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

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**Abstract**

The Inflation Reduction Act (IRA) allocated $27 billion to the Greenhouse Gas Reduction Fund to funnel financing for clean energy and climate solutions. Government-funded Green Banks are delegated to administer the fund to attract and amplify private capital investment in reducing emissions. In this paper, we examine the efficacy of Green Banks in mobilizing local investment in the context of climate-related startups. Pre- *and* post-introduction of IRA in Congress, we show a significant increase in venture capital deals and the total investment amount for local climate-related startups in counties where a Green Bank has issued loans. Our evidence is consistent with Green Banks de-risking climate ventures to facilitate a bottom-up green transition.

**JEL Classification:** G23, G28, O44.
**Keywords:** Green banks, climate tech, renewable energy, green transition.

*For helpful discussions, we thank Martin Lettau and seminar participants at the IESE Business School. We also thank Alonso Vargas Aguilar for excellent research assistance. This project has received funding from the European Union's 2023 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 101152801. All errors are our own.

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## 1. Introduction

The increasing frequency and severity of natural disasters due to global warming have raised awareness regarding the financial costs of climate change and the extent to which markets account for environmental risks. Recent analyses estimate that achieving the 1.5°C global warming target will require $4.5 trillion in clean energy investments annually, yet current investments fall short by $2.7 trillion (International Energy Agency, 2023). This funding gap highlights the urgent need to develop innovative financial mechanisms and policies that bridge this divide, with implications for both government-led and market-driven investment strategies. This gap was central to the recent COP29, so much so that the conference was known as the "finance COP". Specifically, COP29 aimed to "advance a range of financial tools and instruments to support actions to address climate change". As global policymakers convene to define sustainable finance pathways, climate finance's pivotal role—through public and private capital—has never been more apparent.

In response to this funding gap, the U.S. recently introduced the Greenhouse Gas Reduction Fund (GGRF) within the Inflation Reduction Act (IRA), a $27 billion initiative designed to mobilize private and public capital to accelerate the transition to a low-carbon economy. The GGRF seeks to promote energy independence, ensure U.S. competitiveness, and lower energy costs in socio-economic minority communities. This fund will be deployed through Green Banks (GBs), government-funded mission-driven institutions that leverage innovative financing to catalyze green investment and help bridge the climate funding gap. Thus, GBs act as key financial intermediaries, directing funds toward sustainable projects to reduce greenhouse gas emissions. The GGRF exemplifies the blended finance model that COP29 aimed to advance, wherein government seed capital draws in private investors to address shared environmental and economic goals. As green finance mechanisms expand, understanding how different deployment strategies affect private investment in green projects is essential to guide governments' investment strategies.

In this paper, we investigate whether the financing activities of government-funded GBs substitute or complement existing private capital investment in local climate-focused startups. To this end, we center our analyses on venture capital (VC) investment in these startups and study whether the onset of GB lending spurs it. This particular setting offers a clean identification of the "additionality" of GB financing to novel and risky climate projects. Because GBs seldom directly provide capital to startups or participate in a VC syndicate, the directionality of GBs' effect on VC investment in startups, if any, should determine whether

GBs substitute or complement existing start-up financing.[1] Notably, the GGRF mandates grant recipients (i.e., GBs) to support only commercial technologies—classes of technologies already deployed for commercial purposes.[2] That the mandate forces GBs to be at arm's length from the climate-focused startups enables us to precisely quantify GBs' additionality in leveraging private capital for climate transition.

Furthermore, examining the association between VC investment in climate startups and GB financing allows us to deduce plausible mechanisms through which GBs could unlock VC investment. VCs, including impact funds, are profit-driven and among the least likely asset managers to sacrifice returns for non-financial purposes (see Geczy, Jeffers, Musto, and Tucker (2021) and Jeffers, Lyu, and Posenau (2024), for example). Therefore, VCs would reassess their portfolio of startups only if they believe even an arm's length GB financing alters the financial prospect of climate startups. As mentioned before, because hardly any GB funds went into climate startups, if VC deals occur more likely for climate than non-climate startups in a county post GB financing, then it implies VCs interpret GB lending activity in the county as a convincing signal that an investment in residing climate startups generates higher return.[3] Among others would the signal entail certifying a robust governmental backing and a stable flow of public funding for climate startups to maintain or gain momentum for growth.

Indeed, our main results indicate that GB activity significantly boosts VC investment in local climate-tech startups. Using a generalized staggered difference-in-differences (DiD) approach over the sample period from 2015 to 2023, we find that counties receiving at least one GB loan experience an increase of 8.5% to 11.6% in climate startup VC deals over the four years following the loan. The results are robust to different fixed effects specifications, which account for time-invariant startup unobservables as well as time-variant industry and county unobservables. In addition, using a dynamic DiD approach, we cannot reject the parallel-trends assumption, which suggests that local pre-trends do not drive the results. We hypothesize that the introduction of the GGRF within the IRA provide a substantial signal of the availability of funds for investment in the green transition through GBs. We find that, after the IRA was introduced in Congress, VC funding of climate-related startups increased in counties that received GB loans. Conditional on the presence of GBs in a given county,

[1]Some GBs offer small seed investments and grants to startups through incubators. However, these investments are limited to 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.

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

[3]Even if the startups in our sample consist of those deploying commercial technologies, the investment of GBs into the startups is trivial in size vis-à-vis that of VCs.

the deliberation of the IRA sufficed for VCs to expect investments in climate startups in the county to be more profitable. The fact that an increase in VC deals is observed even when the IRA is still in the works rationalizes the signaling mechanism.

We further investigate whether the impact of GB loans on VC investment is heterogeneous across different types of startups and regions in the U.S. Our cross-sectional tests show that the effect of GB activity is most pronounced for older climate-tech startups and those with prior VC financing. This finding aligns with the mandate of the GGRF and the mission of most GBs to focus on proven, commercially viable technologies, such as solar panels and wind turbines, rather than high-risk, early-stage innovations. In counties where startups are more mature and have already achieved some market validation, GB loan activity likely signals to VCs that climate-tech startups in the same area represent lower-risk, high-potential investments, thereby generating a stronger crowding-in effect. In addition, we find that the impact of GB investments is greater in counties where the public is more concerned about climate change and in areas with a higher concentration of Democratic voters. These results suggest that local public support and political alignment with climate initiatives amplify the signaling effect of GBs, resulting in more pronounced private capital inflows into climate-tech startups.

