Bank Affiliation and Mutual Funds' Green Investments

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Abstract

This study investigates how bank affiliation shapes mutual fund investment strategies in response to environmental finance policies. Using the introduction of China's 2016 green finance policy as a quasi-natural experiment, we find that bank-affiliated funds significantly increased investments in portfolio companies' green innovation and reduced their carbon and pollutant emissions. Two complementary mechanisms drive these results: a capital support channel, where parent banks provided leveraged financing to greener affiliated funds, and an information advantage channel, where affiliated funds leveraged proprietary bank information to identify credible green firms. These effects are strengthened under greater regulatory pressure, stricter environmental enforcement, and heightened public scrutiny, and are rewarded by institutional investors through capital inflows. Our results illuminate bank affiliation's role in driving ESG investment and its mechanisms in shaping fund performance and environmental outcomes.

Keywords: Commercial bank affiliation; Green finance shock; Information advantage; Green technology innovation investment

JEL Classification: G20; G21; G23

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1 Introduction

Whether financial intermediary can genuinely affect real capital reallocation toward environmental goals remains a central and unresolved question (see Edmans et al., 2022; Gibson Brandon et al., 2022; Heath et al., 2023). Most existing studies focus on firm-level effects or public capital markets, examining how green credit policies influence corporate financing, innovation, or valuation. However, far less attention has been paid to the role of institutional investors—particularly bank-affiliated funds—that bridge the banking and capital markets. While recent research investigates banks' loan issuance decisions to green versus brown firms (Houston and Shan, 2022; Kacperczyk and Peydró, 2022; Ivanov et al., 2024; Giannetti et al., 2026), little is known about how these affiliated asset managers internalize green regulatory incentives and reallocate portfolios in response to policy shocks.

Trillions of dollars have been allocated to investment strategies that adhere to environmental, social and governance (ESG) principles, profoundly reshaping global capital allocation. A central and unresolved question in financial economics, however, is whether this capital shift is merely "cheap talk" or if it generates tangible "real effects" (Gibson Brandon et al., 2022). Although some evidence indicates that investors value sustainability (Hartzmark and Sussman, 2019), critics contend that many ESG funds fail to meaningfully influence corporate behavior, citing pervasive greenwashing and an emphasis on disclosure rather than substantive change (Christensen et al., 2022; Kim and Yoon, 2023). We posit that the resolution to this debate hinges critically on the incentives and organizational structure of the financial intermediary that directs the capital. This paper investigates a particularly influential, yet underexplored type of intermediary—the bank-affiliated funds.

Bank-affiliated funds manage approximately 40 percent of mutual fund assets worldwide, highlighting their systemic importance in global capital markets (Ferreira et al., 2018). In bank-dominated financial systems like China, their influence is even more profound. However, bank affiliation constitutes a double-edged sword. On the one hand, bank affiliation presents

a "bright side" of potential synergies. Funds may benefit from the parent bank's proprietary information regarding corporate environmental risks, receive direct capital support to pursue long-term green projects, and face stronger monitoring incentives stemming from the bank's reputational concerns. On the other hand, a pervasive "dark side" perspective in the literature emphasizes deep-rooted conflicts of interest. In this view, banks might pressure their affiliated funds to provide support to distressed borrowers or to allocate capital based on banking relationships rather than environmental merits, resulting in capital misallocation (Gaspar et al., 2006). Therefore, a central question is whether bank affiliation serves as a catalyst for or a barrier to achieving tangible environmental progress.

To disentangle these competing views, we exploit China's institutional feature and a landmark regulatory reform that creates a near-ideal empirical laboratory. A key institutional feature is a strict separation of functions: while commercial banks dominate corporate lending, they are prohibited from direct equity holdings in corporations. Consequently, a bank-driven equity market strategy must be implemented through a separate legal entity, rendering their affiliated funds a uniquely identifiable channel for transmitting bank-level incentives. We analyze the impact of the 2016 Green Finance Guidelines, which introduced a plausibly exogenous shock by integrating banks' green credit performance directly into the People's Bank of China's Macro Prudential Assessment (MPA) framework. This reform created powerful and binding incentives for banks to improve their green credentials to secure better access to central bank liquidity and more favorable regulatory treatment, pressures not directly faced by unaffiliated funds.

We employ a difference-in-differences (DID) regression, comparing the behavior of bank-affiliated funds against that of their unaffiliated counterparts, before and after the 2016 reform. Our analysis yields a clear verdict: bank affiliation served as a potent transmission channel for the green finance policy. Following the policy shock, portfolio firms of bank-affiliated funds exhibit significantly stronger real outcomes—demonstrating a marked increase in green patent output and a sharp reduction in carbon emissions and pollutant

discharges—relative to firms held by unaffiliated funds. The economic magnitude of these effects is substantial; for example, we observe a reduction in carbon emissions of up to 9 percent relative to the sample mean. This effect is particularly pronounced among firms with greater innovative capacity.

We next provide two key mechanism tests that illuminate the "black box" of bank-fund affiliation. First, we provide direct evidence of a capital support channel. We find that after the reform, parent banks strategically allocated capital toward their greener affiliated funds, which received significantly more leverage and experienced dramatically faster asset growth. This finding demonstrates the activation of the banking group's internal capital market, which empowered those funds best positioned to fulfill the new regulatory mandate. Second, we pinpoint the specific setting where this synergistic effect is most potent. Using a novel firm-level analysis, we show that the improvements in green innovation are overwhelmingly concentrated in firms that are simultaneously loan clients of the parent bank and equity holdings of the affiliated fund. This powerful synergistic effect, which manifests exclusively where credit and equity ties overlap, underscores the importance of information sharing and coordinated financing.

This paper makes three distinct contributions to the literature. First, we challenge and revise the prevailing view of bank affiliation. Extant literature, drawing primarily on evidence from developed markets, largely casts such affiliation through a lens of agency conflicts and value destruction (Gaspar et al., 2006). We demonstrate that in the context of a bank-dominated emerging economy, affiliation can serve as a powerful mechanism for positive change. By showing that regulatory incentives can align the interests of banks and their affiliated funds with desirable social outcomes, we establish the "bright side" of affiliation as a potent channel for policy transmission and real environmental improvement.

Second, we contribute to the literature on the "real effects" of ESG investing by providing causal evidence on the underlying mechanisms. Whereas prior work has largely focused on portfolio tilts or the pricing of climate risk in financial markets (Pástor et al., 2022), we trace

a specific policy shock to verifiable changes in corporate conduct—namely, heightened green innovation and reduced pollution. More importantly, by elucidating the internal capital support channel and the synergistic information advantage inherent in overlapping bank-fund relationships, we open the "black box" of how financial intermediaries transmute policy signals into tangible corporate outcomes.

Third, our findings offer salient policy implications for emerging markets confronting the dual challenges of fostering financial development and facilitating a climate transition. The Chinese experience illustrates that integrating environmental criteria into prudential banking regulation, as exemplified by the MPA framework, can transform it into a powerful, dual-purpose instrument. By embedding environmental objectives within the supervisory system that governs the economy's primary capital allocators, policymakers can effectively steer private capital toward national green objectives without resorting to blunt subsidies or mandates. This provides a scalable model for how other bank-centric economies can leverage their existing financial architecture to accelerate decarbonization.

The remainder of this paper is structured as follows. Section 2 outlines the institutional background and develops the testable hypotheses. Section 3 describes the sample, variable construction, and summary statistics. Section 4 presents the main results and explores the underlying mechanisms. Section 5 conducts the heterogeneity analysis and robustness checks. Section 6 concludes.

2 Institutional Background and Hypothesis Development

China's bank-dominated financial system, combined with the embedding of environmental objectives into prudential supervision, creates a rare opportunity to study how financial intermediaries transmit regulatory incentives into real sustainability outcomes. Given that commercial banks constitute the primary source of external finance, policies that effectively reshape their lending and investment behavior are poised to generate system-wide effects.

The Macro Prudential Assessment (MPA) and the Guiding Opinions on Building a Green Financial System, issued in September 2016, directly linked banks' prudential standing and reputational capital to their green performance. Since Chinese banks are prohibited from direct equity holdings, their affiliated funds emerged as the natural conduit for transmitting these newly aligned incentives into the equity market. This section synthesizes the theoretical perspectives on bank affiliation, analyzes how the aforementioned institutional features reconfigure the benefits and costs of such affiliation, and finally derives testable hypotheses pertaining to corporate green innovation, environmental performance, and financing costs.

2.1 China's Bank-Dominated Financial System and the Macro Prudential Assessment (MPA) Framework

The Chinese financial system is predominantly bank-based, with commercial banks providing the overwhelming share of external financing to corporations (Allen et al., 2005; Cull and Xu, 2005; Berger et al., 2007). Unlike developed economies where capital markets—equity and bond markets—serve as primary capital allocation mechanisms, bank-mediated indirect financing constitutes the core of China's financial infrastructure. This bank-centric structure carries profound implications for the transmission and effectiveness of ESG investing. Given banks' pivotal role in determining firms' credit access and overall financing capacity, regulatory policies that reshape bank incentives can propagate through the real economy with greater amplitude and speed than in predominantly market-based financial systems.

To strengthen macro-prudential oversight, the People's Bank of China (PBoC) introduced the MPA framework in Q1 2016 as part of its "two-pillar" regulatory system, integrating capital regulation with macro-prudential oversight. The MPA framework superseded the loan-to-deposit ratio as the primary supervisory mechanism. It subjects commercial banks to quarterly evaluations across seven key dimensions: capital and leverage, asset quality, liquidity, pricing behavior, cross-border risk, and—of central relevance to our study—green

finance policy implementation, which includes directives for serving the real economy.

Crucially, a bank's MPA rating directly governs its access to the People's Bank of China's liquidity facilities, such as the Standing Lending Facility (SLF) and the Medium-Term Lending Facility (MLF). A superior rating translates into lower financing costs when borrowing from the PBoC through these channels. Beyond liquidity access, a high MPA rating confers more favorable regulatory treatment overall. Consequently, banks face powerful financial and regulatory incentives to systematically align their activities with the objectives embedded in the MPA framework. This supervisory structure is therefore essential for understanding how the subsequent incorporation of green finance metrics into the MPA framework fundamentally reshaped the incentives of commercial banks and, by extension, their affiliated funds.

2.2 The Rise of Green Finance and the 2016 Guiding Opinions

In recent years, Chinese regulators have launched a series of green finance initiatives. The most comprehensive one was the Guiding Opinions on Building a Green Financial System, jointly issued by the PBoC and six other ministries in September 2016. The policy provided a national blueprint for green finance by establishing a green taxonomy, promoting green bonds, strengthening disclosure, and encouraging equity financing for environmentally friendly projects.

The chronological sequencing is noteworthy. Banks have already become subject to MPA-based evaluations since Q1 2016. The September 2016 Guiding Opinions ensured that green credit metrics were explicitly incorporated into the MPA soon thereafter. Specifically, the share of loans to environmentally friendly projects and firms, the growth of green credit portfolios, and compliance with environmental risk management practices are scored. A higher score can directly improve a bank's overall MPA grade, which in turn determines access to low-cost central bank facilities (such as relending and Medium-term Lending Facility

quotas), affects regulatory treatment, and enhances market reputation.

This policy reform creates hard regulatory incentives for banks to increase their holdings of "green assets," including both green loans and green securities. For bank-controlled mutual funds, these incentives transmit through internal capital allocation and information sharing channels: parent banks, seeking to boost their green asset ratios, may direct affiliated funds to increase allocations to green bonds and equities of high-ESG-rated firms. Affiliated funds also gain a competitive advantage by leveraging the parent bank's proprietary environmental risk assessments and borrower ESG data—information not as readily available to unaffiliated funds.

In contrast, mutual funds without bank affiliation are not subject to these MPA-driven hard incentives and rely instead on market demand, reputational considerations, and their own ESG research capabilities. This regulatory asymmetry forms the institutional foundation of our empirical identification strategy, as the 2016 Green Finance Guidelines, combined with the MPA green credit integration, create a plausibly exogenous shock to the ESG investment incentives of bank-affiliated funds. This institutional context, where prudential regulation and green finance policies intersect, generates sharp and testable predictions about the real effects of affiliation.

2.3 Hypothesis Development

China's bank-dominated financial system and the recent embedding of environmental objectives into its supervisory framework provide a distinctive setting to examine how financial intermediation shapes real sustainability outcomes. Given that commercial banks constitute the principal source of external financing, regulatory shifts that reshape their incentives are poised to propagate throughout the real economy with particular force. The introduction of the MPA in Q1 2016, followed by the Guiding Opinions on Building a Green Financial System in September 2016, directly linked banks' prudential assessments to their green per-

formance. Since Chinese commercial banks are prohibited from direct equity holdings, their affiliated funds emerged as the natural conduit for transmitting these newly aligned regulatory incentives into the equity markets. To motivate our empirical tests, this section reviews the economics of bank affiliation, highlights the mechanisms through which affiliation may benefit or harm ESG outcomes, and derives testable hypotheses in this unique institutional context.

2.3.1 The Economics of Bank Affiliation

The literature on bank affiliation highlights a fundamental trade-off between benefits and costs. On the benefit side, affiliation can reduce information asymmetry and improve capital allocation. Specifically, banks develop proprietary information on borrowers through lending, underwriting, and monitoring relationships. Affiliated funds can leverage this informational advantage to select higher-quality firms and exert stronger corporate governance (Massa and Rehman, 2008; Ferreira et al., 2018). Furthermore, bank affiliation enables coordinated financing. By bundling debt and equity offerings within the same financial group, banks can better support long-horizon investments and mitigate project-level financing risks. Finally, monitoring incentives may be stronger as poor portfolio performance harms both the fund and the parent bank's reputation.

On the cost side, bank affiliation can give rise to conflicts of interest. For instance, a parent bank might pressure its affiliated funds to provide capital to financially distressed or politically connected borrowers despite weak fundamentals—a form of "tunneling" that results in capital misallocation (Gaspar et al., 2006). In the ESG domain, conflicts can manifest as greenwashing. Such strategies may involve relabeling conventional activities as green, prioritizing symbolic disclosure over substantive action, or allocating capital to firms that make superficial ESG commitments without underlying improvement. Collectively, these practices create a façade of sustainability while simultaneously undermining the achievement of

tangible environmental goals.

In summary, prior research identifies three main benefits of affiliation, including informational advantages, coordination of financing and enhanced monitoring incentives. Conversely, it highlights three corresponding costs, including capital misallocation toward underperforming or connected borrowers, conflicts of interest in investment decisions and the risk of greenwashing. The Chinese institutional setting provides a natural laboratory for evaluating these trade-offs. The critical juncture arrived in 2016, when the MPA and the Guiding Opinions on Building a Green Financial System formally tethered banks' regulatory standing to their environmental performance. Given the prohibition on direct equity holdings by banks, their affiliated funds emerged as the necessary conduit for transmitting these newly aligned incentives into the equity market. Consequently, whether the benefits of affiliation dominate the costs in this distinctive setting—and through which specific mechanisms—constitutes the core empirical question that shapes our testable hypotheses.

2.3.2 Bank Affiliation and Green Innovation

Green innovation is distinct from other corporate activities because it requires extended time horizons, substantial capital outlays, and faces both technological and market uncertainty. Clean technology R&D often entails years of sequential investment before yielding patentable outcomes or commercial products, which makes external financing essential. These characteristics further complicate project evaluation: external investors face significant challenges in assessing project viability, while short-term oriented capital providers typically exhibit limited appetite for supplying patient capital. Consistent with these constraints, prior research establishes that long-horizon investors and well-informed institutions are disproportionately important in supporting innovation, whereas short-term market pressures tend to reduce such long-term investments (Chava et al., 2013; Aghion et al., 2016).

Bank affiliation offers a potential solution to these challenges through three complemen-

tary mechanisms. First, affiliated funds gain access to the parent bank's proprietary insights into borrowers' technological capacity and financial resilience, enabling them to identify firms with genuine innovation potential (Massa and Rehman, 2008; Ferreira et al., 2018). Second, the coordination of debt and equity within the same financial group ensures funding continuity for long-term projects. This joint backing mitigates rollover risk and helps firms sustain R&D efforts through temporary setbacks (Ni et al., 2022). Finally, the shared reputation within the banking group strengthens monitoring incentives, as innovation failures would damage both the fund's performance and the parent bank's brand capital. Collectively, these mechanisms position bank affiliation as a viable structure for supporting substantive green innovation.

However, the potential costs of bank affiliation cannot be overlooked. Agency conflicts may lead parent banks to direct affiliated funds toward supporting distressed or politically connected borrowers, even when these firms lack credible innovation prospects (Gaspar et al., 2006). In the context of ESG, such conflicts create a pronounced risk of greenwashing. Portfolio firms might engage in symbolic behavior—such as relabeling existing R&D as "green," prioritizing disclosure over substantive action, or launching superficial initiatives—to signal compliance with policy goals while avoiding the costs and uncertainties of genuine innovation. These practices create a facade of sustainability without yielding patentable technological advances. Ultimately, such agency-driven distortions can significantly undermine the potential for bank affiliation to foster real environmental progress.

China's institutional setting brings both sides of this trade-off into sharp relief. The introduction of the MPA and the Guiding Opinions explicitly linked banks' prudential assessments and reputational standing to their environmental performance. In a system where banks are barred from direct equity investment, affiliated funds emerged as the natural conduit for transmitting these policy-driven incentives into equity portfolios. As a result, while affiliated funds were encouraged to channel equity toward firms with demonstrable green innovation capacity, the same structure also increased the appeal of allocating capital to firms skilled

mainly in symbolic compliance. These institutional features suggest that bank affiliation may play a particularly decisive role in green innovation—a domain heavily dependent on specialized knowledge and sustained financing. However, whether such benefits prevail in practice, or are undercut by capital misallocation and superficial green responses, remains an open empirical question.

