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Green finance and job creation: Analyzing employment effects in China's manufacturing industry within green finance innovation and reform pilot zones

Bowen Fu [a,b], Yixiang Zhang [a,c], Sholeh Maani [b], Le Wen [b,*]

[a] School of Management, Beijing Institute of Technology, Beijing 100081, China
[b] Department of Economics, School of Business and Economics, University of Auckland, Auckland, New Zealand
[c] Center for Energy & Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China

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ABSTRACT

As environmental issues related to global climate change intensify, green finance (GF) policies have emerged as vital tools for promoting sustainable development. This study examines the impact of GF policies on employment in China's manufacturing sector. Using unbalanced panel data of Chinese listed manufacturing enterprises from 2012 to 2021, and employing the difference-in-differences model, this study analyzes the impact of establishing China's GF innovation and reform pilot zones on manufacturing employment. The results show that the implementation of GF policies significantly increases employment in the manufacturing sector, with a more pronounced effect in non-state-owned enterprises, non-heavy-polluting industries, and high-tech manufacturing enterprises. Additionally, the study finds that GF policies alleviate financing constraints, enhancing employment levels in manufacturing enterprises. This research contributes to the existing literature by elucidating the employment effects of GF and providing insights for policymakers to use in fostering GF for economic growth.

1. Introduction

In recent years, the global environment has deteriorated significantly, with climate change, increasing pollution, and resource depletion becoming frequently-discussed issues (Zhang and Fu, 2023). Rising temperatures, extreme weather, and melting glaciers threaten human survival, while air and water pollution severely damage human health and environmental ecosystems. Overexploitation of resources has led to deforestation and desertification, putting immense pressure on ecosystems (Pal et al., 2023).

Against this backdrop, green finance (GF) has emerged as a tool to promote sustainable development projects that mitigate environmental degradation (Zhou et al., 2020). GF synergizes environmental protection with economic development by channeling resources into eco-friendly projects, offering new optimism for global environmental improvement (Zhou et al., 2020). Compared to traditional finance, the most notable feature of GF is the emphasis on coordinating environmental protection with financial activities, ultimately aiming for sustainable economic and social development (Lv et al., 2021). The demand for funds to support the green transformation of enterprises has driven increasing attention toward GF (Lee, 2020).

Globally, GF is advancing, driving the transition toward sustainable and low-carbon economies. In 2020, the European Commission's European Green Deal triggered a surge in GF, with plans to invest one trillion euros in green industries over the next decade to achieve carbon neutrality (Battaglini, 2024). In the United States, some states, such as California, have implemented California's cap-and-trade program to encourage enterprises to adopt cleaner practices and technologies to reduce greenhouse gas emissions (Pauer, 2018). In China, GF began during a critical period of economic restructuring, gradually matured, and evolved into a national strategy (Lv et al., 2021). Between 2009 and 2014, China's GF began to take shape, with energy conservation, emission reduction, and environmental protection gaining importance. The "Green Credit Guidelines", issued by the China Banking Regulatory Commission in 2012, provided direction for the establishment of China's green credit system (Force, 2015). Based on this system, more financial

Abbreviations: GF, Green finance; GFIRPZ, Green finance innovation and reform pilot zones; DID, Difference-in-differences; OC, Ownership concentration; FAR, Fixed asset ratio; PSM, Propensity Score Matching; FC, Financing constraints; SOEs, State-owned enterprises; non-SOEs, Non-state-owned enterprises.

* Corresponding author.
E-mail address: l.wen@auckland.ac.nz (L. Wen).

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institutions began to participate in GF, continuously innovating various green financial products such as green credit asset securitization (Wang et al., 2022a). Since 2015, China's ecological civilization policies have been intensively introduced, leading to the vigorous development of GF (Wang et al., 2019). Initiated in 2017, China's green finance innovation and reform pilot zones (GFIRPZ) were established to serve as practical benchmarks for GF, offering insights and experiences to guide the development of GF nationwide.

During this process, renewable energy gained increased attention, technology was constantly innovating, and the economy continued to develop, impacting the employment scale of enterprises across various industries to varying degrees (Liu and Wang, 2023).

Employment has always been an important livelihood issue in China (Cai and Wang, 2010), receiving continuous attention from all sectors. Because the green development transformation may lead to the displacement of labor and the creation of employment in emerging fields (Bowen, 2012), studying the impact of GF policies on manufacturing employment becomes particularly important. As a pillar industry of China's economy, employment in the manufacturing sector not only affects social stability and livelihood security, it also serves as a key factor in the economic transition process (Su and Yao, 2017). The implementation of GF policies profoundly impacts various aspects of manufacturing enterprises, including production methods, technological upgrades, and cost structures, with supposed direct and indirect effects on employment.

GF policies encourage enterprises to adopt environmentally friendly technologies and equipment, promoting the green transformation of manufacturing (Agrawal et al., 2024). During this process, although some traditional jobs may disappear due to technological upgrades and automation, numerous new employment opportunities are created in areas such as green technology research and development, environmental management, and renewable energy equipment manufacturing (Ge and Zhi, 2016). Additionally, GF policies improve resource optimization, production efficiency, and environmental performance in manufacturing enterprises (Zhang et al., 2021). This can increase the competitiveness of enterprises and expand markets, thereby promoting employment growth. Furthermore, GF policies drive financial market innovation, attracting more social capital into green industries and boosting employment in related sectors. Financial innovations such as green bonds and green credit asset securitization provide funding for environmental projects (Sartzetakis, 2021). However, some small and medium-sized enterprises may face significant pressure during the green transition due to a lack of funds and technical support (Hampton, 2018), leading to short-term employment instability.

Collectively, these factors indicate that studying the impact of GF policies on manufacturing employment is crucial for comprehensively assessing the effectiveness of these policies, ensuring that environmental protection and economic development are achieved while promoting stable and growing employment.

Although GF policies are of popular research interest (Chen et al., 2024; Lee et al., 2024), existing empirical studies on this topic have mostly focused on GF's impact on the environment and energy, while neglecting its potential impact on socio-economic dimensions, especially employment. However, GF is not just a tool for promoting environmental protection and low-carbon development; it also profoundly influences economic structural transformation (Wang and Wang, 2021). The implementation of GF has the capacity to direct capital from high-pollution industries to green industries (Yue et al., 2024), leading to a reallocation of employment. While emerging green industries may create new job opportunities, the contraction of traditional industries could also result in short-term unemployment and social instability (Antal, 2014).

The existing literature on the relationship between GF and employment is still limited, and it provides divergent results. For example, Xie et al. (2024) found that the implementation of the "Green Finance Reform and Innovation Pilot Zone" policy increases enterprises' labor demand by improving operational capability, despite also raising financing pressures. Conversely, Jiang and Jiang (2023) found that the Green Credit Guidelines significantly crowd out labor demand in high-polluting enterprises. This crowding-out effect, however, is not significant in non-state-owned enterprises and those with high analyst coverage. While these studies provide insightful perspectives, they mainly focus on general labor demand and do not address the specific effects on industries such as manufacturing.

The innovations of this research are as follows. First, our study fills this gap by examining the impact of GF policies on employment specifically in China's manufacturing sector. The empirical evidence not only broadens the understanding of GF's sector-specific impacts, but it also contributes new insights into policy-driven employment dynamics in critical economic sectors. Second, studying the impact of GF on employment provides a new perspective for understanding the broader and comprehensive role of GF policies in promoting sustainable development. Specifically, from the perspective of policy effectiveness theory, this research offers theoretical support for optimizing the design of green finance policies, ensuring that while environmental goals are achieved, the socio-economic benefits, particularly employment stability and growth, are maximized. Thus, exploring the impact of GF on employment is both a theoretical innovation and a practical step toward policy improvement.

To comprehensively assess the impact of GF policies on employment in the manufacturing sector, this study uses China's GFIRPZ as a policy shock. Utilizing unbalanced panel data of Chinese listed manufacturing enterprises from 2012 to 2021, and employing the difference-in-differences (DID) model, this study analyzes the actual effects of GF policies by comparing employment changes in the treatment group and the control group before and after policy implementation. The treatment group consists of listed manufacturing enterprises located within the GFIRPZ, whereas the control group comprises similarly listed manufacturing enterprises in the same geographical regions that did not adopt the GFIRPZ policy. The analysis of employment data from these enterprises, both before and after policy implementation, aims to uncover the specific impacts of GF policies on manufacturing employment. Through a detailed examination of these impacts, this study provides empirical evidence to assist policymakers in harmonizing environmental protection with employment objectives. Such insights are crucial for developing and refining GF policies that foster holistic and sustainable economic and social development. The empirical framework of this study is shown in Fig. 1.

