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Green Patenting Takes Time to Pay Off. A Quasi-Experimental Study on the Italian Machinery Industry

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Abstract

Despite extensive research on the relationship between environmental innovation and firm performance, there is still uncertainty about whether and when adopting eco-friendly practices pays off. To address this gap, we investigate whether green patents confer an incremental growth premium relative to other innovations and whether this premium follows a distinct, and possibly more delayed, temporal profile. Using a panel of 6,148 Italian machinery and equipment manufacturers (NACE 28) observed from 2014 to 2023 and a flexible conditional Difference-in-Differences (DID) approach, we estimate the dynamic effects of patenting on firm sales performance. The results indicate that general patenting leads to positive and persistent gains, with effect sizes that become larger at longer horizons. Additionally, green patents provide an extra growth premium that emerges only from the third year after the first green patent and is especially pronounced between three and five years after patenting. By revealing these dynamics, the study reframes the debate from whether it pays to be green to when firms can expect to benefit from environmental innovation.

1. Introduction

Extensive research has analyzed the relationship between environmental innovation and firm performance. However, there is still an ongoing debate regarding whether it is advantageous to adopt eco-friendly practices. Some scholars argue that green innovation enhances performance by reducing costs (Caracuel and Ortiz-de-Mandojana, 2013) or opening up new markets (Beise and Rennings, 2005; Chen, 2008). By contrast, other studies indicate that environmental innovation can have negative effects on performance due to increased development costs (Bai et al., 2019), bureaucratic burdens (Delmas, 2002) and the diversion of resources that could be used for other activities (Hussain et al., 2018).

An element often overlooked in this field of research is the timing of returns to innovation, which is crucial for understanding how new technologies affect firm performance. Technological change, including green innovation, typically unfolds through a sequence of stages and generates payoffs only over the longer run. This reflects the time lags between the various stages, from initial development to the introduction of a new product or process into the market, and only later to improvements in firm performance.

In the case of green innovation, the timing of returns is even more crucial than for innovation in general because of its greater technological complexity (De Marchi, 2012; Petruzzelli et al., 2011). Such technologies require a longer cumulative learning process compared with less complex technologies. Rather than addressing a single issue, such as pollution prevention, they typically tackle multiple environmental challenges, including waste reduction and energy optimization. This complexity calls for a deeper understanding of the underlying technology and greater coordination among different departments within the organization (Przychodzen et al., 2020). Moreover, environmental innovations require increased collaboration both between and within organizations (Messeni Petruzzelli et al., 2011). These innovations are characterized by high levels of novelty, uncertainty, and variety (Cainelli et al., 2015), and they rely on a greater diversity of knowledge sources than other types of innovations (Horbach et al., 2013). Finally, Orsatti et al. (2017) show that green innovations typically stem from exploring uncharted knowledge, whereas non-environmental innovations often involve recombining and enhancing established knowledge. Taken together, these characteristics make it reasonable to expect that benefits from green innovation will emerge only with a delay.

Building on these arguments, performance improvements from green innovations are expected to be gradual rather than immediate. The timing of returns therefore becomes central to understanding how these technologies shape firm outcomes. Accordingly, this paper investigates the relationship between innovation and performance by tracing its evolution over time. The research questions guiding this study are: Does it pay to be innovative? Does it pay to be green? And if so, over what timeframe do these performance gains materialize?

To address these questions, we use panel data on 6,148 Italian manufacturing firms operating in the machinery and equipment sector (NACE 28) from 2014 to 2023. This industry offers an ideal setting to explore the link between patents and firm performance, as it is among the most technologically dynamic and export-oriented sectors in Italy. In 2022, it accounted for 8.1% of total value added and 44.7% of exports (Federmeccanica, 2022). Moreover, machinery and equipment producers supply many of the capital goods and process technologies that enable energy efficiency improvements and the diffusion of low-carbon solutions across manufacturing, making this sector a key upstream driver of the green transition. The sector relies heavily on patenting to sustain competitiveness and long-term growth. Although Italy exhibits relatively modest patenting activity overall, ranking tenth for EPO applications between 2015 and 2018, it ranks fifth worldwide in the mechanical sector (Centro Studi Confindustria, 2022). In addition, the coexistence of large firms and numerous small and medium-sized enterprises (SMEs) creates substantial heterogeneity in innovation strategies and patenting behavior, providing a rich context to examine how innovation translates into performance. Focusing on a single, technologically coherent industry also limits cross-sectoral heterogeneity in demand, regulation, and patenting regimes, thereby improving the comparability of firms and the interpretability of our causal estimates.

The panel dataset was constructed by combining two data sources: Orbis Europe provided by Bureau van Dijk for firms' financial data, and Orbis-IP for patents. We measure firm performance using sales. Methodologically, we employ a flexible conditional Difference-in-Differences (DiD) estimator that allows us to trace the dynamic effects of patenting on sales, exploiting the staggered timing of firms' first patents and controlling for time-invariant firm characteristics and common shocks.

Our contribution to the literature is threefold. First, we shift the focus from whether environmental innovation pays off to when it does, estimating the dynamic effects of innovation on firm performance rather than a single average impact. This approach clarifies part of the mixed evidence in previous studies by considering the time profile of returns. Second, we distinguish between general and green patents within the same empirical framework, quantifying the additional growth premium associated with green patenting and documenting that this premium materializes with a delay. This distinction allows us to compare the timing and magnitude of payoffs from green versus non-green innovation while holding the institutional and sectoral context constant. Third, we contribute to the literature on Italian manufacturing and on the evaluation of innovation policy and strategies by using a large firm–patent matched panel in a technologically advanced and export-oriented sector, combined with a flexible conditional Difference-in-Differences estimator that accounts for staggered adoption and firm heterogeneity in treatment timing.

Our findings show that patenting is associated with a persistent improvement in firm performance: the positive and significant effects emerge soon after the first patent and strengthen over time. When focusing on green patents, the results reveal an additional growth premium that becomes significant around the third year

after patenting and if economically relevant between three and five years after patenting. This pattern suggests that the benefits of green innovation materialize with a time lag, reflecting the longer development, diffusion, and market adoption processes typical of green technologies. Therefore, these results indicate that the relevant question is no longer whether it pays to be innovative, and particularly to be green, but rather how long it takes for the benefits to materialize. All this leads to direct implications for both managers and policy-makers: if the returns to green patenting are delayed but economically substantial, evaluation horizons that are too short are likely to underestimate the benefits of environmental innovation and to discourage long-term investments.

