Government-Funded Green Banks: Catalysts for the Green Transition*

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Abstract

Government-funded Green Banks (GBs) are delegated to administer the Inflation Reduction Act funds to amplify private capital investment in reducing greenhouse-gas emissions. This paper examines how effectively GBs mobilize local private investment into green projects. Focusing on startups, we show a significant increase in venture capital (VC) deals and total investments for climate-tech startups located in counties following a GB loan issuance. The increases capture the additionality of GBs, as they seldom finance startups directly or participate in VC syndicates. Our evidence underscores GBs' pivotal role in building local green ecosystems that de-risk climate ventures and foster bottom-up green transitions.

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1. Introduction

Recent analyses estimate that achieving the 1.5°C global warming gap underscores the urgent need for innovative financial mechanisms and policy interventions to mobilize both public and private capital. As policymakers worldwide seek pathways for sustainable finance, the importance of leveraging public funds to unlock private capital has never been more pronounced. In response, the United States established the $27 billion Greenhouse Gas Reduction Fund (GGRF) as part of the Inflation Reduction Act (IRA). In addition, since 2010, the U.S. has provided approximately $9.1 billion in financing for energy efficiency improvements and climate resiliency upgrades through Residential Property Assessed Clean Energy (PACE) loans (see Bellon, LaPoint, Mazzola, & Xu, 2024).

The GGRF exemplifies the blended finance model of the recent COP29 (dubbed the "finance COP") where government seed capital is used to attract private investors to pursue shared environmental and economic goals, such as promoting energy independence, enhancing U.S. competitiveness, and lowering energy costs, particularly in socio-economically disadvantaged communities. The fund is set to be deployed through Green Banks (GBs), government-funded mission-driven institutions that started operating as early as 1991. For the last decade, GBs have been active financial intermediaries financing environmentally sustainable projects in pursuit of catalyzing local private green investments. Therefore, gauging the "additionality" of GBs over the recent history is crucial for understanding the potential impact of the IRA on the green transition.[1]

To this end, this paper investigates whether the GBs crowd in or crowd out private capital for local climate-focused startups. We focus on venture capital (VC) investment in these startups and examine whether the initiation of GB lending spurs it. The fact that GBs seldom provide capital directly to startups or participate in VC syndicates allows us to identify and measure the additionality of GBs.[2] Hence, any observed change in local VC investment should reflect how GB lending influences a broader green-investment ecosystem—whether

[1]We use the term "green" to refer to any activity, project, or entity focused on reducing greenhouse gas emissions.

[2]None of the VC deals in our sample include a GB. Some GBs offer small seed investments and grants to startups through incubators. However, these investments are limited to a few banks and involve minimal investment volumes. For instance, in 2010, the Maryland Clean Energy Center launched the Clean Energy Technology Incubator and Innovation Network. As of October 2024, this incubator hosted 21 startups.

GBs substitute or complement existing local private financing for green projects. Notably, the GGRF mandates grant recipients (i.e., GBs) to support only commercial technologies—classes of technologies already deployed for commercial purposes.[3] As a result, GBs would continue to be at arm's length from early-stage climate-focused startups testing unproven technologies.[4] This makes our pre-IRA analysis of GBs a valuable benchmark for assessing the expected private capital mobilization ratio of the GGRF in the venture capital market post-IRA.

It is important to note that VCs, including impact funds, are profit-driven and among the least likely asset managers to sacrifice returns for non-financial purposes (see Geczy, Jeffers, Musto, and Tucker (2021) and Jeffers, Lyu, and Posenau (2024), for example). Also, Gompers, Gornall, Kaplan, and Strebulaev (2020) report VCs perform due diligence and consider it as one of the most important contributors to value creation. Therefore, for VCs to reassess their portfolio of climate startups, GBs must exert a broad influence on the overall green ecosystem in their localities. For example, GBs can attract a stable flow of public investment for the long term, help local businesses achieve economies of scale to further commercialize green products, draw in green talent and workforce, and unlock demand potential for green products. In essence, GBs could act as local epicenters of green investment and lay the groundwork for vibrant green economies where VCs can more willingly pursue climate ventures.

Indeed, we find compelling evidence that GBs serve as a promising means to the end of accelerating a bottom-up green transition. Our main results indicate that GB activity significantly boosts VC investment in local climate startups. Using a generalized staggered difference-in-differences (DiD) approach over the sample period from 2015 to 2023, we find that counties receiving at least one GB loan experience an increase of 8.5% to 11.6% in climate startup VC deals over the four years following the loan. The results are robust to different fixed effects specifications, which account for time-invariant startup unobservables as well as time-variant industry and county unobservables. In addition, using a dynamic DiD approach, we cannot reject the parallel-trends assumption, which suggests that local pre-trends do not drive the results.

[3] The detailed definition of commercial technologies can be found at this link.

[4] Even for the startups deploying commercial technologies, and hence, more likely to be GB-fund recipients, the GB investment size into the startups is trivial vis-à-vis that of VCs. In our sample, only two GBs (Massachusetts Clean Energy Center and New York Green Bank) have provided loans to startups that subsequently received VC backing.

We then explore under which conditions GBs catalyze private investment more effectively. First, we study whether the presence of private banks that are Net-Zero Banking Alliance (NZBA) signatories magnifies the effect of GB funding on VC investment in climate startups. By constructing county-level measures of NZBA presence, we assess whether this presence amplifies or limits the impact of GB funding on VC investment in climate-tech startups Our findings reveal that GB activity has a notably greater impact on VC investment in counties with NZBA banks. This finding aligns with the notion that GBs and NZBA banks function as complementary forces in cultivating a supportive financial ecosystem for green innovation. Moreover, the results substantiate that GBs fulfill one of their core mandates: to leverage public capital to crowd in private investment. The observed complementarity between GBs and NZBA banks suggests that coordinated public and private financial commitments can more effectively mobilize capital for the green transition.

Second, we show GBs differentially impact VC investment based on climate-tech startups' commercialization potential. Using a GPT-based large language model (LLM), we match climate startups to 88 climate technologies from Project Drawdown, allowing us to analyze the heterogeneous effects of GBs on VC investment based on startups' technology attributes. We find that GBs spur higher VC capital flows into climate startups with lower implementation costs, lower cost-per-potential-carbon-abatement, broader cross-industry applicability, and less concentrated technologies. The results suggest that, even after GBs activity enhances the overall prospects for green ventures, VCs remain highly selective——directing investment toward climate startups with the strongest commercialization potential. This pattern is consistent with GBs' focus on proven technologies and the GGRF's mandate to support commercially viable solutions (e.g., solar, wind) over high-risk early-stage innovations.

Also, we find that startup characteristics—such as age and prior VC financing—as well as geographical factors like political leaning and public awareness of climate change significantly influence the degree of additionality of GB financing. Cross-sectional analyses reveal that GBs' ability to leverage private investment is particularly pronounced among older climate-tech startups and those with prior VC backing. This suggests that while GB lending plausibly reduces perceived investment risks of all green ventures, relatively more mature ventures with stronger market validation are the first to reap the benefit of VCs increased willingness in green investments. The crowding-in effect is also amplified in counties with heightened public concern about climate change and Democratic-leaning political environments, suggesting that local policy alignment and environmental awareness can enhance the positive spillovers GBs generate for nurturing a greener ecosystem.

In addition to cross-sectional heterogeneity of the GB effect, we document that its impact also evolves over time. Notably, following the introduction of the GGRF within the IRA was introduced in Congress, VC funding of climate-related startups increased in counties that had received GB loans. Since this uptick occurred prior to the actual passage of the legislation and before any funds were deployed, it likely represents a conservative estimate of the IRA's potential to enhance the influence of GBs on local private investment in green projects. Consequently, it is reasonable to anticipate that GBs—the main recipients of GGRF—will play an even more significant role in fostering robust green ecosystems as the legislation is implemented.

The results are robust to a battery of tests which reduce the concerns that the estimated impact of GBs on VC investment in climate-tech startups is related to other federal agencies, measurement error, or choice of model specifications. Specifically, we conduct a placebo test examining whether federal government grants influence VC investment similarly to GB funding. Using grants from the U.S. Environmental Protection Agency (EPA), Department of Energy (DoE), and Department of Agriculture (DoA), we analyze counties without GB investments to isolate the effect of these federal agencies. Indeed, we find that non-GB government grants do not significantly impact VC investment in climate startups, which highlights the distinct role of GBs in cultivating a local green ecosystem that upscales private investment in climate technologies. Moreover, the results remain consistent when restricting the sample to GBs with clear green investment objectives since inception or when limiting counties to those that receive at least one GB loan and their neighboring counties.

Lastly, we conduct a round-level analysis to examine how VC rounds that coincide with GB loans impact outcomes such as startup valuation and exit returns. This analysis is conditional on startups that have already secured VC deals, enabling us to assess how GB activity influence the valuation and performance of climate startups once they have received private funding. Our findings show that climate startups in counties with active GB loans achieve higher valuations and exit returns compared to their non-climate counterparts, suggesting that GB investments enhance both the perceived market value and performance of these startups.

Collectively, our study is the first to investigate GBs and shows that these institutions are valuable for advancing the green transition by attracting VC investment into climate-related startups, positively shaping their market perception, and improving the performance outcomes for climate-tech startups. Not only do GBs leverage public capital to attract private investment in established technologies—such as solar panels and wind turbines—but they also indirectly catalyze investment in new climate-related technologies. The finding is consistent with GBs' shared mission of "de-risking" environmental projects and unlocking private capital for these projects, instead of substituting existing or yet-to-be-deployed capital.[5] Moreover, it is particularly relevant to policymakers as the GGRF is poised to begin distributing $27 billion for green investments through GBs. Also, our findings are relevant to policymakers outside the U.S., as other governments may consider a similar or alternative investment vehicles for climate-related financing.

By providing the first comprehensive analysis of GBs and their role in fostering private investment to mitigate the adverse effects of climate change, our paper contributes to a growing literature exploring governmental initiatives aimed at advancing the green transition and fostering innovation. For instance, Kennedy et al. (2024) highlight how private investments and public grants target different types of startups, with varying risk tolerance levels. Bellon et al. (2024) examine PACE loans, finding that their adoption generates local fiscal income and enhances the resilience of the housing stock to climate impacts. Also, Flammer, Giroux, and Heal (2024) explore blended finance, where public and philanthropic funding mobilizes private capital for impactful sustainable investments. Lastly, Lanteri and Rampini (2025) model heterogeneous capital goods with varying energy needs and ages, and Bellon and Boualam (2024) calibrate a dynamic model featuring endogenous default to respectively identify down payment requirements and pollution-shifting as potential challenges against financially constrained firms from adopting newer and cleaner technologies. We contribute to

[5]For example, one of the missions of Connecticut Green Bank is to leverage limited public resources to scale-up and mobilize private capital investment in the green economy of Connecticut (more details here: `https://www.ctgreenbank.com/about-us/mission-vision-and-values/`).

this literature by focusing on government-funded GBs and finding that their impact extends beyond direct project financing. The wide-ranging effects of GBs on VC investment in green technologies can play a significant role in advancing a bottom-up green transition.

We also extend the literature on the role of banks in facilitating the green transition. Most studies focus on private banks and their environmentally-oriented lending. For example, Sastry, Verner, and Ibanez (2024) show that banks with net-zero commitments have yet to reduce credit supply to environmentally unfriendly sectors or increase financing for renewables, while banks engaging extensively in environmental discourse tend to lend more to "brown" industries (Giannetti, Jasova, Loumioti, & Mendicino, 2023). Other research evaluates whether banks' ESG commitments align with their actual lending practices (Basu, Vitanza, Wang, & Zhu, 2022) and the relationship between environmentally-friendly banks and green firms (Degryse, Goncharenko, Theunisz, & Vadasz, 2023; Houston & Shan, 2022). Scholars have also explored constraints private banks face in supporting the green transition (Degryse, Roukny, & Tielens, 2020), the effects of carbon taxes and environmental liability regulations on bank lending behavior (Laeven & Popov, 2023 and Bellon, 2021, respectively), and banks' exposure to climate transition risks (e.g., Martini, Sautner, Steffen, & Theunisz, 2023 and Jung, Santos, & Seltzer, 2023). Our study contributes by shifting focus to government-funded GBs and their distinctive role in catalyzing local green investments, with a particular emphasis on climate-focused startups.

Our work is related to the recent literature on the effect of VC investments on the performance of climate startups (Burt, Harford, Stanfield, & Zein, 2023) and the effect of funding awards on the success of these startups (Goldstein, Doblinger, Baker, & Anadón, 2020). Other studies explore the drivers behind VC investments in climate startups, such as climate regulation (Park, 2023) and environmental policy uncertainty (Noailly, Nowzohour, & van den Heuvel, 2021, 2022). Furthermore, Cornelli, Frost, Gambacorta, and Merrouche (2023), Gaddy, Sivaram, Jones, and Wayman (2017), and van den Heuvel and Popp (2023) examine the returns to VC investors from investing in climate startups. We contribute to this literature by showing that GBs amplify the value added by VCs, as climate startups in GB-active regions exhibit higher valuations and stronger exit outcomes.