Next, we analyze the heterogeneous effects of Green Bank (GB) investments on VC deal activity by conducting a technology-level analysis. Using a GPT-based large language model (LLM), we match climate-tech startups to 88 climate technologies from Project Drawdown, allowing us to assess whether GB funding differentially impacts VC investment based on technology attributes. Our findings reveal that while GB funding increases VC investment across both high- and low-abatement potential technologies, investors favor startups with low-cost and widely adopted technologies. Specifically, VCs are more likely to invest in startups utilizing climate solutions with lower abatement costs and broader industry applicability, as these exhibit stronger commercialization potential and investment attractiveness. These results highlight how GBs influence the scaling of cost-efficient, widely dispersed climate technologies by mobilizing private capital toward commercially viable solutions.

The results are robust to a battery of tests which reduce the concerns that the estimated impact of GBs on investment in climate techs is related to other federal agencies, measurement error, or choice of model specifications. Specifically, we conduct a placebo test examining whether federal government grants influence VC investment similarly to GB funding. Using grants from the EPA, Department of Energy (DoE), and Department of Agriculture, we

analyze counties without GB investments to isolate the effect of these federal egencies. The results show that government grants do not significantly impact VC investment in climate startups, unlike GB funding, which explicitly mobilizes private capital. This finding highlights the distinct role of GBs in signaling investment quality and fostering market-based scaling of climate technologies. Moreover, the results remain consistent when including only GBs with a clear green investment objective since inception.

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

Collectively, our study shows that GBs are valuable institutions for advancing the green transition by attracting venture capital investment into climate-related startups. Not only do GBs leverage public capital to attract private investment in established technologies—such as solar panels and wind turbines—but they also indirectly catalyze investment in new climate-related technologies. The finding is consistent with GBs' shared mission of "de-risking" environmental projects and "complementing/unlocking" private capital for the projects, instead of substituting existing or yet-to-be-deployed capital.[4] Moreover, it is particularly relevant to policymakers as the GGRF is poised to begin distributing $27 billion for green investments through GBs. Also, our findings are relevant to policymakers outside the US, as other governments may consider a similar or alternative investment vehicles for climate-related financing.

This paper is the first to provide a comprehensive analysis of GBs and examine their role in fostering private investment to mitigate the adverse effects of climate change, thereby contributing to the growing literature on government investment in advancing 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,

[4]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: link with more details.

LaPoint, Mazzola, and Xu (2024) examine Residential Property Assessed Clean Energy (PACE) loans, finding that PACE adoption generates local fiscal income and enhances the resilience of the housing stock to climate impacts. Also, Flammer, Giroux, and Heal (2024) explore blended finance, where public and philanthropic funding mobilizes private capital for impactful sustainable investments. Lastly, Lanteri and Rampini (2022) model heterogeneous capital goods with varying energy needs and ages, concluding that financially constrained firms face challenges in adopting newer, cleaner technologies due to higher down payment requirements, the friction that Howell (2017) finds is attenuated by government-led R&D subsidies. We contribute to this literature by focusing on government-funded GBs and finding the likely mechanism through which GBs spur VC green investments is signaling—a local presence of GBs signals a stable flow of funds to climate startups.

Our work is related to the recent literature on the effect of VC investments on the performance of climate-tech 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-tech 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-tech startups. We contribute to the literature by documenting how GBs multiply VCs value-add on climate-tech startups based on several valuation and performance metrics.

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, Giannetti, Jasova, Loumioti, and Mendicino (2023) show that banks engaging extensively in environmental discourse tend to lend more to "brown" industries, while banks with net-zero commitments have yet to reduce credit supply to these sectors or increase financing for renewables (Sastry, Verner, & Ibanez, 2024). Additionally, 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 on bank lending behavior (Laeven & Popov, 2023), and banks' exposure to climate transition risks (e.g., Martini, Sautner, Steffen, &

Theunisz, 2023 and Jung, Santos, & Seltzer, 2023). Our study contributes by shifting focus to government-funded GBs and their distinctive role in catalyzing local green investments, with a particular emphasis on climate-focused startups.

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, 2023, Kacperczyk & Peydro, 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.

The remainder of the paper is organized as follows. Section 2 discusses the institutional backgrounds related to Green Banks and the GGRF. Section 3 describes the data and summary statistics. Sections 4 outline the empirical approach, results, and additional tests. Finally, Section 5 concludes with a brief summary.

## 2. Institutional Background

### *2.1. What are Green Banks?*

According to the Coalition for Green Capital, "[g]reen banks are mission-driven institutions that use innovative financing to accelerate the transition to clean energy and fight climate change." These Green Banks 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 Coalition for Green Capital categorizes Green Banks as public, non-profit, and quasi-public institutions. Public Green Banks are fully owned by states or are part of a state agency. For instance, the New York Green Bank, a public Green Bank, was established on December 19, 2023, 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 (SBC) III, uncommitted utility EEPS funds, and NYSERDA Renewable Portfolio Standard (RPS) 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 Coalition for Green Capital. 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 Green Bank is the Connecticut Green Bank, the first Green Bank 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 Green Banks is that their initial funding originated from a state government or agency.

A core aspect of Green Bank operations is the use of financing instead of grants. Green banks expect the capital they deploy to be repaid, creating a revolving pool of funds that maximizes the impact of each dollar invested. Thus, Green Banks invest in projects that are past the research and development stage, with very few exceptions, such as investing a 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 Green Banks is their ability to leverage private capital effectively, thereby amplifying their impact. Public-private partnerships have driven substantial growth in clean energy projects, resulting in significant investments.

In 2023, the Coalition for Green Capital (CGC) and its network of Green Banks facilitated over $10.6 billion in public-private investment, representing a 130% increase from 2022. Since 2011, these Green Banks have invested $9.25 billion and mobilized $16.16 billion in private co-investment (as of December 31, 2023). 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 (Consortium, 2024).

