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Green Transformation Innovation*

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Abstract
As the risk of climate change has increased, companies have advanced their research and development in green transformation (GX) technologies. This paper utilizes the GX classification published by the Japan Patent Office to estimate the values of green and non-green innovation, and analyzes their impacts on firms' resource allocation and growth. This paper finds that (1) green innovation has higher value than non-green innovation on average, (2) non-green innovation measures at the firm level predict a future increase in sales, capital and labor, but green innovation measures do not have predictive power in terms of future variation of firm growth or resource allocation.

Keywords: Innovation, Green Transformation, Green Patent, Stock market, Resource allocation
JEL classification: G14, O31, O34, Q55

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1 Introduction

Environment degradation has become a concern for firm activities over the past few decades. Firms aims to be *climate-neutral*, which refers to the idea of achieving net zero greenhouse gas emissions by balancing those emissions so they are equal (or less than) the emissions that get removed through the planet's natural absorption. In the area of corporate environmental responsibility, the development of environmentally friendly technologies is of paramount importance. In Japan, this aspect is prominently emphasized at the policy level. The Japanese government actively encourages the private sector to prioritize and integrate green innovation into their business activities. Green patents pertain to technologies and innovations that have a positive impact on the environment. This includes renewable energy, waste reduction technologies, and products or processes that mitigate environmental impact. In modern society, where there is an increasing concern for the environment, these patents could play a crucial role in enhancing the sustainability of businesses and industries.

This paper aims to explore the economic value of green patents. In particular, this paper aims to investigates value of green patents from the following perspectives. First, we scrutinize whether there exists a disparity in the values of green and non-green patents. Second, we explore the connection between green innovation and firm growth as well as productivity. Through this multifaceted investigation, we aim to shed light on the subtle interaction between sustainability, innovation, and economic value in the modern economic environment.

In our quest to distinguish between green and non-green patents, we lean on resources provided by the Japan Patent Office (JPO). Their Green Transformation Technologies Inventory (GXTI) serves as an invaluable guide[1]. It offers a structured technology classification paired with patent search queries, enabling a precise segregation of patents based on their technological attributes.

The most closely related paper is Andriosopoulos et al. (2022). They investigate whether green innovation increase shareholder value and find no evidence that the announcements of green patent issuance increase stock prices using patent data in the United States. They employ the event study analysis for estimating the increased values by announcements of patent registration. Their results suggest that green patents do not increase shareholder values conditioning several factors that possibly affect stock price responses. However, my paper employs the methodology of valuing patent developed by Kogan et al. (2017). Instead of hypothesizing through event study analysis, they compute individual patent values by using stock price reactions. I believe that this methodology is suitable if the stock price less reacts to the announcement of patent issuance and the resulting stock price reactions are clustered close to zero.

Our paper relates to several strands in the literature. First, our work is linked to the literature on the valuation of innovation. Research on innovation has often considered patents as an output of R&D activities and has attempted to measure the value of patents as the value of innovation. One of the most widely used methods of measuring patent value is the use of stock market information (Griliches, 1981; Pakes, 1985; Austin, 1993; Hall et al., 2005; Kogan et al., 2017; Chen et al., 2019).

[1] https://www.jpo.go.jp/resources/statistics/gxti.html

The advantage of using financial data is that asset prices are forward-looking and hence provide us with an estimate of the private value to the patent holder that is based on ex ante information. The private value need not coincide with the scientific value of the patent – typically assessed using forward patent citations. In particular, Kogan et al. (2017) and Chen et al. (2019) estimate the value of individual patents using the stock market reaction at the time of patent registration. Chen et al. (2019) use machine learning to classify finance-related technologies using textual information from patents to estimate the value of individual patents and test which new technologies are generating greater innovation within FinTech. Similarly, my paper identifies green patents according to the JPO's GXTI and compares their patent value to that of non-green patents.

Second, this paper is related to the literature on asset pricing in terms of ESG factors such as Hong et al. (2019); Bolton and Kacperczyk (2021); Pástor et al. (2021); Pedersen et al. (2021). Typically, asset pricing literature use the ESG scores or the amount of greenhouse gas emission as pricing factors. The results of our paper are interpreted as the higher valuation of environment-friendly technology partially stems from reducing the climate risk exposure.

The rest of our paper is organized as follows: Section 3 demonstrates the way to construct our dataset of patents; Section 4 explains how we estimate the value of innovation; Section 5 tests how valuable green patents are compared to non-green patents; Section 6 examines whether firm-level innovation affects future growth and resource allocation; and finally, Section 7 concludes.

2 Hypothesis

In the first place, how does a green patent differ from a non-green patent? The GXTI, the green technology categorization used in this paper, refers to a set of technologies that are considered important for the conversion from fossil fuels to renewable clean energy sources, such as solar and wind power, to achieve net-zero emissions of greenhouse gas. How are these characteristics of green technology valued in the stock market? I take the following three points in consideration to formulate a hypothesis.

First, the urgency to address environmental challenges has never been higher. Governments, corporations, and consumers alike are increasingly recognizing the necessity of transitioning to sustainable practices. This shift is evident in international accords, national policies, and consumer preferences, setting the stage for a heightened demand for green innovations. Second, in industries that are rapidly greening, holding a green patent can offer a significant competitive edge. As regulatory environments worldwide tighten around environmental standards, companies with green patents are better positioned to navigate these changes, further amplifying their patents' value. Last, while immediate financial returns are a driving force behind many innovations, green patents often promise long-term growth and resilience. As resources become scarcer and environmental crises more frequent, solutions offered by green technologies will become invaluable. Given the above considerations, I can hypothesize:

Hypothesis 1: On average, the value of green patents is higher than that of non-green patents.