The remainder of the study is organized as follows. Section 2 presents the literature review. Section 3 describes the research design (methodology, data and sample, variables). Section 4 shows the results from the econometric analysis, and Section 5 provides the conclusions.

2. Literature review

A large body of research has been devoted to assessing the effects of environmental innovations on firms' economic performance (for recent reviews, see Hermundsdottir and Aspelund, 2021; Hizarci-Payne et al., 2021; Takalo and Tooranloo, 2021; Qing, et al., 2022; Zheng and Iatridis, 2022).

Some arguments support the idea that green innovation benefits performance, whereas others reach the opposite conclusion. On the one hand, green innovation can positively affect performance through reduction of costs, due to the more efficient use of resources through recycling and waste reduction (Caracuel and Ortiz-de-Mandojana, 2013). Moreover, firms can open new markets (Beise and Rennings, 2005), and improve their corporate image (Chen, 2008), thereby reaching consumer segments that are more sensitive to environmental issues. Previous research also highlights market pull as an important driver of green innovations (Horbach et al., 2012; Hojnik and Ruzzier, 2016). On the other hand, environmental innovation is associated with relevant drawbacks, as it entails higher development costs (Bai et al., 2019), adds bureaucratic burdens such as environmental certifications (Delmas, 2002), and requires resources that could be deployed for other activities (Hussain et al., 2018), leading some authors to conclude that it may have a negative impact on performance. Therefore, the net impact of firms' environmental innovation on their economic performance is not easy to predict and remains an empirical question.

From an empirical perspective, green innovation comprises R&D investments, invention activity and patenting, or indicators of innovative output such as the launch of new products or processes. Patent data have a number of advantages: they are readily accessible through standardized databases and avoid the issues of imprecise definitions and lack of comparability that often accompany R&D data. Moreover, green patents effectively identify 'environmental' innovations (Haščič and Migotto, 2015; Oltra et al., 2010), as they can be categorized into specific technological fields, which is essential for studying this type of innovation. In other words, patent classification systems are 'technological' by nature (unlike commodity and industry classifications) and allow for a rich characterization of relevant technologies by describing the engineering features of an invention and its applications at a fine level of detail (Haščič and Migotto, 2015). Accordingly, their use as a measure of the output of the inventive process has become standard in the literature.

A range of empirical studies has been devoted to testing the relationship between green patents and financial performance (Table 1), but the results are inconclusive. Indeed, although some studies find evidence that green innovators exhibit better financial performance than non-green innovators (Colombelli et al., 2021; Corrocher and Ozman, 2020; Farza et al., 2021; Khanchel et al.; 2023), others do not find conclusive support (Aguilera-Caracuel and Ortiz-de-Mandojana, 2013; de Azevedo Rezende et al., 2019; Leyva-De la Hiz and Bolívar-Ramos, 2022).

In more detail, using Return on Assets (ROA) as a measure of firm performance, Khanchel et al. (2023) show that green innovation improves financial performance in the lowest-performing US companies (the most important effect occurs between the 10th and the 50th quantile), while it has no effect for the highest performing companies (the 90th quantile). A similar positive association with different financial performance measures (Return on Assets, Market-to-book ratio and Return on invested capital) can also be found in Farza et al. (2021) for the top 110 German enterprises listed on the Frankfurt Stock Exchange, suggesting that green innovation drives resource efficiency and enhances corporate reputation, which, in turn, boosts financial performance. Along similar lines, Corrocher and Ozman (2020) and Colombelli et al. (2021) confirm a positive relationship between green patents and performance, measured by firm sales, for European firms.

In contrast to this evidence, the study's findings by Aguilera Caracuel and Ortiz-de-Mandojana (2013), using a sample of 140 firms from 14 countries, show that, when compared to non–green innovative firms, green innovative firms do not experience a higher improvement in financial performance. In focusing on green innovative firms, they show that the intensity of green innovation is positively related to firm profitability. In line with Aguilera Caracuel and Ortiz-de-Mandojana's (2013) finding, when considering a sample of 1667 Chinese firms listed, Yin et al. (2022) find that green invention innovation (radical green innovations) does not contribute to firm performance overall, whereas green utility-model innovation (incremental green innovations) positively influences firm performance. Moreover, older firms benefit more from both green invention innovation and green utility-model innovation than younger firms. Finally, Leyva-De la Hiz and Bolívar-Ramos (2022) argue that the relationship between environmental innovation and firm performance is more complex than a simple linear positive or negative relationship. Considering a sample of 75 companies belonging to the electrical components and equipment industry worldwide, the authors find an inverted U relationship: low levels of environmental innovation positively affect firm performance, while higher levels of environmental innovation amplify their intrinsic complexities to a point that these innovations are no longer profitable for the company.

As noted earlier, the empirical evidence on the relationship between green patents and economic performance is far from conclusive. The divergence in results suggests that there are still gaps in understanding, which may depend on specific aspects that have not been adequately considered. The time needed for an innovation cycle is one of these aspects. Indeed, technological innovation typically involves long and high-risk processes. This is because of multiple stages for innovation from the beginning to the insertion of novelty into the market, which takes time lags between its stages and from them to firm performance. Therefore, the output effect of patents could result in a lagged correlation between patent and performance variables (Griliches, 1990).

The timing of innovation processes has already been addressed in innovation studies (e.g., Ernst, 2001) but has been scarcely examined in the context of green innovation. The only exception is the study by de Azevedo Rezende et al. (2019) which, in studying the effect of environmental performance on financial performances

measured as ROA on a sample of 356 multinationals firms, found support for short-term insignificant effects (e.g. one year after implementation) and a positive effect in the long term, namely the second year onwards, reinforcing the need to use time lags in patent studies.

