-Year) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table examines the green premium for innovations by distinguishing between green products with and without patent protection. The dependent variables are the natural logarithm of export value (ln X_{fpcy}), quantity (ln $Quantity_{fpcy}$), and unit value (ln $UnitValue_{fpcy}$). The specification includes a green product indicator and its interactions with patent protection status and green patent classification. The coefficient on GreenProd captures the baseline premium for unpatented green products. The interaction Patent × GreenProd identifies the additional premium from patent protection, while the triple interaction Patent × GreenPat × GreenProd captures the incremental effect when green products are protected by green patents, representing true green innovation. Firm-country (a_{fc}), firm-year (γ_{fy}), and country-year (δ_{cy}) fixed effects are included. Standard errors are clustered at the product-year level. The sample is restricted to patenting firms.

Table 7: Green premium for green innovations elasticities to FX rate

Panel A: All Destinations			
Dependent Variables:	ln X_{fpcy}	ln Quantity$_{fpcy}$	ln UnitValue$_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
Real FX rate	-0.1240***	-0.1071***	-0.0173***
	(0.0061)	(0.0077)	(0.0030)
Green Product	-0.1240***	-0.2242***	0.0985***
	(0.0414)	(0.0597)	(0.0212)
Real FX rate × Green Product	-0.0261**	-0.0509***	0.0262***
	(0.0123)	(0.0181)	(0.0068)
$DPat_{fpct}$	0.1069***	0.0873***	0.0191*
	(0.0250)	(0.0284)	(0.0106)
Real FX rate × DPat$_{fpct}$	-0.0031	0.0173	-0.0200***
	(0.0142)	(0.0161)	(0.0061)
Green Product × DPat$_{fpct}$	0.2455***	0.3441***	-0.1002***
	(0.0595)	(0.0701)	(0.0274)
$DPat_{fpct}$ × Green Patent	0.2305***	0.3585***	-0.1193***
	(0.0788)	(0.0881)	(0.0333)
Real FX rate × Green Product × $DPat_{fpct}$	0.0713**	0.0539	0.0193
	(0.0305)	(0.0355)	(0.0143)
Real FX rate × $DPat_{fpct}$ × Green Patent	-0.0311	-0.0880*	0.0477***
	(0.0402)	(0.0456)	(0.0178)
Green Product × $DPat_{fpct}$ × Green Patent	0.0895	0.0505	0.0328
	(0.1255)	(0.1430)	(0.0549)
Real FX rate × Green Product × $DPat_{fpct}$ × Green Patent	-0.0164	0.0085	-0.0162
	(0.0644)	(0.0748)	(0.0301)
Fit statistics			
Observations	2,256,433	2,241,079	2,241,079
R^2	0.66348	0.75469	0.88436
Within R^2	0.00169	0.00240	0.00209

*Clustered (Product (6-digit)-Year) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table examines how patent protection affects the exchange rate sensitivity of green products. The dependent variables are the natural logarithm of export value (ln X_{fpcy}), quantity (ln Quantity$_{fpcy}$), and unit value (ln UnitValue$_{fpcy}$). The specification includes interactions between green product status, patent protection (both general and green patents), and the PPP-adjusted real exchange rate. The coefficients reveal whether technological innovation insulates green products from exchange rate fluctuations. Patent-protected green innovations may exhibit lower exchange rate sensitivity if they face less price competition due to technological differentiation. The triple and quadruple interactions decompose these effects by innovation type: unpatented green products, patent-protected green products, and green patent-protected green products (true green innovations). Euro area countries are excluded to ensure exchange rate variation. Firm-country (a_{fc}), firm-year (γ_{fy}), and country-year (δ_{cy}) fixed effects are included. Standard errors are clustered at the product-year level.

5. Conclusions

In this work, we have provided empirical evidence on the existence of a green premium. A relevant difference from previous contributions (see among the others Ambec et al., 2013) is that we look at the mechanisms that take place at the level of the transaction of a single product.

