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 (IRA) funds to leverage private capital for reducing greenhouse gas emissions. To contextualize their impact, this paper examines how effectively GBs mobilized local private investment into green projects before the IRA. We show significant increases in venture capital (VC) deals and total investments for climate-tech startups in counties following a GB loan issuance. The increases are concentrated among GB-startup pairs with aligned technological focus, are accompanied by real green output growth, and do not crowd out existing private capital. Our evidence underscores GBs' pivotal role in facilitating 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 current U.S. administration has suspended the GGRF, leading to an ongoing legal dispute, EPA v. Climate United et al. Once resolved in favor of the latter, more than a third of the fund will be deployed through Green Banks (GBs)—government-funded, mission-driven institutions that began operating as early as 1991. Over the past decade, GBs have served as key financial intermediaries, supporting environmentally sustainable projects to stimulate local private green investment. Accordingly, a rigorous evaluation of GBs' historical effectiveness in mobilizing private capital is critical to assessing the IRA's potential influence on the national green transition and represents a material factor in the related legal proceedings.[1]

To this end, this paper investigates whether GBs catalyze private investment for local climate-focused startups. Specifically, we examine whether the initiation of GB lending spurs venture capital (VC) investment in these startups. Our focus on VC investment is for a number of reasons. First, GBs rarely provide equity capital to startups or participate

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

in VC syndicates.[2] The limited direct interaction between GBs and VCs thus makes our setting well-suited to study whether GBs act as substitutes for, or complements to, existing local private financing for nascent green projects. This weak institutional linkage suggests that our estimate of GBs' public-to-private capital multiplier should be interpreted as a lower bound.[3] Secondly, GBs lend to projects deploying proven and commercially viable technologies.[4] Given that early-stage climate-focused startups test unproven technologies, GBs have been and are expected to be at arm's length from VCs. Moreover, the emphasis on proven technologies suggests that any influence GBs may have on VCs does not arise from certifying the quality of these startups, but rather through other economic channels.[5]

Finally, VCs are profit-driven and among the least likely asset managers to sacrifice returns for non-financial purposes. Even for impact funds that take up merely 2% to 3% of all VC investment amount over the past two decades (see Barber, Morse, & Yasuda, 2021 and Cole, Jeng, Lerner, Rigol, & Roth, 2023), Geczy, Jeffers, Musto, and Tucker (2021) and Jeffers, Lyu, and Posenau (2024) document that they generally do not tie GP compensation to impact and are not concessionary. Also, Gompers, Gornall, Kaplan, and Strebulaev (2020) report that VCs perform due diligence in the conviction that it is one of the most important contributors to value creation. Therefore, any observed increase in local VC investment should mainly be attributed to GBs' financial value creation for the local climate-tech startups. Taken together, our pre-IRA analysis of GBs through the lens of VC provides a conservative estimate for the expected private capital mobilization post-IRA and sheds light on plausible economic mechanisms.

Indeed, we find that GB activity significantly boosts VC investment in local climate

[2]None of the VC deals in our sample includes 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.

[3]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.

[4]Post-IRA, the GGRF mandates grant recipients (i.e., GBs) to support only commercial technologies—classes of technologies already deployed for commercial purposes. The detailed definition of commercial technologies can be found at this link. 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.

[5]In fact, the literature on VCs, including de Rassenfosse and Fischer (2016), Hochberg, Serrano, and Ziedonis (2018), and Chen and Lyu (2025), documents the signaling role of VCs, which benefits venture lenders rather than the reverse.

startups, underscoring the role of GBs as a promising vehicle to accelerate a bottom-up green transition. Using a generalized staggered difference-in-differences (DiD) approach over the sample period from 2015 to 2022, we find that counties receiving at least one GB loan experience an increase of 10.1% to 13.2% in climate startup VC deals over the four years following the loan. The results are robust to VC investment amounts, across different fixed-effects specifications accounting for time-invariant startup unobservables and time-variant industry and state unobservables, and in a sample restricted to propensity-score-matched counties. In addition, a dynamic DiD approach fails to reject the parallel-trends assumption, suggesting that local pre-trends do not drive the results.

Notably, we show that GBs' operations most strongly benefit local climate startups whose technological focus aligns closely with their own. To measure GB-startup pair technological alignment, we first use a GPT-based large language model (LLM) to match each climate startup to one of 88 climate technologies identified from Project Drawdown (2020) and refined by Lu, Serafeim, Xu, and Awada (2025). Then, for GBs, all of whose publicized projects and prospectuses are broadly categorizable into five types—solar, wind, building efficiency, green transportation, and recycling—we assign each GB to one or more types. Finally, we manually link each type to Project Drawdown technologies based on their descriptions, so that each GB's technological focus is represented as an aggregate of Project Drawdown technologies linked to the type(s) the GB is assigned to. In the end, using the time-varying topic distance measure for every pair of Project Drawdown technologies, following Lu et al. (2025), we construct a GB-startup alignment measure that evolves annually as technologies' topical distances change. Using this new measure, we show that the aforementioned increases in VC deals and investment amounts in GB-operating counties are concentrated among startups whose technological distance from local GBs is shorter than the median distance among all pairwise distances.

Given that VCs are inherently profit-oriented, a significant increase in their allocation to climate-tech startups following GB loan issuance implies a concurrent integration of climate-tech innovation into the real economy. We find evidence consistent with a GB-driven shift toward broader monetary value creation, as measured by two real variables: job postings and photovoltaic (PV) installations. Using Revelio Labs' comprehensive job posting data, we

examine more than 367 million postings across 3,111 counties from 2016 to 2023 and show that counties hosting GB loans experience up to a 22.6 percent increase in job postings referencing GB-targeted technologies. Furthermore, over the past two decades, counties with GB loans have seen a 22 to 34 percent increase in installed PV capacity and system counts—the data compiled by the Lawrence Berkeley National Laboratory. Note that solar is a targeted project type for all GBs, except for one. Such real effects point to GBs' role in nurturing a local green ecosystem, particularly in sectors that employ GBs' targeted technologies. That the effects persist after netting out time-varying technology-specific components or end-user heterogeneity demonstrates GBs' broad impact throughout both upstream and downstream verticals in targeted sectors, driving growth in both demand and supply of green products and services. While the lack of loan-level data limits us from discerning which means GBs utilize to achieve this (e.g., concessionary contractual terms like interest rate, tenor, rank, or collateral requirement), the real effects explain the subsequent scale-up of VCs backing startups innovating in GB-targeted technologies, which can accelerate bottom-up green transition.

While GBs can accelerate the green transition within their own regions, they may inadvertently disadvantage climate startups in areas without GB presence, particularly if VCs merely redirect capital from climate-tech startups in non-GB counties into those in GB counties. Because our DiD results cannot rule out this possibility, we adopt the empirical approach of Cortés and Strahan (2017) to detect whether such VC reallocation occurs during the sample period. We analyze the changes in VC investments—both in climate-tech and non-climate-tech startups—in counties where the VC has historically invested but that do not receive GB funding ("connected non-GB counties"), and relate these changes to corresponding changes in VC investments in counties that do receive GB funding ("GB counties"). Our analysis suggests that VCs do reallocate investments away from connected non-GB counties as they increase their investments in climate-tech startups in GB counties, but not at the expense of climate-tech startups in the connected non-GB counties. Only VCs' non-climate-tech investments decline upon GBs' operations, implying GBs do not crowd out the existing climate-tech investments.

Armed with the knowledge that GBs nationally scale up VC investments in their target

climate technologies, we further examine environments under which GBs catalyze VCs 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. NZBA launched in 2021 with six major U.S. banks—Bank of America, Citigroup, Morgan Stanley, JPMorgan Chase, Goldman Sachs, and Wells Fargo—joining as signatories in the same year. By constructing county-level measures of NZBA presence, we assess whether this presence amplifies or dampens the GB effect. We find that GBs' impact on VC investments amplifies with the presence of NZBA banks, consistent with GBs and NZBA banks functioning complementarily in cultivating a supportive financial ecosystem for green innovation. Such complementarity substantiates GBs' commitment to leverage public capital to crowd in private investment and spur the green transition.[6]

Furthermore, we show that climate technologies' commercialization potential estimated by Project Drawdown, startup characteristics such as age and prior VC financing, and geographical factors like political leaning and public awareness of climate change contribute to the effectiveness of GBs attracting VC investments. The results suggest that, even as GBs broadly enhance the financial prospects for green ventures innovating GBs' targeted technologies, VCs remain highly selective, prioritizing investment in climate startups with more substantial commercialization potential, stronger market validation, and a higher population of environmentally aware local stakeholders. We also find that, among startups with prior VC deals, climate-tech startups achieve higher valuations and exit multiples than non-climate counterparts in GB counties. This reflects VCs' fundamental objective of financial value creation, and hence, implies that the observed increases in VC investments are attributable to GBs fostering robust local green innovation ecosystems.

The results are robust to a battery of tests that address concerns about the estimated impact of GBs on VC investment in climate-tech startups being influenced by federal grants, measurement error, or choice of empirical 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), the Department

[6]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/`).

of Energy (DoE), and the Department of Agriculture (DoA), we analyze counties without GB investments to isolate the effects 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 upscaling private investment in climate technologies. Moreover, the results remain consistent when restricting the sample to GBs with clear and enduring green investment objectives from their onset, to GB counties and their neighboring counties, and to GB counties and two propensity-score-matched non-GB counties.

By providing the first comprehensive analysis of GBs and their role in expanding private investment in early-stage climate-tech startups and advancing the green transition, our paper contributes to a growing body of literature examining governmental initiatives for the green transition and 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 mobilize 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 this literature by delivering first insights 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 and transition, with a particular emphasis on climate-tech startups.

Our work is also 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 a greener ecosystem, allocating capital into climate-tech ventures can serve as a prudent hedge for these investors against growing climate risks.

2. Green Banks

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.[7] Thus, GBs invest in projects that are past the research and

[7]It is worth noting that public or quasi-public GBs are initially capitalized with public funds before issuing

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 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

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.

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.[8] 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.

3. Data

3.1. Green Banks

We collect information on GBs in the U.S. using publicly available information from each banks' annual report or website.[9] 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.[10]

As the first study on GBs to our knowledge, we provide some descriptive statistics. We

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

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

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

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 2022. In Table 1 Panel A, 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.[11]

For a subset of GBs, we are able to collect data on the amount invested at the county-year level.[12] 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 billion), California ($15 billion), New York ($740 million), and Connecticut ($280 million).