One of the objectives of Green Banks is to reduce the cost of capital for clean energy projects by addressing perceived risks and inefficiencies of scale. They achieve this through tools such as credit enhancements, aggregation of small projects, and co-investment. For example, the Solar and Energy Loan Fund (SELF), one of the Green Banks within the CGC's network, secured a $3 million grant from JPMorgan Chase's Housing Innovation Prize in 2023 to support energy-efficient affordable housing projects in Florida.

Other notable projects include those by Michigan Saves, a Green Bank that received a

$30 million grant from the Michigan Department of Environment, Great Lakes, and Energy to launch a Septic Replacement Loan Program. Additionally, Michigan Saves received $1 million from the American Rescue Plan Act (ARPA) funds to create an incentive program for residents of the City of Sterling Heights to implement energy efficiency and renewable energy improvements (Consortium, 2024). These examples illustrate how Green Banks contribute to the green transition in various regions and sectors, from housing and water infrastructure to solar energy and energy efficiency. Their financing models and ability to mobilize private capital in partnership with public funds make them valuable players in the transition to a low-carbon economy.

### *2.2. Green Bank Networks*

The Coalition for Green Capital (CGC) is not the only network of Green Banks operating in the U.S. and receiving funding from the Greenhouse Gas Reduction Fund (GGRF) within the Inflation Reduction Act (IRA). Other networks that have been allocated funding include: Power Forward Communities ($2 billion), Climate United Fund ($7 billion), Opportunity Finance Network ($2.3 billion), Inclusiv ($1.9 billion), Justice Climate Fund ($1 billion), Native CDFI Network ($0.4 billion), and Appalachian Community Capital ($0.5 billion). Excluding the Climate United Fund, several key differences exist between Green Banks 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. There is some overlap between the CGC and the Justice Climate Fund. However, many of the banks not associated with CGC did not have explicit climate objectives until they applied for the GGRF.

The Climate United Fund is slightly different as it 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 in all 50 states. 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 Green Banks.

Lastly, Calvert Impact is considerably different from the other GBs. Specifically, Calvert Impact operates with a global presence and is not restricted to investing in, or continuing to invest in, a specific location. Unfortunately, we are unable to collect detailed investment data from Calvert Impact. This missing information may introduce measurement error, as counties that received funding from Calvert Impact could be mistakenly classified as counties with no GBs investment. This would potentially bias our estimates downward. In addition, since our analysis focuses on the extensive margin, the absence of data on Calvert Impact's investments in counties where other Green Banks are active should not affect our results.

### *2.3. Green Banks and Local Green Investment*

The presence of government-funded green banks (GBs) is expected to influence local green investment through several mechanisms. By providing targeted financing to projects that meet commercial readiness criteria, GBs can help mitigate perceived risks associated with investing in climate-focused startups—without being directly involved in venture deals. For venture capitalists (VCs), who are profit-driven and typically less willing to trade off financial returns for non-financial objectives, the availability of GB funding may serve as a credible signal of long-term local government commitment, policy stability, and private sector green investment. This signaling effect may lead VCs to reassess the financial prospects of local climate startups, particularly if they perceive GB as indicative of a more favorable investment environment. This mechanism is also consistent with the behavior of impact investors, which heavily invest in climate startups; as shown by Geczy et al. (2021), most impact funds continue to use contracts that maintain traditional financial incentive structures.

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

activity signals a stable and expanding market for green products and services, it could further strengthen the incentives for VCs to invest in climate startups.

GBs are not the only entities providing financing for green projects. Federal agencies—including the Environmental Protection Agency (EPA), Department of Energy (DoE), and Department of Agriculture—also offer grants to eligible startups. However, the investment behavior of federal agencies differs materially from that of GBs. First, startups must apply directly for federal grants, and the agencies act as relatively passive funders, screening applicants based on predefined criterias. Moreover, federal grants typically lack a local focus, implying that lending activity in one county provides little or no signal about the availability of future funding for other local firms. In contrast, GBs actively seek investment opportunities in projects that can be deployed quickly using proven technologies (e.g., solar panels and wind turbines). GBs also have a clearly defined local footprint, often operating within specific jurisdictions—for example, the Connecticut Green Bank invests exclusively within the state of Connecticut.

The local presence of private banks with stated green commitments (e.g., net-zero targets) might, in principle, send a similar signal to that of GBs regarding the availability of capital for green projects. However, empirical evidence suggests otherwise. Studies have shown that banks with green commitments do not necessarily increase lending to green firms and, in some cases, even increase financing to brown firms (Giannetti et al., 2023, Sastry et al., 2024). This suggests that the presence of private banks with sustainability pledges may not be sufficient to foster long-term investment in climate tech. Unlike GBs, private banks are under no obligation to meet these commitments in the short or long term. In addition, the attempt of banks to reduce emissions is quite recent as one of the major voluntary, but one of the strictest, climate initiative is the Net Zero Banking Alliance (NZBA), formed in April 2021. The recent establishment of this initiative further diminishes the likelihood that our results are driven by private banks with green preferences, given that our sample spans from 2015 to 2023 and includes many GBs—such as New York Green Bank, Connecticut Green Bank, and CAEATFA—that were active before 2015.

## 3. Data and Summary Statistics

### *3.1. Green Banks*

We collect information on Green Banks in the US using publicly available information from each banks' annual report or website.[5] We focus our attention on the Coalition for Green Capital (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 for the following Green Banks: 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 at least if the bank issued loans in year $t$ in county $c$. For some of the banks, we also have information on the amount of investment as well as other impact measures, such as jobs created and GHG emission reduce. However, the availability of impact estimates is very limited at this time. The oldest Green Bank is the CPCFA, established in 1972, even though this agency was not explicitly defined as a Green Bank at the time. Note that the year of establishment is not necessarily the year in which the GB starts issuing loans. Table IA1 in the Internet Appendix reports the list of some of the GBs operating in the US, their year of establishment, type (public, quasi-public, or non-profit), and the state where they issue loans. We provide summary statistics for all three types of GBs, but focus our analysis on public and quasi-public Green Banks for a total of 12 GBs. We exclude non-profit banks as they have been established recently, they have a considerably lower investment volume, or operate in only one county (e.g., Abundant Power Group, Montgomery County Green Bank).

