# The Grass Is Actually Greener on the Other Side: Evidence on Green Multipliers from the United States

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**Abstract**

In this paper, I estimate the local multiplier of spending in green energy in the United States. I construct a novel state-level dataset, and isolate the exogenous variation in green energy spending by exploiting the institutional characteristics of the green budget allocation by the Department of Energy (DoE). I find that a \$1 increase in green investment increases state-level output by \$1.1 contemporaneously, and up to \$4.2 within two years of implementation. These estimates are large in comparison to the findings of the literature on public infrastructure multiplier, or the multiplier of non-green investments by DoE. I also find large multipliers at a disaggregated level: green energy spending has significant effects on sectoral output, employment, and investment. I then contrast green and non-green multipliers quantitatively by specifying an open economy New Keynesian model with public capital, where each US state is an open economy within a fiscal and monetary union. I calibrate the public capital to green and non-green energy using a transaction-level dataset on awards by the Department of Energy. Model-based counterfactual experiments suggest that 86% of the difference between the green and non-green multipliers is explained by the initial stock of capital in each energy type. As green public capital is further away from steady-state, the marginal productivity of investment is higher in the short-run, leading to higher multipliers relative to investment in non-green public capital.

**Keywords:** Fiscal policy, public infrastructure, renewable energy, energy efficiency
**JEL Classification:** E62, H54, H72, Q48

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# 1 Introduction

The question of whether green investments have a positive effect on the economy has gained significant attention for two main reasons. Firstly, there is increasing pressure on countries to invest in green energy to accelerate the transition towards a low-carbon economy as evident from major climate summits like the recent COP26.[1] Secondly, the widespread plans of generous fiscal packages to revitalize the economy following the Covid-19 induced recession spurred discussions on how to make use of this stimulus in a more environmentally friendly manner, thereby questioning whether a green recovery is possible. This is of particular importance in the United States given the two recent bills "Building Back Better Framework" and "Bipartisan Infrastructure Deal", and the current administration's goal to transition to a green, low-carbon economy through increased green investments. As such, increased pressure for climate action as well as concerns regarding the Covid-19 recovery have jointly raised an important question: can green investments be beneficial for the environment *and* the economy at the same time?

This paper investigates whether investments in green energy can lead to economic prosperity by estimating the local green multiplier in the United States. The contributions of this paper are threefold. First, I create a novel state-level dataset on the annual requested and actual spending in green energy by the US Department of Energy which can be used to isolate the exogeneous and unanticipated variation in green spending owing to the DoE's institutional structure and features unique to its green budgeting process. Second, it provides the first estimate of a green output multiplier using a dataset on energy efficiency and renewable energy spending with a relatively long time span and rich within-country variation. Third, it provides the first theoretical counterpart for the green output multiplier by interpreting the empirical findings through the lens of an open economy New Keynesian model with public capital calibrated to green energy, and non-green energy for comparison purposes.

Historically, the literature on fiscal policy has mostly focused on multipliers of aggregate fiscal spending at the national level. Following the great financial crisis and the renewed interest in fiscal policy as a tool for boosting economic activity, a new strain of literature emerged exploiting the cross-sectional variation in fiscal spending within a fiscal and monetary union (Acconcia et al., 2014; Auerbach et al., 2020; Brinca et al., 2019; Chodorow-Reich, 2019; De Ridder et al., 2020; Nakamura and Steinsson, 2014; Shoag, 2013). Moreover, given the prominence of infrastructure stimulus packages in policy discussions, a number of papers

[1] In addition to recent calls for Green New Deals by many countries, international organizations, and commissions.

estimated the public infrastructure multipliers specifically (Ilzetzki et al., 2013; Leeper et al., 2010; Kraay, 2012; Ramey, 2020). However, to date, there has been little focus on green multipliers, with two papers as an exception. The first by Popp et al. (2020) which focuses on the aftermath of the US American Recovery and Reinvestment Act (ARRA) and studies the effects of its green spending component on employment growth at the commuting-zone level. The second is by Batini et al. (2021) which examines cross-country effects of total green and non-green investment (from public and private sources) on national output.

Evidence on green multipliers has been limited due to the difficulty in isolating changes in green spending that are unanticipated and exogenous to contemporaneous changes in economic activity. Buchheim and Watzinger (2017) point out several challenges in estimating public infrastructure multipliers more generally. Two of such challenges are particularly relevant for this paper. First, stimulus investment programs, such as the ARRA, are by construction endogenous to economic conditions. Second, public investments face two critical lags: (i) lags in spending denoted by "time-to-spend", which resemble the lag between grants and outlays; and (ii) lags in implementation denoted by "time-to-build" (Ramey, 2020). As a result, this creates anticipation effects which make it challenging to identify the correct window during which the effects of the investments on the economy start materializing. I address the above two concerns by diverting from ARRA and referring instead to the annual DoE state budget reports that cover a longer time span and follow a legal framework behind state-level spending. The DoE state budget reports also present the requested and actual spending by each program-office in a given fiscal year. State-level spending by DoE's Office of Energy Efficiency and Renewable Energy (EERE) will provide us with a measure for green energy spending.[2]

The novelty of my identification strategy lies in isolating the exogenous and unanticipated variation in green spending by estimating the deviation in variation of actual spending from the variation in requested spending. This wedge is unanticipated and exogenous to local macroeconomic conditions owing to the following features unique to EERE spending: (i) the breakdown of EERE spending by DoE across states follows a formula-based system; (ii) fluctuations in green spending are heavily influenced by national politics and preferences of the White House vs. Congress with respect to the environment instead of being influenced by state-level economic activity; (iii) fluctuations in green spending are also due to bureaucratic and procurement delays of projects that have been approved in previous years; and (iv) federal disbursements of apportionments happen all at once and typically at the beginning of the fiscal year (i.e. October) and so are uncorrelated to shocks to output that are yet to

[2] I will use "green spending" and "EERE spending" interchangeably throughout this paper.

take place throughout the calendar year.

My empirical strategy exploits the unanticipated variation in green spending across states and time to investigate their dynamic effects on gross state product and a range of other macroeconomic outcomes. I also incorporate time and state fixed effects to control for national politics, aggregate business cycle fluctuations and national fiscal and monetary policies, as well as baseline differences between states' levels of development, and their structural and geophysical characteristics. Finally, given the transitory nature of this unanticipated spending, the estimation produces the local *temporary* green multiplier (in spirit of Acconcia et al. (2014) and Barro and Redlick (2011)), which represents the short-run effects of unanticipated green spending on local economic activity.

I find that a $1 increase in spending in energy efficiency and renewable energy leads to a $1.1 increase in local economic activity contemporaneously, $2.5 in 1 year and $4.2 in 2 years. This places the green multiplier in the upper range of public infrastructure multipliers previously estimated in the literature (see Ramey (2020) for an overview). I also compare the green multiplier with that of DoE spending on non-EERE activities (total DoE spending less EERE-related spending in a given state-year). Results show that non-EERE spending has smaller multiplier effects than those of EERE investments. Finally, results at a more disaggregated level show that EERE investments also exhibit stronger sectoral, employment and investment multipliers than those of non-EERE investments.

In order to rationalize my empirical findings and understand the underlying differences between the green and non-green multipliers more formally, I construct an open economy New Keynesian model with public capital, similar to Leduc and Wilson (2013), but with green or non-green energy capital. In this model, each US state is an open economy within a fiscal and monetary union. I calibrate the model using micro-data covering the universe of all awards by the Department of Energy at the transaction-level. I classify awards into green and non-green using keywords distinguishing projects on energy efficiency and renewable energy to calibrate green and non-green energy capital in the model. Theoretical results confirm the empirical findings qualitatively and quantitatively. Furthermore, model-based counterfactual exercises show that 86% of the difference between green and non-green multipliers is explained by differences in the initial conditions of public investment levels in the two energy types. As green public capital is further away from the steady state level of energy investment, it exhibits higher marginal productivity in the short-run, leading to higher multipliers than those of non-green energy investments.

The remainder of this paper is structured as follows: Section 2 presents an overview of the relevant literature; Section 3 discusses the identification strategy and institutional background of DoE green spending; Section 4 describes the data; Section 5 discusses the empirical methodology; Section 6 presents the core estimates of the green output multiplier; Section 7 disaggregates the green multiplier at the sectoral, employment and investment levels; Section 8 builds an open economy model with public capital to present a theoretical counterpart of the empirical results; and finally, Section 9 provides concluding remarks.

# 2 Related Literature

This paper lies at the heart of the fiscal policy literature which has witnessed noticeable growth since the great financial crisis. With the economy hitting the infamous "zero lower bound", monetary policy alone was no longer enough to stimulate the economy and this revitalized interest in fiscal policy. Ramey (2011) provides an overview of the seminal papers that explored the effects of government spending from a theoretical lens, including neoclassical models (Barro and King, 1984; Baxter and King, 1993) and New Keynesian models (Galí et al., 2007; Smets and Wouters, 2007), and an empirical lens (Barro and Redlick, 2011; Blanchard and Perotti, 2002; Devries et al., 2011; Ramey and Zubairy, 2018).

Beyond aggregate theoretical estimates, there has been a burgeoning literature exploiting advances in applied microeconometrics to estimate the *local* fiscal multiplier using cross-state variation (Acconcia et al., 2014; Auerbach et al., 2020; Brinca et al., 2019; De Ridder et al., 2020; Nakamura and Steinsson, 2014; Shoag, 2013). This strand of papers estimates the effects of government purchases across states (or cities) within a fiscal and monetary union. These papers therefore address how much an *additional* dollar of federal spending in one city of the union *relative* to another contributes to *relative* output/employment in that city, while holding national effects constant. This gives an estimate of the *local* multiplier which differs from the aggregate multiplier that estimates the effects of government purchases at the national level. One potential advantage of the local multiplier is that it exploits cross-sectional variation in policy which can be greater than policy variation over time and plausibly even more exogeneous (see Chodorow-Reich (2019) for an overview on local multipliers). Moreover, Chodorow-Reich (2019), Nakamura and Steinsson (2014) and Shoag (2013) provide a more detailed comparison between the aggregate and local multiplier estimates, interpreting the latter as an open economy relative multiplier. Translating the local multiplier to the aggregate multiplier will depend on the type of spending, monetary policy stance, and assumptions of the theoretical model.

A subset of the emerging papers on fiscal policy has focused on public infrastructure multipliers specifically given increased policy discussions following the great recession to capitalize on low borrowing costs and ramp up infrastructure spending (see for instance Buchheim and Watzinger (2017); Kraay (2012); Leduc and Wilson (2013); Leeper et al. (2010)). Ramey (2020) provides an overview of the public infrastructure multiplier literature and lists two main features inherent to public infrastructure that distinguish it from other types of fiscal spending: (i) "time-to-spend", which resembles the lag between grants and outlays; and (ii) "time-to-build", which resembles lags in implementation. Ramey (2020) elaborates that these features reduce short-run effects of public infrastructure spending in stimulating economic activity. Her findings are confirmed with a range of other papers that also do not find strong short-run effects of public infrastructure spending. For example, Ilzetzki et al. (2013) find a public infrastructure multiplier of around 0.4 using structural vector autoregressions on a panel of 44 countries under different economic settings (level of development, exchange rate regime, openness to trade, and public indebtedness). Leduc and Wilson (2013) estimate the effects of highway spending using state-level data in the US and find a mean multiplier ranging between 0.6 and 1.7, albeit with great variability between short-run and long-run with the multiplier being positive upon impact, dipping into negative territory in the short-run, and then peaking 6-8 years out, reflecting the time it takes for the benefits of public infrastructure spending on bridges and highways to accrue. Meanwhile, Deleidi et al. (2020) find a short and long-run stimulating effect by public infrastructure as they estimate the public infrastructure fiscal multipliers in 11 Eurozone countries to be on average around 1 euro contemporaneously, 2.2 euros in two years, and reaching up to 3.4 euros six years out. Their estimates are in the higher range of public infrastructure multipliers.

From a more theoretical point of view, Ramey (2020) emphasizes three crucial features that play a huge role in the size of the public infrastructure multiplier: (i) the elasticity of public capital in the aggregate production function (which captures to what extent the public capital is productive); (ii) whether the increase in public capital moves the economy towards the social optimum or away from it; (iii) and how the public capital is financed. The quantitative analysis in Section 8 will showcase the importance of the first two points in estimating the local green multiplier in this paper.

Together with this study, Popp et al. (2020) and Batini et al. (2021) also investigate the multipliers associated with green spending. Popp et al. (2020) focus on within-US variation in the green spending component of ARRA stimulus package and find that every $1 million of green ARRA spending created 15 new jobs in the medium-run. They further show that nearly half of those jobs were in construction and waste-management sectors, and nearly all the jobs created encompassed manual labor positions. Meanwhile, Batini et al. (2021) implement a cross-country study, and find that every \$1 increase in total green energy investments (from public and private sources) increases output by \$1.19 upon impact and has roughly persistent effects 4 years in. Meanwhile, non-green energy investments have an impact multiplier of \$0.65 and its effects wane within 3 years. The findings by both papers are further supported in my analysis.

To the best of my knowledge, this paper is the first to: (i) examine the fiscal multiplier of green spending using within-country data spanning a relatively long time period; (ii) provide detailed empirical evidence of the aggregate and disaggregate dynamic effects of green spending; and (iii) compare effects of green and non-green energy spending from both an empirical and a theoretical perspective.

Beyond the fiscal policy literature, my focus on green multipliers adds to a growing body of academic and policy research that has explored the economic benefits of green spending and innovation beyond their environmental breakthroughs (see for example Garrett-Peltier (2017); Hasna et al. (2021); Hepburn et al. (2020); Jacobs et al. (2012)). I will be touching upon these papers as I explain my results throughout the paper. The next section will explain the data used for the estimation.

# 3 Identification Strategy and DoE Institutional Background

The identification strategy in this paper hinges on isolating a subcomponent of green spending whose fluctuations are plausibly exogenous to contemporaneous macroeconomic events. In order to do so, I refer to the annual Congressional budget reports of the Department of Energy which are available for the 2005-2019 fiscal years. The budget reports detail for each fiscal year (FY) the requested DoE spending for the current fiscal year, and actual DoE spending for the fiscal year two years prior, both at the state and program-office level.

The DoE requests funding for each program-office at the Congressional control level based on the President's as well as the DOE Secretary's priorities. In a typical year, the President's Budget Request is submitted to Congress on the first Monday in February. Knowing that a fiscal year runs from October to September, then the DoE requested amounts are made public to all agents in the economy (at least) eight months prior to disbursement, which typically happens at the beginning of the fiscal year. Next, these requested amounts are submitted for approval to Congress to enact the appropriation bill. Congress typically approves the final budget around July after various Congressional Committees meetings and conferences. Once the final bill is approved by Congress and signed by the President, this spending gets enacted into law and the DoE starts the funds distribution process across its program-offices. The amounts of spending that DoE actually ends up disbursing to states at the beginning of the fiscal year (October) is the actual spending. In Appendix B, I present a timeline that shows how the fiscal year overlaps with the calendar year (CY) as well as the three spending stages: requested, enacted and actual.

Given the focus of this paper on estimating the green multiplier, the DoE program-office of interest is "Office of Energy Efficiency and Renewable Energy". Spending by the EERE Office captures expenses including the purchase, construction, and acquisition of plant and capital equipment, and other expenses necessary for energy efficiency and renewable energy activities (such as building retrofits and energy efficiency installations at homes), in carrying out the purposes of the Department of Energy Organization Act (42 U.S.C. 7101 et seq.). As such, spending by the EERE Office will be the measure of *green spending*. For comparison purposes, I will also consider a measure of non-green spending which is total DoE spending less DoE green spending in a given state-year. Examples of non-EERE spending activities include: ensuring a reliable energy infrastructure (grid research and technology) and enhancing its security, advancing coal energy systems and natural gas technologies, sponsoring research in science and technology, among others.

Next, I exploit the administrative structure of the EERE Office to understand how it apportions its spending across states.[3] The EERE Office predominantly consists of the State Energy Program (SEP) which, after receiving its allocation from Congress, leaves some money for technical assistance and then determines state-level apportionments according to formula 10CFR420 whereby: 1/3 of the allocation is split according to state population (following the latest census), 1/3 of the allocation is split according to energy consumption (based on data from the Energy Information Administration (EIA) from two years prior), and 1/3 is split equally across states. The formulaic allocation of requested and enacted spending by the EERE Office refutes the typical endogeneity argument which would have suggested that the level of EERE spending is entirely dictated by local economic conditions.[4] However, in this

[3]It is important to highlight that DoE spending at the state-level is not requested or approved by Congress. It is only federal DoE spending for every program-office that gets Congressional approval. State-level spending will in turn depend on each program-office's institutional features, whether the program-office follows a formula-based system, or apportions funds across states via other methods such as allowing for bidding, etc.

[4]The EERE Office also includes the Weatherization Assistance Program, which is smaller in scope than SEP, but nevertheless also follows a formula-based allocation system that depends on: (i) climate conditions, (ii) the number of low income-households as a percent of all U.S. income households, and (iii) residential

case, the requested spending is not sufficiently exogenous to be a measure of green spending on its own or even an instrument for spending actually disbursed, as in Kraay (2012) for example.

