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Green Credit Flows and Green Patents as Drivers of Corporate Green Technology in China

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Abstract: As compared to the West, China's lack of fossil fuel energy resources, in particular oil and gas resources, but not so coal reserves (ChinaPower Project, 2025; Forbes, 2025; IEA, 2024; Yale Environment 360, 2021), seem to have led to an acceleration of renewable energy innovation. Yet in order to speed up the energy transition, investment into new technology, and credit flows are needed. We show that green credit policy significantly promotes corporate green patent trading performance, mainly manifested in the expansion of the number of green patent sales and purchases. However, its impact is heterogeneous among heavily polluting and green enterprises. From a mechanism perspective, the impact on heavily polluting enterprises may mainly come from external credit financing constraints, while internal innovation information disclosure may be the main mechanism for the impact on green enterprises. In addition, this green credit policy has a heterogeneous impact on the green patent trading performance of enterprises in regions with different levels of technology trading market development and different degrees of intellectual property protection. This paper finds that green patent trading activities driven by green credit policies can further achieve economic and environmental benefits. The empirical assessment of the role of green credit in promoting green patent transactions and thereby driving energy transition is an important policy implication of this paper.

Keywords: Green credit; Green patents; Patent transactions; Green technology innovation

1. Introduction

The global focus on climate change and the need to reduce CO_2 emissions has intensified. Studies highlight the environmental harm caused by continuous energy consumption, emphasizing the importance of adopting cleaner and more innovative technologies in both developed and developing nations. Promoting green technology transactions, fostering innovation, and transforming these advancements into practical applications are key to establishing a market driven green technology innovation system (Dogah et al., 2024). Green technology plays a vital role in achieving carbon balance, while green credit, through loans, bonds, and incentives, serves as a financial tool supporting low carbon investments (Behera et al., 2023).

Net Zero Strategy (BBC, 2023) commits to achieving net zero emissions by 2050, including plans to ban new petrol and diesel cars by 2030, while carbon pricing (Heine et al., 2019) and green bonds combine to finance the transition to low carbon economies by making polluters pay and encouraging emission reductions. Governments can support green credit for enterprises by reducing investment risks, facilitating access to finance, strengthening green bond markets, enhancing regulatory frameworks, promoting public private partnerships, introducing carbon taxes accompanied by green subsidies, and providing technical and market support. These measures help small businesses commercialize green patents, drive sustainable innovation, and contribute to the green economy. Empirical analysis shows that public involvement in green bond markets, particularly for long term bonds, lowers yields, volatility, and capital costs compared to private green bonds and conventional energy bonds, illustrating how governments and central banks can, by stimulating green credit flows, significantly accelerate the energy transition (Braga et al., 2021).

Against this global backdrop, China has become a central case, combining large-scale green-finance expansion with rapidly developing markets for green patent transactions. This paper investigates whether green credit policies in China promote corporate green technology transactions by stimulating green patent trading among listed firms and how these effects differ across enterprise types. The paper is organized as follows.

Section 2 presents stylized facts on China's green energy efforts and achievements that frame the study, documenting recent trends in green technology transactions and patenting, the expansion of green-credit and green-bond instruments, and key policy milestones (including net-zero pledges, carbon pricing, and carbon-removal initiatives) that shape firms' incentives.

Section 3 reviews the literature on green innovation and green credit, and discusses how academics and policy makers address climate change and CO_2 emissions through policy measures, technological innovation, economic incentives, and international cooperation, including emerging work on carbon capture and atmospheric carbon removal. Building on Schumpeterian growth theory and endogenous innovation, Section 4 develops a micro-modelling framework of directed technical change in the spirit of Acemoglu et al. (2012), extended to incorporate green credit and financial frictions. Additionally, this section provides an analysis for how firms choose between clean (green) and dirty (polluting) technologies and how policy interventions influence these choices. Adding the financial sector, this section also includes the framework of Aghion et al. (2022), examining the relationship between the financial sector and green technologies.

Recognizing that market forces and carbon pricing alone may not be sufficient for a sustainable transition, exploring the impact of green credit on green patent transactions is crucial for micro-enterprises in the new technology trading market. Green credit policies can support the efficient allocation of green patent resources, strengthen market-driven green technology innovation systems, and promote sustainable development. As Acemoglu et al. (2012) argue, in the presence of environmental externalities, government intervention, through subsidies, green innovation policies, or carbon pricing is necessary to redirect innovation from "dirty" to "clean" technologies, reinforcing the notion that policy-driven instruments like green credit can play a pivotal role in accelerating the shift toward a greener economy. Furthermore, the model-guided work of the macro drivers of energy transition supported by credit flows is studied.

Section 5 of the paper examines the impact of green credit on green patent transactions, focusing on enterprises in the technology trading market. Using data from Chinese A-share listed companies (2013–2022), it empirically explores whether green credit can stimulate corporate green technology transactions and facilitate green patent trading, including a comparison of different enterprise types to assess variations in green patent transactions in China. The section also highlights for the Western countries the growing standardization of green credit as a key regulatory mechanism shaping corporate green patent transactions and the emphasis on renewable energy development within broader policy frameworks, such as the Biden administration's Inflation Reduction Act (IRA), the European Union's Green Deal, and the People's Bank of China's 2018 policy on evaluating green credit performance, all of which frame the energy transition as a strategic imperative.

Section 6 discusses external validity and policy context, including how the growing standardization of green credit in Western economies and alignment with frameworks such as the U.S. Inflation Reduction Act, the EU Green Deal, and the People's Bank of

China's 2018 green-credit evaluation policy provides a comparative backdrop for China's experience. Finally, based on the different impact tendencies of green credit on green and heavily polluting enterprises, this section analyzes how the evaluation affects the green patent transactions of green and heavily polluting enterprises, and how it changes them.

The conclusion in the last section focuses on green credit, in its relation to the government guidance influencing green patent transactions, contributing to the literature on determinants of technology transactions, and also provides a possible policy basis for the government to guide the development of the technology transaction market.

2. Background and Stylized Facts on China's Green Energy Transition

Building on the growing academic literature and intensified policy attention to China's green transformation, this section presents key stylized facts to empirically anchor the subsequent analysis (Morales Pedraza, 2024; Ember, 2025). China's energy transition holds global significance: not only is China the world's largest emitter and the leading investor in renewables, but the scale and pace of its decarbonization will shape both domestic and international climate progress (Ember, 2025; Bloomberg NEF, 2025). The country's approach features record-breaking clean energy capacity additions, ambitious targets, and rapidly evolving financial instruments, coexisting with persistent coal dependence, challenges in energy system integration, and ongoing debates about how to balance economic growth, energy security, and environmental responsibility (Bruegel, 2025; IEA, 2025).

This section synthesizes the most recent evidence on China's shifting electricity mix, the magnitude and structure of its renewable investments, and installed capacities that have secured the country's dominant share of global wind, solar, and hydro power (IRENA, 2025; Renewable-Energy-Industry.com, 2025; Ember, 2025). It also examines how China's spending and market shares compare internationally, highlights the notable cost advantages of renewables over coal, and explores the emergence of green finance as a major driver of further decarbonization (Bloomberg NEF, 2025; Climate Bonds Initiative, 2025; Green Finance & Development Center, 2025). Finally, the analysis is anchored by a balanced assessment of persistent challenges and criticisms—including grid integration constraints, the risk of innovation lagging declining costs, and the implications of ongoing fossil fuel expansion (Reuters, 2025; Nyambuu and Semmler, 2023). By empirically grounding these dimensions, the section provides a critical backdrop for evaluating the impacts of green credit and patent policy on technological diffusion and carbon mitigation, and identifying the gaps that remain (Morales Pedraza, 2024).

China's energy transition is fast-moving. In April 2025, wind and solar together generated 26% of China's electricity, the highest monthly share on record, while, in the first half of 2025, clean sources (renewables plus nuclear) delivered almost half of total power generation (Ember, 2025; Climate Energy Finance, 2025). At the same time, fossil fuels remain prominent in annual aggregates: in 2022, coal supplied 61% of electricity (5,397.8 TWh out of 8,848.7 TWh), renewables 30.9% (2,730.5 TWh), and nuclear 4.7% (Morales Pedraza, 2024; IRENA, 2025).[1]1 These shares frame a transition where new clean generation is meeting incremental demand growth while the legacy system still anchors baseload supply (Ember, 2025).

Coal remains prominent in China's power mix, and recent approvals emphasize coal's function in grid adequacy and peaking support as variable renewables scale, with utilization factors trending lower even as nameplate capacity rises (Reuters, 2025; DNV, 2025; Climate Energy Finance, 2025). This framing aligns with the policy focus on flexibility and long-term system resilience, new coal units are primarily structured to provide backup, ramping, and stability, rather than continuous baseload expansion (Bruegel, 2025; Morales Pedraza, 2024).

While wind, solar, and other clean sources met nearly all incremental electricity demand in 2025, total power-sector emissions have not yet shown a persistent decline because the legacy coal fleet is large and dispatched to preserve adequacy during dry hydro years and demand rebounds (Ember, 2025; Climate Energy Finance, 2025; CREA/GEM, 2025). Thus, rapid expansion of clean supply and stable aggregate emissions reflect the inertia of legacy fossil infrastructure and ongoing system reliability requirements (Bruegel, 2025; Morales Pedraza, 2024).

Investment has driven the transition's pace. In 2024, China accounted for roughly two-thirds of global energy transition investment (USD 1.4 trillion), a scale unmatched by any other country and equal to about

4.5% of GDP (Bloomberg NEF, 2025; State Council Information Office, 2025). By late 2025, installed renewable capacity approached 1,500 GW, with solar exceeding 1,100 GW, making China the first country to cross the one-terawatt threshold for a single technology (Renewable-Energy-Industry.com, 2025; IRENA, 2025). The country now holds leading global shares across wind, solar, and hydro (IRENA, 2025).

The levelized cost of new utility-scale solar and wind in China is commonly below USD 0.05/kWh, undercutting the cost of new, and in many regions, existing, coal generation and driving record renewables installation (Wood Mackenzie, 2025; IEA, 2025). At the same time, price compression can erode developer and manufacturer margins, potentially dampening innovation and sector resilience unless policy supports quality upgrading and grid integration (Semmler, 2023; Bruegel, 2025)

China has also claimed the global lead in green finance. By end-2024, China's cumulative aligned green bond issuance exceeded USD 550 billion, with annual new issues near USD 70 billion; proceeds primarily fund low-carbon energy, grid and transport infrastructure, and adaptation projects (Climate Bonds Initiative, 2025; Green Finance & Development Center, 2025). Green credit and equity channels are likewise expanding, supporting the scaling of clean technologies and corporate innovation (Green Finance & Development Center, 2025; Morales Pedraza, 2024).