2. Literature review

2.1. Green finance

As a crucial driver for addressing climate change and environmental degradation, the origin of GF can be traced back to the late 1980s with the introduction of the concept of a green economy in the "Blueprint for a Green Economy" (Pearce et al., 2013). The increasing focus on mitigating climate change and promoting environmental protection has spurred many countries and international organizations to adopt policies that support green and sustainable economic growth. This is achieved by adopting various practices that promote GF and related initiatives, including green credit, green funds, green bonds, green insurance, and carbon trading (Fan and Shahbaz, 2023).

With the growing importance of GF, scholars and international organizations have been working to develop a clear definition of GF. Some scholars define GF as activities that protect the environment while providing fair returns to investors or lenders (Ozili, 2021) or simply as financing for public and private green investments (Lindenberg, 2014). Others describe GF as the combination of environmental protection and economic benefits, encompassing all investments in environmental goods and services (Wang and Zhi, 2016), as well as activities that reduce environmental and climate damage (Lindenberg, 2014). GF is

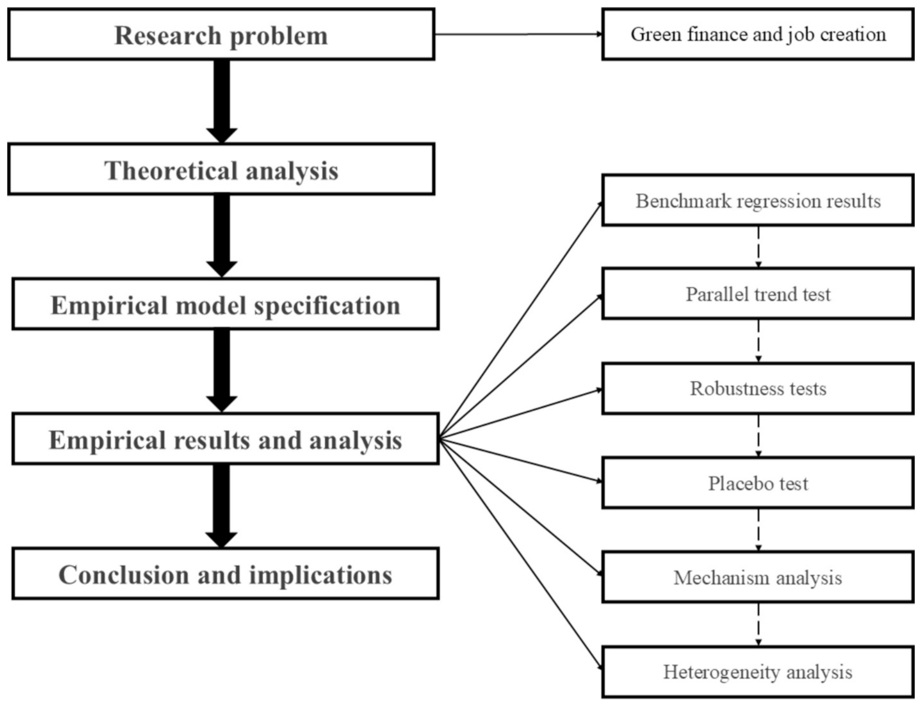

Fig. 1. Empirical framework.

also defined as financing for environmentally friendly activities, green technologies, and pollution reduction projects (Saleem et al., 2022). Most European research on GF focuses on related policy reports, including green bonds, green loans, and green equity investments (Migliorelli and Dessertine, 2019). According to the G20 Green Finance Study Group, GF is defined as "financing of investments that provide environmental benefits in the broader context of environmentally sustainable development. These environmental benefits include, for example, reductions in air, water and land pollution, reductions in greenhouse gas emissions, improved energy efficiency while utilizing existing natural resources, as well as mitigation of and adaptation to climate change and their co-benefits." (Group, G.G.F.S, 2016). In China, scholars define GF based on the principles of a market economy, aiming to promote the construction of an ecological civilization (Yin and Xu, 2022). This involves using credit, insurance, and other financial instruments to drive energy conservation, emission reduction, and the coordinated development of economic resources and the environment (Yin and Xu, 2022). Overall, GF generally involves making investment decisions to support projects and enterprises that are environmentally friendly and socially beneficial (Ozili, 2022).

2.2. Policy background

As the lifeblood of economic development, finance plays a crucial role in resource allocation (Zhang and Liang, 2023). Constructing a GF policy system is essential for supporting the sustainable development of the manufacturing sector. In June 2017, the executive conference of the State Council decided to establish China's green finance innovation and reform pilot zones (GFIRPZ) in eight regions across five provinces (Shi et al., 2022). The Council's aim was to promote the innovation of GF systems and mechanisms (Shi et al., 2022). GFIRPZ's goals are to use financial means to support ecological and environmental improvements as well as the efficient use of resources (Liu and Wang, 2023). Furthermore, the goal of the GFIRPZ is to build GF policies, standards, and systems within specific regions, based on the principles and methods of reform and innovation. Consistent with this goal is exploring new models and paths for financial services to facilitate the green transformation of the real economy (Zhang et al., 2022a). The main tasks of the GFIRPZ include establishing and improving the GF system, fostering a range of financial products and services aligned with green development concepts, such as green credit, green bonds, and green funds (Wang et al., 2022c). Additionally, the establishment of GFIRPZ involves innovating regulatory approaches by establishing differentiated GF regulatory policies and assessment mechanisms. The GFIRPZ also aim to broaden green investment and financing channels, attracting social capital investment in green industries through various means (Zhang et al., 2023). This includes evaluating the environmental credit and risks of enterprises, providing tax reductions and credit support, and encouraging enterprises to adopt cleaner production methods, thereby promoting the green transformation of heavily polluting industries.

The first batch of GFIRPZ includes Ganzhou in Jiangxi Province, Guangzhou in Guangdong Province, Huzhou and Quzhou in Zhejiang Province, Gui'an New District in Guizhou Province, and Hami, Changji, and Karamay in the Xinjiang Uygur Autonomous Region (Zhang et al., 2023).

These regions have introduced a series of innovative policy measures through GF initiatives and institutional reforms, tailored to local realities. Aspects of this innovation include regulation, products, and incentives that promote economic green transformation and sustainable development, injecting new vitality into the local green economy (Zhang et al., 2022a). By exploring institutional and mechanism innovations for financial services to support the green economy within specific regions, the GFIRPZ provides multiple policy supports and institutional guarantees to help manufacturing enterprises achieve green and low-carbon transformation.

2.3. Theoretical analysis

GF policies have a significant impact on employment in manufacturing enterprises, and this can be analyzed from several perspectives. First, GF policies provide easier access to funds for manufacturing enterprises through low-interest loans, green bonds, green funds, and other financial instruments (Dong et al., 2022b). These funds can be used for business expansion, technological upgrades, and process innovation, thus creating new job opportunities (Lee and Lee, 2022). During this process, enterprises will hire more technicians and workers to operate and maintain this new equipment, directly increasing employment positions. Additionally, the reduced financing costs can alleviate financial pressures on enterprises, enabling them to invest more in production and recruitment, further promoting job growth (Soundarrajan and Vivek, 2016).

Second, GF policies encourage enterprises to invest in green technologies and equipment, enhancing production efficiency and product quality (Du et al., 2022). Through technological innovation, enterprises can reduce production costs and increase market competitiveness (Li et al., 2019). This not only directly increases profits, it also requires hiring more skilled employees to develop and manage these new technologies, thereby increasing job opportunities (Acemoglu and Autor, 2011). For example, enterprises may develop new environmentally friendly products or improve the production processes of existing products, which requires a large number of R&D personnel and engineers.

Third, manufacturing enterprises participating in GF can enhance their environmental image and market competitiveness (Wang et al., 2022b). Environmentally conscious consumers and business partners are more likely to choose products and services from these firms, driving sales growth and market expansion (Laroche et al., 2001). This expansion requires increased production capacity and service capabilities, leading to more job opportunities.

Fourth, GF policies are usually accompanied by a series of compliance requirements and incentive mechanisms. To meet these requirements, enterprises may need to implement environmental modifications and management upgrades, which will require hiring more specialized personnel (Minhas et al., 2024). For instance, enterprises may need to hire environmental engineers and compliance experts to ensure that the new production processes meet environmental standards (Hilson and Nayee, 2002).

Additionally, the government may provide tax reductions and subsidies as incentives to support green transformation and job growth (Owen et al., 2018). GF policies help enterprises identify and manage environmental risks, enhancing their capabilities for sustainable development (Lee, 2020). By improving environmental management and reducing pollution, enterprises can avoid legal disputes and fines caused by environmental issues, enhancing their stability and long-term development potential (Zhang and Wen, 2008). This stability helps enterprises maintain and increase employment over the long term.

Finally, GF policies may drive employment growth in related industries through the upstream and downstream industrial supply chains (Qu et al., 2020). For example, manufacturing enterprises that use GF funds for equipment upgrades will drive employment growth in equipment manufacturing, installation, and maintenance services (Qu et al., 2020). Additionally, the R&D and production of environmentally friendly technologies and products promoted by GF policies will also drive employment growth in related supply chain enterprises. For instance, manufacturers of environmental protection equipment, suppliers of green materials, and providers of professional services will all benefit (Qu et al., 2020), increasing job opportunities.