Thus, time is an important variable to better understand the impacts of innovation on performance, and it is particularly relevant for green technology. Indeed, the literature on eco-innovations has shown that environmental innovations have different determinants from innovations in general. Eco-innovations are, on average, more complex than non-green innovations (De Marchi, 2012) and are characterized by higher levels of novelty, uncertainty and variety than other innovations (Cainelli et al., 2015). Moreover, environmental innovations require more heterogeneous sources of knowledge with respect to other innovations (Horbach et al., 2013) and are grounded on higher levels of both inter- and intra-organizational collaborations (Messeni Petruzzelli et al., 2011). Empirical studies support the view that green firms cooperate with external partners to a greater extent than other firms (De Marchi and Grandinetti, 2013; Fabrizi et al., 2018). Finally, compared with non-environmental innovations, the existence of financial barriers and the organizational structures required to support innovation are important distinctive drivers of eco-technologies (De Marchi, 2012; Del Río et al., 2013; Ghisetti et al., 2017). Given these specificities, environmental innovators are likely to have a greater need for human (high-skilled employees and managers) and financial resources to be able to respond to such inputs than non-environmental innovators.

In summary, as highlighted by Hojnik and Ruzzier (2016), green innovations draw on more complex and diversified knowledge and skills and require a greater propensity to take risks, a greater ability to access external sources of funding and more intensive external relationships than other kinds of innovation. Following the above arguments, we expect that green patents may generate differential results compared to non-green patents, not only in magnitude but also in timing. In particular, if environmental innovations involve longer and riskier development and adoption processes, their benefits should emerge more slowly, i.e. along a delayed time profile relative to general innovation. This delayed pattern of returns is the core hypothesis that guides our empirical analysis.

Table 1. An overview of selected empirical studies on the relationship between green patents and performance

Study	Sample	Dependent variable	Focal variables	Method	Main findings
Aguilera-Caracuel and Ortiz-de-Mandojana, 2013	140 firms from 14 countries (Canada, China, Denmark, Finland, France, Germany, Japan, South Korea, Sweden, Switzerland, Taiwan, UK Kingdom e USA.) (2007-2010)	Return on assets (ROA)	Green innovation intensity (proportion of green patents in relation to total patents) and environmental regulations	Matched-pairs analysis and regression analysis	Green innovative firms do not experience a higher improvement in financial performance than non-green innovative firms. Among green innovative firms, the intensity of green innovation is positively related to financial performance. The stringency of a country's environmental regulations negatively moderates this relationship.
Colombelli et al., 2021	456,240 manufacturing firms from six EU countries (France, Germany, Italy, Spain, Sweden e UK) (2002-2010)	Growth rate of sales	Stock of green and non-green patents; Environmental Policy Stringency Index	Quantile regression	Eco-innovations augment the effects of generic innovation on firm growth. Environmental policy stringency is important in moderating the effects of eco-innovation for fast-growing firms and even more so for slow-growing firms
Corrocher and Ozman, 2020	365 ICT companies from 12 EU countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Spain, Sweden e UK) (2009-2013)	Sales	Green patents, Stock of patents, Size	GLS random-effects regression	Technological diversification shows an inverted U-shaped relationship with the likelihood and intensity of green innovations. Firms investing in green technologies perform better than firms with no green patents
de Azevedo Rezende et al., 2019	356 multinational firms (2006-2015)	Return on assets (ROA)	Green innovation intensity (proportion of green patents in relation to total patents) and	Fixed-effects panel regression	The economic return of green innovations is time-dependent, and is not influenced by the level of multinational internationalization

			degree of internationalization		
Farza et al., 2021	Top 110 German enterprises listed on the Frankfurt Stock Exchange (2008-2019)	Return on assets (ROA), Market-to-book ratio (MBR), Return on invested capital (ROIC)	Green innovation	Two-step GMM system and penalised-spline estimation	Green innovations positively affect different financial performance measures
Khanchel et al. 2023	211 S&P 500 US firms (2011-2019)	Return on assets (ROA)	Number of green patents, Environmental, Social and Governance Disclosure	Quantile estimation	Green innovation and the social and governance dimensions of ESG disclosure positively affect ROA
Leyva-De la Hiz and Bolívar-Ramos, 2022	75 companies belonging to the electrical components and equipment industry worldwide	Tobin's Q	Green innovation intensity (proportion of green patents in relation to total patents); firm age	Fixed-effects models	Inverted U relationship between environmental innovation and firm performance. The moderating effect of firm age is negative

Source: authors' elaboration

3. Research design

3.1 Empirical strategy

In this study, we examine the relationship between patenting activity and firm performance across distinct groups of firms: those that have never filed any patent and those that have filed at least one patent. Within the latter group, we further distinguish between firms that have filed at least one green patent and those that have filed only non-green patents.

Analyzing these relationships requires addressing the issues of simultaneity and heterogeneity, which would otherwise confound the estimated performance effects of patenting. Simultaneity refers to the challenge of determining whether patenting activity enhances firm performance or whether higher-performing firms are simply more likely to patent. To minimize potential confounding effects from patents that cannot be explicitly controlled for (i.e., those registered shortly before the focal patent), we restrict the sample to firms that did not file any patent for at least four years prior to the one considered in the analysis. This choice aligns with longitudinal evidence showing that the most significant effects of patents on performance tend to occur within three to five years after filing (Cefis and Ciccarelli, 2005; Farre-Mensa et al., 2019; Maresch et al., 2016).

Heterogeneity, on the other hand, arises from firm-specific characteristics that influence patenting behaviour and may bias direct comparisons between patenting and non-patenting firms. To account for part of this heterogeneity, we apply a multivariate distance matching technique, which allows us to construct a control sample based on observable factors known to drive innovation. Each treated patenting firm is matched with non-patenting firms exhibiting a similar probability of patenting.

To address the issues discussed above, we adopt the flexible conditional DID approach (Dettmann et al., 2020) which extends, the matching and DID method proposed by Heckman et al. (1998) to settings with staggered treatment design (see also Callaway and Sant'Anna, 2020). In this framework, treatment is assumed to be absorbing: once a firm applies for a patent is treated, it is regarded as treated in all subsequent periods, and time is indexed in terms of event time relative to the treatment start.

Following Dettmann et al. (2020), treated and control groups are matched in the pre-treatment period (two years before the first patent filing in our application; see Section 4.1) using combined statistical distance measures. These measures, which integrate mean absolute differences for continuous variables and matching coefficients for categorical variables, have been shown to outperform other distance measures such Mahalanobis distance (Dettmann et al., 2011). Each treated unit is then matched to one or more control firms based on nearest-neighbor matching using these statistical distances. Once the matching process is complete, we compute the mean differences in outcomes between patenting firms and their corresponding controls to obtain the average treatment effect on the treated (ATT).