Criticism and open challenges remain substantial. New coal capacity (13 GW in Q1 2025) continues to be approved for grid stability, and absolute emissions have not yet embarked on a sustained decline (Climate Energy Finance, 2025; Bruegel, 2025). Renewable curtailment and transmission bottlenecks still limit full utilization of clean generation, presenting revenue and planning risks even as capacity rises (Reuters, 2025). Some analysts warn that rapid price compression in wind and solar could dampen innovation and squeeze manufacturer margins over time (Nyambuu and Semmler, 2023). These tensions underscore the need for accelerated market and grid reforms, better dispatch and pricing, and a clearer pathway to fossil asset retirement consistent with long-run decarbonization goals (Bruegel, 2025; Morales Pedraza, 2024).

2.1 Rise of Energy Efficiency

China's ratio of CO_2 emissions per kilowatt-hour (kWh) of electricity, called energy efficiency, has steadily declined over the past decade, owing primarily to rapid large-scale deployment of renewable energy technologies, rather than substantial carbon pricing or taxation policies.

2.1.1 Energy Efficiency: 2015–2025 Trends

In 2015, the average carbon intensity of China's electricity sector was above 600 grams energy efficiency (Climate Transparency, 2023). By 2022, estimates place intensity at 545 g energy efficiency (Carbon Brief, 2025), and the latest figures for 2025 show a continuing drop to 537 g energy efficiency (Climate Transparency, 2023). Studies project further improvements, predicting 614 g energy efficiency in 2025 and 515 g energy efficiency by 2030 due to grid decarbonization and efficiency gains (OUP, 2024). Most reductions have resulted from expanding solar, wind, and hydroelectric capacity, with these sources supplying nearly 40% of electricity in the first half of 2025 (Climate Action Tracker, 2025; China Briefing, 2025).

2.1.2 Role of Carbon Pricing

China's national emissions trading scheme (ETS) was launched in 2021 and covers the power sector and selected heavy industries. Allowance prices are relatively modest (around $10-14 per ton CO_2), and the price signal for reducing emissions intensity is limited (Carbon Herald, 2025; Nature, 2025). The ETS operates mainly through carbon intensity caps, though absolute emission caps are under consideration for the post-2025 period (China Briefing, 2025; Wikipedia, 2025). Studies suggest pilot ETS regions displayed about 10% greater reduction in emissions intensity versus non-pilot areas, but overall progress is dominated by technological and regulatory interventions—not market-based mechanisms (Nature, 2025; NIH, 2025). China does not have a comprehensive carbon tax, so regulatory targets and direct investment in renewables remain the main drivers (Climate Action Tracker, 2025; China Briefing, 2025).

Table1: China Energy Efficiency Trend

Year	CO_2 per kWh (gCO_2)	Main Driver
2015	-650	Coal Dominant
2020	-600	Renewables accelerate
2022	545	Clean energy expansion

Continuation Table:

Year	CO_2 per kWh (gCO_2)	Main Driver
2025	537	Renewables, limited ETS
2030*	515	Renewables, possible cap

(*projected)

Decarbonization of China's electricity sector in the last decade is primarily attributed to technological change and renewable energy deployment, while carbon pricing plays a supporting yet still secondary role. ETS allowance prices have been relatively low, and China has not implemented a broad-based carbon tax. Most emissions reductions are the result of government targets and investment in renewables (Climate Action Tracker, 2025; OUP, 2024; China Briefing, 2025). China's overall climate targets remain "Highly insufficient," but the progress in electricity sector emissions intensity is notable as evidence of transition (Climate Action Tracker, 2025; Climate Transparency, 2023).

3. Literature Review: Towards Energy Transition

The Western world is advancing the renewable energy transition through strategic policy frameworks, financial incentives, and institutional reforms aimed at addressing climate change, boosting competitiveness, and enhancing energy security. To reduce CO_2 emissions, Transatlantic partners are prioritizing a shift to renewable energy sources like solar and wind. They've set ambitious emission reduction targets for 2030 and 2050, implemented carbon pricing tools such as carbon taxes, promoted energy efficiency, and invested in carbon capture technologies. Countries like the UK, Sweden, and France lead with legally binding net-zero targets, though questions remain about policy effectiveness and the need for stronger global collaboration (Wolf, 2024)

In recent decades, growing awareness of climate change has driven a global shift toward carbon neutrality and environmentally sustainable development. (Li et al., 2020). While the global shift to renewable energy is accelerating, the decline of fossil fuel use remains too slow. Many developed nations are expanding their renewable energy capacity and promoting eco-innovation to replace carbon-intensive sources and reduce pollution. Over 130 countries and regions have set carbon neutrality targets, aiming for net-zero CO_2 emissions by the end of the century (Oyebanji & Kirikkaleli, 2022). At COP28 (2023), 118 governments committed to tripling global renewable energy capacity by 2030 (Hayes, 2024).

Addressing climate change requires a balanced energy mix and ongoing innovation. A major challenge lies in decentralizing and upgrading electricity grids, alongside forging national consensus on energy objectives to ensure coherent and well-funded R&D strategies (IEA, 2025). Governments play a key role in reducing investment risks to boost clean energy innovation. Combining subsidies with de-risked interest rates supports innovative firms, especially in low mark-up sectors (Schäfer et al., 2023), while active fiscal policy can minimize long-term risks (Braga et al., 2021). Reducing greenhouse gas emissions remains essential for building sustainable societies, with both governments and NGOs central to this effort. Green patents drive innovation for eco-friendly technologies, promoting clean energy, waste reduction, and resource conservation. By encouraging R&D investment, they support sustainability and economic growth (IP, 2024). Research shows that doubling green patent filings can boost GDP by 1.7% in five years, while a 1% increase in green patents reduces carbon emissions by 0.717% (Cohen et al., 2020).

According to the OECD, climate-related patent filings have declined, and venture capital funding for climate startups has stagnated (Coren, 2019). This slowdown, driven by weak climate policies, stagnant public funding for low-carbon R&D, and slow carbon pricing adoption, focuses more on deploying existing technologies than advancing R&D (Fostering Innovation for Climate Neutrality, 2023; Ziaei, 2024; Rosenbloom et al., 2020). The IEA's Net-Zero Emissions by 2050 Scenario emphasizes that half of global energy-related CO_2 reductions will come from technologies still in the prototype stage (IEA, 2021). Meanwhile, AI is advancing sustainability by supporting the shift to carbon-free energy and promoting decarbonization, renewable energy, and biodiversity through advanced tools and hydrogen-powered technologies (Microsoft, 2025).

4. Conceptual Frameworks of Green Innovation

Next, we want to discuss some model guided work on the micro and macro drivers of the green transition.

4.1 Micro Modelling and Green Funding

Fatih Birol, Executive Director of the International Energy Agency (IEA), emphasizes that the global shift to clean energy is both inevitable and accelerating, stating, "The real question isn't 'if,' but 'how soon' – and the sooner, the better for all of us."(Staff, 2023)

Researchers utilize linear models to evaluate the impact, adoption, and efficiency of green technologies, quantifying the interplay among economic, environmental, and policy factors. These models quantify how financial incentives, carbon pricing, and innovation dynamics influence green technology diffusion.

Built on the Schumpeterian model of endogenous technological change, the directed technical change models of Acemoglu et al. (2012) and Aghion et al. (2022), shows how firms allocate R&D resources between clean and dirty technologies based on expected profitability, influenced by market incentives and policy environments. Firms face a trade-off between investing in dirty technologies with short-term returns or cleaner alternatives requiring upfront investment and policy support. In the Acemoglu et al. (2012) framework, firms allocate R&D resources between two sectors: a "clean" sector (j = c), which uses environmentally friendly inputs, and a "dirty" sector (j = d), which relies on inputs that contribute to environmental degradation. The aggregate production function[1] combines outputs from both sectors, represented as Yc (clean) and Yd (dirty), to generate a single final good in a competitive market, with innovation rates driven by the relative profitability of each sector. Profitability is influenced by market demand, innovation costs, and policy interventions like carbon taxes.

$$\mathrm{Y} = \left[\mathrm{Yc}^{\frac{\varepsilon-1}{\varepsilon}} + \mathrm{Yd}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}$$

The elasticity of substitution ε quantifies how easily clean and dirty inputs can be replaced by one another within the aggregate production function . Both Yc and Yd are produced in a competitive market using labor and a continuous range of sector-specific machines, described by the following production functions:

$$\mathrm{Y_c} = L_c^{1-\alpha} \int_0^1 A_{ci}^{1-\alpha} x_{cit}^{\alpha}\, di \text{ and } \mathrm{Y_d} = L_{dt}^{1-\alpha} \int_0^1 A_{dit}^{1-\alpha} x_{dit}^{\alpha}\, di, \tag{1}$$

where α ϵ (0,1). Here, Ajit characterizes the quality of machine type i used in sector j ϵ (c,d) at time t, and xjit specifies the quantity of that machine. By normalizing total labor supply to one, labor market clearing requires that total labor demand does not exceed supply, formulated as:

$$L_{\mathrm{ct}} + L_{\mathrm{dt}} \leq 1$$

Innovation activities are conducted by scientists. At the outset of each period, each scientist selects either the clean or dirty technology to pursue, based on expected profitability. Once this choice is made, each scientist is randomly assigned to investigate a machine, and the likelihood of innovation in sector j is proportional to ηj. When an innovation occurs, the corresponding machine's quality receives a multiplicative boost of 1+γ for γ > 0. A successful innovator in sector j secures a one-period patent and takes on the role of entrepreneur for the relevant machine type i. Monopoly patent rights are, however, distributed randomly among entrepreneurs in sectors where innovation does not materialize. These entrepreneurs continue using existing technology. Thus, to normalize the allocation of scientists, the condition is:

$$s_{\mathrm{ct}} + s_{\mathrm{dt}} = 1$$

Following Aghion et al. (2022), market clearing for the final consumption good is defined as:

$$C = Y\text{-}\ \left(\int_0^1 x_{ci}\, di + \int_0^1 x_{di}\ \right),$$

Where *C* is total final good consumption, and ψ is the unit cost of producing each machine. Per Acemoglu et al. (2012), ψ is normalized such that ψ = α2

I define

$$A_j = \int_0^1 A_{ji}\, di, \quad j \in \{c, d\}, \tag{2}$$

where A_j is the total productivity level for sector *j* ϵ (c,d). According to the innovation possibilities

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[1] We assume that two inputs are substitutes when > 1 and complements when < 1. For instance, renewable energy that is efficiently storable and transportable would imply a strong potential for replacing dirty inputs with clean ones, as alternative energy sources could offer equivalent production services with less pollution (Acemoglu et al., 2012)

frontier, the dynamics of A_c and A_d are governed by the following equations:

$$A_c = (1 + \gamma\eta_c s_c)\, A_{c,0}$$
$$A_d = (1 + \gamma\eta_d s_d)\, A_{d,0}$$

Where $A_{c,0}$ and $A_{d,0}$ represent the initial average productivity in sectors c and d at time zero, respectively. The model assumes preferences u , C,S) that increase with both C (consumption) and S (scientists/innovation), with a utility function that is twice differentiable and jointly concave. The state of environmental quality, is given by:

$$S = -\xi Y_d + S_0 \tag{3}$$

where ξ reflects the rate of environmental damage resulting from the production of dirty inputs. As demonstrated in Equation (3), elevated production of dirty goods directly reduces environmental quality.