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

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

3.2. 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.[13] Our analysis focuses on startups falling under the "Climate Tech" or "CleanTech" verticals.[14] We consider VC financing rounds taking place from 2015 to 2022. 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;[15] 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 1 provides summary statistics on VC investment activity by year (Panel B) and the industry distribution of startups (Panel C) for both climate-tech and non-climate-tech startups.

3.3. 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,

[13]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`.

[14]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."

[15]This restriction excludes VC rounds financed purely by individuals, angel groups, accelerators/incubators, crowdfunding investors, etc., to minimize any outlier effect.

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).

For each climate-tech startup, we apply the climate solutions topic model developed by Lu et al. (2025) to the startup's business description from PitchBook.[16] This model classifies each startup into one of 88 predefined climate technologies based on the dominant topic identified in the text.

3.4. Job Postings

We collect job postings data from Revelio Labs, one of the most comprehensive workforce databases available. Revelio Labs aggregates all publicly available professional profiles, job postings, and employee sentiment reviews for more than 4.5 million companies worldwide. We focus on U.S. job postings starting in 2016, which marks the effective beginning of systematic data collection, as suggested by the sharp rise in the number of postings that year. Specifically, U.S. postings total 5,284 in 2014 and 305,953 in 2015, compared to 21.6 million in 2016. Counts are even lower for earlier years. The dataset includes, among other variables, the location, job title, description, salary, remote status, and employer. After removing remote jobs, we extract county identifiers for 367,603,804 job postings across 3,111 counties between

[16]Lu et al. (2025) fine-tune a GPT model using the Item 1 "Business Description" sections of 10-K filings for all U.S. public firms from 2005-2022 to identify and classify text describing firms' climate-solution products and services. Using Project Drawdown's taxonomy of decarbonization technologies, their model distinguishes sentences describing the development or deployment of low-carbon technologies—rather than merely using them—and assigns each to one of 88 predefined technology topics.

2016 and 2023.

3.5. Photovoltaic Installations

We utilize project-level data on residential and non-residential photovoltaic (PV) systems collected by the Lawrence Berkeley National Laboratory (Berkeley Lab).[17] The dataset covers approximately three million PV systems installed up to 2022 and provides information on, among other variables, the installation date, installation zip code, system size (in kW), and customer segment (residential, commercial, school, government, non-profit, and other). We aggregate these data to the county–customer-segment–year level, where we compute both the number of projects and the total installed capacity.

3.6. 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 follow Sastry et al. (2024) and 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

[17] A photovoltaic system converts sunlight into electricity. The data from the Berkeley Lab can be downloaded here: `https://emp.lbl.gov/tracking-the-sun/`.

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.[18] 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.

3.7. County Characteristics

The annual 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 annual 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.[19] The county-level presidential votes are from the MIT Election Lab.[20] We define a Republican indicator equal to one if the presidential votes for a Republican candidate in county c are above the median and zero otherwise.

4. Empirical Approach and Results

4.1. Identification Strategy

Our sample period runs from 2015 to 2022, chosen for several reasons. First, 2015 marks the beginning of a significant resurgence in VC interest in green technologies. This period saw

[18] *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.

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

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

massive inflows of private capital into climate-tech startups, with investment growth exceeding 150% between 2015 and 2021 (Cornelli et al., 2023).[21] More importantly, 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 started a momentum for climate-tech investments. Given these trends and considering the programmatic details of GGRF, which started developing in late 2023, we chose the 2015-2022 window to restrict macroeconomic and policy factors confounding our results.[22]

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:

$$\begin{aligned} y_{i,c,t} = {} & \beta_0 + \beta_1 \mathit{GB\ fund}_{c,t} + \beta_2 \mathit{GB\ fund}_{c,t} \times \mathit{Climate\ startup}_i + \gamma' X_{c,t-1} \\ & + \tau_i + \rho_{j,t} + \omega_{s,t} + \varepsilon_{i,c,t} \end{aligned} \tag{1}$$

where startup i, operating in industry j, is headquartered in county c of state s, in year t. We focus on an event window spanning four years before to four years after the startup's county receives GB funding. *GB fund* is an indicator 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.[23] *Climate startup* is an indicator variable equal to one if the

[21] 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).

[22] Results with the sample running until 2023Q3 are robust with increased estimates.

[23] Results are not sensitive to the number of look-back periods for the *GB fund* definition, but not shown for brevity.

startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and the unemployed share of the population. 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.[24] 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, state-year fixed effects ($\omega_{s,t}$) are used to control for local economic conditions or government initiatives that may vary across states and years, ensuring that the effects of GB funding are not confounded by other state-level influences.

4.2. Baseline Estimates

Table 2 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. First, note that GB investments in a county do not lead to an overall increase in VC investments in the local startups. This mitigates the concern that GBs endogenously select counties where they anticipate future growth in overall VC activity. Instead, GBs only benefit local climate-tech startups, which enjoy statistically significant increases in both extensive and intensive margins of VC financing. Specifically, counties that receive GB funding see a 10.1% to 13.2% increase in the probability of climate-tech startup deals relative to other types of startups. These results hold when restricting the

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

analysis to states where we have information on GB loan amounts in each county (columns (3) and (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 (columns (4)-(6)).[25]

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 IA4 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:

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

[25]With VC investment amount as the dependent variable, a back-of-the-envelope calculation based on GBs' average annual county-level investment ($47.8m) and VCs' average climate-tech deal size ($19.1m) yields 1.8-2.9 GB-to-VC mobilization ratio, which is much lower than the GGRF's target of 7 as public-to-private mobilization ratio.

where

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

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.

To further assess the validity of the parallel trends assumption, we run our empirical specification in Equation (2) for $l < 0$ periods where the dependent variables in question are the level and change in income, population, population density, unemployed share of the population, and minority share of the population. The results, as illustrated by Figure IA3, show no statistically significant differences between GB and non-GB counties in the pre-treatment period across these economic and demographic characteristics, indicating no selection bias due to GBs systemically favoring certain economic conditions.

4.3. Topic Distance

The results suggest that GBs generate financial value for local climate-tech startups, as profit-driven VCs would not react meaningfully to GB lending activity otherwise. In fact,

among climate-tech startups, we expect VCs to prioritize investing in those best-positioned to capitalize on GBs' financial impact. For example, a GB loan directed at a utility-scale solar installation may create local complementarities for energy storage startups, which can directly capitalize on increased renewable generation, and for grid-optimization technology startups, which may benefit indirectly through increased local demand for balancing and flexibility solutions. Accordingly, we expect VC investors to concentrate their investments in startups with technological linkages to the GB focus, as these firms are better positioned to benefit from the enhanced local demand and supportive infrastructure generated by GB-backed projects.

To empirically examine whether technological alignment between GB-startup pairs is necessary for VCs to react meaningfully to GB lending activity, we begin with the climate-tech startups that are matched to one of 88 climate technologies identified from Project Drawdown (2020) as described in Section 3.3. Then, to identify technologies from the 88 technologies that GBs focus on financing, we start by categorizing the types of projects funded by GBs into five groups: solar, wind, building efficiency, green transportation, and recycling. We then match each GB to these project types using information from their public reports and websites. For example, the New York Green Bank (NYGB) has financed, among other projects, a solar-plus-storage installation in upstate New York and contributed $250 million to a fund dedicated to building decarbonization. Accordingly, we assign both the building efficiency and solar project types to NYGB, along with any other relevant project types. Finally, by linking each of the five groups to a selection of 88 Project Drawdown technologies, each GB's technological focus is represented by the aggregate of selected technologies for all of its funded project types.[26]

To measure the similarity between the topics that GBs focus on and those of the startups, we use the time-varying topic distance measure in Lu et al. (2025). Specifically, we generate high-dimensional sentence embeddings using a transformer-based language model from the SentenceTransformers library, trained on large English text corpora to capture semantic meaning. These embeddings are then projected into two dimensions with Uniform Manifold

[26]Table IA2 reports the mapping between GBs and project types. Table IA3 shows the mapping from GB project types to Project Drawdown technologies.

Approximation and Projection (UMAP) to calculate the Euclidean distance between the centroids of any two topic-description sentences in a given year. Shorter distances indicate greater similarity. A startup's topic is classified as close (far) to a GB topic if its distance is below (above) the median distance among all pairwise distances for that topic within the same year. Topic distance is defined only for climate-tech startups located in treated GB counties, that is, counties that received GB funding in the current year or within the previous four years. To capture this variation, we create two key indicators. *Close topic GB fund and Climate startup* equals one if the startup is a climate-tech startup whose topic is close to at least one GB-supported topic, and zero otherwise. In contrast, *Far topic GB fund and Climate startup* equals one if the startup is a climate-tech startup whose topic is far from all GB-supported topics, and zero otherwise. We then estimate the following regression:

$$\begin{aligned} \textit{VC deal}_{i,c,t} = \beta_0 + \beta_1 \textit{GB fund}_{c,t} + \beta_2 \textit{Close topic GB fund and Climate startup}_{i,c,t} \\ + \beta_3 \textit{Far topic GB fund and Climate startup}_{i,c,t} + \gamma' X_{c,t} + \tau_i + \rho_{j,t} + \omega_{s,t} + \varepsilon_{i,c,t} \end{aligned} \tag{4}$$

where variable definitions follow those in Equation (1).[27]

Table 3 presents the results. Columns (1) and (3) show that the coefficient on *Close topic GB fund and Climate startup* is positive and statistically significant, whereas the coefficient on *Far topic GB fund and Climate startup* is statistically insignificant. This result indicates that VCs increase their investments only in startups whose technologies are closely related to the sectors supported by GBs, while startups in less similar technology areas do not experience any meaningful change in VC funding.