Finally, our paper adds to another strand of the sustainable finance literature examining how climate risk shapes credit allocation across financial sectors, including by banks (Cortés & Strahan, 2017, Ivanov, Kruttli, & Watugala, 2024, Kacperczyk & Peydró, 2022, Brown, Gustafson, & Ivanov, 2021), mortgage markets (Sastry, 2021), real estate (Baldauf, Garlappi, & Yannelis, 2020, Bernstein, Gustafson, & Lewis, 2019), and insurance (Taylor & Druckenmiller, 2022). Giglio, Maggiori, and Stroebel (2015) and Giglio, Maggiori, Rao, Stroebel, and Weber (2021) further discuss discount rates that reflect the long-term risks of climate change. As GBs establish the foundation for greener ecosystem, allocating capital into climate-tech ventures can serve as a prudent hedge for these investors against growing climate risks.

2. Institutional Background

2.1. What are Green Banks?

According to the Coalition for Green Capital (CGC), "[g]reen banks are mission-driven institutions that use innovative financing to accelerate the transition to clean energy and fight climate change." These GBs do not receive deposits and, unlike traditional financial institutions focused on maximizing profits, they prioritize deploying capital toward environmentally sustainable projects. Their mission is to address climate change and enhance resilience, often focusing on benefiting low-income communities. The CGC categorizes GBs as public, non-profit, and quasi-public institutions. Public GBs are fully owned by states or are part of a state agency. For instance, the New York Green Bank, a public GB, was established on December 19, 2013, and received an initial capital of $165.6 million from the New York State Energy Research and Development Authority (NYSERDA). The funding came from uncommitted funds of the NYSERDA Energy Efficiency Portfolio Standard (EEPS) I, System Benefits Charge III, uncommitted utility EEPS funds, and NYSERDA Renewable Portfolio Standard resources (State of New York Public Service Commission, 2013).

Non-profit GBs are incorporated as 501(c)(3) organizations, maintaining minimal ties with government entities. An example is the Colorado Clean Energy Fund (CCEF), which was established through a collaborative effort involving the Colorado Energy Office, the U.S. Department of Energy, and the CGC. The CCEF received its initial funding as a 501(c)(3) nonprofit in 2018 from the State of Colorado. GBs can be classified as quasi-public if they are incorporated as non-profits but have substantial managerial control or oversight from a government entity. An example of a quasi-public GB is the Connecticut Green Bank, the first GB in the U.S. It was created in July 2011 through Public Act 11-80 by the Connecticut General Assembly. Overall, a common characteristic of almost all GBs is that their initial funding originated from a state government or agency.

A core aspect of GB operations is the use of financing instead of grants. GBs expect the capital they deploy to be repaid, creating a revolving pool of funds that maximizes the impact of each dollar invested.[6] Thus, GBs invest in projects that are past the research and development stage, with very few exceptions, such as investing a very small portion of their capital in incubators. This approach ensures lower investment risk and a direct contribution to clean energy adoption. Another significant feature of GBs is their ability to partner up with private investors in view of investing in clean energy projects at scale.

In 2023, the CGC and its network of GBs facilitated over $10.6 billion in public-private investment, representing a 130% increase from 2022. Some of these investments include large renewable infrastructure projects (e.g., solar, wind), residential solar panels installations, and buildings' energy efficiency improvements. Notably, 26% of the capital invested in 2023, amounting to $2.7 billion, was directed toward low-income and disadvantaged communities (American Green Bank Consortium, 2024).

One of the core objectives of GBs is to reduce the cost of capital for clean energy projects by addressing perceived risks and inefficiencies related to project scale. They achieve this through mechanisms such as credit enhancements, the aggregation of small projects, and co-investment with private lenders. For example, the New York Green Bank provided a $12 million construction-to-term loan to Pioneer Management Group for the development of an all-electric hotel in Albany, NY. The Connecticut Green Bank offers Solar Power Purchase Agreements (PPAs) to businesses and nonprofits, allowing them to transition to solar energy without incurring upfront installation costs or taking on debt. These examples highlight how GBs support the green transition across a range of sectors—from solar energy and energy efficiency to housing and water infrastructure. Their innovative financing models and ability

[6] It is worth noting that public or quasi-public GBs are initially capitalized with public funds before issuing loans, unlike most federal grant recipients who need to request reimbursement after incurring costs. The GGRF, albeit a federal grant, will be fully disbursed to recipients at the outset. This upfront capitalization is expected to preserve the distinctive role of GBs in the post-IRA landscape.

to mobilize private capital alongside public funds make them critical actors in the shift toward a low-carbon economy.

2.2. Green Bank Networks

The CGC is not the only network of GBs operating in the U.S. and receiving funding from the GGRF within the IRA. Other networks that have been allocated funding include: Power Forward Communities ($2 billion), Climate United Fund ($7 billion), Opportunity Finance Network ($2.3 billion), Inclusiv ($1.9 billion), Justice Climate Fund ($1 billion), Native CDFI Network ($0.4 billion), and Appalachian Community Capital ($0.5 billion). Besides the Climate United Fund, several key differences exist between GBs within the CGC network and those in other networks, particularly in terms of green investment focus. For example, Power Forward Communities, Opportunity Finance Network, and Native CDFI Network historically lacked a clear mandate for green investments and will be incorporating green objectives for the first time after they receive funding through the GGRF. Similarly, Inclusiv did not have sustainability or climate-related goals prior to 2020. The Appalachian Community Capital was only recently established on August 16, 2024, and has not yet made any investments. Some GBs are members of both the CGC and the Justice Climate Fund, but the majority of non-CGC affiliates did not articulate explicit climate objectives until they applied for the GGRF.

The Climate United Fund comprises Calvert Impact, Community Preservation Corporation, and Self-Help Credit Union. Together, they have raised and deployed more than $30 billion across partners in various sectors around the world starting from 1976 (Climate United, 2023). Calvert Impact is a global nonprofit investment firm focused on "solutions that people and our planet need." The Self-Help Credit Union was chartered in 1983 and did not have a green investment focus until 2020, when its annual report first mentioned green investments. This included a net-zero building with solar panels for a community health center in Colorado.

Community Preservation Corporation (CPC), established in 1974 in New York City, launched a platform in 2008 "to promote energy and water conservation measures that improve the financial and physical quality of the buildings and communities in which we live and work." By 2015, CPC had financed more than 12,000 sustainable units and originated nearly $2 billion in green lending. Relevant to our study, although CPC currently has a national footprint, as of 2018, its investments were concentrated in New York, Massachusetts, Connecticut, Pennsylvania, and New Jersey—all states where we have data from other GBs.

Lastly, Calvert Impact differs notably from GBs in our sample, maintaining both national and international investment footprints without a specific regional focus—particularly over the past few decades. Additionally, Calvert's investment volume is substantially smaller. Since its founding in 1976, it has invested approximately $5 billion globally.[7] In contrast, the Illinois and California GBs invested roughly $31 billion and $15 billion, respectively, between 2015 and 2023 alone. While we acknowledge the potential for Type I and Type II errors due to Calvert's investment activity, our localized analysis of GBs' impact on VC investment in climate-tech startups should remain robust. This is primarily due to the substantially larger scale of GB investments. Moreover, any systematic correlation between the geographic distribution of GBs and Calvert's funding allocation is unlikely, particularly given Calvert's lack of local focus.

2.3. Green Banks and Local Green Investment

The presence of government-funded GBs is expected to influence local green investment through several mechanisms. By providing a steady flow of targeted financing to projects that meet commercial readiness criteria, GBs can support the development of the local green ecosystem. Although GBs are not directly involved in VC deals, their activity helps mitigate the perceived risks associated with investing in climate-focused startups. For VCs, who are predominantly profit-driven and less willing to trade off financial returns for non-financial objectives, the availability of GB funding may serve as a credible commitment to long-term public investment, policy stability, and broader private sector interest in green initiatives. This perceived stability may prompt VCs to reassess the financial potential of local climate startups, especially when GB activity is viewed as indicative of a supportive investment environment. This mechanism also aligns with the behavior of impact investors, who are active in climate startup financing; as shown by Geczy et al. (2021), most impact funds

[7] This estimate is provided by Impact Assets; however, no further data is available.

continue to use contractual structures that preserve traditional financial incentives.

Another potential effect of GB activity is its influence on the local demand for green products and services. The establishment of GB-funded projects could stimulate broader adoption of climate-focused technologies, which in turn may benefit startups operating in these sectors. Increased demand may enhance the growth prospects of local startups, leading VCs to view these companies as better-positioned to achieve long-term profitability. If GB activity provides a stable and expanding market for green products and services, it could further strengthen the incentives for VCs to invest in climate startups.

Potentially, GBs can directly lend to climate startups, increasing the likelihood and size of VC deals by de-risking investment in these companies. In our data, we identify only 64 startup-year observations (out of approximately 394,000) involving direct lending from two GBs to climate startups. While additional GB lending to startups may occur outside of what is captured in PitchBook, the limited number of observed cases suggests that such activity is likely rare.

Other channels through which GBs unlock local climate-focused private investment likely exist, though identifying them is beyond the scope of this paper. Nevertheless, our analysis reveals that GBs, rather than other financial intermediaries, can serve as primary catalysts for the green transition. Other intermediaries financing green projects include federal agencies such as the EPA, the DoE, and the DoA, which offer grants to eligible startups. Contrary to GBs actively seeking and quickly deploying capital to climate projects with proven technologies (e.g., solar panels and wind turbines), these federal grants solicit applications and passively screen them based on predefined criteria. Moreover, the grants typically lack a local focus and, as a result, play at most a secondary role in developing the local green economy. GBs, on the other hand, have a clearly defined local footprint and operate within specific jurisdictions—for example, the Connecticut Green Bank invests exclusively within the state of Connecticut.

Local private banks with stated green commitments (e.g., net-zero targets) might, in principle, provide similar support to the local green economy as GBs. However, existing empirical evidence suggests otherwise. Studies have shown that banks with green commitments do not necessarily increase lending to green firms and, in some cases, even increase financing to brown firms (Giannetti et al., 2023; Sastry et al., 2024). Unlike GBs, private banks are under no obligation to meet these commitments in the short or long term. In addition, the attempt of banks to reduce emissions is quite recent as one of the major voluntary, but one of the strictest, climate initiative called the NZBA, formed in April 2021. Taken together, it is unlikely for our analysis to be confounded by federal grants or private banks with green preferences, given that our sample spans from 2015 to 2023 and includes many GBs—such as New York Green Bank, Connecticut Green Bank, and CAEATFA—that were active before 2015. We formally examine the role of federal agencies and NZBA signatory banks in Section 4.

3. Data and Summary Statistics

3.1. Green Banks

We collect information on GBs in the U.S. using publicly available information from each banks' annual report or website.[8] We focus our attention on the CGC (current National Green Bank) since they were one of the largest recipients of funding of the GGRF and their objectives are strictly connected to investment in the green transition.

Specifically, we collect information on county-level loans issued by the following GBs: Abundant Power, California Alternative Energy and Advanced Transportation Finance Authority (CAEATFA), California Pollution Control Finance Authority (CPCFA), Colorado Clean Energy Fund (CCEF), Columbus Region Green Fund, Connecticut Green Bank, DC Green Bank, Delaware Sustainable Energy Utility, Efficiency Maine, Finance New Orleans, GO Green Energy Fund, Illinois Climate Bank (ICB), Maryland Clean Energy Center, Massachusetts Clean Energy Center, Montgomery County Green Bank, New Jersey EDA, New York City Energy Efficiency Corporation (NYCEEC), New York Green Bank (NYGB), Philadelphia Green Capital Corp, Rhode Island Infrastructure Bank (RIIB), Solar Energy Loan Fund (SELF), and Virginia Resources Authority (VRA). For these banks, we are able to identify if the bank issued loans in year t in county c.[9]

[8] We are grateful to the Connecticut Green Bank for sharing information not available on their reports.

[9] Table IA1 in the Internet Appendix reports the GBs in our sample, their year of establishment, type, and the state where they issue loans.

3.2. Descriptive Statistics on Green Banks

As the first study on GBs to our knowledge, we provide some descriptive statistics. We report summary statistics for all three types of GBs, but our empirical analysis focuses on public and quasi-public GBs, yielding a sample of 12 GBs. We exclude non-profit GBs from the analysis due to their recent establishment, significantly smaller investment volumes, or limited geographic scope—often operating within a single county (e.g., Abundant Power Group, Montgomery County Green Bank).