4.1.1 Financial Market

Building on the approach of Aghion et al. (2022), the financial sector is incorporated into the model. The likelihood of production failure is introduced as 1−p, which means that the investor's objective must consider the liquidation value when evaluating outcomes. Importantly, the probability of production failure (1−p) is distinct from the probability of a successful innovation. Under this setup, there is a probability 1−p that production using the legacy technology will also result in failure. In the next stage, an additional cost parameter is incorporated for I. Here, O indicates the legacy (old) technology with probability 1−p, N denotes the new technology occurring with probability p, and L identifies the lender type involved. Specifically, T and R refer to transaction lenders and relationship lenders, respectively. Having established how financial markets, including risk of production failure and lender types, influence investment and technological selection, we now turn to the profit-maximization problem faced by machine producers in each sector. Their objective function can be formalized as follows:

$$\max_{x_{ji}}\{p_j L_j^{1-\alpha}\int_0^1 A_{ji}^{1-\alpha}x_{ji}^{\alpha}\,di - wL_J - \int_0^1 p_{ji}x_{ji}\,di\}$$

Where p_j is the price of inputs, L_{ji} denotes the labor demand by input producers j ϵ {c,d},

w represents wages, x_{ij} is the demand for machines, and A captures average productivity. By taking the first-order conditions with respect to L_j and x_{ij}, the optimal choices for labor and machine demand are given by:

$$x_{ji} = (\frac{p_{j\alpha}}{p_{ji}})^{\frac{1}{1-\alpha}} A_{ji}L_j\ , \tag{4}$$

and

$$(1-\alpha)p_C L_c^{-\alpha}\int_0^1 A_{ci}^{1-\alpha}x_{ci}^{\alpha}\,di = w \tag{5}$$

$$(1-\alpha)p_d L_d^{-\alpha}\int_0^1 A_{di}^{1-\alpha}x_{di}^{\alpha}\,di = w \tag{6}$$

Therefore, the profit maximization problem of the monopolistic producer of machine i in sector j ϵ {c,d} is written as:

$$\pi_{ji} = \max_{p_{ji}x_{ji}} \rho(p_{ji} - \psi)\, x_{ji}\,(1 - R_{Lj}^{I}) + (1\text{-}\rho\,)\} \tag{7}$$

Substituting equation (4) into the profit maximization problem specified by equation (7) yields:

$$= \max_{p_{ji}} \rho\ (\frac{p_{j\alpha}}{p_{ji}})^{\frac{1}{1-\alpha}} A_{ji}L_j\, \rho(p_{ji} - \psi)\,(1\text{-}\,R_{Lj}^{I})$$

Given an iso-elastic demand structure, the profit-maximizing price is set as a constant markup over marginal cost, so that $p_{ji} = \frac{\Psi}{\alpha}$ By normalizing $\Psi \equiv \alpha^2$ the price reduces to $p_{ji} = \alpha$. Therefore, the equilibrium demand for machine i in sector j is given by:

$$x_{ji} = p_j^{\frac{1}{1-\alpha}} A_{ji}L_j \tag{8}$$

The equilibrium profits for machine producers equipped with technology i in sector j can be expressed as:

$$\pi_{ji} = \rho\alpha\,(1-\alpha)\,p_j^{\frac{1}{1-\alpha}} A_{ji}L_j\,(1\text{ - }R_{Lj}^{I}) \tag{9}$$

Productivity is endogenously incorporated into the model by directly connecting technological advancement to R&D activity in both clean and dirty sectors. Whenever a scientist successfully innovates, the resulting machine in sector j exhibits a productivity improvement of (1+γ) compared to the previous version A_{jit}-1. The mass of scientists, Sjt, represents the allocation of research effort to sector j at time t. Scientists are randomly assigned across available machines in their chosen sector, ensuring that innovation impact is distributed. Consequently, average productivity in sector j at time t evolves according to the following difference equation:

$$A_{jt} = (1 + \gamma\eta_j s_{jt})\, A_{jt-1} \tag{10}$$

Finally, the profit accrued by scientists can be expressed as:

$$\Pi_j = \rho\eta_j (1 + \gamma)\alpha\,(1 - \alpha)\, p_j^{\frac{1}{1-\alpha}}\, A_{ji0} L_j\, (1 - R^I_{Lj}) \tag{11}$$

4.1.2 Equilibrium

The relative attractiveness of allocating research resources to the clean sector versus the dirty sector is determined by the following ratio:

$$\frac{\Pi_c}{\Pi_d} = \frac{\eta_c}{\eta_d}\, x \left(\frac{p_c}{p_d}\right)^{\frac{1}{1-\alpha}} \quad \text{x} \quad \frac{L_c}{L_d} \quad \text{x} \quad \frac{A_{c0}}{A_{d0}} \quad \text{x} \quad \frac{1-R^N_{T_c}}{1-R^N_{T_d}} \tag{12}$$

Price effect Market size Productivity Financing friction

Equation (12) demonstrates that the incentives to pursue innovation in either clean or dirty sector machines arise from four principal forces: (1) the price effect (captured by the term $\left(\frac{p_c}{p_d})^{\frac{1}{1-\alpha}}\right)$, which motivates innovation in the sector offering higher prices; (2) the market size effect (reflected by $\frac{L_c}{L_d}$), favoring innovation in the sector with greater employment and a larger machine market; (3) the direct productivity effect (summarized by $\frac{A_{co}}{A_{do}}$), which channels innovation toward the sector with superior productivity; and (4) the financing effect (represented by $\frac{1-R^N_{T_C}}{1-R^N_{T_d}}$), promoting innovation in the sector with stronger financial resources.

Within equation (12), when the financing effect $\frac{1-R^N_{T_C}}{1-R^N_{T_d}}$ deviates from one, it alters the profit ratio. Consequently, a higher profit ratio ($\frac{\pi_c}{\pi_d}$) makes R&D investment in clean technologies comparatively more attractive. According to Minetti (2010), innovations are financed exclusively by transactional lenders.

Equation (12) demonstrates that the incentives to innovate in clean or dirty sector machines arise from the price effect, market size effect, direct productivity effect, and financing effect—each shaping the relative profitability of these technologies. Specifically, the profitabilities, $\frac{\Pi_C}{\Pi_d}$ are determined by the prevailing prices, the scale of market demand, sector productivity, and the impact of financial frictions. These frictions, evidenced in equation (12), can impede the shift towards clean technologies, even if optimal carbon taxes or R&D subsidies are available.

Recent research, such as Aghion et al. (2024), highlights the critical roles played by credit allocation and green patents in motivating green innovation. The literature shows that market forces alone, in the absence of targeted policy intervention and supportive financing structures, often fail to drive the transition to clean technologies. Persistent infrastructure and high short-term returns lock in innovation and investment within polluting sectors, a phenomenon known as path dependence. This underscores the value of green financial policies—including credit guarantees and concessional lending—to accelerate the needed transition.

Further, Semmler et al. (2022) introduce a dynamic model illustrating how entry barriers and strategic pricing limit competition in green technology sectors, revealing additional structural obstacles for new firms. Di Bartolomeo et al. (2023) emphasize how global externalities and short-term economic priorities threaten progress toward cleaner innovation.

4.2 Macro Modelling and Green Funding

Macroeconomic models, by contrast, capture broader, economy-wide drivers of the energy transition, including growth, capital accumulation, and shifts across sectors and green funding. They are crucial for analyzing energy innovation and transition, long-term sustainability, evaluating the effectiveness of policies, and understanding how renewable energy integration influences overall economic stability. Models of resource extraction and environmental issues have evolved significantly over time, starting with Hotelling (1931), who introduced the concept of exhaustible resource depletion, where prices increase over time due to limited supply. Krautkraemer (1986) expanded this by introducing positive externalities from natural resources, emphasizing their role in shaping preferences and economic growth. Chichilnisky et al., (1995) combined resource extraction with capital accumulation, highlighting the interconnectedness of resource use and economic development.

In response to the environmental costs of resource consumption, Hoel and Kverndokk (1996) examined the negative externalities of carbon emissions, illustrating the impact of resource depletion on welfare. Nordhaus (1993, 2008, 2013) developed a canonical climate model that focuses on the negative externalities of production and climate change, though it does not incorporate a renewable energy sector. Later models, such as those by Van der Ploeg et al. (2011, 2012), addressed both non-renewable energy sources (oil and coal) and renewable energy, but without considering capital stock. Greiner et al., (2014) study renewable energy policies by analyzing the role of discount rates in determining the appropriate level of taxation and subsidies. More recently, research by Jacobson, (2017). has focused on the transition to a low-carbon economy, exploring the macroeconomic implications of this shift for long-term sustainability.

Greiner, Grüne, and Semmler (2014) developed a growth model analyzing the transition from non-renewable to renewable energy, incorporating environmental damages into household welfare. The study identifies optimal transition paths and demonstrates how subsidies and taxes can facilitate this shift, while considering how initial resource and capital stocks impact transition timing Greiner et al., (2013). Regarding the financial side, recent research on climate disaster risks Mittnik et al. (2020), highlights how large-scale disasters, exacerbated by rising CO_2 emissions, can disrupt financial systems through capital destruction and increased risk premiums. These disruptions pose broader economic challenges, including reduced activity, migration, and poverty traps.

The macro model by Mittnik et al (2020), presents a one-phase model that extends the common integrated assessment model but can be turned into a multi-stage model. The model demonstrates that economic growth increases fossil fuel use, leading to higher CO_2 emissions and rising temperatures, which then harm growth and welfare. While governments can respond with public investment, doing so through debt issuing requires study about long-term debt sustainability.

Proactive efforts to reduce long-term climate risks, like mitigation and adaptation are funded through taxes and government borrowing (such as issuing bonds). The flow of credit and the cost of borrowing (risk premia) are important factors in this process. The model also accounts for different types of climate shocks, which can vary in size and how much they affect the economy.

$$W\left(T,X,U\right) = \int_{O}^{T} e-(\rho-n)t \frac{\left(C(\alpha_2 e_\rho)^{\eta}(M-\underline{M})^{-\varepsilon}(\nu_2 g)^{\omega}\right)^{1-\sigma} -1}{1-\sigma} \tag{13}$$

$$\text{s.t.} \qquad Y\left(K,u\right) = (A_K K + A_u u)^{\alpha} \text{ and} \tag{14}$$

$$\dot{K} = Y(\nu_1 g)^{\beta} - C - e_p - \left(\delta_K + n\right)K - u\psi R^{-\zeta} \tag{15}$$

$$\dot{R} = -u \tag{16}$$

$$\dot{M} = \gamma u - \mu\left(M - \kappa\tilde{M}\right) - \theta(\nu_{3.} g)^{\phi} \tag{17}$$

$$\dot{b} = \left(\underline{r} - n\right)b - \left(1 - \alpha_1 - \alpha_2 - \alpha_3\right)e_\rho, \tag{18}$$

$$\dot{g} = \alpha_1 e_\rho + i_F - (\delta_g + n)g \tag{19}$$

Here K is private (green) capital, R is the stock of the non-renewable resource, M is the atmospheric concentration of CO_2, b is the government's debt, and g is public capital. This dynamic climate-economy model of (Mittnik et al., 2020) aims to maximize social welfare over time (13) by balancing consumption, environmental sustainability, and tax and credit finance of green investment. Welfare (13) depends on economic output, which is produced using private capital (K) and resource inputs (u) , and is negatively affected by excessive CO_2 concentrations above a safe threshold ($\tilde{M}$).