Since "close" topics may capture either exact technological overlaps between the startup and the GB focus or technologies that are similar but not identical, columns (2) and (4) further decompose *Close topic GB fund and Climate startup* into two categories: (i) *Same topic GB fund and Climate startup*, which equals one if the startup is a climate-tech startup whose topic is the same as one of its GB focus topics, and zero otherwise; and (ii) *Close different topic GB fund and Climate startup*, which equals one if the startup is a climate-tech

[27] Unlike Equation (1), which includes an explicit interaction between *GB fund* and *Climate startup*, here the effect of the interaction is embedded in the construction of the *Close topic GB fund and Climate startup* and *Far topic GB fund and Climate startup* indicators.

startup whose topic is close to but different from any of GB focus topics, and zero otherwise. We find that both coefficients are positive and statistically significant, suggesting that VC investments rise not only in startups whose technology focus directly overlaps with GB activity, but also in those with adjacent and complementary technologies.[28]

5. GBs' Real Effects and Complementarity

The results about the technological alignment between GB-startup pairs document a necessary condition for GBs to spur VC investment, but they cannot fully explain how GBs achieve it. In this section, we aim to identify a mechanism through which GBs influence VCs' perception of their local climate-tech startups. Put differently, we study how GBs generate financial value for topic-aligned climate-tech startups, enabling VCs to reap the benefits.

5.1. Job Postings and Photovoltaic (PV) Installations

To this end, we examine job postings and photovoltaic (PV) installations as they can proxy employment and green output. If GBs are shown to accompany such real effects, then they can explain the subsequent scale-up of value-driven VCs backing startups innovating in GB-targeted technologies. Furthermore, such effects would strengthen the case for GBs, as they are designed to accelerate a bottom-up green transition.

For job-posting analysis, we first identify whether a job posting is associated with one of the GB investment focus areas by conducting a keyword search within the title and description. Specifically, we employ the same GB-to-project-type and project-type-to-technology mapping described in Section 4.3. For instance, a job posting is classified as "building efficiency" if it includes at least one keyword assigned to that project type.[29] This approach enables us to search for climate-related jobs directly connected to GB sectoral priorities. We also include an indicator variable equal to one if none of the keywords are found.

Next, we construct a panel dataset at the county–topic–year level using the location information provided by Revelio. We estimate the effect of GB investments on local employment

[28]While the estimated effect for *Same topic GB fund and Climate startup* appears somewhat smaller in magnitude than that for *Close different topic GB fund and Climate startup*, the difference is not statistically significant.

[29]The full list of keywords and corresponding GB project types is provided in Table IA3.

in GB-related sectors using a Poisson pseudo–maximum likelihood (PPML) estimator. PPML is well suited to this setting because our dependent variable—the number of jobs at the county–topic–year level—is a non-negative count with many zeros, many large values, and substantial heteroskedasticity. Unlike log-linear models, PPML naturally accommodates zero outcomes and provides consistent estimates under general forms of heteroskedasticity (Silva & Tenreyro, 2006).

$$E[\textit{Job postings}_{p,c,t}] = exp(\beta_1 \textit{GB fund}_{c,t} + \beta_2 \textit{Same topic GB fund and job posting}_{p,c,t} + \tau_c + \rho_{p,t} + \omega_{s,t} + \gamma' X_{c,t}) + \textit{Total jobs}_{c,t} + \varepsilon_{p,c,t} \tag{5}$$

where *Job Postings* represents the number of jobs within topic p in county c in year t. The definition of *GB fund* is identical to that used in the baseline estimates. *Same topic GB fund and job posting* is an indicator equal to one if the topic of a job posting matches the GB's investment focus. Similar to the topic distance measure, *Same topic GB fund and job posting* is defined only for job postings located in counties that received GB funding in the current year or within the previous four years.[30] When the log of *Total jobs* is included as an offset, the model can be interpreted as estimating the impact of GB investment on the rate of GB-matched jobs per total jobs. The offset enters the model with its coefficient constrained to one, so that total employment scales the expected number of jobs proportionally.

The results reported in Table 4 Panel A show a positive and statistically significant effect of GB investment on job postings that match the GB investment focus. Specifically, counties receiving GB loans experience an increase in GB-related job postings of up to 25.4% ($e^{0.226} - 1$), even after netting out time-varying technology-specific components. The results are robust to estimating the effects using OLS regressions with the ratio of local GB-related job postings to total job postings as the dependent variable (Table IA5 in the Internet Appendix).[31] Collectively, these results highlight the role of GBs in stimulating demand for human capital with skills in GB-targeted technologies.

[30] Unlike Equation (1), which includes an explicit interaction between *GB fund* and *Climate startup*, here the effect of the interaction is embedded in the construction of the *Same topic GB fund and job posting* indicator.

[31] We utilize the total number of job postings at the county–year level for the weights. The results are qualitatively similar when using an unweighted regression model.

Next, we turn to GBs' impact on local PV installations that represent the real green output. Nearly all GBs in the U.S. have invested in PV systems. Using project-level data on PV installations from the Berkeley Lab, we compute two county–customer-segment–year aggregates: (i) the total installed capacity (kW) and (ii) the number of PV projects. We use these measures of local green ecosystem activity as dependent variables and estimate the baseline DiD regression model in Equation (1). The only modification is that we replace industry and industry–year fixed effects with customer-segment and customer-segment–year fixed effects to absorb shocks related to the type of PV installation and end-user heterogeneity. Table 4 Panel B presents the DiD results and shows that counties receiving GB financing experience a statistically significant increase in both the size and number of PV installations. The economic magnitude is substantial: treated counties see increases of between 22 and 34% in installed capacity and project count.[32]

Taken together, the real effects highlight GBs' role in fostering a local green ecosystem, particularly in sectors that are closely related to GBs' targeted technologies. Determining which aspects of GB loans contribute most to GBs developing a more robust green ecosystem is left for future research, mainly due to the current inaccessibility of GB loan-level data. Yet, the observed connections between GBs and VCs can result from the former cultivating a green ecosystem and the latter recognizing the financial value it delivers for climate-tech startups.[33]

5.2. Reallocation of VC investments

While the aforementioned real effects demonstrate GBs' value creation, verifying GBs' role as catalysts for the green transition requires further evidence. Specifically, VC investment increases in GB counties should not come at the expense of existing private capital green investment in both GB and non-GB counties. Because our DiD results cannot rule out this possibility, we adopt the empirical approach of Cortés and Strahan (2017) to detect whether VCs merely redirect capital from climate-tech startups in non-GB counties into those in

[32]The results are robust when using the year-over-year change in installation size and number of installations as outcome variables.

[33]Absence of pre-trends for job postings and PV results, not shown for brevity, corroborates this ecosystem mechanism by which GBs influence VCs.

GB counties during the sample period. We examine the changes in VC investments—both in climate-tech and non-climate-tech startups—in counties where the VC has historically invested but that do not receive GB funding ("connected non-GB counties"), and relate these changes to corresponding changes in VC investments in counties that do receive GB funding ("GB counties").

Empirically, we construct a panel dataset at the VC–county–year level from 2015 to 2022. For each VC–year, we include all startups' headquarter counties in which this VC invested in the prior calendar year. These counties are assumed to represent the relevant regions for the VC's investment activity. Once a VC–county enters the dataset, we retain it in all subsequent years, even if during some years that VC made no investments in that county. We then flag each county in the year it first receives GB funding and keep the flag on for the following four years. We drop these flagged county–years from the VC–county–year dataset because our aim is to identify how GB funding shocks affect investments in connected non-GB counties.

To measure the incremental investments in climate-tech and non-climate-tech startups made by each VC in the flagged county–years associated with GB funding, we construct the following variables at the VC–year level:

$$\Delta \textit{VC GB climate inv}_{k,t} = \frac{\Delta \textit{Investments in climate-tech in GB counties}_{k,t}/N_{k,t}}{\textit{Total investments}_{k,t}}, \quad (6)$$

$$\Delta \textit{VC GB non-climate inv}_{k,t} = \frac{\Delta \textit{Investments in non-climate-tech in GB counties}_{k,t}/N_{k,t}}{\textit{Total investments}_{k,t}}, \quad (7)$$

where k indexes VC, c indexes county, and t indexes year. The term $\Delta \textit{Investments in climate-tech in GB counties}_{k,t}$ equals to the change in the dollar value of investments in climate-tech startups between year t and year $t-1$ for VC k, summed across all GB counties in year t. Because a VC typically invests in multiple connected non-GB counties, we allocate this change equally across the number of connected non-GB counties. Accordingly, we define $N_{k,t}$ as the number of connected non-GB counties for VC k in year t. Finally, we divide by each VC's total investments, defined as the sum of all investments (climate-tech and non-climate-tech, across both GB and non-GB counties) over the current year and the prior four years. This calculated $\textit{Total investments}_{k,t}$ normalizes $\Delta \textit{VC GB climate inv}_{k,t-4}$ to

Δ *VC GB climate inv*$_{k,t}$ to ensure they are all bounded between -1 and 1, which helps reduce heteroskedasticity in the following panel regressions. The variable Δ *VC GB non-climate inv*$_{k,t}$ is defined analogously. Notice that both variables vary at the VC–year level (as opposed to the VC–county–year level).

Using the constructed dataset, we estimate how changes in a VC's investments in GB counties affect its investments in connected non-GB counties, as follows:

$$y_{k,c,t} = \alpha + \sum_{l=1}^{4} \beta_l \Delta \textit{ VC GB climate inv}_{k,t-l} + \sum_{l=1}^{4} \gamma_l \Delta \textit{ VC GB non-climate inv}_{k,t-l} + \text{F.E.} + \varepsilon_{k,c,t} \tag{8}$$

for VC k, county c, and year t. We consider three outcome variables at the VC–county–year level. First, we examine changes in a VC's total investments in all startups headquartered in a connected non-GB county: *Connected VC non-GB inv*$_{k,c,t}$, defined as the change in the dollar value of investments in all startups between year t and year $t-1$ in connected non-GB county c for VC k, normalized by *Total investments*$_{k,t}$. Second, we separately consider changes in a VC's investments in climate-tech and non-climate-tech startups in connected non-GB counties, denoted by Δ*Connected VC non-GB climate inv*$_{k,c,t}$ and Δ*Connected VC non-GB non-climate inv*$_{k,c,t}$, which are defined analogously. All regressions include VC, county, and year fixed effects, and standard errors are clustered at the VC level. The coefficients of interest are the four lags of Δ *VC GB climate inv* and Δ *VC GB non-climate inv*, which capture the extent to which VCs reallocate investments away from connected non-GB counties in response to increased investment activity in GB counties.