The DoE budget reports also provide the actual amounts disbursed by DoE to the state in every program-office two years prior. Having the actual and requested amount of DoE spending for every state-program-year, I can isolate an exogenous component in the variation of DoE spending which captures the difference between the variation in actual DoE spending and the variation in requested DoE spending. In other words, the institutional characteristics of this spending allows us to look at the changes in actual DoE spending *on top* of what has been expected to change. The only thing that remains is to ensure that this difference is truly *exogenous* to current economic conditions and *unanticipated* for identification purposes.

Digging deeper into the institutional setup of the DoE EERE spending, the reason the variation in actual spending deviates from that in requested spending is attributed to two main factors: (i) political factors at the federal level, and/or (ii) bureaucratic and implementation delays of projects that had been already approved in previous years. The former factor is not surprising given that environmental stances are highly political, and the national DoE budget for green investments will depend on the administration's priorities and political leanings. As such, national politics will affect the amount of total federal spending in a given year at the national level and is therefore uncorrelated with state economic conditions. State-level spending will vary in line with the size of the annual budget.[5] Meanwhile, the latter factor on bureaucratic and implementation delays will have a direct effect on state-level spending. Such delays are a distinguishing feature of public infrastructure projects, and have been highlighted extensively in the literature. Indeed, Deleidi et al. (2020); Fernald (1999); Ramey (2020) stress on the dependence of public investment decisions on bureaucratic and institutional decisions that could last longer than the fiscal year. This is because public investment decisions include feasibility studies, as well as projecting and planning activities which typically over-arch multiple institutions (policy, public and private) - all of which could shock the decision and disbursement processes. Additionally, public infrastructure projects can be subject to implementation delays or opportunities due to unforeseen technical problems or advancements in project implementation, procurement delays, failure for a contractor to meet the conditions specified in project agreement, or new opportunities arising allowing ac-

energy expenditure.

[5] Although the changes in the size of the pie, and national politics more generally, will be differenced out via time fixed effects, they still contribute to a wedge between actual and requested state-level spending in the DoE state budget reports (to the extent that total spending is changing) and that is why it is important to highlight the role of national politics here.

celerated implementation or project expansion, etc. (Kraay, 2012; Leduc and Wilson, 2013; Ramey, 2020). As such, these surprises can change the distribution of spending over time (i.e. the time profile of the planned disbursements), and in some cases, can also lead to supplemental funding requests that could increase the amount of spending initially planned for a given state-program-year. What is critical to highlight for identification purposes is that these supplemental funds, when demanded, are for projects that have been previously approved and initiated and therefore unlikely to be correlated to contemporaneous macroeconomic shocks. Finally, federal disbursements of apportionments happen all at once and typically at the beginning of the fiscal year and so are uncorrelated to shocks to output that take place later in the year.

Therefore, my identification strategy relies on isolating an exogenous source of variation in green spending to study the green multiplier which consists of the wedge between the variation in actual spending and the variation in requested spending. Fluctuations in this component of spending is due to national politics and state-specific bureaucratic and procurement delays in projects previously approved and initiated, both of which are plausibly exogenous to local economic conditions. Beyond endogeneity and anticipation concerns, this measure also refutes typical forecastibility concerns since DoE spending data is available at a year-by-year basis and is not similar, for example, to investments in public highways that are available by multi-year bills and lay out spending for many years ahead as in Leduc and Wilson (2013).

# 4 Data

I construct an annual state-level dataset on total and green spending by the DoE. In order to do so, I scrape the DoE budget reports available for FY2005-FY2021 to get for every state: (i) the annual *actual* amount of EERE spending from 2003-2019; (ii) the annual *actual* amount of total spending from 2003-2019; (iii) the annual *requested* amount of EERE spending from 2005-2021; and (iv) the annual *requested* amount of total spending from 2005-2021.[6] Having the total and EERE spending for a given state-year, I can also calculate non-EERE spending for every observation in requested and actual terms, where the non-EERE spending is simply total DoE spending less EERE spending in a given state-year.

[6]The earliest available budget report is for 2005, that is why the requested time series starts in 2005, while actual starts 2003, since the 2005 budget report announces the actual spending two years prior. Similarly, the latest budget report available at time of writing is FY2021, which means the latest complete data on actual spending is 2019. For more information, the annual DoE Congressional budget reports are available here: https://www.energy.gov/cfo/listings/budget-justification-supporting-documents.

After collecting the data from the Department of Energy for all fiscal years, I convert the DoE data to calendar years (CY) to be in line with the outcome macroeconomic variables to be investigated.[7] I also convert the data to real terms using the GDP deflator series from the Bureau of Economic Analysis (BEA) which, similar to Barro and Redlick (2011), assumes that the productivity advances for publicly purchased inputs are the same as those in the private economy.

Figure 1 presents the time series of actual DoE spending in EERE and non-EERE activities. Two main features stand out: the left panel shows that the evolution of spending by the DoE is similar for green and non-green activities which suggests the influence of national shocks on DoE spending; the right panel emphasizes the small (yet relatively constant) share that green spending constitutes from the DoE's total spending, which averages roughly 6.3% between 2005-2019. One criticism that might arise is that the DoE is only a subset of green investments in the US, as such green might well constitute a larger share of aggregate US investment. In Appendix A, I look at the universe of all patent filings and inventions in the US since 1960 and show that the composition of DoE data is indeed representative of the overall green vs. non-green energy investment in the United States.

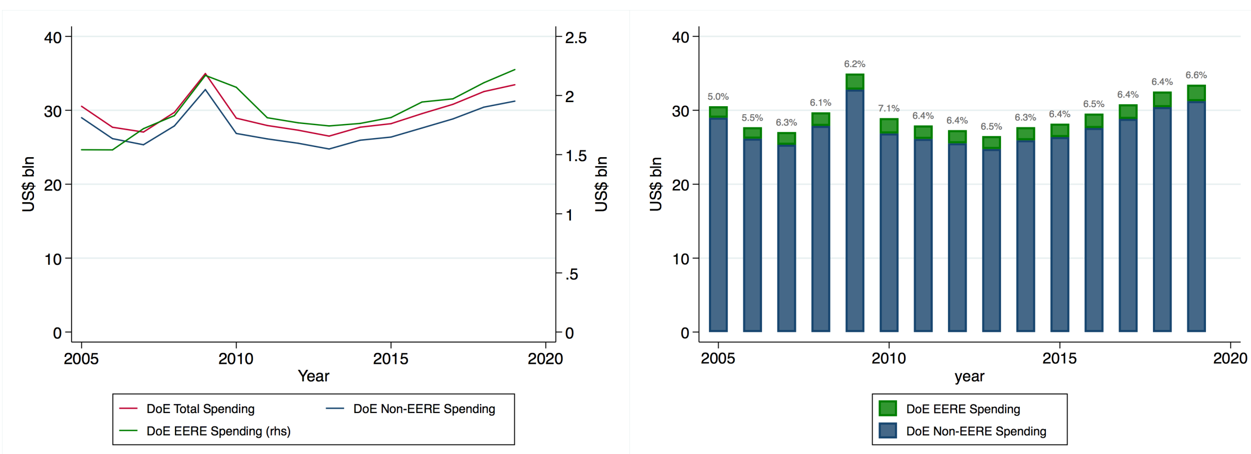


**Figure 1:** DoE: EERE vs. Non-EERE Spending Over Time

As previously mentioned, there are two major concerns in estimating fiscal multipliers of public infrastructure: ensuring exogeneity of fiscal spending, and addressing anticipation effects. Given that fiscal multipliers are calculated using variation in spending and not

[7] Given that a calendar year overlaps with three fourths of the same fiscal year and one fourth of the following fiscal year, then in order to deal with anticipation effects in the last quarter, spending is adjusted as follows:

$$\text{Spending in CY}_t = 0.75 * \text{Spending in FY}_t + 0.25 * \text{Spending in FY}_{t+1}.$$

Results are also robust to regressing calendar year changes in output on fiscal year changes in spending.

levels, I address the aforementioned two concerns by exploiting the rich data availability by the DoE state-budget reports that allows me to construct a measure of a shock in EERE and non-EERE spending, which is the difference between the variation of actual spending and the variation in requested spending. In Figure 2, I plot the variation in actual and requested spending by DoE for EERE and non-EERE projects in the left panel; and in the right panel, I plot the difference between the two which is the EERE and Non-EERE spending shock, respectively, such that $shock_t = \Delta g_t^{actual} - \Delta g_t^{requested}$. Another way to think of the shock is by decomposing actual spending into the *requested* component and the *new* unanticipated component, such that: $g_{it}^{actual} = g_{it}^{requested} + g_{it}^{new}$, which means that $shock_t = \Delta g_t^{new}$.

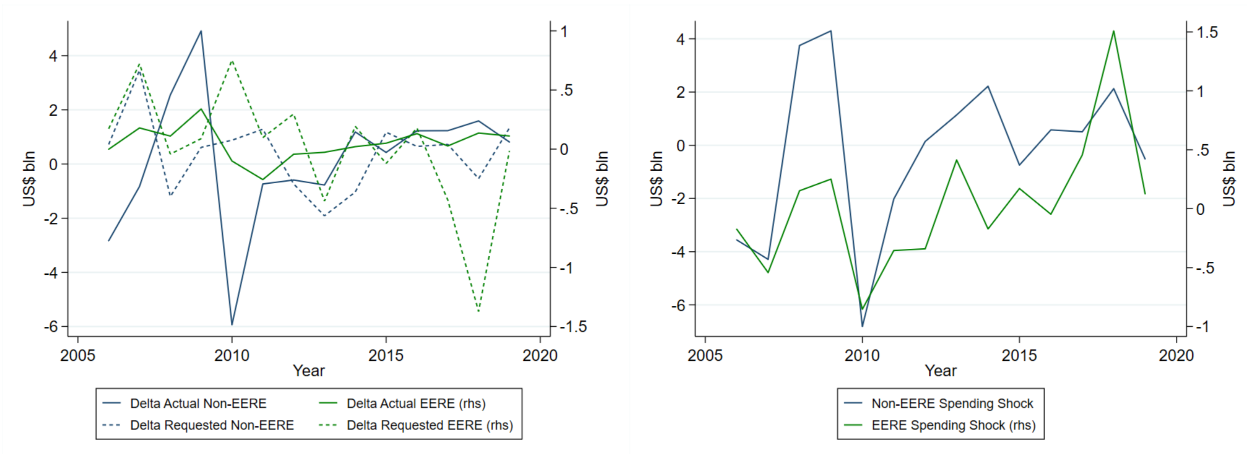


**Figure 2:** Variations in Actual, Requested and Unanticipated Spending

Figure 2 clearly demonstrates the variation in the shock series over time for both EERE and non-EERE spending. Besides time variation, the analysis will also hinge on the rich cross-state variation in green and non-green spending shocks by DoE as well as cross-state variation in economic output. In Figure 3, I plot two scatterplots for the average change in new unanticipated spending against average change in state-output for EERE and non-EERE spending, respectively. The scatterplots reveal significant cross-sectional heterogeneity and show that there are no obvious patterns in spending shocks relating to state output (with an insignificant correlation in both cases).

Having shown the time and cross-sectional variation of the shock in Figures 2 and 3, respectively, what is also important for the analysis is to demonstrate that the shock explains a sizable share of the variation in actual spending. With a simple growth decomposition exercise, I can quantify the magnitude of variation in actual spending that is driven by variation in the requested spending or the variation in the new unanticipated spending (i.e. the shock),

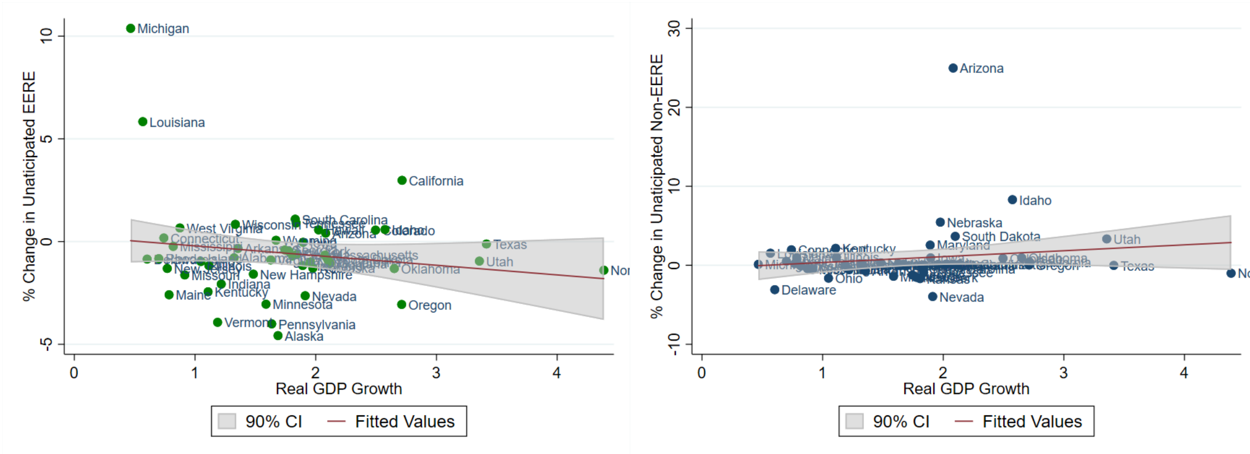


**Figure 3:** Scatterplots of Average EERE and Non-EERE Spending Shocks and Average Output Growth By State

such that:

$$\frac{g_t^{actual} - g_{t-1}^{actual}}{g_{t-1}^{actual}} = \frac{g_t^{requested} - g_{t-1}^{requested}}{g_{t-1}^{requested}} \cdot \frac{g_{t-1}^{requested}}{g_{t-1}^{actual}} + \frac{g_t^{new} - g_{t-1}^{new}}{g_{t-1}^{new}} \cdot \frac{g_{t-1}^{new}}{g_{t-1}^{actual}}$$

In Figure 4, I plot the decomposed annual variation in actual EERE and non-EERE spending and show that the shock explains, on average, at least 60% of the variation in actual EERE spending and 55% of the variation in actual non-EERE spending. Additionally, in Figure 5, I show the breakdown at the state-level, highlighting the importance of the shock in driving overall variation in actual spending in EERE and non-EERE activities, not only at the national level, but also in each state.[8]

Finally, in terms of data sources, the outcome variables concerning state-level output and sectoral output are all obtained from Bureau for Economic Analysis (BEA). I also consider EERE effects on energy capacity and generation at the state-level - obtained from the Energy Information Administration; and EERE effects on employment, labor force, and unemployment rates - all employment indicators are collected from the Bureau of Labor Statistics (BLS). All data is measured in annual frequency out of necessity given the lack of availability for more high frequency green spending data. Table C1 provides more details on the variables used, their time coverage and their sources.

[8]In Appendix D, I also show map visualizations of the average new unanticipated spending in green and non-green activities by DoE and average gross state product per capita for each state. The maps also confirm that there are no obvious patterns in level of unanticipated spending in green or non-green relating to state size or output.

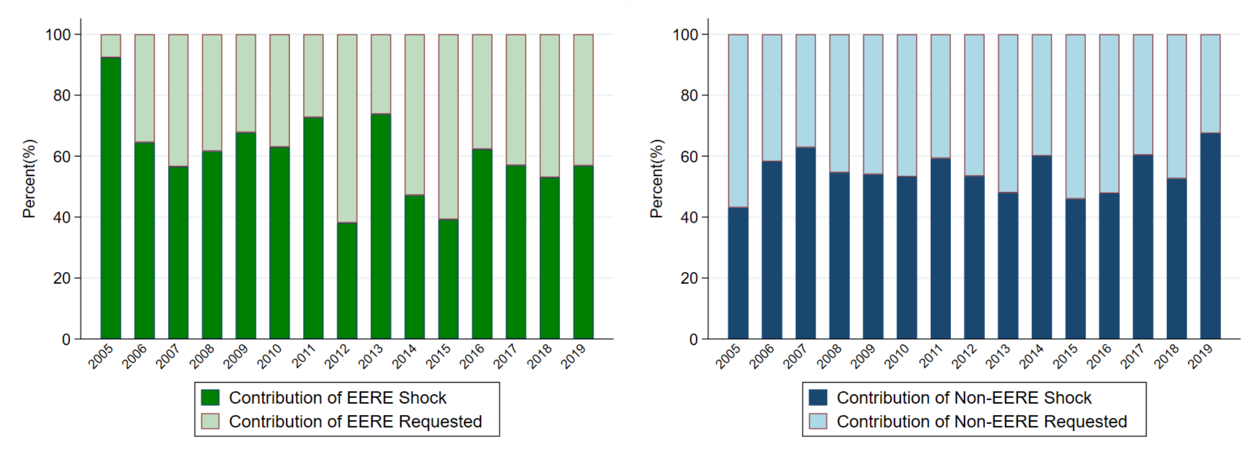


**Figure 4:** Decomposing the Variation in Actual EERE and Non-EERE Spending at the Yearly Level

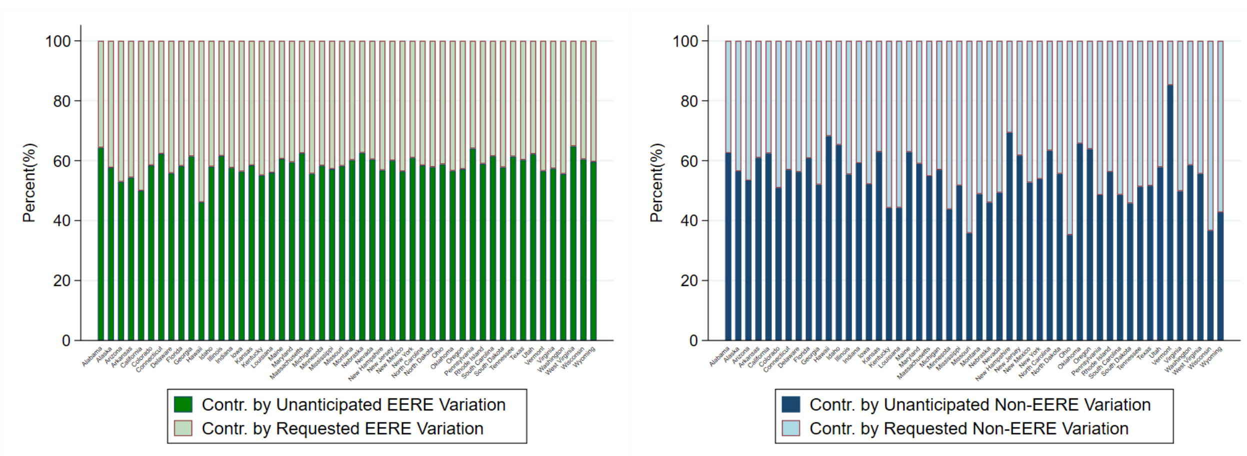


**Figure 5:** Decomposing the Variation in Actual EERE and Non-EERE Spending at the State Level

# 5 Empirical Methodology

I build on Acconcia et al. (2014), Barro and Redlick (2011), and Kraay (2012) to estimate the effect of EERE spending on local economic activity. Given that the effects of public infrastructure spending (from which EERE is a subset) tend to portray delayed effects as thoroughly covered by Ramey (2020); I estimate the dynamic effects of the exogenous and unanticipated component of EERE spending over three horizons, in spirit of Jordà (2005), using the following specification:[9]

[9] I only include three time horizons given the short time dimension of my panel dataset.

$$\frac{y_{i,t} - y_{i,t-h}}{y_{i,t-h}} = \beta_h \frac{\Delta^h g_{i,t}^{actual} - \Delta^h g_{i,t}^{requested}}{y_{i,t-h}} + \alpha_i + \lambda_t + \epsilon_{i,t};\ h = 1, 2, 3, \quad (1)$$

where the unit of observation is state-year such that $i$, $t$ and $h$ index state, time and horizon respectively, $y_{i,t}$ is the real gross state product per capita in state $i$ at time $t$, $g_{i,t}^{actual}(g_{i,t}^{requested})$ is actual (requested) real spending (in EERE or non-EERE activities) per capita in state $i$ at time $t$, and $\Delta^h x_{i,t} = x_{i,t} - x_{i,t-h}$.