The model captures the trade-offs between using non-renewable resources (which increase atmospheric CO_2) and investing in green capital and adaptation (9). Equation (16) indicates the stock of the non-renewable resource R, which depletes by (u) units in each period. The non-renewable resource emits carbon dioxide and thus increases the atmospheric concentration of CO_2 at the rate (γ) in equation (17). CO_2 accumulation (M) rises with resource use (u), but can be reduced through natural processes, technological mitigation, and public green investment financed by taxation and debt of finance (18). Capital and public infrastructure (19) accumulate through investment but are subject to depreciation, climate shocks, and adaptation costs. Public investment g (18) is financed through domestic taxes $e\rho$ and foreign transfers if, while government debt b (17) evolves in response to interest payments and fiscal policy allowing for finance of mitigation and adaptation through financial funds.. This multi-phase dynamic model captures how climate finance, risk premia, and adaptation policies interact to shape economic vulnerability and long-term development paths.

Furthermore, the dynamic macroeconomic model by (Nyambuu & Semmler, 2023) integrates climate risks into macroeconomic analysis, showing how fossil fuel–driven growth increases CO_2 emissions and temperatures, which in turn reduce growth and welfare. This aligns with integrated assessment models (Fisher, 2019). Building on this, (Roy, Chen, and Semmler, 2024) use a regime-switching framework to evaluate policy effectiveness across shifting energy regimes. A particular emphasis on green credit flows in macro models is given in (Braga and Semmler, 2005), where Central Bank’s role on the energy transition is structured.

The above discussed micro and macro models offer a detailed view of the micro-level dynamics driving the energy transitions as well as help assess the impact of environmental policies on overall economic performance, including growth, employment, and financial flow, and they provide frameworks for evaluating global challenges like climate risk and resource depletion, while offering a comprehensive understanding of how economies adapt to environmental constraints, balance short-term costs with long-term sustainability, and navigate the complex transition to a low-carbon economy. The role of green technology and renewable energy over load capacity factor and ecological footprint is integral to SDG agenda of the UN (Sharif et al., 2024b).

4.3 China’s Green Funding Policy

Next China’s green funding policy will be discussed. In 2019, China was responsible for over 28% of global CO_2 emissions, highlighting its critical role in addressing climate change (IRENA, 2022). The country has pledged to peak its carbon emissions before 2030 and achieve carbon neutrality by 2060, aligning with global climate targets (IRENA, 2022). Concurrently, China's technology transaction market has experienced rapid expansion. According to the Statistical Communiqué of the People's Republic of China on National Economic and Social Development, the total national technology contract transaction volume reached 6.15 trillion yuan in 2023, an almost eightfold increase from 747 billion yuan in 2013 (National Bureau of Statistics of China, 2024). The February 2025 edition of this communique reports that 2024's figure rose to 6.84 trillion yuan, now representing a more than nine fold increase from 2013, indicating a robust trajectory of innovation-led growth (National Bureau of Statistics of China, 2025). This growth reflects a shift toward decarbonization, with emerging technologies playing a key role in addressing climate challenges.

Decarbonization initiatives have been actively pursued across leading global economies, with the European Union’s Green Deal offering a roadmap to climate neutrality by 2050 and the United States’ Inflation Reduction Act (IRA) of 2022 committing over $369 billion to clean energy and emissions reduction programs (European Commission, 2020; The White House, 2022). These state-led strategies reflect theoretical and evolutionary approaches to green innovation, emphasizing adaptive policy, long-term investment, and system-wide transformation. The EU’s Horizon Europe and mission-driven R&D initiatives embrace systems thinking, while the IRA combines subsidies, tax credits, and industrial policy to stimulate green entrepreneurship and clean energy adoption (Mazzucato, 2018; Rodrik, 2022). Together, these policies acknowledge uncertainty and path dependency, promoting a dynamic environment for sustainable technological change.

Green credit plays a crucial role in channeling financial resources toward environmentally sustainable projects, influencing firm behavior and innovation in green technology. By internalizing environmental costs and shaping incentives, green credit drives corporate green patent transactions, making it essential to understand its firm-level effects. This paper investigates whether green credit effectively promotes green technology transactions in China.

This inquiry intersects with two strands of literature: (1) the determinants of technology transactions, which are commonly analyzed in terms of external factors (such as transaction subject characteristics and transaction environment) and technical factors; and (2) the evaluation of how green credit policies affect micro enterprises. External influences include the attributes of transaction entities and their environments. Prior studies emphasize that factors such as supply and absorption capacity (Duan et al., 2018; Jian & Zhan, 2009), mutual trust (Jensen et al., 2015), and relational distances—geographical, technological, and cultural (Zhu et al., 2006)—significantly affect outcomes. Infrastructure like university tech transfer offices, intermediaries, and consulting agencies also help reduce information asymmetries and transaction costs (Fang & Shi, 2003; Wu & Yu, 2023).

China holds that intellectual property protection (Liu et al., 2024), R&D support (Wang & Li, 2013), and regional innovation capacity (Gu & Jiang, 2019) shape the broader transaction environment. Technological characteristics also play a crucial role—factors such as patent value, ownership type, industry context, timing, and quality all influence transaction outcomes (Serrano, 2010; Qian et al., 2020). While existing literature thoroughly explores market-led drivers of technology transactions, it largely overlooks the role of financial policy, particularly green credit, in shaping the flow and effectiveness of green technology transactions.

Green credit policies in China aim to reallocate financial resources to support environmentally friendly enterprises while restricting heavily polluting ones. For green enterprises, these policies facilitate access to lower-cost financing, promoting green technology innovation (Shu et al., 2021; Li et al., 2023). However, the impact on heavily polluting enterprises is mixed. Some studies indicate that green credit policies can stimulate green innovation in these firms, particularly those under financial constraints or with state ownership (Hu et al., 2021). Conversely, other research suggests that such policies may inhibit substantive green innovation due to increased financing constraints and reduced government subsidies (Lin et al., 2023).

Green credit policies have been shown to discourage inefficient innovation investments among heavily polluting enterprises (Song et al., 2024). However, most studies emphasize the quantity of green patents rather than the efficiency of green technology transformation and application, with limited analysis of differences in patent transactions across enterprise types.

This study also examines the impact of the People's Bank of China's 2018 Notice on Conducting Green Credit Performance Evaluation (hereinafter "the Evaluation") on green patent transactions among micro-enterprises. The Evaluation standardizes green credit practices using both quantitative (e.g., green loan ratios) and qualitative (e.g., policy implementation) indicators. By assessing its differential impact on environmentally friendly and heavily polluting firms, the study sheds light on the policy's effect on green innovation.

This research expands the literature by evaluating green credit's influence on the efficiency of green technology transformation and application at the micro-enterprise level. It also explores transaction heterogeneity across enterprise types through horizontal comparisons, offering guidance for targeted interventions. Finally, it deepens understanding of how government-led evaluations shape green technology markets and supports improvements in policy mechanisms.

5. Theoretical Analysis and Hypothesis Development

5.1 Theoretical Effect of Green Credit Policy on Green Patent Transactions

Green credit, an environmental regulatory tool using market mechanisms, guides credit allocation towards green technologies by internalizing environmental externalities (Zhou, 2023; Xu et al., 2023). It requires banks to assess environmental and social risks in loan approvals, setting environmental thresholds. By raising the cost of pollution emissions, green credit encourages technological innovation to reduce environmental harm (Tombe and Winter, 2015). Changes in relative factor prices drive firms to innovate, focusing on the efficient use of scarce resources (Acemoglu, 2002). However, innovation decisions are path-dependent, with firms investing more in green R&D if they have a higher stock of green technology knowledge (Aghion et al., 2016; Jia and Zhang, 2014). Green credit also signals government support for low-carbon development, expanding market demand for green technologies and facilitating the flow of green patents through technology trading.

Green credit internalizes environmental pollution costs, prompting companies to reassess the cost-benefit of green patent R&D and transactions. Companies engaging in R&D incur costs but can profit from patent sales or applications, while those not engaging face higher pollution costs or must pay for green patents to reduce emissions (Zhou, 2023; Xu et al., 2023).

Green companies, with advantages in green knowledge and R&D success, benefit from preferential green credit, driving further innovation (Magdalena et al., 2022). This credit signals government support for green development, increasing demand and market value for green patents. These companies can reduce pollution and profit from patent sales.

In contrast, heavily polluting companies, constrained by outdated technologies, find green patent R&D difficult (Sun and Jing, 2012; Li and Peng, 2013). Green credit imposes penalties for environmental externalities, making it harder for them to innovate independently. As a result, these companies are more likely to seek green patents to meet regulatory requirements (Shu et al., 2023). Thus, this paper proposes research Hypothesis 1.

Hypothesis 1: Green credit promotes corporate green patent trading activities, especially in the acquisition and purchase of green patents by heavily polluting enterprises and in the transfer and sale of green patents by green enterprises.

External credit financing constraints

In China, business activities, including green patent trading, rely on credit funds (Xu, 2019; Liang and Wang, 2021). Green credit redirects credit resources from polluting sectors to green sectors, creating an exogenous shock that influences corporate behavior in green patent trading. Changes in available credit resources prompt enterprises to adjust their R&D and trading decisions. Green enterprises, benefiting from favorable green credit terms, are more likely to invest in green patent R&D, increasing green patent supply and market demand. Green credit signals government support for green development, boosting market value for green patents. Green enterprises, driven by competitive advantage (Ding et al., 2022), are incentivized to engage in green patent trading to enhance profits and market share. Conversely, heavily polluting enterprises face credit financing challenges due to environmental risk controls, weakening their R&D competitiveness. In the short term, heavily polluting firms may engage in green patent transactions to bolster external green ratings and ease financing constraints, with such behavior prompted by environmental public opinion and disclosure pressures. Based on these dynamics, the following research hypotheses are proposed:

Hypothesis 2: External credit financing constraints may be a possible channel through which green credit promotes green patent transactions by enterprises, especially for green companies, but may fail within heavily polluting enterprises.

Internal Innovation Disclosure

As noted, green patent R&D in enterprises exhibits path dependence, leading to division of labor and specialization across different sectors. This specialization causes information asymmetry, increasing transaction costs in green patent trading (Liu, 2000; Zhang and Huang, 2005). The disclosure of R&D and innovation information can reduce this asymmetry, lowering transaction costs and increasing the likelihood of patent transactions (Narayanan et al., 2000). Under green credit, the motivation for internal information disclosure depends on a company’s fundamental goals. Green enterprises, driven by profit and market share motives, may hesitate to disclose detailed innovation information due to its proprietary value, as competitors might steal or imitate it (Zhang et al., 2023; Lu et al., 2023). In contrast, heavily polluting enterprises, pressured by green credit penalties and environmental access conditions, may be more inclined to disclose innovation information to improve their green rating and secure financial support for patent transactions. Such disclosure clarifies market conditions, encouraging more patent transactions.