3 Data and Sample Construction

3.1 Patent Data

This section outlines the data source and provides details on how the sample was constructed. I obtained patent information form J-PlatPat, an information search platform for patents offered by the JPO. By specifying a time frame for events, we can acquire a list of patents that experienced the specified events during that period. The selectable events include patent applications, publications, registrations, and public announcements of registration, among others. In this study, we selected the registration date as the event. We downloaded the list of patents obtained by specifying each day from January 1, 2001, to December 31, 2022, as the registration date. This is because the list items of obtainable patents are limited to the following: document number, application number, application date, publication date, title of invention, applicant/owner, FI, publication number, announcement number, registration number, trial number, other, and document URL. To these list items, we added the registration date.

There are some different points from patent events in the United States. In Japan, information that a patent has been register is made public by publication in the Patent Gazette approximately two weeks later.[2] The JPO published on every Wednesday, unless there is a national holiday, until 2021, and on everyday since 2022. The means of transmitting patent information have experienced different transitions. The Patent Gazette has been published in DVD from July 2004 and on Internet from April 2015. Since the JPO provides both the publication date of the Patent Gazette after 2004 and the means that identify which patents are listed in each Gazette through their registration number, these dates have been included as release dates of registrations.

3.2 Green Transformation Technologies

The JPO provides Green Transformation Technologies Inventory (GXTI), which classifies various green technologies and facilitates searches based on the International Patent Classification (IPC) system.[3] The GXTI has five level-1 categories: (A) Energy supply, (B) Energy saving, electrification, demand-supply flexibility, (C) Batteries, energy storage, (D) CO2 reduction in non-energy sector, (E) Capture, storage, utilization and removal of greenhouse gas. Table 1 presents the level-1 and level-2 categories of GXTI.[4] Although Aghion et al. (2016) classifies patents in the auto industry into clean, dirty and grey patents categories by IPC code, I classify green patents based on GXTI and non-green patents which are not classified into GXTI categories.

By utilizing the aforementioned search query on J-PlatPat, we can identify patents that fall under the green transformation technologies category and subsequently merge them based on their document numbers. Consequently, a variable indicating whether a patent is a GX patent or not is

[2]In the United States, the issue date of a patent is the same as the publication date of the Official Gazette.

[3]The GXTI was prepared after two rounds of discussions (January 6, 2022 and April 6, 2022) by a study group consisting of six external experts with in-depth knowledge of GX technologies, who selected technologies that are expected to have significant GHG reduction effects.

[4]For more detailed level-3 categories, see https://www.jpo.go.jp/resources/statistics/document/gxti/gxti_en.pdf.

added to the patent dataset based on the registration date.

[Table 1]

3.3 Constructing dataset

Our study focuses on green transformation innovation by listed firms in Japan, then it is necessary to filter the acquired patent dataset to a dataset of patents by listed firms. To obtain the dataset, we do the following steps. First, we keep only patents containing "Kabushiki Kaisha", which means corporation in Japanese, as the applicant name, excluding individuals, universities, foreign companies, etc. Next, we match the list of listed companies with the applicants for the patents by name. The list of listed companies that includes security codes enables us to join other data such as financial and accounting information. For each firm in the name-matched sample, we gather data on financials, stock prices, TSE sector codes, and year of founding. We obtain all the data from Astramanager of Quick, Inc. After filtering, we obtain a final sample of 1,712,224 patents, which includes 117,597 green patents and 1,594,627 non-green patents.

4 The Value of Innovation

This section explains how I compute the market value of patents following the methodology developed by Kogan et al. (2017).

4.1 Identifying information events

On the patent event date, the investors learn that the patent application has been successful. If there is no other news, the firm's stock market reaction ΔV_{ij} on the day the patent j of the firm i is issued is given by

$$\Delta V_{ij} = (1 - \pi_j)\xi_{ij}, \tag{1}$$

where π_j is the market's ex ante probability assessment that the patent application is successful and ξ_{ij} is the value (in Japanese yen) of patent j of a firm i. The market's response to the issuance of a patent does not fully reflect the patent's overall effect on the firm's value. This is because the market is already aware of the likelihood of the patent being granted prior to the resolution of the uncertainty surrounding the patent application. To calculate the patent value based on equation (1), it is necessary to extract the change in the firm value at the patent event. Kogan et al. (2017) use an event study analysis of stock turnovers to identify event windows for calculating stock price reactions around the patent event date.

We have two concerns regarding the straightforward application of the Kogan et al. (2017) method to the Japanese stock market to determine event windows. First, information that a patent has been issued is made public a few weeks subsequent to the actual issue date in Japan. In

Japan, information about patent issuances is typically made public through a patent gazette or publication. This publication is an official record that contains details about newly issued patents, including information about the patent holder, the patent's title, and its filing date. The publication of this information usually occurs a few weeks after the actual patent has been granted. This process ensures that the public and other interested parties are informed about the newly granted patents and their details. Thus, it is necessary to identify the information event and its window for estimating patent values. Second, Japanese listed companies are heterogenous in the market capitalization and turnover. Therefore, it is expected that a simple comparison between turnovers of firms with and without patent issuances make no statistically significant differences.

To adjust the unbalance between firm groups with and without patent issuances, we apply the propensity score matching method. We estimate propensity scores for each patent event and select the nearest firms. We set the ratio of treatment to control as one to five. The control variables include total assets, R&D, and cash.