The oldest GB is the California Pollution Control Finance Authority (CPCFA), established in 1972, even though this agency was not explicitly defined as a GB at the time. Note that the year of establishment is not necessarily the year in which the GB starts issuing loans. Figure 1 illustrates the geographical distribution of GBs' lending activity. Counties are marked in blue if a GB reported issuing at least one loan there between 2015 and 2023. In Table 1, we find that, on average, GB loans are more commonly issued in counties with larger populations, slightly higher average incomes, higher house prices, and more Democratic-leaning political preferences.

The primary focus of GB investments is in energy efficiency and clean energy, including building efficiency projects such as heat pumps and insulation, as well as renewable energy installations like solar panels, wind turbines (both on- and offshore), and biomass facilities. Also, many of these banks aim to increase lending to socio-economically marginalized communities and small businesses. Specifically, they often include objectives to support low-income households and minority communities to promote a just and equitable green transition. Seventeen of the 21 GBs are solely dedicated to green investment, while the remaining four have a more diversified portfolio that includes, for example, non-green infrastructure loans, and loans to farmers.[10]

For a subset of GBs, we are able to collect data on the amount invested at the county-year level.[11] The average (median) annual county-level investment is \$47.8 million (\$4.7 million). The states with the highest total investment volume over the sample period are Illinois (\$31

[10]A description of the GBs investment focus is provide in Table IA2 in the Internet Appendix.

[11]The GBs with county-level investment volume data include CAEATFA, CCEF, CPCFA, CTGB, DCGB, ICB, MCGB, NYGB, and VRA.

billion), California ($15 billion), New York ($740 million), and Connecticut ($280 million).

3.3. Startups and Venture Capital Investment

Our sample consists of startups headquartered in the U.S. identified with data from PitchBook. This dataset has comprehensive coverage of various aspects of startup financing rounds, including details such as timing, stage (e.g., Seed, Series A, B, C, etc.), investment amount, and the identity of investors involved in each round. PitchBook further categorizes startups into "verticals" based on their technological orientation (e.g., FinTech, Nanotechnology, Software-as-a-Service, etc.). These verticals group startups into clusters that concentrate on a shared niche or specialized market.[12] Our analysis focuses on startups falling under the "Climate Tech" or "CleanTech" verticals.[13] We consider VC financing rounds taking place from 2015 to 2023. To be included in our sample, a financing round must meet the following criteria: 1) it is explicitly identified in the PitchBook database as a "Venture Capital" round with at least one investor in the syndicate identified as a VC investor by PitchBook;[14] 2) it must have non-missing data for deal size and deal date; and 3) it must involve the raising of new equity (debt-only and secondary-sale rounds are excluded). The final sample comprises 102,937 deals involving 51,158 startups, including a subset of 5,339 deals for 2,533 climate-related startups. Table 2 provides summary statistics on VC investment activity by year (Panel A) and the industry distribution of startups (Panel B) for both climate-tech and non-climate-tech startups.

[12] A single vertical may be comprised of companies that span multiple industries. PitchBook explains the differences between verticals and industry classifications here: `https://pitchbook.com/what-are-industry-verticals`.

[13] Based on PitchBook's definition, the "Climate Tech" vertical includes "companies developing technologies intended to help mitigate or adapt to the effects of climate change. The majority of companies in this vertical are focused on mitigating rising emissions through decarbonization technologies and processes. Applications within this vertical include renewable energy generation, long duration energy storage, the electrification of transportation, agricultural innovations, industrial process improvements, and mining technologies, among others." Similarly, the "CleanTech" vertical includes "developers of technology which seeks to reduce the environmental impact of human activities or to significantly reduce the amount of natural resources consumed through such activities."

[14] This restriction excludes VC rounds financed purely by individuals, angel groups, accelerators/incubators, crowdfunding investors, etc.

3.4. Technology-level Data

We collect technology-level information from Project Drawdown, a comprehensive database of climate technologies compiled by a network of scientists and researchers (Project Drawdown, 2020). Project Drawdown includes 88 climate technologies that aim to reduce greenhouse gas concentrations in the atmosphere, along with detailed descriptions and estimates of each technology's abatement potential and associated costs.

The abatement potential is the CO_2 equivalent reduction brought by the technology between 2020 and 2050. The abatement cost represents the net initial implementation cost, which is the upfront capital expenditure required to implement the climate solution, and is based on the relative cost to implement these climate technologies between 2020 and 2050 compared to a baseline scenario. The baseline scenario is defined as a scenario where such a climate solution does not exist. For example, the baseline for the climate technology wind turbines is based on electricity generated using fossil fuel power plants. As such, negative costs can happen if the climate technology results in lower cost relative to the baseline scenario (such as the use of LED lighting). We match these technologies to startups using business descriptions from PitchBook, employing a GPT-based large language model (LLM) following the approach in Lu, Serafeim, Xu, and Awada (2024).

3.5. Private Banks and the Net-Zero Banking Alliance

We collect information on bank branches across the U.S. using the Summary of Deposits (SOD) survey data from the Federal Deposit Insurance Corporation (FDIC). This dataset includes all bank branches and provides detailed information such as local deposits, geographic location, institutional assets, and the associated Federal Reserve Bank.

In addition, we gather data on banks that are signatories to the NZBA, including their names and the dates they signed the commitment. The NZBA was established in April 2021 and formally announced at COP26 in October of the same year. Joining the alliance is voluntary; signatories pledge to support the transition to a net-zero economy and limit global temperature increases to 1.5°C by 2050. To meet this goal, banks are expected to reduce their financed emissions. Although participation is voluntary, all signatories must, within three years of joining, set sectoral emission reduction targets aligned with NZBA guidelines. These targets, along with progress toward them, must be disclosed and verified by a third party. The lending behavior of NZBA banks has recently been studied in the literature, including by Sastry et al. (2024).

For our analysis, we define a bank as an NZBA signatory if it has set a net-zero target year and discloses emissions. Among NZBA signatories, 37 banks operate in the U.S. We hand-match these institutions to the SOD dataset, which enables us to compute county-year level measures of NZBA exposure. Specifically, we construct three exposure variables. First, *NZBA Sign Target* is an indicator variable equal to one if the county contains at least one branch of an NZBA signatory bank. Second, *NZBA Sign Target (% Deposit)* denotes the share of total county deposits held by NZBA banks. Lastly, *NZBA Sign Target (% HHI)* represents the Herfindahl-Hirschman Index (HHI) of deposit concentration among NZBA banks relative to all banks in the county.[15] Each measure incorporates the year in which a bank signs the NZBA agreement. A bank is considered an NZBA bank starting in the year of its official commitment.

3.6. County Characteristics

The county-level economic data, including population, personal income, and unemployment rate, are collected from the U.S. Bureau of Economic Analysis (BEA) and the U.S. Bureau of Labor Statistics (BLS). We collect information on house prices from Zillow (Zillow Home Value Index or ZHVI). We use the Yale Climate Opinion Survey data and, in particular, the response to the question: "How worried are you about global warming?" to define the $Worried$ indicator. This indicator equals one for counties where the percentage of respondents who state to be worried is greater than the median and zero otherwise.[16] The county-level presidential votes are from the MIT Election Lab.[17] We define a Republican indicator equal to one if the presidential votes for a Republican candidate in county c are above the median

[15] *NZBA Sign Target (% HHI)* is computed as follows: $\frac{\sum_{i\in \text{NZBA Banks}}\left(\frac{D_i}{\sum_j D_j}\times 100\right)^2}{\sum_{i\in \text{All Banks}}\left(\frac{D_i}{\sum_j D_j}\times 100\right)^2}$, where D_i is the deposits of bank i in the county-year.

[16] The possible responses are very worried, somewhat worried, not very worried, and not at all worried. We consider the first two responses as worried.

[17] `https://electionlab.mit.edu/data`

and zero otherwise.

4. Results

4.1. Identification Strategy

Our sample period runs from 2015 to 2023, chosen for several reasons. First, 2015 marks the beginning of a significant resurgence in VC interest in green technologies. This period saw massive inflows of private capital into climate-tech startups, with investment growth exceeding 150% between 2015 and 2021 (Cornelli et al., 2023).[18] Also, prior to 2015, many of the GBs did not exist or did not have a specific focus on the green transition (e.g., Virginia Resources Authority, Rhode Island Infrastructure Bank, and New Jersey Economic Development Authority). The policy landscape also shifted in 2015 with the signing of the Paris Agreement, which created a favorable environment for climate-tech investments. Given these trends, 2015 is a natural starting point for examining the intersection of GB loans and VC investment in climate tech startups.

Our primary econometric model examines the relation between VC investment outcomes and the interaction of an indicator for GB funding in the county where a startup is headquartered and an indicator for climate-tech startups. Specifically, we use a generalized staggered DiD estimator to compare changes in VC investment outcomes for climate-tech startups relative to non-climate-tech startups headquartered in counties that receive GB funding with those in counties that do not. This strategy exploits variation driven by the staggered timing of GB funding across counties and multiple time periods.

Formally, we estimate the following empirical specification:

$$y_{i,c,t} = \beta_0 + \beta_1 \mathit{GB\ fund}_{c,t} + \beta_2 \mathit{GB\ fund}_{c,t} \times \mathit{Climate\ startup}_i + \tau_i + \rho_{j,t} + \omega_{c,t} + \varepsilon_{i,c,t} \tag{1}$$

where startup i, operating in industry j, is headquartered in county c, in year t. We focus on an event window spanning four years before to four years after the startup's county receives

[18] Prior to 2015, most VC investments in climate tech were concentrated in wind and solar technologies. However, many investors experienced significant losses, largely due to the capital-intensive nature of these technologies and their long payback periods, compounded by the impact of the Great Financial Crisis (Gaddy et al., 2017). As a result, the climate tech sector fell out of favor, with VC investment flows being redirected to other industries (van den Heuvel & Popp, 2023).

GB funding. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a GB in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. The standard errors are clustered at the headquarter county level to adjust for potential issues with grouped error terms as GB funding is assigned at this geographic level (Gu, Huang, Mao, & Tian, 2022; Guernsey, John, & Litov, 2022).

We consider two sets of fixed effects in our analysis. First, we include startup, industry, county, and year fixed effects.[19] Second, we implement a more stringent set of fixed effects (Acharya, Baghai, & Subramanian, 2014; Gormley & Matsa, 2016). These include startup fixed effects (τ_i), which control for unobserved, time-invariant characteristics specific to each startup that might influence VC investment outcomes, such as the startup's reputation or management quality. We also include industry-year fixed effects ($\rho_{j,t}$), which account for shocks or trends common to all startups within the same industry during a given year, such as industry-wide technological advancements or regulatory changes. Finally, county-year fixed effects ($\omega_{c,t}$) are used to control for local economic conditions or government initiatives that may vary across counties and years, ensuring that the effects of GB funding are not confounded by other county-level influences.

4.2. Baseline Estimates

Table 3 reports the results of the DiD estimation using Equation (1). The dependent variable in columns (1)-(3) is a binary indicator representing whether a startup received VC investment in a given year, while columns (4)-(6) use the natural logarithm of one plus the dollar amount of VC investment received. The results show that while GB investments in a county has a positive and statistically significant effect on the likelihood of VC investment for all startups in that county, the effect is even stronger for climate-tech startups. Specifically, counties that receive GB funding see an 8.5% to 11.6% increase in the probability of climate-tech startup deals relative to other types of startups. These results hold when restricting the analysis to states where we have information on GB loan amounts in each county (columns (3) and

[19] Startup fixed effects subsume the main effects for *Climate startup*.

(6)). In addition, the results are robust across different fixed effects specifications and remain consistent when using the continuous VC investment amount as the dependent variable.

To provide further robustness of the results, we replace the indicator for GB funding with a continuous treatment variable that captures variation in the intensive margin of loans issued by GBs in a given county. Specifically, we define *GB fund amt* as the log of one plus the dollar amount of funding that a county, where the startup is located, receives from a GB in the current year and the previous four years. We then estimate the DiD model in Equation (1) using this continuous treatment. The results, presented in Table IA3 in the Internet Appendix, show that counties with higher volumes of GB funding see an increase in both the likelihood of VC deals and the dollar amount of VC investment in climate-tech startups. Overall, these findings underscore the effectiveness of GBs in mobilizing private capital for climate-focused ventures, supporting the policy goal of promoting green investment and sustainable development.