Table 5 reports the results. In column (1), the coefficients on the first three lags of Δ *VC GB climate inv* are negative and statistically significant, while all lags of Δ *VC GB non-climate inv* are statistically insignificant. These findings indicate that VCs reallocate investments away from connected non-GB counties when increasing their investments in climate-tech startups in GB counties, but no reallocation occurs for non-climate-tech startups. Moreover, the magnitude of the coefficients on Δ *VC GB climate inv* decreases monotonically from the first to the fourth lag, suggesting that most of the reallocation toward climate-tech startups occurs in the year immediately following a county's GB funding, with the effect

tapering off over time.

Columns (2) and (3) examine whether the reallocation away from connected non-GB counties is concentrated in non-climate-tech or climate-tech startups in those counties. The results show that increases in investments in climate-tech startups in GB counties are associated with significant declines in non-climate-tech investments in connected non-GB counties (column 2), but not with changes in climate-tech investments in those counties (column 3). All coefficients on Δ *VC GB non-climate inv* remain insignificant, consistent with non-climate-tech investments in GB counties having no effect on investments in connected non-GB counties. Taken together, these patterns suggest that the reallocation toward climate-tech investments in GB counties does not come at the expense of climate-tech investments in connected non-GB counties; rather, it is primarily driven by reductions in non-climate-tech investments in those counties.

To interpret the economic magnitude of the reallocation, recall that the regression in Equation (8) is based on dollar changes in (normalized) investments, parceled evenly across connected non-GB counties. Accordingly, the sum of the β and γ coefficients represents the total effect per dollar of increased investments in climate-tech and non-climate-tech startups, respectively, in GB counties on investments in the VC's connected non-GB counties. By construction, this sum lies between -1 and 0. In column (2) of Table 5, we find that non-climate-tech investments in connected non-GB counties decline by about 4 cents for every additional dollar invested in climate-tech startups in GB counties, an effect that is statistically significant with an F-statistic of 7.69. In contrast, column (3) shows that the sum of the β coefficients is statistically insignificant, implying no measurable effect on climate-tech investments in connected non-GB counties.

5.3. GBs and NZBA Complementarity

Not only do GBs not crowd out VC investments in climate-tech startups located in non-GB counties, but they are also found to crowd in existing private capital in green projects. NZBA signatory banks are an example of such climate-conscious private capital with explicit green preferences. To test the complementarity between GBs and NZBA banks, 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 6 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 at least 4.7% 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 crowds in more VC investments into local climate-tech startups when NZBA banks are present, indicating that VCs do not substitute NZBA capital for such startups. Rather, it is more likely that NZBA banks assist GBs in enhancing local green ecosystems, given that GBs almost always partner with private banks offering complementary financing.

Notably, the coefficients for *GB fund*, the coefficients for *NZBA Sign Target*, and the sum of the coefficients for *GB fund* and *GB fund* $\times$ *NZBA Sign Target* are either not statistically different from zero or negative. This not only mitigates the concern of GBs or NZBA banks endogenously operating in counties with more active VC market but also reinforces the interpretation that the complementarity between GBs and NZBA banks lies in supporting green innovation. The positive and significant coefficient on *GB fund* $\times$ *Climate Startup* is another supporting evidence that NZBA banks' presence is complementary, but not necessary, for GBs to spur VC investment in climate-tech startups. 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.

6. GB-to-VC Impact Heterogeneity and Robustness

6.1. Technology-level Analysis

In this section, we examine the heterogeneous effects of GB investments on VC deal activity by conducting an additional technology-level analysis. The Project Drawdown data includes estimates for each climate technology's abatement potential and costs to achieve the carbon abatement. As each climate-tech startup is already matched to a Project Drawdown technology, we can assess whether GB funding differentially impacts VC deals based on specific attributes of startups' underlying technologies.

Table 7 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, 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.[34] 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

[34]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. (2025).

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.

Overall, the findings 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. Knowing that GBs focus on proven and commercializable technologies, which are predominantly low-cost and scalable, the results highlight the importance of GB-startup pairs' technological alignment for VC mobilization

6.2. Startup age, Prior VC Investment, Local Beliefs

We further analyze how the impact of GB funding on VC investment in climate-tech startups varies according to both startup-specific and county-level characteristics. We augment Equation (1) by including triple interaction terms with variables that measure these characteristics.

In column (1) of Table 8, we find that older climate-tech startups attract more VC investment when GBs make investments in the same county, compared to younger startups. Column (2) demonstrates 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. In columns (3) and (4), we assess the effects of local public opinion on climate change and those of political leaning on GBs' impact, respectively, and find stronger GB-to-VC mobilization in counties where a larger share of the population is concerned about global warming or Democratic-leaning.[35]

[35]Local public opinion measures the percentage of adults in a county who are worried about global warming, based on the Yale Program on Climate Change Communication (YPCCC) survey (see Howe, Mildenberger, Marlon, and Leiserowitz (2015)). The result on counties' political leaning is consistent with Burt et al. (2023),

These results indicate that profit-driven VCs remain highly selective: channeling investment toward climate-tech startups that exhibit greater commercialization potential, stronger evidence of market traction, and are situated in communities with a more engaged, environmentally conscious stakeholder base. This underscores VCs' fundamental pursuit of financial returns and suggests that observed GB-to-VC mobilization primarily arises from the real effects GBs generate.

6.3. Additional Tests

Thus far, our analyses have shed light on the determinants of VC financing for climate-tech startups to highlight GBs' role in unlocking VC investments in local climate-tech startups. For additional evidence, we conduct a couple of round-level analyses to assess whether GBs' involvement predicts the performance of local climate-tech startups at VC rounds.[36] While using such performance metrics restricts us to startups that have already secured VC financing, we find that VC rounds associated with GB investments not only increase the perceived valuation of climate-tech startups but also generate higher returns for investors, providing financial benefits for those who participate in these rounds (Tables IA10 and IA11). The results suggest that the value-added of GBs not just resides in the extensive and intensive margins of VC investments in climate-tech startups but also extends to post-VC-round performance. The superior performances of these startups indicate that VCs choose to scale their investments in them because GBs' involvement enhances their value proposition, prompting greater commitment by profit-driven VCs.

We now provide additional robustness to the baseline 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 IA7 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

showing that climate-related startups backed by Democrat VC partners tend to outperform those backed by non-Democrat ones.

[36]Further details on the empirical approach are provided in the Internet Appendix A.

amount in climate-tech startups.[37] 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 IA8 and Figure IA1 in the Internet Appendix) or using the DiD estimator developed by de Chaisemartin and d'Haultfoeuille (2020, 2024) that addresses the issues of treatment effect heterogeneity and negative weights that may bias the standard two-way fixed effects estimator (Figure IA2 in the Internet Appendix).[38]

We further restrict the sample to treated counties and two propensity-score-matched (PSM) control counties. The propensity score matching is based on the levels and changes in county income, population, population density, minority share, unemployment share, average wind speed, and estimated average annual PV output.[39] As shown in Table IA9, the results remain robust when using matched counties. Overall, these analyses suggest that our findings are not driven by omitted variables correlated with GB investment or county selection.

It is possible that federal government investment might have a similar impact as GBs in catalyzing green investment. However, as opposed to GBs, federal grants do not provide a continuous flow of capital in a specific location. We test whether federal government grants also foster local green investment by conducting a placebo. 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 IA6 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 highlight the distinctive role of GBs in fostering green ecosystems that support the growth of climate-tech startups and encourage market-based scaling of climate

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

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

[39] The results are qualitatively similar when utilizing different combinations of matching variables or including median home prices.

technologies.

7. 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 the subset of climate-tech startups whose technological focus aligns with their corresponding GBs reaps the most benefit, as GBs accompany real green employment and output growth in the sectors employing their targeted technologies. Importantly, this GB-driven increase in VC investments in climate-tech startups does not crowd out VCs' climate-tech startup investments in non-GB counties or existing NZBA banks' green investments in GB counties. We also document that, even as GBs broadly enhance the value propositions of green ventures innovating GBs' targeted technologies, VCs exhibit prioritizing investment in climate startups with more substantial commercialization potential, stronger market validation, and a higher population of environmentally aware local stakeholders. That VCs are inherently value-oriented lends credibility to the proposed economic mechanism linking GBs and VCs: profit-driven VCs must react meaningfully to real green output growth that occurs concurrently with GBs' lending activity.

Our findings have significant policy implications, especially in light of the ongoing legal dispute between the EPA and Climate United et al. regarding the effectiveness of GBs in mobilizing private capital. By focusing on VC outcomes, our framework yields a conservative estimate of GBs' public-to-private capital mobilization, which can serve as a useful benchmark to inform legal assessments concerning the distribution of GGRF to GBs.

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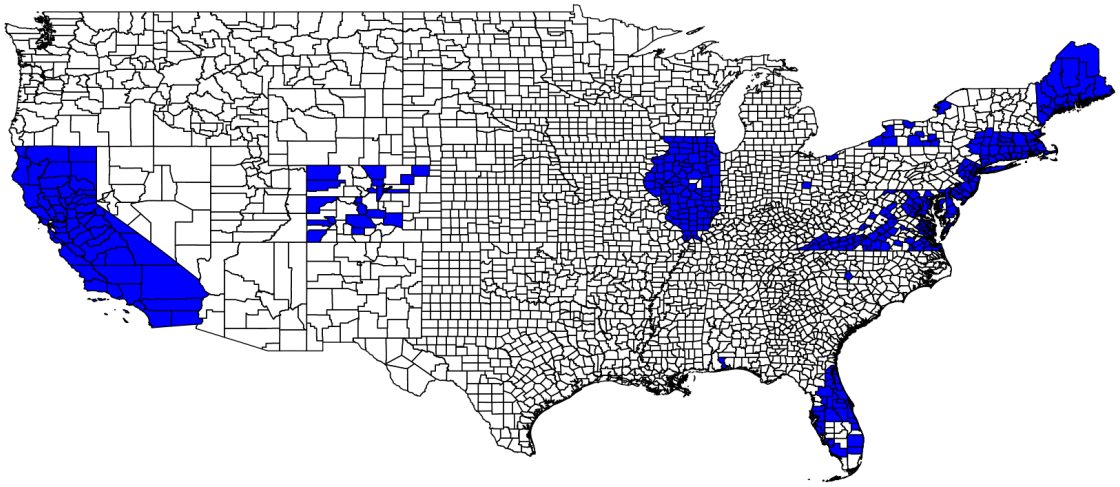
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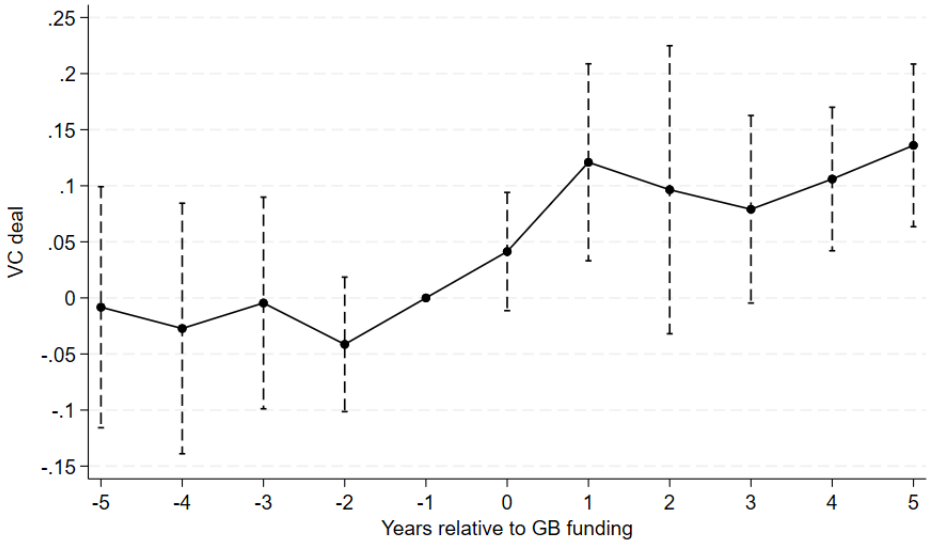
Figure 1
Green Banks across the U.S.