After filtering the sample firms, we use the event study analysis by estimating the following specification:

$$Turnover_{i,d} = aI_{i,d} + \sum_l b_l(I_{i,d} \times D_{d,l}) + \sum_l c_l D_{d,l} + dZ_{id} + \eta_{i,d}, \tag{2}$$

where i and d indices firm and publication date, and l ($l \in \{-1, 0, 1, 2, 3\}$) represents lead-lag days, which means that we set two days before patent events as a benchmark. The vector of controls Z_{id} includes firm-year and day of week fixed effects and standard errors are clustered by year.

Table 2 shows the results of event study analysis of Eq. (2) for patent issuance date and issuance publication date. In Column (1), we do not find that turnovers of firms whose patents are issued are different from those without patent issuances. In column (2), on the other hand, turnover increases from the date of publication until two days later. Based on these results, we measure the patent values using stock returns within the three-day window. Even though prices can adjust to new information absent any trading, the fact that stock turnover increases following a patent grant is consistent with the view that patent issuance conveys important information to the market.

[Table 2]

4.2 Estimating the value of patent

The next step in constructing an innovation measure involves isolating the reaction due to the announcement of patent issuance. It is reasonable to assert that the stock prices of firms fluctuate around the announcement dates due to factors unrelated to the dissemination of innovation information. In line with standard empirical papers, I hypothesize that the individual stock returns co-move with the market factor. To remove market movements, we calculate the firm's idiosyncratic return, defined as the firm's return minus the return on the market portfolio (TOPIX). I assume that the idiosyncratic stock return, R_j, for a given firm around the date of announcing that patent

j is issued, is decomposed as:

$$R_j = v_j + \varepsilon_j,$$

where v_j denotes the value of patent j and ε_j represents the component of the firm's stock return that is unrelated to the patent. It should be noted that v_j is defined as a fraction of the firm's market capitalization.

Kogan et al. (2017) construct the estimate ξ_j of economic value of patent j as the product of the estimate of the stock market reaction due to the value of the patent times the market capitalization M of the firm that is issued patent j on the day prior to the announcement of the patent issuance:

$$\xi_j = (1-\bar{\pi})^{-1} \frac{1}{N_j} E\left[v_j \mid R_j\right] M_j. \tag{3}$$

where $\bar{\pi}$is unconditional probability that the patent application is successful and N_j is the number of patents that granted at the same date. Following Kogan et al. (2017), I use the unconditional probability of a successful patent application and its value is equal to 0.50 which is average patent registration rate during 2006-2015.

To compute the conditional expectation term in Eq. (3), Kogan et al. (2017) make assumptions regarding the distributions of v and ε. Given their implicit assumption that the market value of the patent v is a positive random variable, they propose that v is distributed according to a normal distribution truncated at 0, denoted as $v_j \sim \mathcal{N}^+(0, \sigma^2_{vft})$. They also assume that the factor unrelated to the patent value, ε_j, follows a normal distribution, $\varepsilon_j \sim \mathcal{N}(0, \sigma^2_{\varepsilon ft})$. Consequently, the expected value of v_j conditioned on R_j is given by:

$$E\left[v_j \mid R_j\right] = \delta R_j + \sqrt{\delta}\sigma_{\varepsilon ft} \frac{\phi\left(-\sqrt{\delta}\frac{R_j}{\sigma_{\varepsilon ft}}\right)}{1-\Phi\left(-\sqrt{\delta}\frac{R_j}{\sigma_{\varepsilon ft}}\right)} \tag{4}$$

where ϕ and Φ represent the standard normal probability density function and cumulative distribution function, respectively. The signal-to-noise ratio, δ, is defined as

$$\delta_{ft} = \frac{\sigma^2_{vft}}{\sigma^2_{vft} + \sigma^2_{\varepsilon ft}}.$$

The conditional expectation in equation 4 is characterized as an increasing and convex function of the idiosyncratic firm return R.

To compute the signal-to-noise ratio, Kogan et al. (2017) conducted a regression analysis where the log squared returns were regressed on the dummy variable for announcements of patent issuance, I_{fd}, represented as:

$$\log\left(R_{fd}\right)^2 = \gamma I_{fd} + cZ_{fd} + u_{fd},$$

where R_{fd} denotes the three-day idiosyncratic return of firm f, starting on day d. Controls Z for day of week and firm-year interactions were included to account for seasonal fluctuations in volatility and the time-varying nature of firm-level volatility. The signal-to-noise ratio estimate is derived from the estimated value of γ, using $\hat{\delta} = 1 - e^{-\hat{\gamma}}$. Our estimate, $\hat{\gamma} = 0.0424$, implies $\hat{\delta} \approx 0.0415$. Therefore, we use this value to calculate the patent value using equations (3) and (4).

4.3 Descriptive statistics

In Table 3, I report the sample distribution of ξ along with ones for each patent type: green and non-green patents. It represents that the distributions of calculated innovation values are positively skewed. The average innovation value across all observations is 614.596. The mean value for green innovations is slightly lower at 613.561, while it is slightly higher for non-green innovations at 614.672. The means of the two groups are very close to each other. Regarding the standard deviations, green innovations have a smaller standard deviation (1438.159) compared to non-green innovations (5438.456), indicating that green innovation values are more tightly clustered around their mean relative to non-green innovations.