Due to heterogeneous treatment durations, the observation horizons differ across treated firms, so the ATT is a weighted average of different post-treatment periods:

$$ATT = \frac{1}{N} \sum_{i=1}^{N} \left[\left(Y_{i,t_{0i+\beta_i}} - Y_{i,t_{0i}} \right) - \left(Y_{j,t_{0i+\beta_i}} - Y_{j,t_{0i}} \right) \right]$$

1

where *i* is the i-*th* treated unit, with i=1,...,N, *j* is the j-*th* untreated unit matched with the i-*th* treated unit, *t* is the t-*th* year, with t=1,...,T, t_{0i} refers to firms' treatment start years, t_{0i} +β_i indicates the individual duration from the time of formalization to outcome observation and *Y* is the outcome.

3.2 Data and sample

The sample was drawn from Bureau van Dijk's Orbis Europe database in May 2025. This source provides detailed balance sheet and financial information for European firms. Patent data were obtained from Orbis Intellectual Property (Orbis IP), also by Bureau van Dijk, which integrates information from the PATSTAT database maintained by the European Patent Office. The main advantage of using Orbis IP lies in the availability of a unique firm identifier, enabling the linkage between patent records and firm-level financial data in Orbis Europe.

To mitigate potential sources of bias highlighted in the previous section, the final dataset was built through a multistage process described below.

First, we refined the dataset of patenting firms. Starting with 14,354 Italian manufacturing firms in the machinery and equipment sector (NACE 28) linked to at least one patent in Orbis, we identified all patents filed by these Italian firms between 2015 and 2019, resulting in a sample of 2,219 firms. The observation period begins in 2014, consistent with data availability in Orbis Europe, and extends to 2023, allowing us to include at least five years of post-application performance data for patents filed up to 2019. To avoid confounding effects from unobservable prior patents, we retained only firms that had not registered any patent for at least four years before the one included in our analysis. After excluding firms that filed another patent within four years after the previous patent, 1,009 firms remained.

Next, we constructed a potential control group. Starting from the initial sample of 14,354 firms, we excluded 4,720 firms that had filed one or more patents in their patent portfolios, resulting in 9,634 potential non-patenting firms. This procedure yielded an unbalanced panel of 10,643 firms (9,634 non-patenting and 1,009 patenting). Subsequently, we built a balanced panel comprising 693 treated and 5,455 control firms, for a total of 6,148 firms observed over ten years, corresponding to 61,480 firm-year observations.

Finally, we applied nearest-neighbor matching to identify the control firms used in the statistical analysis (see Sub-section 4.1). We implement one-to-one nearest-neighbor matching based on the composite statistical distance functions described in Dettmann et al. (2011, 2020), selecting for each treated firm the control unit with the smallest distance value a set of pre-defined covariates. The same matching procedure was then applied to compare firms that filed green patents with those that filed non-green patents.

3.3 Variable definition and measurements

3.3.1 *Dependent variable*

Previous studies have employed a wide range of measures to assess the relationship between environmental and firm performance, including profit margin (Yin et al., 2022), return on sales (ROS) (Ghisetti and Rennings, 2014), return on assets (ROA) (de Azevedo Rezende et al., 2019; Farza et al., 2021; Khanchel et al., 2023), return on equity (ROE) (Przychodzen and Przychodzen, 2015), and sales (Colombelli et al., 2021; Corrocher and Ozman, 2020).

In line with this literature, we use firm sales as our measure of economic performanc, and in all econometric specifications the dependent variable is the natural logarithm of sales, ln(*Sales*).While sales data do not capture all dimensions of profitability, they offer several advantages as a performance indicator. First, sales provide direct market feedback, whereas profitability can be substantially influenced by internal corporate policies. Indeed, unlike financial metrics such as ROE, ROI, or Tobin's Q, sales are less susceptible to accounting manipulation (Ernst, 2001). Second, sales are a commonly accepted indicator in similar studies (e.g., Colombelli et al., 2021; Corrocher and Ozman, 2020; Lambrecht et al., 2025). Third, in our study, sales data are collected over a ten-year period, which helps mitigate the effects of short-term fluctuations in the sales variable.

3.3.2 Independent variable

Innovative output is measured using patent data. While patents have some drawbacks as indicators of innovative activity (not all inventions are patented, and patenting incentives vary across sectors and markets),

they offer several advantages over alternative measures of innovation. In particular, patent data are easily accessible via databases and are not subject to the problems of imprecise definition and lack of comparability between firms that beset R&D data. For this reason, their use as a measure of inventive output has become standard in the literature (Griliches, 1990). Moreover, green patents are particularly well suited to identifying 'environmental' innovations (Haščič and Migotto, 2015; Oltra et al., 2010), since they can be categorized into specific technological fields, which are crucial when studying environmental innovation. In other words, patent classification systems are 'technological' by nature (unlike commodity and industry classifications) and allow for a rich characterization of relevant technologies by describing the engineering features of an invention and its applications at a fine level of detail (Haščič and Migotto, 2015). Consequently, the use of patents in environmental fields is widespread (among others, Aiello et al., 2021; Brunnermeier and Cohen, 2003; Laurens et al., 2017; Montobbio and Solito, 2018; Nameroff et al., 2004).

Our treatment variable for the analysis is a dummy variable (Patent or Green patent), where units that are treated once in the observation period are regarded as treated units from that date onwards and where time is defined in relation to the start of the treatment.

Green patents are identified based on the Green Inventory developed by the World Intellectual Property Organization (WIPO). This inventory lists International Patent Classification (IPC) classes associated with environment-friendly technologies, such as alternative energy production, transportation, energy conservation, waste management, agriculture and forestry, administrative or regulatory activities, and nuclear power generation. If a patent includes multiple IPC codes listed in the Green Inventory, all of them are considered. Patents containing at least one IPC code corresponding to green technology were classified as green patents.

3.3.3 Matching variables

Our analysis includes several matching variables.

To begin with, firm age is a well-established determinant of innovation performance (Balasubramanian and Lee, 2008). We control for a firm's age for two opposing reasons. On the one hand, younger firms might file fewer patents due to additional resource constraints. On the other hand, patents play a more important role for younger firms than for established ones in their quest to be successful in the marketplace (Griliches, 1990). Accordingly, firm age is defined as the logarithm of the number of years since the firm's founding (*Age*).