Equation (1) allows us to exploit the institutional characteristics of the DoE spending in green to isolate the exogenous and unanticipated source of variation in EERE spending by gauging the effect of a change in actual EERE spending *on top* of what was expected to change. Specifically, by using difference in differences of actual and requested spending, I overcome the problems of: (i) anticipation since the economic agent's and the econometrician's information sets are now aligned (Abiad et al., 2016); (ii) and endogeneity given the institutional setup of the DoE data and the reasons behind this wedge being independent of local economic activity.[10]

My identification argues that unanticipated changes in EERE spending are uncorrelated to contemporaneous economic activity. To the extent that there might be persistent changes in output over time, I regress the unanticipated changes in EERE spending on lagged changes in local output over the horizons considered. Results in Table E2 are nil, suggesting that changes in output do not forecast future unanticipated changes in spending. Results are also nil when regressing unanticipated changes in non-EERE spending on lagged output.

The coefficient $\beta_h$ represents the *temporary* local EERE spending multiplier, whereby a dollar increase in unanticipated EERE spending will lead to a $\beta_h$ dollar increase in output within $h$ horizons.[11] The reason why $\beta_h$ is considered temporary is because the changes in spending considered at hand are transitory in nature as they are driven by temporary processes (political influence, national priorities, bureaucratic and procurement surprises, etc.) and do not constitute long-term shocks to the permanent expected value of lifetime green spending as in Leduc and Wilson (2013) and Ramey and Zubairy (2018), for example. Moreover, as explained by Kraay (2012), given that government spending is not a deep structural param-

[10] Another way to think of it is by writing Equation 1 as:

$$\frac{\Delta^h y_{i,t}}{y_{i,t-h}} = \beta_h \frac{\Delta^h g_{i,t}^{new}}{y_{i,t-h}} + \alpha_i + \lambda_t + \epsilon_{i,t};\ h = 1, 2, 3$$

whereby $g_{i,t}^{new} = g_{i,t}^{actual} - g_{i,t}^{requested}$, with $\Delta^h g^{new}$ representing the unanticipated variation in spending.

[11] $\beta_h$ can be interpreted in dollar terms straightforwardly as both dependent and independent variables are normalized by the same dollar value, which is lagged output.

eter and may coincide with a range of other factors, the multiplier $\beta_h$ is simply a reduced form empirical summary of the short-run effects of unanticipated annual fluctuations in green spending on local economic activity.

I include state fixed effects, $\alpha_i$, and (calendar year) time fixed effects $\lambda_t$. The state fixed effects are meant to remove baseline differences across states which is crucial to identify the correct effect of EERE spending as some states might have better geophysical characteristics to produce renewable energy or better institutions to roll out projects faster or even enforce environmental policies. As such, the state fixed effects will allow us to control for such time in-variant characteristics that could be correlated with EERE spending. Moreover, time fixed effects will control for national politics, aggregate/common shocks, as well as national policies such as federal fiscal policy (e.g. distortionary or lump sum taxation) and monetary policy which are proven to be major determinants of the transmission of government spending (Christiano et al., 2011; Corsetti et al., 2012; Woodford, 2011). Finally, I control for arbitrary serial correlation at the state-level, and heteroskedasticity, by clustering standard errors at the state level. This provides us with conservative standard errors.

Finally, it is important to note that one of the advantages for using the projections method over vector auto-regressive models (VARs) is due to the former method's flexibility in estimating Equation (1) separately for each horizon $h$ instead of estimating the full system simultaneously. Given the finite dimensionality of our data, the projections method is more robust to mis-specification that could be resulting from omitted variable bias (see also Leduc and Wilson (2013) for a more thorough discussion of projection methods vs. VAR). Nevertheless recent research shows that *in population* local projections and vector autoregressive models estimate the same impulse response functions (Plagborg-Møller and Wolf, 2021).

# 6 The Green Output Multiplier

Table 1 shows the dynamic effects of EERE spending on output. In Column (1), I regress the contemporaneous, 1-year, and 2-year changes in state-level output on unanticipated changes in EERE spending. Results show that a \$1 increase in EERE spending increases output by \$1.1 contemporaneously, \$2.5 in 1 year and \$4.2 in 2 years. All these effects are statistically significant. The fact that the green multiplier is increasing over the short term is consistent with the idea that benefits of public infrastructure spread over time to build new physical capital. Moreover, the estimates of the green multiplier in Table 1 places it in the upper range of estimates on public infrastructure multipliers previously circulated in the literature (see Ramey (2020) for an overview), suggesting that investing in green energy can indeed stimulate the economy in the short-run thereby lending support to the green recovery notion.

Moreover, given the context of my dataset on DoE spending, I can also compare the green multiplier to the non-green multiplier.[12] Column (2) of Table 1 shows the dynamic effects of non-EERE spending on output. Results show that non-EERE spending seems to have a smaller, and insignificant, multiplier effect on output than that of EERE spending.

The fact that green spending has a larger multiplier effect on economic activity than non-green spending is consistent with existing estimates from the literature. For example, Batini et al. (2021) find that a \$1 increase in spending in renewable energy leads to a \$1.1-\$1.5 increase in output compared to a \$0.5-\$0.6 from a dollar increase in fossil fuel energy investment. The results also corroborate with findings by Cavalcanti et al. (2021) whereby the GDP drop post introducing a carbon tax is lower when the tax revenue is used to subsidize the green energy sector compared to when used to subsidize all sectors. Their results therefore suggest that investments in green have higher returns than investments in non-green activities which led to a smaller drop in GDP. Additionally, and diverting slightly from investment onto innovation, Hasna et al. (2021) find that while both green and non-green innovation have positive and significant effects on economic growth, a persistent yearly doubling of green patents increases real economic growth by 4.8 percentage points, while a yearly doubling of non-green patents increases economic growth by 3.4 percentage points.

## 6.1 Robustness of the Main Result

One concern of my empirical strategy is that unanticipated EERE and non-EERE spending might be correlated. In order to address any correlation concerns between the two types of spending, I augment Specification (1) by adding non-EERE DoE investments as a control. Results from estimating the EERE and non-EERE output multipliers simultaneously are presented in Table E3 and are robust to estimating the two multipliers separately as in Table 1, further suggesting that the two spending types are not correlated. This is also apparent from the map visualizations in Appendix D.

[12] Although the requested non-EERE spending does not follow the same apportionment rule as requested EERE spending since it stems from multiple offices - each with an apportionment system different to that of the EERE Office, the wedge between actual and requested is nevertheless similar to that of EERE spending. Non-EERE spending follows the same spending time profile as EERE, with requested spending announced in February and actual spending disbursed in October in a typical year, which supports its orthogonality to current macroeconomic conditions, similar to the unanticipated EERE spending. Additionally, given that unanticipated non-EERE also survived the same econometric tests as unanticipated EERE spending, I will refer to the non-EERE spending by DoE for comparison purposes against the green multiplier.

**Table 1:** Temporary Green and Non-Green Multipliers

| | **Green** Output Multiplier | **Non-Green** Output Multiplier |
|---|---|---|
| Impact Multiplier | 1.101** | -0.198 |
| | [0.52] | [0.59] |
| 1-Year Multiplier | 2.534*** | 0.395 |
| | [0.75] | [1.18] |
| 2-Year Multiplier | 4.222*** | 1.133 |
| | [1.14] | [1.34] |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real green (or non-green) spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states. The impact, 1-year and 2-year multipliers are estimated using 637, 587 and 537 state-year observations, respectively.

The results in Table 1 are based on Specification (1) which avoids the inclusion of lags since estimates might be spurious in a fixed effects setting, especially since the time dimension is smaller than the cross-sectional dimension in my dataset and concerns of Nickel bias arise (Nickell, 1981). Nevertheless, one objection to my identification strategy could be that unanticipated changes in spending might be correlated to current macroeconomic conditions to the extent that macroeconomic shocks are persistent over time. I address this in Appendix E4 by including the first and second lags of output per capita (in levels and changes) for robustness. I also include lags of EERE (or non-EERE) government spending per capita (in levels and changes) to eradicate concerns of a potential correlation between lagged government spending and contemporaneous growth. Results for the green multiplier are robust, albeit with larger standard errors which is unsurprising given the added strain on the time dimension of the panel dataset by losing two additional data points (Table E4). Interestingly, in some specifications, the non-EERE multiplier might actually exhibit significant positive effects in the later horizons. As such, two main points stand out regardless of specification choice: First, EERE investments have larger multiplier effects than non-EERE investments - at least 1.5 times larger point estimates- stressing that investing in green energy is at least as beneficial to the economy as investing in non-green energy, if not more beneficial. Second, the benefits of EERE investments are faster to materialize than those of non-EERE investments. EERE investments have large multiplier effects contemporaneously, meanwhile non-EERE investments - when significant - tend to exhibit more delayed effects. This is intuitive on the grounds that non-EERE investments tend to be subject to longer delays either because they are more capital intensive (e.g. oil rigs) or because they involve more research and development and less deployment projects (such as building retrofits and energy efficiency installations which can be rolled over quite quickly).

Results of Table 1 are also robust to dropping one state at at time indicating that overall green and non-green multiplier estimates are not driven by one state only, see Table E.3 for the full result display.

# 7 A Disaggregated View of the Green Multiplier

The previous section covered the core estimates of the green output multiplier and its main robustness checks along the time and cross-sectional dimensions. This section will provide a disaggregated analysis of the green spending multiplier that will feed into the aggregate output result further confirming that green investments have sizable economic benefits in the short-run.

## 7.1 Sectoral Multipliers

In order to validate that the investments under investigation are targeting the right sectors, in this sub-section, I estimate Specification (1) separately by major sectoral groupings:

$$\frac{s_{i,t} - s_{i,t-h}}{y_{i,t-h}} = \beta_h \frac{\Delta^h g_{i,t}^{actual} - \Delta^h g_{i,t}^{requested}}{y_{i,t-h}} + \alpha_i + \lambda_t + \epsilon_{i,t};\ h = 1, 2, 3, \tag{2}$$

where $s_{i,t}$ is real sectoral output per capita. Since both dependent and independent variables are divided by the same denominator, output per capita, $\beta_h$ is still interpreted in \$ terms: one dollar in spending for $\beta_h$ dollars in sectoral output.

Panel A in Table 2 shows that EERE spending has positive and significant multiplier effects on Construction, Services and Government (which also constitute the lion share of the economy with an average value added share of around 70% of GDP). This is reassuring since the type of DoE EERE investments I am investigating mostly encompass building retrofits and efficiency installations and therefore one would expect them to have the strongest effect on Construction and Services sectors. EERE spending has a negative effect on the Natural Resources sector (Agriculture and Mining) which is also intuitive. The green nature of the spending will automatically lead to less reliance on mining activities. Additionally, deploying renewable energy installations (e.g. solar panels) might require a diversion in land use from crops and agriculture production hence contributing to an overall negative multiplier effect on agriculture. With respect to manufacturing, EERE investments have an insignificant, and potentially negative, multiplier effect that could be possibly explained by the fact that the industrial sector tends to be quite brown-energy intensive, therefore investing in EERE might require a cost of switching, at least in the short-run.[13] Finally, EERE investments seem to have an insignificant effect on Utilities. In Appendix F, I focus on the electricity subcomponent of the Utilities sector and find that green energy investments have a positive and significant multiplier effect on green energy generation and capacity, although latter effect is delayed.

For comparison purposes, I show in Panel B the sectoral multipliers of non-green investments. Results show that non-green spending has insignificant multiplier effects on most major sectors in the economy justifying its smaller overall multiplier on the economy. It is interesting to see the positive effect of non-EERE spending on manufacturing (which is known to be energy-intensive), albeit it is delayed. This potentially supports the aggregate non-green multiplier results in Table E4 suggesting that it takes time for benefits of non-green investments to accrue as they might be subject to longer delays.

Finally, the fact that EERE projects have stronger effects on the more domestic sectors (e.g. Construction and Services) in the economy than non-EERE investments is in line with findings by Batini et al. (2021); Garrett-Peltier (2017); Hepburn et al. (2020); Jacobs et al. (2012); Popp et al. (2020) which showcase a higher domestic content of green investments, while non-green investments tend to rely more on imports.

## 7.2 Employment Multipliers

Another dimension to better understand whether EERE investments can have a positive effect on economic activity is employment. In this subsection, I use state-level data on employment, labor force, and unemployment rates to explore the effects of EERE and non-EERE spending on labor market dynamics.

[13] A closer look with more disaggregated data would be helpful to understand the effects of EERE spending on manufacturing better.

**Table 2:** Effect of EERE and Non-EERE Spending on Sectoral Output

| **Panel A: Effect of EERE Spending on Sectoral Output** | Natural Resources[1] | Utilities | Manufacturing | Construction | Services | Government |
|---|---|---|---|---|---|---|
| Impact Multiplier | -1.791** | 0.064 | -0.245 | 1.660*** | 2.072*** | 0.256* |
| | [0.742] | [0.0656] | [0.222] | [0.483] | [0.653] | [0.137] |
| 1-Year Multiplier | -1.436* | 0.087 | -1.079** | 1.318** | 4.039*** | 0.772** |
| | [0.727] | [0.0667] | [0.494] | [0.642] | [1.396] | [0.361] |
| 2-Year Multiplier | -2.820** | 0.164 | -0.326 | 1.436* | 5.407*** | 0.722* |
| | [1.319] | [0.152] | [0.333] | [0.828] | [1.591] | [0.386] |

| **Panel B: Effect of Non-EERE Spending on Sectoral Output** | Natural Resources[1] | Utilities | Manufacturing | Construction | Services | Government |
|---|---|---|---|---|---|---|
| Impact Multiplier | 0.0333 | 0.00496 | 0.307 | -0.0511 | 0.0847 | -0.169 |
| | [0.288] | [0.0519] | [0.572] | [0.191] | [0.447] | [0.149] |
| 1-Year Multiplier | 0.784 | -0.00353 | 0.736 | -0.267 | 0.0955 | -0.0345 |
| | [0.764] | [0.0562] | [0.453] | [0.255] | [0.614] | [0.163] |
| 2-Year Multiplier | 1.016 | -0.0476 | 0.689** | -0.091 | 0.0908 | 0.11 |
| | [0.733] | [0.0625] | [0.288] | [0.316] | [1.096] | [0.175] |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the change in real state-level sectoral output per capita, over the horizon considered, as a share of lagged state-level output per capita. Independent variable is the change in real green (or non-green) spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states. The impact, 1-year and 2-year multipliers are estimated using 637, 587 and 537 state-year observations, respectively.
[1]Natural Resources sector includes Agriculture and Mining & Quarrying.