Both the overall dataset and the non-green subset are highly positively skewed, with skewness values of 1019.263 and 991.190, respectively. This indicates a long tail on the right, meaning there are a few very high innovation values that skew the distribution. The green innovation subset is also positively skewed but to a much lesser extent, with a skewness value of 49.419. At the median, green innovations (324.196) have a higher value than non-green innovations (231.611). This suggests that the typical green innovation has a higher value than its non-green counterpart. Overall, while the average values of green and non-green innovations are similar, their distributions exhibit differences. Green innovations are distributed with less extreme variation, while non-green innovations have a broader spread and extreme high values.

[Table 3]

4.4 Aggregated Innovation Value

This subsection describes the aggregated innovation values of green and non-green patents issued in each year. Table 8 represents the time-series evolution of aggregated values of green and non-green patents from 2004 to 2021. Both green and non-green patents have shown a general growth trend in their aggregated innovation values over the period. However, the growth patterns are not uniform and exhibit fluctuations.

The non-green patents consistently hold a significantly larger portion of the aggregated innovation value compared to green patents, and shows more volatility over the years. The value of green patents, although significantly smaller, displays a more steady and consistent increase over the years. This consistent upward trajectory, especially notable after 2009, could suggest a growing recognition of the importance of green technologies and a gradual increase in investment and development in this area.

The sharp decrease in the value of both green and non-green patents in 2009, followed by a gradual recovery, could be attributed to the global financial crisis of 2008-2009. It highlights the sensitivity of innovation values to economic conditions. In the most recent years, particularly from 2016 onwards, there's a noticeable increase in the value of green patents. This could reflect an increased focus on sustainable and environmentally friendly technologies, possibly driven by global environmental concerns and policy initiatives.

While the absolute value of green patents is much lower than non-green, the proportional increase in green patents from 2004 to 2021 is noteworthy. It started at 1.71 trillion yen and grew to 6.32 trillion yen, almost quadrupling over 17 years. In contrast, non-green patents grew from 32.42 trillion yen to 66.38 trillion yen, a little over doubling in the same period. This indicates a relatively faster growth rate for green patents, although from a much smaller base.

In summary, the dynamics of aggregated innovation values for green and non-green patents over these years reflect broader economic trends, the evolving importance of sustainable technologies, and the potentially cyclical nature of innovation values introduced by Kogan et al. (2017).

[Table 8]

5 How valuable are green patents?

5.1 Regressions and Results

This section examines whether green patents have different private values compared to non-green patents. We estimate the following specification:

$$\hat{\xi}_{ijt} = \beta_1 GX_{ijt} + \gamma X_{it} + FE + \varepsilon_{ijt}, \tag{5}$$

where $\hat{\xi}_{ijt}$ is the calculated innovation value of patent j of firm i at date t. GX is a dummy variable that equals to one if patent j of firm i is labeled as green and zero otherwise, X is a vector of control variables (R&D and the number of patents issued at the same date). FE represents combinations of fixed effects of fiscal year, industry and firm.

Table 4 shows the results from estimating equation (5). Columns (1) - (3) use a dummy variable that equals one if a patent is classified as green patent and zero otherwise, and columns (4) - (6) use dummy variables that classify the GX patent into five sub-categories (gxA - gxE). First, I demonstrate the results of columns (1) - (3). I use only the year fixed effect in column (1), I add the industry fixed effect on column (2) and the firm fixed effect on column (3). The estimated coefficients of GX dummy variable are positive and statistically significant at 10 percent in column (1) and 5 percent in column (2). In other words, on average, green patents have higher values compared to non-green patents in cross-section and within industries, respectively. However, column (3) suggests that we cannot conclude the values of green patents are different from those of non-green patents within firm. The cross-sectional variations of the patent values are explained by whether they are green or non-green patents, but the firm-specific time-invariant factor explains a large part of the variation of the patent values within firm. This suggests that high-valued green patents are produced by innovative firms that invent non-green patents at the same level, then green patents do not make a difference in patent values within the firm. Turning to the estimated parameters of log(R&D), a similar tendency is observed. Although the parameter of R&D is positive and statistically significant in the cross-section, it is not statistically significant when using firm fixed effects. Overall, this raises a potential reverse causality issue, suggesting that innovative firms may inherently be more inclined to produce green innovations.

[Table 4]

Revisiting the definition of the innovation measure (Eq. 3), one might be concerned that patents issued at the same date have the same value even if they include both green and non-green patents. Therefore, even though they potentially have different values on average, their values might be estimated to be close to each other. To address this concern, I estimate the aforementioned specification by using the subset includes the dates on which only green or non-green patents are issued, and Table 5 shows the results. Surprisingly, dummy variables for green patents including subcategories are positive and statistically significant all specifications.

[Table 5]

Furthermore, we estimate the equation 5 using only patents of firms that possess both green and non-green patents. Table 6 shows the result and the tendency of coefficients is similar to that of Table 5. Combining two subsample analysis, I find that positive value of green patents compared to the non-green patents.

[Table 6]

5.2 Industries with high GHG Emissions

This subsection explores the variability in the effects of GHG (greenhouse gas) emission levels across different industries. It posits that firms within industries characterized by high GHG emissions, such as the steel and chemical sectors, are likely to encounter increased pressures to enhance the ecological sustainability of their technology. In industries with high GHG emissions, GX patents are anticipated to hold greater value compared to industries with lower GHG emissions. To examine this prediction, I introduce three industry-level variables that capture the GHG emission levels at the industry-level: The total GHG emissions at the TSE sector level (log(GHG)), the rank that sorts sector's GHG emission in ascending order (Rank), the dummy variable that equals to one if an industry is classified into a top tertile group by year (High Emission). I estimate equation (5) with the industry-level variables and the interaction term of them with GX dummy variable and show the results in Table 7. For all three industry factors, coefficients of interaction terms are positive and statistically significant. This result implies that, in industries with high GHG emissions, GX patents are valued higher than those in industries with low GHG emissions. In industries with high GHG emissions, inventions of environmentally friendly technologies are valued more highly in the stock market than inventions of traditional (non-green) technologies, suggesting that sustainability in their environmental aspects create the firm value.