Similarly, firm size is measured by the number of employees (*Size*), expressed in logs as it is highly skewed. The size of a firm significantly affects its managerial capabilities and innovation potential (Cohen & Klepper, 1996). Due to their higher visibility and stronger signaling capacity toward stakeholders, larger firms are typically more effective in building and sustaining corporate reputations (Fombrun & Shanley, 1990), while simultaneously experiencing fewer resource constraints in pursuing innovation (Clausen et al., 2013).

Furthermore, we include *capital intensity*, measured as the ratio of tangible to total assets. This variable controls for differences in firms' structural and technological characteristics (Almus & Czarnitzki, 2003), ensuring that treated and control firms are comparable in their production structure.

Firm financial condition is controlled for by including *leverage* and the ratio of *cash flow* to total assets, which account for differences in capital structure and financial condition. Given the substantial costs associated

with patent filing, it is essential to select a control firm with similar financial capacity to the patenting firm. Finally, an exact matching variable is included, which is expected to have a significant influence on the focal outcome. Because firms located in different regions may differ in their development dynamics, *geographic location* is used as an exact matching variable in this study.

In summary, the matching set combines firm size, age, capital intensity, financial condition and geographic location, ensuring that treated and control firms are comparable along the key dimensions that shape both innovation and performance

4. Results

4.1 Matching results

In this study, we use a matching procedure based on a combined statistical distance measure. The distance is the weighted average of scale-specific distance functions (Dettmann et al., 2021).

The matching period is set two periods before the treatment start, which serves as the baseline for the subsequent DiD analysis. After matching, we obtained 518 firms in the treatment group (*patenting firms*) and 454 firms in the control group (*non-patenting firms*). Specifically, 518 of the 693 treated firms were matched with partners during the procedure, while only 454 of the 5,455 non-treated firms were used as matches (see Figure 1, Panel A, for the treatment status of treated firms over time). This implies that some control firms were matched to multiple treated firms.

To verify the quality of the matching procedure, several diagnostic checks were performed. The results indicate that the covariate distributions of the treated and matched control groups no longer differ significantly, suggesting that any pre-existing differences were successfully accounted for. In other words, both groups exhibit similar firm characteristics on average.

Appendix Table A1 reports the mean values of the treated and control groups for each matching variable, together with the standardized percentage differences. The corresponding *t*-statistics confirm that all covariates are balanced at the time of matching, two years prior to the filing of the focal patents. Second, the Kolmogorov–Smirnov test was applied to assess the equality of distributions across the matching variables. As shown in Table A2, the adjusted *p*-values for all variables exceed 0.1, indicating no statistically significant differences between patenting and matched non-patenting firms. Finally, the quantile–quantile plots of the matching variables (Figure A1) provide a visual assessment of covariate balance. The data points closely follow the 45° line, suggesting minimal deviations between the two groups and only minor discrepancies at the tails of the distributions. Taken together, these diagnostics indicate that the matching procedure delivers well-balanced comparison groups, at the cost of discarding only a moderate fraction of treated firms.

When considering the subsample of firms that filed green and non-green patents, the matching process yielded 65 firms in the treatment group (*green patenting firms*) and 62 firms in the control group (*non-green patenting firms*). Specifically, 65 of the 77 treated firms were matched with partners during the process, while 62 of the 616 non-treated firms were used as control partners (see Figure 1, Panel B, for the treatment status of treated firms over time).

The matching diagnostics confirm that the covariate distributions of green and matched non-green firms do not differ significantly, suggesting that the matching procedure effectively balanced the two groups (see Tables A3–A4 and Figure A2). This provides a credible basis for interpreting subsequent differences in outcomes as being driven by green versus non-green patenting, rather than by pre-existing observable differences.

4.2 Testing the Identifying Assumptions

The validity of the results relies on the assumption that no differential trends exist between the treated and control groups during the pre-treatment period. For instance, if sales were already increasing among treated firms prior to the patent application, the estimates could be upwardly biased. To address this concern, we formally test the parallel trends assumption by examining pre-treatment dynamics in the outcome variable over the two years preceding the event.

We do so by following Wooldridge (2021, 2023), considering cohort-year-specific placebo effects in the years before treatment onset. Figure 2 shows the resulting placebo treatment effects aggregated across cohorts by event time.[1] The results show no evidence of violations of the identifying assumptions prior to patent filing. The pre-treatment point estimates are small and statistically insignificant in the years before treatment onset, indicating that treated and control firms followed similar sales trajectories in the absence of treatment. The parallel trends assumption is thus satisfied, supporting the internal validity of our difference-in-differences estimates. On this basis, we proceed with the main analysis.

4.3 Difference-in-Differences Estimation Results

As a preliminary step, we test whether patenting firms perform better than non-patenting firms. This empirical exercise serves as a robustness check to better characterize our sample of patenting firms and to document whether patenting is associated with superior performance relative to non-patenting firms.

Given the large sample and the ten-year observation period, we apply the dynamic DID model outlined in Sub-section 3.1. The treatment variable is a binary indicator that takes the value 1 starting from the year of firm's first patent (by priority date) and 0 otherwise. Each firm is therefore considered treated from the first time it applies for a patent. The outcome variable and regressors are described in Section 3.3.

Table 2 reports the results of the dynamic DID estimation associated with the first patenting event (Column 1) and the first green patent (Column 2). In Column (1), the estimated coefficients are positive and become statistically significant from the first year after patenting (t+1, 0.0697, $p < 0.1$), remaining so throughout the observation period. The magnitude of the effect generally increases over time, rising to 0.1624 ($p < 0.05$) four years after the first patent and peaking at 0.2803 ($p < 0.05$) six years after, with only minor fluctuations in intermediate years. This pattern indicates that patenting firms experience a sustained improvement in sales performance relative to non-patenting firms, with the positive impact strengthening as patented innovations are progressively commercialized.

Column (2) reports the estimates for green patenting. The coefficients become positive and statistically significant from the third year (t+3, 0.2907, $p < 0.05$), suggesting that firms developing green technologies experience an additional growth premium compared to those holding only non-green patents. The magnitude

of this effect further rises to 0.4704 ($p < 0.1$) at t+4 and 0.6504 ($p < 0.1$) at t+5, indicating that the benefits of green innovation tend to materialize in the medium term and remain economically meaningful over time.[2] At t+6, the point estimate remains positive but loses statistical significance, reflecting both increased sampling variability and the progressive decline in the number of cohorts that can be followed over such a long horizon.