4.2.1. Dynamic Effects

Our identification strategy relies on the parallel-trends assumption, which posits that both climate-tech and non-climate-tech startups would exhibit similar trends in VC investment outcomes prior to GB investments. To test for pre-trends, we estimate a dynamic version of Equation (1), focusing on the four years before and after GB funding. As our treatment variable is staggered, we follow the approach employed in previous studies (Fuest, Peichl, & Siegloch, 2018; Smith, Yagan, Zidar, & Zwick, 2019) to estimate the dynamic treatment effects based on the intensity of treatment as follows:

$$y_{i,c,t} = \sum_{\substack{\ell=-5 \\ \ell\neq-1}}^{\ell=+5} \gamma_\ell \mathit{GB\ fund\ intensity}^{\ell}_{c,t} + \sum_{\substack{\ell=-5 \\ \ell\neq-1}}^{\ell=+5} \lambda_\ell \mathit{GB\ fund\ intensity}^{\ell}_{c,t} \times \mathit{Climate\ startup}_i + \tau_i + \rho_{j,t} + \omega_{c,t} + \varepsilon_{i,c,t} \quad (2)$$

where

$$
GB\ fund\ intensity^{\ell}_{c,t} = \begin{cases} \sum_{s=-\infty}^{\ell} \Delta GB\ fund_{c,t-s}, & \text{if } \ell = -5 \\ \Delta GB\ fund_{c,t-\ell}, & \text{if} -4 \leq \ell \leq +4 \\ \sum_{s=\ell}^{\infty} \Delta GB\ fund_{c,t-s}, & \text{if } \ell = +5 \end{cases} \tag{3}
$$

The dynamic effects λ_ℓ provide event-study estimates that capture changes in VC investment outcomes over time for climate-tech and non-climate-tech startups in counties receiving GB funding. We normalize $\ell = -1$ as the reference period, with event time $\ell = 0$ indicating the year of GB funding. To identify the dynamic effects during the event window, we bin the endpoints ($\ell = -5, +5$) according to Equation (3).

Our results do not reject the parallel-trends assumption, as shown in Figure 2. The dynamic effects indicate no significant differences in trends between climate-tech and non-climate-tech startups prior to GB funding. Panel A shows that the likelihood of VC deals does not exhibit any pre-treatment differential response, and Panel B shows a similar pattern for the VC investment amount. In the years following GB funding, we observe a notable increase in both VC outcomes for climate-tech startups, suggesting a positive and sustained impact of GB funding. While it is possible that GBs target counties further along in the green transition, which could influence our results, we do not find evidence of pre-existing trends to substantiate this concern.

4.3. Complementarity Between Green Banks and Private Finance

One of the stated objectives of GBs is to leverage public capital to unlock private investment, thereby accelerating the green transition and reducing the perceived risk of investing in green technologies. In recent years, private banks have also shown increasing interest in "greening" their portfolios and pursuing net-zero targets. One of the most prominent initiatives in this space is the NZBA, launched in April 2021. Consequently, GBs are likely to crowd in private capital more effectively in areas where NZBA signatory banks—those with explicit green preferences—are already active.

Hence, we hypothesize that counties with greater NZBA presence should experience larger increases in climate tech VC investment following GB funding. To test this hypothesis, we augment the main regression with a triple interaction term between GB investment, an indicator equal to one for climate-tech startups, and NZBA exposure. We estimate county-level exposure to NZBA signatories using three measures: (1) an indicator for the presence of at least one NZBA bank branch (*NZBA Sign Target*); (2) the share of county deposits held by NZBA banks (*NZBA Sign Target (% Deposit)*); and (3) the Herfindahl-Hirschman Index (HHI) of NZBA deposit concentration relative to all banks (*NZBA Sign Target (% HHI)*). Note that a bank is considered an NZBA signatory starting from the year it signs the NZBA agreement.

The results in Table 4 show that across multiple NZBA exposure measures, the triple interaction coefficients are positive and statistically significant. Specifically, the effect of GB financing on the likelihood of a VC deal is between 4.6% to 4.8% higher for climate-tech startups in counties with at least one branch of an NZBA bank (columns (1)-(2)). The results are consistent when using continuous measures of counties' exposure to NZBA banks (columns (3)-(6)). This suggests that GB funding is more effective at catalyzing VC investment in climate tech startups when NZBA banks are also locally present. These NZBA banks are not directly participating in VC deals, but their presence may enhance the local financial ecosystem as GBs almost always partner with private banks, which offer complementary financing.

This pattern is further supported by the negative coefficient on the interaction between GB funding and NZBA exposure for non-climate tech startups. Since the sum of the GB fund effect and the interaction between GB fund and NZBA exposure is not statistically different from zero, these results suggest that while GBs and NZBA banks together help crowd in capital for climate tech, there is no effect on non-climate tech startups. This reinforces the idea of complementarity between GBs and NZBA banks in supporting green innovation, rather than a generalized boost to all types of startup activity.

We argue that our findings demonstrate the complementarity and additionality of both GBs and NZBA banks in the financing of climate tech startups. Since neither GBs nor NZBA banks typically participate directly in VC syndicates, their presence and activity appear to create enabling conditions for VC financing rather than directly supplying capital. This amplifying effect highlights their role as catalysts in the green transition.

Lastly, although concerns of reverse causality are valid—e.g., GBs choosing to operate in counties already more engaged with green finance—the strong positive coefficient on the *GB fund* × *Climate Startup* × *NZBA* interaction suggests that even in the presence of such sorting, GBs play a catalytic role. Furthermore, the robustness of the positive and significant coefficient on *GB fund* × *Climate Startup* supports our interpretation that GBs independently contribute to increased VC investment in climate tech.

Overall, these findings suggest that GBs are effective in achieving their goal of leveraging public capital to attract private investment—one of their core mandates. Moreover, the results highlight the strategic value of aligning public financial institutions (GBs) with private banks committed to net-zero targets (NZBAs). Together, they help cultivate a local financial ecosystem that supports climate tech innovation.

4.4. Technology-level Analysis

In this section, we examine the heterogeneous effects of GB investments on VC deal activity by conducting technology-level analysis. Specifically, each climate-tech startup is matched to one of 88 climate technologies from Project Drawdown based on its business description in PitchBook, utilizing a GPT-based LLM following Lu et al. (2024). The data includes estimates for each climate technology's abatement potential and costs to achieve the carbon abatement.[20] The matching allows us to assess whether GB funding differentially impacts VC deals based on specific attributes of startups' underlying technologies.

Table 5 presents the results of this technology-level analysis, which decomposes the interaction between GB funding and climate-tech startups across several dimensions. First, we distinguish between high- and low-cost climate technologies. The results in column (1) indicate that climate-tech startups with low-cost technologies are significantly more likely to receive VC investments than those with high-cost technologies in response to GB funding. This finding aligns with the notion that technologies with lower abatement costs are perceived as having a sustainable competitive advantage, as they provide cost-effective emissions reductions and are more likely to achieve widespread commercial adoption. In contrast,

[20] The abatement cost represents the net initial implementation cost, referring to the upfront capital expenditure required to deploy the climate solution. It is calculated based on the relative cost of implementing each technology between 2020 and 2050, compared to a scenario in which the climate solution is not adopted.

high-cost technologies face greater commercialization barriers, which limit their scalability and investment attractiveness. A similar trend emerges in column (2) when examining cost efficiency, defined as the ratio of abatement cost to abatement potential—where only technologies with lower cost efficiency exhibit a higher likelihood of receiving VC investment following GB funding.

Next, we examine the dispersion of climate technologies in columns (3) and (4). Column (3) analyzes industry spread, which captures the extent to which a climate technology is adopted across multiple industries. Each year, for every climate technology, we count the number of unique six-digit GICS industries in which the technology is present among incumbent U.S. public firms.[21] A climate technology is classified as high (low) spread if the number of unique industries in which it appears is above (below) the median for that year. The results indicate that climate-tech startups with technologies exhibiting broader industry adoption are significantly more likely to receive VC funding following GB investments. Column (4) examines the industry concentration of each climate technology using the Herfindahl-Hirschman Index (HHI). Each year, the HHI is computed for every climate technology by summing, across all six-digit GICS industries, the squared ratio of the number of incumbent public firms using the technology within each industry to the total number of firms using the technology. Technologies with an HHI above (below) the median in a given year are classified as high (low) concentration. The results indicate that low-concentration technologies—those more widely dispersed across industries—are significantly more likely to receive VC investment following GB funding. This finding, along with the industry spread results in column (4), suggests that VCs prioritize climate technologies with broader applicability across industries, as these are associated with greater commercialization potential and larger market opportunities.

Overall, the findings in this section suggest that, following GB funding, VCs are more likely to finance climate-tech startups with low-cost and widely dispersed technologies, as these exhibit stronger commercial viability and greater return potential. These results also support the interpretation that the observed increase in VC investment stems from GB activity rather than time-varying, county-specific unobserved factors. Notably, GBs prioritize investments

[21]We identify incumbent firms engaged in a given climate technology by applying a LLM to analyze the "Item 1 Business Description" section of 10-K filings, following Lu et al. (2024).

in commercially proven technologies. The cost and diffusion of these technologies depend heavily on their maturity, as economies of scale drive production efficiencies and broader adoption. Consequently, GBs tend to invest in low-cost, scalable climate solutions—such as building retrofitting, energy efficiency measures, heat pumps, utility-scale photovoltaics, and wind turbines—all of which are defined as low-cost or widely adopted.

4.5. Heterogeneity

We conduct additional cross-sectional tests based on startup and county characteristics to examine the heterogeneity in the impact of GB funding. We augment Equation (1) by including triple interaction terms with variables that measure these characteristics.

In columns (1) and (2) of Table 6, we find that older climate-tech startups attract more VC investment when GBs make investments in the same county, compared to younger startups. This result aligns with the mandate of the GGRF and the mission of most GBs, which prioritize supporting proven technologies. By investing in counties with more mature startups, GBs help cultivate local green ecosystems that reduce the perceived risk of investing in these firms. As a result, VCs are more likely to back established climate-tech companies, which are better positioned to benefit from the supportive environment GBs help create. In this context, GBs play a catalytic role by channeling private capital toward scaling proven technologies, rather than funding speculative or nascent innovations.

Columns (3) and (4) demonstrate that prior VC financing amplifies the effect of GB funding. The positive and significant interaction between *GB fund* × *Climate startup* × *Past VC financing* indicates that climate-tech startups with a history of VC investment are more likely to attract additional VC funding when GB investments are made in the same county. This result suggests that GB activity provides an additional layer of institutional validation, reinforcing the credibility of startups that have already demonstrated their viability in the VC market. In doing so, GBs help facilitate the scaling of these startups by encouraging further investment.

In columns (5) and (6), we assess the moderating effect of public opinion on climate change using data from the Yale Program on Climate Change Communication (YPCCC) survey, which measures the percentage of adults in a startup's headquarter county who are worried about global warming (Howe, Mildenberger, Marlon, & Leiserowitz, 2015). Counties with a higher proportion of individuals expressing concern about climate change are likely to create a more favorable environment for climate-tech startups, as public opinion influences both policy decisions and market demand for climate solutions. The results show that GB funding has a stronger effect on VC investment in climate-tech startups in counties where a larger share of the population is concerned about global warming. In these regions, GB support aligns with public sentiment, likely boosting demand for climate-tech products and attracting further private investment.

In the last two columns of Table 6, we find that in more Republican areas, where there may be less public and political support for climate initiatives, GB funding has a more limited impact on attracting VC deals for climate-tech startups. These results suggest that political alignment influences the effectiveness of GB funding in attracting private capital for climate-related investments. Our results are in line with the findings in Burt et al. (2023), which show that climate-related startups backed by Democrat VC partners tend to outperform those backed by non-Democrat ones.

4.6. GBs and the Inflation Reduction Act

The announcement of the GGRF within the IRA conveys to stakeholders that financing for green investments will be substantial and sustained over time. Since these funds will be deployed through GBs, counties where GBs have already invested are at a significant advantage. As highlighted earlier, climate startups often focus on innovative technologies and only a few are likely to be directly funded by GBs through the GGRF. Moreover, none of the GGRF funds have been deployed to date. Therefore, when estimating the impact of GBs after the GGRF announcement, we can reasonably rule out that the observed effects are driven by direct capital flows from GBs to climate-related startups. Rather, it is plausible for VCs to expect GBs to be better-capitalized and take on an expanded role in leveraging local private investments in climate-related startups.

We find evidence consistent with this in Table 7, which shows that after 2021—the year when the IRA began being discussed in Congress—counties with prior GB loans experience an additional increase in both the likelihood of VC deals and the amount invested in climate startups. Specifically, after 2021, climate tech startups located in counties that received GB funding saw a 4.6–4.9% increase in the likelihood of securing a deal, relative to other startups. We also show an increase in both deal likelihood and size of the deals for climate startups relative to the rest of the sample, regardless of GB presence. Given that it was widely known IRA funds would be deployed through public and quasi-public institutions, including GBs, the finding that the impact of GBs intensified after initial IRA discussions underscores their ongoing and central role in fostering local green ecosystems throughout the last decade. However, we note that the analysis is limited by the short time period following the IRA announcement.

4.7. Placebo Test

It is possible that federal government investment might have a similar impact as GBs in catalyzing green investment. To test this hypothesis, we conduct a placebo test to examine whether federal government grants influence VC investment similar to GB funding. Specifically, we first identify grants issued by the EPA, DoE, and DoA to startups in the Pitchbook dataset. Next, we limit our sample to counties with no GB investment to exclude the possibility that GBs are driving the results in the placebo test. Lastly, we define a county as treated (*Government grant*=1) if at least one startup has received funding from a government agency in the current year or in the previous four years.