[Table 7]

5.3 Discussions

The results in this paper show that green patents have higher value contrast to non-green patents, unlike existing literature such as Andriosopoulos et al. (2022). This contrast may stems from the cross-country difference of investors' perceptions about environmental issues, firms' capability to reduce GHG emissions, and strictness of environmental policy. For example, Bolton and Kacperczyk (2021) find higher stock returns of firms with high GHG emissions using U.S. companies data and explain that investors require risk premium. On the other hand, Goshima and Yagi (2022) find the opposite result showing negative carbon premium in the Tokyo Stock Exchange. Because there are different responses to GHG emissions of companies across countries, it is expected that the responses to green patent issuance are different across countries.

However, it should be noted that there are some limitations in my analysis. First, this paper assume that GXTI classifies patents properly into the categories of green transformation technology. Second, the patent values of firms with large market capitalization tend to be large because they are calculated by multiplying a price impact by market capitalization. If firms with large market capitalization have a tendency to issue green patents, there is a possibility that the above relationship is a spurious correlation. Third, a simple comparison of whether it is green or not green does not appropriately compare the technologies that should be compared. For example, it is reasonable to compare a patent of renewable energy technology with a patent of fossil fuel power generation. However, the patents of Carbon dioxide Capture and Storage (CCS), which is included in category gxE, have no substitute technologies in the space of non-green technology. Accordingly, we should be careful to conclude that green technologies are more highly valued in the market.

6 Resource Allocation

In this section, I discuss the impact of innovation on firms' growth and resource allocation. This is motivated by predictions of growth models that innovation causes resource reallocation and subsequent growth (e.g., Klette and Kortum, 2004). At the same time, it is predicted that the innovation of competing firms in the same industry has negative impacts on the focal firm because innovation gains market shares in the industry. To check this predictions, Kogan et al. (2017) define the measure of firm-level innovation produced by a given firm f in year t by summing up all the values of patents j that were granted to that firm,

$$\Theta_{f,t} = \sum_{j \in P_{f,t}} \xi_j$$

where $P_{f,t}$ denotes the set of patents issued to firm f in year t. By scaling the measure above by firm's book value of total asset, they introduce the firm-level innovation measure as:

$$\theta_{f,t} = \frac{\Theta_{f,t}}{B_{f,t}}$$

where B_{ft} is total assets of firm f in year t. We also define a measure of innovation by competing firms. In addition, I define the set of competing firms as all firms in the same industry excluding firm f at the three-digit level of JSIC (Japanese Standard Industry Classification). Accordingly, I define the innovation measure of compering firms in the same industry as:

$$\theta_{I \setminus f,t} = \frac{\sum_{f' \in I \setminus f} \Theta^i_{f',t}}{\sum_{f' \in I \setminus f} B_{f',t}}.$$

Using these firm-level innovation measures, Kogan et al. (2017) examine the relationship between innovative activity of a given firm and its competitors and its future growth and productivity. Following Kogan et al. (2017), I use growth rates of (a) gross profits, (b) sales, (c) capital stock, and (d) the number of employees as dependent variables, and estimate the following specification:

$$\log X_{f,t+\tau} - \log X_{f,t} = a_\tau \theta_{f,t} + b_\tau \theta_{I \setminus f,t} + cZ_{f,t} + u_{f,t+\tau}. \tag{6}$$

where the vector Z includes the log value of the capital stock and the log number of employees.

In addition to the firm-level innovation measure, I define green and non-green innovation measures at the firm level as $\theta^g_{f,t}$ and $\theta^n_{f,t}$, respectively, by summing up all the values of green and non-green patens. We decompose the predictability of the innovation measures in the right-hand side of equation (6) into green and non-green innovation measures, which is assumed to have different effects on firm growth and resource allocation. To estimate both effects of green and non-green innovation measures, I use the following specification:

$$\log X_{f,t+\tau} - \log X_{f,t} = a^g_\tau \theta^g_{f,t} + a^n_\tau \theta^n_{f,t} + b^g_\tau \theta^g_{I \setminus f,t} + b^n_\tau \theta^n_{I \setminus f,t} + cZ_{f,t} + u_{f,t+\tau}. \tag{7}$$

Table 9 shows the results from estimating equation (6) and Table 10 shows the results from estimating equation (7). First, using the same measure of Kogan et al. (2017), we find that firm's innovation measures predict future increases in sales, capital and labor, but competitors innovation does not predict the focal firm's future decrease in growth rates and resource allocations unlike the results of Kogan et al. (2017).

Next, I demonstrate the results in Table 10, where the innovation measure is decomposed into green and non-green ones. Although non-green innovation measure for a focal firm predicts future increase of sales, capital and labor, green innovation one does not have predict power for future variations. Similar to Table 9, I cannot reject null hypothesis that innovations of competitor firms do not predict future variations of growth and resource allocation of a focal firm.