Overall, these dynamic patterns suggest that while both conventional and green innovations enhance firms' performance, the latter require longer investment horizons to fully realize their economic potential. The comparison between Columns (1) and (2) therefore reinforces our central argument: green patenting pays off, but its payoff profile is delayed and steeper than that of non-green innovation. These estimates should, however, be interpreted as average effects for firms that actually start patenting after a period without patents. They do not imply that all firms in the sector would attain comparable gains if induced to patent, nor do they rule out substantial heterogeneity in returns across different types of firms (for example by size or age), which is beyond the scope of the present analysis.

Table 2. Results of the dynamic difference-in-differences

	Treatment variable					
Period	First patent	(Column 1)		First green patent (Column 2)		
	DID	SE	N.firms	DID	SE	N.firms
t	0.0392	0.0323	972	0.0302	0.0923	127
t+1	0.0697*	0.0414	972	0.0402	0.1134	127
t+2	0.1306***	0.0478	972	0.1208	0.1244	127
t+3	0.0990**	0.0511	972	0.2907**	0.1366	127
t+4	0.1624**	0.0637	743	0.4704*	0.2579	87
t+5	0.2090**	0.0830	531	0.6504*	0.3906	71
t+6	0.2803**	0.1290	315	0.3357	0.3604	36

Notes: Abadie-Imbens's robust standard errors; t=first year post treatment.

*p<0.10, **p<0.05, ***p<0.01

4.4 Robustness checks

Figure 3 displays the dynamic treatment effects estimated using alternative difference-in-differences estimators, following the approach proposed by Borusyak et al. (2024). Panel A presents the results comparing firms with patents to those without, while Panel B compares green patents to non-green ones. The dependent variable is again the natural logarithm of sales. The X-axis shows time relative to the event, and the Y-axis plots the estimated coefficients. Dots represent the estimated effects at each event time, and the solid lines indicate 95% confidence intervals.

As shown in Panel A, across all estimators, the coefficients for the pre-treatment periods (t–2 to t–1) are close to zero and statistically insignificant, suggesting the absence of differential pre-trends between treated and control units. This finding supports the validity of the parallel trends assumption. Following the event (t = 0 onward), all estimators display positive and gradually increasing effects, indicating that the first patenting event has a sustained and growing impact on sales performance over time. While the magnitude and precision of estimates differ slightly across methods, the overall pattern is consistent: the average causal effect becomes positive shortly after treatment and continues to rise up to seven years post-event. The similarity of results across alternative estimators (Borusyak et al.; de Chaisemartin & D'Haultfœuille; Callaway & Sant'Anna; and Sun & Abraham) reinforces the robustness of the findings and mitigates concerns about estimator-specific biases. Because these estimators explicitly accommodate staggered treatment adoption and heterogeneous dynamic effects, their close agreement with our baseline results strengthens the credibility of the timing pattern documented in Table 2.

When focusing on the impact of green patenting, Panel B shows that the coefficients for the pre-treatment periods (t–2 and t–1) are small and statistically insignificant across all estimators, indicating that green and non-green patentees followed similar sales trends prior to treatment. Starting from the third year after the green patent application (t+3), the estimated effects become positive and increase over time, suggesting that firms developing green technologies outperform those focused on non-green patents in terms of sales performance. Although the magnitude and precision of the effects vary slightly across estimators, the overall pattern is again consistent: the sales advantage of green-patenting firms emerges with a lag and strengthens over the medium term, consistent with the longer development and commercialization cycles typically associated with green innovations. This robustness to alternative DiD estimators provides further support for interpreting the delayed but sizeable payoffs to green patenting as a genuine feature of the data rather than an artefact of a particular identification strategy.

Viewed jointly with the matching diagnostics and pre-trend tests discussed above, these robustness checks suggest that our main findings are not driven by a specific estimator, a particular comparison group, or spurious pre-treatment dynamics, but rather reflect a stable empirical regularity in our matched sample.

[1] The test for parallel pre-treatment trends indicates no significant differences prior to treatment: $F(4, 971) = 1.35$ (p-value<0.2507) for First patent and $F(4, 126) = 2.08$ (p-value<0.0877) for First green patent.

[2] The number of green-patenting firms decreases markedly after t+4 (N=87 at t+4, N=71 at t+5, and N=36 at t+6). Therefore, the lack of statistical significance at later horizons may reflect reduced statistical power rather than a genuine decline in the effect.

5. Discussion and Conclusion

This study advances the understanding of how green innovation affects firm performance by explicitly incorporating the temporal dimension. Addressing the ongoing debate on the profitability of environmentally oriented practices, it provides systematic empirical evidence on the time profile of such investments, a perspective largely overlooked in prior research. The main contribution lies in showing that the benefits of green innovation unfold along a distinct and delayed trajectory compared with those of general innovation.

Using a flexible conditional DID model on a matched panel of Italian manufacturing firms (NACE 28) from 2014 to 2023, our analysis reveals that patenting activity is associated with relatively rapid and persistent improvements in firm performance, measured by sales. Positive effects emerge soon after patenting and strengthen over time, reflecting firms' broader innovation capabilities and strategic orientation toward knowledge appropriation. Firms that engage in patenting typically exhibit stronger R&D and absorptive capacities, enabling them to transform technological efforts into economic outcomes more efficiently (Hall et al., 2005; Belderbos et al., 2014). In addition, patents may generate immediate reputational and signaling effects that enhance firms' credibility with investors, partners, and customers, producing short-term advantages even before the commercialization of patented technologies (Hsu & Ziedonis, 2013). Our estimates therefore capture the average payoff to "entering" patenting after a period without patents, rather than the effect of marginal changes in already dense patent portfolios.