I update Specification (1) as follows:

$$e_{i,t} - e_{i,t-h} = \beta_h \underbrace{(\Delta^h g_{i,t}^{actual} - \Delta^h g_{i,t}^{requested})}_{\text{in \$100,000}} + \alpha_i + \lambda_t + \epsilon_{i,t}; h = 1, 2, 3, \tag{3}$$

where the dependent variable captures the change in employment, labor force and unemployment rates, respectively, and the spending variable is now reported in units of \$100,000 in line with the employment multiplier literature (see for example Chodorow-Reich (2019); Shoag (2013)). The employment multiplier, $\beta^h$, now reads as the number of jobs generated by \$100,000 of spending (when the dependent variable is the employment rate).

Table 3, Columns 1-3, demonstrate that EERE spending has a strong employment multiplier, whereby a \$100,000 increase in EERE spending generates 3.2 jobs contemporaneously, 5.8 jobs in 1-year and 7.4 jobs in 2-years. Furthermore, and similar to Shoag (2013), I decompose this effect into changes in labor force and unemployment rates, respectively. I find that the bulk of the effect of EERE spending on employment stems from increased labor force participation. Columns 1-3 suggest that a \$100,000 increase in EERE spending creates 3.2 jobs contemporaneously while drawing 3.4 people into the labor force and pushing 0.2 people into unemployment.

In comparison, Columns 4-6 in Table 3 replicate the same analysis but with non-EERE spending. Results show that a \$100,000 increase in non-EERE spending actually has an insignificant multiplier effect on labor market dynamics.

The results on employment multipliers go hand in hand with the output multipliers estimated in Table 1. Output increases more with EERE spending than with non-EERE spending, which creates greater ripple effects in the economy and thus leads to more hiring as the economy grows (EPA, 2020; IEA, 2020a). Finally, from a more theoretical point of view, Ramey (2020) explains that for the government spending to have a short-run effect on output then it must be via labor input since both private and public capital tend to be relatively fixed in the short-run.

### 7.2.1 Is the green employment multiplier this high?

Many studies to date have confirmed that green projects have stronger employment spillovers than non-green thereby strengthening the case for a green recovery. Garrett-Peltier (2017) analyzes the short-to-medium term employment impacts of energy efficiency and renewable energy using a synthetic industry approach where she treats clean energy spending as a demand shock. She finds that, on average, spending \$1 million in renewable energy or energy efficiency would generate 7.49-7.72 full-time equivalent jobs, while the same amount of spending in fossil fuels would only generate 2.65 full-time equivalent jobs. She suggests three reasons why green energy spending exhibit higher employment multipliers: (i) higher labor intensity; (ii) higher domestic content; and (iii) lower average compensation of workers. Moreover, a recent report by IEA also shows that energy efficiency installations and solar PV together have the highest employment investment-multipliers, generating 10-15 jobs for every million dollars invested owing to the labor intensity of these projects (IEA, 2020b).

The fact that green energy sectors are more labor intensive than fossil fuel production corroborates with my findings for the US in Table 3 and also findings from other countries. For example, Tourkolias and Mirasgedis (2011) find that developing the renewable energy power sector in Greece will generate at least the same number, if not more, jobs than the fossil fuel power sector. Markaki et al. (2013) also finds similar findings for Greece whereby green investments of 47.9 billion euros in green energy would generate 108,000 jobs over 2010-2020 (that is 4.4 jobs generated by 100,000 euro investment in green energy) with the bulk of employment generation coming from energy saving projects in buildings and transport in comparison to power generation from renewable energy sources. Moreover, Malik et al. (2014) focus on Australia and find that the future biofuel industry will be employment-positive, that is it will generate more jobs than those lost in the petrol supply chain throughout Australia's green transition. Finally, Lehr et al. (2012) analyze labor market implications of large investment into renewable energy in Germany and find that, under sensible assumptions on the development of renewable energy markets and Germany's involvement in these markets, expansion in renewable energy can lead to an increase of up to 150,000 in net employment by 2030.

Another explanation for why green projects have larger employment multipliers is explained by Hepburn et al. (2020) as they elaborate that green projects require labor at all skill levels (from construction workers to execute a building retrofit to an engineer to build a more efficient wind turbine) which feeds into higher employment multipliers. Additionally, the fact that non-green projects are more import dependent (Jacobs et al., 2012), this means that a smaller fraction of the investment budget in non-EERE projects will be available for labor hiring given import expenses (Batini et al., 2021). This also means that their higher capital intensity renders them susceptible to longer implementation delays which suppresses the productivity of capital and consequently labor demand (Leeper et al., 2010).

## 7.3 Investment Multipliers

In this subsection, I investigate the effect of the DoE spending in EERE and non-EERE activities on aggregate investment. The data used in my analysis so far is only sourced from the Department of Energy and is therefore not exhaustive of all federal spending in EERE or non-EERE activities in the United States. In fact, federal transfers to local governments might crowd-in further public spending (from local governments and state expenditures) and also private sector investment, known as the *flypaper effect*. In what follows, I show that green projects tend to crowd in investments from private and other public sources more so than non-green projects. One potential reason could be that green projects are more *shovel-ready*, i.e. fast-acting, and are subject to less delays in implementation which in turn crowds in more investment.

**Table 3:** Employment Multipliers

| | Effect of EERE Spending | | | Effect of Non-EERE Spending | | |
|---|---|---|---|---|---|---|
| | (1) Employ-ment | (2) Labor Force | (3) Unemploy-ment | (4) Employ-ment | (5) Labor Force | (6) Unemploy-ment |
| Impact Multiplier | 3.218*** | 3.380** | 0.162 | -0.378 | 0.261 | 0.638 |
| | [0.955] | [1.603] | [0.804] | [0.675] | [0.636] | [0.438] |
| 1-Year Multiplier | 5.767*** | 6.597*** | 0.831 | -0.412 | 0.544 | 0.956** |
| | [0.814] | [1.134] | [0.882] | [0.977] | [0.825] | [0.419] |
| 2-Year Multiplier | 7.376*** | 8.278*** | 0.902 | -0.668 | 0.417 | 1.085** |
| | [1.027] | [2.132] | [1.497] | [1.226] | [1.109] | [0.443] |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variables are the percentage point changes in employment, labor force participation, and unemployment rates over the horizon considered. Independent variable is the change in real green (or non-green) spending per capita as a share of lagged state-level output per capita over the horizon considered. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states. The impact, 1-year and 2-year multipliers are estimated using 637, 587 and 537 state-year observations, respectively.

Data on total investments in energy from public and private sources is only available at the national level. To the best of my knowledge, there is no exhaustive data source on public and private investment in energy at the state-level in the US. As such, I utilize annual data from the Energy Information Administration (EIA) on total (private and public) annual investment in green and non-green energy sources in the United States. In Figure 6, I show in the left panel a strong positive correlation between annual DoE EERE spending and annual total green energy investment at the national level, while I show in the right panel that the correlation between non-green DoE spending and total non-green spending is flat. This suggests that green investments by DoE tend to crowd in more investment (either from private or other public sources or both) than non-green investments in the short-run.

Knowing that the fiscal multiplier is meant to capture the change in output driven by a change in public spending $\frac{\partial y_{i,t}}{\partial g_{i,t}}$, one can apply chain rule to formalize the crowding in channel more explicitly:

$$\frac{\partial y_{i,t}}{\partial g^e_{i,t}} = \underbrace{\frac{\partial y_{i,t}}{\partial I^e_{i,t}} \cdot \frac{\partial I^e_{i,t}}{\partial g^e_{i,t}}}_{\text{investment channel}} + \underbrace{\Omega_t}_{\text{other channels}}, \text{ such that } e \in \{green, nongreen\} \tag{4}$$

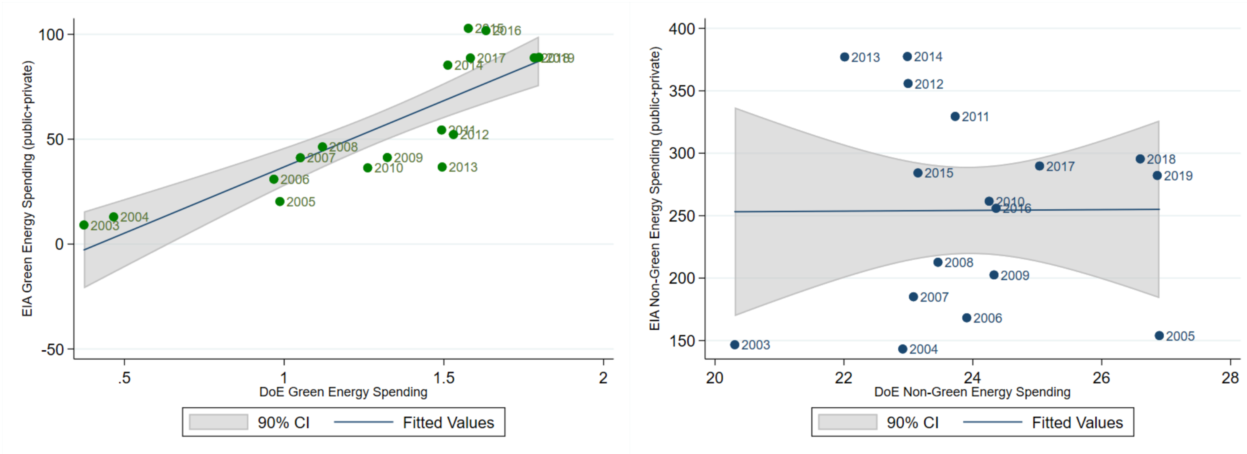


**Figure 6:** Correlation Between DoE and Total Energy Spending in United States

where $I^e_{i,t}$ represents real total green (or non-green) spending per capita in state $i$ year $t$, $g^e_{i,t}$ is real DoE spending per capita in green (or non-green), $\frac{\partial y_{i,t}}{\partial I^e_{i,t}}$ is the green (or non-green) investment multiplier, and $\frac{\partial I^e_{i,t}}{\partial g^e_{i,t}}$ measures the crowding in effect.

Since there is no exhaustive measure of state-level spending in energy from private and public sources (be it for green or non-green), I cannot quantify $\frac{\partial y_{i,t}}{\partial I^e_{i,t}}$ or $\frac{\partial I^e_{i,t}}{\partial g^e_{i,t}}$. For the sake of exposition, I perform a mechanical exercise to compare the extents of crowding in (or lack thereof) with each energy type. I construct a state-level data series of proxy *actual* total spending in green and non-green, $I^e_{i,t}$, by breaking down the EIA national time series across states using the DoE state shares within a given year as follows:

$$I^{actual,e}_{i,t} = I^{actual,e}_{t} \cdot \frac{g^{actual,e}_{i,t}}{\sum_{i=1}^{50} g^{actual,e}_{i,t}}, \text{ such that } e \in \{green, nongreen\} \tag{5}$$

where $I^{actual,e}_{t}$ is the actual total (private and public) spending by EIA at the national level in year $t$.

In order to generate an unanticipated variation in total spending similar to DoE data, I also construct a requested series for $I^e_{i,t}$ at each state-year observation such that:

$$I^{requested,e}_{i,t} = I^{actual,e}_{i,t} \cdot \frac{g^{requested,e}_{i,t}}{g^{actual,e}_{i,t}}, \text{ such that } e \in \{green, nongreen\} \tag{6}$$

In Table 4, I show the empirical estimates of the investment channel highlighted in Equation 4. In Panel A, I focus on green investments, and show in Column 1, the aggregate green investment multiplier by regressing changes in real output per capita on unanticipated changes in total green investment (from public and private sources). The green investment multiplier is positive and loosely significant at the 10% (p-values are 12.8%, 10.1% and 10.2%, respectively). In Column 2, I show the outcome of regressing unanticipated changes in total green investment on unanticipated changes in DoE green investment, which will proxy the extent of crowding in. Results show that $1 of green spending by DoE crowds in $38.7 in total green spending contemporaneously, $37.8 in 1-year and $39.3 in 2-years. Finally, as a litmus test, Column 3 presents the product of the two estimates which should square up quite closely with the green multiplier estimated in Table 1 since I constructed the state-level total investment dataset mechanically using DoE shares.

In Panel B of Table 4, I repeat the same exercise but with non-green investments. What is important to highlight is that Column 2 shows that non-EERE investments do in fact crowd in total investment, but to a lesser extent than green investments. In fact, taking the ratios of crowding in from Panel A and Panel B, I find that a $1 increase in green spending crowds in 4 times as much total investment as a $1 increase in non-green spending does contemporaneously, and 3.2 times more within 1- and 2-years, respectively.

Moreover, there might be other demand channels through which the effect of DoE spending can affect state-level output. In Appendix G, I investigate cross-border effects as a potential demand channel captured by $\Omega_t$ in Equation 4. Overall evidence of cross-border effects is weak with both types of spending, green and non-green.

Finally, the crowding in results align with the employment multipliers and further validate the overall output mutlipliers by eradicating forecastibility concerns in my data. Ramey (2011) explains this from the lens of a neoclassical model with unproductive government spending financed by lump-sum taxes. She elaborates that when government spending is indeed unforecastible, then an increase in government spending lowers private wealth contemporaneously (via the aggregate resource constraint). As such, consumers respond to the negative wealth effect by supplying more labor, consuming less, and investing more. The increase in labor supply will thus increase output in the short-run, which my results on green output, employment and investment multipliers confirm.

### 7.3.1 Micro-evidence of crowding in with green investments and potential explanations

I examine micro-data on DoE contracts and square it with prominent theoretical findings in the literature to better understand why green can possibly crowd in more investment from other sources than non-green. I look at the universe of all awards by DoE from usaspend-

**Table 4:** Investment Multipliers

| **Panel A: Effect of Green Spending** | Investment Multiplier $\frac{\partial y_{i,t}}{\partial I_{i,t}^{green}}$ | Crowding In $\frac{\partial I_{i,t}^{green}}{\partial g_{i,t}^{green}}$ | DoE Multiplier $\frac{\partial y_{i,t}}{\partial g_{i,t}^{green}}$ |
|---|---|---|---|
| Impact | 0.03 | 38.71*** | 1.01 |
| | [0.0168] | [0.322] | |
| 1 Year | 0.0601 | 37.83*** | 2.27 |
| | [0.036] | [2.64] | |
| 2 Year | 0.0896 | 39.32*** | 3.52 |
| | [0.0538] | [3.002] | |

| **Panel B: Effect of Non-Green Spending** | Investment Multiplier $\frac{\partial y_{i,t}}{\partial I_{i,t}^{nongreen}}$ | Crowding In $\frac{\partial I_{i,t}^{nongreen}}{\partial g_{i,t}^{nongreen}}$ | DoE Multiplier $\frac{\partial y_{i,t}}{\partial g_{i,t}^{nongreen}}$ |
|---|---|---|---|
| Impact | -0.0235 | 9.416*** | -0.22 |
| | [0.0462] | [1.486] | |
| 1-Year | 0.01 | 11.39*** | 0.06 |
| | [0.0835] | [1.476] | |
| 2-Year | 0.0373 | 11.83*** | 0.44 |
| | [0.108] | [1.433] | |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. In the first column, the dependent variable is the growth in real state-level output per capita over the horizon considered, and the independent variable is the change in real total (private and public) spending per capita as a share of lagged output over the horizon considered. In the second column, the dependent variable is the real total (private and public) spending per capita as a share of lagged output over the horizon considered, and the independent variable is the real DoE spending per capita as a share of lagged output over the horizon considered. The third column is the product of the point estimates in the first two columns. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states. The impact, 1-year and 2-year multipliers are estimated using 637, 587 and 537 state-year observations, respectively.

ing.gov and classify awards as green or non-green. I classify any contract with descriptions containing the following keywords as *green*: "Solar energy", "wind energy", "bioenergy technologies", "clean energy", "energy efficiency", "renewable energy", "weatherization", "building technologies", "carbon capture", "carbon storage", "water power", "geothermal technologies”, “hydrogen & fuel cell technologies”. All other programs will be classified as non-green. There are 14,529 awards given by DoE between 2008-2021; 2,108 of which are classified as green using the textual algorithm described above (i.e. 14.5% of total awards are classified as green).

Amongst the rich variables presented for each award in the micro-data, one variable presents the breakdown of funding for every contract between federal and non-federal sources. Looking at the averages of each of these shares within green and non-green projects, I find that 94.95% of funding for non-green projects is federal compared to 74.76% with green projects. This further confirms that green projects tend to crowd in or rely more on non-federal sources of energy, which could be state and local funding or private sector funding, than non-green projects.

Additionally, the micro-data on awards also presents details on both the expected and actual start and end dates for the projects. On average, a green project is expected to take 2.58 years to be completed, while a non-green project takes 3.11 years. More importantly, a green project on average is subject to 0.47 years of delay in implementation while non-green projects are subject to 1.16 years of delay (approximately 2.5 times more). This is not surprising as it has been well-documented in the literature that green projects tend to be more “shovel ready” than non-green projects hence the policy push to invest more in green (Hepburn et al., 2020). One reason green projects are faster-acting than non-green could be because they are less reliant on imports and more so on domestic inputs (Garrett-Peltier, 2017). This is intuitive given the context of our data as well which are mostly related to building retrofits and efficiency installations that are easier to roll over and are less susceptible to offshoring of imports (Jacobs et al., 2012), as also evident from the sectoral multipliers in Section 7.1.