This analysis reveals a close relationship between GF policies and employment in the manufacturing sector. GF policies enhance employment in manufacturing by funding expansion and innovation, encouraging adoption of green technologies, requiring compliance upgrades, and other beneficial impacts. This leads to creation of job opportunities and stimulation of employment growth directly in participating companies and indirectly in related industries.

As such, it is evident that financing constraints (FC) serve as a foundational mechanism influencing how GF policies impact employment. GF policies, while promoting sustainability, often restrict finance access for high-polluting enterprises, which can reduce labor demand initially but incentivize firms to improve efficiency over time. Given the importance of FC in shaping these dynamics, this study focuses on testing this mechanism in our empirical analysis. To measure FC, this study uses the FC index from the CSMAR database, which captures enterprises' financial health and credit availability. In the mechanism analysis (Section 4.5), this study explores how GF promotes employment in the manufacturing sector through the FC mechanism, emphasizing its role as a critical pathway in our study.

3. Model and data

3.1. Model specification

In recent years, the important impact modern econometrics can have on policy evaluation has been widely recognized. As a result, a range of causal inference methods based on counterfactual ideas has emerged to assess the effect of specific events on outcome variables, such as the difference-in-differences (DID) method and synthetic control method (Cerqua and Letta, 2020). This study analyzes the impact of GF policies on manufacturing employment using the DID method.

DID is a quasi-experimental method used to assess the effects of policies or interventions (Rockers et al., 2015). By comparing the changes in the treatment group and the control group before and after the policy implementation, the DID method can control for time trends and inter-group differences, providing relatively accurate estimates of causal effects (Guo and Zhong, 2022). The basic principle involves measuring two differences. First is the time difference, which compares changes in the treatment and control groups before and after the implementation of the policy. Second is the group difference, which compares the treatment and control groups at the same time point (Abadie, 2005). The DID method effectively eliminates the influence of exogenous factors that change over time but are unaffected by the policy, thereby more accurately reflecting the actual impact of the policy (Li et al., 2012). The DID method is highly applicable, particularly when panel data is available. It circumvents the challenge of identifying instrumental variables and is commonly employed in the evaluation of various policy impacts (Dong et al., 2022a; Yu and Zhang, 2022; Zhou and Zhang, 2022). The key assumption is underlying this method is the common trend assumption, which implies that, in the absence of the policy intervention, the individuals in both the treatment and control groups would exhibit similar patterns of change (Card and Krueger, 1994).

The key benefit of the DID model lies in its ability to provide reliable estimates of policy impacts while controlling for external confounding factors (Wing et al., 2018). Also, its logic is simple and intuitive, making it easy to understand and interpret (Wing et al., 2018). Additionally, it is suitable for various practical situations, such as policy evaluation and social science research, where randomized controlled trials are not feasible. Under the parallel trends assumption, the DID model offers robust support for causal inference, becoming an important tool for policy formulation and impact assessment (Roth et al., 2023). Therefore, the DID model has wide applicability and strong explanatory power in both academic research and practical applications. Following Zhang et al. (2022b), this study uses the DID model to evaluate the impact of GF policies on manufacturing employment.

The construction of the DID model first requires defining two dummy variables for the experimental and control groups (Zhang et al., 2022b). Since the official launch of the GFIRPZ in 2017, the experimental group is defined as manufacturing listed enterprises in eight cities in the five provinces that implemented the policy. The control group is defined as manufacturing listed enterprises in other cities within these five provinces. Using the 2017 implementation of the GFIRPZ as the policy impact time point, a time dummy variable is defined, with the year 2017 and subsequent years coded as 1 and the years before 2017 coded as 0. The basic form of the DID model is established as follows:

$$EM_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 \sum Controls_{it} + \gamma_t + \delta_i + \lambda_r + \mu_s + \varepsilon_{it} \tag{1}$$

where i represents manufacturing listed enterprises, and t represents the year. EM_{it} is the dependent variable, representing the employment of each manufacturing listed enterprise. DID_{it} is the policy dummy variable, derived from the interaction of the grouping dummy variable $Treat_i$ and the time dummy variable $Time_t$ (i.e., $DID_{it} = Treat_i \times Time_t$).

If the office of the manufacturing listed enterprise is located in one of the eight cities within the five provinces designated as GFIRPZ, then $Treat_i$ is assigned a value of 1; otherwise, it is assigned a value of 0. The time dummy variable $Time_t$ takes the value 0 for the period before the policy shock (before 2017) and 1 for the period after the policy shock (after 2017). $Controls_{it}$ represents the control variables at the manufacturing enterprise level; β_0 denotes the constant; β_1 is the coefficient of the key explanatory variable; β_2 is the coefficient of the control variables; γ_t denotes the time fixed effects; δ_i represents the firm fixed effects; λ_r denotes the regional fixed effects; μ_s represents the industry fixed effects; and ε_{it} is the random error.

3.2. Sample selection and data source

This study uses the data of China's A-share listed enterprises from 2012 to 2021 as the research sample. To avoid significant differences between the treatment and control group samples, only enterprises with office addresses located in Zhejiang Province, Guangdong Province, Guizhou Province, Jiangxi Province, and the Xinjiang Uygur Autonomous Region are retained. This approach helps minimize potential interference from unobservable macro factors between regions.

The firm-level data are sourced from the China Stock Market and Accounting Research (CSMAR) database. Additionally, the following treatments are applied to the listed enterprises: According to the "Guidelines for Industry Classification of Listed Companies (2012 Edition)" by the China Securities Regulatory Commission, enterprises from the primary and tertiary industries are excluded, retaining only manufacturing enterprises with a category code of C. Financial and insurance enterprises, ST, and *ST enterprises are excluded. Samples with severe missing variables and those with a leverage ratio greater than 1 or less than 0 are also excluded. After processing, a balanced panel dataset of 3140 observations from 331 listed enterprises is obtained.

The descriptive statistics of specific variables are presented in Table 1. For the selection of the dependent variable, the logarithm of the number of employees of each listed manufacturing enterprise in the CSMAR database is chosen to measure its employment. Also, the explanatory variable is constructed as an interaction term. Based on whether the office address of a listed enterprise is located in the GFIRPZ during the sample period, policy group dummy variables and time dummy variables are constructed separately. Enterprises located in the GFIRPZ are coded as 1 (treat), otherwise as 0. Similarly, for the year of policy implementation and subsequent years, the time variable is coded as 1, otherwise as 0. The GFIRPZ is thus represented as an interaction term (*DID*) of the policy group dummy variable and the time dummy variable.

The firm-level control variables include measures of the enterprise's basic characteristics: firm size (*Size*), firm age (*Age*), and fixed asset ratio (*FAR*). Measures of the enterprise's financial condition include profitability (*ROE*), leverage ratio (*Lev*), and Tobin's Q (*Tobin*). A measure reflecting corporate governance is ownership concentration (*OC*) and the firm size is the logarithm of the total assets of the enterprise. The descriptive statistics of the data are shown in Table 1.

4. Empirical results and analysis

4.1. Benchmark regression results

This study uses Stata software to perform the DID model regression to examine the impact and extent of the GF policy on manufacturing employment. The test results are shown in Table 2. In Table 2, Column (1) presents the regression results with all control variables added, without considering firm fixed effects, time fixed effects, industry fixed effects, or province fixed effects. It can be observed that the estimated coefficient of the core DID explanatory variable is significantly positive at the 5 % level. Columns (2), (3), (4), and (5) present the results with the gradual addition of firm fixed effects, time fixed effects, industry fixed effects, and province fixed effects, respectively. The results show that the estimated coefficient of the core explanatory variable decreases compared to before, but remains significant at the 5 % level. Column (5) represents the benchmark model of this study, with the coefficient of the core explanatory variable being 0.1016, indicating that, compared to non-pilot areas, the GF policy can significantly promote employment in the manufacturing sector of the pilot zones.

4.2. Parallel trend test

The applicability of the DID method relies on the data passing the parallel trend test (Wen and Liu, 2022), which means that there is no significant difference in the level of employment between the experimental group and the control group before the policy implementation. Fig. 2 shows the results of the parallel trend test for this study. The results show that all regression results before 2017 are not significant, indicating that before the implementation of the GF policy, the trends in the treatment group and the control group are consistent and there are no significant differences. However, after 2017, employment in the treatment group increases significantly compared to the control group. Therefore, the sample passes the parallel trend test required for the DID estimation, indicating that the listed manufacturing enterprises in the GFIRPZ and those in the non-pilot areas satisfy the parallel trend assumption. This demonstrates that using the DID model to evaluate the policy effect in this study is entirely reasonable.