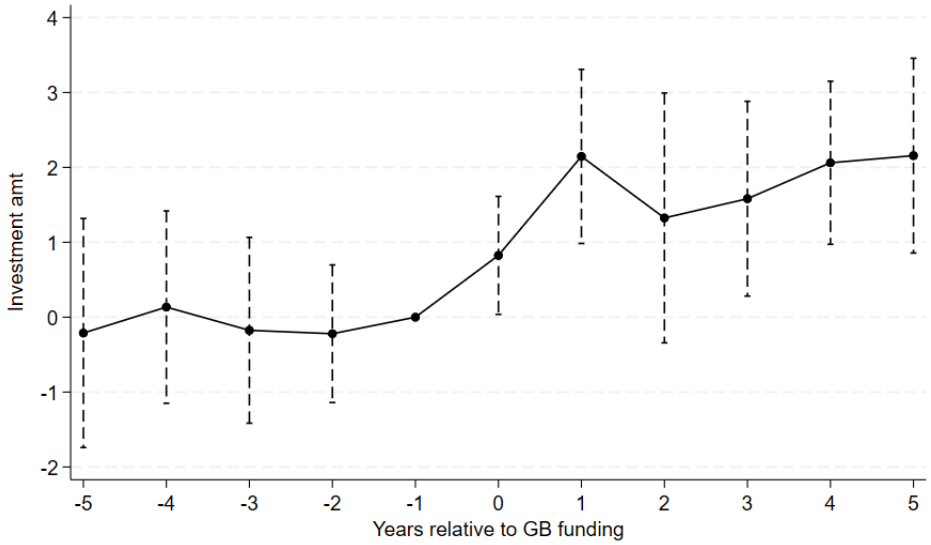
This figure highlights in blue the counties that received at least one loan from Green Banks for which county-level activity is available.

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
County characteristics summary statistics split by counties with and without Green Banks and startup sample description.

Panel A: County characteristics

	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

Panel B: 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

Panel C: Startup industry distribution

	Climate-tech		Non-climate-tech	
PitchBook industry sector	Number of startups	Percent	Number of startups	Percent
B2B Products and Services	843	33.28	6,254	12.22
B2C Products and Services	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

Panel A reports summary statistics for counties with and without Green Bank activity. Panels B and C report summary statistics for the climate-tech and non-climate-tech startups from Pitchbook for the period 2015-2022.

Table 2
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	-0.009	0.008	0.013	-0.178	-0.061	-0.013
	(-1.06)	(0.46)	(0.73)	(-1.38)	(-0.26)	(-0.05)
GB fund × *Climate startup*	0.132***	0.115***	0.101***	1.975***	1.747***	1.508***
	(6.42)	(5.32)	(3.67)	(6.18)	(5.66)	(4.72)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	No	Yes	No	No
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	No	No	Yes	No	No
Industry × Year F.E.	No	Yes	Yes	No	Yes	Yes
State × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	337,894	337,801	166,617	337,894	337,801	166,617
R^2	0.21	0.22	0.22	0.25	0.26	0.26

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* and *Investment amt* as the dependent variables. *VC deal* is an indicator 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 an indicator 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 an indicator variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). 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 2022. 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 3
Topic distance between GB and climate-tech startup.

Dep. variable: *VC deal*	(1)	(2)	(3)	(4)
GB fund	-0.008	-0.008	0.010	0.010
	(-0.92)	(-0.90)	(0.56)	(0.57)
Close topic GB fund and Climate startup	0.112***		0.099***	
	(4.85)		(3.92)	
Same topic GB fund and Climate startup		0.081***		0.072**
		(2.85)		(2.53)
Close different topic GB fund and Climate startup		0.155***		0.136***
		(4.97)		(3.95)
Far topic GB fund and Climate startup	-0.006	-0.011	-0.018	-0.023
	(-0.09)	(-0.17)	(-0.28)	(-0.34)
Controls	Yes	Yes	Yes	Yes
Startup F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	No	No
County F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	No	No
Industry × Year F.E.	No	No	Yes	Yes
State × Year F.E.	No	No	Yes	Yes
Observations	336,798	336,798	336,718	336,718
R^2	0.21	0.21	0.22	0.22

This table reports estimates of the difference-in-differences (DiD) regression (Equation (4)) with *VC deal* as the dependent variable. *VC deal* is an indicator variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *GB fund* is an indicator 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. *Close topic GB fund and Climate startup* equals one if the startup is a climate-tech startup whose topic is close to at least one GB-supported topic, and zero otherwise. *Same topic GB fund and Climate startup* equals one if the startup is a climate-tech startup whose topic is the same as a GB focus, and zero otherwise. *Close different topic GB fund and Climate startup* equals one if the startup is a climate-tech startup whose topic is close to but different from a GB focus, and zero otherwise. *Far topic GB fund and Climate startup* equals one if the startup is a climate-tech startup whose topic is far from all GB-supported topics, and zero otherwise. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2022. 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 Green Bank funding on topic-matched job postings and PV installations.

Panel A: Job postings				
Dep. variable: *Job Postings*	(1)	(2)	(3)	(4)
GB fund	-0.000	-0.000	-0.000***	-0.000
	(-0.66)	(-0.52)	(-2.89)	(-0.71)
Same topic GB fund and job posting	0.214***	0.214***	0.226***	0.110**
	(4.30)	(4.30)	(4.53)	(2.23)
Controls	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes
State F.E.	Yes	No	No	No
Year F.E.	Yes	No	No	No
Topic F.E.	Yes	Yes	No	No
State × Year F.E.	No	Yes	Yes	Yes
Topic × Year F.E.	No	No	Yes	Yes
Observations	158,620	158,620	158,620	16,968

Panel B: PV installations						
Dep. variable:	*Installation size*			*Number of installations*		
	(1)	(2)	(3)	(4)	(5)	(6)
GB fund	0.342***	0.329***	0.240***	0.221***	0.222***	0.144***
	(4.24)	(4.12)	(2.90)	(4.41)	(4.65)	(3.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Cust. Segment F.E.	Yes	No	No	Yes	No	No
Cust. Segment × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	18,871	18,867	7,171	18,871	18,867	7,171
R^2	0.71	0.72	0.74	0.74	0.77	0.84

Panel A reports estimates of the difference-in-differences (DiD) regression (Equation (5)) with *Job Postings* as the dependent variable. Panel B reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *Installation size* and *Number of installations* as the dependent variables. *Job Postings* is the number of job postings within each topic. *Same topic GB fund and job posting* is an indicator variable equal to one if the job posting topic matches the GB investment topic of focus. *GB fund* is an indicator variable equal to one if the county received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Installation size* is the log of one plus total size in kW of PV systems installed in a county in a given year. *Number of installations* is the log of one plus the total number of PV systems installed in a county in a given year. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). In Panel A (B), Column (4) ((3) and (6)) restricts the sample to startups located in California, Connecticut, Illinois, New York, and Virginia. The sample period in Panel A (B) is 2016 to 2023 (2000 to 2022). 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
Reallocation of VC investments.

Dep. variable:	Δ *Connected VC non-GB* $inv_{k,c,t}$	Δ *Connected VC non-GB non-climate* $inv_{k,c,t}$	Δ *Connected VC non-GB climate* $inv_{k,c,t}$
	(1)	(2)	(3)
Δ *VC GB climate* $inv_{k,t-1}$	-0.034*	-0.029*	-0.004
	(-1.91)	(-1.66)	(-1.32)
Δ *VC GB climate* $inv_{k,t-2}$	-0.018***	-0.016***	-0.001
	(-2.71)	(-2.58)	(-0.57)
Δ *VC GB climate* $inv_{k,t-3}$	-0.010***	-0.008***	-0.003
	(-3.05)	(-2.60)	(-0.47)
Δ *VC GB climate* $inv_{k,t-4}$	-0.000	-0.001	0.000
	(-0.28)	(-0.43)	(0.51)
Δ *VC GB non-climate* $inv_{k,t-1}$	-0.000	-0.001	0.000
	(-0.08)	(-0.20)	(1.09)
Δ *VC GB non-climate* $inv_{k,t-2}$	-0.005	-0.003	-0.001
	(-1.30)	(-0.95)	(-1.18)
Δ *VC GB non-climate* $inv_{k,t-3}$	-0.002	-0.003	0.000
	(-1.03)	(-1.16)	(0.50)
Δ *VC GB non-climate* $inv_{k,t-4}$	-0.000	-0.000	-0.000
	(-1.56)	(-1.55)	(-0.63)
sum of Δ*VC GB climate inv*	-0.062***	-0.054***	-0.008
F(sum of Δ*VC GB climate inv*)	(8.50)	(6.71)	(0.93)
sum of Δ*VC GB non-climate inv*	-0.007	-0.006	-0.001
F(sum of Δ*VC GB non-climate inv*)	(0.96)	(0.78)	(0.91)
Controls	Yes	Yes	Yes
VC F.E.	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	165,257	165,257	165,257
R^2	0.20	0.20	0.14