These institutional features suggest that bank affiliation may play a particularly decisive role in green innovation of their portfolio companies—a domain heavily dependent on specialized knowledge and sustained financing. However, whether such benefits prevail in practice, or are undercut by capital misallocation and superficial green responses, remains an open empirical question. This leads to the following testable predictions.

Hypothesis 1a (bright side): After the 2016 reform, firms held by bank affiliated funds experience greater increases in green patent applications than comparable firms held by unaffiliated funds.

Hypothesis 1b (dark side): If agency conflicts dominate, firms held by bank affiliated funds reduce green patent applications than comparable firms held by unaffiliated funds.

In practice, the bright side mechanism should be stronger where parent banks have greater green credit exposure and where portfolio firms had stronger pre-policy innovative capacity. The dark side mechanism may be more pronounced where affiliated funds are pressured to support weak or connected borrowers or where disclosure-oriented ESG practices are widespread. These implications guide the empirical analysis and provide a bridge between the institutional background and the hypotheses we test.

2.3.3 Bank Affiliation, Carbon Emissions, and Pollutant Discharges

Carbon emissions and pollutant discharges reflect a firm's immediate environmental footprint. Cutting them requires changes in processes, cleaner inputs, energy efficiency upgrades, and credible compliance systems. While these measures often entail significant near-term

costs, their outcomes tend to be observable and readily verifiable. Prior studies show that firms can respond to investor pressure by improving disclosure rather than undertaking costly abatement, which leaves room for symbolic compliance rather than real reductions. The near term and measurable nature of these outcomes make them a natural laboratory for testing whether financial intermediaries transmit incentives into verifiable environmental progress.

We posit that bank affiliation facilitates their their portfolio company environmental improvement through three distinct mechanisms. First, affiliated funds to leverage proprietary information gained through banking relationships. Banks develop nuanced understanding of firms' production technologies, emission profiles, and abatement capabilities through their lending activities and ongoing monitoring. This knowledge allows affiliated funds to identify companies with substantive decarbonization strategies while avoiding those engaged primarily in symbolic environmental gestures (Massa and Rehman, 2008). Second, banking groups can structure funding disbursements through financing channel to align with verifiable abatement milestones, thereby reducing project abandonment risk and helping firms manage the substantial upfront investments required for cleaner technologies and compliance infrastructure. Third, the reputational channel creates aligned monitoring incentives through shared brand capital concerns. Since environmental failures would damage both the fund's performance and the parent bank's reputation, affiliation strengthens the incentives for rigorous implementation oversight and outcome verification—particularly valuable when environmental outcomes, though measurable, remain vulnerable to reporting manipulation.

China's institutional landscape amplifies these mechanisms significantly. The 2016 policy reforms—notably the MPA launched in the first quarter and the Guiding Opinions issued in September—explicitly tied banks' regulatory assessments and reputational standing to their environmental performance. In a system where commercial banks are prohibited from direct equity investments, affiliated funds naturally became the equity transmission channel for these policy-driven incentives. This institutional design elevates the value of verifiable emission reductions. Unlike narrative disclosures, quantifiable improvements in environmen-

tal metrics directly enhance the parent bank's prudential rating and public reputation. In contrast, unaffiliated funds operate outside the MPA framework and thus face considerably weaker incentives to move beyond disclosure-based ESG practices.

The potential benefits of affiliation, however, must be weighed against persistent agency costs. There remains a risk that banks may direct their affiliated funds to support financially distressed or politically connected borrowers with weak fundamentals, diverting capital away from firms genuinely committed to environmental upgrades (Gaspar et al., 2006). In the ESG domain, such conflicts often manifest as greenwashing that firms may engage in symbolic actions such as rebranding routine maintenance as environmental improvements, framing minor efficiency adjustments as major emission reductions, or prioritizing disclosure while delaying substantive—and costly—operational changes. In regions with uneven regulatory enforcement, these strategies can create an illusion of environmental progress while actual emissions remain largely unaffected. These risks constitute a significant countervailing force that may undermine the positive channels of bank affiliation.

Because emissions and pollutants are both observable and costly to reduce, they provide a sharp test of whether affiliation with commercial banks produces genuine environmental progress or merely symbolic disclosure. This contrast yields the following predictions.

Hypothesis 2a (bright side): After the 2016 reform, firms held by bank affiliated funds exhibit larger reductions in carbon emissions and pollutant discharges than comparable firms held by unaffiliated funds.

Hypothesis 2b (dark side): If conflicts and symbolic compliance dominate, firms held by bank affiliated funds increase carbon emissions and pollutant discharges than comparable firms held by unaffiliated funds.

A straightforward implication is that the beneficial effects (bright side) of affiliation should be more pronounced where parent banks maintain substantial green credit portfolios and where robust local enforcement and public oversight enhance the value of verifiable outcomes. Conversely, the detrimental aspects (dark side) are likely to emerge more strongly

in environments characterized by relationship lending to underperforming or politically connected firms, and where disclosure-oriented ESG practices predominate. These contingent predictions inform our examination of heterogeneous effects while remaining neutral toward specific empirical specifications.

2.3.4 Bank Affiliation and the Capital Support Channel: Financing Advantages within the Conglomerate

Our first two hypotheses address the ultimate outcomes of green investment—green innovation and environmental performance. We now examine a more direct mechanism through the financing advantages arising from internal capital allocation. While existing literature has focused on how ESG affects firms' cost of capital, we emphasize a prior and more strategic channel through the flow from parent banks to their affiliated funds. Banking conglomerates effectively function as internal capital markets, directing resources toward subsidiaries best positioned to advance group-wide objectives. The 2016 Green Finance Guidelines, by incorporating green metrics into the MPA framework, made "green asset expansion" a central strategic priority for Chinese commercial banks. We therefore propose that a key transmission mechanism operated through parent banks' decisions to augment the financial capacity of their affiliated funds.

Internal capital market theory posits that corporate parents, armed with superior information, can often allocate capital more efficiently than external markets (Stein, 1997). In our setting, a parent bank possesses deep, proprietary information about the financial health and operational capabilities of its corporate clients through its lending relationships (Berger et al., 2007; Liu et al., 2018). This information, when transmitted to the asset management arm, allows affiliated funds to more accurately evaluate risk and identify promising investment opportunities (Ferreira et al., 2018). Faced with strong regulatory incentives from the MPA, a rational parent bank would leverage this information to strategically deploy resources

to the most effective channel available: its affiliated funds. This support can manifest in two tangible ways that confer a significant competitive advantage. First, the parent bank can provide direct credit lines or guarantees, allowing the affiliated fund to increase its leverage. Second, and perhaps more powerfully, the bank can leverage its vast branch network and client relationships to drive investor inflows into specific funds, leading to rapid growth in total net assets (TNA) (Golez and Marin, 2015).

However, such capital support is unlikely to be unconditional. A parent bank seeking to efficiently meet its regulatory targets would not provide resources indiscriminately to all its affiliated funds. Instead, it would strategically direct capital toward those funds with a demonstrated expertise or pre-existing tilt toward green innovation. This conditional allocation creates a powerful incentive structure and a clear, testable prediction which implies that the financing advantage of affiliation should be significantly stronger for funds with a higher green portfolio intensity. This "winner-picking" strategy allows the banking group to maximize its response to the policy shock, creating a virtuous cycle where successful green funds are rewarded with more capital, enabling them to further expand their green investments.

The "bright side" view of internal capital allocation stands in contrast to the well-documented "dark side" of affiliation, which emphasizes conflicts of interest and capital misallocation. Agency theory suggests that capital within a conglomerate may be diverted for reasons other than efficiency, such as propping up politically connected but underperforming divisions (Scharfstein and Stein, 2000) or engaging in socialist-style cross-subsidization (Shin and Stulz, 1998). In our context, such distortions could manifest as parent banks pressuring their funds to support financially distressed or politically connected borrowers despite weak fundamentals (Gaspar et al., 2006). This behavior could lead banks to direct capital to support funds for reasons entirely unrelated to their green credentials. If such conflicts dominate, we would expect to see little or no differential capital support flowing to the greener affiliated funds after the reform.

This theoretical tension yields our final set of competing hypotheses, focused on the direct financing channel between the parent bank and its affiliated fund:

Hypothesis 3a (bright side): After the 2016 reform, bank-affiliated funds with stronger green investment portfolios experience superior growth in financial capacity (measured by increased leverage and asset growth) compared to both their less-green affiliated peers and unaffiliated funds.

Hypothesis 3b (dark side): If agency conflicts dominate, the capital support from parent banks is not systematically directed toward greener affiliated funds, and no such differential financing advantage will be observed.

3 Data and Methodologies

To test the hypotheses developed in Section 2, we assemble a dataset that allows us to measure three dimensions of firm-level environmental performance. Green patents represent long-term, uncertain innovation outcomes, whereas reductions in carbon emissions and pollutant discharges reflect shorter-term operational improvements that—though verifiable—often require substantial upfront investment.

Our data sources are standard in the literature on Chinese capital markets and have been widely used in studies of ESG and green finance. Each dataset has limitations, but they provide the most credible evidence available. Appendix A presents the detailed formulas used to construct the ESG variables, and Appendix B lists all variable definitions.

3.1 Sample Selection and Data Resources

We begin with all open-end mutual funds in China between January 2010 and December 2022. The sample is restricted to actively managed domestic equity and hybrid funds because these products allocate capital strategically and thus serve as the channel through which banks transmit incentives into equity markets. Index and QDII funds are excluded following Yan

(2012) since they follow benchmarks or invest overseas.

Fund-level information is obtained from the China Stock Market and Accounting Research (CSMAR) database, which is the standard data provider for research on Chinese mutual funds. We collect inception dates, assets under management, returns, expense ratios, and portfolio holdings. Bank affiliation is classified based on ownership structure following established rules in the literature, including Ferreira et al. (2018).

We acknowledge that some affiliation relationships are complex because banks often hold stakes indirectly through financial groups. To minimize misclassification, we adopt conservative rules. Any remaining error would bias against finding systematic differences between affiliated and unaffiliated funds, making our tests more conservative.

3.2 Main Variables

3.2.1 Green Innovation

We measure green innovation using firm-level patent applications from the China National Intellectual Property Administration (CNIPA). Green patents are identified following the World Intellectual Property Organization classification, separated into green invention and green utility models, and then aggregated to the fund level using portfolio weights. Construction details are provided in Appendix A, and variable definitions such as *Green_Inv*, *Green_Uti*, and *Green_Sum* are listed in Appendix B.

Patent-based measures provide an observable proxy for innovative output and capture the long horizon and uncertain nature of R&D. Prior work has established their use in studying the effect of environmental policy on innovation (Chava et al., 2013; Aghion et al., 2016). While not all innovations are patented and patent quality varies, these data remain the most widely accepted measure of innovative activity in the finance and economics literature.

3.2.2 Carbon Emissions and Pollutants

We construct firm-level carbon emissions using the China Emission Accounts and Datasets (CEADs) and pollutant discharges from the Ministry of Ecology and Environment. Pollutants include sulfur dioxide, chemical oxygen demand, ammonia nitrogen, and industrial dust. Emissions and pollutants are standardized and aggregated following the procedures described in Appendix A.

These variables capture near-term operational changes that are verifiable but costly, making them natural measures for testing whether bank affiliation leads to substantive abatement or symbolic disclosure. Data limitations include partial reliance on industry-level allocations and uneven regional enforcement. Such noise would attenuate differences, which implies that significant findings provide conservative evidence.

3.2.3 Control Variables

We control for characteristics at both the fund and firm level. Fund-level controls include age, size, expense ratios, past performance, and whether the fund is managed by a team. Firm-level controls include size, leverage, profitability, and cash holdings. Regional controls include GDP growth and public environmental attention measured by Baidu search intensity. All variable definitions are reported in Appendix B.

These controls ensure that observed differences in outcomes are not driven by confounding factors. For example, larger firms may have greater capacity to innovate, while regional environmental enforcement affects incentives for abatement.

3.3 Summary Statistics

Table 1 reports the descriptive statistics for the main variables. The distributional characteristics of our sample reveal several economically meaningful patterns. For example, green innovation exhibits pronounced positive skewness across all measures, with the mean

of *Green_Sum* (0.169) substantially exceeding its median (0.085) and the maximum value (42.206) dwarfing the 99th percentile (1.086), consistent with the highly concentrated nature of environmental R&D outcomes where few firms account for most innovation. Simultaneously, we observe considerable heterogeneity in environmental performance, as evidenced by the standard deviation of 1.901 in *Log_Carbon_Emission* and the interquartile range of approximately 2.6 units between the 25th and 75th percentiles, suggesting meaningful cross-sectional variation in pollution abatement potential. The fund-level statistics indicate that approximately 15.7% of observations represent bank-affiliated funds, while the temporal distribution shows sufficient policy exposure with 81.4% of observations falling post-reform. Crucially, the coexistence of these distributional features—highly skewed innovation outputs, dispersed environmental performance, and systematic differences in fund characteristics—creates a promising empirical setting for identifying how regulatory incentives transmitted through banking relationships affect corporate environmental behavior.

Finally, the sample exhibits substantial variation in fund characteristics, e.g., *FundFAM* (with the mean value of 4.937 and the SD value of 0.945) reflects heterogeneity in management scale; most funds employ team management (the median of *FundTeam* equals to 1.000); expense ratios cluster at 1.200% yet range from 0.000% to 1.600%; *LogTNA* spans from 12.330 to 25.103, indicating significant size dispersion; and returns show expected volatility (with a mean value of 1.9% and a SD value of 5.9%). These patterns provide empirical grounding for testing how fund-level attributes moderate bank affiliation effects.

[Insert Table 1 here]

4 Empirical Results

This section presents our core empirical findings, structured to establish the policy's ultimate environmental impacts and the economic consequences. We begin by analyzing effects on

green innovation (Section 4.1) and environmental performance (Section 4.2). After establishing these baseline results, we directly examine the potential investor implications (Section 4.3). The subsequent sections then test the proposed capital support mechanism (Section 4.4), and information mechanism (Section 4.5)).

4.1 Green Innovation: Long Horizon Outcomes

We begin with green innovation, which provides the most natural test of whether the benefits of bank affiliation outweigh its costs. As emphasized in Section 2, clean technology innovation requires extended horizons, large upfront capital outlays, and faces considerable technological and market uncertainty. These features make external financing essential but also risky. Bank affiliation may facilitate their portfolio company green innovation if affiliated funds use proprietary borrower information from parent banks and coordinate with bank credit to sustain long-horizon projects. Conversely, bank affiliation may also misallocate resources to weak or politically connected firms or promote symbolic disclosure rather than substantive investment in new technologies.

Table 2 shows that affiliated funds' portfolio firms raise green patenting more than unaffiliated funds' portfolio firms after the 2016 reform. For the total of green invention and utility model applications (*Green_Sum*) the after minus before change is 0.191 for affiliated and 0.144 for unaffiliated, with a difference-in-differences of 0.047 ($t = 3.86$). For green invention patents (*Green_Inv*) the corresponding difference-in-differences is 0.051 ($t = 5.53$). For green utility models (*Green_Uti*) it is 0.066 ($t = 10.82$). These descriptive gaps preview the causal estimates that follow.

[Insert Table 2 here]

Table 3 reports event-time regressions. The interactions of *Affiliated* with the pre-event indicators are statistically indistinguishable from zero for *Green_Sum* and *Green_Inv*, and

only a small negative for *Green_Uti* in the long pre-period (-0.014, t = -1.76). Post-event coefficients are positive and significant, appearing in 2016 to 2018, peaking in 2019, and remaining positive thereafter. This pattern supports the parallel-trends assumption and suggests persistence of the post-reform effect.

[Insert Table 3 here]

In the baseline difference-in-differences specification reported in Table 4, the coefficient on the interaction of *Affiliated *Shock* is positive and statistically significant across all three measures of green innovation. For the aggregate of invention and utility model patents (*Green_Sum*), the estimate is 0.098 (t = 2.18). Given that the sample mean of *Green_Sum* is 0.169 (Table 1), this represents an increase of roughly 58 percent relative to the mean, and nearly one-half of the interquartile range. For invention patents (*Green_Inv*), the interaction coefficient is also 0.098 (t = 2.26), which amounts to approximately 110 percent of the sample mean of 0.089 and nearly the full interquartile range. For utility model patents (*Green_Uti*), the coefficient is 0.017 (t = 2.18), which translates to about 21 percent of the mean of 0.081. These estimates imply that the increase in patenting among affiliated funds' portfolio firms following the reform is economically meaningful, with the largest relative effect concentrated in invention patents—projects that typically involve longer horizons, higher fixed costs, and greater uncertainty.

[Insert Table 4 here]

Taken together, these results provide strong support for Hypothesis 1a, which predicts that affiliated funds' portfolio firms increase green innovation after the reform, consistent with the information and financing advantages of bank affiliation. The evidence does not support Hypothesis 1b, which predicts no substantive improvement if agency conflicts dominate. The combination of descriptive evidence, validated parallel trends, and baseline regressions provides a coherent and credible case that bank affiliation fosters real innovation in the wake of China's green finance reforms.

4.2 Environmental Performance: Emissions and Pollutants

We now examine environmental performance, focusing on corporate carbon emissions and pollutant discharges. Unlike green innovation, these metrics reflect operational adjustments aimed at curbing emissions—changes that entail significant costs yet yield verifiable outcomes in the short to medium term. As emphasized in Section 2, affiliated funds may pressure firms to take genuine emission-reduction measures because their parent banks' prudential evaluations and reputational capital are now tied to measurable environmental performance. At the same time, affiliation with commercial banks could still foster symbolic compliance, with firms emphasizing disclosure or reporting intensity without substantive reductions. Hypotheses 2a and 2b capture these competing predictions.

To test these hypotheses, we estimate DID regressions of log emissions (or pollutants) on the interaction of a bank-affiliation indicator and a post-2016 reform indicator, controlling for firm and year fixed effects, fund characteristics, as well as regional economic and environmental controls. This empirical approach mirrors the baseline specification adopted for green innovation in Section 4.1.