Thanks to highly disaggregated Italian export data, at the level of the firm-product-country, it is possible to investigate the transaction of goods classified as green (Mealy and Teytelboym, 2022). The transaction level export data are then matched with patents registered by companies; then, by exploiting a patent-to-product crosswalk (Lybbert and Zolas, 2014), we are able to track the export transaction of products protected by patents in the specific country of destination. Finally, resorting to the existing classification of green patents (Haščič and Migotto, 2015) enables us to further classify patent protection for a given transaction as green.

Our results reveal a conditional relationship between environmental attributes, innovation, and international market performance. Unpatented green products consistently face market constraints: price premia are more than offset by quantity losses, resulting in lower export values. They exhibit limited exchange rate absorption capacity and amplified demand volatility during exchange rate shocks. These patterns suggest that environmental attributes alone are insufficient for robust market penetration.

Patent protection converts green products from commercially constrained niche goods into export successes with stable international demand. This transformation operates primarily through an innovation- enabled green premium that shifts greenness from a price effect into a scale effect: patent-protected green products may sacrifice some price advantage but achieve higher volumes and substantially improved resilience to exchange rate fluctuations. This mechanism clarifies how firms can translate green demand into export performance by pairing environmental attributes with protectable innovation.

These findings carry important implications for environmental innovation policy. Effective policy should emphasize not just the development of green technologies but also the institutional frame- works—particularly patent systems—that enable their international diffusion and large-scale deployment.

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A. Note on plausibility of WIPO classification

Based on the environmental impact and sustainability criteria, here are the classifications that can be considered **somewhat green technologies:**

Green technologies

Renewable energy

- **F03D** – Wind turbines and wind energy conversion
- **F24S** – Solar thermal collectors and systems
- **H02S** – Solar photovoltaic (PV) systems
- **F03C** – Positive-displacement engines driven by liquids (includes hydropower)
- **F24T** – Geothermal energy collection

Waste management and remediation

- **B09B** – Disposal of solid waste (recycling, recovery)
- **B09C** – Reclamation of contaminated soil
- **C02F** – Treatment of water, wastewater, sewage
- **E03F** – Sewers and sewerage systems
- **C05F** – Organic fertilizers from waste (composting)
- **B65F** – Gathering or removal of refuse

Sustainable Transportation

- **B62K** – Cycles, bicycles (zero-emission transport)

System Optimization

- **G01R** – Measuring electric variables (enables energy conservation)
- **G06Q** – Data processing for administration (can optimize resource use)
- **G08G** – Traffic control systems (reduces emissions through efficiency)

Conditionally green

F01K – Steam engine plants

- Green if using renewable heat sources (solar thermal, geothermal)
- Not green if using fossil fuels

F23G – Combustion of waste

- Green aspect: Reduces landfill volume, can generate energy.
- Concern: Air emissions need careful control
- A01H – New plants or processes for obtaining them.
- Green if developing drought-resistant or high-yield crops.
- Concern if related to intensive monoculture

Questionable as green

C10G – Petroleum refining

- While it includes some cleaner processes, it's fundamentally about fossil fuel processing.
- Should be classified as "transitional" or "cleaner fossil" technology, not truly green.

Nuclear (G21B, G21C, G21D)

- **Pros:** Very low carbon emissions during operation.
- **Cons:** Radioactive waste, mining impacts, catastrophic risk potential.
- Highly debated whether it qualifies as green.

The WIPO classification appears to use a broad definition of green. For stricter environmental standards, one might only consider renewable energy, waste management, sustainable transport, and efficiency technologies as truly green. C10G and nuclear should be in a separate "low-carbon transitional" category.

B Patent protection effects along De Rassenfosse et al. (2022)

B.1 Motivation and methodological considerations

This appendix presents a series of specifications that follow the approach of De Rassenfosse et al. (2022) to identify the causal effect of patent protection on export performance. As no evidence to date was available for Italy, before presenting the analysis reported in the main body of the text, it was necessary to perform this consistency check. The key methodological point is the inclusion of product-level fixed effects interacted with all other dimensions (firm, country, and time) to address endogeneity concerns in patent protection decisions.