This table reports estimates of the regressions (Equation (8)) with Δ*Connected VC non-GB* $inv_{k,c,t}$, Δ*Connected VC non-GB climate* $inv_{k,c,t}$, and Δ*Connected VC non-GB non-climate* $inv_{k,c,t}$ as the dependent variables. Δ*Connected VC non-GB* $inv_{k,c,t}$ is the change in a VC's total investments in all startups headquartered in a connected non-GB county, defined as the change in the dollar value of investments in all startups between year t and year $t-1$ in connected non-GB county c for VC k, normalized by the VC's total investments. Δ*Connected VC non-GB climate* $inv_{k,c,t}$ and Δ*Connected VC non-GB non-climate* $inv_{k,c,t}$ are changes in a VC's investments in climate-tech and non-climate-tech startups, respectively, in connected non-GB counties, which are defined analogously. Δ*VC GB climate* $inv_{k,t}$ (Δ*VC GB non-climate* $inv_{k,t}$) is the change in the dollar value of investments in climate-tech (non-climate-tech) startups between year t and year $t-1$ for VC k, summed across all GB counties in year t, parceled evenly across the number of connected non-GB counties for VC k in year t, and normalized by the VC's total investments. The sample period is 2015 to 2022. Robust t-statistics based on standard errors clustered at the VC level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6

Impact of Net-Zero Banking Alliance signatories.

Dep. variable *VC deal*	(1)	(2)	(3)	(4)	(5)	(6)
GB fund	-0.008	0.007	-0.009	0.011	-0.009	0.010
	(-0.90)	(0.38)	(-0.94)	(0.55)	(-0.94)	(0.55)
NZBA Sign Target	-0.014	-0.031**				
	(-1.33)	(-2.48)				
NZBA Sign Target (% Deposit)			0.000	-0.000**		
			(0.05)	(-2.25)		
NZBA Sign Target (% HHI)					0.003	-0.032*
					(0.28)	(-1.76)
GB fund × *Climate startup*	0.100***	0.090***	0.108***	0.097***	0.109***	0.098***
	(4.85)	(4.19)	(5.18)	(4.51)	(5.44)	(4.78)
GB fund × *NZBA Sign Target*	-0.005	0.009				
	(-0.82)	(0.53)				
GB fund × *NZBA Sign Target (% Deposit)*			-0.000*	-0.000		
			(-1.72)	(-0.93)		
GB fund × *NZBA Sign Target (% HHI)*					-0.016*	-0.016
					(-1.84)	(-0.61)
Climate startup × *NZBA Sign Target*	0.043***	0.055***				
	(2.95)	(3.51)				
Climate startup × *NZBA Sign Target (% Deposit)*			0.001***	0.001***		
			(3.01)	(3.61)		
Climate startup × *NZBA Sign Target (% HHI)*					0.074***	0.093***
					(3.00)	(3.50)
GB fund × *Climate startup* × *NZBA Sign Target*	0.048**	0.047**				
	(2.52)	(2.44)				
GB fund × *Climate startup* × *NZBA Sign Target (% Deposit)*			0.001**	0.001*		
			(2.04)	(1.83)		
GB fund × *Climate startup* × *NZBA Sign Target (% HHI)*					0.074**	0.070**
					(2.21)	(2.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes	No	Yes	No
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	No	Yes	No	Yes	No
Industry × Year F.E.	No	Yes	No	Yes	No	Yes
State × Year F.E.	No	Yes	No	Yes	No	Yes
Observations	337,863	337,770	337,863	337,770	337,863	337,770
R^2	0.21	0.22	0.21	0.22	0.21	0.22

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* as the dependent variable. *VC deal* is an indicator variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *GB fund* is an indicator 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 an indicator 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 an indicator 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. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2022. 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
Technology-level analysis.

Dep. variable: *VC deal*	(1)	(2)	(3)	(4)
GB fund	0.009	0.010	0.009	0.009
	(0.53)	(0.53)	(0.52)	(0.51)
GB fund × *Climate startup (High cost)*	0.083**			
	(2.26)			
GB fund × *Climate startup (Low cost)*	0.130***			
	(4.77)			
GB fund × *Climate startup (High cost per potential)*		0.086*		
		(1.75)		
GB fund × *Climate startup (Low cost per potential)*		0.133***		
		(3.85)		
GB fund × *Climate startup (High spread)*			0.119***	
			(4.54)	
GB fund × *Climate startup (Low spread)*			0.039	
			(0.62)	
GB fund × *Climate startup (High concentration)*				0.086*
				(1.67)
GB fund × *Climate startup (Low concentration)*				0.116***
				(4.44)
Controls	Yes	Yes	Yes	Yes
Startup F.E.	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
State × Year F.E.	Yes	Yes	Yes	Yes
Observations	336,718	336,718	336,560	336,560
R^2	0.22	0.22	0.22	0.22

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* as the dependent variable. 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 cost)* (*Climate startup (Low cost)*) is an indicator 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 an indicator 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 an indicator 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 an indicator 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 an indicator variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *GB fund* is an indicator 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. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2022. 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
Cross-sectional analysis.

Dep. variable: *VC deal*	(1)	(2)	(3)	(4)
GB fund	0.013	0.037*	0.069	0.009
	(0.76)	(1.74)	(1.45)	(0.49)
GB fund × *Climate startup*	0.066***	0.060**	-0.208	0.118***
	(2.85)	(2.16)	(-1.35)	(5.39)
GB fund × *Climate startup* × *Startup age*	0.051**			
	(2.24)			
GB fund × *Climate startup* × *Past VC fin.*		0.070***		
		(2.73)		
GB fund × *Climate startup* × *High worried*			0.324**	
			(2.13)	
GB fund × *Climate startup* × *High Rep.*				-0.735***
				(-6.09)
Controls	Yes	Yes	Yes	Yes
Startup F.E.	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
State × Year F.E.	Yes	Yes	Yes	Yes
Observations	337,801	337,801	337,801	337,801
R^2	0.22	0.25	0.22	0.22

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* as the dependent variable. *VC deal* is an indicator variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *GB fund* is an indicator 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 an indicator 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 an indicator variable equal to one if the startup received VC financing in the previous five years, and zero otherwise. *High worried* is an indicator 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 an indicator 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. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). Industry fixed effects are based on PitchBook's industry classification for startups. The sample period is 2015 to 2022. 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

A. *Startup Performance 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:

$$y_{i,r,c,t} = \beta_0 + \beta_1 \textit{GB fund round}_{c,t} + \beta_2 \textit{GB fund round}_{c,t} \times \textit{Climate startup}_i + \gamma' X_i + \tau_i + \omega_c + \mu_t + \delta_r + \varepsilon_{i,r,c,t} \tag{9}$$

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 an indicator 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 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 (9) 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.[40] 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 IA10, 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* $\times$ *Climate startup* indicate that VC rounds coinciding with GB investments enhance the perceived valuation of climate-tech startups.[41] 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.[42] 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 IA11, we estimate Equation (9) 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.[43] 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* $\times$ *Climate startup* suggests that VC rounds coinciding with GB investments have a strong positive impact on the exit performance of climate-tech startups.[44] Thus, VC rounds associated with GB investments not only increase the perceived valuation of climate-tech startups but also generate higher returns for investors, providing financial benefits for those who participate in these rounds.

[40] Results are robust to including state-times-year fixed effects, not reported for brevity.

[41] The results are qualitatively similar when adding state-year fixed effects as reported in Table **??** of the Internet Appendix.

[42] 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".

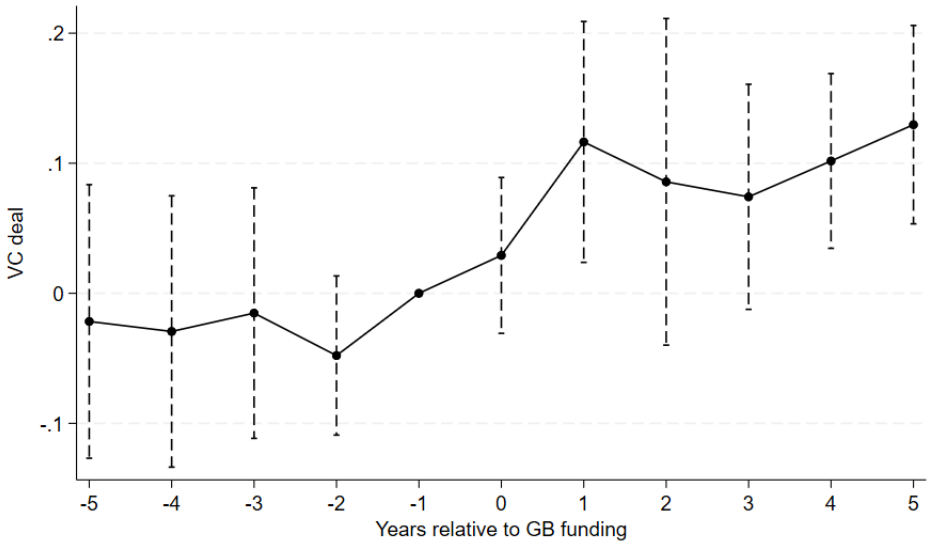
[43] Coefficients from regressions using asinh-transformed variables can be interpreted similarly to those from log-transformed data. However, asinh has the advantage of being defined at zero.

[44] The results are qualitatively similar when adding state-year fixed effects as reported in Table **??** of the Internet Appendix.