Table 5 presents the baseline DID regressions for firm-level carbon emissions. The coefficient on *Affiliated *Shock* is -0.189 (t = -2.28) in the baseline specification without the triple interaction term and -0.360 (t = -3.78) in the extended specification that includes *Affiliated *Shock *Green_Sum*. Relative to the mean carbon emissions reported in Table 1, these coefficients correspond to reductions of roughly 4.7 percent and 9 percent, respectively. Both estimates are economically meaningful, as they represent nontrivial declines in emissions relative to the interquartile range. The triple interaction term *Affiliated *Shock *Green_Sum* is -3.053 (t = -9.87), showing that reductions are particularly concentrated among firms with greater green patent intensity. This result strongly suggests that affiliated funds directed capital toward firms that complemented innovation with genuine operational abatement.

[Insert Table 5 here]

Table 6 presents the DID estimates for pollutant emissions, including industrial wastewater (chemical oxygen demand, ammonia nitrogen), industrial waste gas (sulfur dioxide, nitrogen oxides), and their sum. The interaction term *Affiliated *Shock* is negative and significant across all specifications. For example, portfolio firms of affiliated funds experienced a -0.368 (t = -3.60) decline in water pollution, a -0.500 (t = -6.48) decline in air pollution, and a -0.431 (t = -6.33) decline in total pollutant emissions, relative to unaffiliated funds. These estimates translate into reductions of about 0.26 percent of mean water pollution, 0.33 percent of mean air pollution, and 0.30 percent of mean total pollutant levels, representing economically meaningful abatement.

[Insert Table 6 here]

The effects are even stronger once green intensity is considered. The triple interaction *Affiliated *Green_Sum *Shock* is -2.273 (t = -3.33) for water pollution, -1.941 (t = -3.15) for air pollution, and -2.044 (t = -3.40) for total pollution. These magnitudes indicate that affiliated funds particularly targeted firms combining green innovation with operational upgrades, suggesting that affiliation with commercial banks did not merely encourage disclosure but also facilitated substantive compliance improvements.

Overall, the results in Table 6 provide robust support for Hypothesis 2a, demonstrating that bank affiliation contributes to statistically and economically meaningful reductions in both water and air pollutants among their portfolio companies.. These patterns align with the information advantage and enhanced monitoring mechanisms developed in Section 2.3, and stand in contrast to Hypothesis 2b, which anticipated symbolic ESG responses unaccompanied by measurable environmental improvement.

4.3 Economic Consequences for Investors

The evidence in Sections 4.1 to 4.2 shows that bank affiliation improved firms' green innovation and reduced their emissions and pollutants after the 2016 reform. If these bright-side

effects reflect genuine economic value, they should ultimately translate into measurable benefits for mutual funds and their investors. In this section, we examine whether affiliated funds generated superior investment performance and whether investors rewarded them for credible ESG engagement.

4.3.1 Fund Performance: Position-level Evidence

We first test whether bank affiliation improves performance at the level of portfolio holdings. Table 7 presents a within-fund analysis that compares, for the same fund and month, the performance of equity positions in firms borrowing from the parent bank against positions in firms without such credit relationships. This design controls for fund-specific styles and temporal effects, isolating the incremental value derived from bank–firm lending ties.

[Insert Table 7 here]

The results strongly support an informational advantage. We demonstrate that borrower-linked positions consistently outperform non-borrower positions. As shown in Panel A, the raw return spread is 0.009 per month ($t = 3.76$). When abnormal returns are estimated using factor models, the advantage remains. For example, the CAPM alpha spread is 0.009 ($t = 3.75$), the FF-3 alpha spread is 0.009 ($t = 3.59$), and the FF-5 alpha spread is 0.010 ($t = 4.01$). These magnitudes translate into roughly 1.1-1.3 percent higher returns per year, which are both statistically and economically significant.

Taken together, the evidence in Table 7 indicates that the same information and monitoring channels that improved firm-level outcomes also delivered tangible performance advantages for affiliated funds. These gains arise specifically in positions where the parent bank has an active lending relationship, highlighting how proprietary information and sustained financing interact to create value.

4.3.2 Fund Performance: Fund-level Regressions

We next test whether these performance advantages also appear at the fund level after the reform. Table 8 presents regression estimates in which rolling 24-month fund performance measures—including raw returns CAPM alpha, FF-3 alpha, and FF-5 alpha—are regressed on fund affiliation, the policy shock indicator, green portfolio intensity, and their interaction terms. The specifications include fund category and year fixed effects, alongside a comprehensive set of fund-level and regional control variables.

[Insert Table 8 here]

First, the average post-reform effect of affiliation on fund performance is statistically negative but economically modest. The coefficient on *Affiliated *Shock* equals -0.004 for raw returns (t = -2.24), -0.007 for CAPM alpha (t = -3.89), -0.008 for FF-3 alpha (t = -3.77), and -0.007 for FF-5 alpha (t = -4.16), indicating that bank affiliation alone did not enhance fund-level performance following the policy implementation.

Second, the performance benefits of affiliation emerge most strongly when accounting for environmental commitment. The triple interaction *Affiliated *Green_Sum *Shock* is positive and statistically significant across all performance measures, with coefficients ranging from 0.011 (t = 2.42) for raw returns to 0.030 (t = 3.44) for the five-factor alpha. This pattern indicates that the post-reform outperformance of affiliated funds concentrates specifically among those with higher green portfolio intensity.Consistent with this interpretation, the *Affiliated *Green_Sum* interaction also shows economically meaningful magnitudes—ranging from 0.021 to 0.023 across risk-adjusted measures—further confirming that the value of bank affiliation increases with environmental orientation.

When combined with the position-level evidence from Table 7, these findings demonstrate that the performance benefits of bank affiliation concentrate precisely where information and monitoring advantages are most potent—specifically, in portfolios with higher green intensity.

The average *Affiliated *Shock* effect is not positive by itself, but the incremental effect for greener funds is sizable and statistically precise. This pattern provides direct support for the bright-side hypotheses developed in our theoretical framework, while rejecting a simplistic narrative that bank affiliation uniformly enhances fund performance.

4.3.3 Investor Recognition: Fund Flows

Evidence from Tables 7 and 8 establishes that bank-affiliated funds achieved performance gains at both the position and portfolio levels, particularly within their greener holdings. This raises a consequential question: Did investors recognize and reward these outcomes? If affiliation with commercial banks genuinely enhances ESG performance, we would expect affiliated funds—especially those with greener portfolios—to experience stronger capital inflows following the regulatory reform.

To test this, Table 9 reports regressions of fund flows on affiliation, the policy shock, green intensity, and their interactions. Following Yan (2012), fund flows are measured as the growth in total net assets minus portfolio returns. We further decompose flows into institutional and retail components based on the respective shareholdings of these investor groups, allowing us to assess whether sophisticated investors respond differently from retail investors.

[Insert Table 9 here]

Two central patterns emerge. First, we show that the coefficient on *Affiliated *Shock* is -0.047 for total flows (t = -1.80), -0.073 for institutional flows (t = -2.89), and -0.011 for retail flows (t = -1.05, not significant). This suggests that bank affiliation did not mechanically attract capital after the reform. Meanwhile, the coefficient on *Green_Sum *Shock* is positive across specifications, consistent with a general reallocation of flows toward greener funds in the post-reform period.

Second, we find that the triple interaction term *Affiliated *Green_Sum *Shock* shows positive and statistically significant coefficients of 0.301 for total flows ($t = 1.93$) and 0.488 for institutional flows ($t = 3.24$), while the coefficient for retail flows remains small at 0.064 and statistically insignificant. These findings demonstrate that following the reform, affiliated funds with higher environmental commitment attracted substantially more capital, with this response driven primarily by institutional investors rather than retail participants.

Overall, the results in Table 9 reveal that market rewards for bank affiliation are highly selective. Institutional investors—who possess greater capacity to assess ESG fundamentals—systematically allocated capital to affiliated funds only when those funds maintained substantively greener portfolios. This pattern supports the bright-side hypotheses, wherein the confluence of banking relationships and environmental commitment signals credible information advantages and enhanced monitoring, while contradicting the interpretation that affiliation primarily promotes superficial ESG compliance.

4.4 Financing Mechanism: Capital Support and Fund Growth

The findings presented thus far demonstrate that bank affiliation promotes both green innovation and environmental performance, while the preceding analysis has examined their economic consequences. We now turn to testing a central mechanism proposed in our conceptual framework, i.e., the capital support channel. This mechanism posits that parent banks provide enhanced financing to affiliated funds advancing policy-aligned green objectives. To evaluate this channel directly, we examine whether affiliated funds with greater green investment intensity gained superior access to capital following the 2016 reform, using two complementary measures—changes in fund leverage and growth in total net assets (TNA).

Table 10 reports the results from a triple-difference specification that captures the differential response of affiliated funds based on their pre-existing green investment levels. The

findings provide strong and consistent support for the capital support channel.

[Insert Table 10 here]

Panel A examines how fund leverage responds to the interplay of affiliation, environmental orientation, and regulatory reform. The estimated coefficients on the triple-interaction term *Affiliated *Green_Sum *Shock* are positive and statistically significant across all three green investment measures. The evidence indicates that following the policy shock, bank-affiliated funds gain expanded access to leverage, though this advantage is strongly moderated by their environmental credentials. Affiliated funds maintaining higher green patent intensity secure significantly greater leverage compared to both their less environmentally-oriented peers within the same banking group and the full set of unaffiliated funds.

Panel B examines fund size growth and reveals a particularly pronounced treatment effect. The triple-difference coefficients range from 4.175 to 8.940 with high statistical significance, indicating that affiliated funds with established green portfolios achieve substantially faster asset expansion following the reform. This growth appears to derive from two complementary sources including direct capital injections from parent banks and increased investor inflows attracted by the funds' demonstrated environmental commitment.

Overall, these results offer direct evidence of the capital support channel. The 2016 green policy appears to have triggered a strategic reallocation of capital within banking groups, where parent banks empowered their green-focused affiliated funds with greater financial firepower through both debt (leverage) and equity (inflows). This created a virtuous cycle, providing these funds with a distinct competitive advantage and reinforcing their capacity to invest in green innovation.

4.5 Information Advantages Versus Conflicts Mechanisms

A key question is how bank affiliation shapes ESG investment outcomes. Two competing channels have been emphasized in the literature. The informational advantage channel

suggests that banks can transmit superior borrower information to affiliated funds, thereby improving screening and monitoring of green firms. By contrast, the conflict of interest channel implies that banks may pressure affiliated funds to absorb exposures to weaker borrowers, potentially distorting ESG allocations. To distinguish between these mechanisms, we conduct a series of tests. We begin with a firm-level design that directly examines the role of joint bank–fund exposure (Section 4.5.1) and then turn to additional fund-level analyses (Sections 4.5.2 and 4.5.3).

4.5.1 Joint Bank-Fund Exposure: Firm-Level Evidence

To sharpen our understanding of the underlying mechanism, we begin by examining whether the effect of bank affiliation is concentrated in firms that simultaneously maintain both lending and equity relationships with the same banking group. If the informational advantage channel is at work, then the benefits of affiliation should be most pronounced precisely when the credit and equity ties overlap, enabling superior information sharing, coordinated monitoring, and more efficient capital allocation. By contrast, if affiliation merely reflects conflicts of interest or incidental correlations, we would not expect such dual ties to matter.

To test this idea, we classify all sample firms into four mutually exclusive groups: (i) *Bank + Fund* firms, which are both loan clients of a commercial bank and held by that bank's affiliated fund; (ii) *Bank Only* firms with credit exposure but no affiliated fund ownership; (iii) *Fund Only* firms that are held by an affiliated fund but maintain no borrowing ties; and (iv) *Neither* firms without either type of connection. This empirical design constitutes a compelling falsification test—should the proposed information and financing channels indeed be operative, the treatment effect would necessarily concentrate within the *Bank + Fund* group.

Table 11 presents the results. As shown in Panel A, significant pre-treatment differences emerge across firm categories—firms in the *Bank + Fund* group exhibit substantially higher

green innovation levels even prior to the policy shock, , with a mean green patent count (*Green_Sum*) of 0.905, far exceeding the *Loan Only* (0.137), *Fund Only* (0.061), and *Neither* (0.031) groups. This confirms that these dual-relationship firms are distinct and central to the green innovation landscape. This pattern confirms that firms maintaining simultaneous banking and fund relationships occupy a distinctive and central position within the green innovation ecosystem.

[Insert Table 11 here]

The difference-in-differences estimates in Panels B, C, and D provide compelling evidence for our hypothesized channel. Following the 2016 reform, firms in the *Bank + Fund* group exhibit by far the largest increase in green patenting. The DID estimator comparing the *Bank + Fund* group to the control (*Neither*) group is 0.420 and highly significant ($t = 5.58$) for total green patents. This effect is an order of magnitude larger than the pre-post changes within the other groups, indicating a powerful synergistic effect. When we decompose the patents, we find the effect is pronounced for both high-quality invention patents ($DID = 0.125$) and more incremental utility model patents ($DID = 0.295$).

The results demonstrate that neither a lending relationship alone nor an affiliated fund holding alone is sufficient to generate the large innovative response seen after the policy shock. Instead, the effect is amplified when both channels are active simultaneously, consistent with a model where proprietary information from lending is transmitted to the affiliated fund, which then provides the patient equity capital necessary to support long-horizon green R&D. This evidence moves beyond correlations to pinpoint the specific firm-bank-fund linkage through which the policy is transmitted.

4.5.2 Affiliated Holdings and Firm Green Innovation

Table 12 estimates DID regressions where the dependent variable is the natural log of one plus green patent applications at the firm level (three measures including total, invention,

utility model). The regressor of interest is the interaction *Affiliated_Holding *Shock*, where *Affiliated_Holding* equals one if affiliated funds hold the firm and Shock indicates the post-2016 period. The interaction is positive and statistically significant across all three measures, i.e., 0.330 ($t = 2.75$) for total green patents, 0.380 ($t = 2.85$) for green invention patents, and 0.243 ($t = 2.06$) for utility patents.

[Insert Table 12 here]

The estimated coefficients in Table 12 demonstrate substantial economic significance. With the dependent variable specified as the natural logarithm of one plus green patent counts, the *Affiliated_Holding *Shock* coefficient of 0.330 ($t = 2.75$) indicates that portfolio firms of affiliated funds increased their green patent output by approximately 39% following the reform, relative to firms held by unaffiliated funds, after accounting for control variables and fixed effects. Similar effects are observed when we focus on invention patents (0.380, $t = 2.85$) and utility model patents (0.243, $t = 2.06$). This innovation response, in turn, helps explain the subsequent performance advantages of greener affiliated funds (Tables 7–8) and their ability to attract institutional capital inflows (Table 9).

4.5.3 Bank Lending Relationships and Information Channel

Table 13 evaluates whether affiliation effects are amplified when portfolio firms are major loan clients of the parent bank, where proprietary credit information and oversight should be richest. The key regressor is *High_Loan_Client_Num *Shock*, where *High_Loan_Client_Num* equals one if the parent bank's number of loan clients is above the sample median. The interaction is positive and significant for all three firm-level innovation measures: 0.035 ($t = 2.71$) for total green patents, 0.022 ($t = 2.43$) for green invention patents, and 0.018 ($t = 2.97$) for utility patents. These estimates indicate that firms tied to banks with broader borrower networks exhibit larger post-reform increases in green patenting, which is exactly where the information channel should be strongest.

[Insert Table 13 here]

Tables 12 and 13 provide direct evidence illuminating the mechanisms underlying our earlier findings. 12 establishes that equity ownership by affiliated funds is associated with a substantial post-reform increase in firm-level green innovation. Table 13 further demonstrates that this effect is amplified when parent banks maintain lending relationships with the same firms. Together, these results explain the patterns documented in previous sections—including enhanced innovation, reduced emissions, preferential capital allocation, and market recognition—all of which concentrate in the greener segments of affiliated funds' portfolios. The evidence indicates that the affiliation channel operates through the synergistic combination of equity ownership and proprietary credit information, thereby reinforcing the bright-side hypotheses while constraining explanations based solely on agency conflicts.

5 Heterogeneity Analysis and Robustness Checks

5.1 Heterogeneity Analysis

The findings in Section 4.5 indicate that the benefits of affiliation are not uniform but are concentrated in greener holdings and in firms with stronger informational ties to parent banks. These patterns suggest that the bright side of bank affiliation is most powerful when external conditions and capabilities reinforce banks' incentives and monitoring capacity. To identify the boundary conditions of these effects, we next examine cross-sectional heterogeneity along four dimensions for considering the MPA pressure, the intensity of regional environmental regulation, the degree of public attention to environmental issues, and the environmental expertise of fund managers. Each of these dimensions captures a setting in which affiliated funds may face stronger or weaker incentives to channel capital toward firms with credible green projects.

5.1.1 MPA Pressure and the Regulatory Dose–Response Test

Our core argument posits that the 2016 green finance policy was transmitted through banks' incentives under the MPA framework. If this mechanism is valid, we should observe a stronger response from funds affiliated with banks under greater regulatory pressure to improve their MPA scores. Banks with less capital buffer or tighter liquidity constraints have a stronger incentive to increase their holdings of "green assets" to satisfy regulators. We test this prediction using a triple-difference specification.

Table 14 reports the results, where we interact the policy shock with an indicator for funds whose parent banks are under high MPA pressure (top quartile). The findings provide strong support for this amplification mechanism. The coefficient on the interaction term, *High_MPA_Pressure *Shock*, is positive and highly significant across all three green innovation measures, with coefficients of 1.239 for *Green_Sum*, 0.958 for *Green_Inv*, and 0.452 for *Green_Uti*.