The results in Table 8 show that government grants do not impact local VC investment or VC investment in local climate startups, as the coefficients on *Government grant* and the interaction between *Government grant* and *Climate startup* are not statistically different from zero. These findings suggest that traditional government grants may be less effective in cultivating the local conditions needed to attract private capital. In contrast, this placebo test highlights the distinctive role of GBs in fostering green ecosystems that support the growth of climate-tech startups and encourage market-based scaling of climate technologies.

4.8. Additional Robustness Tests

We provide additional robustness to the results by replicating the main analysis using only the states in which the GBs have a clear green investment objective since their inception and we were able to verify the activity of each GB. These states include California, Connecticut, Florida, Illinois, Ohio, Maine, Maryland, Massachusetts, Pennsylvania, Rhode Island, New York, and New Jersey. The results reported in Table IA4 in the Internet Appendix are stronger than the main analysis. Specifically, climate-focused GBs' loan activity in a county is more positively related to the number of VC deals and investment amount in climate-tech startups.[22] In addition, the results remain robust when we replicate the main analysis using a restricted sample that includes only counties receiving at least one GB loan during the sample period and their neighboring counties (Table IA5 and Figure IA1 in the Internet Appendix).[23]

4.9. Round-level Analysis

The DiD analysis thus far examines the determinants of VC financing for climate-tech startups, focusing on how GB investments influence the likelihood of securing a deal. To shed light on the performance of these startups, we conduct round-level analysis conditional on startups that have already secured VC financing. Specifically, we explore differences in round-level outcomes, such as startup valuation and exit performance, when the financing round coincides with GB investments in the same county. We estimate the following regression model:

$$\begin{aligned} y_{i,r,c,t} = \beta_0 + \beta_1 \mathit{GB\ fund\ round}_{c,t} + \beta_2 \mathit{GB\ fund\ round}_{c,t} \times \mathit{Climate\ startup}_i + \gamma' X_i \\ + \tau_i + \omega_c + \mu_t + \delta_r + \varepsilon_{i,r,c,t} \end{aligned} \tag{4}$$

for startup i, in VC round r, headquartered in county c, in year t. The outcome variables, defined below, include measures of startup valuation and exit performance. We define a VC round as coinciding with GB investment if it occurs in the year immediately following the GB funding. Specifically, *GB fund round* is a dummy variable equal to one if the startup is located in a county that received GB funding in the year prior to the VC round, and zero otherwise. This approach aligns with the typical time horizon over which VCs make investment decisions. For example, Gompers et al. (2020, p. 177) find that "VCs devote substantial resources to conducting due diligence on (i.e., investigating) their investments. The average deal takes 83 days to close; the average firm spends 118 hours on due diligence

[22] In unreported results, we find that the estimates remain qualitatively unchanged when excluding California.

[23] We define neighboring counties as those whose geographic boundaries intersect at any point.

over that period." Therefore, VCs are more likely to base their investment decisions on recent information, making the prior year's GB investment more relevant than those made further in the past.

We include a set of startup-level control variables, denoted by X_i, in line with the existing literature (Burt et al., 2023; Pham, Rezaei, & Zein, 2023). Due to data limitations, we are constrained in capturing a wide range of startup attributes. Specifically, we control for the startup's age, whether it received VC financing in the past five years, and whether it was generating revenue at the time of the current VC financing round. These variables are intended to capture a startup's level of maturity beyond what is implied by its current financing stage. Also, variations in outcome variables may be influenced by investor characteristics; for instance, a prominent lead VC can attract other investors, potentially boosting the startup's valuation and exit performance. To account for this, we include controls for the lead VC's age and its investment activity over the past five years. However, as these startup-level controls are available only for a subset of the sample, we estimate Equation (4) with and without these variables.

We include in the model several types of fixed effects that account for many confounding factors influencing round outcomes. Startup fixed effects (τ_i) control for time-invariant characteristics specific to each startup, such as inherent quality, founding team strength, or business model. County fixed effects (ω_c) capture differences across geographic locations that may influence VC availability and investor interest, including local economic conditions and regulatory environments. Round year fixed effects (μ_t) control for time-specific factors, such as macroeconomic trends and policy changes, that impact all startups in a given year. Finally, VC round fixed effects (δ_r) account for differences in funding stages (e.g., Seed, Series A, Series B) that reflect the startup's development phase and typical financing needs at each stage.

In Table 9, we examine outcome variables related to the startups' valuation at the VC financing round. These variables include the log of the deal size (*ln(Deal size)*), the post-money valuation of the startup (*ln(Post valuation)*), whether the round was classified as an "up" round (i.e., an increase in valuation relative to previous rounds), and the log of startup revenue at the time of the VC round (*ln(Revenue)*). The positive and significant coefficients on *GB fund round* × *Climate startup* indicate that VC rounds coinciding with GB investments enhance the perceived valuation of climate-tech startups. Together with the earlier findings, this result suggests that GB investments not only increase the likelihood of attracting private capital but also contribute to elevating the market valuation of climate-tech startups. These patterns are consistent with the interpretation that GBs foster local green ecosystems that support the scaling of climate innovations.

Next, we perform a round-to-exit performance analysis by restricting the sample to firms for which we can observe a full set of rounds until an exit event. We use two outcome variables to assess round-level performance: (i) the round-to-exit multiple, and (ii) the annualized round-to-exit return. The round-to-exit multiple is calculated as the exit valuation divided by the post-money valuation at the current round. For IPO exits, we use the pre-money IPO valuation (i.e., the company's value before raising public capital) as the exit valuation. For M&A exits, we use the reported acquisition deal value. For liquidated startups, the exit multiple is set to zero.[24] The round-to-exit return is an annualized return associated with the round-to-exit multiple, based on the holding period measured as the number of days between the current round and the exit date. Liquidated deals are assigned a return of −100%.

In Table 10, we estimate Equation (4) using the round-to-exit multiples and returns associated with each specific VC round. We first winsorize returns and multiples at the 1% level to control for major outliers. In addition, because returns and exit multiples are highly skewed but can include zero values, we apply the inverse hyperbolic sine (asinh) transformation to these variables in all specifications.[25] The negative and significant coefficients on *GB fund round* across all specifications indicate that VC rounds coinciding with GB funding are associated with lower exit multiples and returns for non-climate-tech startups. In contrast, the positive and highly significant interaction term *GB fund round* × *Climate startup* suggests that VC rounds coinciding with GB investments have a strong positive impact on the exit performance of climate-tech startups. Thus, VC rounds associated with GB investments not only increase the perceived valuation of climate-tech startups but also generate higher

[24]We classify startups as liquidated if Pitchbook directly identifies these firms as exited through liquidation or bankruptcy, or if Pitchbook lists the company's current status as "out of business".

[25]Coefficients from regressions using asinh-transformed variables can be interpreted similarly to those from log-transformed data. However, asinh has the advantage of being defined at zero.

returns for investors, providing financial benefits for those who participate in these rounds.

5. Conclusion

This paper provides the first comprehensive analysis of government-funded GBs and their role in fostering local green ecosystems that attract private investment in climate-related startups. We begin by outlining key institutional features of GBs—including their incorporation type, investment focus, and geographic footprint—and then examine their impact on local green investment. Leveraging the staggered loan activity of GBs across time and counties, we provide evidence of the positive impact of GBs on the green transition. Our findings indicate that counties receiving GB funding experience a significant increase in both the likelihood of VC deals and the amount of investment in climate-related startups. These effects are robust to a range of fixed effects, dynamic specifications, and are not driven by pre-existing local trends.

Further analyses demonstrate that GBs appear particularly effective in catalyzing private capital in counties where NZBA signatory banks are active, highlighting the importance of complementary public-private financial infrastructure. Technology-level analysis reveals that GB activity is most closely associated with increased VC investment in startups developing low-cost, scalable, and broadly applicable climate technologies. Counties with prior GB activity experience increased VC funding for climate-tech startups, suggesting that GBs help establish local environments that are poised to benefit from future public and private investment.

Cross-sectional analyses show that GB additionality is strongest among older startups and those with prior VC backing, as well as in counties characterized by greater public concern about climate change and Democratic political leanings. Moreover, the impact of GBs becomes even more pronounced following the introduction of the GGRF within the IRA. At the investment-round level, GB activity is associated with higher valuations and stronger exit outcomes for climate-tech startups, reinforcing the notion that GBs help create conditions that enhance both market perception and the realized performance of these ventures.

These findings have significant implications for policymakers and practitioners. They highlight the effectiveness of government-funded GBs in mobilizing private capital toward climate-related investments, thereby helping to bridge the substantial funding gap required to meet global warming targets. The evidence suggests that GBs are crucial for accelerating the low-carbon transition by catalyzing local green innovation.

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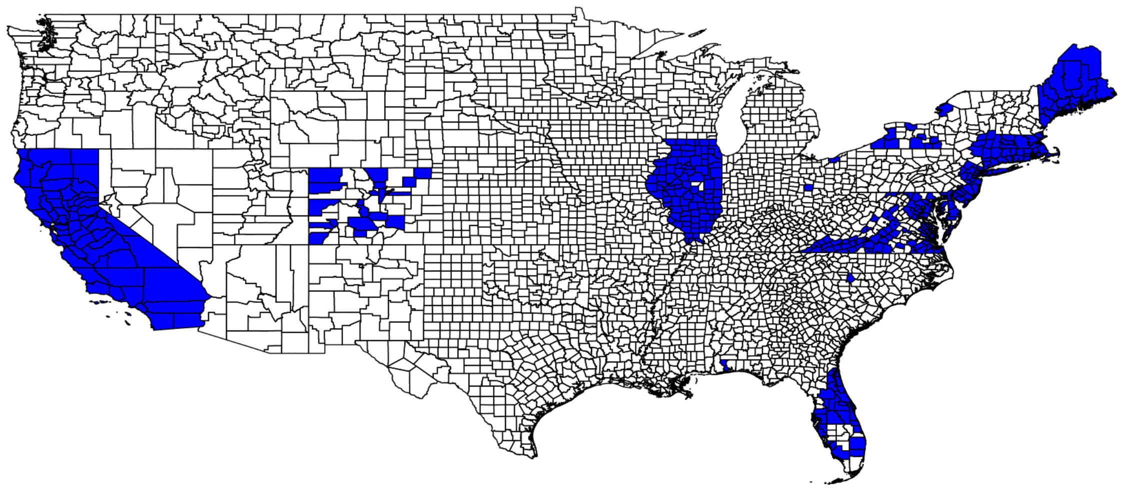
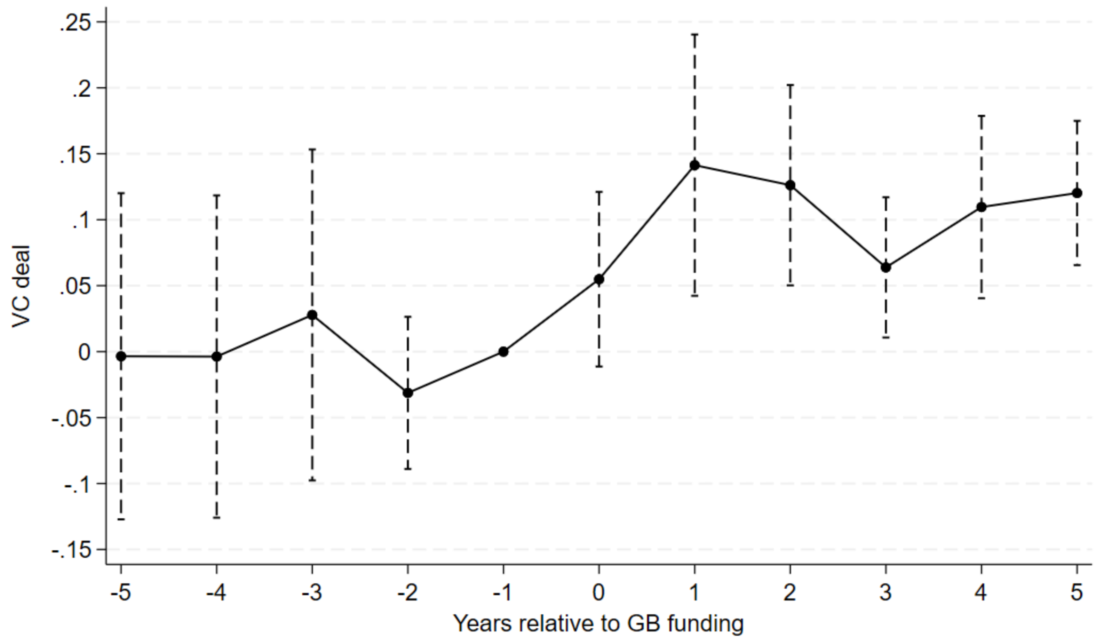
Figure 1
Green Banks across the U.S.