Based on this analysis, the following research hypothesis is proposed:

Hypothesis 3: Green credit influences the level of information disclosure in green patent transactions, with green enterprises being less likely to disclose proprietary innovation information, while heavily polluting enterprises may disclose more information to improve their green ratings and secure financing for green patent transactions.

5.2 Methodology and Data

Sample selection and data sources

To effectively verify the theoretical hypothesis of this paper, an empirical analysis was conducted using data on green patents and related information from all A-share listed companies from 2013 to 2022. Companies in the financial and insurance sector, as defined by the China Securities Regulatory Commission's "Guidelines for the Classification of Industries for Listed Companies (Revised in 2012)," were excluded, as were companies with abnormal trading statuses (including ST, ST*, and PT) during the observation period, those with a debt-to-asset ratio less than 0 or greater than 1, and companies with missing relevant data. Additionally, to control for the influence of outliers without losing observations, a 1% winsorization was applied to the main continuous variables.

In terms of data sources, the green patent transaction data of listed companies comes from the Patent Transfer Research Database (PTRD) under the China National Research Data Service (CNRDS), which records the transfer of green patents of listed companies that meet the standards of the State Intellectual Property Office's "Green Technology Patent Classification System". Additionally, other data mainly includes characteristic data of listed companies from the GTA Securities Market Research Database (CSMAR) and detailed environmental emission data used for further analysis, data for constructing indicators of regional technology transaction market development level and innovation text information disclosure from CNRDS, and data on the level of intellectual property protection in various provinces disclosed in the "China Intellectual Property Development Status Evaluation Report" published by the State Intellectual Property Office over the years. After matching the above data, a total of 22,551 annual observations were obtained. Combining theoretical analysis, the observations were screened and classified based on differences in corporate environmental pollution and green credit differences, among which there were 7,081 observations for green companies, 7,341 observations for heavily polluting companies, and 8,129 observations for the control group.

5.3 Model Specification and Variable Definitions

To further verify the hypothesis proposed above, this paper examines the impact of green credit on corporate green patent transactions by setting up the following difference-in-differences model for empirical analysis:

$$y_{it} = \alpha_0 + \alpha_1 \mathrm{treat}_i \times \mathrm{policy}_t + \theta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{20}$$

$$y_{it} = \alpha_0 + \alpha_1 \mathrm{treat1}_i \times \mathrm{policy}_t + \theta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{21}$$

In this case, the explained variable y_{it} represents the green patent transactions of enterprises i in a certain year t. The time dummy variable "Evaluation" $\mathrm{policey}_t$ is set to 1 for the period after the introduction of the green credit policy (2018-2022) and 0 otherwise. The model in equ. (20) only retains samples of heavily polluting enterprises and other types of enterprises, excluding green enterprises, to test the impact of the green credit policy on heavily polluting enterprises. The group binary variable treat_i is used to distinguish whether an enterprise is a heavily polluting industry enterprise, with 1 indicating that the enterprise is classified as a heavily polluting enterprise and 0 otherwise. Similarly, Model (21) only retains samples of green enterprises and other types of enterprises, excluding heavily polluting enterprises, to test the impact of the green credit policy on green industry enterprises. The group binary variable $\mathrm{treat1}_i$ is used to distinguish whether an enterprise is a green industry enterprise, with 1 indicating that the enterprise is classified as a green enterprise and 0 otherwise. Other control variables X_{it} that may affect the green patent transactions of enterprises are included; if the estimated coefficient of the core explanatory variable is statistically significant, it indicates that "Evaluation" indeed has a recognizable effect on the green patent transactions of enterprises. In addition, to control for unobservable firm-specific and time factors, the model introduces firm fixed effects μ_i and time fixed effects λ_t, and the standard errors of the model estimates are clustered at the firm level to ensure the robustness of the empirical results, with ε_{it} representing the random error term.

Variable description

Enterprise green patent transactions. To comprehensively measure the performance of enterprises in green patent transactions, this article divides the performance into two transactional aspects: outpatent, the number of green patents sold by enterprises (sellers) and inpatent, the number of green patents purchased by enterprises (buyers). Given the availability of data, the total number of green patent transfers by enterprises is used to represent the selling aspect, and the total number of green patent acquisitions by enterprises is used to represent the purchasing aspect. Considering the right-skewed distribution of patent data, this article adopts the common method of handling patent data, adding 1 to the number of green patent transactions and then taking the logarithm.

Enterprises in heavily polluting industries. To promote green credit work among banking financial institutions, in July 2014, the original China Banking Regulatory Commission issued the "Key Evaluation Indicators for the Implementation of Green Credit," which requires banking institutions to classify and manage customers based on their environmental and social risks. At the same time, this document also provides a practical basis for identifying heavily polluting enterprises in this article. Based on this, enterprises classified as categories A and B [2] in terms of environmental and social risks are considered heavily polluting enterprises.

Green industry enterprises. To further scientifically clarify the boundaries of the industry and guide limited policies and funds to the most important, key, and urgent industries for promoting green development, the National Development and Reform Commission, in conjunction with relevant departments, has formulated the "Green Industry Guidance Directory (2019 Edition)" (hereinafter referred to as the "Directory"). This article matches the main business of enterprises with the Directory to define green enterprises accordingly.

Control variables. To control for other economic characteristics that may affect corporate green patent transactions and to minimize the impact of omitted variable bias, this paper refers to previous studies (Liu et al., 2024; Yuan and Zhou, 2022) and introduces a series of control variables. Specifically, these include: corporate age (age), number of employees (employee), profitability (profitc), corporate value (value), debt-to-asset ratio (debt), operating cash flow (cash), proportion of fixed assets (fixed), ownership concentration (stock), board independence (boardi), board size (boards), corporate ownership (ownership), and industry competition level (hhi). Variable definitions are shown in **Table 2**.

5.4 Empirical Results and Analysis

Descriptive analysis

Table 3 reports the descriptive results of the main variables categorized by enterprise type. It is not difficult to observe that: in terms of green patent sales, the mean for green enterprises is 0.278, which is the highest among the three types of enterprises, significantly higher than the mean of 0.139 for other enterprises; in terms of green patent purchases, the mean for heavily polluting enterprises is 0.367, which is the highest among the three types of enterprises.

Test of parallel trends assumption and dynamic analysis

The core premise of applying DID is that the trends in the treatment behavior of the treatment and control groups are similar or predictable before the treatment occurs. To test whether the parallel trends assumption is met, this paper takes the first year of the sample observation period (2013) as the base year and generates year dummy variables for each year from 2014 to 2022. It then interacts these with the enterprise attribute group variables to

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[2] The key evaluation indicators for the implementation of green credit classify industries into two categories. Category A includes nine industries such as nuclear power generation, hydropower generation, water conservancy and inland river port engineering construction, coal mining and washing, oil and natural gas extraction, ferrous metal ore mining and dressing, non-ferrous metal ore mining and dressing, non-metallic ore mining, and other mining industries. Category B includes twenty-five industries such as cotton printing and dyeing finishing, leather tanning processing, petroleum processing, coking, and nuclear fuel processing.

construct the following model:

Table 2. Variable definition.

	Variable	Variable ID	Definition
Dependent variables	Green patents for sale	outpatent	ln(The number of green patent transfers of listed companies in the year +1)
	Green patents for purchase	inpatent	ln(The number of green patents transferred by listed companies in the year +1)
Core independent variables	Double difference component	treati×policyt	Green credit policy and heavy polluting enterprise attribute interaction item
		treat1i×policyt	Green credit policy and green enterprise attribute interaction item
Control variables	Enterprise age	age	ln(Establishment years of enterprises)
	Number of employees	employee	Ln(number of employees)
	Profitability	profitc	Net profits/total assets
	Debt-to-assets ratio	debt	Total indebtedness/total assets
	Proportion of fixed assets	fixed	Net fixed assets/ending total assets
	Cash flow from operating activities	cash	Net cash flow from operating/total assets
	Ownership concentration	stock	Share proportion of the largest shareholder
	Board independence	boardi	Number of independent directors/total number of directors
	Board size	boards	ln(Number of directors)
	Enterprise ownership	ownership	Judging by the actual control nature, the state takes 1, otherwise it is 0
	Degree of industry competition	hhi	The Herfindahl index is measured by business income

Table 3. Summary Statistics

	Heavy polluting enterprise(treat=1)				Green enterprise (treat1=1)				Others (treat=0&treat1=0)			
	Observation:7081				Observation:7341				Observation:8129			
Variables	Variables	Mean	S.D.	Min	Variables	Mean	S.D.	Min	Variables	Mean	S.D.	Min
outpatent	0.271	0.633	0.000	3.045	0.278	0.658	0.000	3.045	0.139	0.475	0.000	3.045
inpatent	0.367	0.714	0.000	3.091	0.348	0.711	0.000	3.091	0.182	0.514	0.000	3.091
age	2.924	0.316	1.099	3.738	2.868	0.322	1.386	3.738	2.926	0.325	1.386	4.159
employee	7.951	1.271	2.944	13.207	7.709	1.141	4.357	12.376	7.768	1.300	2.398	13.254
profitc	0.043	0.055	-0.217	0.198	0.037	0.058	-0.217	0.198	0.035	0.060	-0.217	0.198
debt	0.423	.194	0.064	0.843	0.407	0.177	0.064	0.843	0.419	0.197	0.064	0.843
fixed	0.279	0.161	0.003	0.672	0.188	0.132	0.003	0.672	0.163	0.137	0.003	0.672
cash	0.061	0.062	-0.125	0.238	0.046	0.060	-0.125	0.238	0.048	0.067	-0.125	0.238
stock	34.909	14.765	9.066	74.095	33.346	14.212	9.066	74.095	33.800	14.598	9.066	74.095
boardi	37.279	5.209	33.330	57.140	37.840	5.369	33.330	57.140	38.007	5.476	33.330	57.140
boards	2.153	0.198	1.099	2.890	2.097	0.188	1.386	2.890	2.107	0.200	1.386	2.890
ownership	0.416	0.493	0.000	1.000	0.285	0.452	0.000	1.000	0.341	0.474	0.000	1.000
hhi	0.115	0.113	0.022	0.843	0.128	0.119	0.025	0.843	0.205	0.177	0.016	0.843

$$y_{it} = \delta_0 + \sum_{t=2014}^{2022} \delta_t treat_i \times period_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (22)$$

$$y_{it} = \delta_0 + \sum_{t=2014}^{2022} \delta_t treat1_i \times period_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (23)$$

In this model see equ. (22) and (23), periodd$_t$ is the time variable before and after the implementation of the policy (in 2018), and other variables are the same as in equations (20) and (21). Here, the regression coefficient δ_t of the interaction term between the green credit policy and firm attributes is used to determine whether the parallel trend assumption holds. If it is not significant before the policy implementation, it indicates that there is no significant difference in the performance of green patent transactions between the treatment group and the control group firms before the introduction of the "Evaluation", and thus the parallel trend assumption holds. Figures 1-4 are dynamic graphs of the regression coefficients for firms, where **Figures 1 and 2** are dynamic graphs for heavily polluting firms, and **Figures 3 and 4** are dynamic graphs for green firms. It is not difficult to find that both heavily polluting firms and control group firms, as well as green firms and control group firms, have no significant difference in the performance of green patent transactions (transfers and acquisitions) before the introduction of the "Evaluation", indicating that the parallel trend assumption holds for both. Further analysis of the dynamic effects of the policy shows that, at the level of green patent transfers, the coefficient for heavily polluting firms after policy implementation is not significantly different from zero and lacks persistence; whereas the estimation results for green firms become significantly positive in the fourth year after policy implementation, possibly due to the time lag involved in transferring patent rights for green patents. At the level of green patent acquisitions, the coefficient for heavily polluting firms becomes significantly positive in the second year after policy implementation, but not in other years; whereas the regression coefficient for green firms after policy implementation is not significantly different from zero, lacking persistence.