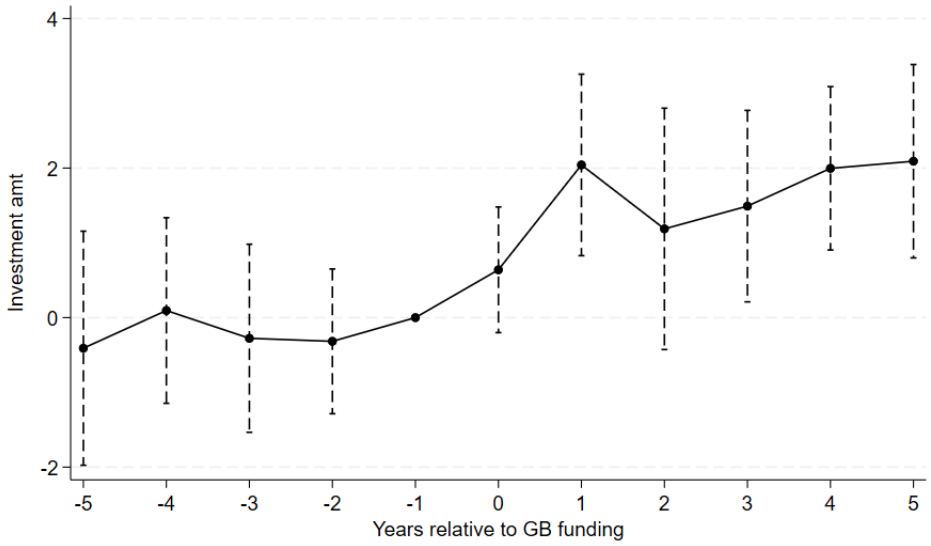
B. Additional Figures & Tables

Figure IA1
Dynamic effects: neighboring counties.

Panel A: GB funding and VC deal likelihood



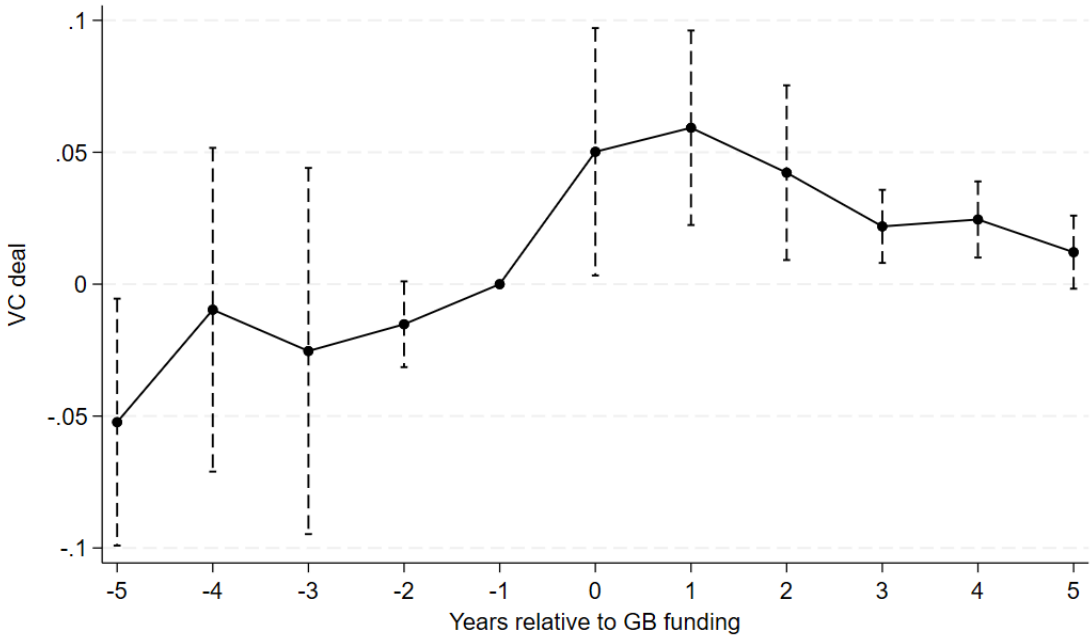
Panel B: GB funding and VC investment amount



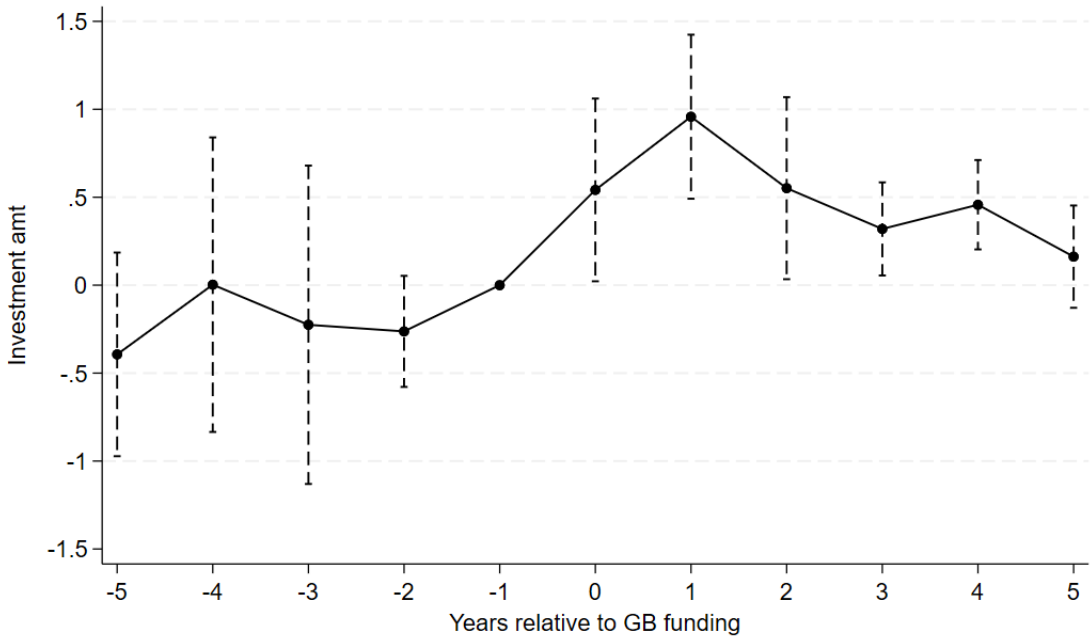
This figure plots the event study estimates and corresponding 95% confidence intervals according to the specification in Equation (2). The sample includes counties that receive at least one GB loan and their neighboring counties. The dot represents the coefficient on the interaction between the GB fund 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



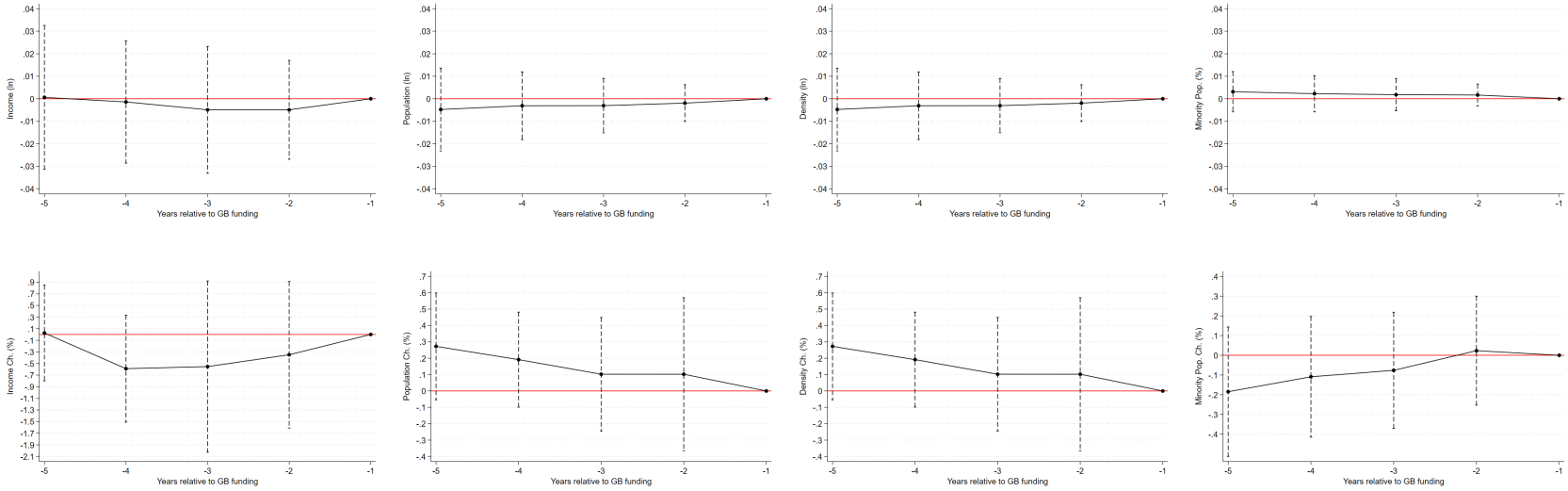
Panel B: GB funding and VC investment amount



This figure plots the event study estimates and corresponding 95% confidence intervals using the DiD estimator developed by de Chaisemartin and d'Haultfoeuille (2020, 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.

Figure IA3

Dynamic effects: local characteristics.



This figure plots the event study estimates and corresponding 95% confidence intervals according to the specification in Equation (2). The dependent variables are the level and change in income, population, density, and minority population. The dot represents the coefficient on the GB fund relative year indicator. 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 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?	Project types
Abundant Power Group	Yes	Building efficiency, solar
California Alternative Energy and Advanced Transportation Finance Authority	Yes	Building efficiency, solar, wind
California Pollution Control Finance Authority	No	Recycling
Colorado Clean Energy Fund	Yes	Building efficiency, solar
Columbus Region Green Fund	Yes	Building efficiency, solar, clean transportation
Connecticut Green Bank	Yes	Building efficiency, solar
DC Green Bank	Yes	Building efficiency, solar
Delaware Sustainable Energy Utility	Yes	Building efficiency, solar, clean transportation
Efficiency Maine	Yes	Building efficiency, solar, clean transportation
GO Green Energy Fund	Yes	Solar
Illinois climate bank	Yes	Building efficiency, solar, clean transportation
Maryland Clean Energy Center	Yes	Building efficiency, solar, clean transportation, wind
Massachusetts Clean Energy Center	Yes	Building efficiency, solar, clean transportation, wind
Montgomery County Green Bank	Yes	Building efficiency, solar, clean transportation
New Jersey Economic Development Authority	No	Building efficiency, solar, clean transportation, wind
New York City Energy Efficiency Corporation	Yes	Building efficiency, solar
New York Green Bank	Yes	Building efficiency, solar, clean transportation, wind
Philadelphia Green Capital Corp	Yes	Building efficiency, solar
Rhode Island Infrastructure Bank	No	Building efficiency, solar, wind
Solar Energy Loan Fund (SELF)	Yes	Building efficiency, solar
Virginia Resources Authority	No	Building efficiency, solar, wind

This table reports some of the investment characteristics of Green Banks.