**Table 5:** DoE Awards: Green vs. Non-Green

| | Non-Green Projects | Green Projects |
|---|---|---|
| **Award Count** | | |
| Number of Awards | 12,421 | 2,108 |
| **Funding Breakdown** | | |
| Avg Federal Share of Funding | 94.95% | 74.76% |
| Avg Non-Federal Share of Funding | 4.65% | 23.98% |
| **Implementation Duration** | | |
| Avg Years of Expected Implementation | 3.11 | 2.58 |
| Avg Years of Actual Implementation | 4.27 | 3.05 |
| Avg Years of Delay | 1.16 | 0.47 |

Connecting the above stylized facts with theory, one reason implementation delays (and longer project durarations) could lead to less crowding in with non-green projects is because of their effect on marginal productivity of capital. As Leeper et al. (2010) clearly put it, implementation delays associated with public projects can discourage private investment in the short-run since private investment projects do not exhibit as substantive delays as public projects. Private investment will therefore only pick up later when the public capital is expected to kick in and increase the productivity of private investments. As such, longer implementation delays can crowd out private investment. Additionally, implementation delays on their own can mute the multiplier as the expectations of government spending will generate a positive wealth effect under the premise of productive public capital, this will in turn cause labor and output to rise less (or even decline) depending if the positive wealth effect partially (or more than) offsets the negative wealth effect that is expected from increasing government purchases. As such, implementation delays can mute the benefits of government spending via two channels: discouraging private investment and generating a positive wealth effect.

# 8 Predictions of an Open-Economy Model with Public Capital

Similar to other papers in the fiscal multiplier literature, the green spending multiplier might reflect other key issues such as changes in preferences, regulations and other manifestations of structural transitions to a low-carbon economy that are especially relevant in the policy circles now. In order to have a deeper understanding of the underlying differences between the green and non-green output multipliers, I compare in this section the empirical predictions to those of an open economy model with public capital.

I build on the theoretical framework developed by Leduc and Wilson (2013) to evaluate the multiplier of green and non-green energy public investment. The theoretical framework involves an open economy model to replicate the empirical setting and remove the effects of nation-wide shocks, monetary policy and federal fiscal policy, à la Nakamura and Steinsson (2014). It also builds on seminal contributions by Baxter and King (1993), Leeper et al. (2010) and Ramey (2020) who highlight the role of public capital and some of its unique features compared to other forms of public spending, such as delays in spending and implementation.

The model consists of a cashless economy made of two regions, Home ($H$) and Foreign ($F$), that belong to a fiscal and monetary union. In comparison with my empirical setting, the

Home region will resemble a US state and it is where the government spending shock will occur, while the Foreign region will represent the rest of the economy. The population of the entire economy is normalized to 1. The two regions are of different sizes, Home region has population of measure $n$ and Foreign region has population of measure $(1 - n)$, respectively.

The national government invests in public infrastructure projects in the two regions and finances these investments by levying taxes. Each region specializes in one type of tradable good, produced in a number of differentiated industries defined over a continuum of unit mass. These varieties are indexed by $h \in$ [0,1] for Home region and $f \in$ [0,1] for Foreign region. A firm producing variety $h$ (or $f$) in each industry is a monopolistic supplier of one good, and they combine public and private capital with domestic labor to produce one variety of the good. The model features complete financial markets.[14]

In what follows, I present the household preferences, monetary and fiscal policy, and production structures in both regions. As standard in the literature, I will focus on the Home region bearing in mind that similar expressions hold for the Foreign region. Variables referring to Foreign entities will be marked with an asterisk.

## 8.1 The Household's Problem

The Home region is populated by a continuum of infinitely-lived households who seek to maximize their expected value of lifetime utility given by

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, L_t), \tag{7}$$

where $\beta \in (0, 1)$ denotes household's subjective discount factor, $C_t$ denotes household's consumption basket, and $L_t$ household's hours worked.[15]

Home household's consumption basket is a composite of Home and Foreign produced goods. Households in Home region consume all the different varieties of the tradable goods produced in both regions, with $c_t(h)$ representing the consumption of Home brand $h$ and $c_t(f)$ representing the consumption of Foreign brand $f$, both at time $t$. There is a continuum of measure one of brands in each region, and the brands are imperfect substitutes of one another within

[14] Nakamura and Steinsson (2014) discuss the government spending multiplier in incomplete markets, however their model abstracts from public capital.

[15] Similar to Leduc and Wilson (2013), I do not index households by type for easier exposition.

every region with an elasticity of substitution $\eta$:

$$C_{H,t} = \left[ \int_0^1 C_t(h)^{\frac{\eta-1}{\eta}} dh \right]^{\frac{\eta}{\eta-1}} \quad \text{and} \quad C_{F,t} = \left[ \int_0^1 C_t(f)^{\frac{\eta-1}{\eta}} df \right]^{\frac{\eta}{\eta-1}}. \tag{8}$$

Home household's full consumption basket, $C_t$, is a composite of Home and Foreign produced goods given by:

$$C_t = \left[ a_H^{\frac{1}{\phi}} C_{H,t}^{\frac{\phi-1}{\phi}} + (1-a_H)^{\frac{1}{\phi}} C_{F,t}^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}} \tag{9}$$

where $\phi$ denotes the elasticity of substitution between home and foreign goods and $a_H$ determines the household's degree of home bias (or lack thereof). If $a_H > n$, then household preferences are biased towards home goods.

Goods markets are completely integrated across regions. Home and foreign households thus face the same prices for each of the differentiated brands produced in the economy. Prices for home produced varieties are denoted by $P_t(h)$ and those for foreign produced varieties are denoted by $P_t(f)$ and they are all expressed in the common national currency. The price sub-indices for home and foreign produced goods are given by $P_{H,t}$ and $P_{F,t}$, respectively, and the aggregate price index associated with the consumption aggregator in the Home region is given by $P_t$.

The household in the Home region has four sources of income: (i) labor income, $W_t L_t$; (ii) rental of private capital to firms, $R_t K_t$, (iii) state-contingent payoffs of the portfolio of financial securities held by households, $B_t(s)$ in state of nature $s$,[16] and (iv) profits of Home firms which are rebated back to households as dividends, $\Pi_t(h)$.

Similar to Leduc and Wilson (2013), I assume that public infrastructure spending is financed with a consumption tax levied by the government in time $t$, $\tau_t^c$.[17] As such, households in the Home region use their disposable income to consume, invest in domestic (private) capital, and buy state-contingent assets $B_{t+1}(s)$ priced at $M_{t,t+1}$.

Aggregate private investment is assumed to be a CES composite of Home and Foreign tradable goods with identical weight and elasticity as with aggregate consumption. Moreover, private

[16]Households have access to complete financial markets in this economy. Nakamura and Steinsson (2014) discuss a version of their model with incomplete financial markets across regions.

[17]Note that given this is an open economy setup, the effect of federal policy is differenced out similar to the empirical setup with introduction of time fixed effects.

capital accumulates according to the following law of motion:

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{10}$$

where $\delta \in (0,1)$ denotes the depreciation rate of private capital.

As such, the representative Home household faces the following flow budget constraint

$$(1+\tau_t^c)(P_{H,t}C_{H,t}+P_{F,t}C_{F,t})+P_tI_t+E_t\Big[\int_s M_{t,t+1}B_{t+1}(s)\Big] \leq W_tL_t+R_tK_t+B_t(s)+\int_0^1 \Pi_t(h)dh. \tag{11}$$

In each period, households choose how much to consume, how much of each differenced good to consume, how many of hours to work and what assets to purchase. Household's intertemporal consumption choice is given by the consumption Euler equation:

$$\frac{U_c(C_{t+1}, L_{t+1})}{U_c(C_t, L_t)} = \frac{M_{t,t+1}}{\beta} \cdot \frac{P_{t+1}}{P_t} \cdot \frac{1+\tau_{t+1}^c}{1+\tau_t^c}, \tag{12}$$

as well as a standard transversality condition. In addition, households face an intra-temporal trade-off between consumption and labor given by the following condition:

$$\frac{U_l(C_t, L_t)}{U_c(C_t, L_t)} = \frac{W_t}{(1+\tau_t^c)P_t}. \tag{13}$$

The demand curves of Home household's optimal consumption and investment choice of home and foreign goods are given by:

$$C_{H,t} = a_H C_t \Big(\frac{P_{H,t}}{P_t}\Big)^{-\phi} \quad \text{and} \quad C_{F,t} = (1-a_H)C_t\Big(\frac{P_{F,t}}{P_t}\Big)^{-\phi}, \tag{14}$$

$$I_{H,t} = a_H I_t \Big(\frac{P_{H,t}}{P_t}\Big)^{-\phi} \quad \text{and} \quad I_{F,t} = (1-a_H)I_t\Big(\frac{P_{F,t}}{P_t}\Big)^{-\phi}, \tag{15}$$

and demand curves of consumption and investment of each of the differentiated brands are given by the following:

$$C_t(h) = \left(\frac{P_t(h)}{P_{H,t}}\right)^{-\eta} C_{H,t} \quad \text{and} \quad C_t(f) = \left(\frac{P_t(f)}{P_{F,t}}\right)^{-\eta} C_{F,t}, \tag{16}$$

$$I_t(h) = \left(\frac{P_t(h)}{P_{H,t}}\right)^{-\eta} I_{H,t} \quad \text{and} \quad I_t(f) = \left(\frac{P_t(f)}{P_{F,t}}\right)^{-\eta} I_{F,t}, \tag{17}$$

where:

$$P_{H,t} = \left[ \int_0^1 P_t(h)^{1-\eta} dh \right]^{\frac{1}{1-\eta}} \quad \text{and} \quad P_{F,t} = \left[ \int_0^1 P_t(f)^{1-\eta} df \right]^{\frac{1}{1-\eta}}, \tag{18}$$

and

$$P_t = \left[ a_H P_{H,t}^{1-\phi} + (1-a_H) P_{F,t}^{1-\phi} \right]^{\frac{1}{1-\phi}}. \tag{19}$$

As previously mentioned, the problem of the foreign household is analogous.

## 8.2 Fiscal and Monetary Policies

The federal government conducts fiscal and monetary policy. As highlighted by Leeper et al. (2010) and Ramey (2020), public infrastructure spending has two distinctive features compared to other forms of public spending which has to do with being subject to two types of delay that will affect the aftermath of the fiscal policy intervention: (i) a delay between what was authorized to spend and what was actually outlayed, denoted by "time-to-spend"; (ii) delay in implementation, denoted by "time-to-build".

Building on Leduc and Wilson (2013), I denote the federal grants per capita for public capital in energy type $e$, which could be *green* or *non-green*, by $A^e_{H,t}$. The apportionment processes is assumed to follow an AR(1) process:

$$A^e_{H,t} = (1-\rho^e_A)\bar{A}^e_H + \rho^e_A A^e_{H,t-1} + \epsilon^e_{A,t}, \quad \text{where } e \in \{green,\ \ nongreen\}, \tag{20}$$

and $\bar{A}^e_H$ is the average level of region H's apportionments and $\epsilon^e_{A,t}$ is the unanticipated spending shock in energy type $e$. Next, I denote the actual outlayed government infrastructure spending per capita (net of inter-governmental transfers) in Home region in energy type $e$ by $I^e_{H,t}$, which evolves according to the following process:

$$I^e_{H,t} = \sum_{n=0}^{N-1} \Phi^e_n A^e_{H,t-n}, \quad \text{where } e \in \{green,\ \ nongreen\}, \tag{21}$$

and $\sum_{n=0}^{N-1} \Phi^e_n = 1$. The $\Phi_n$'s determine the spend-out rates unique to each energy type of energy spending, and reflect *time-to-spend* whenever $\Phi_0 \neq 1$.

Next, I introduce *time-to-build* whereby government funds outlayed in time $t$ impact the public capital stock $J$ periods later:

$$K^e_{H,t+1} = (1-\delta^e)K^e_{H,t} + I^e_{t-J}, \quad \text{where } e \in \{green, \;\; nongreen\}, \tag{22}$$

and $\delta^e$ is the rate of depreciation of public capital in energy type $e$. As such, there is a delay in implementation whenever $J > 0$.

I assume that public investment in energy type $e$ in a region is a CES composite good of the differentiated goods in that region *only*, and for simplicity, it takes the same form and elasticity as consumption and private investment, such that:

$$I^e_{H,t} = \left[\int_0^1 I^e_t(h)^{\frac{\eta-1}{\eta}} dh\right]^{\frac{\eta}{\eta-1}}, \quad \text{where } e \in \{green, \;\; nongreen\}. \tag{23}$$

As previously discussed, the government levies consumption tax, $\tau_c$, to finance its spending such that its budget balances according to the following:

$$\tau^c\Bigg(nP_tC_t + (1-n)P^*_tC^*_t\Bigg) = nP_{H,t}I^e_{H,t} + (1-n)P^*_{F,t}I^e_{F,t}, \tag{24}$$

where asterisk denotes foreign variables and public investment $I^e_t$, which could be in green or non-green energy.

Monetary policy is common to the two regions as it is federal. The policy consists of a Taylor rule for the economy-wide nominal interest rate that is a function of aggregate consumer price inflation gap, $\hat{\pi}^{ag}$, and aggregate output gap, $\hat{y}^{ag}_t$, as follows:

$$\hat{r}_t = \rho_R\hat{r}_{t-1} + \beta_\pi(1-\rho_R)\hat{\pi}^{ag}_t + \beta_y(1-\rho_R)\hat{y}^{ag}_t, \tag{25}$$

where hatted variables denote percentage deviations from the steady-state. $\hat{r}_t$ is the nominal interest rate and it responds to the weighted sums of consumer price inflation and output gap in the two regions, such that:

$$\hat{\pi}^{ag}_t = n\hat{\pi}_t + (1-n)\hat{\pi}^*_t \qquad \text{and} \qquad \hat{y}^{ag}_t = n\hat{y}_t + (1-n)\hat{y}^*_t. \tag{26}$$

## 8.3 Firms

There is a continuum of firms in the Home region. Firms are monopolistic in producing their differentiated brand $h$. Each firm produces output $y_t(h)$ by employing three factors of production: labor, private capital and public capital, according to the following Cobb-Douglas production function

$$Y_t(h) = L_t(h)^{\alpha} K_{t-1}(h)^{1-\alpha} K^e_{t-1}(h)^{\alpha_e}, \quad \text{where } \alpha \in (0,1), \;\; \alpha_e \geq 0 \tag{27}$$

where $K^e_{t-1}(h)$ represents the public capital in energy type $e$ used in the production of good $h$. In the baseline model, this public capital will either be green energy or non-green energy, such that: $K^e_{t-1}(h) \in \{K^g_{t-1}(h), K^{ng}_{t-1}(h)\}$. Similar to previous research on public capital by Baxter and King (1993), Leduc and Wilson (2013), Leeper et al. (2010) and Ramey (2020), the elasticity of output to public capital in the production function $\alpha_e$ is positive, i.e. public capital is productive, which makes the production function increasing returns to scale in public capital. This means that for given labor and private capital, increasing public capital will lead to higher output as it will raise the marginal productivities of both inputs.

Similar to Leduc and Wilson (2013), there are no trade frictions across the two regions so the law of one price holds in this model. However, there are frictions arising from nominal rigidities as firms' prices are set according to a Calvo scheme (Calvo, 1983). At any given time, a firm can re-optimize its price with probability $(1-\theta)$ or leave its price unchanged with probability $\theta$. When a firm can update its price, it will act to maximize its expected discounted sum of profits, thus turning the firm's profit maximization problem into a dynamic one, as follows:

$$\Pi_t(h) = E_t\Bigg\{ \sum_{k=0}^{\infty} M_{t,t+k}\theta^k \Big[ P_t(h)Y_{t+k}(h) - MC_{t+k}Y_{t+k}(h) \Big] \Bigg\}, \tag{28}$$

where $MC_t$ is the nominal marginal cost for the firm. The marginal cost is not indexed by $h$ since all firms face the same factor prices and have identical production functions, therefore they all end up facing the same marginal cost. Also, note that firms' profits, which are later rebated as dividends to households, have to be discounted with the same stochastic discount factor $M_{t,t+1}$ as that of the households to align the incentives. Finally, firms must satisfy the demand for their brand $h$ which comes from five sources: home consumption, foreign consumption, home private investment, foreign private investment and home public investment, as represented by:

$$Y_t(h) = \left(\frac{P_t(h)}{P_{H,t}}\right)^{-\eta} \underbrace{\left(nC_{H,t} + (1-n)C^*_{H,t} + nI_{H,t} + (1-n)I^*_{H,t} + nI^e_{H,t}\right)}_{Y_{H,t}}. \tag{29}$$

Optimal price setting by firm $h$ in periods when it can adjust its price is given by:

$$P^*_t(h) = \frac{\eta}{\eta - 1} \frac{\sum_{k=0}^{\infty} M_{t,t+k}\theta^k MC_{t+k} Y_{H,t+k} P_{H,t+k}{}^{\eta}}{\sum_{k=0}^{\infty} M_{t,t+k}\theta^k Y_{H,t+k} P_{H,t+k}{}^{\eta-1}}. \tag{30}$$

Since all elements in Equation (30) are independent of $h$, then the optimally reset equilibrium price is symmetric to all firms, so we can denote $P^*_t(h)$ with $P^*_{H,t}$.