[Table 9 and 10]

To sum up, the firm-level innovation measure, in particular, non-green one is positively correlated with future growth, while green one does not predict the firm's future growth. These results are interpreted as the follows: Despite the increasing global emphasis on sustainability and environmental responsibility, many markets may not yet be fully ready to adopt or reward green innovations at scale. It is possible that non-green innovations address immediate market demands, leading to quicker returns on investment and observable growth. In contrast, green innovations may have longer gestation periods, with their value realized over extended time horizons. To better understand and leverage this insight, firms should consider both short-term growth objectives and long-term sustainability goals. While non-green innovations might provide immediate growth impetus, the future undoubtedly lies in sustainable, green innovations. As markets mature and global priorities shift, the value of green innovations in driving firm growth will likely to realize.

7 Concluding Remarks

Leveraging the GX categorization from the Japan Patent Office, this study evaluates the economic value of green versus non-green innovations and delves into their repercussions on corporate resource allocation and expansion. Our findings reveal that: (1) on average, green innovations carry a higher economic value than their non-green counterparts, and (2) while non-green innovation indicators at the corporate level presage future surges in sales, capital, and workforce, green innovation metrics do not offer predictive insights into upcoming fluctuations in company growth or resource distribution.

Interpretations of these results are as follows. The observation that investors place high value on environmentally friendly technologies may contribute to reducing the cost of capital when companies seek funding for such technologies in the market. Furthermore, given that these technologies often do not yield immediate corporate growth, it can be inferred that investors demonstrate a tolerance towards companies that invest in the research and development of green technologies. Considering that environmental issues represent long-term challenges, the provision of time by investors for companies to develop solutions to environmental problems may play a supportive role in the efficacy of environmental policies.

There are two issues in estimating patent values using market reactions. First, the patent values of firms with large market capitalization tend to be large because they are calculated by multiplying a price impact by market capitalization. Second, when a certain firm has multiple patents registered on the same day, the estimated stock price impact is divided by the number of patents to measure the value of each individual patent. Consequently, both green patents and non-green registered on the same day are considered to possess the same value. Furthermore, the main result raises a potential reverse causality issue, suggesting that innovative firms may inherently be more inclined to produce green innovations. Addressing these issues will be required in future studies.

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Tables

Table 1: Green Transformation Technologies Inventory

Level 1		Level 2
gxA	Energy Supply	01 Solar Photovoltaic Power Generation, 02 Solar Thermal Energy Utilization, 03 Wind Power Generation, 04 Geothermal Utilization, 05 Hydro-Power Generation, 06 Hydro-Power Generation, 07 Biomass, 08 Nuclear Power Generation, 09 Fuel Cells, 10 Hydrogen Technology, 11 Ammonia Technology
gxB	Energy Saving, Electrification, Demand-Supply Flexibility	01 Energy Saving in Buildings (ZEB, ZEH, etc.), 02 High-Efficiency Motors and Inverters, 03 Combined Heat and Power (CHP), 04 Energy Saving and Supply/Demand Flexibility in Treatment of Water, Wastewater, Sewage, and Sludge, 05 Electromobilities, 06 Electrification of Industrial Heat, 07 Power Transmission and Distribution, Smart Grids, 08 Demand-Supply Flexibility of Power Systems
gxC	Batteries, Energy Storage	01 Secondary Batteries, 02 Mechanical Energy Storage, 03 Thermal Energy Storage, 04 Electric Double Layer Capacitors, Hybrid Capacitors
gxD	CO2 Reduction in Non-Energy Sector	01 Chemical Production from Biomass, 02 Reduction of CO2 Emission in Steelmaking Process, 03 Recycling
gxE	Capture, Storage, Utilization and Removal of Greenhouse Gas	01 CCS, CCUS, Negative Emission, 02 Measures Against Non-CO2 Greenhouse Gases

Table 2: Event study analysis for patent events

The table below shows the results of regressions to determine the length of event windows for the patent events of issuance and publication. Standard errors are clustered by firm and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	Turnover (%)	
Patent Event:	Issuance Date	Publication Date
	(1)	(2)
Issuance$\times D_{l=-1}$	0.002	-0.001
	(0.003)	(0.003)
Issuance$\times D_{l=0}$	0.015***	0.010**
	(0.004)	(0.004)
Issuance$\times D_{l=1}$	-0.005	0.014***
	(0.004)	(0.004)
Issuance$\times D_{l=2}$	-0.003	0.026***
	(0.003)	(0.006)
Issuance$\times D_{l=3}$	0.004	0.001
	(0.004)	(0.004)
$D_{l=-1}$	-0.0001	-0.003
	(0.004)	(0.010)
$D_{l=0}$	-0.006	0.011
	(0.005)	(0.012)
$D_{l=1}$	0.001	-0.002
	(0.005)	(0.009)
$D_{l=2}$	-0.0001	-0.009
	(0.003)	(0.008)
$D_{l=3}$	-0.002	-0.001
	(0.002)	(0.003)
Issuance	-0.004	-0.013**
	(0.004)	(0.005)
Observations	6,453,778	5,315,079
R squared	0.191	0.209

Table 3: Summary Statistics of Innovation Value

This table shows the summary statistics of innovation value, $\hat{\xi}$, calculated by equation (3). The summary statistics of innovation value for both green and non-green patents are also shown in the table. Each moment is shown in million yen.