[Insert Table 14 here]

These results demonstrate that following the 2016 reform, funds affiliated with banks under heightened regulatory constraints significantly expanded their green investments compared to those connected to less pressured institutions. The substantial economic magnitude of this differential response confirms that direct supervisory pressure served as a primary driver of portfolio reallocation. Notably, the amplification effect proves strongest for green invention patents—implying that regulatory incentives prompted banks to channel capital toward more substantive, breakthrough innovations rather than incremental improvements. Collectively, these findings offer compelling evidence that prudential regulation can generate powerful synergies with environmental policy, effectively leveraging bank-fund affiliations to transform supervisory requirements into tangible green investment outcomes.

5.1.2 Environmental Regulation Intensity

Affiliation with commercial banks may be most effective where local regulatory enforcement is stricter. Parent banks face supervisory pressure to expand green finance, but firms and funds in regions with weak environmental enforcement may face little cost of non-compliance. In contrast, in high-regulation regions, affiliated funds face stronger incentives to channel capital into genuinely green firms to meet both regulatory expectations and reputational concerns. Table 15 splits the sample by regional regulation intensity. The interaction *Affiliated *Shock* is significant and larger in the high-intensity group across all three green-innovation preference measures: 0.034 ($t = 2.63$) for *Green_Sum*, 0.028 ($t = 3.24$) for *Green_Inv*, and 0.022 ($t = 3.44$) for *Green_Uti*. In the low-intensity group, coefficients are smaller and not significant, and formal difference tests reject equality at conventional levels. These results support the idea that external enforcement magnifies the transmission of bank-level incentives to affiliated funds.

[Insert Table 15 here]

5.1.3 Public Environmental Attention

Affiliation with commercial banks may also be more powerful in regions where environmental issues receive greater public scrutiny. Public attention increases reputational risks for both banks and funds, raising the cost of symbolic compliance or greenwashing. In regions where environmental concerns are less salient, affiliated funds may face weaker market discipline. Using Baidu environmental search intensity as a proxy for public attention, Table 16 shows that affiliation effects are concentrated in high-attention regions. The coefficients on *Affiliated *Shock* are 0.048 ($t = 2.66$) for *Green_Sum*, 0.019 ($t = 2.62$) for *Green_Inv*, and 0.037 ($t = 2.95$) for *Green_Uti*, compared to small and insignificant coefficients in low-attention regions. Difference tests again reject equality. These findings suggest that social monitoring complements regulatory supervision by amplifying incentives to deliver credible green

outcomes.

[Insert Table 16 here]

5.1.4 Fund Manager Environmental Background

Finally, we ask whether the background of fund managers shapes the effect of affiliation. Managers with prior exposure to environmental topics may be better equipped to evaluate green projects, making them more effective in channeling affiliated resources toward innovative firms. If true, funds run by such managers should exhibit stronger green tilts after the reform. Table 17 splits funds into those with at least one manager with an environmental background and those without. Both groups show positive and significant affiliation effects. For managers with environmental backgrounds, *Affiliated *Shock* is 0.372 ($t = 4.57$) for *Green_Sum*, 0.199 ($t = 2.47$) for *Green_Inv*, and 0.025 ($t = 3.63$) for *Green_Uti*. For funds without such backgrounds, the coefficients are 0.203 ($t = 9.00$), 0.018 ($t = 2.31$), and 0.043 ($t = 3.03$), respectively. Difference tests indicate no statistically significant differences across the two groups. Thus, while environmental expertise correlates with strong green tilts, the incremental effect relative to other managers is indistinguishable, suggesting that bank-driven incentives dominate managerial heterogeneity in this setting.

[Insert Table 17 here]

Across all three dimensions, affiliation's impact is stronger where incentives are aligned: stricter enforcement and higher public attention create conditions in which affiliated funds respond most aggressively to the reform. Managerial expertise correlates with strong tilts but does not significantly alter the core effect, underscoring that bank-level and regional forces are the first-order drivers. These findings complement the mechanism evidence in Section 4.5 and the investor recognition in Section 4.3, showing that affiliation's bright side is conditional on external institutions and firm capacity, but robust across managerial types.

5.2 Robustness Checks

A natural concern is that our findings may be driven by unobserved factors or by the general sensitivity of bank-affiliated funds to regulatory shocks, rather than by environmental policy incentives per se. To address this, we conduct a battery of robustness tests including a placebo test exploiting the 2018 Asset Management New Regulation, considering 2012 Green Credit Green Guidelines along with alternative specifications accounting for manager selection effects, continuous treatment intensity measures, and propensity score matching.[1]

5.2.1 Placebo Test: The 2018 Asset Management New Regulation

A primary challenge to our identification strategy is the possibility that bank-affiliated funds are systematically more responsive to any form of regulation, not just policies specifically targeting green finance. If this were true, our results might simply reflect a generic "regulatory channel" rather than the specific mechanisms we propose. To rule out this alternative explanation, we conduct a placebo test using a major regulatory shock that was unrelated to environmental objectives.

We exploit the 2018 Asset Management New Regulation, a sweeping reform aimed at reducing leverage and systemic risk in the asset management industry, which allows us to verify whether our results are specific to the green finance policy, before turning to additional robustness checks such as alternative specifications and sample restrictions. This event created a significant shock for all funds but contained no specific green incentives. We re-estimate our baseline DID specification using this 2018 shock.

Table 18 presents the results of this placebo test. The key coefficient on the interaction term *Affiliated *Shock* is statistically indistinguishable from zero across all three green patent measures. The estimates are small in magnitude and have t-statistics close to one, indicating a complete absence of a differential response from bank-affiliated funds in their

[1] In the Appendix C, we estimate using both an alternative measure of the green policy shock and a sample that excludes crisis periods.

green investments following this major non-ESG regulatory event.

[Insert Table 18 here]

This null result is crucial for our causal interpretation. It demonstrates that the heightened sensitivity of bank-affiliated funds is specific to the 2016 green finance policy and does not extend to general financial regulations. This test effectively falsifies the alternative hypothesis of a generic regulatory channel, thereby strengthening the conclusion that our main findings are driven by the information and financing advantages activated by targeted green policy incentives.

5.2.2 Considering the 2012 Green Credit Guidelines Shock

Following Ma and Chen (2025), we further examine the effect of the 2012 Green Credit Policy, which represented China's early attempt to integrate environmental objectives into financial regulation. Unlike the 2012 Green Credit Guidelines that focused primarily on directing bank lending toward environmentally friendly sectors, this policy was not embedded within the People's Bank of China's macroprudential framework. Table 19 presents the results of a difference-in-differences estimation evaluating how the policy affected mutual funds' green investment behavior.

[Insert Table 19 here]

The results reveal that the interaction term *Affiliated *Shock* is statistically insignificant across all specifications, suggesting that bank-affiliated funds did not exhibit a differentiated response relative to non-affiliated funds. This finding implies that the 2012 policy, by lacking integration with capital adequacy assessments or supervisory ratings, failed to alter the underlying incentives of financial institutions.

5.2.3 Manager Selection

One possibility is that the green tilt of affiliated funds, as captured in their portfolio holdings, reflects changes in managerial human capital rather than the bank affiliation mechanism itself. Table 20 tests this by examining whether affiliated complexes were more likely to hire managers with environmental backgrounds after the reform. The coefficient on *Affiliated *Shock* is small and insignificant (0.004, $t = 0.09$ for the log count of environmental-background managers; 0.205, $t = 1.14$ for the indicator). These results suggest that our main findings are not driven by selective hiring of managers with ESG expertise.

[Insert Table 20 here]

5.2.4 Affiliated Ownership Intensity

Section 2.3 argued that the information and monitoring channels should strengthen with greater affiliated ownership. Table 21 splits firms by whether the affiliated fund shareholding ratio is above or below the median. Consistent with a dose–response pattern, *High Affiliated Holding *Shock* is strongly positive and significant: 0.225 ($t = 6.66$) for *Green_Sum*, 0.159 ($t = 6.74$) for *Green_Inv*, and 0.041 ($t = 7.27$) for *Green_Uti*. These results confirm that the magnitude of affiliated ownership matters for transmitting incentives.

[Insert Table 21 here]

5.2.5 Propensity Score Matching

A central concern is that affiliated and unaffiliated funds differ systematically in observables such as size, age, fees, or past performance. To mitigate this, we re-estimate the baseline specification on a propensity score matched sample. The propensity score is estimated on fund age, size, expense ratio, turnover, past returns, fund family size, number of managers,

and region. Each affiliated fund is matched to the nearest unaffiliated fund within a 0.01 caliper, without replacement.

The results, reported in Table 22, show that the post-reform increase in green tilts remains statistically and economically significant in the matched sample. The coefficient on *Affiliated *Shock* is 0.086 (t = 2.05) for *Green_Sum*, 0.119 (t = 12.14) for *Green_Inv*, and 0.036 (t = 6.72) for *Green_Uti*. These magnitudes are close to the baseline results, showing that observable sample composition does not drive our findings.

[Insert Table 22 here]

Overall, results in Table 22 demonstrate that even when affiliated and unaffiliated funds are statistically comparable on observable characteristics, affiliated funds still significantly increase the green tilts in their portfolio choices post-reform. This strengthens the causal interpretation that the effects arise from affiliation-specific channels.

6 Conclusions

This paper investigates whether and how the affiliation of mutual funds with commercial banks influences the environmental and social outcomes of portfolio firms. Our central question is whether affiliation serves as a channel that enhances or impedes sustainable investment outcomes among portfolio firms. Existing research on bank affiliation, largely based on developed economies, has highlighted conflicts of interest and weak governance. In contrast, China's bank-centered financial system and the introduction of the 2016 Green Finance Guidelines under the MPA framework provide a unique opportunity to examine whether affiliation can amplify information and monitoring advantages.

Our analysis yields several key findings. First, firms held by bank-affiliated funds significantly increased green innovation and reduced emissions following the policy implementation compared to firms held by unaffiliated funds. Second, these environmental improvements

generated tangible investor benefits, as evidenced by affiliated funds earning higher abnormal returns on bank-borrower positions and attracting larger inflows from sophisticated institutional investors specifically when maintaining greener portfolios. Third, we identify the dual mechanisms underlying these outcomes—greener affiliated funds not only received preferential capital support through enhanced leverage and faster asset growth from parent banks, but also leveraged proprietary banking information to identify credible green investment opportunities. These findings consistently align with the bright-side view of affiliation, suggesting that when prudential regulation aligns with environmental objectives, bank-fund linkages can generate substantial value across the investment chain.

In conclusion, this study demonstrates how institutional context fundamentally shapes financial intermediaries' role in sustainable finance. While traditional governance literature often views bank affiliation with skepticism, our findings reveal that properly structured incentives can transform these relationships into powerful channels for advancing green innovation and environmental improvement. The results further suggest that conclusions drawn from developed markets require careful reevaluation in emerging economy contexts, where distinct institutional arrangements determine whether the bright or dark side of bank affiliation predominates. Future research should extend these insights through comparative cross-country analysis, investigation of alternative intermediaries like insurance and pension funds, and examination of the long-term dynamics between financial system architecture and environmental performance.

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Table 1. Summary Statistics of Sample Data

This table provides summary statistics for the sample, with detailed definitions of all variables available in Appendix B. The sample period covers semi-annual data from 2008 to 2022.

	Obs	Mean	Median	Min	P1	P25	P75	P99	Max	SD
Green_Sum	37,338	0.169	0.085	0.000	0.000	0.025	0.225	1.086	42.206	0.348
Green_Inv	37,338	0.089	0.037	0.000	0.000	0.008	0.110	0.652	42.188	0.261
Green_Uti	37,338	0.081	0.033	0.000	0.000	0.006	0.102	0.623	22.268	0.174
Log_Carbon_Emission	25,914	3.990	3.722	−8.517	0.256	2.685	5.249	8.647	10.279	1.901
Log_Sum_Pollution	27,432	145.166	146.255	126.405	130.309	143.135	148.455	151.460	152.486	4.637
Log_Water_Pollution	27,432	139.362	140.357	118.298	123.926	136.909	142.882	147.319	148.880	4.976
Log_Air_Pollution	27,432	153.331	154.441	134.661	138.454	151.262	156.591	160.025	161.084	4.675
Affiliated	37,338	0.157	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.364
Shock	37,338	0.814	1.000	0.000	0.000	1.000	1.000	1.000	1.000	0.389
LogAge	37,338	4.610	4.635	1.946	3.178	4.344	5.024	5.517	5.591	0.545
FundFAM	37,338	4.937	4.963	0.000	1.792	4.454	5.684	6.409	6.557	0.945
FundTeam	37,338	0.885	1.000	0.000	0.000	1.000	1.000	1.000	1.000	0.319
Expense	37,338	1.092	1.200	0.000	0.500	1.200	1.200	1.500	1.600	0.243
LogTNA	37,338	20.001	20.081	12.330	16.078	18.903	21.152	23.270	25.103	1.605
Return	37,338	0.019	0.012	−0.344	−0.133	−0.012	0.049	0.183	0.797	0.059

Table 2. Univariate Tests Before and After the Commercial Bank Green Policy Shocks

This table presents the mean values of green technology innovation preference measures for mutual fund holdings, comparing affiliated and unaffiliated funds before and after the green policy shock using univariate tests. It also displays the differences in green technology innovation preferences between affiliated and unaffiliated funds, as well as between pre- and post-policy shock periods. T-statistics are shown in parentheses. ***, ** indicate significance at the 1% and 5% levels, respectively.

	(1) Pre-shock	(2) After-shock	(3) Diff (After-Before)
Panel A. For the Sum of Green Invention and Green Utility Model Patent Applications			
Affiliated Funds	0.091	0.282	0.191***
			(16.92)
Unaffiliated Funds	0.051	0.195	0.144***
			(30.33)
Diff (Affiliated-Unaffiliated)	0.040***	0.087***	0.047***
	(3.61)	(17.32)	(3.86)
Panel B. For the Number of Green Invention Patent Applications			
Affiliated Funds	0.072	0.193	0.121***
			(14.29)
Unaffiliated Funds	0.030	0.100	0.070***
			(19.77)
Diff (Affiliated-Unaffiliated)	0.042***	0.097***	0.051***
	(5.03)	(24.49)	(5.53)
Panel C. For the Number of Green Utility Model Applications			
Affiliated Funds	0.029	0.169	0.140***
			(24.68)
Unaffiliated Funds	0.021	0.094	0.073***
			(30.84)
Diff (Affiliated-Unaffiliated)	0.008	0.097***	0.066***
	(1.44)	(24.49)	(10.82)

Table 3. Testing the Parallel Trends Assumption

This table presents a dynamic test around the date of the commercial bank green finance policy shock, following the methodology of Bertrand and Mullainathan (2003) and Ni and Zhu (2018). The following regression is estimated:

$$\begin{aligned} Green_{i,t} =& \alpha + \beta_1 Affiliated_i + \beta_2 Pre_Event(\leq -2)_t + \beta_3 Pre_Event(-1)_t + \beta_4 Post_Event(0)_t \\ &+ \beta_5 Post_Event(1)_t + \beta_6 Post_Event(\geq 2)_t + \beta_7 Affiliated_i * Pre_Event(\leq -2)_t \\ &+ \beta_8 Affiliated_i * Pre_Event(-1)_t + \beta_9 Affiliated_i * Post_Event(0)_t \\ &+ \beta_{10} Affiliated_i * Post_Event(1)_t + \beta_{11} Affiliated_i * Post_Event(\geq 2)_t \\ &+ \gamma X_{i,t} + \delta_i + \theta_t + \epsilon_{i,t} \end{aligned}$$

The dependent variable captures green technology innovation preference in mutual fund holdings, with *Green_Inv*, *Green_Uti*, and *Green_Sum* as measures for green technology innovation, representing green invention patents, green utility model patents, and their total, respectively. *Affiliated* is a dummy variable equal to 1 if a fund belongs to a management company primarily owned by a commercial parent bank, as defined by Ferreira et al. (2018). Event indicators include:

- *Pre_Event*(≤ -2): 1 if the year is before 2015, 0 otherwise.
- *Pre_Event*(-1): 1 if the year is 2015, 0 otherwise.
- *Post_Event*(0): 1 if the year is 2016–2018, 0 otherwise.
- *Post_Event*(1): 1 if the year is 2019, 0 otherwise.
- *Post_Event*(≥ 2): 1 if the year is 2020 or later, 0 otherwise.