The optimal price $P^*_{H,t}$ can also be written recursively such that $P^*_{H,t} = \frac{\Gamma_t}{\Sigma_t}$, where:

$$\Gamma_t = \frac{\eta}{\eta - 1} MC_t Y_{H,t} + \theta E_t M_{t,t+1} \Gamma_{t+1}, \tag{31}$$

$$\Sigma_t = Y_{H,t} + \theta E_t M_{t,t+1} \Sigma_{t+1}. \tag{32}$$

## 8.4 Calibration of Preferences and Technology

In the baseline calibration, I largely follow the calibration of Leduc and Wilson (2013) except when it comes to the parameters related to the public capital. I set the size of the Home region to correspond to a U.S. state in the empirical setup such that $n = 1/50$. Household preferences are separable in consumption and labor and take the following form:

$$U(C_t, L_t) = \frac{C_t^{1-\sigma}}{1-\sigma} - \psi \frac{L_t^{1+\zeta}}{1+\zeta}, \tag{33}$$

where the coefficient of risk aversion, $\sigma$ is set to 1, and $\zeta$ is set to 1.33 to imply a Frisch elasticity of labor supply to be $1/1.33 = 0.75$. The model is set at annual frequency with $\beta = 0.96$. The elasticity of substitution across varieties within a region, $\eta$ is set to 6 to target a markup of 20% in the steady-state. The elasticity of substitution between home and foreign goods, $\phi$, is set to 4.

With respect to firms' production functions, labor share, $\alpha$ is set at 70%. The output elasticity of public capital $\alpha^e$ is set to match the steady-state share of DoE energy spending in the United States which is 0.2% of output, knowing that $\frac{I^e}{Y} = \frac{\delta}{1/\beta - 1 + \delta} \cdot \alpha^e$. Moreover, the initial levels of DoE spending in green and non-green energy as a share of GDP are

$I^{green}/Y = 0.011\%$ and $I^{nongreen}/Y = 0.168\%$, respectively.

For the green and non-green energy public capital apportionment processes, I set the persistence of the shocks to apportionments to 0.56 for green capital and 0.79 for non-green capital, each obtained from regressing state-level unanticipated DoE spending on its one year lag including state and time fixed effects.

As to delay in spending for public capital, I refer to the micro-data on all awards by the DoE available at the transaction level. I replicate the same methodology as before and classify projects as green or non-green using textual analysis. I calculate the spending rates for every project by calculating the share of each transaction disbursed (in a given year) from total funding in that project (across all the project's years). I then calculate the averages of all those shares for green projects and non-green projects separately. I find that for both types of energy capital, more than 70% of the funds are obligated in the first year, and the remainder is split in the following three years. Estimates of $\Phi_t^g$'s and $\Phi_t^{ng}$'s are presented in Table 6.

As to delay in implementation associated with public capital, I also refer to the DoE micro-data on awards and calculate the difference between the actual duration of implementation and the expected duration of implementation which, when rounded to closest year, shows that $J^g = 0$ and $J^{ng} = 1$, as shown in Table 5. Finally, the depreciation of the public capital stock is set at 10% for both green and non-green energy, similar to Leduc and Wilson (2013).

Regarding the frequency at which firms update their prices, I set $\theta = 0.75$ such that firms reoptimize their prices on average once a year, in line with Nakamura and Steinsson (2014) and Leduc and Wilson (2013). While monetary policy will not play an important role in the magnitude of the local multiplier as it will be differenced out, the coefficients in the Taylor rule are given by $\rho_R = 0.8$, $\beta_\pi = 1.5$, and $\beta_y = 0.5$.

## 8.5 Quantitative Results

In this section, I solve the model twice, replacing the public capital with green and non-green energy, respectively. In each exercise, I simulate a 1 percent shock in government spending in the examined energy public capital. Figure 7 reports the theoretical counterpart of the green and non-green multipliers which replicates the same qualitative features of both green and non-green multipliers, and roughly same quantitative magnitudes. The green multiplier rises directly upon impact as it is not subject to implementation delays, while the non-green multiplier is stalled for the first year, although its magnitude still does not change much throughout the simulated period.

**Table 6:** Calibration

| Parameters | Description | Values | Source |
|---|---|---|---|
| **Open Macro** | | | |
| $n$ | size of Home region | 1/50 | Leduc and Wilson (2013) |
| $a_H$ | degree of Home bias | 0.69 | Leduc and Wilson (2013) |
| **Household Utility** | | | |
| $\sigma$ | degree of risk aversion | 1 | Leduc and Wilson (2013) |
| $\xi$ | inverse of Frisch elasticity | 1.33 | Leduc and Wilson (2013) |
| $\beta$ | discount factor | 0.96 | Leduc and Wilson (2013) |
| **Demand** | | | |
| $\eta$ | elas of sub across brands within a region | 6 | Leduc and Wilson (2013) |
| $\phi$ | elas of sub between home and foreign goods | 4 | Leduc and Wilson (2013) |
| **Production (Labor and Private Capital)** | | | |
| $\alpha$ | labor share in production function | 0.7 | Leduc and Wilson (2013) |
| $\delta$ | rate of depreciation of private capital | 0.1 | Leduc and Wilson (2013) |
| $\theta$ | degree of price stickiness | 0.75 | Leduc and Wilson (2013) |
| **Production (Public Capital)** | | | |
| $\alpha^e$ | public capital in total energy share in production function | 0.002 | $(I^e/Y) * (1/\beta - 1 + \delta)/\delta$ |
| $\delta^g$, $\delta^{ng}$ | rate of depreciation of public capital | 0.1 | Leduc and Wilson (2013) |
| $J$ | time to build | 0 for green | Micro-data at award level |
| | | 1 for nongreen | Micro-data at award level |
| $I/Y$ | initial levels of public capital as share of output | 0.01% for green | DoE state-level data |
| | | 0.2% for non-green | DoE state-level data |
| **Apportionments** | | | |
| $\rho_A^g$ | degree of persistence | 0.56 | DoE State-level data |
| $\rho_A^{ng}$ | degree of persistence | 0.79 | DoE State-level data |
| $\{\Phi_n^g\}_{n=0}^4$ | spend out rates for green capital | $\Phi_0$=0.73, $\Phi_1$=0.14, | Micro-data at award x transaction level |
| | | $\Phi_3$=0.05, $\Phi_4$=0.09 | |
| $\{\Phi_n^{ng}\}_{n=0}^4$ | spend out rates for non-green capital | $\Phi_0$=0.71, $\Phi_1$=0.12, | Micro-data at award x transaction level |
| | | $\Phi_3$=0.06, $\Phi_4$=0.09 | |
| [1em] | **Monetary Policy** | | |
| $\rho_R$ | Taylor rule, persistence of interest rate | 0.8 | Leduc and Wilson (2013) |
| $\beta_\pi$ | Taylor rule, weight of inflation deviation | 1.5 | Leduc and Wilson (2013) |
| $\beta$ | Taylor rule, weight of output gap | 0.5 | Leduc and Wilson (2013) |

**Notes:** Superscripts $g$ and $ng$ indicate *green* and *non-green* public capital, respectively.

In order to better understand the underlying differences between green and non-green multipliers, I refer back to the calibration strategy and highlight four differences between green and non-green public capital in this model: (i) initial levels of investment in each energy type, (ii) degree of persistence of apportionments, (iii) delays in implementation, and (iv) spending rates. In Panel A of Table 7, I document the contemporaneous green and non-green multipliers which stand at \$2.28 and \$0.38, respectively. I then re-simulate a non-green spending shock while shutting off the aforementioned four differences one at a time. In Panel B of Table 7, I document the contemporaneous non-green multiplier in each experiment and its deviation from the original green multiplier. The four experiments show that changing the initial level of non-green spending to that of green, while keeping other parameters the same as that of non-green capital (i.e. persistence, spending rates, and 1-year implementation delay), reduces the difference between the green and non-green multipliers upon impact by

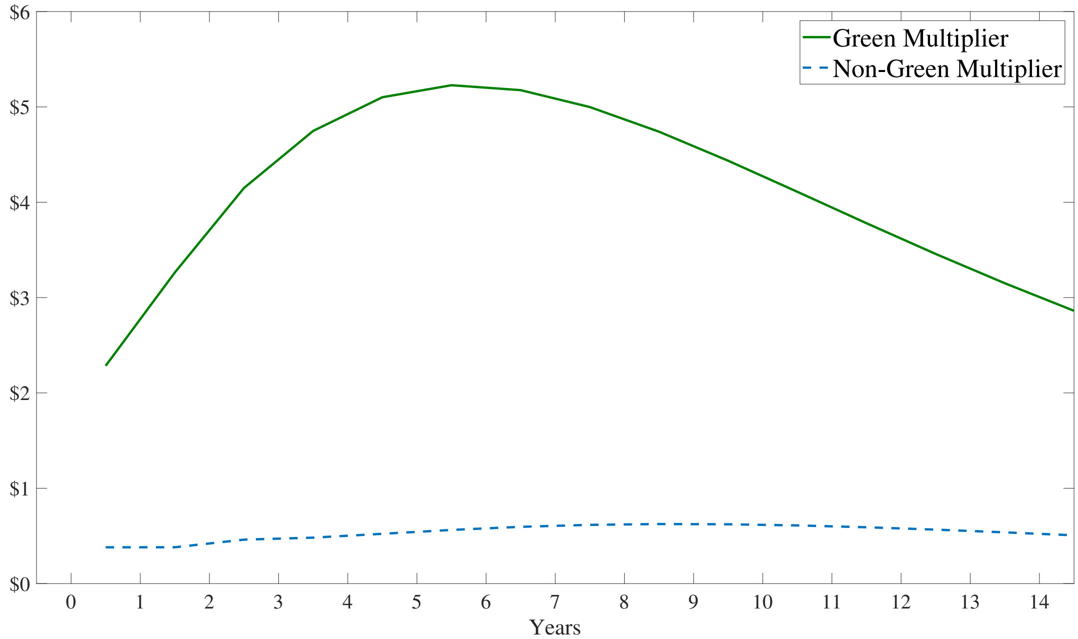


**Figure 7:** Green vs. Non-Green Theoretical Multipliers

86.2%. As such, initial levels of investment are the main reason why green multipliers are larger than non-green. This is not surprising since the further away capital is from its desired steady-state level of energy spending, the larger is its marginal productivity and thus the higher is its multiplier. This corroborates with previously mentioned statistics on how the US has under-invested in green energy relative to non-green as evident from Figure 1 on the breakdown of DoE spending between green and non-green activities and Figure A1 on aggregate green vs. non-green patent activity in the US. This is also perfectly in line with Ramey (2020) whereby the public infrastructure multiplier is larger when the economy is further away from its optimal amount.

In Figure 8, I show the results of the counterfactual experiments across all the simulated years, not just contemporaneously. Again, changing the initial level of non-green energy to that of green has the strongest effect in reducing the wedge between the two multipliers. The non-green multiplier is now close to the green estimates in the first two years, and then even overshoots it year 3 and beyond given that non-green investments depict a larger degree of persistence in apportionments (as calculated from an AR(1) regression using the state-level DoE data, see Table 6).

**Table 7:** Mechanism Decomposition of Impact Multiplier

| Public Capital Type | Changed Mechanism | Multiplier | Green-Nongreen Multiplier | Absolute Share of Difference |
|---|---|---|---|---|
| **Panel A: Theoretical Core Results** | | | | |
| Green Energy | | \$2.28 | | |
| Non-Green Energy | | \$0.38 | \$1.90 | |
| **Panel B: Counterfactual Experiments** | | | | |
| Non-Green Energy | Initial Level as Green | \$2.02 | \$0.26 | 86.2% |
| Non-Green Energy | Persistence as Green | \$0.28 | \$2.01 | 5.5% |
| Non-Green Energy | Delay in Implementation as Green | \$0.45 | \$1.84 | 3.6% |
| Non-Green Energy | Delay in Spending as Green | \$0.40 | \$1.89 | 0.8% |

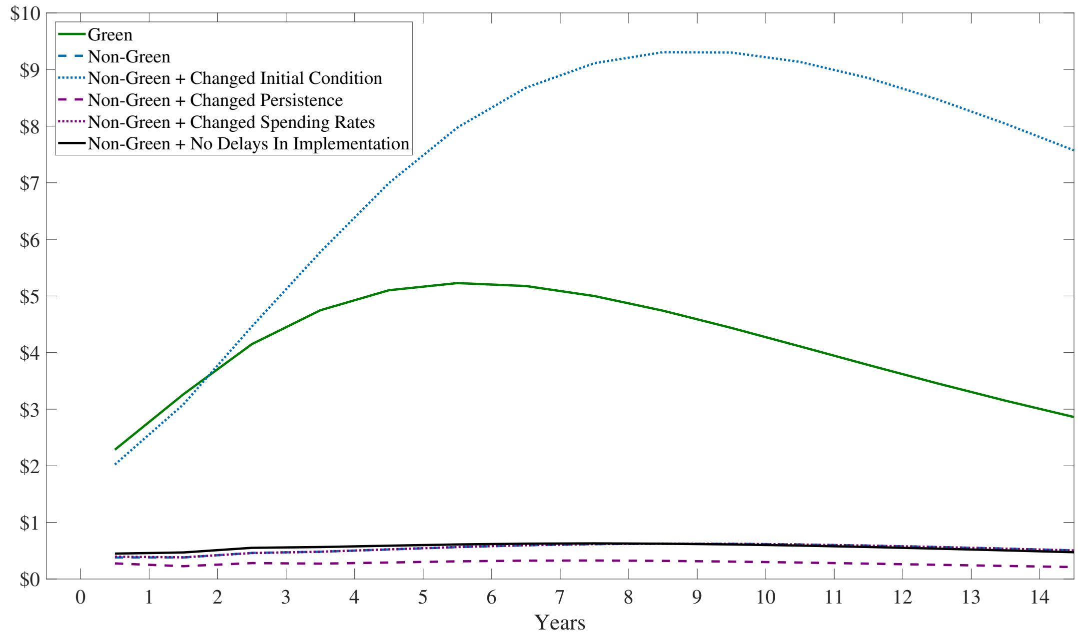


**Figure 8:** Counterfactual Non-Green Multipliers

# 9 Conclusion

Given President Biden's goals to transition to a green low-carbon economy, the United States has to ramp up its energy efficiency installations in buildings, transport and industry and its investments in renewable energy. In order to do so, it is important to understand whether such scaling of green investments will also lead to economic prosperity. In this paper, I provide an estimate of the local green multiplier in the US using a novel state-level dataset on green spending constructed from the Congressional budget reports by the Department of Energy. By exploiting the institutional setup of the Department of Energy coupled with unique features of the apportionment process by the Office of Energy Efficiency and Renewable Energy, I isolate a source of variation in green spending that is unanticipated and exogeneous to current macroeconomic conditions.

I find that a \$1 increase in green investment can increase local output by \$1.1 contemporaneously, \$2.5 in 1-year, and up to \$4 in 2-years. The green estimates are in the upper range of public infrastructure multipliers previously estimated in the literature. Moreover, in comparison to non-green investments by the DoE, green investments have larger output multiplier effects. Results at a more disaggregated level show that green investments also have larger sectoral, employment and investment multipliers than those of non-green investments.

I then compare the green and non-green output multipliers to predictions of an open economy model with public capital, calibrated to green and non-green energy. Model-based counterfactual experiments suggest that 86% of the difference between the green and non-green multipliers is explained by the initial level of public capital in green energy being further away from the steady-state energy investment levels than the initial level of public capital in non-green energy. This enables green spending to exhibit higher marginal productivity and generate larger multipliers in the short-run. The findings of this paper therefore lend support to the notion of a green recovery and show that it is indeed possible for green investments to save the environment and the economy at the same time, especially in the short-run.

This paper has focused on the short-run effects of green and non-green spending empirically and theoretically. Given the importance of initial levels of green spending in driving its overall multiplier, such high returns from these investments might not be sustained in the long-run since increasing green capital levels will reduce its marginal productivity. However, green infrastructure spending in particular has an advantage over other types of infrastructure spending to the extent that it can, and probably will, have a strong effect on total factor productivity by reducing feedback effects of climate on output in the long-run.[18] Therefore, long-run multipliers of green spending are still expected to be larger than non-green, although more research needs to be done to quantify this more formally.

[18]Climate damages can be quite sizable. For example Kahn et al. (2021) find that a persistent increase in average global temperature by 0.04°C per year, in the absence of mitigation policies, can reduce world real GDP per capita by more than 7 percent by 2100.

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# Appendix

## A Patent Data

In order to get a more comprehensive sense of green activity in the United States, I refer to PATSTAT to look at the evolution of patents in the United States.[19] I look at both patent inventions and filings in the US from 1960-2018,[20] and their breakdown into green and non-green as a proxy of their investment.[21] Within green patents, I also look at the subcategory related to energy production and dissemination which I presume is the closest in nature to the DoE investment. As Figure A1 shows, the shares of green and green-energy patents of total patents (in terms of both inventions and filings) have been quite low in the United States. This lends support to the DoE data, suggesting that the low shares of green spending by DoE are not a manifestation of the time period or the institution we are looking at and instead reflect the broader structural breakdown of investments between green and non-green over the past few decades in the United States.

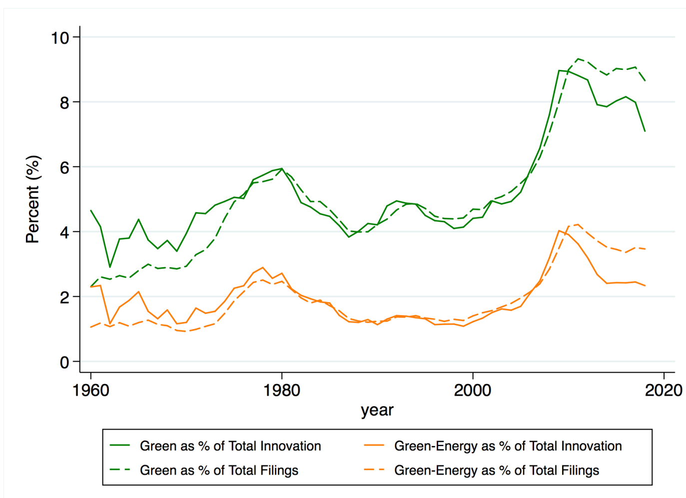


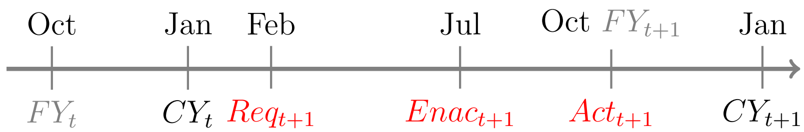

**Figure A1:** Green and Green-Energy Patents as Share of Total Patents

[19]Worldwide Patent Statistical Database (PATSTAT) 2021- Spring edition.