Figure 1 illustrates the geographical distribution of Green Bank lending activity. Counties are marked in blue if a Green Bank reported issuing at least one loan there between 2015 and 2023. We find that, on average, Green Bank loans are more commonly issued in counties with

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

larger populations, slightly higher average incomes, higher house prices, and more Democratic-leaning political preferences (Table 1). We also hand-collected information on the investment focus of the GBs. 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. The primary focus of the 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.[6]

### *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.[7] Our analysis specifically focuses on startups falling under the "Climate Tech" or "CleanTech" verticals.[8] We consider VC financing rounds taking place from 2015 to 2023. To be included in our sample, a financing round must meet the following criteria: 1) it is explicitly identified in the PitchBook database as a "Venture Capital" round with at least one investor in the syndicate identified as a VC investor by PitchBook;[9] 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

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

[7] 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`.

[8] 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."

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

involving 51,158 startups, including a subset of 5,339 deals for 2,533 climate-related startups.

### *3.3. County Characteristics*

The county-level economic data, including population, personal income, and unemployment rate, are collected from the U.S. Bureau of Economic Analysis (BEA) and the U.S. Bureau of Labor Statistics (BLS). We collect information on house prices from Zillow (Zillow Home Value Index or ZHVI). We use the 2014 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.[10] The county-level presidential votes are from the MIT Election Lab.[11] We define a Republican indicator equal to one if the presidential votes in county $c$ are above the median and zero otherwise.

## 4. Results

### *4.1. Identification Strategy*

Our sample period runs from 2015 to 2023, chosen for several reasons. First, 2015 marks the beginning of a significant resurgence in VC interest in green technologies. This period saw massive inflows of private capital into climate-tech startups, with investment growth exceeding 150% between 2015 and 2021 (Cornelli et al., 2023).[12] Also, prior to 2015, many of the Green Banks did not exist or did not have a specific focus on the green transition (e.g., Virginia Resources Authority, Rhode Island Infrastructure Bank, and New Jersey Economic Development Authority). The policy landscape also shifted in 2015 with the signing of the Paris Agreement, which created a favorable environment for climate tech investments. Given these trends, 2015 is a natural starting point for examining the intersection of Green Bank loans and VC investment in climate tech startups.

Our primary econometric model examines the relationship between VC investment outcomes and the interaction of an indicator for Green Bank 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

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

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

[12]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).

startups relative to non-climate-tech startups headquartered in counties that receive Green Bank funding with those in counties that do not. This strategy exploits variation driven by the staggered timing of Green Bank funding across counties and multiple time periods.

Formally, we estimate the following empirical specification:

$$y_{i,c,t} = \beta_0 + \beta_1 GB\ fund_{c,t} + \beta_2 GB\ fund_{c,t} \times Climate\ startup_i + \tau_i + \rho_{j,t} + \omega_{c,t} + \varepsilon_{i,c,t} \quad (1)$$

where startup $i$, operating in industry $j$, is headquartered in county $c$, in year $t$. We focus on an event window spanning four years before to four years after the startup's county receives Green Bank funding. *GB fund* is a dummy variable equal to one if the startup is located in a county that received funding from a Green Bank in the current year or in the previous four years, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. The standard errors are clustered at the headquarter county level to adjust for potential issues with grouped error terms as Green Bank 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.[13] Second, we implement a more stringent set of fixed effects (Acharya, Baghai, & Subramanian, 2014; Gormley & Matsa, 2016). These include startup fixed effects ($\tau_i$), which control for unobserved, time-invariant characteristics specific to each startup that might influence VC investment outcomes, such as the startup's reputation or management quality. We also include industry-year fixed effects ($\rho_{j,t}$), which account for shocks or trends common to all startups within the same industry during a given year, such as industry-wide technological advancements or regulatory changes. Finally, county-year fixed effects ($\omega_{c,t}$) are used to control for local economic conditions or government initiatives that may vary across counties and years, ensuring that the effects of Green Bank funding are not confounded by other county-level influences.

### *4.2. Baseline Estimates*

Table 3 reports the results of the DID estimation using Equation (1). The dependent variable in columns (1)-(3) is a binary indicator representing whether a startup received VC investment in a given year, while columns (4)-(6) use the natural logarithm of one plus the dollar amount of VC investment received. The results show that while Green Bank investments in a county

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

has a positive and statistically significant effect on the likelihood of VC investment for all startups in that county, the effect is even stronger for climate-tech startups. Specifically, counties that receive Green Bank funding see an 8.5% to 11.6% increase in the probability of climate-tech startup deals relative to other types of startups. These results hold when restricting the analysis to states where we have information on Green Bank 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.

To provide further robustness of the results, we replace the indicator for Green Bank funding with a continuous treatment variable that captures variation in the intensive margin of loans issued by Green Banks 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 Green Bank in the current year and the previous four years. We then estimate the DiD model in Equation (1) using this continuous treatment. The results, presented in Table IA3, show that counties with higher volumes of Green Bank 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 Green Banks 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 Green Bank investments. To test for pre-trends, we estimate a dynamic version of Equation (1), focusing on the four years before and after Green Bank 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:

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

where

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

The dynamic effects, $\lambda_\ell$ provide event-study estimates that capture changes in VC investment outcomes over time for climate-tech and non-climate-tech startups in counties receiving Green Bank funding. We normalize $\ell = -1$ as the reference period, with event time $\ell = 0$ indicating the year of Green Bank 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 Green Bank 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 Green Bank funding, we observe a notable increase in both VC outcomes for climate-tech startups, suggesting a positive and sustained impact of Green Bank funding. While it is possible that Green Banks target counties further along in the green transition, which could influence our results, we do not find evidence of pre-existing trends to substantiate this concern.