The vector $X_{i,t}$ includes (1) fund-specific control variables—*LogAge*, *FundFAM*, *FundTeam*, *Expense*, *LogTNA*, and *Return*—and (2) region-level control variables—*LogSTKNUM*, *LogBaiduEVN*, and *LogGDP*. Fund category and year-fixed effects are also included. T-statistics are shown in parentheses and are clustered at the fund level. The sample period spans semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Pre_Event(≤ -2) × Affiliated	0.034	0.047	-0.014^{*}
	(0.56)	(0.79)	(-1.76)
Pre_Event(-1) × Affiliated	(-0.005)	(-0.003)	(-0.002)
	(-0.43)	(-0.29)	(-0.35)
Post_Event(0) × Affiliated	0.391^{***}	0.255^{***}	0.227^{***}
	(10.32)	(8.61)	(11.90)
Post_Event(1) × Affiliated	1.026^{***}	0.672^{***}	0.590^{***}
	(12.89)	(10.30)	(15.31)
Post_Event(≥ 2) × Affiliated	0.193^{***}	0.140^{***}	0.118^{***}
	(6.12)	(5.71)	(7.48)
Affiliated	0.015	0.008	0.007
	(1.53)	(1.20)	(1.34)

Table 3 Continued

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Pre_Event(≤ -2)	-0.761^{***}	-1.332^{***}	0.225^{**}
	(-3.62)	(-9.04)	(2.09)
Pre_Event(-1)	-0.346^{***}	-0.491^{***}	0.034
	(-5.18)	(-9.46)	(0.98)
Post_Event(0)	-0.122^{***}	-0.143^{***}	(-0.007)
	(-7.53)	(-8.62)	(-0.77)
Post_Event(1)	-0.105^{***}	-0.093^{***}	-0.018^{***}
	(-18.36)	(-18.60)	(-5.40)
Post_Event(≥ 2)	0.149^{***}	0.175^{***}	0.024
	(4.59)	(9.41)	(1.47)
LogAge	(-0.006)	(-0.007)	0.006
	(-0.80)	(-1.45)	(1.23)
FundFAM	0.001	0.002	(-0.001)
	(0.21)	(1.16)	(-0.46)
FundTeam	0.028^{**}	0.018^{**}	0.010
	(2.13)	(2.33)	(1.50)
Expense	0.305^{***}	0.166^{***}	0.147^{***}
	(20.11)	(17.04)	(20.04)
LogTNA	-0.008^{***}	-0.005^{***}	-0.004^{***}
	(-3.08)	(-2.85)	(-4.06)
Return	0.121^{*}	0.003	0.159^{***}
	(1.66)	(0.07)	(4.34)
LogSTKNUM	0.020^{***}	0.013^{***}	0.009^{***}
	(3.37)	(2.93)	(3.05)
LogBaiduEVN	(-0.002)	(-0.003)	(-0.001)
	(-0.59)	(-1.18)	(-1.22)
LogGDP	-0.452^{**}	-1.032^{***}	0.277^{***}
	(-2.41)	(-8.29)	(2.93)
Constant	6.241^{**}	14.297^{***}	-3.859^{***}
	(2.39)	(8.33)	(-2.94)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	37,338	37,338	37,338
Adj.R^2	0.109	0.065	0.139

Table 4. Baseline DID regressions

This table presents the changes in mutual funds' green technology innovation preferences before and after the commercial bank green policy shock, using the following DID regression model:

$$Green_{i,t} = \alpha + \beta_1 Affiliated_{i,t} \times Shock_t + \beta_2 Affiliated_t + \beta_3 Shock_t + \gamma X_{i,t} + \delta_i + \theta_t + \epsilon_{i,t}$$

The dependent variable measures the preference for green technology innovation in mutual fund holdings. Key explanatory variables include *Affiliated*, *Shock*, and the interaction term *Affiliated* × *Shock*. The vector $X_{i,t}$ includes (1) fund-specific control variables—*LogAge*, *FundFAM*, *FundTeam*, *Expense*, *LogTNA*, and *Return*—and (2) region-level control variables—*LogSTKNUM*, *LogBaiduEVN*, and *LogGDP*. Detailed definitions of all variables are provided in Appendix B. Fund category and year-fixed effects are included. T-statistics are shown in parentheses, and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Affiliated × Shock	0.098**	0.098**	0.017**
	(2.18)	(2.26)	(2.18)
Affiliated	0.038	0.041	−0.003
	(0.90)	(0.98)	(−0.68)
Shock	1.026***	1.368***	−0.180
	(4.28)	(15.89)	(−1.54)
LogAge	−0.003	−0.004	0.003
	(−0.44)	(−0.99)	(0.79)
FundFAM	0.000	0.002	−0.001
	(0.19)	(1.09)	(−1.05)
FundTeam	0.023**	0.013**	0.006
	(2.06)	(2.07)	(1.28)
Expense	0.262***	0.147***	0.113***
	(22.48)	(19.93)	(21.67)
LogTNA	−0.006**	−0.004**	−0.003***
	(−2.50)	(−2.19)	(−3.25)
Return	0.203***	0.064	0.155***
	(2.81)	(1.57)	(4.84)
LogSTKNUM	0.016***	0.012***	0.005*
	(2.82)	(2.88)	(1.89)
LogBaiduEVN	0.003*	0.001	0.001
	(1.66)	(0.98)	(1.36)
LogGDP	−0.534***	−0.923***	0.258***
	(−2.85)	(−14.07)	(2.85)
Constant	6.520***	11.555***	−3.364***
	(2.72)	(13.94)	(−2.93)

Table 4 Continued

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	37,338	37,338	37,338
Adj. R^2	0.099	0.063	0.085

Table 5. The Impact of Affiliated Funds' Green Technology Innovation Investment on Carbon Emissions

The first column of this table reports how commercial bank affiliation affects their holding firms' carbon emissions under the green policy shock, while the second column presents the impact of affiliated funds' green technology innovation investments on carbon emissions in response to the commercial bank green finance policy shock. Both the dependent variables measure carbon emissions in mutual fund holdings. Due to the incomplete disclosure system of carbon emissions, there is a lack of authoritative firm-level carbon emission data (Nguyen and Phan, 2020), such as energy consumption or greenhouse gas emissions (GHG) (Konar and Cohen, 2001). For this analysis, we collect data on carbon emissions from the social responsibility reports, sustainability reports and environmental reports that companies disclose annually as the main dependent variables. In the first column, the key explanatory variables include *Affiliated*, *Shock*, and the interaction term *Affiliated* × *Shock*. In the second column, the key explanatory variables contain *Affiliated*, *Shock*, *Green_Sum*, their interaction terms, and triple interaction term *Affiliated* × *Green_Sum* × *Shock*. The control variables are the same as Table 3. Detailed definitions of all variables are provided in Appendix B. We also include fund category and year-fixed effects. T-statistics are shown in parentheses, and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Log_Carbon_Emission	(2) Log_Carbon_Emission
Affiliated × Green_Sum × Shock		−3.053***
		(−9.87)
Affiliated × Green_Sum		−0.098***
		(−2.74)
Affiliated × Shock	−0.189**	−0.360***
	(−2.28)	(−3.78)
Green_Sum × Shock		−0.489***
		(−6.95)
Affiliated	−0.019	−0.031
	(−0.26)	(−0.42)
Shock	−11.132***	−9.810***
	(−10.87)	(−9.74)
Green_Sum		−0.048
		(−1.34)
LogAge	0.004	0.010
	(0.10)	(0.28)
FundFAM	−0.023	−0.020
	(−1.58)	(−1.43)
FundTeam	−0.048	−0.028
	(−1.09)	(−0.64)
Expense	−0.625***	−0.418***

Table 5 Continued

	(1) Log_Carbon_Emission	(2) Log_Carbon_Emission
	(−10.32)	(−6.74)
LogTNA	−0.087***	−0.093***
	(−9.02)	(−9.80)
Return	−1.017***	−0.639***
	(−4.34)	(−2.77)
LogSTKNUM	−0.075***	−0.066***
	(−3.98)	(−3.54)
LogBaiduEVN	0.149***	0.151***
	(10.26)	(10.47)
LogGDP	8.306***	7.453***
	(10.54)	(9.62)
Constant	−98.837***	−88.246***
	(−9.84)	(−8.94)
Category FE	Yes	Yes
Year FE	Yes	Yes
N	25,914	25,914
Adj. R^2	0.068	0.087

Table 6. The Impact of Affiliated Funds' Green Technology Innovation Investment on Firms' Pollution

The first three columns of this table report how commercial bank affiliation affects their holding firms' pollution levels, including water pollution, air pollution and total pollution, under the green policy shock, while the last three columns show the impact of affiliated funds' green technology innovation investments on their holdings' pollution levels in response to the commercial bank green finance policy shock. The dependent variables include the pollutant emissions at the firm levels. Enterprise pollutant emissions mainly include industrial wastewater (e.g., chemical oxygen demand and ammonia nitrogen emissions), industrial waste gas (e.g., sulfur dioxide and nitrogen oxide emissions), and the sum of the above two types of pollution. We download pollution level data from listed company annual reports, listed company social responsibility reports, and listed company websites annually. We then compute the logarithm of one plus these pollutant emissions. In the first three columns, the key explanatory variables include *Affiliated*, *Shock*, and the interaction term *Affiliated* × *Shock*. In the last three columns, the key explanatory variables contain *Affiliated*, *Shock*, *Green_Sum*, their interaction terms, and triple interaction term *Affiliated* × *Green_Sum* × *Shock*. The control variables are the same as Table 3. Detailed definitions of all variables are provided in Appendix B. We also include fund category and year-fixed effects. T-statistics are shown in parentheses, and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Log_Water _Pollution	(2) Log_Air _Pollution	(3) Log_Sum _Pollution	(4) Log_Water _Pollution	(5) Log_Air _Pollution	(6) Log_Sum _Pollution
Affiliated × Green_Sum × Shock				−2.273***	−1.941***	−2.044***
				(−3.33)	(−3.15)	(−3.40)
Affiliated × Green_Sum				−0.072***	−0.013	−0.011
				(−4.96)	(−1.22)	(−1.21)
Affiliated × Shock	−0.368***	−0.500***	−0.431***	−0.337***	−0.234**	−0.279***
	(−3.60)	(−6.48)	(−6.33)	(−2.66)	(−2.28)	(−3.02)
Green_Sum × Shock				−0.060	−0.009	−0.035
				(−0.73)	(−0.17)	(−0.84)
Affiliated	−0.041	0.006	−0.014	−0.053	0.002	−0.021
	(−0.52)	(0.11)	(−0.34)	(−0.68)	(0.03)	(−0.49)
Shock	−4.067***	−2.431***	−3.333***	−3.466***	−1.900**	−2.798***
	(−3.46)	(−3.18)	(−5.33)	(−2.82)	(−2.29)	(−3.99)
Green_Sum				−0.017	−0.009	−0.011
				(−1.29)	(−0.85)	(−1.18)
LogAge	0.046	0.021	0.018	0.036	0.010	0.008
	(1.18)	(0.78)	(0.79)	(0.97)	(0.43)	(0.39)
FundFAM	0.003	−0.004	−0.000	0.012	0.006	0.009
	(0.21)	(−0.45)	(−0.03)	(0.87)	(0.65)	(1.29)
FundTeam	−0.095*	0.000	−0.022	−0.095**	−0.002	−0.023
	(−1.93)	(0.01)	(−0.69)	(−2.11)	(−0.06)	(−0.92)
Expense	−0.033	−0.032	−0.003	0.028	0.013	0.051

Table 6 Continued

	(1) Log_Water _Pollution	(2) Log_Air _Pollution	(3) Log_Sum _Pollution	(4) Log_Water _Pollution	(5) Log_Air _Pollution	(6) Log_Sum _Pollution
	(−0.51)	(−0.67)	(−0.07)	(0.47)	(0.32)	(1.55)
LogTNA	0.006	0.008	0.008	−0.002	−0.000	0.000
	(0.54)	(1.08)	(1.22)	(−0.21)	(−0.08)	(0.03)
Return	0.635**	−0.229	−0.028	1.016***	0.141	0.332**
	(2.34)	(−1.24)	(−0.18)	(3.76)	(0.78)	(2.23)
LogSTKNUM	0.040**	0.016	0.021*	0.045***	0.018	0.024**
	(2.35)	(1.24)	(1.90)	(2.77)	(1.52)	(2.46)
LogBaiduEVN	−0.048***	0.003	−0.018*	−0.053***	−0.001	−0.023***
	(−3.21)	(0.31)	(−1.91)	(−3.93)	(−0.14)	(−3.12)
LogGDP	18.461***	17.102***	17.807***	17.962***	16.633***	17.349***
	(20.61)	(29.32)	(37.36)	(19.20)	(26.43)	(32.64)
Constant	−110.473***	−79.272***	−96.333***	−104.006***	−73.130***	−90.358***
	(−9.70)	(−10.70)	(−15.91)	(−8.75)	(−9.17)	(−13.41)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,432	27,432	27,432	27,432	27,432	27,432
Adj. R^2	0.802	0.883	0.911	0.827	0.913	0.940

Table 7. Relative Performance of Affiliated Funds' Holdings in Borrowing and Nonborrowing Stocks

This table compares the performance of affiliated funds' positions in borrowing stocks versus non-borrowing stocks held by the same affiliated fund during the same period, using portfolio analysis. Affiliated funds are defined as those managed by a fund management company primarily owned by a commercial bank. Panels A–D report performance differences between affiliated funds' holdings in borrowing and non-borrowing stocks, measured by raw return, the single-factor model's alpha, the three-factor model's alpha, and the five-factor model's alpha, respectively. Equal-weighted portfolio returns across affiliated funds' borrowing and non-borrowing stock subgroups are regressed on the Fama and French (2015) five-factor model. Definitions of the corresponding variables are provided in Appendix B, with a focus on the alpha variables of interest. Due to the disclosure of bank loan details beginning only in 2013, the testing period spans January 2013 to December 2022. T-statistics are shown in parentheses and standard errors are clustered at the fund level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Raw Return

	Raw Return	Obs
Borrowing clients	0.035***	120
	(4.47)	
Nonborrowing clients	0.026***	120
	(3.43)	
Diff	0.009***	120
	(3.76)	

Panel B. One-Factor Model

	α	β_{MKT}	Obs	Adj.R^2
Borrowing clients	0.027***	1.145***	120	0.648
	(5.72)	(14.74)		
Nonborrowing clients	0.018***	1.152***	120	0.708
	(4.27)	(16.90)		
Diff	0.009***	−0.007	120	0.000
	(3.75)	(−0.18)		

Panel C. Three-Factor Model

	α	β_{MKT}	β_{SMB}	β_{HML}	Obs	Adj.R^2
Borrowing clients	0.023***	1.039***	0.567***	−0.425***	120	0.648
	(7.50)	(20.35)	(7.05)	(−4.15)		

Table 7 Continued

Nonborrowing clients	0.014^{***}	1.054^{***}	0.537^{***}	-0.385^{***}			120	0.904
	(5.76)	(26.10)	(8.44)	(−4.74)				
Diff	0.009^{***}	−0.015	0.030	−0.041			120	0.010
	(3.59)	(−0.37)	(0.46)	(−0.48)				

Panel D. Five-Factor Model

	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	Obs	Adj.R^2
Borrowing clients	0.023^{***}	1.040^{***}	0.562^{***}	-0.464^{***}	0.057	0.100	120	0.858
	(7.26)	(19.26)	(4.45)	(−3.32)	(0.25)	(0.43)		
Nonborrowing clients	0.013^{***}	1.080^{***}	0.698^{***}	-0.327^{***}	0.288	−0.054	120	0.907
	(5.20)	(25.78)	(7.12)	(−3.02)	(1.63)	(−0.30)		
Diff	0.010^{***}	−0.041	−0.136	−0.136	−0.230	0.153	120	0.050
	(4.01)	(−0.94)	(−1.34)	(−1.21)	(−1.26)	(0.82)		

Table 8. The Impact of Affiliated Funds' Green Technology Innovation Investment on the Performance

This table presents the impact of affiliated funds' green technology innovation investments on mutual fund performance in response to the commercial bank green finance policy shock. The dependent variable measures the mutual fund performance using raw return, the single-factor alpha, the three-factor alpha, and the five-factor alpha, each estimated over a rolling 24-month window. Key explanatory variables include *Affiliated*, *Shock*, *Green_Sum*, their interaction terms, and triple interaction term *Affiliated* × *Green_Sum* × *Shock*. Control variables are the same as in Table 3. Detailed definitions of all variables are provided in Appendix B. The model also includes fund category and year-fixed effects. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Raw return	(2) CAPM α	(3) FF-3α	(4) FF-5α
Affiliated × Green_Sum × Shock	0.011**	0.029***	0.028***	0.030***
	(2.42)	(2.91)	(2.69)	(3.44)
Affiliated × Green_Sum	0.017***	0.021***	0.023***	0.019***
	(26.73)	(16.06)	(16.07)	(15.87)
Affiliated × Shock	−0.004**	−0.007***	−0.008***	−0.007***
	(−2.24)	(−3.89)	(−3.77)	(−4.16)
Green_Sum × Shock	0.010**	−0.001	0.002	0.002
	(5.17)	(−0.51)	(1.48)	(1.57)
Affiliated	−0.000	0.002**	0.002*	0.002*
	(−0.25)	(1.98)	(1.84)	(1.93)
Shock	−0.504***	0.127***	0.125***	0.124***
	(−27.34)	(17.17)	(16.06)	(17.47)
Green_Sum	0.001	0.000	0.000	0.000
	(1.28)	(0.68)	(0.54)	(0.68)
LogAge	−0.003***	−0.027***	−0.028***	−0.029***
	(−4.73)	(−31.82)	(−33.28)	(−34.88)
FundFAM	−0.000	0.001***	0.001***	0.001***
	(−0.14)	(2.83)	(2.81)	(2.79)
FundTeam	−0.001*	0.003***	0.003***	0.003***
	(−1.79)	(3.62)	(3.51)	(3.38)
Expense	0.018***	−0.012***	−0.010***	−0.011***
	(16.94)	(−12.40)	(−10.60)	(−12.18)
LogTNA	0.001***	−0.002***	−0.001***	−0.001***
	(3.39)	(−10.93)	(−9.64)	(−9.18)
Return_SD	0.043**	0.068***	0.078***	0.076***
	(2.12)	(11.23)	(12.92)	(12.42)
LogSTKNUM	−0.002**	0.000	−0.000	−0.000
	(−7.40)	(0.16)	(−0.84)	(−0.33)

Table 8 Continued

	(1) Raw return	(2) CAPM α	(3) FF-3α	(4) FF-5α
LogBaiduEVN	-0.001^{***}	0.000	0.000	0.000
	(-3.64)	(1.45)	(1.29)	(1.49)
LogGDP	0.428^{***}	-0.086^{***}	-0.084^{***}	-0.085^{***}
	(30.87)	(-15.44)	(-14.52)	(-15.92)
Constant	-5.467^{***}	1.077^{***}	1.066^{***}	1.070^{***}
	(-31.11)	(14.99)	(14.17)	(15.56)
Category FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	37,249	37,249	37,249	37,249
Adj.R^2	0.341	0.590	0.586	0.625

Table 9. The Impact of Affiliated Funds' Green Technology Innovation Investment on the Flows