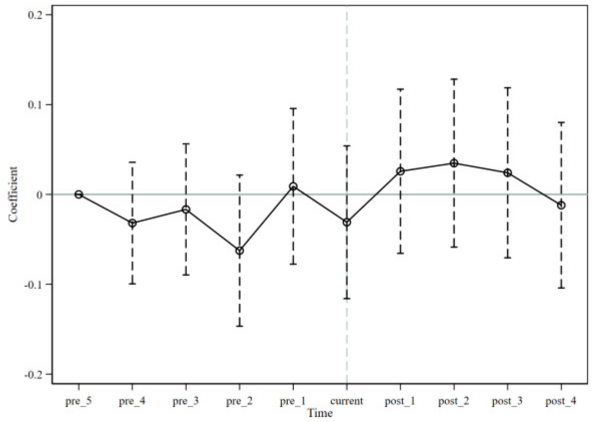

Fig.1. Heavy Polluting Enterprise(outpatent)

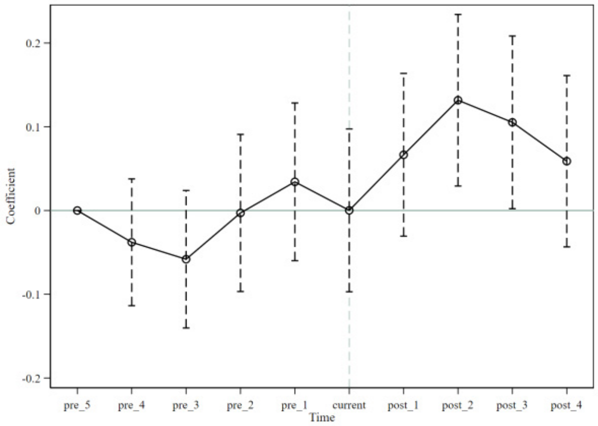

Fig.2. Heavy Polluting Enterprise (inpatent)

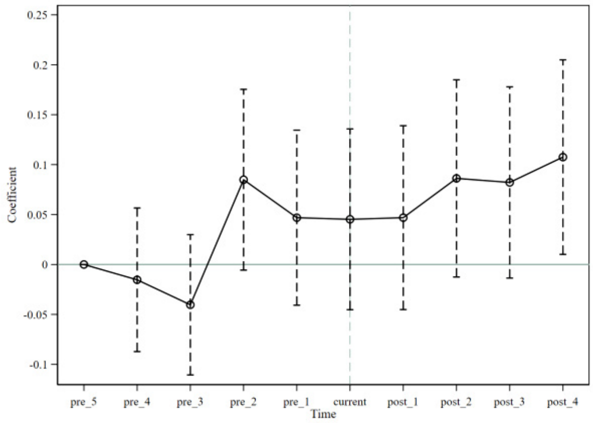

Fig.3. Green Enterprise(outpatent)

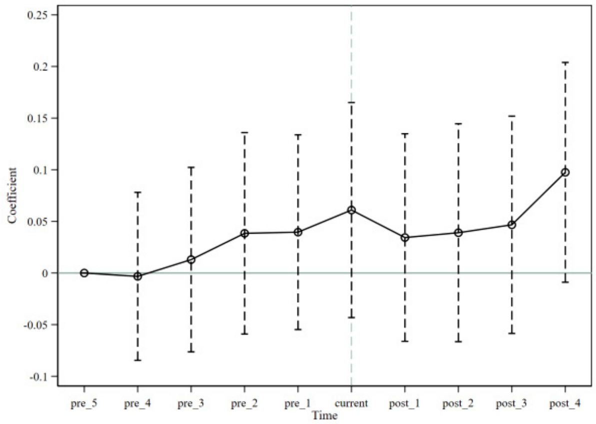

Fig.4. Green Enterprise(inpatent)

Benchmark Regression

Table 4 presents the specific results of the benchmark regression. Columns 1-2 of Table 4 show the regression results for heavily polluting enterprises without controlling for variables, where the coefficients of the core explanatory variables $treat_i \times policy_t$ are significantly positive at the 1% level. After considering the impact of various factors such as the characteristics of the enterprises, financial characteristics, and executive characteristics, the results in columns 3-4 of **Table 4** remain highly significant. The coefficient value of $treat_i \times policy_t$ shown in column 3 is 0.07, which is a relatively small change compared to the average value of the number of green patents sold by the sample heavily polluting enterprises (0.27), and is equivalent to a change of 0.11 standard deviations (0.63); whereas the coefficient value shown in column 4 of Table 4 is 0.12, meaning that after the implementation of the "Evaluation" green credit policy, the number of green patents sold by heavily polluting enterprises increased by 13%, which is a relatively large change compared to the average value of the number of green patents purchased by the sample enterprises (0.37), equivalent to a change of 0.17 standard deviations (0.71). After eliminating interference at various levels, the "Evaluation" green credit policy still exhibits a strong driving effect on the green patent transactions of heavily polluting enterprises, especially at the level of purchasing green patents.

Columns 5-6 show the regression results for green enterprises without control variables, where the coefficients of the core explanatory variables $treat1_i \times policy_t$ are significantly positive at the 1% level. In columns 7-8, after adding control variables, the results remain highly significant. Specifically, the coefficient of the interaction term $treat1_i \times policy_t$ in column 7 is 0.09, indicating that after the implementation of the green credit policy "Evaluation," the number of green patents sold by green enterprises increased by 9%. This is a relatively large change compared to the average number of green patent sales for the sample green enterprises (0.28), equivalent to a change of 0.14 standard deviations (0.66). In contrast, the coefficient in column 8 is also 0.09, but it represents a relatively smaller change compared to the average number of green patent purchases for the sample enterprises (0.35), equivalent to only 0.12 standard deviations (0.71). These results suggest that the green credit policy "Evaluation" has promoted the performance of green enterprises in green patent transactions, particularly at the level of selling green patents.

Table 4. Baseline regression results.

	Panel A: heavy polluting enterprise				Panel B: green enterprise			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	outpatent	inpatent	outpatent	inpatent	outpatent	inpatent	outpatent	inpatent
$treat_i \times policy_t$	0.0654***	0.1238***	0.0654***	0.1241***				
	(0.0197)	(0.0221)	(0.0193)	(0.0218)				
$treat1_i \times policy_t$					0.0950***	0.1074***	.0872***	0.0946***
					(0.0226)	(0.0243)	(0.0224)	(0.0242)
Constant	.0657***	0.0874***	-0.8758**	-1.0640***	0.0399***	0.0629***	-0.4662	-0.4620
	(0.0129)	(0.0140)	(0.3798)	(0.3895)	(0.0133)	(0.0146)	(0.3630)	(0.3901)
Control	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	15210	15210	15210	15210	15470	15470	15470	15470
R Square	0.0281	0.0467	0.0306	0.0508	0.0332	0.0382	0.0365	0.0441

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

Robustness analysis

Placebo test

To rule out the impact of non-policy or other random factors, especially to avoid subjective changes in enterprises due to prior knowledge that the "Evaluation" is to be implemented, which could lead to an overestimation of the "policy effect." This paper employs a method of randomly selecting the baseline regression interaction term for a placebo test. Specifically: Based on the distribution of the interaction terms $treat_i \times policy_t$ and $treat1_i \times policy_t$ In the baseline regression, we construct a "pseudo-policy dummy variable" through random sampling. To enhance the validity of the test, this article randomly samples 1,000 times, ultimately obtaining the scatter distribution chart and kernel density chart of the placebo coefficient estimates and corresponding p-values as shown in **Figures 5-8**. The p-value at the horizontal dotted line is 0.1, and the coefficient value at the vertical dotted line is its true estimated value. It can be seen that the coefficient estimates after randomization are concentrated around 0 and follow a normal distribution, with the vast majority of the p-values for these estimates being above the 0.1 threshold level line, meaning that at the 10% confidence level, these estimates obtained from randomly selected interaction terms are not statistically significant; at the same time, it is observed that the mean of the randomized estimated coefficients is far from the baseline regression estimates (true values) listed in **Table 4**, which is consistent with the expectations of the placebo test. The above results indicate that after the implementation of the "Evaluation," it has played a substantial role in promoting green patent transactions between heavily polluting and green enterprises. This result is not influenced by other random factors, thereby further enhancing the credibility of this study.

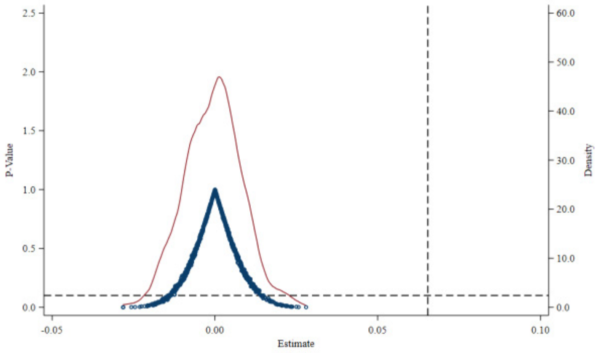

Fig.5. Heavy Polluting Enterprise(*outpatent*)

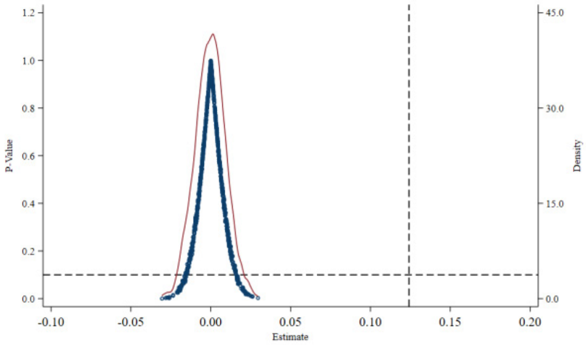

Fig.6. Heavy Polluting Enterprise(*inpatent*)