[20]Patent inventions count the number of patents by American inventors. Patent filings count the number of patents filed in the United States. The two counts of patents need not be the same, an American inventor can file their patent in another country and it will still count as 1 patent invention in the United States. Conversely, a non-American inventor can file their patent in the United States and it will count as 1 patent filing in the United States.

[21]The Cooperative Patent Classification (CPC) attributes patents related to climate-change mitigation technologies with the Y02 tag, and henceforth is referred to as green patents (see for example Acemoglu et al. (2019)).

# B Timeline: Fiscal vs. Calendar Year




# C Data Sources

**Table C1:** Data Sources

| Variable | Time Coverage | Source |
|---|---|---|
| Actual total, EERE, non-EERE spending at state-level | 2003-2019 | US Department of Energy State Budget Reports |
| Requested total, EERE, non-EERE spending at state-level | 2005-2021 | US Department of Energy State Budget Reports |
| US green and green-energy patents | 1960-2018 | PATSTAT Spring 2021 Edition |
| Gross State Product (in 2012 chained dollars) | 2003-2019 | Bureau of Economic Analysis |
| Sectoral State Product (in 2012 chained dollars) | 2005-2019 | Bureau of Economic Analysis |
| GDP deflator (base year = 2012) | 2003-2019 | Bureau of Economic Analysis |
| Population | 2003-2019 | Federal Reserve Bank of St Louis |
| State Labor Force, Employment, Unemployment Heads[1] | 2003-2019 | US. Bureau of Labor Statistics |
| Net Generation by State by Type of Producer by Energy Source[2] | 2005-2019 | US Energy Information Administration |
| Existing Nameplate Capacity by Energy Source, Producer Type and State[3] | 2005-2019 | US Energy Information Administration |

**Notes:**
[1]Employment data is seasonally-adjusted.
[2]Forms EIA-906, EIA-920, and EIA-923.
[3]Form EIA-860.

# D Maps

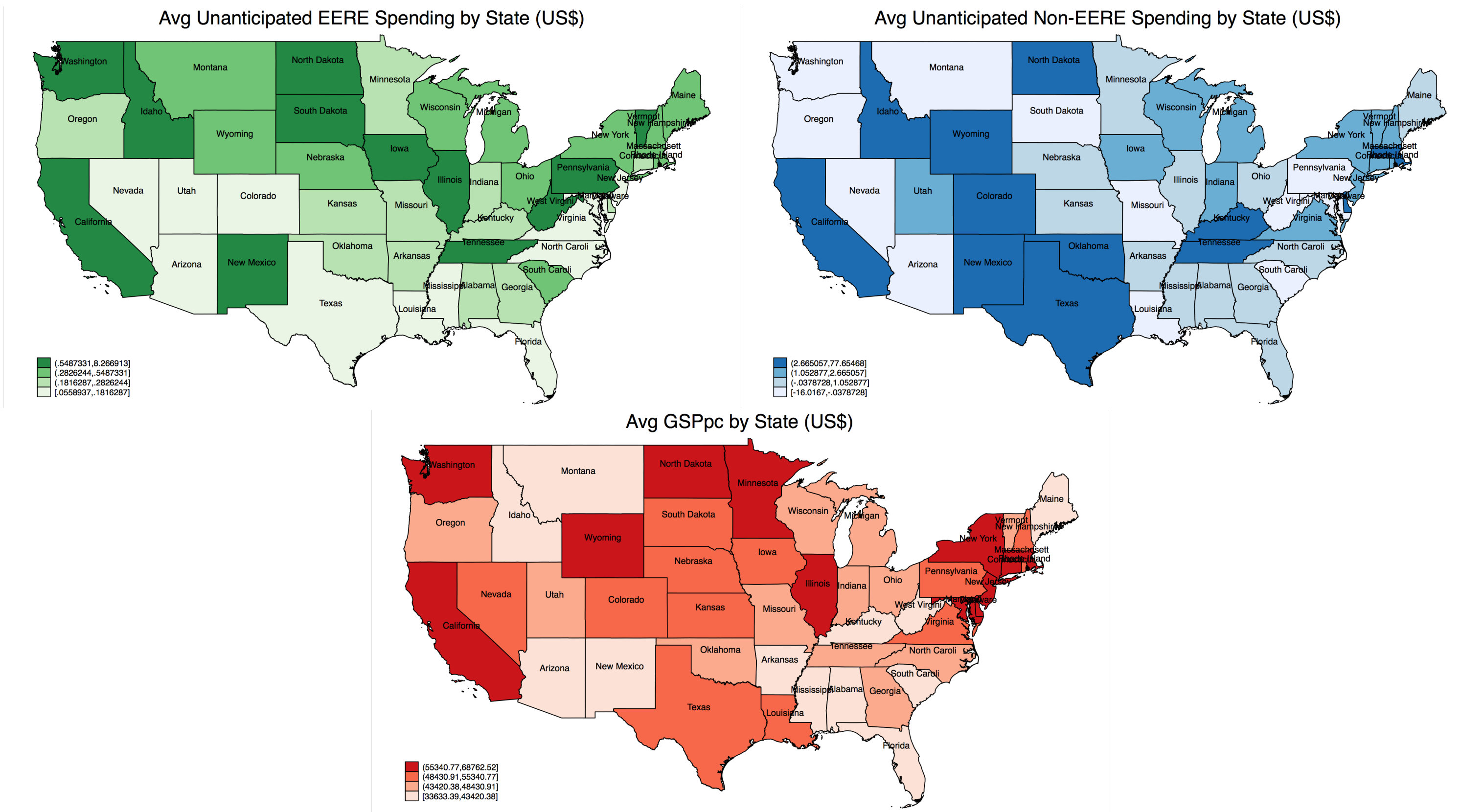



**Figure D2:** Cross-Sectional Averages of Unanticipated Green and Non-Green Spending, and Gross State Product, respectively.

# E Robustness

## E.1 Predictability Robustness

**Table E2:** Predictability Test

| | Unanticipated Changes in EERE Spending | Unanticipated Changes in Non-EERE Spending |
|---|---|---|
| **Lagged Changes in Output** | | |
| Contemporaneous Effect | 0.000343 | 0.000916 |
| | [0.000219] | [0.000854] |
| 1-Year Effect | 0.000376 | 0.00115 |
| | [0.00032] | [0.000971] |
| 2-Year Effect | 0.000389 | 0.00156 |
| | [0.00034] | [0.00109] |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the change in real green (or non-green) spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Independent variable is the lagged growth in real state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states. The impact, 1-year and 2-year multipliers are estimated using 637, 587 and 537 state-year observations, respectively.

**Table E3:** Correlation between EERE and Non-EERE Spending Test

| | Green Output Multiplier | Non-Green Output Multiplier |
|---|---|---|
| Impact Multiplier | 1.185* | -0.257 |
| | [0.661] | [0.627] |
| 1-Year Multiplier | 2.619*** | 0.46 |
| | [0.798] | [1.15] |
| 2-Year Multiplier | 4.526*** | 1.274 |
| | [1.292] | [1.22] |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variables are the changes in real green and non-green spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states. The impact, 1-year and 2-year multipliers are estimated using 637, 587 and 537 state-year observations, respectively.

## E.2 Lag Robustness

**Table E4:** Lag Robustness

| | Green Output Multiplier | Non-Green Output Multiplier | Green Output Multiplier | Non-Green Output Multiplier | Green Output Multiplier | Non-Green Output Multiplier |
|---|---|---|---|---|---|---|
| Impact Multiplier | 0.976* | 0.131 | 1.471* | 0.361 | 1.885** | 0.291 |
| | [0.562] | [0.551] | [0.845] | [0.724] | [0.858] | [0.619] |
| 1-Year Multiplier | 2.228** | 1.203 | 3.105* | 2.094* | 3.857*** | 1.843* |
| | [0.932] | [1.235] | [1.905] | [1.075] | [1.282] | [1.024] |
| 2-Year Multiplier | 4.178*** | 1.859 | 3.725 | 2.661** | 4.396*** | 2.192** |
| | [1.327] | [1.271] | [2.776] | [1.156] | [1.124] | [0.923] |
| **Controls** | | | | | | |
| 2 Lagged Changes in Output | Yes | Yes | Yes | Yes | | |
| 2 Lagged Changes in Actual Spending | | | Yes | Yes | | |
| 2 Lagged Levels in Output and Actual Spending | | | | | Yes | Yes |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real green (or non-green) spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states.

## E.3 Cross-Sectional Robustness

### E.3.1 Green Multiplier

**Table E5:** Cross-Sectional Robustness

| | Full Sample | Excl. Alabama | Excl. Alaska | Excl. Arizona | Excl. Arkansas | Excl. California | Excl. Colorado | Excl. Connecticut | Excl. Delaware | Excl. Florida | Excl. Georgia | Excl. Hawaii | Excl. Idaho | Excl. Illinois | Excl. Indiana | Excl. Iowa | Excl. Kansas |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output |
| Impact Multiplier | 1.101** | 1.157** | 1.227** | 1.192** | 1.063** | 1.147** | 0.896 | 1.080** | 1.057* | 1.097** | 1.111** | 1.147** | 0.900 | 1.152** | 1.032* | 1.112** | 1.124** |
| | (0.520) | (0.521) | (0.506) | (0.520) | (0.526) | (0.518) | (0.678) | (0.518) | (0.537) | (0.522) | (0.502) | (0.518) | (0.544) | (0.527) | (0.519) | (0.521) | (0.528) |
| 1-Year Multiplier | 2.534*** | 2.646*** | 2.717*** | 2.735*** | 2.479*** | 2.619*** | 2.460** | 2.580*** | 2.312*** | 2.534*** | 2.587*** | 2.620*** | 2.637*** | 2.285*** | 2.629*** | 2.487*** | 2.448*** |
| | (0.747) | (0.749) | (0.740) | (0.741) | (0.748) | (0.761) | (1.211) | (0.765) | (0.702) | (0.747) | (0.769) | (0.775) | (0.756) | (0.714) | (0.744) | (0.750) | (0.738) |
| 2-Year Multiplier | 4.222*** | 4.357*** | 4.463*** | 4.477*** | 4.178*** | 4.342*** | 4.000** | 4.286*** | 3.902*** | 4.335*** | 4.415*** | 4.379*** | 3.935*** | 4.312*** | 4.205*** | 4.120*** | 4.238*** |
| | (1.141) | (1.140) | (1.135) | (1.082) | (1.159) | (1.112) | (1.989) | (1.126) | (1.150) | (1.097) | (1.132) | (1.116) | (1.189) | (1.144) | (1.154) | (1.121) | (1.147) |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real green spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Each column is based on a sample of 49 states.

| VARIABLES | Excl. Kentucky Output | Excl. Louisiana Output | Excl. Maine Output | Excl. Maryland Output | Excl. Massachusetts Output | Excl. Michigan Output | Excl. Minnesota Output | Excl. Mississippi Output | Excl. Missouri Output | Excl. Montana Output | Excl. Nebraska Output | Excl. Nevada Output | Excl. New Hampshire Output | Excl. New Jersey Output | Excl. New Mexico Output | Excl. New York Output | Excl. North Carolina Output |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Impact Multiplier | 1.073** | 1.085** | 1.054* | 1.113** | 1.071** | 1.175** | 1.094** | 1.072** | 1.077** | 1.153** | 1.054* | 1.177** | 1.064** | 1.103** | 1.357*** | 1.069** | 1.084** |
| | (0.523) | (0.513) | (0.525) | (0.529) | (0.531) | (0.516) | (0.521) | (0.519) | (0.520) | (0.515) | (0.526) | (0.522) | (0.522) | (0.519) | (0.453) | (0.517) | (0.523) |
| 1-Year Multiplier | 2.533*** | 2.523*** | 2.635*** | 2.495*** | 2.522*** | 2.503*** | 2.607*** | 2.491*** | 2.555*** | 2.528*** | 2.588*** | 2.408*** | 2.697*** | 2.491*** | 2.555*** | 2.264*** | 2.571*** |
| | (0.756) | (0.751) | (0.769) | (0.763) | (0.752) | (0.760) | (0.743) | (0.752) | (0.768) | (0.763) | (0.750) | (0.732) | (0.747) | (0.751) | (0.765) | (0.725) | (0.755) |
| 2-Year Multiplier | 4.235*** | 4.356*** | 4.255*** | 4.287*** | 4.218*** | 4.254*** | 4.193*** | 4.257*** | 4.226*** | 4.245*** | 4.133*** | 4.443*** | 4.223*** | 4.237*** | 3.828*** | 4.222*** | 4.210*** |
| | (1.160) | (1.125) | (1.162) | (1.169) | (1.166) | (1.153) | (1.155) | (1.138) | (1.147) | (1.144) | (1.178) | (1.087) | (1.156) | (1.132) | (1.174) | (1.184) | (1.132) |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real green spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Each column is based on a sample of 49 states.

| | Excl. North Dakota | Excl. Ohio | Excl. Oklahoma | Excl. Oregon | Excl. Pennsylvania | Excl. Rhode Island | Excl. South Carolina | Excl. South Dakota | Excl. Tennessee | Excl. Texas | Excl. Utah | Excl. Vermont | Excl. Virginia | Excl. Washington | Excl. West Virginia | Excl. Wisconsin | Excl. Wyoming |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output |
| Impact Multiplier | 1.274** | 1.077** | 1.079** | 1.133** | 0.947* | 1.046* | 1.078** | 1.146** | 1.104* | 1.118** | 1.108** | 1.112** | 1.148** | 1.090* | 0.699 | 1.120** | 1.038* |
| | (0.482) | (0.529) | (0.528) | (0.525) | (0.519) | (0.521) | (0.529) | (0.537) | (0.551) | (0.521) | (0.527) | (0.521) | (0.517) | (0.543) | (1.432) | (0.525) | (0.528) |
| 1-Year Multiplier | 2.527*** | 2.772*** | 2.484*** | 2.402*** | 2.569*** | 2.295*** | 2.474*** | 2.558*** | 2.523*** | 2.391*** | 2.541*** | 2.545*** | 2.603*** | 2.609*** | 2.477*** | 2.755** | 2.534*** |
| | (0.760) | (0.698) | (0.748) | (0.741) | (0.762) | (0.734) | (0.748) | (0.761) | (0.743) | (0.749) | (0.759) | (0.761) | (0.745) | (0.754) | (0.771) | (1.301) | (0.751) |
| 2-Year Multiplier | 4.580*** | 4.141*** | 3.913*** | 4.278*** | 4.116*** | 4.191*** | 4.325*** | 4.224*** | 4.026*** | 4.164*** | 4.264*** | 4.371*** | 4.338*** | 4.206*** | 3.146 | 4.227*** | 4.179*** |
| | (1.124) | (1.150) | (1.110) | (1.125) | (1.132) | (1.162) | (1.132) | (1.167) | (1.202) | (1.139) | (1.131) | (1.144) | (1.149) | (1.167) | (2.137) | (1.156) | (1.127) |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real green spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Each column is based on a sample of 49 states.