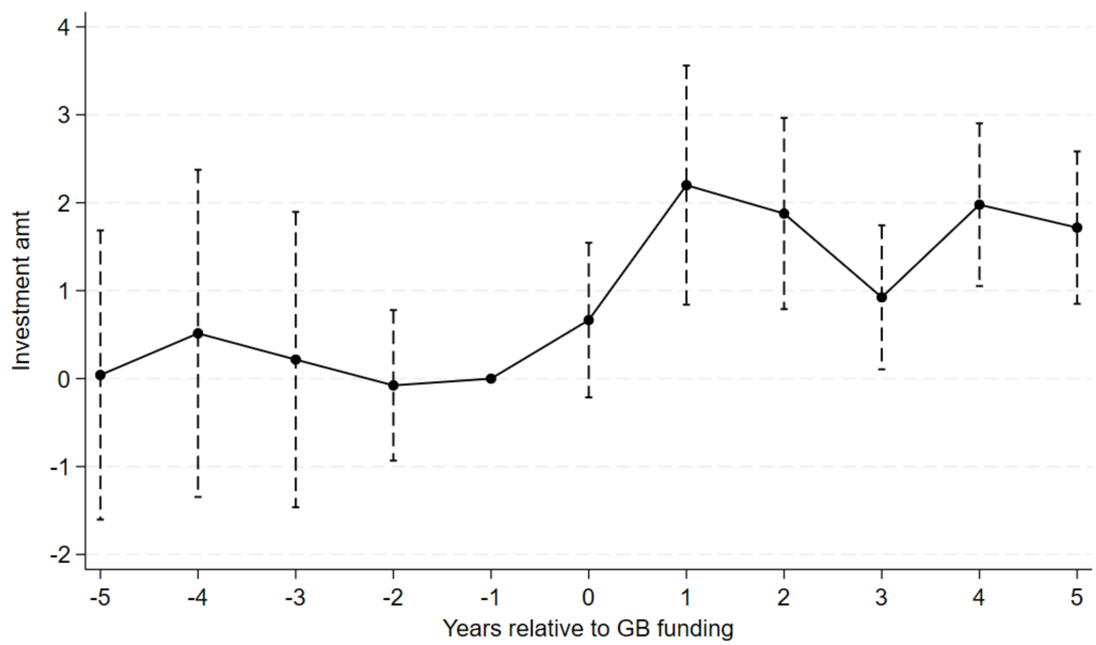
This figure highlights in blue the counties that received at least one loan from Green Banks for which county-level activity is available.

Figure 2
Dynamic effects.

Panel A: GB funding and VC deal likelihood



Panel B: GB funding and VC investment amount



This figure plots the event study estimates and corresponding 95% confidence intervals according to the specification in Equation (2). The dot represents the coefficient on the interaction between the GB fund relative year indicator and the climate startup indicator. We focus on an event window of four years before to four years after the county where the startup is located receives funding from a Green Bank. We bin up event dummies at the endpoints of the event window following Equation (3). Event year $\ell = -1$ is the omitted category, implying that all coefficient estimates are relative to this year.

Table 1
Summary statistics split by counties with and without Green Banks.

	Counties with GB activity	Counties without GB activity
Population	350,268	73,159
Income	53,593	44,914
Republican Votes (%)	53%	68%
White Pop. (%)	73%	78%
Black Population (%)	9%	9%
Minority Population (%)	27%	22%
Worried about Climate Change (%)	60%	54%
House Price	280,670	168,358
N. Counties	362	2,696

This table reports summary statistics for counties with and without Green Bank activity.

Table 2
Startup sample description.

Panel A: Startup deals by year				
	Climate-tech		Non-climate-tech	
	Number of deals	Avg deal size ($M)	Number of deals	Avg deal size ($M)
Year	(1)	(2)	(3)	(4)
2015	376	10.700	8,487	10.565
2016	385	15.027	8,017	10.668
2017	416	11.365	9,007	10.544
2018	493	18.976	9,904	15.282
2019	522	18.419	10,947	14.013
2020	608	20.769	11,014	16.632
2021	905	34.251	15,913	23.916
2022	973	23.491	14,880	19.006
2023	508	25.144	7,493	15.297

Panel B: Startup industry distribution				
	Climate-tech		Non-climate-tech	
PitchBook industry sector	Number of startups	Percent	Number of startups	Percent
Business Products and Services (B2B)	843	33.28	6,254	12.22
Consumer Products and Services (B2C)	352	13.90	9,416	18.41
Energy	529	20.88	128	0.25
Financial Services	35	1.38	1,777	3.47
Healthcare	40	1.58	10,699	20.91
Information Technology	420	16.58	22,369	43.73
Materials and Resources	314	12.40	515	1.01
Total	2,533	100	51,158	100

This table reports summary statistics for the climate-tech and non-climate-tech startups from Pitchbook for the period 2015-2023.

Table 3
Impact of Green Bank funding on venture capital investment in climate-tech startups.

Dep. variable:	*VC deal*			*Investment amt*		
	(1)	(2)	(3)	(4)	(5)	(6)
GB fund	-0.002	0.151***	0.151***	-0.072	1.903***	1.898***
	(-0.21)	(9.82)	(10.12)	(-0.57)	(7.15)	(7.43)
GB fund × *Climate startup*	0.116***	0.098***	0.085***	1.625***	1.393***	1.155***
	(5.40)	(4.37)	(3.21)	(4.91)	(4.22)	(3.46)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	No	Yes	No	No
County F.E.	Yes	No	No	Yes	No	No
Year F.E.	Yes	No	No	Yes	No	No
Industry × Year F.E.	No	Yes	Yes	No	Yes	Yes
County × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	394,337	391,039	198,723	394,337	391,039	198,723
R^2	0.04	0.05	0.05	0.09	0.09	0.09

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *Investment amt* is the log of one plus the dollar amount of VC investment the startup receives in a given year. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. Columns (3) and (6) restrict the sample to startups located in California, Connecticut, Illinois, New York, and Virginia. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4
Impact of Net-Zero Banking Alliance signatories.

Dep. variable: *VC deal*	(1)	(2)	(3)	(4)	(5)	(6)
GB fund	0.006	0.167***	0.004	0.164***	0.003	0.162***
	(0.60)	(16.02)	(0.39)	(16.16)	(0.36)	(15.47)
NZBA Sign Target	-0.014					
	(-1.60)					
NZBA Sign Target (% Deposit)			0.000			
			(0.94)			
NZBA Sign Target (% HHI)					0.022*	
					(1.93)	
GB fund × *NZBA Sign Target*	-0.030***	-0.198***				
	(-3.95)	(-3.43)				
GB fund × *NZBA Sign Target (% Deposit)*			-0.001***	-0.004***		
			(-4.26)	(-2.91)		
GB fund × *NZBA Sign Target (% HHI)*					-0.051***	-0.276**
					(-4.15)	(-2.58)
GB fund × *Climate startup*	0.081***	0.071***	0.090***	0.080***	0.092***	0.081***
	(3.85)	(3.26)	(4.31)	(3.68)	(4.39)	(3.78)
NZBA Sign Target × *Climate startup*	0.035***	0.039***				
	(2.82)	(2.81)				
NZBA Sign Target (% Deposit) × *Climate startup*			0.001***	0.001***		
			(2.97)	(3.20)		
NZBA Sign Target (% HHI) × *Climate startup*					0.062***	0.072***
					(2.91)	(3.06)
GB fund × *Climate startup* × *NZBA Sign Target*	0.048***	0.046***				
	(2.85)	(2.73)				
GB fund × *Climate startup* × *NZBA Sign Target (% Deposit)*			0.001**	0.001**		
			(2.36)	(2.12)		
GB fund × *Climate startup* × *NZBA Sign Target (% HHI)*					0.077***	0.072**
					(2.61)	(2.46)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes	No	Yes	No
County F.E.	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No
Industry × Year F.E.	No	Yes	No	Yes	No	Yes
County × Year F.E.	No	Yes	No	Yes	No	Yes
Observations	393,761	390,473	393,761	390,473	393,761	390,473
R^2	0.05	0.05	0.05	0.05	0.04	0.05

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. *NZBA Sign Target* is a dummy variable equal to one if the county has a branch of a NZBA bank that has set a target year and discloses emissions, from the year of the bank's NZBA signing onward, and zero otherwise. *NZBA Sign Target (% Deposit)* is the percentage of deposits in a county held by NZBA banks that have set a target year and disclose emissions, measured from the year of each bank's NZBA signing onward. *NZBA Sign Target (% HHI)* is the share of market concentration in a county-year attributable to NZBA banks that have set a target year and disclose emissions, from the year of each bank's NZBA signing onward. It is calculated as $\frac{\sum_{i \in \text{NZBA Banks}} \left(\frac{D_i}{\sum_j D_j} \times 100 \right)^2}{\sum_{i \in \text{All Banks}} \left(\frac{D_i}{\sum_j D_j} \times 100 \right)^2}$, where D_i is the deposits of bank i in the county-year. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5
Technology-level analysis.

Dep. variable: *VC deal*	(1)	(2)	(3)	(4)
GB fund	0.151***	0.151***	0.151***	0.150***
	(9.89)	(9.83)	(9.23)	(9.19)
GB fund × *Climate startup (High implementation cost)*	0.038			
	(0.86)			
GB fund × *Climate startup (Low implementation cost)*	0.122***			
	(5.18)			
GB fund × *Climate startup (High cost per potential)*		0.046		
		(1.10)		
GB fund × *Climate startup (Low cost per potential)*		0.123***		
		(3.93)		
GB fund × *Climate startup (High spread)*			0.102***	
			(3.36)	
GB fund × *Climate startup (Low spread)*			0.033	
			(0.48)	
GB fund × *Climate startup (High concentration)*				0.081
				(1.49)
GB fund × *Climate startup (Low concentration)*				0.098***
				(3.24)
Startup F.E.	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
County × Year F.E.	Yes	Yes	Yes	Yes
Observations	389,740	389,740	387,320	387,320
R^2	0.05	0.05	0.05	0.05

Each climate-tech startup is matched to the most similar climate technology among the 88 defined in the Project Drawdown 2020 report, based on its business description in PitchBook. *Climate startup (High implementation cost)* (*Climate startup (Low implementation cost)*) is a dummy variable equal to one if the climate-tech startup's climate technology has a net initial implementation cost classified as high (low) according to the Project Drawdown 2020 report, and zero otherwise. *Climate startup (High cost per potential)* (*Climate startup (Low cost per potential)*) is a dummy variable equal to one if the climate-tech startup's climate technology has an implementation cost per unit of abatement potential classified as high (low) according to the Project Drawdown 2020 report, and zero otherwise. *Climate startup (High spread)* (*Climate startup (Low spread)*) is a dummy variable equal to one if the climate-tech startup's climate technology is spread across a high (low) number of industries, and zero otherwise. Each year, for each climate technology, we count the number of unique six-digit GICS industries in which the technology appears among incumbent U.S. public firms. Technologies with a count above (below) the median in a given year are classified as high (low) spread. *Climate startup (High concentration)* (*Climate startup (Low concentration)*) is a dummy variable equal to one if the climate-tech startup's climate technology has a high (low) HHI, and zero otherwise. Each year, the HHI for each technology is calculated by summing, across all six-digit GICS industries, the squared ratio of the number of incumbent public firms using that technology within each industry to the total number of firms using that technology. Technologies with an HHI above (below) the median in a given year are classified as high (low) concentration. *VC deal* is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6

Cross-sectional analysis.

Dep. variable: *VC deal*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GB fund	-0.001	0.131***	0.039***	0.244***	0.095**	1.585***	-0.002	0.151***
	(-0.11)	(9.34)	(4.17)	(13.73)	(2.36)	(53.16)	(-0.18)	(9.79)
GB fund × *Climate startup*	0.070***	0.063***	0.058***	0.050**	-0.469***	-0.471	0.126***	0.103***
	(3.29)	(2.80)	(2.59)	(2.07)	(-2.60)	(-1.53)	(6.51)	(4.70)
GB fund × *Climate startup* × *Startup age*	0.054***	0.042**						
	(2.75)	(2.22)						
GB fund × *Climate startup* × *Past VC fin.*			0.066***	0.060***				
			(3.02)	(2.77)				
GB fund × *Climate startup* × *High worried*					0.590***	0.572**		
					(3.28)	(2.35)		
GB fund × *Climate startup* × *High Rep.*							-0.718***	-0.961***
							(-7.06)	(-8.62)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes	No	Yes	No	Yes	No
County F.E.	Yes	No	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No	Yes	No
Industry × Year F.E.	No	Yes	No	Yes	No	Yes	No	Yes
County × Year F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Observations	394,337	391,039	394,337	391,039	393,802	390,507	394,337	391,039
R^2	0.05	0.05	0.07	0.08	0.04	0.05	0.04	0.05

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. *Startup age* is the age (in years) of the startup based its founding year according to PitchBook. *Past VC fin.* is a dummy variable equal to one if the startup received VC financing in the previous five years, and zero otherwise. *High worried* is a dummy variable equal to one if the percentage of the adult population in the startup's headquarter county who are worried about global warming (according to the Yale Program on Climate Change Communication survey) is above the median for a given year, and zero otherwise. *High Rep.* is a dummy variable equal to one if the percentage of Republican presidential votes in the county where the startup is located is above the median for a given year, and zero otherwise. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 7
Impact of the IRA.