### *4.3. Signaling and the Inflation Reduction Act*

The announcement of the Greenhouse Gas Reduction Fund (GGRF) within the Inflation Reduction Act signals that financing for green investments will be available for an extended period. Since these funds will be deployed through GBs, counties where GBs have already invested are at a significant advantage. However, because climate startups often focus on innovative technologies, only a few are likely to be directly funded by GBs through the GGRF. This expected lack of direct funding to startups supports the hypothesis that the effect is driven by signaling rather than a direct injection of funds. We find evidence for this in Table 4, which shows that after 2021, the year when the IRA began being discussed in Congress, counties with prior GB loans experienced an additional increase in both the likelihood of VC deals and the amount invested in climate startups. These results suggest that signaling plays a key role, though the analysis is limited by the short time period post-IRA.

### *4.4. Heterogeneity*

In this section, we examine the heterogeneity in the impact of Green Bank funding by conducting cross-sectional tests based on startup and county characteristics. We augment Equation (1) by including triple interaction terms with variables that measure these characteristics.

In columns (1) and (2) of Table 5, we find that older climate-tech startups attract more VC investment when Green Banks make investments in the same county, compared to younger startups. This result aligns with the mandate of the GGRF and the mission of most Green Banks, which prioritize supporting proven technologies. By investing in counties with more mature startups, Green Banks signal to VCs that these startups are viable, lower-risk investment opportunities. Consequently, VCs are more likely to invest in these established companies, recognizing the Green Banks' endorsement of their market potential. In this context, Green Banks play a catalytic role by signaling VCs to channel private capital toward scaling proven technologies, rather than funding speculative or nascent innovations.

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

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

In the last two columns of Table 5, we find that that in more Republican areas, where

there may be less public and political support for climate initiatives, Green Bank funding has a more limited impact on attracting VC deals for climate-tech startups. This result is consistent those of Burt et al. (2023), who show that climate-related startups backed by Democrat VC partners tend to outperform those backed by non-Democrats, suggesting that political alignment influences the effectiveness of Green Bank funding in attracting private capital for climate-related investments.

### *4.5. Technology-level Analysis*

In this section, we examine the heterogeneous effects of Green Bank investments on VC deal activity by conducting technology-level analysis. Specifically, each climate-tech startup is matched to one of 88 climate technologies from Project Drawdown based on its business description in PitchBook, utilizing a GPT-based large language model (LLM) following Lu, Serafeim, Xu, and Awada (2024). Project Drawdown contains a list of climate technologies that can reduce greenhouse gases in the atmosphere, and are compiled by a network of scientists and researchers (Project Drawdown, 2020). This matching allows us to assess whether Green Bank funding differentially impacts VC deals based on specific attributes of startups' underlying technologies.

Table 6 presents the results of this technology-level analysis, which decomposes the interaction between GB funding and climate-tech startups across several dimensions. First, Project Drawdown provides estimates for each climate technology's abatement potential and costs to achieve the carbon abatement. The abatement potential is the CO2 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.[14]

In Column (1), we classify climate-tech startups based on whether their underlying technology has high or low carbon abatement potential according to the Project Drawdown 2020 report. We find that both high and low abatement potential technologies are more likely to receive VC investments following GB funding. Specifically, the difference between the coefficients on the interaction terms *GB fund* $\times$ *Climate startup (High abatement potential)* and *GB fund* $\times$ *Climate startup (Low abatement potential)* is not statistically significant

[14]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).

($p$-value = 0.331), suggesting that VC investors do not selectively favor climate technologies based on their emissions reduction potential in response to GB funding.

In Column (2), we distinguish between high- and low-cost climate technologies. The results 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 (3) 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 (4) and (5). Column (4) 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.[15] A climate technology is classified as high (low) spread if the number of unique industries in which it appears is above (below) the median for that year. The results indicate that climate-tech startups with technologies exhibiting broader industry adoption are significantly more likely to receive VC funding following GB investments. Column (5) examines the industry concentration of each climate technology using the Herfindahl-Hirschman Index (HHI). Each year, the HHI is computed for every climate technology by summing, across all six-digit GICS industries, the squared ratio of the number of incumbent public firms using the technology within each industry to the total number of firms using the technology. Technologies with an HHI above (below) the median in a given year are classified as high (low) concentration. The results indicate that low-concentration technologies—those more widely dispersed across industries—are significantly more likely to receive VC investment following GB funding. This finding, along with the industry spread results in column (4), suggests that VCs prioritize climate technologies with broader applicability across industries, as these offer greater commercialization potential and signal larger market opportunities.

Overall, the findings in this section suggest that, following GB funding, VCs are more likely

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

to finance climate-tech startups with low-cost and widely dispersed technologies, as these exhibit stronger commercial viability and greater return potential. These results also support the interpretation that the observed increase in VC investment stems from GB activity rather than time-varying, county-specific unobserved factors. Notably, GBs prioritize investments in commercially proven technologies. The cost and diffusion of these technologies depend heavily on their maturity, as economies of scale drive production efficiencies and broader adoption. Consequently, GBs tend to invest in low-cost, scalable climate solutions—such as building retrofitting, energy efficiency measures, heat pumps, utility-scale photovoltaics, and wind turbines—all of which are defined as low-cost or widely adopted.

### *4.6. Placebo Test*

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

The results in Table 8 show that government grants do not impact local VC investment or VC investment in local climate startups, as the coefficients on *Government grant* and the interaction between *Government grant* and *Climate startup* are not statistically different from zero. These findings suggest, unlike Green Banks, which explicitly aim to mobilize private capital and de-risk investments, traditional government grants appear insufficient to signal investment quality to VCs. This placebo test highlights the unique role of GBs in shaping private sector investment behavior in climate tech and fostering market-based scaling of climate technologies.