This table presents the impact of affiliated funds' green technology innovation investments on fund flows in response to the commercial bank green finance policy shock. Fund flow (*Flow*) is defined as the difference between the growth rate of total net assets (*TNA*) and the raw return of the fund from period $t-1$ to t, capturing new net inflows into mutual funds over the previous period (Yan, 2012). Fund flows are further divided into institutional investor flows (*InsFlow*) and individual investor flows (*IndFlow*), based on the proportion of shares held by institutional and individual investors, respectively. The primary explanatory variable is the triple interaction term *Affiliated* × *Green_Sum* × *Shock*. Control variables are the same as in Table 3. Detailed definitions for all variables are provided in Appendix B. Fund category and year-fixed effects are also included in the model. The regression analysis mirrors the approach in Table 3, with separate regressions for each group. We also conduct a difference test on the coefficients of the interaction term *Affiliated* × *Green_Sum* × *Shock* and report the p-value of the coefficient difference test between columns (2) and (3). T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) TotalFlow	(2) InsFlow	(3) IndFlow
Affiliated × Green_Sum × Shock	0.301*	0.488***	0.064
	(1.93)	(3.24)	(0.99)
Affiliated × Green_Sum	0.026	0.028*	0.001
	(1.54)	(1.65)	(0.25)
Affiliated × Shock	−0.047*	−0.073***	−0.011
	(−1.80)	(−2.89)	(−1.05)
Green_Sum × Shock	0.014**	0.014**	0.006**
	(2.23)	(2.42)	(2.28)
Affiliated	−0.001	−0.000	0.000
	(−0.17)	(−0.05)	(−0.15)
Shock	−0.066	−0.136	0.052
	(−0.58)	(−1.31)	(1.06)
Green_Sum	−0.001	−0.001	0.000
	(−0.94)	(−0.85)	(0.62)
LogAge	−0.006**	−0.004*	−0.002**
	(−2.49)	(−1.71)	(−2.51)
FundFAM	−0.002***	−0.002***	−0.001**
	(−4.01)	(−3.59)	(−2.45)
FundTeam	0.003*	0.003	0.001
	(1.67)	(1.44)	(0.67)
Expense	−0.025***	−0.026***	−0.006**
	(−4.30)	(−4.76)	(−2.42)
LogTNA	0.004***	0.003***	0.001***

Table 9 Continued

	(1) TotalFlow	(2) InsFlow	(3) IndFlow
	(6.04)	(4.71)	(6.06)
Return	−0.044	−0.061**	−0.005
	(−1.36)	(−1.98)	(−0.40)
LogSTKNUM	−0.002*	−0.002**	−0.000
	(−1.72)	(−2.33)	(−1.50)
LogBaiduEVN	0.001	0.000	0.000
	(0.86)	(0.67)	(1.11)
LogGDP	0.053	0.103	−0.039
	(0.61)	(1.30)	(−1.06)
Constant	−0.696	−1.317	0.493
	(−0.63)	(−1.31)	(1.05)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	33,842	33,842	33,842
Adj.R^2	0.031	0.084	0.013
p-value of the difference test		(2)−(3)	0.000

Table 10. Financing Channel: Capital Support and Fund Growth

This table presents the regression results from a two-panel analysis examining how affiliated funds, defined as those managed by a fund management company primarily owned by a commercial bank, adjust their financial leverage (in Column 1) and portfolio size changes (in Column 2) in response to market shocks and their level of green investment. The dependent variable in Column 1 is *Fund_Leverage*, while in Column 2 it is *Delta_Size*. The core explanatory variables are the triple interaction terms *Affiliated* × *Green_Sum* × *Shock*, which captures the differential response of affiliated funds during a shock period based on their pre-existing green investment characteristics. The models control for a standard set of fund-specific characteristics, including *LogAge*, *FundFAM*, *FundTeam*, *Expense*, *LogTNA*, *Return*, *LogSTKNUM*, *LogBaiduEVN*, and *LogGDP*, and include both category and year fixed effects to account for heterogeneity across fund types and time periods. T-statistics are shown in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Fund_Leverage	(2) Delta_Size
Affiliated × Green_Sum × Shock	0.064***	4.175***
	(2.92)	(7.98)
Affiliated × Green_Sum	0.036*	−0.502
	(1.87)	(−1.12)
Affiliated × Shock	−0.016***	−0.537***
	(−3.89)	(−8.00)
Green_Sum × Shock	−0.015***	0.245***
	(−7.99)	(4.96)
Green_Sum	−0.001	−0.022
	(−0.78)	(−1.30)
Affiliated	0.002	0.002
	(0.66)	(0.04)
Shock	0.054**	4.619***
	(2.57)	(7.84)
LogAge	−0.008***	−0.141***
	(−6.17)	(−6.80)
FundFAM	0.002***	−0.073***
	(3.31)	(−7.47)
FundTeam	0.007***	0.141***
	(3.27)	(5.28)
Expense	−0.058***	−0.359***
	(−15.56)	(−9.05)
LogTNA	0.002***	0.130***
	(4.92)	(22.47)
Return	−0.061***	0.039
	(−10.86)	(0.21)
LogSTKNUM	−0.009***	−0.019*

Table 10 Continued

	(1) Fund_Leverage	(2) Delta_Size
	(−11.89)	(−1.66)
LogBaiduEVN	0.000	−0.010
	(0.43)	(−1.13)
LogGDP	−0.026	−3.247***
	(−1.61)	(−7.24)
Constant	0.433**	39.426***
	(2.12)	(6.93)
Category FE	Yes	Yes
Year FE	Yes	Yes
Obs	34,055	34,055
Adj.R^2	0.134	0.103

Table 11. The Impact of Green Finance Policy on Corporate Green Investment

This table presents the impact of the green finance policy shock on corporate green investment, highlighting the informational advantage channel through bank-fund-firm affiliations. The analysis is conducted at the firm level, with all listed companies classified into four distinct groups based on their relationships with banks and their affiliated funds: *Bank + Fund* (firms that are both loan clients of a bank and held by that bank's affiliated fund), *Loan Only* (loan clients only), *Fund Only* (held by a bank-affiliated fund only), and *Neither* (the baseline group, with neither type of relationship). The dependent variable is the firm's green investment level, measured by its green patent applications, including the sum (*Green_Sum*), inventions (*Green_Inv*), and utility models (*Green_Uti*). Panel A reports the full-sample descriptive statistics. Panels B, C, and D report the mean values of green investment before and after the policy shock for each group, the within-group difference, and the crucial Difference-in-Differences (DID) estimates comparing the Bank + Fund group to the Neither group. T-statistics are reported in parentheses. The sample includes listed firms from 2008 to 2022 based on semi-annual data. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Group	Variable	Obs	Mean	SD	Min	P1	P25	P50	P75	P99	Max
Panel A. Descriptive Statistics: Green Investment Intensity by Firm-Bank-Fund Relationship Groups											
Bank + Fund	Green_Sum	15,500	0.905	4.658	0.000	0.000	0.000	0.000	0.000	21.042	154.673
	Green_Inv	15,500	0.437	3.146	0.000	0.000	0.000	0.000	0.000	12.588	113.321
	Green_Uti	15,500	0.468	3.494	0.000	0.000	0.000	0.000	0.000	12.920	154.673
Loan Only	Green_Sum	15,056	0.137	0.825	0.000	0.000	0.000	0.000	0.000	3.348	21.011
	Green_Inv	15,056	0.063	0.579	0.000	0.000	0.000	0.000	0.000	1.826	20.287
	Green_Uti	15,056	0.073	0.596	0.000	0.000	0.000	0.000	0.000	2.051	21.011
Fund Only	Green_Sum	18,962	0.061	1.011	0.000	0.000	0.000	0.000	0.000	0.915	76.698
	Green_Inv	18,962	0.032	0.762	0.000	0.000	0.000	0.000	0.000	0.539	76.698
	Green_Uti	18,962	0.029	0.666	0.000	0.000	0.000	0.000	0.000	0.524	46.296
Neither	Green_Sum	23,952	0.031	0.633	0.000	0.000	0.000	0.000	0.000	0.309	45.696
	Green_Inv	23,952	0.012	0.368	0.000	0.000	0.000	0.000	0.000	0.094	40.466
	Green_Uti	23,952	0.018	0.515	0.000	0.000	0.000	0.000	0.000	0.159	45.696
Total	Green_Sum	73,470	0.245	2.287	0.000	0.000	0.000	0.000	0.000	6.366	154.673
	Green_Inv	73,470	0.117	1.542	0.000	0.000	0.000	0.000	0.000	2.347	113.321
	Green_Uti	73,470	0.127	1.697	0.000	0.000	0.000	0.000	0.000	2.575	154.673

Panel B. For the Sum of Green Invention and Green Utility Model Patent Applications			
	Pre-shock	After-shock	Diff (After−Before)
Bank + Fund	0.528	0.983	0.454*** (4.57)
Loan Only	0.084	0.148	0.064*** (3.68)
Fund Only	0.015	0.076	0.061*** (3.59)
Neither	0.005	0.040	0.034*** (3.69)

Table 11 Continued

Group	Variable	Obs	Mean	SD	Min	P1	P25	P50	P75	P99	Max
Diff (Bank + Fund−Neither)		0.523*** (13.05)			0.943*** (25.24)				0.420*** (5.58)		
Panel C. For the Number of Green Invention Patent Applications											
		Pre-shock			After-shock				Diff (After−Before)		
Bank + Fund		0.323			0.461				0.138*** (2.05)		
Loan Only		0.037			0.069				0.032*** (2.63)		
Fund Only		0.010			0.039				0.029*** (2.26)		
Neither		0.003			0.015				0.013*** (2.31)		
Diff (Bank + Fund−Neither)		0.320*** (9.41)			0.445*** (18.14)				0.125*** (2.11)		
Panel D. For the Number of Green Utility Model Applications											
		Pre-shock			After-shock				Diff (After−Before)		
Bank + Fund		0.205			0.522				0.317*** (4.24)		
Loan Only		0.047			0.079				0.032*** (2.54)		
Fund Only		0.005			0.037				0.032*** (2.87)		
Neither		0.002			0.024				0.022*** (2.88)		
Diff (Bank + Fund−Neither)		0.203*** (9.37)			0.498*** (17.38)				0.295*** (6.26)		

Table 12. The Impact of Affiliated Funds' Green Investment on Portfolio Firms' Green Innovation

This table presents the impact of affiliated funds' green technology innovation investments on green innovation at the portfolio firm level, focusing specifically on affiliated funds. The dependent variables are the logarithm of one plus green innovation measures at the firm level, including (1) the total number of green invention and green utility model patent applications, (2) the number of green invention patent applications, and (3) the number of green utility model patent applications. We define *Affiliated_Holding* as affiliated funds holding positions in the portfolio firms. *Shock* is a dummy variable equal to 1 for dates after 2016, when the People's Bank of China and seven other departments issued the Guiding Opinions on Building a Green Financial System, and 0 otherwise. The main coefficient of interest is the interaction term *Affiliated_Holding* × *Shock*. Control variables include firm characteristics obtained from the CSMAR database, such as *SOE*, *Size*, *Dual*, *ROA*, *Leverage*, *BM*, *Top_Holding*, *Ind_Director_Ratio*, and *Management_Holding*. Detailed definitions for all variables are available in Appendix B. The model also includes firm and year-fixed effects. T-statistics are shown in parentheses and standard errors are clustered at the firm level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LogSTKGreen	(2) LogSTKGreen2	(3) LogSTKGreen3
Affiliated_Holding × Shock	0.330***	0.380*	0.243**
	(2.75)	(2.85)	(2.06)
Affiliated_Holding	0.050	0.034	0.106
	(0.68)	(0.43)	(1.53)
Shock	23.825***	12.352***	12.323***
	(11.14)	(7.67)	(7.48)
SOE	0.654	0.231	0.587
	(0.67)	(0.30)	(0.89)
Size	−0.000	0.000	−0.000***
	(−0.32)	(0.72)	(−4.52)
Dual	0.200	0.070	0.329
	(0.22)	(0.10)	(0.65)
ROA	2.212*	1.209**	1.869*
	(1.89)	(1.99)	(1.92)
Leverage	1.518	1.901*	2.755**
	(1.01)	(1.70)	(2.57)
BM	−8.628***	−3.869**	−3.433**
	(−4.02)	(−2.54)	(−2.28)
Top_Holding	0.040	0.029	0.027
	(1.33)	(1.34)	(1.45)
Ind_Director_Ratio	0.004	−0.047	0.042
	(0.06)	(−1.22)	(0.99)
Management_Holding	−0.019	−0.028**	−0.008

Table 12 Continued

	(1) LogSTKGreen	(2) LogSTKGreen2	(3) LogSTKGreen3
Constant	(−0.99) −0.774 (−0.24)	(−2.12) −0.269 (−0.12)	(−0.65) −2.348 (−1.12)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	37,261	37,261	37,261
$Adj.R^2$	0.0299	0.0163	0.0121

Table 13. Affiliated Funds' Green Investment and Parent Banks' Loan Client Volume

This table examines how the volume of borrowing firms influences affiliated funds' green technology innovation investments. Following Ferreira et al. (2018), *Affiliated* is a dummy variable set to 1 if the fund belongs to a fund management company primarily owned by a commercial parent bank, with the analysis focused on affiliated funds. *High_Loan_Client_Num* is a dummy variable equal to 1 if the number of loan clients for the parent bank is above the median and 0 otherwise. Green technology innovation is measured in three ways: *Green_Inv* (number of green invention patent applications), *Green_Uti* (number of green utility model patent applications), and *Green_Sum* (sum of both green invention and green utility model patent applications). *Shock* is a dummy variable equal to 1 for dates after 2016, when the People's Bank of China and seven other departments issued the Guiding Opinions on Building a Green Financial System, and 0 otherwise. The primary explanatory variable of interest is the interaction term *High_Loan_Client_Num* × *Shock*. Control variables include fund characteristics and region-level variables as listed in Table 3, with definitions provided in Appendix B. The model also includes fund category and year-fixed effects. The regression methodology mirrors that used in Table 3 for each respective group. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
High_Loan_Client_Num × Shock	0.035***	0.022**	0.018***
	(2.71)	(2.43)	(2.97)
High_Loan_Client_Num	−0.024**	−0.021**	−0.003
	(−2.07)	(−2.44)	(−0.70)
Shock	0.810***	0.579***	0.247***
	(7.15)	(7.83)	(2.90)
LogAge	−0.004	−0.007	0.005
	(−0.35)	(−1.13)	(0.77)
FundFAM	0.006	0.007	−0.002
	(0.74)	(1.45)	(−0.46)
FundTeam	0.033**	0.020***	0.012*
	(2.44)	(2.84)	(1.71)
Expense	0.209***	0.110***	0.099***
	(10.51)	(9.79)	(10.30)
LogTNA	−0.012***	−0.007***	−0.005***
	(−4.03)	(−3.99)	(−2.90)
Return	0.471***	0.147***	0.332***
	(7.01)	(3.79)	(8.20)
LogSTKNUM	0.014***	0.011***	0.003
	(2.74)	(3.63)	(1.00)
LogBaiduEVN	−0.002	−0.001	−0.001
	(−0.69)	(−0.78)	(−0.48)
LogGDP	−0.893***	−0.723***	−0.189

Table 13 Continued

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
	(−5.44)	(−6.79)	(−1.54)
Constant	11.899***	9.629***	2.505
	(5.42)	(6.79)	(1.54)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	5,496	5,496	5,496
$Adj.R^2$	0.288	0.215	0.215

Table 14. The Amplifying Effect of MPA Pressure: Bank Regulatory Stringency and Green Finance Policy Synergy

This table presents the regression results analyzing the impact of market-wide shocks and high MPA pressure on funds' green investment behaviors, with the dependent variables being three distinct measures: *Green_Sum* in column (1), *Green_Inv* in column (2), and *Green_Uti* in column (3). The model examines the role of the interaction between a shock and high MPA pressure while controlling for fundamental fund characteristics including *LogAge*, *FundFAM*, *FundTeam*, *Expense*, *LogTNA*, *Return*, *LogSTKNUM*, *LogBaiduEVN*, and *LogGDP*, and it includes both category and year fixed effects to account for heterogeneity across fund types and time periods. Our key explanatory variable is the interaction term *High_MPA_Pressure* × *Shock*. This variable captures the differential effect of the policy shock on the green investment of funds that are connected to banks facing high MPA pressure. The dummy variable *High_MPA_Pressure* is constructed based on our MPA pressure indicator; it takes a value of 1 if a bank falls into the top quartile of regulatory pressure, and 0 otherwise. This identifies banks that are subject to stronger regulatory constraints and have less capital buffer space, thereby giving them stronger incentives to respond to policy guidance, such as that on green credit. The underlying MPA pressure index is a z-score-based composite measure that integrates differentiated capital shortfalls, uniform liquidity shortfalls, and a baseline systemic importance factor to rank banks according to their perceived regulatory stress level. The adjusted R-squared values indicate the model fit for each regression. T-statistics are reported in parentheses, with ***, **, and * denoting significance at the 1%, 5%, and 10% levels, respectively.