Dep. variable:	*VC deal*		*Investment amt*	
	(1)	(2)	(3)	(4)
GB fund	0.006	0.167***	0.040	2.129***
	(0.59)	(15.74)	(0.29)	(15.96)
GB fund × *Climate startup*	0.079***	0.069***	1.127***	1.018***
	(3.75)	(3.19)	(3.50)	(3.17)
GB fund × *IRA*	-0.030***	-0.192***	-0.428***	-2.734**
	(-4.03)	(-3.35)	(-4.64)	(-2.13)
Climate startup × *IRA*	0.037***	0.042***	0.605***	0.611***
	(3.14)	(3.14)	(3.65)	(3.16)
GB fund × *Climate startup* × *IRA*	0.049***	0.046***	0.545***	0.527**
	(3.05)	(2.86)	(2.59)	(2.51)
Startup F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes	No
County F.E.	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No
Industry × Year F.E.	No	Yes	No	Yes
County × Year F.E.	No	Yes	No	Yes
Observations	394,337	391,039	394,337	391,039
R^2	0.04	0.05	0.09	0.09

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *Investment amt* is the log of one plus the dollar amount of VC investment the startup receives in a given year. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. *IRA* is a dummy variable equal to one from year 2021 onwards, and zero otherwise. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 8
Placebo test.

Dep. variable: *VC deal*	(1)	(2)
Government grant	0.027	0.018
	(0.98)	(0.34)
Government grant × *Climate startup*	0.008	-0.049
	(0.20)	(-0.71)
Startup F.E.	Yes	Yes
Industry F.E.	No	No
County F.E.	Yes	No
Year F.E.	Yes	No
Industry × Year F.E.	No	Yes
County × Year F.E.	No	Yes
Observations	10,831	10,167
R^2	0.04	0.05

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *Government grant* is a dummy variable equal to one if the startup receives a grant from either the Environmental Protection Agency (EPA), Department of Energy (DoE), or Department of Agriculture (DoA) in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. The sample consists of startups in the same counties and same PitchBook industries as those that receive government grants. We exclude all startups that are located in a county that ever received funding from a Green Bank. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 9
Round-level analysis: startup valuation.

Dep. variable:	*ln(Deal size)*		*ln(Post valuation)*		*Up round*		*ln(Revenue)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GB fund round	0.075*	0.028	0.085***	0.069***	0.022*	0.024**	-0.180	-0.245*
	(1.86)	(1.10)	(3.17)	(2.90)	(1.76)	(2.12)	(-1.48)	(-1.75)
GB fund round × *Climate startup*	0.427***	0.272***	0.078***	0.154***	0.192**	0.232**	1.828***	1.833***
	(2.61)	(3.20)	(3.65)	(2.65)	(2.47)	(2.39)	(5.46)	(6.59)
Past VC financing		-0.059*		-0.054*		0.024		-0.091
		(-1.72)		(-1.80)		(1.19)		(-0.72)
Startup age		0.682***		0.462***		-0.020		1.596***
		(18.91)		(11.00)		(-0.46)		(5.65)
Established operation		0.086***		-0.011		-0.005		-0.405***
		(2.99)		(-0.63)		(-0.26)		(-3.01)
VC age		0.099***		0.032***		0.010**		-0.042
		(5.87)		(4.08)		(2.25)		(-1.15)
VC past investments		-0.013		0.020***		-0.002		-0.004
		(-1.17)		(3.41)		(-0.54)		(-0.17)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,534	32,055	27,072	20,532	10,457	8,268	3,308	2,199
R^2	0.64	0.69	0.84	0.85	0.01	0.01	0.85	0.86

ln(Deal size) is the log of the dollar amount of the deal size of the VC round. *ln(Post valuation)* is the log of the post-money valuation of the startup. *Up round* is a dummy variable equal to one if the round is classified as an "Up" round according to PitchBook, and zero if classified as a "Flat" or "Down" round. *ln(Revenue)* is the log of the startup's revenue at the time of the VC round. *GB fund round* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the year prior to the VC round, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. *Past VC financing* is a dummy variable equal to one if the startup received VC financing in the previous five years, and zero otherwise. *Startup age* is the age (in years) of the startup based its founding year according to PitchBook. *Established operation* is a dummy variable equal to one if the startup is classified as "Generating Revenue" or "Profitable" in a given round, and zero otherwise. *VC age* is the age (in years) of the lead VC investor based its founding year according to PitchBook. *VC past investments* is the log of one plus the number of investments made in the previous five years by the lead VC investor before the current round. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 10
Round-level analysis: startup exit performance.

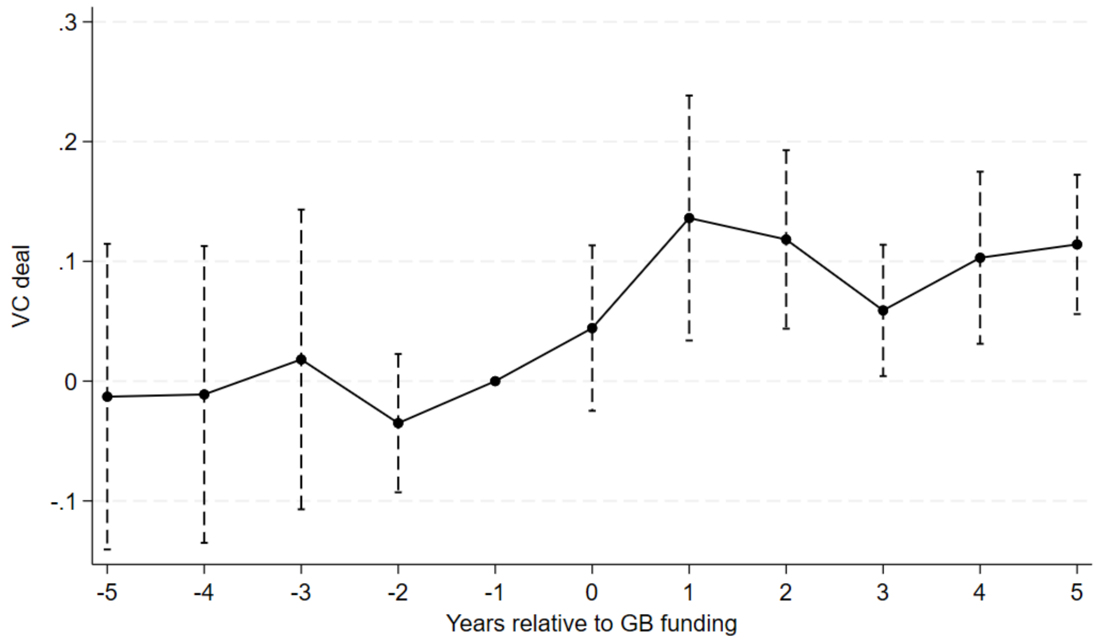
Dep. variable:	*Exit multiple*		*Exit return*	
	(1)	(2)	(3)	(4)
GB fund round	-0.214***	-0.239***	-0.088***	-0.099***
	(-4.00)	(-3.77)	(-3.50)	(-3.40)
GB fund round × *Climate startup*	0.773***	0.895***	0.138***	0.144***
	(13.24)	(11.50)	(5.95)	(3.76)
Past VC financing		0.052		0.025
		(0.97)		(0.71)
Startup age		-0.046		-0.118***
		(-0.42)		(-2.65)
Established operation		0.068		0.060*
		(1.14)		(1.79)
VC age		0.021		0.004
		(0.77)		(0.35)
VC past investments		-0.010		-0.012
		(-0.66)		(-1.34)
Startup F.E.	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Stage F.E.	Yes	Yes	Yes	Yes
Observations	3,557	2,400	3,553	2,396
R^2	0.81	0.81	0.90	0.89

Exit multiple is the inverse hyperbolic sine transformation of the round-to-exit multiple of a deal. The round-to-exit multiple is defined as the exit valuation scaled by post-money valuation at the focal round. For an IPO exit, we use the pre-money IPO value as the exit valuation. For M&A exits, we take the reported deal acquisition value as the exit valuation. For liquidated startups, the exit multiple is zero. *Exit return* is the inverse hyperbolic sine transformation of the annualized round-to-exit return of a deal. The round-to-exit return is annualized based on the holding period of the number of days between the focal round and the exit date. Liquidated deals are assigned a return of -100%. *GB fund round* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the year prior to the VC round, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. *Past VC financing* is a dummy variable equal to one if the startup received VC financing in the previous five years, and zero otherwise. *Startup age* is the age (in years) of the startup based its founding year according to PitchBook. *Established operation* is a dummy variable equal to one if the startup is classified as "Generating Revenue" or "Profitable" in a given round, and zero otherwise. *VC age* is the age (in years) of the lead VC investor based its founding year according to PitchBook. *VC past investments* is the log of one plus the number of investments made in the previous five years by the lead VC investor before the current round. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

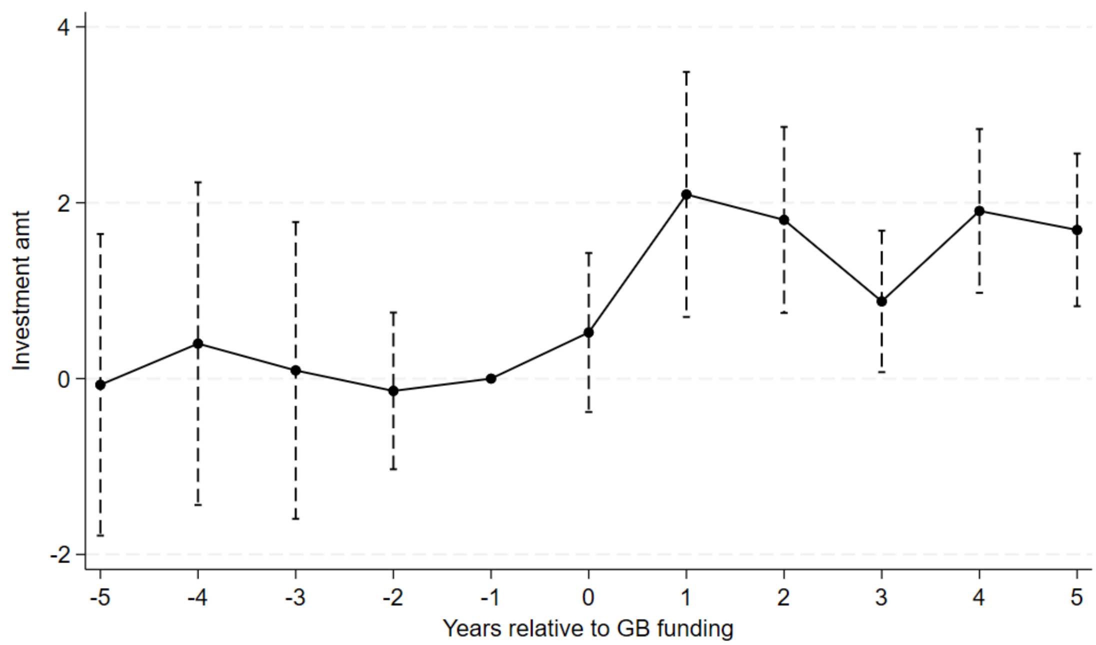
Internet Appendix for
Government-Funded Green Banks: Catalysts for the Green Transition

Figure IA1
Dynamic effects: neighboring counties.