	$\hat{\xi}$	Green	Non-Green
N	1,712,224	117,597	1,594,627
Mean	614.596	613.561	614.672
Std. dev.	5261.891	1438.159	5438.456
Skewness	1019.263	49.419	991.190
Percentiles			
Min	1.679	1.901	1.679
p5	43.295	55.614	42.543
p10	61.723	79.618	60.764
p25	115.013	152.601	112.941
p50	237.038	324.196	231.611
p75	535.513	656.239	524.390
p90	1191.964	1260.822	1184.831
p95	2015.524	1940.722	2023.734
Max	6319169	231087.7	6319169

Table 4: Regression results of GX patent value

The table below shows the results of regressions using sample of green and non-green patents. GX represents the dummy variable which equals one if a patent is green and zero otherwise. gxA - gxE are dummy variables that equal one if a patent is classified into each group. Control variable includes log(R&D) and the number of patents that are registered at the same date. Year, Industry, and Firm FEs represent the fixed effects that are used in an estimation. Standard errors are clustered by firm and shown in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Dependent Variable:	log(Patent Value)					
	(1)	(2)	(3)	(4)	(5)	(6)
GX	0.178*	0.046**	0.005			
	(0.099)	(0.020)	(0.008)			
gxA				0.217**	0.039	0.009
				(0.093)	(0.025)	(0.011)
gxB				0.107	0.029	-0.004
				(0.099)	(0.021)	(0.009)
gxC				0.211	0.062**	0.006
				(0.124)	(0.030)	(0.013)
gxD				0.286***	0.099***	0.035
				(0.077)	(0.058)	(0.022)
gxE				0.304	0.096	0.047
				(0.137)	(0.058)	(0.040)
log(R&D)	0.298***	0.324***	0.030	0.298***	0.3243***	0.030
	(0.035)	(0.023)	(0.049)	(0.035)	(0.023)	(0.049)
#Multiple Patents	-0.019***	-0.014***	-0.017***	-0.019***	-0.014***	-0.017***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Observations	1,696,405	1,696,405	1,696,405	1,696,405	1,696,405	1,696,405
Adjusted R^2	0.285	0.620	0.743	0.285	0.620	0.743

Table 5: Regression results of GX patent value with sub-sample

The table below shows the results of regressions using sample of green and non-green patents which are issued on different dates. GX represents the dummy variable which equals one if a patent is green and zero otherwise. gxA - gxE are dummy variables that equal one if a patent is classified into each group. Control variable includes log(R&D) and the number of patents that are registered at the same date. Year, Industry, and Firm FEs represent the fixed effects that are used in an estimation. Standard errors are clustered by firm and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:			log(Patent Value)			
	(1)	(2)	(3)	(4)	(5)	(6)
GX	0.736***	0.560***	0.426***			
	(0.084)	(0.047)	(0.028)			
gxA				0.948***	0.607***	0.383***
				(0.092)	(0.057)	(0.036)
gxB				0.550***	0.468***	0.416***
				(0.117)	(0.072)	(0.044)
gxC				0.521***	0.485***	0.375***
				(0.086)	(0.060)	(0.043)
gxD				1.026***	0.626***	0.466***
				(0.117)	(0.060)	(0.046)
gxE				1.063***	0.545***	0.273***
				(0.217)	(0.115)	(0.072)
log(R&D)	0.394***	0.408***	0.087**	0.394***	0.408***	0.087**
	(0.037)	(0.026)	(0.044)	(0.037)	(0.026)	(0.044)
#Multiple Patents	-0.042***	-0.033***	-0.041***	-0.042***	-0.033***	-0.041***
	(0.008)	(0.026)	(0.007)	(0.008)	(0.026)	(0.007)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Observations	890,694	890,694	890,694	890,694	890,694	890,694
Adjusted R^2	0.331	0.615	0.757	0.331	0.615	0.757

Table 6: Regression results of GX patent value with sub-sample

The table below shows the results of regressions using sample of green and non-green patents which are applied by the same firms and issued on different dates. GX represents the dummy variable which equals one if a patent is green and zero otherwise. gxA - gxE are dummy variables that equal one if a patent is classified into each group. Control variable includes log(R&D) and the number of patents that are registered at the same date. Year, Industry, and Firm FEs represent the fixed effects that are used in an estimation. Standard errors are clustered by firm and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	log(Patent Value)					
	(1)	(2)	(3)	(4)	(5)	(6)
GX	0.713***	0.530***	0.406***			
	(0.080)	(0.052)	(0.042)			
gxA				0.936***	0.588***	0.370***
				(0.088)	(0.062)	(0.048)
gxB				0.521***	0.436***	0.394***
				(0.115)	(0.074)	(0.052)
gxC				0.497***	0.447***	0.352***
				(0.083)	(0.066)	(0.051)
gxD				1.005***	0.600***	0.450***
				(0.116)	(0.062)	(0.050)
gxE				1.040***	0.506***	0.255***
				(0.219)	(0.115)	(0.074)
log(R&D)	0.398***	0.416***	0.019	0.398***	0.416***	0.019
	(0.037)	(0.026)	(0.044)	(0.037)	(0.026)	(0.044)
#Multiple Patents	-0.036***	-0.046***	-0.051***	-0.036***	-0.046***	-0.051***
	(0.008)	(0.026)	(0.007)	(0.008)	(0.026)	(0.007)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Observations	558,492	558,492	558,492	558,492	558,492	558,492
Adjusted R^2	0.301	0.582	0.729	0.301	0.582	0.729