### *4.7. Additional Robustness Tests*

We provide additional robustness to the results by replicating the main analysis using only the states in which the GBs have a clear green investment objective since their inception and we were able to verify the activity of each GB. These states include California, Connecticut, Florida, Illinois, Ohio, Maine, Maryland, Massachusetts, Pennsylvania, Rhode Island, New

York, and New Jersey. The results reported in Table IA4 in the Internet Appendix are stronger than the main analysis. Specifically, GBs' loan activity in a county is positively related to the number of VC deals and investment amount in climate-tech startups.[16]

### *4.8. Round-level analysis*

The DiD analysis thus far examines the determinants of VC financing for climate-tech startups, focusing on how Green Bank investments influence the likelihood of securing a deal. In this section, 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 Green Bank investments in the same county. We estimate the following regression model:

$$y_{i,r,c,t} = \beta_0 + \beta_1 GB\ fund\ round_{c,t} + \beta_2 GB\ fund\ round_{c,t} \times Climate\ startup_i + \gamma X_i + \tau_i + \omega_c + \mu_t + \delta_s + \varepsilon_{i,r,c,t} \quad (4)$$

for startup $i$, in VC round $r$, headquartered in county $c$, in year $t$. The outcome variables, defined below, include measures of startup valuation and exit performance. We define a VC round as coinciding with Green Bank investment if it occurs in the year immediately following the Green Bank funding. Specifically, *GB fund round* is a dummy variable equal to one if the startup is located in a county that received Green Bank 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, Gornall, Kaplan, and Strebulaev (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 Green Bank 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.

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

Also, variations in outcome variables may be influenced by investor characteristics; for instance, a prominent lead VC can attract other investors, potentially boosting the startup's valuation and exit performance. To account for this, we include controls for the lead VC's age and its investment activity over the past five years. However, as these startup-level controls are available only for a subset of the sample, we estimate Equation (4) with and without these variables.

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

In Table 9, we examine outcome variables related to the startups' valuation at the VC financing round. These variables include the log of the deal size (*ln(Deal size)*), the post-money valuation of the startup (*ln(Post valuation)*), whether the round was classified as an "up" round (i.e., an increase in valuation relative to previous rounds), and the log of startup revenue at the time of the VC round (*ln(Revenue)*). The positive and significant coefficients on *GB fund round* $\times$ *Climate startup* indicate that VC rounds coinciding with Green Bank investments enhance the perceived valuation of climate-tech startups. Together with the prior results, this finding suggests that Green Bank investments not only increase the likelihood of attracting private capital but also raise the market valuation of climate-tech startups that receive such funding. These results support the signaling mechanism, as Green Bank investments likely convey to VCs the long-term market potential for climate-related innovations, leading to higher valuations and greater financial commitments during the round.[17]

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

[17]Table IA5 suggests that the aforementioned valuation effects coincide with the expansion in the set of investor types in the syndicate backing climate startups at GB-active counties. Such crowding-in effect due to GB presence can partially explain superior performances of VC-backed climate startups.

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.[18] The round-to-exit return is an annualized return associated with the round-to-exit multiple, based on the holding period measured as the number of days between the current round and the exit date. Liquidated deals are assigned a return of -100%.

In Table 10, we estimate Equation (4) using the round-to-exit multiples and returns associated with each specific VC round. We first winsorize returns and multiples at the 1% level to control for major outliers. Additionally, 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.[19] The negative and significant coefficients on *GB fund round* across all specifications indicate that VC rounds coinciding with Green Bank funding are associated with lower exit multiples and returns for non-climate-tech startups. In contrast, the positive and highly significant interaction term *GB fund round* × *Climate startup* suggests that VC rounds coinciding with Green Bank investments have a strong positive impact on the exit performance of climate-tech startups. Thus, VC rounds associated with Green Bank 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.

## 5. Conclusion

This paper investigates the role of government-funded GBs in stimulating local green investment, focusing on climate-related startups. This is the first study to focus on GBs and, for this reason, we provide the first description of these institutions, highlighting their investment focus, location of operation, and incorporation type. In addition to the description of the institutions, we examine their impact on local green investment. Leveraging the staggered loan activity of Green Banks over time and geography and the introduction of the GGRF within the Inflation Reduction Act, 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 results are robust when using binary and dynamic treatments,

[18] 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".

[19] 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.

across various fixed-effects specifications, and samples. The results do not seem to be driven by existing local trends before the GB loans.

We hypothesize that the introduction of the GGRF serves as a substantial signal to investors about the availability of funds for green projects through GBs. Consistent with this hypothesis, we observe that, after the Inflation Reduction Act was introduced in Congress, VC funding for climate-related startups increased in counties with GB loans. This suggests that venture capitalists perceive GB lending activities as an opportunity to invest in local climate startups, possibly due to reduced information asymmetry or enhanced credibility of these startups.

Our exploration of heterogeneity across regions reveals that the impact of GBs is more pronounced in areas with higher concern about climate change and in counties that lean more Democratic. Additionally, we find that older startups and those with prior VC financing benefit the most from GB presence. This aligns with the GGRF's mandates and many GBs' mission to invest in established technologies such as solar panels and wind turbines. Lastly, our analysis at the investment round level shows that climate startups in counties with GB loans exhibit better performance across various measures, indicating that GBs not only facilitate access to capital but also contribute to the overall success of these ventures.

These findings have significant implications for policymakers and practitioners. They highlight the effectiveness of government-funded Green Banks in mobilizing private capital toward climate-related investments, thereby helping to bridge the substantial funding gap required to meet global warming targets. The evidence suggests that GBs play a crucial role in enhancing regional economic resilience and accelerating the transition to a low-carbon economy by acting as catalysts for green innovation at the local level.