Panel A: GB funding and VC deal likelihood



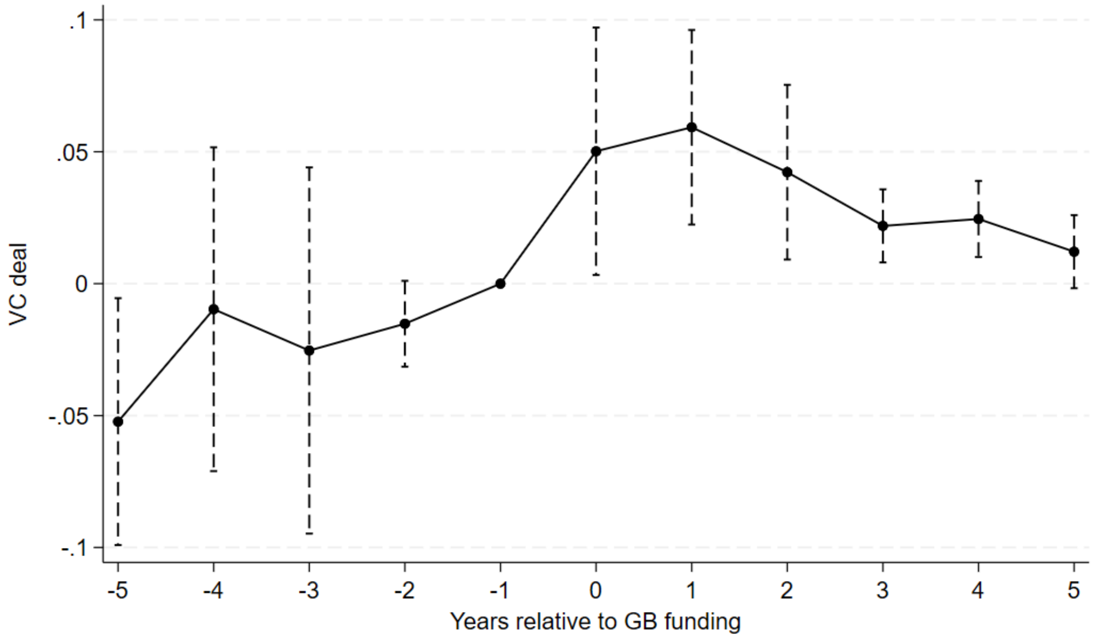
Panel B: GB funding and VC investment amount



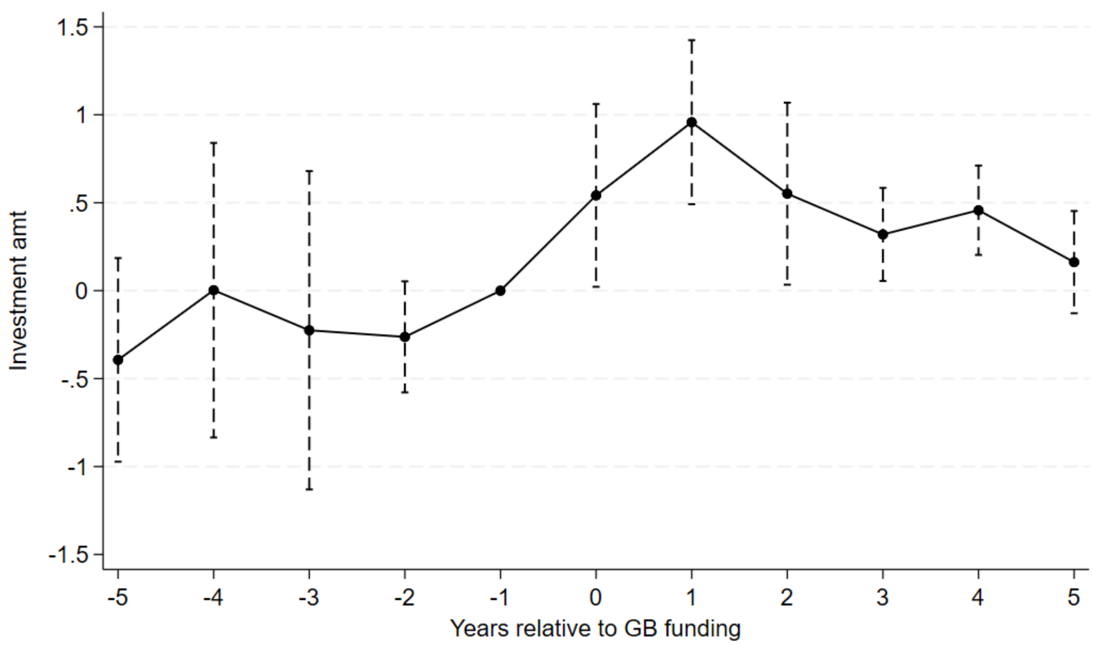
This figure plots the event study estimates and corresponding 95% confidence intervals according to the specification in Equation (2). The sample includes counties that receive at least one GB loan and their neighboring counties. The dot represents the coefficient on the interaction between the GB fund relative year indicator and the climate startup indicator. We focus on an event window of four years before to four years after the county where the startup is located receives funding from a Green Bank. We bin up event dummies at the endpoints of the event window following Equation (3). Event year $\ell = -1$ is the omitted category, implying that all coefficient estimates are relative to this year.

Figure IA2
Dynamic effects: heterogeneous treatment effects.

Panel A: GB funding and VC deal likelihood



Panel B: GB funding and VC investment amount



This figure plots the event study estimates and corresponding 95% confidence intervals using the DiD estimator developed by de Chaisemartin and D'Haultfoeuille (2020); De Chaisemartin and d'Haultfoeuille (2024), which addresses the issues of treatment effect heterogeneity and negative weights that may bias the standard two-way fixed effects estimator. The dot represents the coefficient on the interaction between the GB fund relative year indicator and the climate startup indicator. We focus on an event window of five years before to five years after the county where the startup is located receives funding from a Green Bank. Event year $\ell = -1$ is the omitted category, implying that all coefficient estimates are relative to this year.

Table IA1
Green Banks' characteristics.

Green Bank	Year established	Type	jurisdiction
Abundant Power Group	2009	Non-profit	North Carolina
California Alternative Energy and Advanced Transportation Finance Authority	2009	Public	California
California Pollution Control Finance Authority	1972	Public	California
Colorado Clean Energy Fund	2021	Non-profit	Colorado
Columbus Region Green Fund	2021	Non-profit	Ohio
Connecticut Green Bank	2011	Quasi-public	Connecticut
DC Green Bank	2011	Non-profit	DC
Delaware Sustainable Energy Utility	2007	Non-profit	Delaware
Efficiency Maine	2010	Quasi-public	Maine
GO Green Energy Fund	2020	Non-profit	Ohio
Illinois Finance Authority/Illinois Climate Bank	2004	Quasi-public	Illinois
Maryland Clean Energy Center	2008	Quasi-public	Maryland
Massachusetts Clean Energy Center	2009	Public	Massachusetts
Montgomery County Green Bank	2016	Non-profit	Maryland
New Jersey Economic Development Authority	1974	Public	New Jersey
New York City Energy Efficiency Corporation	2011	Non-profit	New York
New York Green Bank	2013	Public	New York
Philadelphia Green Capital Corp	2016	Quasi-public	Pennsylvania
Rhode Island Infrastructure Bank	1989	Quasi-public	Rhode Island
Solar Energy Loan Fund (SELF)	1995	Non-profit	Florida
Virginia Resources Authority	1984	Public	Virginia

This table reports the year of establishment, type, and jurisdiction of the Green Banks for which county-level activity is available.

Table IA2

Green Banks' investment focus.

Green Bank	Only green investments?	Environmental investment focus	Sector focus	Social investment focus
Abundant Power Group	Yes	Energy efficiency & clean energy	Infrastructure, building, agriculture, methane capture	N/A
California Alternative Energy and Advanced Transportation Finance Authority	Yes	Energy efficiency & clean energy	Residential/commercial buildings, lithium batteries	N/A
California Pollution Control Finance Authority	No	Waste control	Water, landfills, compost, recycling	Small business & economically disadvantaged community support
Colorado Clean Energy Fund	Yes	Energy efficiency & clean energy	Residential/commercial/municipal buildings, industrial, agricultural, solar, heat pumps	Affordable housing
Columbus Region Green Fund	Yes	Clean energy	Solar	Focus on rejected borrowers and disproportionately impacted by climate change
Connecticut Green Bank	Yes	Energy efficiency & clean energy	Residential/commercial/municipal buildings, industrial, agricultural	Goal of 40% investment in vulnerable communities
DC Green Bank	Yes	Energy efficiency & clean energy	Residential/commercial buildings, industrial, infrastructure	Favor low-to-moderate income households
Delaware Sustainable Energy Utility	Yes	Energy efficiency & clean energy	Residential/commercial buildings, agricultural/infrastructure	Programs for low-income households
Efficiency Maine	Yes	Energy efficiency & clean energy	Residential/commercial/municipal buildings	Low-income, small-business focused
GO Green Energy Fund	Yes	Clean energy	Solar	Low-to-moderate income communities, minority-focused
Illinois Finance Authority/Illinois Climate Bank	Yes	Energy efficiency & clean energy	Solar, wind, commercial buildings, agriculture, clean water	N/A
Maryland Clean Energy Center	Yes	Energy efficiency & clean energy	Solar, wind, biomass	N/A
Massachusetts Clean Energy Center	Yes	Energy efficiency & clean energy	Buildings, solar, wind, transportation	Diversity, equity, inclusion, and environmental justice
Montgomery County Green Bank	Yes	Energy efficiency & clean energy	Residential/commercial buildings, solar	N/A
New Jersey Economic Development Authority	No	Clean energy	Solar, offshore wind	Equitable
New York City Energy Efficiency Corporation	Yes	Energy efficiency & clean energy	Residential/commercial buildings, solar	Equitable
New York Green Bank	Yes	Energy efficiency & clean energy	Residential/commercial buildings, infrastructure, solar, wind, storage, transportation	N/A
Philadelphia Green Capital Corp	Yes	Energy efficiency & clean energy	Residential/commercial buildings, solar	Improve public health, alleviate poverty, promoting economic development
Rhode Island Infrastructure Bank	No	Energy efficiency & clean energy	Solar, wind, residential/commercial buildings, infrastructure, climate resilience	N/A
Solar Energy Loan Fund (SELF)	Yes	Energy efficiency & clean energy, Climate Resilience	Residential buildings, solar	Low and moderate income households
Virginia Resources Authority	No	Energy efficiency & clean energy	Solar, wind, residential/commercial buildings, infrastructure, agriculture, climate resilience	N/A

This table reports some of the investment characteristics of Green Banks for which county-level activity is available

Table IA3
Baseline results using the loan volume of Green Bank funding.

Dep. variable:	*VC deal*			*Investment amt*		
	(1)	(2)	(3)	(4)	(5)	(6)
GB fund amt	0.001	0.019***	0.019***	0.010	0.279***	0.280***
	(0.65)	(3.68)	(3.64)	(0.63)	(3.31)	(3.27)
GB fund amt × *Climate startup*	0.010***	0.009***	0.008***	0.131***	0.117***	0.104***
	(6.88)	(5.38)	(3.75)	(6.74)	(5.33)	(4.05)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	No	Yes	No	No
County F.E.	Yes	No	No	Yes	No	No
Year F.E.	Yes	No	No	Yes	No	No
Industry × Year F.E.	No	Yes	Yes	No	Yes	Yes
County × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	394,337	391,039	198,723	394,337	391,039	198,723
R^2	0.04	0.05	0.05	0.09	0.09	0.09

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *Investment amt* is the log of one plus the dollar amount of VC investment the startup receives in a given year. *GB fund amt* is the log of one plus the dollar amount of funding that a county, where the startup is located, receives from a Green Bank in the current year and in the previous four years. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. Columns (3) and (6) restrict the sample to startups located in California, Connecticut, Illinois, New York, and Virginia. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA4

Robustness tests: state exclusions.

Dep. variable:	*VC deal*		*Investment amt*	
	(1)	(2)	(3)	(4)
GB fund	0.155***	0.154***	1.934***	1.918***
	(11.02)	(10.87)	(7.61)	(7.48)
GB fund × *Climate startup*	0.108***	0.110***	1.442***	1.473***
	(5.16)	(5.02)	(5.19)	(5.13)
Startup F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	No
County F.E.	No	No	No	No
Year F.E.	No	No	No	No
Industry × Year F.E.	Yes	Yes	Yes	Yes
County × Year F.E.	Yes	Yes	Yes	Yes
Observations	326,163	198,773	326,163	198,773
R^2	0.05	0.05	0.09	0.09

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *Investment amt* is the log of one plus the dollar amount of VC investment the startup receives in a given year. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. Columns (1) and (3) exclude the following states: District of Columbia, North Carolina, Delaware, Colorado, Texas, Michigan, Virginia, New Jersey, and Louisiana. Columns (2) and (4) exclude the previous states and California. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA5
Robustness tests: neighboring counties.

Dep. variable:	*VC deal*			*Investment amt*		
	(1)	(2)	(3)	(4)	(5)	(6)
GB fund	0.003	0.150***	0.151***	-0.015	1.888***	1.902***
	(0.29)	(9.91)	(10.14)	(-0.11)	(7.12)	(7.43)
GB fund × *Climate startup*	0.116***	0.095***	0.084***	1.631***	1.346***	1.157***
	(5.37)	(4.06)	(3.18)	(4.95)	(4.11)	(3.47)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	No	Yes	No	No
County F.E.	Yes	No	No	Yes	No	No
Year F.E.	Yes	No	No	Yes	No	No
Industry × Year F.E.	No	Yes	Yes	No	Yes	Yes
County × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	284,772	283,862	198,198	284,772	283,862	198,198
R^2	0.20	0.21	0.21	0.23	0.25	0.25

VC deal is a dummy variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *Investment amt* is the log of one plus the dollar amount of VC investment the startup receives in a given year. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. The sample includes counties that receive at least one GB loan and their neighboring counties. Columns (3) and (6) restrict the sample to startups located in California, Connecticut, Illinois, New York, and Virginia. Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2023. Robust t-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.