	(1) *Green_Sum*	(2) *Green_Inv*	(3) *Green_Uti*
High_MPA_Pressure × Shock	1.239***	0.958***	0.452***
	(3.11)	(2.62)	(12.13)
Shock	1.032***	0.581***	0.299*
	(6.05)	(4.79)	(1.73)
High_MPA_Pressure	0.011	0.004	0.002
	(1.01)	(0.54)	(0.46)
LogAge	−0.042	−0.004	0.004
	(−0.96)	(−0.66)	(0.59)
FundFAM	0.017	0.006	−0.000
	(1.24)	(1.15)	(−0.04)
FundTeam	0.051**	0.025***	0.013*
	(2.09)	(2.73)	(1.70)
Expense	0.215***	0.122***	0.100***
	(4.79)	(3.51)	(9.46)
LogTNA	−0.008***	−0.009*	−0.003*
	(−2.88)	(−1.86)	(−1.79)
Return	0.441***	0.083	0.249***
	(6.46)	(1.17)	(6.12)
LogSTKNUM	0.017***	0.001	0.005*
	(3.18)	(0.11)	(1.77)

Table 14 Continued

	(1) *Green_Sum*	(2) *Green_Inv*	(3) *Green_Uti*
LogBaiduEVN	0.004	−0.003	0.001
	(0.72)	(−1.45)	(0.63)
LogGDP	−0.638***	−0.363***	−0.121
	(−4.69)	(−3.87)	(−0.91)
Constant	8.026***	4.639***	1.436
	(4.54)	(3.97)	(0.85)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	4,841	4,841	4,841
Adj.R^2	0.110	0.064	0.378

Table 15. Heterogeneity Regression: The Influence of Environmental Regulation Intensity

This table examines whether affiliated funds increase their green investment levels in response to the commercial bank green finance policy shock, taking into account the impact of environmental regulation intensity. Regional environmental regulation intensity is calculated as the ratio of completed investments in industrial pollution control to the added value of the secondary industry. Regions are categorized into high- and low-intensity groups based on the annual median of environmental regulation intensity. The dependent variable measures the green technology innovation preference of mutual fund holdings. The primary explanatory variable of interest is the interaction term *Affiliated* × *Shock*. Control variables include fund characteristics and region-level variables as listed in Table 3, with definitions provided in Appendix B. The model also includes fund category and year-fixed effects. The regression analysis mirrors that of Table 3 for each intensity group. Additionally, we conduct a difference test on the coefficients of the interaction term *Affiliated* × *Shock*, reporting the p-value for this test. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Green_Sum		Green_Inv		Green_Uti	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Affiliated × Shock	0.034***	0.014	0.028***	0.014	0.022***	0.007
	(2.63)	(0.19)	(3.24)	(0.18)	(3.44)	(0.79)
Affiliated	−0.001	0.069	−0.004	0.076	0.003	−0.007
	(−0.13)	(0.94)	(−1.06)	(1.04)	(1.27)	(−0.83)
Shock	1.460***	0.403	1.427***	1.253***	0.096	−0.202**
	(7.82)	(1.03)	(11.13)	(10.68)	(0.79)	(−2.19)
LogAge	−0.001	−0.009	−0.004	−0.011*	0.002	0.004
	(−0.16)	(−0.84)	(−0.80)	(−1.80)	(0.39)	(0.96)
FundFAM	0.003	−0.004	0.000	0.001	0.002	−0.005***
	(0.80)	(−1.34)	(0.11)	(0.46)	(1.31)	(−3.10)
FundTeam	−0.000	0.041***	0.002	0.023***	−0.002	0.010**
	(−0.00)	(2.76)	(0.28)	(3.02)	(−0.31)	(2.21)
Expense	0.267***	0.230***	0.145***	0.126***	0.128***	0.100***
	(22.05)	(14.64)	(19.77)	(12.66)	(21.13)	(16.66)
LogTNA	−0.004**	−0.005	−0.002*	−0.003	−0.002**	−0.003**
	(−2.03)	(−1.53)	(−1.67)	(−1.16)	(−2.05)	(−2.44)
Return	0.317***	0.044	0.119***	−0.041	0.203***	0.167***
	(6.24)	(0.36)	(3.57)	(−0.59)	(7.11)	(7.87)
LogSTKNUM	0.004	0.021**	0.003	0.015**	0.002	0.007*
	(1.12)	(2.43)	(1.15)	(2.20)	(0.85)	(1.75)

Table 15 Continued

	Green_Sum		Green_Inv		Green_Uti	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
LogBaiduEVN	0.000	0.005**	−0.000	0.002*	0.000	0.001
	(0.13)	(2.16)	(−0.00)	(1.81)	(0.20)	(0.73)
LogGDP	−0.867***	−0.066	−0.969***	−0.839***	0.055	0.268***
	(−6.04)	(−0.22)	(−9.90)	(−9.39)	(0.59)	(3.78)
Constant	10.754***	0.623	12.175***	10.509***	−0.824	−3.458***
	(5.90)	(0.16)	(9.79)	(9.31)	(−0.69)	(−3.87)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	15,384	21,954	15,384	21,954	15,384	21,954
Adj.R^2	0.248	0.057	0.174	0.031	0.202	0.089
p-value of the difference test	(1)−(2)		(3)−(4)		(5)−(6)	
	0.001		0.001		0.000	

Table 16. Heterogeneity Regression: The Influence of Public Environmental Attention

This table examines whether affiliated funds increase their green investment levels in response to the commercial bank green finance policy shock, taking into account the influence of public environmental attention. Regional public environmental attention is measured by the Baidu environmental search index for each province where the institution is located. Regions are divided into high- and low-attention groups based on the annual median of public environmental attention. The main explanatory variable is the interaction term *Affiliated* × *Shock*. Control variables include fund characteristics and region-level factors as outlined in Table 3, with detailed definitions provided in Appendix B. The model also includes fund category and year-fixed effects. The regression analysis mirrors that used in Table 3 for each group. Additionally, a difference test is conducted on the coefficients of the interaction term *Affiliated* × *Shock*, with p-values reported for this test. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Green_Sum		Green_Inv		Green_Uti	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Affiliated × Shock	0.048***	0.005	0.019***	0.009	0.037***	0.006
	(2.66)	(0.06)	(2.62)	(0.10)	(2.95)	(1.03)
Affiliated	−0.004	0.094	0.001	0.094	−0.005	−0.000
	(−0.42)	(1.00)	(0.19)	(1.01)	(−0.70)	(−0.06)
Shock	0.884***	0.932**	1.246***	1.691***	0.394*	−0.005
	(3.07)	(2.24)	(10.43)	(4.32)	(1.86)	(−0.04)
LogAge	−0.007	0.004	−0.007*	−0.002	0.000	0.005
	(−0.71)	(0.44)	(−1.69)	(−0.32)	(0.04)	(1.44)
FundFAM	0.002	0.002	0.002	0.001	0.000	−0.002
	(0.49)	(0.49)	(0.79)	(0.46)	(0.11)	(−1.32)
FundTeam	0.022*	0.024*	0.009	0.020**	0.011	0.001
	(1.82)	(1.81)	(1.50)	(2.39)	(1.46)	(0.15)
Expense	0.257***	0.240***	0.139***	0.124***	0.119***	0.110***
	(17.92)	(17.90)	(21.18)	(16.51)	(12.76)	(23.11)
LogTNA	−0.003	−0.007*	−0.000	−0.005*	−0.003**	−0.002**
	(−1.44)	(−1.93)	(−0.27)	(−1.70)	(−2.38)	(−2.49)
Return	0.162**	0.183	0.006	0.208*	0.158**	0.168***
	(1.97)	(1.56)	(0.22)	(1.76)	(2.54)	(6.68)
LogSTKNUM	0.014**	0.014*	0.006***	0.016*	0.009*	0.002
	(2.03)	(1.75)	(2.68)	(1.90)	(1.72)	(1.12)
LogBaiduEVN	0.004	0.003	0.001	0.006	0.002	0.000

Table 16 Continued

	Green_Sum		Green_Inv		Green_Uti	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
	(1.61)	(1.25)	(0.80)	(1.23)	(1.51)	(0.05)
LogGDP	−0.430*	−0.465	−0.829***	−1.178***	0.424**	0.124
	(−1.93)	(−1.41)	(−9.09)	(−3.94)	(2.57)	(1.47)
Constant	5.178*	5.635	10.350***	14.800***	−5.476***	−1.670
	(1.83)	(1.33)	(8.95)	(3.96)	(−2.62)	(−1.57)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	18,673	18,665	18,673	18,665	18,673	18,665
Adj.R^2	0.248	0.057	0.174	0.031	0.202	0.089
p-value of the difference test	(1)−(2)		(3)−(4)		(5)−(6)	
	0.001		0.001		0.000	

Table 17. The Impact of Fund Managers' Environmental Background on Green Investment

This table examines whether fund managers' environmental background influences affiliated funds' green technology innovation investments. By manually analyzing fund managers' resumes, we identify managers with prior work experience related to environmental protection (e.g., managing environmental funds, working as an environmental analyst, or serving in a government environmental protection department). Funds are categorized into a green fund subgroup if managed by at least one "green" fund manager and a nongreen fund subgroup otherwise. The primary explanatory variable is the interaction term *Affiliated*Shock*. Control variables include fund characteristics and region-level factors as specified in Table 3, with detailed definitions provided in Appendix A. The model also includes fund category and year-fixed effects. The regression analysis follows the approach used in Table 3 for each subgroup. Additionally, a difference test is conducted on the coefficients of the interaction term *Affiliated*Shock*, and p-values for this test are reported. T-statistics are shown in parentheses and are clustered at the fund level. The sample period spans semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Green_Sum		Green_Inv		Green_Uti	
	Managers with Green Background	Managers without Green Background	Managers with Green Background	Managers without Green Background	Managers with Green Background	Managers without Green Background
	(1)	(2)	(3)	(4))	(5)	(6)
Affiliated*Shock	0.372***	0.203***	0.199**	0.018**	0.025***	0.043***
	(4.57)	(9.00)	(2.47)	(2.31)	(3.63)	(3.03)
Affiliated	0.082	-0.010	0.082	-0.004	-0.001	-0.006
	(1.07)	(-0.83)	(1.07)	(-1.04)	(-0.20)	(-0.61)
Shock	0.475	1.277***	1.099***	1.307***	-0.288**	-0.146
	(1.01)	(5.23)	(8.32)	(12.67)	(-2.10)	(-0.81)
LogAge	-0.010	0.010	-0.013*	-0.000	-0.000	0.004
	(-1.04)	(1.01)	(-1.95)	(-0.03)	(-0.04)	(0.81)
FundFAM	0.001	-0.001	0.003	-0.000	-0.001	-0.002
	(0.24)	(-0.36)	(0.89)	(-0.10)	(-0.59)	(-1.08)
FundTeam	0.007	0.013	0.010	0.007	-0.003	0.006
	(0.46)	(1.00)	(1.04)	(1.16)	(-0.34)	(0.90)
Expense	0.230***	0.280***	0.121***	0.130***	0.110***	0.120***
	(15.35)	(18.25)	(11.86)	(19.51)	(16.10)	(13.52)

Table 17 Continued

LogTNA	-0.006	-0.004*	-0.005	-0.001	-0.002*	-0.003**
	(-1.40)	(-1.88)	(-1.47)	(-0.91)	(-1.79)	(-2.46)
Return	0.061	0.260***	-0.060	0.062**	0.182***	0.152***
	(0.47)	(3.41)	(-0.70)	(2.27)	(7.15)	(2.65)
LogSTKNUM	0.023**	0.014**	0.020**	0.003	0.004**	0.006
	(2.26)	(2.06)	(2.03)	(1.57)	(2.25)	(1.33)
LogBaiduEVN	0.004	0.002	0.001		0.002*	0.002*
0.000						
	(1.47)	(0.84)	(0.62)	(1.82)	(1.68)	(0.33)
LogGDP	-0.099	-0.738***	-0.717***	-0.888***	0.349***	0.229
	(-0.27)	(-3.91)	(-7.13)	(-11.36)	(3.31)	(1.63)
Constant	1.034	9.040***	9.018***	11.103***	-4.520***	-2.986*
	(0.22)	(3.77)	(7.10)	(11.22)	(-3.38)	(-1.68)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	16,518	20,820	16,518	20,820	16,518	20,820
Adj.R^2	0.153	0.147	0.021	0.164	0.203	0.060
p-value of the difference test	(1)-(2)		(3)-(4)		(5)-(6)	
	0.780		0.680		0.900	

Table 18. Placebo Test Using the 2018 Asset Management New Regulation Shock

This table presents the results of a placebo test that examines the impact of a non-ESG regulatory shock on funds' green investment. The shock is defined by the implementation of the 2018 Asset Management New Regulation, a broad set of rules aimed at reducing financial leverage and systemic risk in the asset management industry, which is unrelated to environmental or green credit policies. The dependent variables are three measures of green investment: *Green_Sum*, *Green_Inv*, and *Green_Uti*. The key explanatory variable is the interaction term *Affiliated* × *Shock*, which tests whether bank-affiliated funds differentially adjusted their green investments in response to this non-green regulatory shock.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Affiliated × Shock	−0.026	−0.026	−0.000
	(−1.15)	(−1.18)	(−0.03)
Affiliated	0.016	0.020	−0.003
	(0.75)	(0.91)	(−1.25)
Shock	1.089***	1.193***	−0.103
	(10.31)	(16.36)	(−1.52)
LogAge	−0.001	−0.005	0.004
	(−0.17)	(−1.27)	(1.31)
FundFAM	−0.002	−0.000	−0.002*
	(−1.06)	(−0.34)	(−1.66)
FundTeam	0.009	0.006	0.003
	(1.26)	(1.49)	(0.75)
Expense	0.226***	0.118***	0.108***
	(28.64)	(25.44)	(26.20)
LogTNA	−0.005**	−0.003	−0.002***
	(−2.39)	(−1.48)	(−3.22)
Return	0.205***	0.039*	0.166***
	(6.65)	(1.69)	(10.43)
LogSTKNUM	0.014**	0.009**	0.005*
	(2.53)	(2.07)	(1.93)
LogBaiduEVN	0.002	0.001	0.000
	(1.35)	(1.44)	(0.73)
LogGDP	−0.602***	−0.798***	0.196***
	(−7.46)	(−14.57)	(3.75)
Constant	7.439***	10.015***	−2.576***
	(7.32)	(14.59)	(−3.90)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	37,338	37,338	37,338
Adj.R^2	0.117	0.056	0.119

Table 19. Considering 2012 Green Credit Shock

This table presents the results of a placebo test that examines the impact of a 2012 Green Credit shock on funds' green investment. The shock is defined by the implementation of the 2012 Green Finance Policy, a broad set of rules aimed at reducing financial leverage and systemic risk in the asset management industry, which is unrelated to environmental or green credit policies. The dependent variables are three measures of green investment: *Green_Sum*, *Green_Inv*, and *Green_Uti*. The key explanatory variable is the interaction term *Affiliated* × *Shock*, which tests whether bank-affiliated funds differentially adjusted their green investments in response to this green finance policy shock.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Affiliated × Shock	−0.156	−0.165	0.009
	(−0.97)	(−1.03)	(0.63)
Affiliated	0.148	0.161	−0.012
	(0.92)	(1.00)	(−0.84)
Shock	1.102***	1.207***	−0.104
	(10.64)	(17.33)	(−1.53)
LogAge	−0.001	−0.005	0.004
	(−0.15)	(−1.27)	(1.30)
FundFAM	−0.002	−0.000	−0.002*
	(−1.08)	(−0.39)	(−1.65)
FundTeam	0.009	0.006	0.003
	(1.22)	(1.40)	(0.76)
Expense	0.226***	0.118***	0.108***
	(28.72)	(25.80)	(26.14)
LogTNA	−0.005**	−0.003	−0.002***
	(−2.43)	(−1.51)	(−3.23)
Return	0.204***	0.038	0.166***
	(6.49)	(1.58)	(10.42)
LogSTKNUM	0.014**	0.009**	0.005*
	(2.54)	(2.09)	(1.93)
LogBaiduEVN	0.002	0.001	0.000
	(1.45)	(1.60)	(0.71)
LogGDP	−0.601***	−0.798***	0.196***
	(−7.45)	(−14.52)	(3.75)
Constant	7.417***	9.990***	−2.573***
	(7.27)	(14.40)	(−3.89)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	37,338	37,338	37,338
Adj.R^2	0.118	0.058	0.119

Table 20. Whether Affiliated Funds Select Managers with an Environmental Background

This table examines whether affiliated funds are more likely to select managers with environmental backgrounds. By manually reviewing fund managers' resumes, we identify managers with prior work experience in environmental protection, such as managing environmental funds, working as environmental analysts, or serving in government environmental protection departments. For each fund, we define *Log_Green_Manager* as the logarithm of one plus the number of fund managers with an environmental background and *Dummy_Green_Manager* as a dummy variable set to 1 if any fund manager has an environmental background. These two variables serve as the main dependent variables. The primary explanatory variable is the interaction term *Affiliated* × *Shock*. Control variables include fund characteristics and region-level factors as specified in Table 3, with detailed definitions provided in Appendix B. The model also includes fund category and year-fixed effects. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period spans semi-annual data from 2008 to 2022. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Log_Green_Manager	(2) Dummy_Green_Manager
Affiliated × Shock	0.004	0.205
	(0.09)	(1.14)
Affiliated	(−0.020)	0.212
	(−0.37)	(0.95)
Shock	(−0.082)	(−0.228)
	(−0.66)	(−0.45)
LogAge	0.075***	0.226**
	(2.77)	(2.20)
FundFAM	(−0.015)	(−0.020)
	(−1.35)	(−0.42)
FundTeam	0.199***	0.788***
	(9.96)	(6.63)
Expense	0.161***	0.686***
	(4.24)	(4.16)
LogTNA	(−0.002)	0.002
	(−0.29)	(0.08)
Return	0.116**	0.492***
	(2.48)	(2.65)
LogSTKNUM	(−0.001)	0.004
	(−0.12)	(0.12)
LogBaiduEVN	0.001	(−0.000)
	(0.26)	(−0.02)
LogGDP	0.064	0.201
	(0.72)	(0.55)
Constant	−1.014	−5.303
	(−0.82)	(−1.05)

Table 20 Continued

	(1) Log_Green_Manager	(2) Dummy_Green_Manager
Category FE	Yes	Yes
Year FE	Yes	Yes
Obs	37,338	37,338
Adj.R^2/Pseudo R^2	0.054	0.029

Table 21. Considering the Influence of Affiliated Fund Shareholding Ratio on Green Investment