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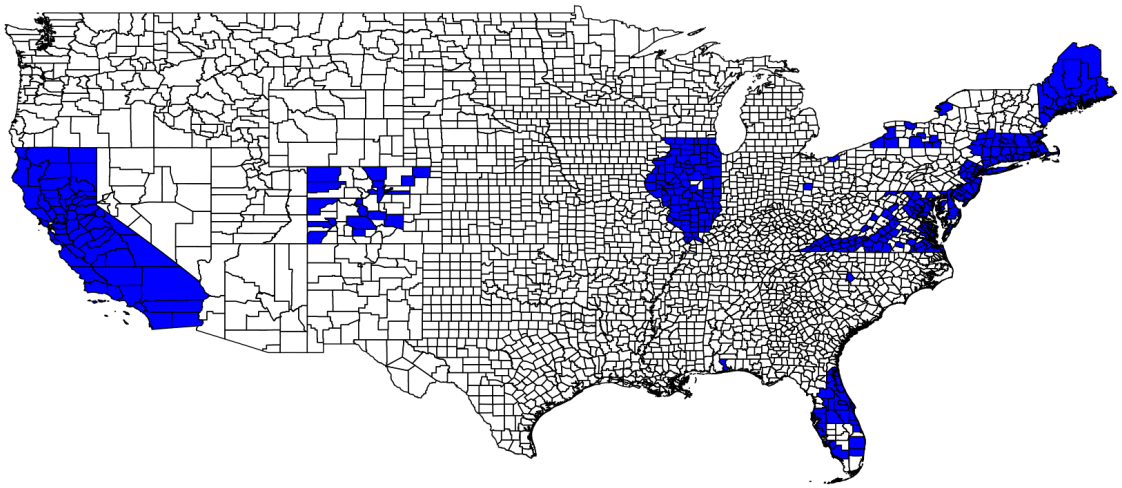
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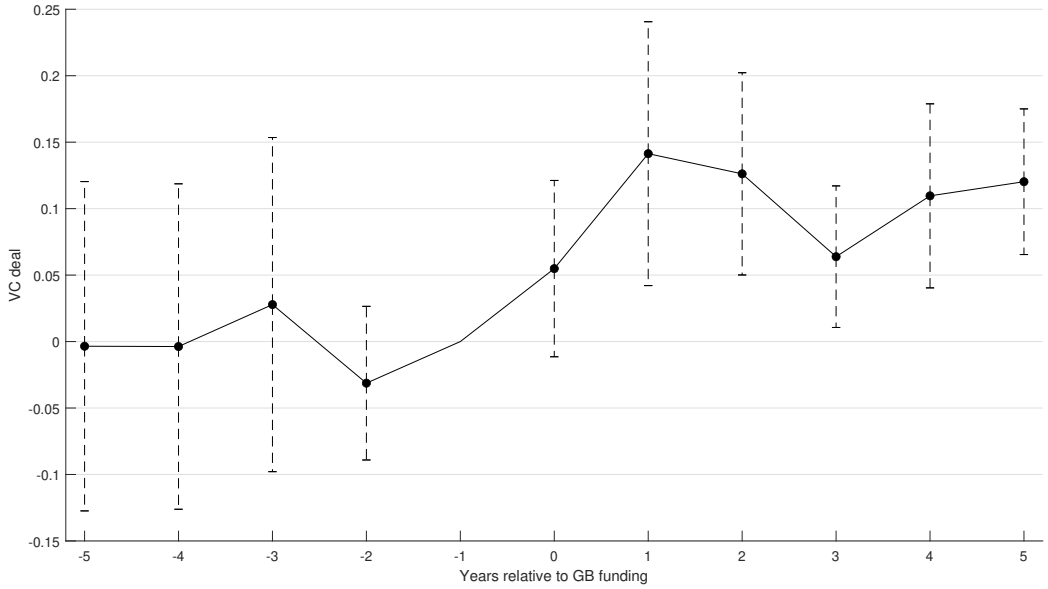
**Figure 1**
Green Banks across the U.S.



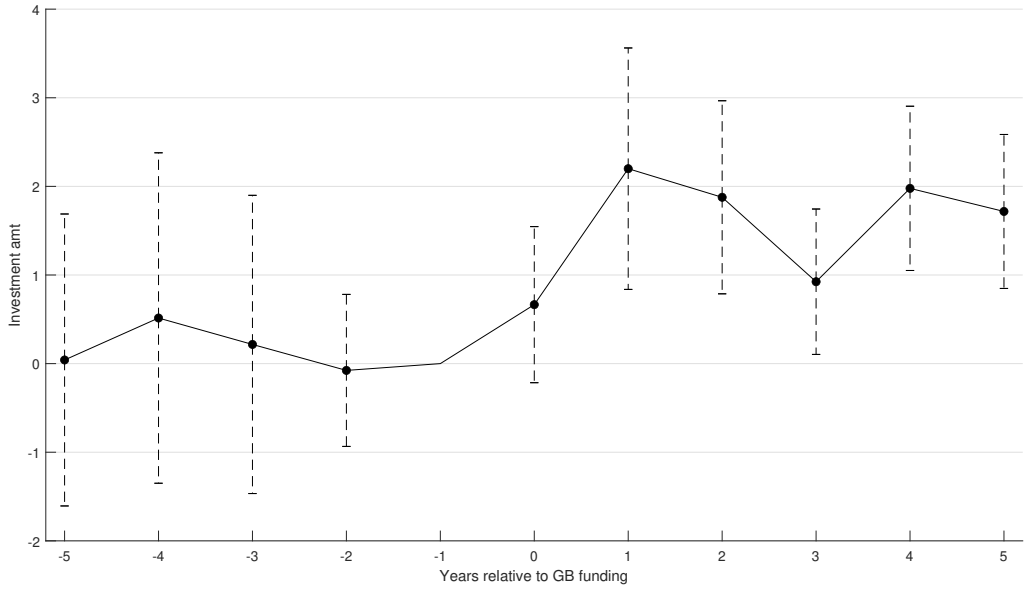
This figure reports in blue the counties that received at least one loan from the Green Banks that report county-level activity.