4.3. Robustness tests

This study conducts robustness checks on the main empirical results to further validate the accuracy of the empirical conclusions.

To eliminate sample selection bias and better estimate the policy effects, this study first employs the PSM-DID method to evaluate the GF policy. Specifically, the Propensity Score Matching (PSM) method is based on all control variables. Table 3 presents the comparison results before and after matching. It can be seen that, after matching, the bias of all control variables is less than 10 %, and the bias of most control variables is less than 5 %. According to the balance test, the null

Table 1
Descriptive statistics.

Variables	Definition	Symbol	Sample size	Mean	Std.Dev.	Min	Max
Employment	Logarithm of number of employees	*Em*	3140	8.0392	1.0884	4.5326	11.8298
DID	Interaction effect term in the model	*DID*	3140	0.0373	0.1894	0	1
Firm size	Logarithm of the firm's total assets	*Size*	3140	22.2524	1.1275	19.2406	26.5439
Firm age	Years since the enterprise was founded	*Age*	3140	11.6691	6.2008	2	30
Return on equity	Ratio of net income to shareholders' equity	*ROE*	3140	0.0541	0.2031	−6.5799	0.8466
Debt-to-asset ratio	Ratio of total debt to total assets	*Lev*	3140	0.4020	0.1757	0.0080	0.9694
Tobin's Q	Ratio of market value to replacement cost of assets	*Tobin*	3094	2.1140	1.2218	0.7455	13.5269
Ownership concentration	Sum of the shareholding ratio of the top 10 circulating shareholders	*OC*	3140	38.5609	19.1950	0.7345	92.8996
Fixed asset ratio	Ratio of fixed assets to total assets	*FAR*	3140	0.2281	0.1284	0.0002	0.7255

Table 2
Test of the impact of GFIRPZ on employment in manufacturing enterprises.

	(1)	(2)	(3)	(4)	(5)
Variables	*Em*	*Em*	*Em*	*Em*	*Em*
DID	0.0850*	0.1082**	0.1007**	0.1027**	0.1016**
	(0.0474)	(0.0474)	(0.0481)	(0.0485)	(0.0481)
Size	0.6661***	0.6558***	0.6553***	0.6469***	0.6631***
	(0.0344)	(0.0398)	(0.0411)	(0.0394)	(0.0385)
Age	−0.0303***	−0.0326***	−0.0339***	−0.0325***	−0.0341***
	(0.0043)	(0.0050)	(0.0054)	(0.0052)	(0.0052)
ROE	0.0148	−0.0045	−0.0031	0.0071	0.0047
	(0.0269)	(0.0291)	(0.0293)	(0.0325)	(0.0318)
Lev	0.2538**	0.2217**	0.2242**	0.2092*	0.2112*
	(0.1061)	(0.1100)	(0.1099)	(0.1080)	(0.1082)
Tobin	0.0177**	0.0209**	0.0269***	0.0285***	0.0294***
	(0.0081)	(0.0081)	(0.0104)	(0.0105)	(0.0105)
OC	0.0006	0.0004	0.0002	0.0001	−0.0001
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
FAR	0.6476***	0.6356***	0.6408***	0.6164***	0.6612***
	(0.1483)	(0.1534)	(0.1559)	(0.1515)	(0.1514)
Constant	−6.7493***	−6.4666***	−6.4526***	−5.8569***	−6.0900***
	(0.7284)	(0.8411)	(0.8641)	(0.8846)	(0.8942)
Firm FE	×	√	√	√	√
Time FE	×	×	√	√	√
Industry FE	×	×	×	√	√
Province FE	×	×	×	×	√
Observations	3094	3094	3094	3094	3094
R-squared	0.5719	0.5725	0.5737	0.5835	0.5924
Number of id	331	331	331	331	331

Notes: Robust standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

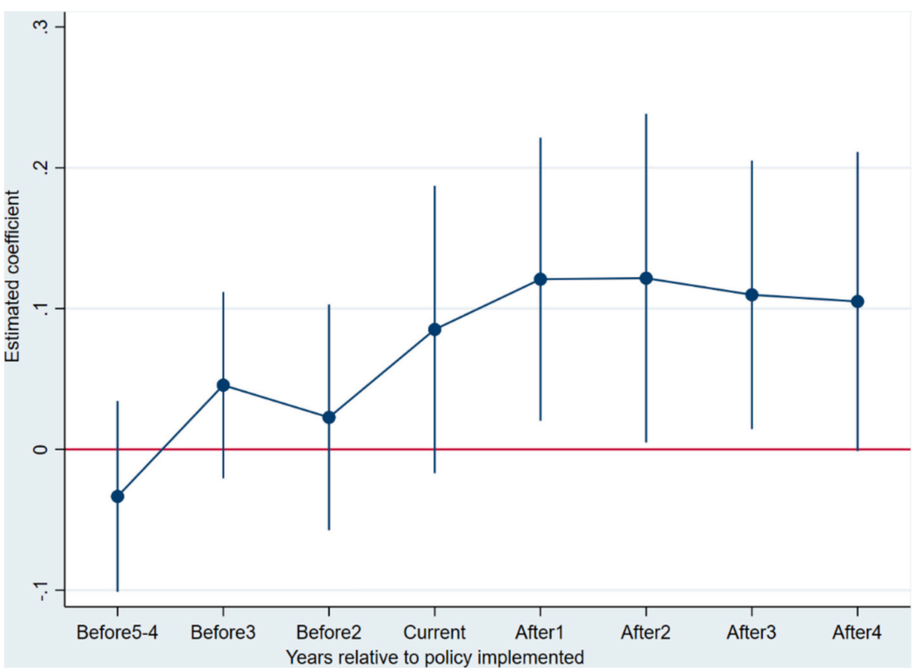

Fig. 2. Parallel trend test.

hypothesis that there is no systematic difference between the treatment and control groups cannot be rejected, meeting the balance assumption. For example, in the total sample of enterprises, the average age of enterprises in the treatment group is approximately 10.41 before matching, while it is 11.81 in the control group, indicating a significant difference between the two groups. This suggests that the treatment group consists of younger enterprises, and conclusions drawn from unmatched data may be unstable. After matching, the average age of enterprises in the control group is 10.63, compared to 10.41 in the treatment group, with no significant difference between the two groups, demonstrating the effectiveness of the PSM method. Similarly, the balance check results in Fig. 3 also validate the PSM-DID results.

Column (2) of Table 4 presents the PSM-DID test results, with PSM using kernel density matching. It can be observed that the coefficient of the interaction term remains significant at the 0.05 level, demonstrating that after eliminating sample selection bias through propensity score matching, the main empirical conclusion of this study remains unchanged. This indicates that the GFIRPZ policy can significantly improve employment in the manufacturing sector.

Additionally, outliers in experimental data can introduce errors,

Table 3
Comparison of differences in covariates before and after matching.

Variables	Match	Means		%Bias	%Reduced |bias|	T	
		Treated	Control			t	P > |t|
Size	U	22.24	22.26	−1.9		−0.29	0.769
	M	22.24	22.22	1.5	23.8	0.17	0.862
Age	U	10.41	11.81	−23.0		−3.63	0.000
	M	10.41	10.63	−3.6	84.2	−0.45	0.065
ROE	U	0.06	0.05	4.8		0.71	0.479
	M	0.06	0.06	1.6	67.5	0.18	0.857
Lev	U	0.35	0.41	−31.9		−4.94	0.000
	M	0.35	0.37	−9.7	69.6	−1.18	0.240
Tobin	U	2.23	2.10	10.8		1.70	0.089
	M	2.23	2.15	7.1	33.9	0.85	0.398
OC	U	40.39	38.41	10.0		1.65	0.098
	M	40.39	39.23	5.9	41.2	0.69	0.490
FAR	U	0.20	0.23	−21.5		−3.30	0.001
	M	0.20	0.21	−6.2	71.3	−0.77	0.441

Notes: U represents the difference between the control and control groups before pairing; M is the difference between the experimental and control groups after pairing.