Table IA3
Green Banks' project types to Project Drawdown technologies.

Green Bank project type	Project Drawdown technologies
Building efficiency	LED Lighting, High-Efficiency Heat Pumps, District Heating, Energy Efficiency, Green and Cool Roofs, Insulation, Low-Flow Fixtures, Building Retrofitting, Alternative Cement, Alternative Refrigerants
Solar	Distributed Energy Storage, Concentrated Solar Power, Solar Hot Water, Utility-Scale Solar Photovoltaics, Distributed Solar Photovoltaics, Renewable Energy, Utility-Scale Energy Storage
Wind	Micro Wind Turbines, Offshore Wind Turbines, Onshore Wind Turbines, Renewable Energy, Utility-Scale Energy Storage
Clean transportation	Walkable Cities, High-Speed Rail, Fuel Cell, Electric Bicycles, Building Automation Systems, Electric Cars, Bicycle Infrastructure, Hybrid Cars, Electric Trains, Efficient Trucks, Carpooling, Public Transit
Recycling	Reduced Food Waste, Composting, Recycling, Recycled Paper, Landfill Methane Capture

This table reports the Green Banks sectors with the matched Project Drawdown solutions.

Table IA4
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	0.000	0.001	-0.011	-0.003	0.000
	(-1.12)	(0.26)	(0.90)	(-1.11)	(-0.27)	(0.02)
GB fund amt × *Climate startup*	0.009***	0.008***	0.006***	0.109***	0.099***	0.082***
	(6.24)	(5.15)	(3.54)	(4.90)	(4.62)	(3.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	No	Yes	No	No
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	No	No	Yes	No	No
Industry × Year F.E.	No	Yes	Yes	No	Yes	Yes
State × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	337,894	337,801	166,617	345,153	345,060	173,850
R^2	0.21	0.22	0.22	0.25	0.26	0.26

This table reports estimates of the difference-in-differences (DiD) regression (eq. (1)) with *VC deal* and *Investment amt* as the dependent variables. *VC deal* is an indicator 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 an indicator 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 control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). The sample period is 2015 to 2022. 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
Impact of Green Bank funding on topic-matched share of job postings.

Dep. variable *Share of job postings*	(1)	(2)	(3)	(4)
GB fund	0.000	-0.000	-0.000	0.000
	(0.50)	(-0.23)	(-0.34)	(0.10)
Same topic GB fund and job posting	0.001***	0.077***	0.081***	0.031**
	(4.07)	(4.06)	(4.27)	(2.09)
Controls	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes
State F.E.	Yes	No	No	No
Year F.E.	Yes	No	No	No
Topic F.E.	Yes	Yes	No	No
State × Year F.E.	No	Yes	Yes	Yes
Topic × Year F.E.	No	No	Yes	Yes
Observations	158,620	158,620	158,620	16,968
R^2	1.00	1.00	1.00	1.00

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *Share of Job Postings* as the dependent variable. *Share of Job Postings* is the ratio of the number of job postings within each topic over the total county job postings. *Same topic GB fund and job posting* is an indicator variable equal to one if the job posting topic matches the GB investment topic of focus. *GB fund* is an indicator variable equal to one if the county received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). Column (4) restricts the sample to startups located in California, Connecticut, Illinois, New York, and Virginia. The sample period is 2016 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 IA6
Placebo test.

Dep. variable: *VC deal*	(1)	(2)
Government grant	0.038	0.005
	(1.23)	(0.12)
Government grant × *Climate startup*	0.004	0.010
	(0.08)	(0.15)
Controls	Yes	Yes
Startup F.E.	Yes	Yes
Industry F.E.	Yes	No
County F.E.	Yes	Yes
Year F.E.	Yes	No
Industry × Year F.E.	No	Yes
State × Year F.E.	No	Yes
Observations	8,922	8,669
R^2	0.21	0.26

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* as the dependent variable. *VC deal* is an indicator variable equal to one if the startup receives VC investment in a given year, and zero otherwise. *Government grant* is an indicator 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 an indicator 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 2022. 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 IA7
Robustness tests: state exclusions.

Dep. variable:	*VC deal*		*Investment amt*	
	(1)	(2)	(3)	(4)
GB fund	0.009	0.002	-0.037	-0.121
	(0.50)	(0.10)	(-0.16)	(-0.47)
GB fund × *Climate startup*	0.110***	0.115***	1.609***	1.698***
	(4.49)	(4.34)	(4.79)	(4.83)
Controls	Yes	Yes	Yes	Yes
Startup F.E.	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
State × Year F.E.	Yes	Yes	Yes	Yes
Observations	283,956	172,416	283,956	172,416
R^2	0.22	0.22	0.26	0.26

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* and *Investment amt* as the dependent variables. *VC deal* is an indicator 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 an indicator 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 an indicator 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 control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). The sample period is 2015 to 2022. 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 IA8
Robustness tests: neighboring counties.

Dep. variable:	*VC deal*			*Investment amt*		
	(1)	(2)	(3)	(4)	(5)	(6)
GB fund	-0.010	0.014	0.015	-0.195	0.014	0.023
	(-1.13)	(0.76)	(0.83)	(-1.53)	(0.06)	(0.09)
GB fund × *Climate startup*	0.133***	0.110***	0.099***	1.986***	1.658***	1.493***
	(6.49)	(4.79)	(3.63)	(6.21)	(5.48)	(4.67)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	No	Yes	No	No
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	No	No	Yes	No	No
Industry × Year F.E.	No	Yes	Yes	No	Yes	Yes
State × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	241,692	241,583	166,151	241,692	241,583	166,151
R^2	0.21	0.22	0.22	0.25	0.26	0.26

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* and *Investment amt* as the dependent variables. *VC deal* is an indicator 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 an indicator 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 an indicator 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 control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). The sample period is 2015 to 2022. 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 IA9
Propensity-score-matched counties.

Dep. variable:	*VC deal*			*Investment amt*		
	(1)	(2)	(3)	(4)	(5)	(6)
GB fund	-0.010	0.039***	0.044***	-0.184	0.249**	0.335***
	(-1.04)	(5.43)	(6.78)	(-1.31)	(2.42)	(3.48)
GB fund × *Climate startup*	0.108***	0.089***	0.075***	1.770***	1.489***	1.329***
	(9.43)	(6.14)	(4.19)	(5.26)	(5.12)	(4.95)
Startup F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	No	Yes	No	No
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	No	No	Yes	No	No
Industry × Year F.E.	No	Yes	Yes	No	Yes	Yes
State × Year F.E.	No	Yes	Yes	No	Yes	Yes
Observations	224,276	224,163	154,686	224,276	224,163	154,686
R^2	0.22	0.23	0.23	0.26	0.27	0.27

This table reports estimates of the difference-in-differences (DiD) regression (Equation (1)) with *VC deal* and *Investment amt* as the dependent variables. *VC deal* is an indicator 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 an indicator 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 an indicator variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. The *Climate startup* dummy is interacted with year indicators. The sample includes two propensity-score-matched control counties for each treated county. Matching is based on levels and changes in county income, population, population density, minority share, unemployment share, average wind speed, and estimated average annual PV output. The control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). 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 2022. 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 IA10

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	0.039	0.014	0.034	0.047*	0.018	0.027**	-0.169	-0.141
	(0.89)	(0.53)	(1.25)	(1.78)	(1.42)	(2.18)	(-1.30)	(-0.90)
GB fund round × *Climate startup*	0.326***	0.259**	0.085***	0.164***	0.193**	0.232**	1.814***	1.750***
	(2.59)	(2.37)	(2.98)	(2.79)	(2.49)	(2.33)	(5.40)	(5.99)
Past VC financing		-0.077**		-0.067**		0.032		-0.022
		(-2.19)		(-2.18)		(1.62)		(-0.16)
Startup age		0.683***		0.465***		-0.013		1.262***
		(17.87)		(10.11)		(-0.27)		(4.26)
Established operation		0.090***		-0.011		-0.005		-0.349**
		(3.48)		(-0.58)		(-0.29)		(-2.60)
VC age		0.104***		0.033***		0.008**		-0.026
		(6.50)		(4.12)		(2.07)		(-0.74)
VC past investments		-0.012		0.019***		-0.000		-0.013
		(-1.15)		(3.25)		(-0.03)		(-0.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	55,984	28,703	24,682	18,849	9,423	7,523	2,993	2,014
R^2	0.79	0.82	0.90	0.91	0.43	0.43	0.92	0.93

This table reports estimates of the difference-in-differences (DiD) regression (Equation (9)) with *ln(Deal size)*, *ln(Post valuation)*, *Up round*, and *ln(Revenue)* as the dependent variables. *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 an indicator 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 an indicator 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 an indicator 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 an indicator 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 an indicator 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 2022. 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 IA11
Round-level analysis: startup exit performance.

Dep. variable:	*Exit multiple*		*Exit return*	
	(1)	(2)	(3)	(4)
GB fund round	-0.191***	-0.222***	-0.091***	-0.099***
	(-3.56)	(-3.82)	(-3.51)	(-3.34)
GB fund round × *Climate startup*	0.803***	0.917***	0.142***	0.145***
	(13.30)	(11.57)	(6.11)	(3.74)
Past VC financing		0.060		0.026
		(1.13)		(0.72)
Startup age		-0.050		-0.128***
		(-0.45)		(-2.86)
Established operation		0.071		0.063*
		(1.18)		(1.89)
VC age		0.019		0.003
		(0.72)		(0.27)
VC past investments		-0.009		-0.012
		(-0.59)		(-1.33)
Controls	Yes	Yes	Yes	Yes
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	3,517	2,367	3,513	2,363
R^2	0.90	0.90	0.95	0.94

This table reports estimates of the difference-in-differences (DiD) regression (Equation (9)) with *Exit multiple* and *Exit return* as the dependent variables. *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 an indicator 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 an indicator 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 an indicator 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 an indicator 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 control variables include lagged county population (ln), per capita income (ln), population density (ln), and unemployed share of the population (%). The sample period is 2015 to 2022. 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.