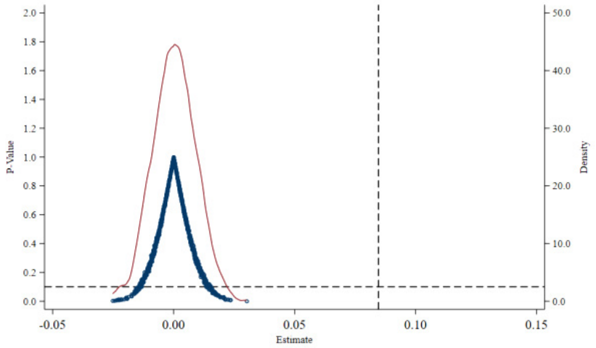

Fig.7. Green Enterprise (*outpatent*)

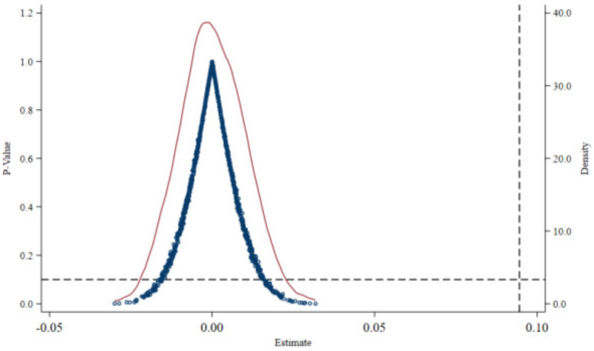

Fig.8. Green Enterprise(*inpatent*)

Non-random selection discussion

Given that sample self-selection bias may cause significant estimation errors, this paper employs propensity score methods to address the issue of multi-dimensional matching factors, constructing a hypothetical randomized experiment, that is, using PSM-DID to regress the model. The regression results using nearest neighbor matching and kernel matching methods in **Table 5** show that whether it is heavily polluting enterprises or green enterprises, the regression coefficients of the interaction term remain significantly positive, which again confirms the stability of the benchmark regression results in **Table 4**. The results after considering sample self-selection bias more rigorously estimate the treatment effect, further strengthening the scientific nature of the conclusions in this paper

Table 5. Baseline regression results

	Panel A: heavy polluting enterprise				Panel B: green enterprise			
	Nearest neighbor matching		kernel matching		Nearest neighbor matching		kernel matching	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	outpatent	inpatent	outpatent	inpatent	outpatent	inpatent	outpatent	inpatent
$treat_i \times policy_t$	0.0671***	0.1215***	0.0499**	0.1037***				
	(0.0195)	(0.0222)	(0.0225)	(0.0264)				
$treat1_i \times policy_t$					0.0857***	0.0943***	0.1049***	0.1154***
					(0.0225)	(0.0243)	(0.0219)	(0.0235)
Constant	-0.8608**	-.1406***	-.2696***	-1.3297***	0.3673	-0.3457	-0.3674	-0.4102
	(0.4066)	(0.4171)	(0.4851)	(0.4802)	(0.3911)	(0.4209)	(0.3795)	(0.4067)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	14696	14696	14849	14849	15032	15032	15119	15119
R Square	0.4716	0.4638	0.4771	0.4724	0.4573	0.4330	0.4589	0.4356

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

Change the definition of industry scope

To avoid the impact of sample definition bias in the experimental group on the regression results, only classify the A category in the "Key Evaluation Indicators for the Implementation of Green Credit" as the experimental group of heavily polluting enterprises, narrowing the scope of heavily polluting enterprises. Exclude green enterprises and only retain A category heavily polluting enterprises and other types of enterprises to test the impact of green credit policies on the green patent transactions of heavily polluting enterprises; similarly, retain green enterprises and other types of enterprises, exclude A category heavily polluting enterprises, to test the impact of green credit policies on the green patent transactions of green enterprises. The specific results are shown in **Table 6**, and the estimation results of the interaction term are still significant at least at the 5% level, indicating that after excluding the definition bias of the experimental group, the baseline regression results are reliable.

Table 6. Adjust the scope of industry definition

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	outpatent	inpatent	outpatent	inpatent
$treat_i \times policy_t$	0.0762**	0.2500***		
	(0.0387)	(0.0394)		
$treat1_i \times policy_t$			0.0609***	0.0570**
			(0.0209)	(0.0227)
Constant	-0.8929**	-1.0870***	-0.6465**	-0.7422**
	(0.3797)	(0.3879)	(0.3204)	(0.3412)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observation	15210	15210	21311	21311
R Square	0.0299	0.0520	0.0358	0.0456

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

Adjust the time window

Three years before and after the policy node. Given that a longer observation period may include other potential significant events or policy influencing factors, which could lead to biased results, the window width range before and after the implementation of the green credit policy is adjusted. Samples from three years before and after the policy implementation are used for re-estimation. **Table 7** shows that the interaction term coefficients have all passed the 5% significance level statistical test at least.

Table 7. Adjustment time window: three years before and after the policy (2015-2021).

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	outpatent	inpatent	outpatent	inpatent
$treat_i \times policy_t$	0.0589***	0.1076***		
	(0.0206)	(0.0236)		
$treat1_i \times policy_t$			0.0601**	0.0629**
			(0.0238)	(0.0258)
Constant	-1.1554**	-1.3133**	-0.9979*	-0.1963
	(0.5420)	(0.6350)	(0.5415)	(0.5997)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observation	10805	10805	10974	10974
R Square	0.0206	0.0400	0.0213	0.0265

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

Control for systemic factors

The introduction of this green credit policy may lead local governments to respond with corresponding policy regulations, thereby affecting the effectiveness of policy implementation. Based on this, this article further introduces the interaction effect of region and year in **Table 8**, columns (3) and (4), to control for potential regional-level impacts. It is not difficult to find that the results are basically consistent with the benchmark regression. In addition, compared with the benchmark regression model, the model after introducing the interaction effect of region and year has significantly improved, with increased explanatory power, and can better reflect the actual relationships behind the data.

Table 8. Control the influence of regional macro system factors.

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	outpatent	inpatent	outpatent	inpatent
$treat_i \times policy_t$	0.0652***	0.1210***		
	(0.0207)	(0.0230)		
$treat1_i \times policy_t$			0.0860***	0.0900***
			(0.0223)	(0.0241)
Constant	-0.7155*	-0.8858**	-0.3444	-0.3360
	(0.4058)	(0.4264)	(0.4038)	(0.4350)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province×Year FE	Yes	Yes	Yes	Yes
Observation	14945	14945	15107	15107
R Square	0.4780	0.4760	0.4677	0.4451

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

Mitigate endogeneity

Control variables are lagged by one period. Since in reality, green patent transactions require a certain amount of time to connect, and observable changes take time to occur, to better understand and capture these dynamic relationships, and also to further deal with the interference of potential endogeneity issues, this paper lags the control variables in **Table 9** by one period. It is not difficult to find that further lagging the control variables by one period does not affect the regression results. The conclusion that the green credit policy "Evaluation" significantly improves the performance of corporate green patent transactions still holds.

Table 9. The control variable lags one phase.

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	outpatent	inpatent	outpatent	inpatent
$treat_i \times policy_t$	0.0676***	0.1251***		
	(0.0201)	(0.0231)		
$treat1_i \times policy_t$			0.0864***	0.0953***
			(0.0235)	(0.0257)
Constant	-0.7442*	-0.6996*	-0.2681	0.0814
	(0.4005)	(0.4163)	(0.3796)	(0.4167)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observation	12985	12985	13030	13030
R Square	0.0262	0.0437	0.0308	0.0347

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

5.5 Mechanism Analysis

Based on the theoretical analysis of the previous text, under the background of green credit policy, the introduction of internal innovation information disclosure and external financing constraints forces companies to re-examine their decision-making behaviors, driving them to engage in green patent trading activities. In light of this, this article draws on Jiang (2022) research and further relies on models (24) and (25) to verify the hypothesis 2 mentioned above.

$$med_{it} = \beta_0 + \beta_1 treat_i \times policy_t + \phi X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{24}$$

$$med_{it} = \beta_0 + \beta_1 treat1_i \times policy_t + \phi X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{25}$$

Among them, med_{it} represents the intermediary variables, which are internal innovation information disclosure information and external credit financing constraints constraint, respectively. Other variables are set the same as in the benchmark model. If the coefficient of the interaction term is significant and the sign is consistent with expectations, and if existing literature has demonstrated that med_{it} can significantly affect corporate green patent transactions, this can indicate that the green credit policy "Evaluation" can drive companies to engage in green patent trading activities through med_{it}.

Internal innovation information disclosure

Building on Liu and Jiang (2023) and Zhang et al. (2023), the proportion of innovation-related keywords in annual reports is calculated to measure internal innovation information disclosure. Regression results (Table 10) indicate that, for heavily polluting enterprises, the "Evaluation" green credit policy significantly enhances environmental constraints, prompting these firms to disclose innovation information to mitigate financing challenges and engage in green patent trading. This aligns with findings by Hedge et al. (2018) and Kim and

Valentine (2023), who note that such disclosures reduce information asymmetry and facilitate patent transactions. Conversely, for green enterprises, the disclosure mechanism is not significant, possibly due to proprietary costs and the risk of knowledge spillovers benefiting competitors (Huang et al., 2021; Glaeser and Landsman, 2021; Li et al., 2024).

External credit financing constraints

Building on Cao Tingqiu et al. (2021), this study uses the ratio of total borrowings (short-term and long-term) to total assets as a proxy for external credit financing constraints. A higher ratio indicates greater credit availability and thus lower financing constraints.

Table 10's Columns (2) and (4) reveal that external credit financing constraints do not significantly mediate the relationship between the "Evaluation" green credit policy and green patent transactions in heavily polluting enterprises. This suggests that while the policy imposes financing constraints, these enterprises may counteract the impact by proactively disclosing internal innovation information. Such disclosures can signal project benefits to investors, reduce information asymmetry, and attract external investment, thereby offsetting the constraints imposed by the policy. This inference is indirectly supported by the significant positive results observed in Column (1) of **Table 10**.

Column (4) of **Table 10** reveals that the "Evaluation" green credit policy significantly increased the credit availability for green enterprises, as indicated by a positive regression coefficient at the 5% confidence level. This policy signals governmental support for green economic development, prompting banks to extend more credit to green enterprises, thereby alleviating their financing constraints and facilitating green patent transactions. This finding aligns with previous research: Serrano (2010) noted that firms engaged in patent transactions often face substantial financing constraints; Qiu and Wan (2015) found that firms hold more precautionary cash to navigate technology transactions; and Shan and Feng (2017) demonstrated that financial support promotes corporate technology transactions.

Table 10. Results of impact mechanism testing

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	information	constraint	information	constraint
$treat_i \times policy_t$	0.0162**	0.0052		
	(0.0079)	(0.0036)		
$treat1_i \times policy_t$			-0.0127	0.0072**
			(0.0088)	(0.0034)
Constant	0.4675***	-0.0496	0.8130***	-0.0189
	(0.1411)	(0.0668)	(0.1479)	(0.0601)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observation	14944	13602	15210	13554
R Square	0.0454	0.4077	0.0694	0.3870

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%,5%,and 1% level.