By contrast, green patents yield a delayed yet durable performance premium. This pattern aligns with the literature emphasizing the greater complexity, uncertainty, and knowledge heterogeneity of environmental innovations (De Marchi, 2012; Cainelli et al., 2015; Horbach et al., 2013). These characteristics often imply longer development and diffusion processes before firms can fully appropriate the economic benefits of green technologies. Moreover, green innovations often require intensive collaboration, both within and across organizations, and greater coordination with external partners (Messeni Petruzzelli et al., 2011; De Marchi & Grandinetti, 2013; Fabrizi et al., 2018), which may further extend the time required for coordination and integration of new knowledge. Financial and organizational barriers (De Marchi, 2012; Del Río et al., 2013; Ghisetti et al., 2017) can further slow the realization of economic returns. Consequently, the delayed premium associated with green patents reflects the resource-intensive and structurally complex nature of environmental innovation. Ultimately, while general patenting delivers immediate competitive gains, the economic benefits of green patenting emerge over a longer horizon, with the additional growth premium becoming statistically discernible only after roughly three years.

Overall, our results reveal a dual dynamic: general patenting provides immediate performance gains driven by superior innovation capabilities and signaling effects, whereas green patenting generates delayed benefits. In the context of the ongoing green industrial transition, this suggests that the alignment between private and collective incentives materializes over time, with firms beginning to reap the rewards of green R&D roughly three years after patenting. The evidence that green patents yield significant, albeit delayed, performance improvements indicates that environmentally oriented technological investments are compatible with profitability and represent a strategic path to long-term growth. This interpretation aligns with prior studies showing that the returns to eco-innovation tend to emerge more slowly yet persist over time (Ghisetti & Rennings, 2014; Horbach et al., 2012; Semenova, 2023). At the same time, the widening gap between green and non-green patentees at medium horizons suggests that once the fixed costs of green innovation have been absorbed, the payoff profile can become steeper than for conventional technologies.

This paper contributes to the existing literature in several ways. Empirically, it advances understanding of how the timing of innovation returns shapes the link between patenting and firm performance, an aspect often neglected in environmental innovation research. By combining a flexible conditional DID framework with rich panel data, we capture the dynamic nature of innovation outcomes and provide credible evidence of the delayed but persistent payoff of green patents. To our knowledge, this study is one of the first to

systematically examine how the performance effects of green patenting evolve over time relative to non-green patenting, within a dynamic treatment-effects framework. Previous work has recognized the importance of time lags in green innovation outcomes, but none has identified the additional growth premium associated with green innovation using comparably rigorous empirical methods (Azevedo Rezende et al., 2019; Siedschl and Yan, 2023; Zhang et al., 2019; Zhang et al., 2025). In this sense, our results can be interpreted as local average treatment effects for firms that start patenting after a patent-free period, conditional on observable characteristics and on balanced pre-treatment trends.

The results also enrich the debate on the relationship between green innovation and performance by providing firm-level evidence that environmental innovation can enhance competitiveness, albeit with a time lag. Methodologically, the paper contributes by applying a robust matching strategy combined with modern DiD estimators that mitigate selection bias and handle staggered treatment adoption, offering a replicable approach for future analyses of innovation payoffs over time.

The findings carry practical implications for both managers and policymakers. For firms committed to sustainability, they highlight the need for patience and strategic foresight, as immediate gains are unlikely. Managers should view green innovation as a long-term investment rather than a short-term cost, aligning internal evaluation horizons with the empirically observed three- to five-year payoff window. For policymakers, the results underscore the importance of sustained support mechanisms (such as R&D tax incentives or subsidies) that extend beyond the initial development phase to the critical diffusion period, typically three to five years after patenting. Such long-term commitment can simultaneously advance environmental sustainability and enhance the competitiveness of manufacturing firms. Short-lived or highly procyclical policy interventions, by contrast, risk underestimating the true returns to green innovation and may inadvertently discourage firms from undertaking more ambitious environmental projects. Ultimately, the key question is not whether “it pays to be green,” but how long firms must strategically endure before realizing the returns from their environmental innovations.

Some limitations should be acknowledged. Although our model controls for observable heterogeneity, unobserved factors (such as managerial capabilities, collaboration intensity, or organizational culture) may still influence both innovation and performance. Moreover, our focus on a single manufacturing sector, while technologically dynamic, may not capture sectoral differences in innovation patterns or regulatory exposure. In addition, our performance measure is based on sales rather than profitability, which may overstate or understate the returns to innovation in contexts where margins change substantially after patenting. Future research could address these limitations by (i) incorporating patent quality indicators and richer performance measures, (ii) extending the analysis across industries and countries to compare regulatory and market contexts, and (iii) exploring heterogeneity in the payoff profile by firm size, age, ownership structure, and financial constraints, thereby identifying which firms are best positioned to benefit from green patenting.

Declarations

Conflict of Interest Statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Figures

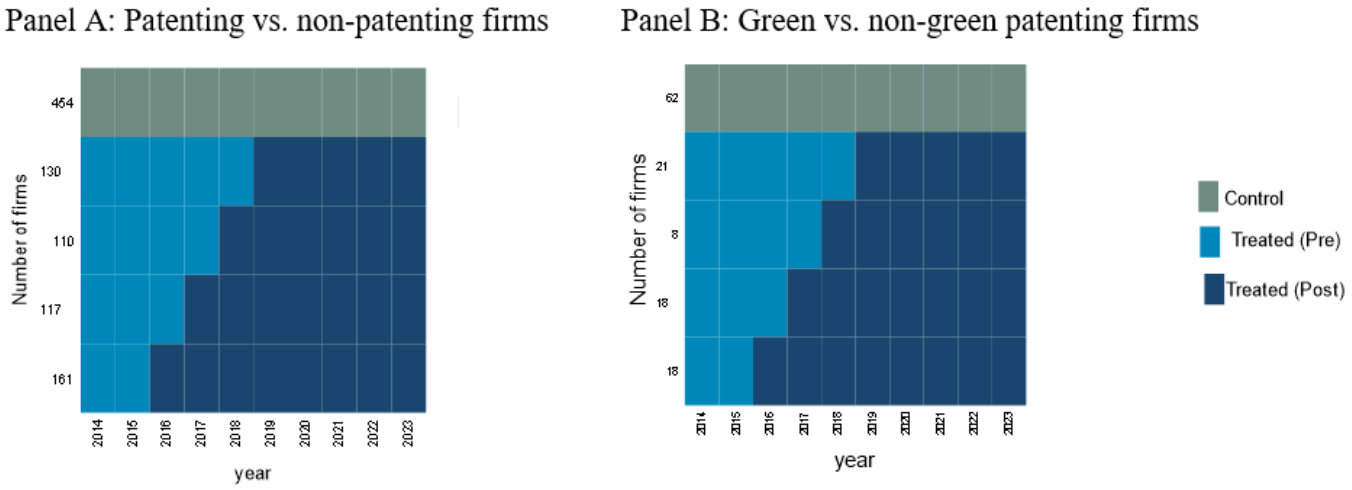


Figure 1

Cohort and treatment status over time

Notes: This figure shows the treatment status of treated firms over time. Pre-treatment years are coloured in light blue. Post-treatment years are coloured in dark blue. Note that, as explained in the main text, the treatment onset was shifted forward by two years to capture anticipation facts. As a result, for example, the post-treatment years for the 2016 cohort already begin in 2014.