Table 7: Regression results of GX patent value with industry GHG emissions

The table below shows the results of regressions with industry GHG factors using sample of green and non-green patents which are applied by the same firms and issued on different dates. GX represents the dummy variable which equals one if a patent is green and zero otherwise. The industry factors include log(GHG), Rank, and High Emission. log(GHG) represents the total GHG emissions at the TSE sector level, Rank represents the rank that sorts sector's GHG emission in ascending order, High Emission represents a top tertile industry group of GHG emissions. Control variable includes log(R&D) and the number of patents that are registered at the same date. All specifications control the year fixed effect. Standard errors are clustered by firm and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	log(Patent Value)					
Industry Factor:	log(GHG)		Rank		High Emission	
	(1)	(2)	(3)	(4)	(5)	(6)
GX	0.726***	-2.165***	0.732***	0.054	0.730***	0.574***
	(0.079)	(0.773)	(0.081)	(0.268)	(0.081)	(0.110)
Industry Factor	-0.001	-0.005	-0.006	-0.007	-0.063	-0.067
	(0.034)	(0.034)	(0.007)	(0.007)	(0.085)	(0.085)
GX×Industry Factor		0.176***		0.032***		0.300***
		(0.047)		(0.012)		(0.139)
log(R&D)	0.398***	0.416***	0.019	0.398***	0.416***	0.019
	(0.037)	(0.026)	(0.044)	(0.037)	(0.026)	(0.044)
#Multiple Patents	-0.036***	-0.046***	-0.051***	-0.036***	-0.046***	-0.051***
	(0.008)	(0.026)	(0.007)	(0.008)	(0.026)	(0.007)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	511,133	511,133	511,133	511,133	511,133	511,133
Adjusted R^2	0.305	0.306	0.306	0.307	0.306	0.306

Table 8: Macro-level Innovation Values

The table below shows the evolution of aggregated value of innovation value. Both the values of non-green and green patents are represented in trillion yen.

Fiscal Year	Green	Non-green
2004	1.71	32.42
2005	2.23	41.90
2006	3.63	57.13
2007	4.95	69.56
2008	4.54	66.11
2009	2.98	45.55
2010	2.43	33.86
2011	2.54	33.99
2012	2.70	32.84
2013	4.24	47.17
2014	4.09	45.90
2015	5.63	68.05
2016	4.54	61.10
2017	4.37	60.05
2018	4.70	72.14
2019	4.77	66.69
2020	5.83	79.11
2021	6.32	66.38

Table 9: Innovation measures, growth and resource allocation

Firm (Horizon)					Competitors (Horizon)				
1	2	3	4	5	1	2	3	4	5
Panel A. Profit									
0.008*	0.011	0.011	0.016	0.023	0.007	0.002	0.016	0.015	0.015
(0.005)	(0.009)	(0.013)	(0.015)	(0.018)	(0.011)	(0.019)	(0.016)	(0.041)	(0.055)
Panel B. Sales									
0.010**	0.019**	0.023**	0.030***	0.037***	0.004	0.001	0.006	-0.001	-0.007
(0.004)	(0.007)	(0.008)	(0.010)	(0.011)	(0.010)	(0.018)	(0.025)	(0.035)	(0.047)
Panel C. Capital									
0.018***	0.035***	0.048***	0.061***	0.071***	0.010	0.017	0.025	0.032	0.042
(0.002)	(0.004)	(0.006)	(0.008)	(0.010)	(0.008)	(0.018)	(0.029)	(0.039)	(0.050)
Panel D. Labor									
0.011***	0.021***	0.029***	0.037***	0.046***	0.008	0.017	0.026	0.028	0.034
(0.002)	(0.003)	(0.005)	(0.006)	(0.008)	(0.006)	(0.012)	(0.017)	(0.024)	(0.031)

Table 10: Green/non-green innovation measures, growth and resource allocation

	Firm (Horizon)					Competitors (Horizon)				
	1	2	3	4	5	1	2	3	4	5
Panel A. Profit										
Green	0.002	0.003	0.001	-0.0001	-0.002	-0.005	-0.006	-0.005	-0.006	-0.009
	(0.003)	(0.005)	(0.005)	(0.007)	(0.008)	(0.003)	(0.005)	(0.006)	(0.007)	(0.007)
Non-green	0.008	0.010	0.011	0.016	0.024	0.004	0.005	0.009	0.012	0.012
	(0.006)	(0.011)	(0.014)	(0.016)	(0.019)	(0.002)	(0.004)	(0.006)	(0.007)	(0.007)
Panel B. Sales										
Green	0.001	0.003	0.002	0.001	0.0005	-0.003	-0.005	-0.005	-0.005	-0.007
	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Non-green	0.010**	0.017**	0.022**	0.029***	0.036***	0.003	0.006	0.010*	0.013*	0.016*
	(0.004)	(0.007)	(0.009)	(0.010)	(0.013)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Panel C. Capital										
Green	0.002	0.005*	0.006	0.004	0.002	0.0001	-0.0003	-0.001	-0.001	-0.003
	(0.001)	(0.003)	(0.004)	(0.005)	(0.007)	(0.001)	(0.003)	(0.004)	(0.006)	(0.008)
Non-green	0.018***	0.034***	0.048***	0.061***	0.073***	0.002	0.003	0.004	0.004	0.006
	(0.002)	(0.004)	(0.006)	(0.008)	(0.010)	(0.002)	(0.003)	(0.005)	(0.007)	(0.009)
Panel D. Labor										
Green	0.001	0.003	0.003	0.002	0.001	0.002	-0.0004	-0.00001	0.001	-0.0001
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Non-green	0.011***	0.021***	0.029***	0.039***	0.048***	0.0003	0.001	0.002	0.002	0.003
	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)	(0.001)	(0.002)	(0.004)	(0.005)	(0.007)