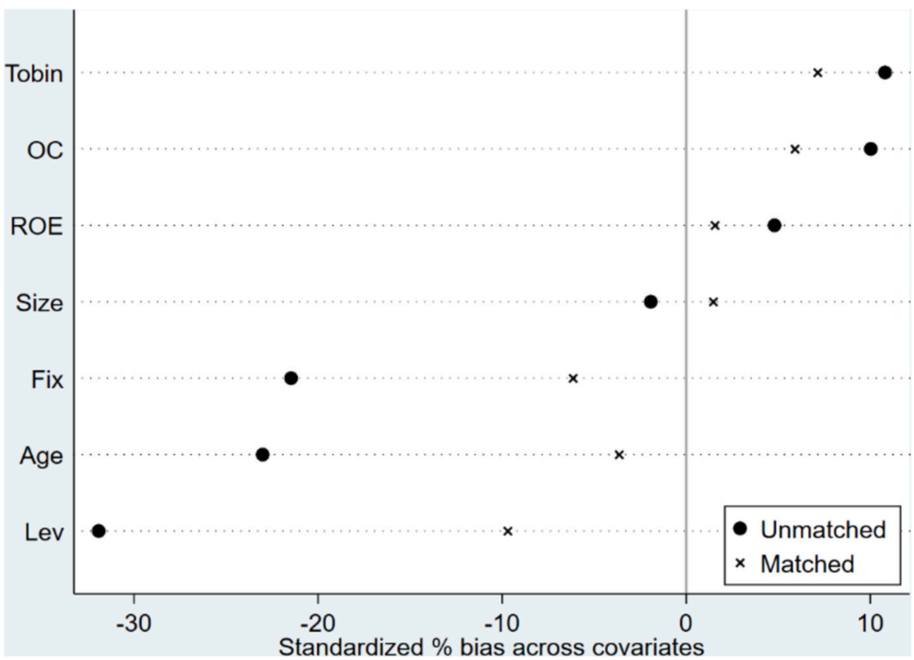

Fig. 3. Balance check results of PSM-DID.

Table 4
Robustness test results.

	(1)	(2)	(3)
Variables	*Em* DID	*Em* PSM-DID	*Em* Winsorized
DID	0.1016**	0.1010**	0.0979**
	(0.0481)	(0.0480)	(0.0475)
Control variables	√	√	√
Constant	−6.0900***	−6.6755***	−6.6755***
	(0.8942)	(0.9136)	(0.9136)
Firm FE	√	√	√
Time FE	√	√	√
Industry FE	√	√	√
Province FE	√	√	√
Observations	3094	2991	3094
R-squared	0.5924	0.6048	0.5984
Number of id	331	330	331

Notes: Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *p < 0.1; the control variables include *Size, Age, ROE, Lev, Tobin, OC, and FAR*.

leading to erroneous research conclusions. This means that if there are some extreme values in the data, they might unreasonably influence the statistical analysis results, making the research conclusions inaccurate. To mitigate the impact of outliers, this study performs winsorization at the 1 % level on all empirical data before evaluating the policy effects during robustness testing. Winsorization is a statistical method that reduces the influence of extreme values by replacing them with specific percentile values. Column (3) of Table 4 shows the policy evaluation results after winsorization. These results remain significant, indicating that the empirical study's conclusions remain robust after accounting for outliers. Therefore, it can be concluded that the research results are not affected by outliers.

4.4. Placebo test

This study follows Chetty et al. (2009) by performing 500 random repetitions and randomly selecting hypothetical experimental groups for placebo tests to avoid the influence of random factors on the empirical results. Fig. 4 shows the results of the placebo test (Tao et al., 2023). As can be seen from Fig. 4, after 500 repetitions of random sampling, the *p*-

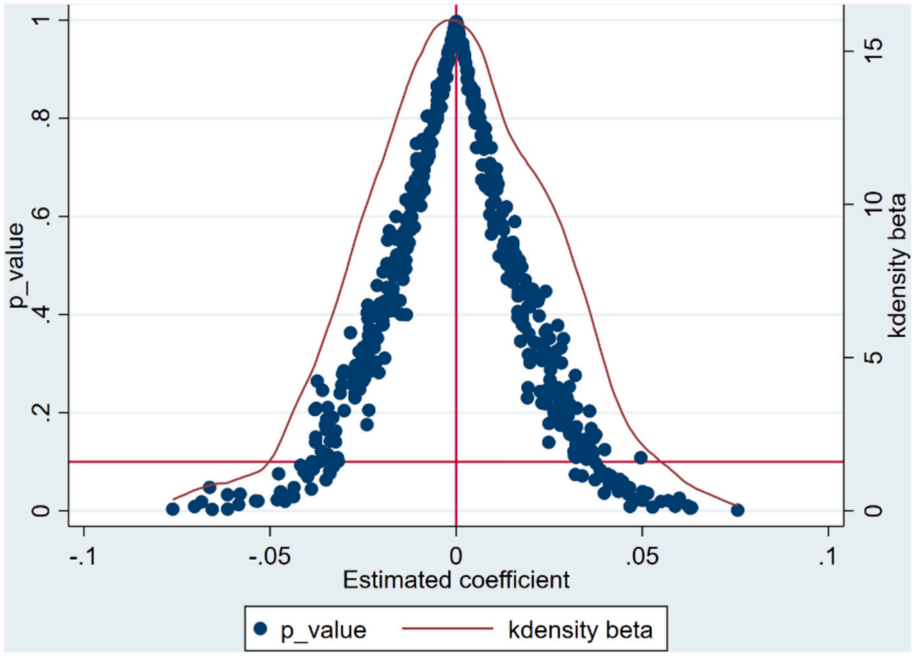

Fig. 4. Placebo test.

values of the vast majority of the regression results are greater than the p-value of the baseline regression, which is 0.1, as indicated by the horizontal line in Fig. 4. The fact that most points are above the horizontal line means that the DID results based on random sampling are not significant, which precisely proves that the previous results are robust. Therefore, the probability that the empirical results are influenced by random factors is low, indicating that the results of this test are reliable.

4.5. Mechanism analysis

The empirical analysis presented above demonstrates that the initiation of GFIRPZ has promoted employment in China's manufacturing sector. To further explore the pathway mechanisms behind this effect, this paper conducts a mechanism analysis from the perspective of financing constraints (FC). The mechanism through which GF promotes employment in manufacturing by reducing FC can be understood in several ways. GF policies typically include low-interest loans or other financial support for projects that meet environmental standards (Taghizadeh-Hesary and Yoshino, 2020). These policies make it easier for manufacturing enterprises to obtain the funds necessary for expansion and investment. With reduced financing costs, enterprises can increase investment in green technologies, equipment, and production processes (Gong et al., 2020). This investment can increase production efficiency and product quality, enhancing output and market competitiveness. Funds obtained through GF can be used to expand production lines, establish new factories, or upgrade existing facilities (Zhang and Zhao, 2024). This business expansion can directly create more job opportunities to meet production needs. GF incentivizes enterprises to adopt new technologies and processes, thereby promoting technological innovation (Sethi et al., 2024). These innovations can boost productivity, lower production costs, and foster long-term growth and employment opportunities. GF also helps enterprises improve their environmental and social responsibility image, thereby enhancing brand value and market competitiveness (Han, 2024). Enhanced competitiveness can lead to more orders and sales, further promoting business expansion and employment growth (Ogunyemi, 2020).

For instance, a manufacturing enterprise can use funds obtained through GF to purchase energy-saving equipment and improve production processes (Jin et al., 2021). These investments reduce energy consumption and production costs, increasing production efficiency. As production capacity improves, the enterprise can expand its scale and add product lines, necessitating the hiring of more workers to meet growing production demands. Due to the improvement in technologies and processes, the enterprise's market competitiveness is enhanced, further boosting sales growth and employment.

To verify whether GF policies can influence manufacturing employment through FC, this study uses the FC index from the CSMAR database to measure FC faced by the enterprises and specifies the following model:

$$FC_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_2 \sum Controls_{it} + \gamma_t + \delta_i + \lambda_r + \mu_s + \varepsilon_{it} \tag{2}$$

$$EM_{it} = \alpha_0 + \alpha_3 DID_{it} + \alpha_4 FC_{it} + \alpha_5 \sum Controls_{it} + \gamma_t + \delta_i + \lambda_r + \mu_s + \varepsilon_{it} \tag{3}$$

where FC represents the financing constraints faced by the enterprises. According to these equations, and following Tao et al. (2023), this study adheres to two steps. First, it examines the correlation between enterprises' FC and GFIRPZ. Second, it investigates the correlation between enterprises' FC and employment in the manufacturing sector. If α_1 is statistically significant, it indicates that the GFIRPZ has a certain impact on enterprises' FC. Similarly, if α_4 is significant, it can be concluded that the GFIRPZ policy promotes manufacturing employment by reducing enterprises' FC.

Table 5 presents the mediating effect of FC on enterprise employment outcomes. Column (5) in Table 2 shows the results of the baseline regression, while Column (1) of Table 5 represents the impact of GF policies on the FC of listed manufacturing enterprises in China. The DID coefficient in Column (1) of Table 5 is −0.0370, and it is significant at the 5 % level. This means that the introduction of GF policies significantly reduces the FC of manufacturing enterprises. Furthermore, The FC coefficient in Column (2) is −0.1494 and is significant at the 5 % level, indicating that GF policies can improve the employment of manufacturing enterprises by alleviating their FC.

In summary, GF policies can reduce FC, alleviate financial pressures on enterprises, and promote technological innovation and investment. This, in turn, stimulates the expansion and growth of the manufacturing sector, thereby increasing employment in manufacturing enterprises.

Table 5
Mechanism analysis results.