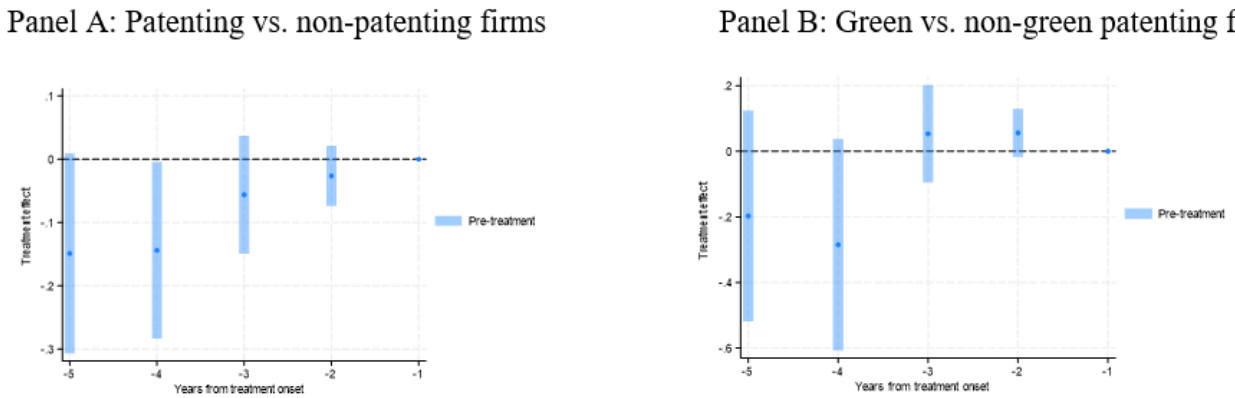


Figure 2

Pre-treatment effects

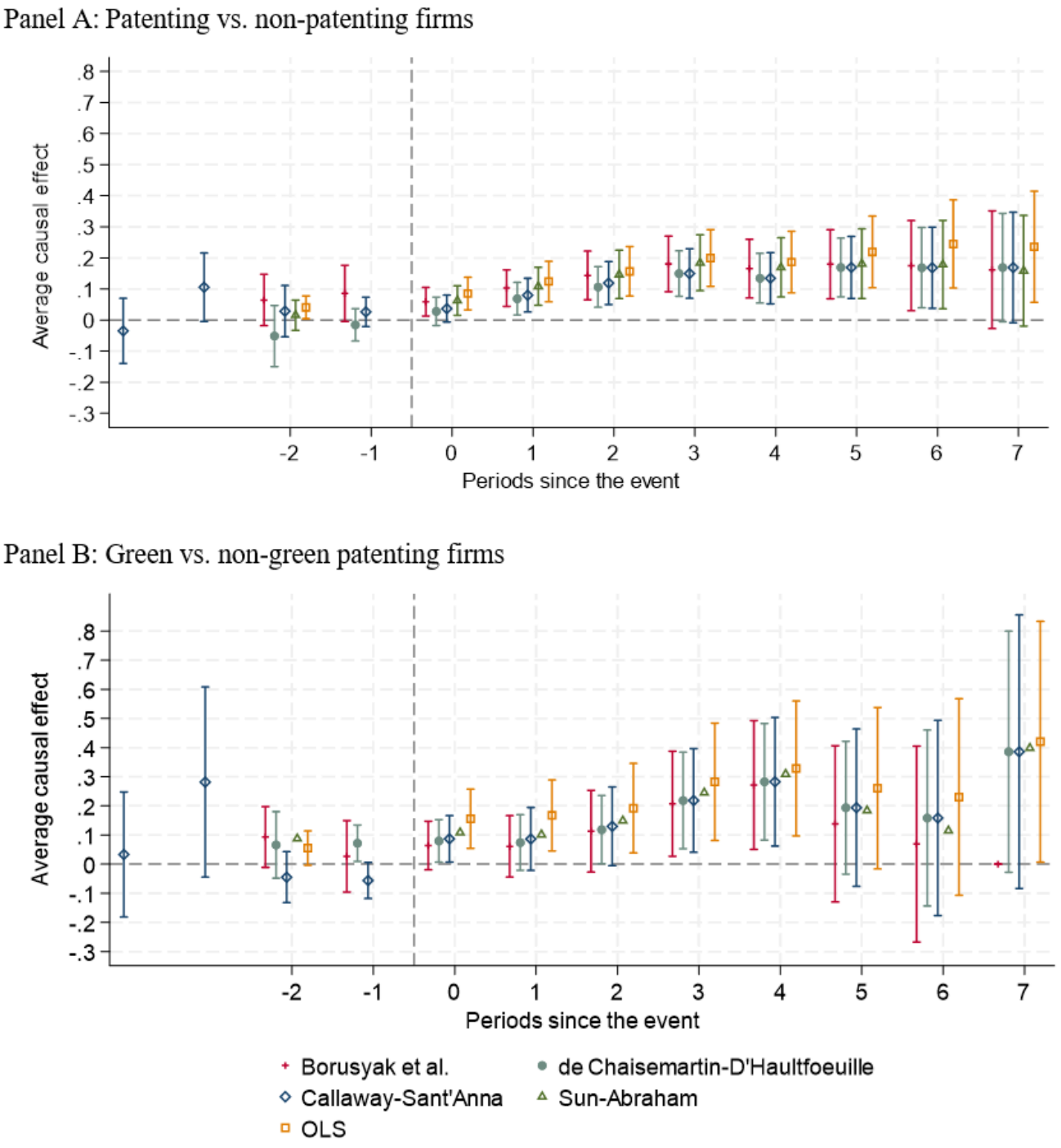


Figure 3

Event Study Estimates of the Effects of Patenting and Green Patenting on Firm Sales

Supplementary Files

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