### E.3.2 Non-green Multiplier

**Table E6:** Cross-Sectional Robustness

| | Full Sample | Excl. Alabama | Excl. Alaska | Excl. Arizona | Excl. Arkansas | Excl. California | Excl. Colorado | Excl. Connecticut | Excl. Delaware | Excl. Florida | Excl. Georgia | Excl. Hawaii | Excl. Idaho | Excl. Illinois | Excl. Indiana | Excl. Iowa | Excl. Kansas |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output | Output |
| Impact Multiplier | -0.198 | -0.162 | -0.170 | -0.214 | -0.215 | -0.261 | -0.148 | -0.181 | -0.235 | -0.203 | -0.175 | -0.208 | -0.165 | -0.196 | -0.184 | -0.182 | -0.172 |
| | (0.590) | (0.590) | (0.587) | (0.594) | (0.590) | (0.596) | (0.599) | (0.599) | (0.583) | (0.595) | (0.601) | (0.597) | (0.812) | (0.586) | (0.589) | (0.588) | (0.596) |
| 1-Year Multiplier | 0.395 | 0.404 | 0.426 | 0.387 | 0.375 | 0.350 | 0.491 | 0.436 | 0.412 | 0.431 | 0.415 | 0.383 | 0.322 | 0.396 | 0.369 | 0.396 | 0.395 |
| | (1.183) | (1.178) | (1.152) | (1.202) | (1.183) | (1.223) | (1.197) | (1.193) | (1.178) | (1.207) | (1.222) | (1.197) | (1.882) | (1.181) | (1.188) | (1.186) | (1.191) |
| 2-Year Multiplier | 1.133 | 1.127 | 1.044 | 1.175 | 1.105 | 1.125 | 1.208 | 1.183 | 1.120 | 1.210 | 1.105 | 1.138 | 0.653 | 1.155 | 1.138 | 1.146 | 1.151 |
| | (1.344) | (1.342) | (1.333) | (1.370) | (1.342) | (1.402) | (1.364) | (1.358) | (1.331) | (1.371) | (1.426) | (1.364) | (2.008) | (1.336) | (1.344) | (1.339) | (1.352) |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real non-green spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Each column is based on a sample of 49 states.

| VARIABLES | Excl. Kentucky Output | Excl. Louisiana Output | Excl. Maine Output | Excl. Maryland Output | Excl. Massachusetts Output | Excl. Michigan Output | Excl. Minnesota Output | Excl. Mississippi Output | Excl. Missouri Output | Excl. Montana Output | Excl. Nebraska Output | Excl. Nevada Output | Excl. New Hampshire Output | Excl. New Jersey Output | Excl. New Mexico Output | Excl. New York Output | Excl. North Carolina Output |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Impact Multiplier | -0.203 | -0.151 | -0.169 | -0.240 | -0.174 | -0.253 | -0.186 | -0.127 | -0.104 | -0.209 | -0.251 | -0.0826 | -0.210 | -0.164 | -0.443 | -0.322 | -0.177 |
| | (0.590) | (0.594) | (0.591) | (0.596) | (0.602) | (0.588) | (0.592) | (0.595) | (0.586) | (0.597) | (0.587) | (0.590) | (0.592) | (0.597) | (0.655) | (0.576) | (0.597) |
| 1-Year Multiplier | 0.375 | 0.481 | 0.425 | 0.307 | 0.435 | 0.316 | 0.384 | 0.427 | 0.495 | 0.369 | 0.346 | 0.666 | 0.393 | 0.431 | -0.791 | 0.252 | 0.423 |
| | (1.178) | (1.182) | (1.188) | (1.194) | (1.186) | (1.197) | (1.185) | (1.186) | (1.165) | (1.190) | (1.174) | (1.152) | (1.184) | (1.189) | (1.157) | (1.192) | (1.194) |
| 2-Year Multiplier | 1.114 | 1.185 | 1.159 | 1.044 | 1.161 | 1.101 | 1.133 | 1.153 | 1.199 | 1.044 | 1.059 | 1.593 | 1.119 | 1.178 | -0.104 | 1.101 | 1.177 |
| | (1.335) | (1.358) | (1.355) | (1.358) | (1.331) | (1.356) | (1.343) | (1.354) | (1.331) | (1.361) | (1.328) | (1.230) | (1.345) | (1.352) | (1.865) | (1.341) | (1.355) |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real non-green spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Each column is based on a sample of 49 states.

| VARIABLES | Excl. North Dakota Output | Excl. Ohio Output | Excl. Oklahoma Output | Excl. Oregon Output | Excl. Pennsylvania Output | Excl. Rhode Island Output | Excl. South Carolina Output | Excl. South Dakota Output | Excl. Tennessee Output | Excl. Texas Output | Excl. Utah Output | Excl. Vermont Output | Excl. Virginia Output | Excl. Washington Output | Excl. West Virginia Output | Excl. Wisconsin Output | Excl. Wyoming Output |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Impact Multiplier | -0.581 | -0.173 | -0.136 | -0.266 | -0.0441 | -0.231 | -0.220 | -0.244 | 0.0121 | -0.189 | -0.202 | -0.225 | -0.213 | -0.278 | -0.101 | -0.218 | -0.0760 |
| | (0.455) | (0.591) | (0.590) | (0.616) | (0.581) | (0.589) | (0.641) | (0.598) | (0.609) | (0.590) | (0.592) | (0.594) | (0.591) | (0.642) | (0.676) | (0.590) | (0.590) |
| 1-Year Multiplier | 0.0190 | 0.382 | 0.475 | 0.569 | 0.590 | 0.379 | 0.345 | 0.294 | 0.571 | 0.398 | 0.418 | 0.337 | 0.389 | 0.499 | 0.847 | 0.365 | 0.541 |
| | (1.068) | (1.190) | (1.170) | (1.189) | (1.153) | (1.181) | (1.276) | (1.176) | (1.223) | (1.186) | (1.198) | (1.174) | (1.180) | (1.313) | (1.092) | (1.186) | (1.177) |
| 2-Year Multiplier | 0.769 | 1.100 | 1.217 | 1.412 | 1.269 | 1.092 | 0.973 | 0.989 | 1.097 | 1.114 | 1.177 | 1.054 | 1.101 | 1.395 | 1.854* | 1.114 | 1.248 |
| | (1.196) | (1.354) | (1.318) | (1.313) | (1.301) | (1.341) | (1.434) | (1.331) | (1.448) | (1.354) | (1.362) | (1.331) | (1.346) | (1.359) | (1.069) | (1.344) | (1.352) |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variable is the change in real non-green spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Each column is based on a sample of 49 states.

# F Electricity Multipliers

In this subsection, I explore the Utilities sector more closely. In the United States, the Utilities sector covers the provision of basic amenities such as: water, sewage services, electricity, dams, and natural gas. Although EERE and non-EERE spending had an insignificant multiplier effect on Utilities value added in Table 2, this could mask sizable heterogeneity within the Utilities sector given the clear relevance of some of its sub-components, in particular electricity, to the nature of DoE investments under investigation.

Knowing that the BEA does not provide value added data for the sub-sectors of the economy, I get annual data from the US Energy Information Administration on electricity generation and capacity by energy source at the state-level.[22] I break down the energy sources into green (as in renewable) and non-green energy and generate for every state-year four variables: (i) green energy generation (Megawatt-hours), (ii) non-green energy generation (Megawatt-hours), (iii) green energy capacity (Megawatts), and (iv) non-green energy capacity (Megawatts).[23] Figures F3 and F4 present the evolution of energy generation and capacity and their breakdown into renewable and non-renewable in the United States. Non-surprisingly, the bulk of energy generation and capacity is produced from non-renewable energy sources, showcasing once again the reliance on non-green energy sources in the US. However, there seems to be a timid change in the breakdown, with green energy share gradually increasing over my time period of analysis.

Next, I estimate the effect of EERE and non-EERE spending on the four measures of electricity. Since the dependent variable is in megawatt hours or magawatts and is no longer in monetary value, I update Specification 1 to study the effect of spending on the percentage change in electricity generation or capacity:

$$\frac{u_{i,t} - u_{i,t-h}}{u_{i,t-h}} = \beta_h \frac{\Delta^h g_{i,t}^{actual} - \Delta^h g_{i,t}^{requested}}{y_{i,t-h}} + \alpha_i + \lambda_t + \epsilon_{i,t}; h = 1, 2, 3, \tag{34}$$

whereby $u_{i,t}$ is one of the four electricity measures in megawatt hours or magawatts per capita. The interpretation of $\beta_h$ now reads as: increasing unanticipated spending by 1% of local economic activity leads to a $\beta_h$% change in the dependent variable.

Panel A of Table F7 shows that increasing EERE spending by 1% of local economic activ-

[22] Energy generation is a measure of electricity produced over time, whereby capacity is the maximum level of electricity that a power plant can supply at a specific point in time.

[23] As per the EIA website, I classify the following energy sources as renewable: hydroelectric conventional, wind, wood and wood derived fuels, other biomass, geothermal, solar thermal and photovoltaic. I classify the rest as non-renewable: coal, natural gas, petroleum, nuclear, other gases, other.

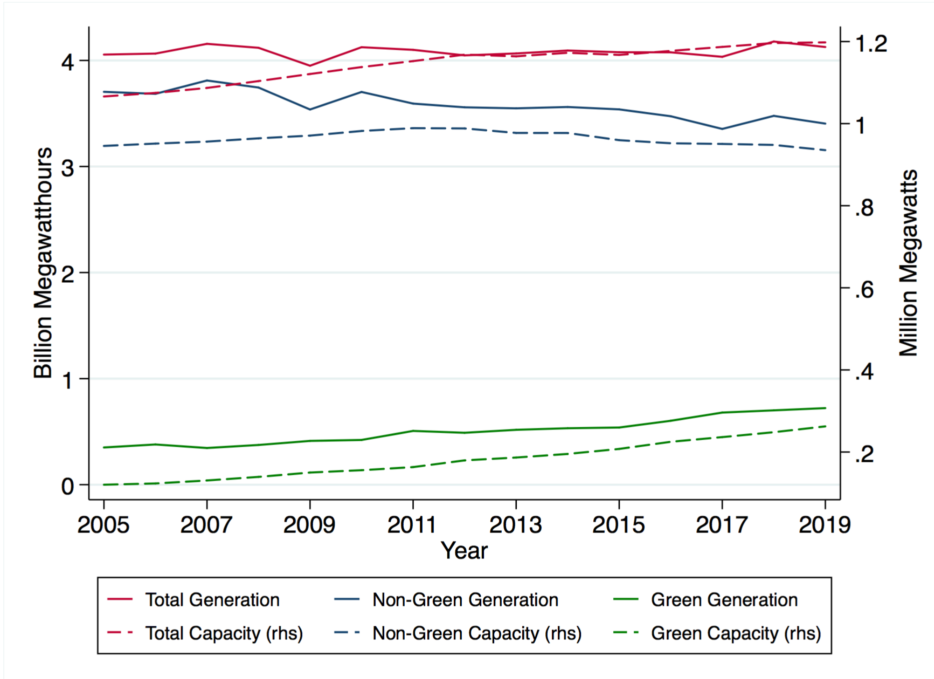



**Figure F3:** Electricity Generation and Capacity in the United States

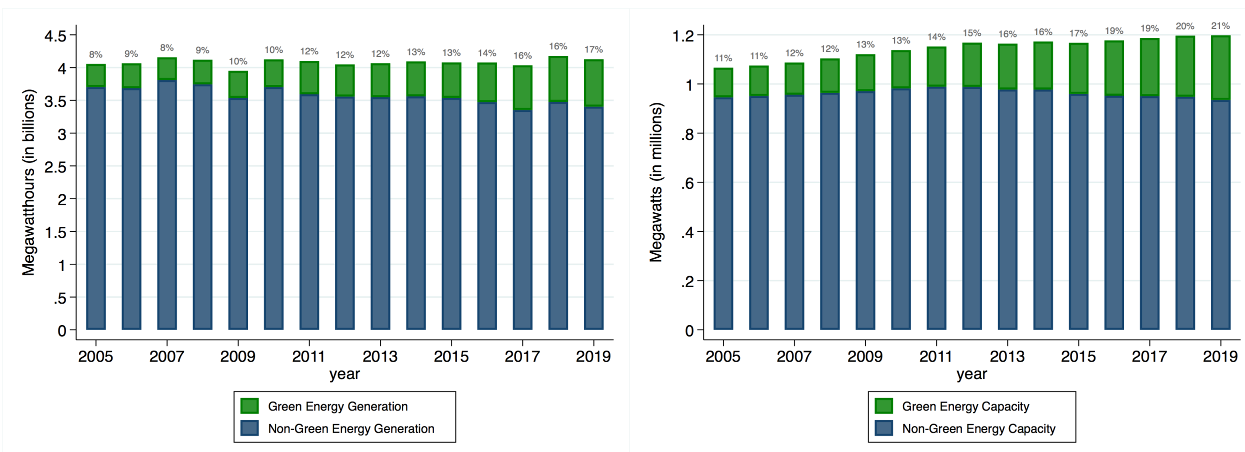



**Figure F4:** Electricity Generation and Capacity in the United States

ity has an insignificant multiplier effect on non-green energy generation and capacity, but a positive significant multiplier on green energy generation and capacity. Increasing EERE spending by 1% of local economic activity leads to a 24% increase in renewable energy generation contemporaneously, and 24% and 47% percent increases in renewable energy generation in 1 and 2 years, respectively. Meanwhile on the capacity front, increasing EERE spending by 1% of local economic activity only has a significant effect on green capacity in the third time horizon (21% increase in renewable energy capacity within 2-years), which is intuitive given that energy capacity building is a long-term process, especially when starting from sub-optimal green investment levels.[24]

Panel B of Table F7 shows that non-EERE spending has a positive significant multiplier effect on non-green energy generation and capacity but an insignificant multiplier effect on green energy generation and capacity. Again, the fact that the results of both panels are intuitive provides further support to the quality of the shock measure in capturing and identifying the right type of investments in each case.

**Table F7:** Effect of EERE and Non-EERE Spending on Energy Generation and Capacity

| **Panel A: Effect of EERE Spending** | | | | |
|---|---|---|---|---|
| | Generation | | Capacity | |
| | Non-Green | Green[1] | Non-Green | Green[1] |
| Impact Multiplier (%) | -8.269 | 23.75*** | -1.404 | 15.27 |
| | [7.335] | [8.211] | [5.651] | [15.91] |
| 1-Year Multiplier (%) | 2.86 | 23.93** | -3.636 | 15.08 |
| | [8.781] | [9.511] | [7.802] | [14.86] |
| 2-Year Multiplier (%) | 4.92 | 46.98*** | -3.75 | 20.55* |
| | [8.999] | [14.41] | [10.33] | [11.54] |

| **Panel B: Effect of Non-EERE Spending** | | | | |
|---|---|---|---|---|
| | Generation | | Capacity | |
| | Non-Green | Green[1] | Non-Green | Green[1] |
| Impact Multiplier (%) | 13.9 | -2.769 | 6.907** | -9.501 |
| | [10.59] | [15.57] | [2.909] | [8.758] |
| 1-Year Multiplier (%) | 24.14** | -9.287 | 4.486 | -2.641 |
| | [11.97] | [13.59] | [3.333] | [9.324] |
| 2-Year Multiplier (%) | 8.997 | -3.636 | 0.0289 | 5.405 |
| | [8.265] | [19.05] | [4.812] | [12.55] |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the percentage change in electricity generation or capacity per capita over the horizon considered. Independent variable is the change in real green (or non-green) spending per capita, over the horizon considered, as a share of lagged state-level output per capita. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states.
[1]Green energy is composed of renewable energy sources, it excludes nuclear in this case. Results are robust to including nuclear as part of green energy generation and capacity, and are available upon request.

[24]Results are robust to including nuclear energy as part of green energy generation and capacity.

# G Cross-border Multipliers

In Equation 4, I highlighted that there might be other demand channels through which DoE spending can affect output besides the flypaper effect. For example, there might be demand spillovers from neighboring cities that also have an impact on local economic activity - although direction of which depends on the forces of substitution vs. complementarity of goods across states interplay. A spending expansion in one state can increase demand locally, but if a state has rich input-output linkages with other states in the same region, this will have positive spillover effects to neighboring states - i.e. *complementarity effect*. However, it can also be that a fiscal expansion in one state might draw in a reallocation of factors into that state and hence have a negative effect on neighboring states - i.e. *substitution effect*.[25] Either way, it is important to see if any of those two effects materializes with DoE spending.

I replicate the cross-border analysis as in Acconcia et al. (2014) to investigate whether there are cross-regional effects to DoE green (and non-green) investments. I use the BEA regional classification of states and split the 50 states into eight regions. Then, I augment Specification 1 to include adjacent states within the same region, such that:

$$\frac{\Delta^h y_{i,t}}{y_{i,t-h}} = \beta_h \frac{\Delta^h g_{i,t}^{actual} - \Delta^h g_{i,t}^{requested}}{y_{i,t-h}} + \gamma_h \frac{\Delta^h R g_{i,t}^{actual} - \Delta^h R g_{i,t}^{requested}}{R y_{i,t-h}} + \alpha_i + \lambda_t + \epsilon_{i,t} \quad (35)$$

whereby $Ry$ and $Rg$ are real output and spending per capita in the region to which state i belongs, but the variables exclude the output and spending of state i itself so that they only encompass the output and spending of the neighboring states of state i that belong to the same region.

Table G8 shows that the evidence for cross-border effects is overall quite weak for green and non-green spending. A more geographically disaggregated dataset will be helpful to take a more conclusive stance on cross-border effects of EERE and non-EERE spending, see for example Auerbach et al. (2020) and Popp et al. (2020).

[25] See also Acconcia et al. (2014) and Auerbach et al. (2020) for a more elaborated discussion on cross-border effects.

**Table G8:** Cross-border Effects

| | Variable | Green Output Multiplier | Non-Green Output Multiplier |
|---|---|---|---|
| Impact | Local Spending | 1.135** | -0.198 |
| | | [0.534] | [0.589] |
| | Regional Spending | 2.425 | 0.074 |
| | | [3.116] | [2.862] |
| 1 Year Multiplier | Local Spending | 2.588*** | 0.446 |
| | | [0.76] | [1.177] |
| | Regional Spending | 3.434 | 3.858 |
| | | [3.426] | [5.537] |
| 2 Year Multiplier | Local Spending | 4.287*** | 1.175 |
| | | [1.169] | [1.344] |
| | Regional Spending | 5.29 | 5.764 |
| | | [4.474] | [7.876] |

**Notes:** In line with local projection methods, each horizon is estimated separately, outcome of which is presented in a separate row. Dependent variable is the growth in real state-level output per capita over the horizon considered. Independent variables are the change in real state-level green (or non-green) spending per capita, over the horizon considered, as a share of lagged state-level output per capita, as well as the change in real regional-level green (or non-green) spending per capita, over the horizon considered, as a share of lagged regional-level output per capita, excluding the state itself. Each regression includes state and time fixed effects. Standard errors clustered at the state level are in parentheses below each estimate. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The sample includes all 50 states.