	(1)	(2)
Variables	*FC*	*Em*
DID	−0.0370**	0.1000**
	(0.0165)	(0.0482)
FC		−0.1494**
		(0.0722)
Control variables	√	√
Constant	4.6125***	−5.3401***
	(0.2247)	(0.9292)
Firm FE	√	√
Time FE	√	√
Industry FE	√	√
Province FE	√	√
Observations	3066	3066
R-squared	0.6022	0.5938
Number of id	331	331

Notes: Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$; the control variables include *Size, Age, ROE, Lev, Tobin, OC, and FAR*.

4.6. Heterogeneity analysis

Considering the heterogeneity of different types of enterprises in response to GF policies, in this section we examine the possible heterogeneity of factors affecting the employment promotion impact of GF policies, by considering separate results for relevant sub-samples. The results are shown in Table 6. Specifically, this study divides the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs), heavy-polluting and non-heavy-polluting industries, and high-tech and non-high-tech industries. This segmentation allows us to capture the varying impacts of GF policies on different categories of firms, each with unique characteristics and challenges. The results of these sub-sample analyses are presented in Table 6 and discussed in Subsections 4.6.1 to 4.6.3. This approach provides a nuanced understanding of how GF policies influence employment across diverse sectors of the manufacturing industry.

4.6.1. SOEs and non-SOEs

From the perspective of enterprise ownership, manufacturing enterprises are divided into SOEs and non-SOEs. Columns (1) and (2) in Table 6 respectively show the impact of GF policies on employment in non-SOEs and SOEs manufacturing enterprises. These results show that GF significantly increases employment in non-SOEs manufacturing enterprises, but its impact on employment in state-owned manufacturing enterprises is not significant.

Several factors may explain these results. First, this may be because non-SOEs are typically more flexible and efficient in financing, allowing them to quickly leverage funds provided by GF policies for expansion and innovation (Zeng et al., 2023). In contrast, SOEs have more complex decision-making processes and lower financing efficiency, making it difficult for them to swiftly utilize GF funds for effective investment. Second, non-SOEs are usually more market-driven, with stronger profit motives and growth pressures, making them more proactive in seeking support from GF policies to achieve expansion and employment growth. SOEs, on the other hand, may be constrained by government policies and administrative directives, resulting in weaker market-driven motives and profitability pressures (Yu et al., 2023). Third, GF policies may offer more policy incentives and support to non-SOEs, helping them reduce financing costs and compliance expenses. Conversely, SOEs may not be as flexible in enjoying these policy incentives, and their compliance costs could be higher, preventing them from fully capitalizing on GF opportunities. Fourth, non-SOEs may have better governance structures and management efficiency than SOEs, enabling them to utilize resources and opportunities brought by GF policies more effectively, quickly respond to changes, and make adjustments. In contrast, the management efficiency and governance structures of SOEs may be more rigid, limiting their ability to take advantage of GF policies.

4.6.2. Heavy-polluting and non-heavy-polluting industries

According to the notice issued by the Ministry of Ecology and Environment of China on the "Listed Company's Environmental Protection Industry Classification Management Directory," and following Lin et al. (2021), industries such as coal mining are defined as heavy-polluting industries. Based on the "Industry Classification Guidelines for Listed Companies," revised by the China Securities Regulatory Commission in 2012, heavy-polluting industries within the manufacturing sector include petroleum processing, coking, nuclear fuel processing, chemical raw materials, chemical products, and others. Columns (3) and (4) in Table 6 respectively show the impact of GF policies on employment in heavy-polluting and non-heavy-polluting manufacturing enterprises.

The results show that GF policies can significantly increase employment in non-heavy-polluting industries, but their impact on employment in heavy-polluting industries is not significant. This may be because non-heavy-polluting industries face less pressure in terms of environmental and policy compliance, making it easier for them to meet the requirements of GF policies (Wang et al., 2023). This enables non-heavy-polluting enterprises to obtain GF funds more quickly, which can be used to expand production and increase employment. In contrast, heavy-polluting industries may encounter higher environmental renovation costs and technical bottlenecks, making it difficult for them to quickly comply with GF policy standards and effectively utilize GF policy support (Peng et al., 2022). Furthermore, non-heavy-polluting industries typically possess strong market adaptability and competitiveness. They can leverage GF funds for technological upgrades and product innovation, improving production efficiency and market share,

Table 6
Heterogeneity analysis results.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*Em* Non-SOEs	*Em* SOEs	*Em* Heavy-polluting	*Em* Non-heavy-polluting industries	*Em* High-tech industries	*Em* Non-high-tech industries
DID	0.1013**	−0.0444	−0.0196	0.1141**	0.1374**	0.1071
	(0.0473)	(0.1548)	(0.0682)	(0.0544)	(0.0578)	(0.0819)
Control variables	√	√	√	√	√	√
Constant	−6.4503***	−3.6011	−5.1664***	−6.7328***	−6.8921***	−5.0231***
	(0.9289)	(2.2950)	(1.2580)	(0.9972)	(0.8956)	(1.5610)
Firm FE	√	√	√	√	√	√
Time FE	√	√	√	√	√	√
Industry FE	√	√	√	√	√	√
Province FE	√	√	√	√	√	√
Observations	2896	217	751	2343	2502	592
R-squared	0.6073	0.5763	0.5173	0.6041	0.6039	0.4795
Number of id	329	61	87	256	270	69

Notes: Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$; the control variables include *Size, Age, ROE, Lev, Tobin, OC, and FAR*.

which leads to more employment opportunities. Conversely, heavy-polluting industries may face greater challenges in environmental renovation and technological upgrades, with relatively weaker market adaptability and competitiveness, making it difficult for them to achieve significant employment growth through GF policies. Lastly, heavy-polluting industries might encounter more regulations and restrictions during the implementation of policies, resulting in higher financing and compliance costs (Tu et al., 2020). These additional costs may offset some of the benefits brought by GF policies, making it difficult for heavy-polluting enterprises to achieve significant employment growth. On the other hand, non-heavy-polluting industries can better utilize policy incentives and financial support to reduce financing costs and operational pressures, thereby achieving employment growth.

4.6.3. High-tech and non-high-tech industries

By referencing the "Strategic Emerging Industries Classification Catalogue," "Strategic Emerging Industries Classification (2012, Trial)," and relevant the Organization for Economic Co-operation and Development (OECD) documents, and comparing them with the "Industry Classification Guidelines for Listed Companies," listed enterprises in the high-tech industry are identified. High-tech industries within the manufacturing sector primarily include pharmaceutical manufacturing, chemical fiber manufacturing, and general equipment manufacturing. Columns (5) and (6) in Table 6 respectively show the impact of GF policies on employment in high-tech and non-high-tech manufacturing enterprises.

The results show that GF policies significantly increase employment in high-tech manufacturing enterprises, but have no significant impact on employment in non-high-tech manufacturing enterprises (Pan et al., 2022). A key reason that could explain these results is the strong capability and demand for innovation and continuous technological upgrading in high-tech manufacturing enterprises. GF policies provide these enterprises with financial support, enabling them to more easily invest in new technologies and equipment, thereby improving production efficiency and product competitiveness. This technological innovation and upgrading lead to more employment opportunities, as enterprises require additional highly skilled employees to develop and manage these new technologies. A second reason is that high-tech manufacturing enterprises typically possess strong market adaptability and flexibility. They can quickly respond to changes in market demand and utilize the opportunities brought by GF policies to expand and diversify production. Therefore, these enterprises are more likely to create employment opportunities by increasing production capacity and expanding into new markets. In contrast, non-high-tech manufacturing enterprises may be relatively weaker in technological innovation and market adaptability. Their production processes and products are more traditional, making it more difficult for them to fully leverage the funds provided by GF policies for innovation and upgrading. Additionally, GF policies usually have high requirements for environmental protection and sustainable development. High-tech manufacturing enterprises, due to their technological advantages, are more likely to meet these requirements, thus obtaining GF policy support and funding. On the other hand, non-high-tech manufacturing enterprises typically face more challenges and costs in environmental protection, making it difficult for them to receive the same level of policy support, which limits their potential for employment growth.

5. Conclusion and implications

As global climate change and related environmental issues become increasingly severe, countries around the world are taking measures to promote the development of a green economy. As a crucial means to this end, green finance (GF) policies provide financial support and incentives to encourage investments in green environmental technologies and sustainable development. The establishment of China's green finance innovation and reform pilot zones (GFIRPZ) is significant for building a GF system, promoting orderly GF development, and contributing toward achieving China's carbon reduction goals. GFIRPZ in Zhejiang, Jiangxi, Guangdong, Guizhou, and other regions are tasked with exploring and advancing the construction of the GF system. At the same time, China's manufacturing sector plays a vital role in economic development and employment in the world's largest manufacturing nation. The implementation of GF policies not only has a positive impact on environmental protection and resource utilization efficiency, but also profoundly affects the production methods, technological upgrades, and cost structures of manufacturing enterprises, thereby having direct and indirect effects on employment.