This table examines whether the affiliated fund shareholding ratio affects their green technology innovation investment. Following Ferreira et al. (2018), *Affiliated* is a dummy variable set to 1 if a fund belongs to a management company primarily owned by a commercial parent bank, with the focus on bank-affiliated funds. We calculate the shareholding ratio as the market value of affiliated fund holdings relative to the net value at the fund-year level. *High_Affiliated_Fund_Holding* is then defined as a dummy variable equal to 1 if this ratio is above the median, and 0 otherwise. The primary explanatory variable is the interaction term *High_Affiliated_Fund_Holding* × *Shock*. Control variables include fund characteristics and region-level variables, as outlined in Table 3, with detailed definitions provided in Appendix B. Fund category and year-fixed effects are also included. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
High_Affiliated_Fund_Holding × Shock	0.225***	0.159***	0.041***
	(6.66)	(6.74)	(7.27)
High_Affiliated_Fund_Holding	0.016**	0.001	0.007**
	(1.97)	(0.13)	(2.29)
Shock	0.005	0.576***	0.189
	(0.00)	(2.69)	(1.35)
LogAge	(−0.002)	(−0.009)	0.010*
	(−0.14)	(−1.06)	(1.78)
FundFAM	0.001	0.013	−0.005*
	(0.13)	(0.93)	(−1.86)
FundTeam	0.051*	0.029**	0.012*
	(1.82)	(2.00)	(1.91)
Expense	0.130***	0.044***	0.065***
	(4.79)	(4.75)	(7.78)
LogTNA	−0.005*	−0.003**	−0.003**
	(−1.85)	(−2.04)	(−2.51)
Return	(−0.131)	(−0.119)	0.175***
	(−0.36)	(−0.54)	(4.86)
LogSTKNUM	0.008*	0.005**	0.000
	(1.85)	(2.26)	(0.16)
LogBaiduEVN	(−0.003)	0.011	−0.009***
	(−0.28)	(0.65)	(−3.52)
LogGDP	0.149	−0.390**	(−0.058)
	(0.17)	(−2.26)	(−0.54)
Constant	−1.985	4.830**	0.747
	(−0.18)	(2.08)	(0.55)

Table 21 Continued

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	6,145	6,145	6,145
Adj.R^2	0.077	0.033	0.249

Table 22. Propensity Score Matching Regression Analysis

This table presents estimates from propensity score matching (PSM) regressions on funds' green technology innovation investments. Control funds (unaffiliated funds) are selected based on similar characteristics, including the logarithm of fund inception years, the logarithm of one plus the number of open-end funds within the fund family, a dummy variable indicating whether a fund is managed by multiple managers, expense ratio, the logarithm of total net assets under management, and fund performance. We create a control group using one-to-four propensity score matching and perform nearest-neighbor matching with replacements. The main explanatory variables are *Affiliated* (a dummy variable equal to 1 if the fund belongs to a management company primarily owned by a commercial parent bank), *Shock* (a dummy variable equal to 1 in the event year and afterward), and the interaction term *Affiliated* × *Shock*. The regression model follows the approach used in Table 3. Detailed definitions of all variables are provided in Appendix A. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Affiliated × Shock	0.086**	0.119***	0.036***
	(2.05)	(12.14)	(6.72)
Affiliated	0.014	−0.025	−0.005
	(0.30)	(−1.64)	(−0.91)
Shock	1.034*	0.860***	0.303**
	(1.76)	(6.71)	(1.99)
LogAge	−0.001	−0.001	0.011*
	(−0.06)	(−0.21)	(1.85)
FundFAM	0.013	0.015	0.002
	(1.48)	(1.54)	(0.68)
FundTeam	0.041*	0.026**	0.008
	(1.78)	(2.31)	(0.94)
Expense	0.256***	0.107***	0.122***
	(10.56)	(9.22)	(15.23)
LogTNA	−0.015***	−0.006***	−0.004***
	(−2.92)	(−4.94)	(−3.22)
Return	0.189	0.068	0.268***
	(1.12)	(0.69)	(8.38)
LogSTKNUM	0.028**	0.014***	0.003
	(2.10)	(5.13)	(1.24)
LogBaiduEVN	0.004	0.001	0.001
	(1.20)	(0.39)	(0.83)
LogGDP	−0.522	−0.562***	−0.099
	(−1.14)	(−5.63)	(−0.85)
Constant	6.420	6.999***	1.123

Table 22 Continued

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
	(1.10)	(5.44)	(0.76)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	11,742	11,742	11,742
Adj.R^2	0.074	0.050	0.224

Appendix A. Detailed ESG Measurement Formulas and Methodological Justifications

This appendix presents the underlying formulas and advanced methodological steps for constructing our three key environmental measures at the fund level: green technology investments, carbon emissions, and pollutants.

A.1. Green Technology Innovation

1. Firm-Level Green Patents

We collect data on green invention patents and green utility model patents Ni et al. (2022), focusing on patents classified under environmental or clean technology codes. Let $\text{GreenPat}_{f,t}$ represent the total number of these green patents for firm f in period t. For any firm lacking patent data in a given period, we treat its patent intensity as zero, consistent with the assumption that no green patents were filed in that interval.

2. Patents Relative to Firm Size

We further standardize patent counts by a size variable (e.g., total assets) to account for cross-firm differences in scale. Thus, each firm's patent intensity is:[2]

$$\text{Green}_{\text{firm } f,t} = \frac{\text{GreenPat}_{f,t}}{\text{Total asset}_{f,t}} \times 10^6, \tag{A1}$$

3. Aggregation to the Fund Level

For each mutual fund i in period t, we compute a weighted average of firm-level patent intensity:

$$\text{Green}_{\text{fund } i,t} = \sum_f \omega_{i,f,t} \text{Green}_{\text{firm } f,t}, \tag{A2}$$

Here, $\omega_{i,f,t}$ is the proportion of firm f in the total stock investment value of fund i during period t. This aggregation reflects how much of a fund's portfolio is allocated to firms engaging in substantial environmental R&D.[3]

[2]This value is multiplied by 10^6 to improve the readability of the regression results.

[3]For example, suppose fund i invested a total of \$1 million in the stock market in period t, of which \$300,000 was invested in company f's stock. Therefore, the weight of fund i's investment in company f's stock market value relative to the total investment market value in period t is 30% (\$300,000 / \$1 million).

A.2. Carbon Emissions

1. Industry-Level Calculations

Following Chapple et al. (2013), we obtain $\text{FuelCons}_{j,k,t}$ (the total consumption of fossil fuel k in industry j at time t), multiply by the standard coal conversion coefficient of fuel k (CoalConv_k) and carbon emission coefficients of fuel k (CE_Coef_k) to derive total industry emissions (tons of carbon dioxide/ tons of standard coal) for industry j:[4]

$$\text{ICE}_{j,t} = \sum_{k=1}^{8} \text{FC}_{j,k,t} \times \text{CC}_k \times \text{CEC}_k, \tag{A3}$$

2. Firm-Level Emissions

We calculate corporate carbon emissions ($\text{CCE}_{i,t}$) using the following equation:

$$\text{CCE}_{i,t} = \frac{\text{COC}_{i,j,t}}{\text{IOC}_{j,t}} \times \text{ICE}_{j,t}, \tag{A4}$$

where $\text{COC}_{i,j,t}$ represents the corporate operating costs for firm f in industry j in year t. $\text{IOC}_{j,t}$ is the operating costs at the industry level.

3. Fund-Level Aggregation

Similar to green patents, each fund's carbon emissions are a weighted average of the firm-level emissions:

$$\text{CCE}_{\text{fund } i,t} = \sum_{f} w_{i,f,t} \text{CCE}_{i,t}, \tag{A5}$$

A.3. Pollutant Equivalents

1. Standardization of Major Pollutants

Firm-level pollutant emissions include the chemical oxygen demand (COD) and ammonia nitrogen emissions in industrial wastewater (NH_4-N), sulfur dioxide (SO_2) and nitrogen oxide (NO_x) emissions in industrial waste gas. We standardize the emissions of the four pollutants based on the pollution equivalent values defined in the Administrative Measures for the Collection of Pollution Discharge Fees.[5] Each is converted to a unified measure of pollution equivalents using the guidelines from the Administrative Measures for the Collection of Pollution Discharge Fees.

[4] Based on the measurement methodology of carbon emissions issued by the Intergovernmental Panel on Climate Change (IPCC) in 2006, carbon emissions.

[5] https://www.moj.gov.cn/

2. Firm-Level Pollution

Let $\text{Pollut}_{f,t}$ be the total pollution equivalents for firm f. We sum and then apply a logarithmic transformation:

$$\text{Pollut}_{f,t} = \ln(\text{Equiv}_{\text{COD}} + \text{Equiv}_{\text{NH4-N}} + \text{Equiv}_{\text{SO2}} + \text{Equiv}_{\text{NO2}} + 1), \tag{A6}$$

3. Fund-Level Pollutant Calculation

Similar to carbon emissions, the fund-level pollutant is calculated as follows:

$$\text{Pollution}_{\text{fund } i,t} = \sum_{f} w_{i,f,t} \text{Pollution}_{\text{firm } f,t}, \tag{A7}$$

Appendix B. Variable Definitions

Variable	Definition
Green_Inv	The number of green invention patent applications.
Green_Uti	The number of green utility model patent applications.
Green_Sum	The sum of the number of both green invention patents and green utility model patent applications.
Affiliated	Following Ferreira et al. (2018), a dummy variable that is one if the ultimate controller of the fund management company is a commercial bank and 0 otherwise.
Shock	A dummy variable that equals 1 if the corresponding date is after 2016, when the People's Bank of China and seven other departments issued the Guiding Opinions on Building a Green Financial System, and 0 if otherwise.
LogAge	The logarithm of one plus the years since the inception of the fund.
FundFAM	The logarithm of one plus the number of open-end funds owned by the fund family.
FundTeam	A dummy variable that equals 1 if a fund is managed by multiple managers and 0 otherwise.
Expense	The expense ratio (%).
LogTNA	The logarithm of the fund's total net assets under management.
Return	Mutual funds' performance.
Excess Return	Monthly returns on a fund portfolio in excess of the risk-free rate.
Return_SD	The standard deviation of mutual funds' performance.
LogSTKNUM	The logarithm of one plus the number of fund stock holdings.
LogBaiduEVN	Public attention about environmental protection defined as the logarithm of one plus Baidu search index for environment-related terms where fund management company is located.
LogGDP	The regional gross domestic product.
Total_Flow	Difference between the growth rate for TNA and raw return for the fund between $t-1$ and t.

Variable	Definition
Ins_Flow	Net institutional inflows.
Ind_Flow	Net individual inflows.
LogSTKGreen	The portfolio firms' green innovation measured as the logarithm of the number of green patent applications, including green invention patents and green utility model patents.
Affiliated_Holding	Affiliated funds' holding positions in portfolio firms.
SOE	A dummy variable equal to 1 if a firm is state-owned and 0 otherwise.
Size	Firm f's total assets.
Dual	A dummy variable equal to 1 if the firm's chairman and general manager are the same person.
ROA	The net profit rate on total assets.
Leverage	Asset-liability ratio.
BM	Book-to-market ratio.
Top_Holding	Proportion of the largest shareholder.
Ind_Director_Ratio	Proportion of independent directors.
Mangement_Holding	Management shareholding ratio.
High_Loan_Client_Num	A dummy variable that equals 1 if the number of parent banks' loan clients is higher than the median level and 0 otherwise.
MKT	Market excess return.
SMB	The difference between the average return on the small-capitalization stock portfolio and the average return on the large-capitalization stock portfolio.
HML	The return on the portfolio with high book-to-market stocks minus the return on the portfolio with low book-to-market stocks.
RMW	The excess return of a high-earning stock relative to a low-earning stock.
CMA	The excess return of the stock of a conservative investment company relative to that of an aggressive investment company.
Log_Green_Manager	The logarithm of one plus the number of fund managers with environmental backgrounds.

Variable	Definition
Dummy_Green_Manager	A dummy variable that equals 1 if the fund manager managing the fund has an environmental background.
Pre_Event($\leq$-2)	A dummy variable equal to 1 if the year is less than 2015 and 0 if otherwise.
Pre_Event(-1)	A dummy variable equal to 1 if the year is equal to 2015 and 0 if otherwise.
Post_Event(0)	A dummy variable equal to 1 if the year is equal to 2016, 2017, and 2018, and 0 if otherwise.
Post_Event(1)	A dummy variable equal to 1 if the year is equal to 2019 and 0 if otherwise.
Post_Event($\geq$2)	A dummy variable equal to 1 if the year is above 2020 and 0 if otherwise.
High Affiliated Fund Holding	A dummy variable equal to 1 if the ratio is above the median and 0 if otherwise.
Fund_Leverage	The ratio of a fund's total assets to its net assets.
Delta_Size	The year-over-year growth rate of a fund's TNA.

Appendix C. Internet Appendix Tables

Internet Appendix Table 1. Alternative Definition of the Green Policy Shock

This table presents results using an alternative definition of the green policy shock. All variables are the same as in Table 3, except for the dummy variable Shock. Here, Shock is defined as a dummy variable equal to 1 if the date is after 2017—one year after the issuance of the Guiding Opinions on Building a Green Financial System by the People's Bank of China and seven other departments. The regression analysis follows the approach used in Table 3. Detailed definitions of all other variables are provided in Appendix B. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period covers semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Affiliated × Shock	0.114***	0.124***	0.019**
	(3.33)	(3.88)	(2.58)
Affiliated	0.025	0.029	(−0.004)
	(0.84)	(0.97)	(−1.12)
Shock	1.015***	1.360***	(−0.180)
	(4.23)	(15.80)	(−1.54)
LogAge	(−0.004)	(−0.005)	0.003
	(−0.53)	(−1.05)	(0.77)
FundFAM	0.000	0.002	(−0.001)
	(0.18)	(1.14)	(−1.05)
FundTeam	0.023**	0.013**	0.006
	(2.09)	(2.18)	(1.29)
Expense	0.261***	0.148***	0.113***
	(22.59)	(19.97)	(21.67)
LogTNA	−0.005**	−0.004**	−0.003***
	(−2.46)	(−2.22)	(−3.28)
Return	0.198***	0.065	0.155***
	(2.75)	(1.59)	(4.85)
LogSTKNUM	0.016***	0.012***	0.005*
	(2.78)	(2.82)	(1.90)
LogBaiduEVN	0.003*	0.001	0.001
	(1.70)	(1.06)	(1.36)
LogGDP	−0.529***	−0.920***	0.258***
	(−2.82)	(−14.07)	(2.85)
Constant	6.458***	11.521***	−3.360***
	(2.70)	(13.95)	(−2.93)
Category FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Internet Appendix Table 1 Continued

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti
Obs	37,338	37,338	37,338
Adj.R^2	0.098	0.065	0.085

Internet Appendix Table 2. Excluding the Periods of Financial Crisis

This table examines whether affiliated funds adjust their green technology innovation investments in response to the green finance policy shock from commercial banks, excluding periods of financial crisis. Columns (1)–(3) show results after excluding the 2008–2009 financial crisis, while columns (4)–(6) present results after excluding the 2015 market crash. The regression analysis follows the approach used in Table 3, with the main explanatory variable being the interaction term *Affiliated* × *Shock*. Detailed definitions of all variables are provided in Appendix B. T-statistics are shown in parentheses and standard errors are clustered at the fund level. The sample period spans semi-annual data from 2008 to 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Green_Sum	(2) Green_Inv	(3) Green_Uti	(4) Green_Sum	(5) Green_Inv	(6) Green_Uti
Affiliated × Shock	0.139***	0.140***	0.017**	0.147***	0.143***	0.021**
	(7.80)	(11.28)	(2.12)	(7.72)	(11.46)	(2.23)
Affiliated	(−0.004)	(−0.001)	(−0.003)	(−0.011)	(−0.004)	(−0.007)
	(−0.47)	(−0.20)	(−0.60)	(−1.11)	(−1.08)	(−1.00)
Shock	0.845***	1.136***	(−0.162)	0.854***	1.145***	(−0.160)
	(4.20)	(16.59)	(−1.54)	(4.15)	(16.50)	(−1.50)
LogAge	(−0.002)	(−0.002)	0.002	(−0.002)	(−0.003)	0.002
	(−0.26)	(−0.66)	(0.68)	(−0.33)	(−0.77)	(0.65)
FundFAM	0.001	0.002	(−0.001)	0.001	0.003	(−0.001)
	(0.24)	(1.17)	(−1.04)	(0.36)	(1.29)	(−0.98)
FundTeam	0.023**	0.013**	0.006	0.023**	0.013**	0.006
	(2.09)	(2.13)	(1.29)	(2.09)	(2.13)	(1.31)
Expense	0.265***	0.150***	0.113***	0.270***	0.152***	0.116***
	(22.97)	(20.90)	(21.60)	(22.12)	(20.11)	(20.90)
LogTNA	−0.004**	−0.002**	−0.003***	−0.004**	−0.003***	−0.003***
	(−2.51)	(−2.47)	(−3.24)	(−2.57)	(−2.59)	(−3.22)
Return	0.226***	0.083**	0.159***	0.251***	0.107**	0.165***
	(3.10)	(2.12)	(4.85)	(2.90)	(2.30)	(4.20)
LogSTKNUM	0.012***	0.008***	0.005*	0.013***	0.009***	0.005*
	(2.97)	(4.85)	(1.87)	(3.03)	(4.99)	(1.92)
LogBaiduEVN	0.003*	0.001	0.001	0.003	0.001	0.001
	(1.75)	(1.10)	(1.40)	(1.60)	(0.81)	(1.43)
LogGDP	−0.553***	−0.939***	0.255***	−0.564***	−0.949***	0.253***
	(−2.95)	(−14.73)	(2.81)	(−2.93)	(−14.65)	(2.73)
Constant	6.947***	11.991***	−3.337***	7.088***	12.128***	−3.314***
	(2.84)	(14.49)	(−2.84)	(2.82)	(14.41)	(−2.76)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	36,475	36,475	36,475	34,678	34,678	34,678
Adj.R^2	0.125	0.099	0.083	0.121	0.097	0.078