B.1.1 The endogeneity problem

Patent protection is not randomly assigned. Firms strategically choose whether to patent an innovation, where to seek patent protection, when to file for patents

These decisions are likely correlated with unobserved product success, creating endogeneity. For in- stance, a firm may seek protection in a specific country precisely because the product is performing well in that market, leading to reverse causality.

B.1.2 Fixed effects strategy

A comprehensive fixed effects structure is an attempt to tame the endogeneity:

$$\ln Y_{fpcy} = \beta \cdot \text{Patent}_{fpct} + \alpha_{fpc} + \gamma_{fpy} + \delta_{cpy} + \varepsilon_{fpcy} \quad (5)$$

where:

- α_{fpc} : Firm-product-country fixed effects
- γ_{fpy} : Firm-product-year fixed effects
- δ_{cpy} : Country-product-year fixed effects

This specification controls for:

1. **Time-invariant firm-product-country characteristics** (α_{fpc}): Product-specific advantages a firm has in particular markets.
2. **Firm-product life cycles** (γ_{fpy}): Natural evolution of product sales over time within a firm.
3. **Market-product trends** (δ_{cpy}): Country-specific demand trends for specific products.

B.1.3 Limitations for green premium analysis

While this approach provides clean identification of patent effects, it is unsuitable for studying green premiums because:

- Product fixed effects absorb all cross-product variation.
- Green premiums are inherently about differences between products.
- The variation exploited is within firm-product-country triplets over time.
- Environmental attributes are typically time-invariant product characteristics.

B.2 Model 1: Baseline patent protection effect

$$\ln Y_{fpcy} = \beta \cdot \text{DPat}_{fpct} + \alpha_{fpc} + \gamma_{fpy} + \delta_{cpy} + \varepsilon_{fpcy} \quad (6)$$

This baseline specification identifies the patent premium by comparing the same product, exported by the same firm to the same country, in periods with and without patent protection. The coefficient β captures the average effect of patent protection on export outcomes.

Identification: The effect is identified from within-firm-product-country variation in patent protection status over time, controlling for all product-specific trends.

B.3 Model 2: Patent family size

$$\ln Y_{fpcy} = \beta_1 \cdot \text{DPat}_{fpct} + \beta_2 \cdot (\text{DPat}_{fpct} \times \text{FamSize}_{fpct}) + \alpha_{fpc} + \gamma_{fpy} + \delta_{cpy} + \varepsilon_{fpcy} \quad (7)$$

Patent family size (the number of countries where protection is sought) proxies for patent value and quality, firm commitment to the technology, expected market potential. Thus, β_1 represents the effect of minimal patent protection, while β_2 captures how this effect scales with patent breadth.

B.4 Model 3: Forward citations

$$\ln Y_{fpcy} = \beta_1 \cdot \text{DPat}_{fpct} + \beta_2 \cdot (\text{DPat}_{fpct} \times \#\text{FwdCit}_{fpct}) + \alpha_{fpc} + \gamma_{fpy} + \delta_{cpy} + \varepsilon_{fpcy} \quad (8)$$

Forward citations measure technological impact and quality. Patents with more citations represent: i) More fundamental innovations; ii) Technologies with broader applications; iii) Higher technical merit as validated by subsequent innovators. Thus, the interaction term tests whether higher-quality patents (as measured by citations) generate larger export premiums.

B.5 Model 4: Number of patent families protecting the transaction

$$\ln Y_{fpcy} = \beta_1 \cdot \text{DPat}_{fpct} + \beta_2 \cdot (\text{DPat}_{fpct} \times \#\text{NumFam}_{fpct}) + \alpha_{fpc} + \gamma_{fpy} + \delta_{cpy} + \varepsilon_{fpcy} \quad (9)$$

Multiple patent families protecting the same transaction may indicate, complex technologies requiring multiple inventions, cumulative innovation building on previous patents or strategic patent portfolios.