Against this backdrop, this study employs the difference-in-differences (DID) model to investigate the impact of the establishment of innovation zones on manufacturing employment. The results show that the establishment of GFIRPZ significantly increases employment in the manufacturing sector. The DID coefficient of 0.1016 is significant at the 5 % level, indicating that the establishment of GFIRPZ led to an approximate 10.16 % increase in manufacturing employment in pilot zones compared to non-pilot areas. Furthermore, the creation of these zones can improve manufacturing employment by reducing financing constraints (FC). The results also show the establishment of GFIRPZ primarily enhances employment in non-state-owned manufacturing enterprises, non-heavy-polluting manufacturing enterprises, and high-tech manufacturing enterprises.

This study makes several research contributions. First, while previous research has primarily focused on the indicators and evaluation of GF levels, few scholars have studied the impact of GF on employment. From a micro perspective, this study focuses on the impact of GF policies on employment in manufacturing enterprises, thus filling a research gap in this field. Second, this study employs the DID model to examine the impact of GF policies on employment in manufacturing enterprises. This approach effectively controls for time effects and individual effects, reducing the influence of confounding variables and improving the accuracy of the estimates.

The empirical results also provide valuable insights for policymakers. First, the findings support the vigorous promotion of the GF system in China and offer experiential evidence for the long-term construction of GFIRPZ. By understanding the impact of GF policies on employment, policymakers can be assured that these policies not only aid environmental protection, but also promote economic growth and employment. Second, our results reveal the differential impact of GF policies on employment across various types of manufacturing enterprises, continuously driving the precise implementation of GF-related policies and enabling differentiated and targeted policies for different types of enterprises.

This study also has several limitations. First, this study only examines the impact of the establishment of GF policy zones on employment in the manufacturing sector and did not investigate the specific measures taken by various regions in their subsequent participation in GF construction and their effects on employment. Second, this study's perspective is limited to the manufacturing sector, without a focus on the policies and measures of GF participation in other industries, which introduces a certain degree of limitation to the study. Additionally, the data in this study are constrained by time and sample size. Both GF construction and employment issues are part of the country's long-term development strategy. The relationship between the construction of a GF policy system and employment requires further in-depth research, as relevant data are continuously being accumulated and refined.

CRediT authorship contribution statement

Bowen Fu: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Visualization, Writing – review & editing, Investigation. **Yixiang Zhang:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Funding acquisition. **Sholeh Maani:** Writing – review & editing, Validation,

Supervision, Resources, Funding acquisition, Conceptualization. **Le Wen:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization, Investigation.

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Appendix A. Supplementary data

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References

Abadie, A., 2005. Semiparametric difference-in-differences estimators. Rev. Econ. Stud. 72, 1–19.
Acemoglu, D., Autor, D., 2011. Chapter 12 - skills, tasks and technologies: Implications for employment and earnings. In: Card, D., Ashenfelter, O. (Eds.), Handbook of Labor Economics. Elsevier, pp. 1043–1171.
Agrawal, R., Agrawal, S., Samadhiya, A., Kumar, A., Luthra, S., Jain, V., 2024. Adoption of green finance and green innovation for achieving circularity: an exploratory review and future directions. Geosci. Front. 15, 101669.
Antal, M., 2014. Green goals and full employment: are they compatible? Ecol. Econ. 107, 276–286.
Battaglini, F., 2024. Will the European green Deal enhance Europe's security towards Russia? A political economy perspective. Energy Econ. 134, 107551.
Bowen, A., 2012. 'Green' Growth, 'Green' Jobs and Labor Markets. World Bank Policy Research Working Paper.
Cai, F., Wang, M., 2010. Growth and structural changes in employment in transition China. J. Comp. Econ. 38, 71–81.
Card, D., Krueger, A., 1994. Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania. Am. Econ. Rev. 84, 772–793.
Cerqua, A., Letta, M., 2020. Local Economies Amidst the COVID-19 Crisis in Italy: A Tale of Diverging Trajectories. University Library of Munich, Germany.
Chen, D., Hu, H., Wang, N., Chang, C.-P., 2024. The impact of green finance on transformation to green energy: evidence from industrial enterprises in China. Technol. Forecast. Soc. Change. 204, 123411.
Chetty, R., Looney, A., Kroft, K., 2009. Salience and taxation: theory and evidence. Am. Econ. Rev. 99, 1145–1177.
Dong, F., Li, Y., Qin, C., Zhang, X., Chen, Y., Zhao, X., Wang, C., 2022a. Information infrastructure and greenhouse gas emission performance in urban China: a difference-in-differences analysis. J. Environ. Manag. 316, 115252.
Dong, Z., Xu, H., Zhang, Z., Lyu, Y., Lu, Y., Duan, H., 2022b. Whether green finance improves green innovation of listed companies—evidence from China. Int. J. Environ. Res. Public Health 19, 10882.
Du, M., Zhang, R., Chai, S., Li, Q., Sun, R., Chu, W., 2022. Can green finance policies stimulate technological innovation and financial performance? Evidence from Chinese listed green enterprises. Sustainability 14, 9287.
Fan, S., Shahbaz, M., 2023. Chapter 10 - carbon neutrality and green finance. In: Shahbaz, M., Dong, K., Balsalobre-Lorente, D., Gedikli, A. (Eds.), Recent Developments in Green Finance, Green Growth and Carbon Neutrality. Elsevier, pp. 217–238.
Force, G.F.T., 2015. Establishing China's Green Financial System. People's Bank of China & United Nations Environment Programme, Beijing, China.
Ge, Y., Zhi, Q., 2016. Literature review: the green economy, clean energy policy and employment. Energy Procedia 88, 257–264.
Gong, R., Wu, Y.-Q., Chen, F.-W., Yan, T.-H., 2020. Labor costs, market environment and green technological innovation: evidence from high-pollution firms. Int. J. Environ. Res. Public Health 17, 522.
Group, G.G.F.S, 2016. G20 Green Finance Synthesis Report.
Guo, Q., Zhong, J., 2022. The effect of urban innovation performance of smart city construction policies: evaluate by using a multiple period difference-in-differences model. Technol. Forecast. Soc. Change. 184, 122003.
Hampton, S., 2018. 'It's the soft stuff that's hard': investigating the role played by low carbon small- and medium-sized enterprise advisors in sustainability transitions. Local Econ. 33, 384–404.
Han, B., 2024. Fostering sustainability: integrating social responsibility, green finance, and corporate performance. Econ. Chang. Restruct. 57, 64.
Hilson, G., Nayee, V., 2002. Environmental management system implementation in the mining industry: a key to achieving cleaner production. Int. J. Miner. Process. 64, 19–41.
Jiang, P., Jiang, H., 2023. Green finance policy and labor demand. Econ. Lett. 225, 111065.
Jin, Y., Gao, X., Wang, M., 2021. The financing efficiency of listed energy conservation and environmental protection firms: evidence and implications for green finance in China. Energy Policy 153, 112254.
Laroche, M., Bergeron, J., Barbaro-Forleo, G., 2001. Targeting consumers who are willing to pay more for environmentally friendly products. J. Consum. Mark. 18, 503–520.
Lee, J.W., 2020. Green finance and sustainable development goals: the case of China. J. Asian Finance Econ. Bus. 7, 577–586.
Lee, C.-C., Lee, C.-C., 2022. How does green finance affect green total factor productivity? Evidence from China. Energy Econ. 107, 105863.
Lee, C.-C., Li, J., Wang, F., 2024. The role of green finance in the construction of new energy system: evidence from China. Energy Econ. 139, 107878.
Li, H., Graham, D.J., Majumdar, A., 2012. The effects of congestion charging on road traffic casualties: a causal analysis using difference-in-difference estimation. Accid. Anal. Prev. 49, 366–377.
Li, G., Wang, X., Su, S., Su, Y., 2019. How green technological innovation ability influences enterprise competitiveness. Technol. Soc. 59, 101136.
Lin, Y., Huang, R., Yao, X., 2021. Air pollution and environmental information disclosure: an empirical study based on heavy polluting industries. J. Clean. Prod. 278, 124313.
Lindenberg, N., 2014. Definition of Green Finance.
Liu, S., Wang, Y., 2023. Green innovation effect of pilot zones for green finance reform: evidence of quasi natural experiment. Technol. Forecast. Soc. Change. 186, 122079.
Lv, C., Bian, B., Lee, C.-C., He, Z., 2021. Regional gap and the trend of green finance development in China. Energy Econ. 102, 105476.
Migliorelli, M., Dessertine, P., 2019. The rise of green finance in Europe. In: Opportun. Chall. Issuers, Invest. Mark, 2. Palgrave Macmillan, Cham, p. 2019.
Minhas, A.S., Maqsood, N., Shahid, T.A., Rehman, A.U., 2024. Investment performance in green finance: assessing the impact of environmental social and governance integration. iRASD J. Econ. 6, 27–44.
Ogunyemi, A.O., 2020. Competitive strategies to improve small and medium enterprise sales. Walden University, United States, Minnesota, p. 223.
Owen, R., Brennan, G., Lyon, F., 2018. Enabling investment for the transition to a low carbon economy: government policy to finance early stage green innovation. Curr. Opin. Environ. Sustain. 31, 137–145.
Ozili, P.K., 2021. Digital finance, green finance and social finance: is there a link? Financ. Internet Q. 17, 1–7.
Ozili, P.K., 2022. Green finance research around the world: a review of literature. Int. J. Green Econ. 16, 56–75.
Pal, S.C., Chatterjee, U., Chakrabortty, R., Roy, P., Chowdhuri, I., Saha, A., Towfiqul Islam, A.R.M., Alam, E., Islam, M.K., 2023. Anthropogenic drivers induced desertification under changing climate: issues, policy interventions, and the way forward. Prog. Disast. Sci. 20, 100303.
Pan, K., He, F., Liu, R., 2022. Does high-tech industry agglomeration promote its export product upgrading? Based on the perspective of innovation and openness. Sustainability 14, 8148.
Pauer, S.U., 2018. Including electricity imports in California's cap-and-trade program: a case study of a border carbon adjustment in practice. Electr. J. 31, 39–45.
Pearce, D., Markandya, A., Barbier, E., 2013. Blueprint 1: For a Green Economy. Routledge.
Peng, B., Yan, W., Elahi, E., Wan, A., 2022. Does the green credit policy affect the scale of corporate debt financing? Evidence from listed companies in heavy pollution industries in China. Environ. Sci. Pollut. Res. 29, 755–767.
Qu, C., Shao, J., Cheng, Z., 2020. Can embedding in global value chain drive green growth in China's manufacturing industry? J. Clean. Prod. 268, 121962.
Rockers, P.C., Røttingen, J.-A., Shemilt, I., Tugwell, P., Bärnighausen, T., 2015. Inclusion of quasi-experimental studies in systematic reviews of health systems research. Health Policy 119, 511–521.
Roth, J., Sant'Anna, P.H.C., Bilinski, A., Poe, J., 2023. What's trending in difference-in-differences? A synthesis of the recent econometrics literature. J. Econ. 235, 2218–2244.
Saleem, H., Khan, M.B., Mahdavian, S.M., 2022. The role of green growth, green financing, and eco-friendly technology in achieving environmental quality: evidence from selected Asian economies. Environ. Sci. Pollut. Res. 29, 57720–57739.
Sartzetakis, E.S., 2021. Green bonds as an instrument to finance low carbon transition. Econ. Chang. Restruct. 54, 755–779.
Sethi, L., Behera, B., Sethi, N., 2024. Do green finance, green technology innovation, and institutional quality help achieve environmental sustainability? Evidence from the developing economies. Sustain. Dev. 32, 2709–2723.
Shi, J., Yu, C., Li, Y., Wang, T., 2022. Does green financial policy affect debt-financing cost of heavy-polluting enterprises? An empirical evidence based on Chinese pilot zones for green finance reform and innovations. Technol. Forecast. Soc. Change. 179, 121678.
Soundarrajan, P., Vivek, N., 2016. Green finance for sustainable green economic growth in India. Agric. Econ. 62, 35.
Su, D., Yao, Y., 2017. Manufacturing as the key engine of economic growth for middle-income economies. J. Asia Pac. Econ. 22, 47–70.
Taghizadeh-Hesary, F., Yoshino, N., 2020. Sustainable solutions for green financing and investment in renewable energy projects. Energies 13, 788.
Tao, M., Dagestani, A.A., Goh, L.T., Zheng, Y., Le, W., 2023. Do China's anti-corruption efforts improve corporate productivity? A difference-in-difference exploration of Chinese listed enterprises. Socio-Econ. Plan. Sci. 87, 101594.
Tu, W.-J., Yue, X.-G., Liu, W., Crabbe, M.J.C., 2020. Valuation impacts of environmental protection taxes and regulatory costs in heavy-polluting industries. Int. J. Environ. Res. Public Health 17, 2070.
Wang, X., Wang, Q., 2021. Research on the impact of green finance on the upgrading of China's regional industrial structure from the perspective of sustainable development. Res. Policy 74, 102436.