5.6 Heterogeneity Analysis

The previous text has verified the incentive effect of the green credit policy "Evaluation" on the performance of corporate green patent transactions. To further strengthen the causal relationship discussed above, this article conducts grouped regression based on the development level of regional technology trading markets and the degree of intellectual property protection to further test the differences in the impact of the green credit policy "Evaluation" on corporate green patent transactions. Additionally, Fisher's combined test is used to demonstrate the statistical significance of these differences.

The development level of regional technology trading markets

Regional technology trading markets are vital for corporate green patent transactions, as more developed markets reduce transaction costs and information asymmetry, thereby enhancing the effectiveness of green credit policies. This study assesses regional market development using the volume of technology inflow contract transactions, categorizing regions based on whether their transaction volumes exceed the annual sample median. This approach follows the methodology of Zhang et al. (2023), who employed patent trading data to analyze technology markets. The specific results are shown in **Tables 11**. For outpatent, whether it is heavily polluting enterprises or green enterprises, as long as they are in regions with a high level of development in the technology trading market, the interaction term coefficients are at least significantly positive at the 5% level, while the interaction term coefficients in regions with a low level of development in the technology trading market are positive but not significant; at the same time, the empirical p-values of the inter-group coefficient differences obtained by the Fisher combination test are all less than 0.05, passing the statistical test. For , as shown in columns (3)-(4) of **Table 11**, the interaction terms of heavily polluting enterprises are all significantly positive, but the empirical p-values have not passed the statistical test; similarly, in columns (7)-(8) of Table 11, the interaction terms of green enterprises are positive but not significant and the empirical p-values are greater than 0.1. This series of results indicates that the implementation of the green credit policy "Evaluation" can produce more positive green patent transaction effects in enterprises located in regions where the technology trading market is more developed, especially at the level of green patent sales.

Table 11. Degree of development of technology trading market.

	Panel A: heavy polluting enterprise				Panel B: green enterprise			
	outpatent		inpatent		outpatent		inpatent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	High	Low	High	Low	High	Low	High	Low
$treat_i \times policy_t$	0.1515***	0.0178	0.1350***	0.0910***				
	(0.0430)	(0.0296)	(0.0459)	(0.0342)				
$treat1_i \times policy_t$					0.1063**	0.0204	0.0683	0.0499
					(0.0422)	(0.0332)	(0.0484)	(0.0382)
Constant	-1.3723	-0.1860	-1.8573**	-1.0054*	0.6372	-0.5446	0.9299	-0.7471
	(0.8407)	(0.4755)	(0.8242)	(0.5697)	0.6826)	(0.5065)	(0.7689)	(0.6094)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	7550	7660	7550	7660	7774	7696	7774	7696
R Square	0.0224	0.0304	0.0285	0.0533	0.0182	0.0337	0.0202	0.0388
Empirical P-value	0.001***		0.139		0.013**		0.322	

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

The degree of regional intellectual property protection.

Intellectual property (IP) protection enhances corporate patent trading behavior by incentivizing innovation and reducing imitation risks (Liu et al., 2024). This study measures regional IP protection levels using the index released by the China National Intellectual Property Administration (CNIPA) in its "National Intellectual Property Development Status Report" (CNIPA, 2022). Regions are categorized based on whether their provincial IP protection index exceeds the annual sample median, following the methodology of Zhou et al. (2022). The specific results are shown in **Tables 12**. Whether it is heavily polluting enterprises or green enterprises, as long as they are in regions with a high degree of intellectual property protection, the interaction term coefficient is significantly positive at the 1% level. However, the interaction term coefficient in regions with a low degree of intellectual property protection is positive but significantly different. At the same time, the empirical p-value of the group coefficient difference obtained from the Fisher combination test is less than 0.05, passing the statistical test. The above results indicate that enterprises located in regions with a high level of intellectual property protection, the "Evaluation" can better strengthen their motivation for green patent transactions, promoting the realization of green patent sales and purchases.

Table 12. Degree of intellectual property protection.

	Panel A: heavy polluting enterprise				Panel B: green enterprise			
	outpatent		inpatent		outpatent		inpatent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	High	Low	High	Low	High	Low	High	Low
$treat_i \times policy_t$	0.0849***	0.0169	0.1452***	0.0630**				
	(0.0297)	(0.0277)	(0.0327)	(0.0297)				
$treat1_i \times policy_t$					0.1411***	0.0237	0.1393***	0.0294
					(0.0322)	(0.0313)	(0.0347)	(0.0341)
Constant	-0.6743	-0.7948	-1.1371**	-0.4908	-0.2474	-0.5618	-0.3985	-0.0706
	(0.4905)	(0.6029)	(0.5330)	(0.6441)	(0.4654)	(0.6881)	(0.4917)	(0.7750)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	8451	6759	8451	6759	8655	6815	8655	6815
R Square	0.0320	0.0330	0.0489	0.0521	0.0484	0.0287	0.0577	0.0310
Empirical P-value	0.041**		0.029**		0.002***		0.008***	

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%, 5%, and 1% level.

6. Extended Analysis: Validity Test of Corporate Green Patent Transactions

The previous discussion has explored the impact of green credit policies on corporate green patent transactions and their potential mechanisms. The real question is whether green credit policies effectively drive corporate green patent transaction performance, that is, whether they can further influence the economic and environmental benefits of enterprises.

6.1 Based on Economic Benefits

To assess the economic impact of green credit policies on corporate green patent transactions, this study follows Liu et al. (2024) by measuring economic benefits through the natural logarithms of total assets and net profit. This approach quantifies the relationship between green credit incentives and firms' economic performance, providing insights into the policy's effectiveness in promoting green innovation. As shown in **Table 13** columns (1)-(2), the green credit policy "Evaluation" significantly increased the net profit of heavily polluting enterprises, and its impact on the total assets of enterprises is positive, but not statistically significant. Column (3)-(4) shows that "Evaluation" can significantly expand the total assets of green enterprises, but its impact on the net profit of enterprises is not statistically significant. The above results indicate that, under certain conditions, "Evaluation" can not only drive enterprises to expand green transfer transactions but may also further improve the economic benefits of enterprises.

Table 13. Economic benefit.

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	size	netprofit	size	netprofit
$treat_i \times policy_t$	0.0130	0.0137***		
	(0.0182)	(0.0052)		
$treat1_i \times policy_t$			0.0325*	-0.0009
			(0.0187)	(0.0046)

Continuation Table:

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	size	netprofit	size	netprofit
Constant	17.3962***	-0.5844***	17.3007***	-0.4107***
	(0.4252)	(0.1162)	(0.3741)	(0.0944)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observation	15210	15210	15470	15470
R Square	0.6699	0.2479	0.7083	0.2187

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%,5%,and 1% level.

6.2 Based on Environmental Effects

The coordinated development of environmental and economic benefits is crucial for sustainable enterprise growth. To assess whether the "Evaluation" green credit policy enhances green patent trading and reduces pollution, this study follows Mao (2022) by standardizing emissions of chemical oxygen demand (COD), ammonia nitrogen (NH_3), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) using pollution equivalent values from China's "Pollutant Discharge Fee Collection Standard Management Measures." Emissions are converted into unified pollution equivalent numbers, summed, and adjusted by adding 1 and taking the natural logarithm to reflect overall pollution levels. Additionally, SO_2 is separately standardized as a distinct variable due to its prominence in China's pollution reduction targets. The specific results are shown in **Table 14**, where the regression results in columns (1)-(2) show that green credit policies can significantly suppress the overall pollution emission levels of heavily polluting enterprises, and the impact on sulfur dioxide emissions is also negative, but not statistically significant; while Table 14 columns (3)-(4) show that the "Evaluation" has a significantly negative impact on sulfur dioxide emissions of green enterprises, but the impact on the overall pollution emission level is not significant. In summary, this indicates that the green patent trading induced by the policy, through the transfer and acceptance of green patents, serves the reduction of pollution in the production process of enterprises, achieving a certain level of environmental benefits.

Table 14. Environmental benefit.

	Panel A: heavy polluting enterprise		Panel B: green enterprise	
	(1)	(2)	(3)	(4)
Variables	pollution	so2	pollution	so2
$treat_i \times policy_t$	-0.0001**	-0.0056		
	(0.0000)	(0.0044)		
$treat1_i \times policy_t$			-0.0000	-0.0084**
			(0.0000)	(0.0042)
Constant	0.1389***	6.8818***	0.1389***	6.9098***
	(0.0007)	(0.0710)	(0.0007)	(0.0664)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observation	15210	15210	15470	15470
R Square	0.9033	0.6550	0.9006	0.6518

Notes: Robust standard errors corrected for clustering at the firm level are shown in parentheses. *, **, and*** represent statistical significance at 10%,5%,and 1% level.

7. Conclusions and Implications

This study first presents model-guided work on the role of invention and innovation in non-renewable energy technology, analyzing both microeconomic firm behavior and macroeconomic system trends. The modeling framework reflects and connects with a substantial body of international research, where major policy initiatives, such as carbon pricing, targeted R&D subsidies, and large-scale financial incentives, are similarly structured to shape firm choices, promote the adoption of clean technologies, and drive systemic transformation in innovation dynamics and environmental performance.

Second, the paper examines the impact of China's "Evaluation" green credit policy on corporate green patent transactions, revealing that the policy significantly enhances transaction performance, particularly in green patent sales among green firms and purchases among heavily polluting enterprises. These outcomes are primarily facilitated by relaxing external credit constraints for polluting firms and through improved innovation information disclosure within green enterprises. In both China and Western economies, such as through the European Union's Green Deal, Germany's KfW Bank, the U.S. Inflation Reduction Act, and India's Green Credit Programme, green finance mechanisms provide direct and indirect financial incentives that stimulate green patent activity, de-risk private investment, and accelerate clean technology adoption.

As evidenced in China and the West, the effectiveness of these green finance mechanisms depends not only on the policies themselves but also on local context, especially the development and efficiency of technology trading markets and the strength of intellectual property frameworks. Under favorable regional conditions, increases in green patent transactions contribute to both economic and environmental objectives, supporting emissions reduction and carbon neutrality, and highlighting the need for well-targeted policy design to support green technology innovation and diffusion.

To strengthen policy implementation, it is important to tailor and enhance green credit mechanisms to real-world conditions, including aligning credit allocation with firms' comparative advantages in green patent reserves and innovation capacity. Policymakers should refine implementation details, develop actionable schemes, and foster synergy between market forces and government intervention; measures such as post-loan inspections, green patent transaction reviews, and green innovation evaluations can be integrated into performance assessments to encourage banks to actively support green patent activities and their diffusion.

Simultaneously, improving the green technology trading system is crucial: efficient market trading platforms can reduce transaction costs, improve technology diffusion, and ensure better resource allocation. Strengthening intellectual property rights enforcement, through legal reforms and anti-infringement actions, can lower barriers to trade and boost market confidence, while specialized green technology trading platforms tailored to regional strengths can professionalize the market, offer customized services, and better connect supply with demand, thereby stimulating a vibrant ecosystem for green technology transfer.

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