**Figure 2**
Dynamic effects.

Panel A: Pretrends when the outcome variable is *VC deal*




Panel B: Pretrends when the outcome variable is *Investment amt*




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

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

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

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

**Table 2**
Startup sample description.

*Panel A: Startup deals by year*

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

*Panel B: Startup industry distribution*

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

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

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

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

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

**Table 4**
Impact of IRA.

| Dep. variable: | *VC deal* | | *Investment amt* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *GB fund* | 0.006 | 0.167*** | 0.040 | 2.129*** |
| | (0.59) | (15.74) | (0.29) | (15.96) |
| *GB fund* × *Climate startup* | 0.079*** | 0.069*** | 1.127*** | 1.018*** |
| | (3.75) | (3.19) | (3.50) | (3.17) |
| *GB fund* × *Climate startup* × *IRA* | 0.049*** | 0.046*** | 0.545*** | 0.527** |
| | (3.05) | (2.86) | (2.59) | (2.51) |
| Startup F.E. | Yes | Yes | Yes | Yes |
| Industry F.E. | Yes | No | Yes | No |
| County F.E. | Yes | No | Yes | No |
| Year F.E. | Yes | No | Yes | No |
| Industry × Year F.E. | No | Yes | No | Yes |
| County × Year F.E. | No | Yes | No | Yes |
| Observations | 394,337 | 391,039 | 394,337 | 391,039 |
| $R^2$ | 0.04 | 0.05 | 0.09 | 0.09 |

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

**Table 5**
Cross-sectional analysis.

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

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

**Table 6**
Technology level analysis.

| Dep. variable: *VC deal* | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *GB fund* | 0.151*** | 0.151*** | 0.151*** | 0.151*** | 0.150*** |
| | (9.76) | (9.89) | (9.83) | (9.23) | (9.19) |
| *GB fund* × *Climate startup (High abatement potential)* | 0.073* | | | | |
| | (1.92) | | | | |
| *GB fund* × *Climate startup (Low abatement potential)* | 0.104*** | | | | |
| | (4.61) | | | | |
| *GB fund* × *Climate startup (High abatement cost)* | | 0.038 | | | |
| | | (0.86) | | | |
| *GB fund* × *Climate startup (Low abatement cost)* | | 0.122*** | | | |
| | | (5.18) | | | |
| *GB fund* × *Climate startup (High cost per potential)* | | | 0.046 | | |
| | | | (1.10) | | |
| *GB fund* × *Climate startup (Low cost per potential)* | | | 0.123*** | | |
| | | | (3.93) | | |
| *GB fund* × *Climate startup (High spread)* | | | | 0.102*** | |
| | | | | (3.36) | |
| *GB fund* × *Climate startup (Low spread)* | | | | 0.033 | |
| | | | | (0.48) | |
| *GB fund* × *Climate startup (High concentration)* | | | | | 0.081 |
| | | | | | (1.49) |
| *GB fund* × *Climate startup (Low concentration)* | | | | | 0.098*** |
| | | | | | (3.24) |
| Startup F.E. | Yes | Yes | Yes | Yes | Yes |
| Industry × Year F.E. | Yes | Yes | Yes | Yes | Yes |
| County × Year F.E. | Yes | Yes | Yes | Yes | Yes |
| Observations | 389,740 | 389,740 | 389,740 | 387,320 | 387,320 |
| $R^2$ | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |

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

## Table 7

Net-zero banking alliance.

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

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

**Table 8**
Placebo test.

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

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

**Table 9**
Round-level analysis: startup valuation.

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

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

**Table 10**
Round-level analysis: startup exit performance.

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

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

# Internet Appendix for Government-Funded Green Banks

**Table IA1**
Green Banks' characteristics.

| Green Bank | Year Established | Bank 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 Climate Bank | 2021 | 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 and type of the Green Banks analyzed in the paper.

## Table IA2

Green Banks' Investment Focus.

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

This table reports the investment characteristics of Green Banks.

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

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

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

**Table IA4**
Robustness tests.

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

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

**Table IA5**
Round-level analysis: investor type.

| Dep. variable: | *Impact investor* | | *Corporate VC* | | *VC-backed company* | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *GB fund round* | -0.006 | -0.004 | 0.007 | 0.005 | 0.011*** | 0.010*** |
| | (-1.23) | (-0.79) | (0.68) | (0.34) | (3.54) | (2.77) |
| *GB fund round* × *Climate startup* | 0.136*** | 0.100* | 0.146** | 0.127* | 0.061*** | 0.062** |
| | (2.63) | (1.82) | (2.06) | (1.68) | (3.83) | (2.39) |
| *Past VC financing* | | 0.003 | | -0.007 | | -0.008 |
| | | (0.59) | | (-0.78) | | (-1.63) |
| *Startup age* | | 0.004 | | 0.086*** | | 0.015** |
| | | (0.53) | | (6.95) | | (2.31) |
| *Established operation* | | 0.006* | | 0.031*** | | 0.005* |
| | | (1.66) | | (3.80) | | (1.89) |
| *VC age* | | -0.000 | | -0.002 | | 0.002 |
| | | (-0.12) | | (-0.49) | | (1.49) |
| *VC past investments* | | 0.001 | | 0.003* | | -0.000 |
| | | (0.82) | | (1.67) | | (-0.32) |
| Startup F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| County F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Year F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Stage F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 44,640 | 39,566 | 44,640 | 39,566 | 44,640 | 39,566 |
| $R^2$ | 0.29 | 0.30 | 0.28 | 0.29 | 0.18 | 0.19 |

*Impact investor* is a dummy variable equal to one if an investor in the syndicate at the current round is classified as an impact investor by PitchBook, and zero otherwise. *Corporate VC* is a dummy variable equal to one if an investor in the syndicate at the current round is classified as a corporate venture capital by PitchBook, and zero otherwise. *VC-backed company* is a dummy variable equal to one if an investor in the syndicate at the current round is classified as a VC-backed company by PitchBook, and zero otherwise. *GB fund round* is a dummy variable equal to one if the startup is located in a county that received funding from a green bank in the year prior to the VC round, and zero otherwise. *Climate startup* is a dummy variable equal to one if the startup is labeled under the "Climate Tech" or "CleanTech" verticals in PitchBook, and zero otherwise. *Past VC financing* is a dummy variable equal to one if the startup received VC financing in the previous five years, and zero otherwise. *Startup age* is the age (in years) of the startup based its founding year according to PitchBook. *Established operation* is a dummy variable equal to one if the startup is classified as "Generating Revenue" or "Profitable" in a given round, and zero otherwise. *VC age* is the age (in years) of the lead VC investor based its founding year according to PitchBook. *VC past investments* is the log of one plus the number of investments made in the previous five years by the lead VC investor before the current round. The sample period is 2015 to 2023. Robust $t$-statistics based on standard errors clustered at the county level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.