Wang, Y., Zhi, Q., 2016. The role of green finance in environmental protection: two aspects of market mechanism and policies. Energy Procedia 104, 311–316.
Wang, L., Qiu, X., Zhang, X., Ma, R., Jiang, Y., 2019. Development status and environmental impact evaluation of China's green finance. Appl. Ecol. Environ. Res. 17.
Wang, K.-H., Zhao, Y.-X., Jiang, C.-F., Li, Z.-Z., 2022a. Does green finance inspire sustainable development? Evidence from a global perspective. Econ. Anal. Policy 75, 412–426.
Wang, Q.-J., Wang, H.-J., Chang, C.-P., 2022b. Environmental performance, green finance and green innovation: What's the long-run relationships among variables? Energy Econ. 110, 106004.
Wang, X., Sun, X., Zhang, H., Xue, C., 2022c. Does green financial reform pilot policy promote green technology innovation? Empirical evidence from China. Environ. Sci. Pollut. Res. 29, 77283–77299.
Wang, L., Chen, C., Zhu, B., 2023. Earnings pressure, external supervision, and corporate environmental protection investment: comparison between heavy-polluting and non-heavy-polluting industries. J. Clean. Prod. 385, 135648.
Wen, S., Liu, H., 2022. Research on energy conservation and carbon emission reduction effects and mechanism: quasi-experimental evidence from China. Energy Policy 169, 113180.
Wing, C., Simon, K., Bello-Gomez, R.A., 2018. Designing difference in difference studies: best practices for public health policy research. Annu. Rev. Public Health 39, 453–469.
Xie, Y., Jiang, J., Wang, D., 2024. Green finance policy and labor demand: evidence from China. Pac. Basin Financ. J. 86, 102434.
Yin, X., Xu, Z., 2022. An empirical analysis of the coupling and coordinative development of China's green finance and economic growth. Res. Policy 75, 102476.
Yu, Y., Zhang, N., 2022. Does industrial transfer policy mitigate carbon emissions? Evidence from a quasi-natural experiment in China. J. Environ. Manag. 307, 114526.
Yu, H., Zhao, Y., Qiao, G., Ahmad, M., 2023. Can green financial reform policies promote enterprise development? Empirical evidence from China. Sustainability 15, 2692.
Yue, H., Zhou, Z., Liu, H., 2024. How does green finance influence industrial green total factor productivity? Empirical research from China. Energy Rep. 11, 914–924.
Zeng, S., Hu, J., Gu, F., Carlos, L.-A., 2023. Financial information, green certification, government subsidies and green bond credit spreads–evidence from China. Int. Entrep. Manag. J. 19, 321–341.
Zhang, Y., Fu, B., 2023. Impact of China's establishment of ecological civilization pilot zones on carbon dioxide emissions. J. Environ. Manag. 325, 116652.
Zhang, C., Liang, Q., 2023. Natural resources and sustainable financial development: evidence from South Asian economies. Res. Policy 80, 103282.
Zhang, K.-M., Wen, Z.-G., 2008. Review and challenges of policies of environmental protection and sustainable development in China. J. Environ. Manag. 88, 1249–1261.
Zhang, W., Zhao, D., 2024. Industry analysis in the context of the green finance development in China. In: Zhang, W., Zhao, D. (Eds.), Green Finance in China: Policies, Experiences and Challenges. Springer Nature Singapore, Singapore, pp. 95–121.
Zhang, S., Wu, Z., Wang, Y., Hao, Y., 2021. Fostering green development with green finance: an empirical study on the environmental effect of green credit policy in China. J. Environ. Manag. 296, 113159.
Zhang, C., Cheng, X., Ma, Y., 2022a. Research on the impact of green finance policy on regional green innovation-based on evidence from the pilot zones for green finance reform and innovation. Front. Environ. Sci. 10.
Zhang, X.-M., Lu, F.-F., Xue, D., 2022b. Does China's carbon emission trading policy improve regional energy efficiency?—an analysis based on quasi-experimental and policy spillover effects. Environ. Sci. Pollut. Res. 29, 21166–21183.
Zhang, Z., Wang, J., Feng, C., Chen, X., 2023. Do pilot zones for green finance reform and innovation promote energy savings? Evidence from China. Energy Econ. 124, 106763.
Zhou, T., Zhang, N., 2022. Does high-speed rail make firms cleaner in China? J. Environ. Manag. 311, 114901.
Zhou, X., Tang, X., Zhang, R., 2020. Impact of green finance on economic development and environmental quality: a study based on provincial panel data from China. Environ. Sci. Pollut. Res. 27, 19915–19932.