B.6 Model 5: Green patent protection

$$\ln Y_{fpcy} = \beta_1 \cdot \text{DPat}_{fpct} + \beta_2 \cdot (\text{DPat}_{fpct} \times \text{GreenPat}_{fpct} \times \text{GreenProd}_{fpcy}) + \alpha_{fpc} + \gamma_{fpy} + \delta_{cpy} + \varepsilon_{fpcy} \quad (10)$$

This specification tests whether green patents protecting green products generate additional premiums beyond standard patent protection. However, note that the green product indicator is largely absorbed by product fixed effects and the identification comes only from time variation in patent protection. Thus, this specification

Table 8: Exports performance and patents.

Dependent Variables:	$\ln X_{fpcy}$	$\ln \text{Quantity}_{fpcy}$	$\ln \text{UnitValue}_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
$DPat_{fpct}$	0.0503***	0.0552***	-0.0037
	(0.0127)	(0.0148)	(0.0062)
Fixed-effects			
Firm-Product-Country	Yes	Yes	Yes
Firm-Product-Year	Yes	Yes	Yes
Country-Product-Year	Yes	Yes	Yes
Fit statistics			
Observations	3,055,527	3,036,124	3,036,124
R^2	0.89790	0.92092	0.94942
Within R^2	1.59×10^{-5}	1.34×10^{-5}	2.6×10^{-7}

*Clustered (Product-Year) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Exports performance and patents. Effect of the family size.

Dependent Variables:	ln X_{fpcy}	ln Quantity$_{fpcy}$	ln UnitValue$_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
$DPat_{fpct}$	0.0474***	0.0457***	0.0037
	(0.0156)	(0.0182)	(0.0080)
$DPat_{fpct}$ × FamSize	0.0005	0.0016	-0.0012
	(0.0015)	(0.0018)	(0.0010)
Fixed-effects			
Firm-Product-Country	Yes	Yes	Yes
Firm-Product-Year	Yes	Yes	Yes
Country-Product-Year	Yes	Yes	Yes
Fit statistics			
Observations	3,055,527	3,036,124	3,036,124
R^2	0.89790	0.92092	0.94942
Within R^2	1.6×10^{-5}	1.42×10^{-5}	2.13×10^{-6}

Table 10: Exports performance and patents. Effect of the number of families protecting a product.

Dependent Variables:	ln X_{fpcy}	ln Quantity$_{fpcy}$	ln UnitValue$_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
$DPat_{fpct}$	0.0502***	0.0546***	-0.0026
	(0.0131)	(0.0152)	(0.0063)
$DPat_{fpct}$ × #NumFam	3.27×10^{-5}	0.0003	-0.0006
	(0.0019)	(0.0021)	(0.0009)
Fixed-effects			
Firm-Product-Country	Yes	Yes	Yes
Firm-Product-Year	Yes	Yes	Yes
Country-Product-Year	Yes	Yes	Yes
Fit statistics			
Observations	3,055,527	3,036,124	3,036,124
R^2	0.89790	0.92092	0.94942
Within R^2	1.59×10^{-5}	1.35×10^{-5}	7.39×10^{-7}

*Clustered (Product-Year) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Exports and patents (controlling for firm-product-country specificities and product cycle - non controlling for firm product cycle).

Dependent Variables:	ln X_{fpcy}	ln Quantity$_{fpcy}$	ln UnitValue$_{fpcy}$
Model:	(1)	(2)	(3)
Variables:			
$DPat_{fpct}$	0.0334***	0.0328**	0.0017
	(0.0120)	(0.0134)	(0.0059)
$DPat_{fpct}$ × Green Patent × Green Product	-0.0417	0.0178	-0.0559**
	(0.0488)	(0.0553)	(0.0239)
Fixed-effects			
Firm-Product-Country	Yes	Yes	Yes
Firm-Year	Yes	Yes	Yes
Country-Product-Year	Yes	Yes	Yes
Fit statistics			
Observations	3,385,357	3,363,373	3,363,373
R^2	0.85248	0.88787	0.92682
Within R^2	7.23×10^{-6}	5.18×10^{-6}	4.1×10^{-6}

*Clustered (Product-Year) standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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