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Building Back Better: How Big Are Green Spending Multipliers?

by Nicoletta Batini, Mario Di Serio, Matteo Fragetta,
Giovanni Melina, and Anthony Waldron

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Building Back Better: How Big Are Green Spending Multipliers?[1]

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Abstract

This paper provides estimates of output multipliers for spending in clean energy and biodiversity conservation, as well as for spending on non-ecofriendly energy and land use activities. Using a new international dataset, we find that every dollar spent on key carbon-neutral or carbon-sink activities can generate more than a dollar's worth of economic activity. Although not all green and non-ecofriendly expenditures in the dataset are strictly comparable due to data limitations, estimated multipliers associated with spending on renewable and fossil fuel energy investment are comparable, and the former (1.1-1.5) are larger than the latter (0.5-0.6) with over 90 percent probability. These findings survive several robustness checks and lend support to bottom-up analyses arguing that stabilizing climate and reversing biodiversity loss are not at odds with continuing economic advances.

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Keywords: green multiplier, green stimulus, clean energy, conservation spending, nuclear energy, biodiversity, nature-based solutions, agricultural subsidies, fossil fuels.

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In memory of Greg Kaser

I. INTRODUCTION

While the ongoing coronavirus pandemic continues to threaten millions of lives around the world, the first half of 2020 saw an unprecedented decline in CO_2 emissions—larger than during the financial crisis of 2008, the oil crisis of the 1979, or even World War II. Research shows that in the first six months of 2020, 6.4 percent less carbon dioxide was emitted than in the same period in 2019 (Liu et al., 2021).

The 2020 climate jackpot, however, offers little to celebrate, for four distinct reasons. First, it is linked to a world health emergency of biblical proportions that, by the end of 2020, had infected over 90 million people globally and killed almost 2 million, causing factories to close down, massive job losses and the paralysis of large swathes of economic activity. These makes the recent climate gains clearly unsustainable. Second, recent UN reports indicate that global emissions would need to drop by the same exaggerated rate seen during the pandemic (7.6 percent per year) in every year for the next few decades, to ensure that global temperatures do not increase more than 1.5°C relative to the pre-industrial era, a necessary target to stave off the worst effects of climate change (IPCC, 2019). Third, the severe economic shock triggered by the pandemic has generated an outpouring of public policy action around the world and the rapid crafting of trillion-dollar stimulus packages, but some of this action actually risks to hamper progress on mitigating climate change because it is predicated on supporting non-eco-friendly industries—the same industries that need to be drastically reformed to meet the climate goals (Hepburn et al. 2020; Carney, 2021). Finally, virtually none of the measures taken so far to sustain activity have been directly targeted at mitigating emissions via fostering conservation—a necessary condition for meeting the 1.5°C target, which would also help shelter humanity from the spread of new, deadly zoonotic diseases (OECD, 2020).

Global Earth champions argue that fixing the twin climate and biodiversity crises that affect our planet is still possible, but it requires to 'build back better', stewarding the global economy within limits set by nature (Rockström et al., 2017; Attenborough, 2020; Georgieva, 2020; Stiglitz, 2020; Gates, 2021; Carney, 2021).[2] Often, however, cutting emissions and protecting wildlife and natural resources has been portrayed at odds with creating jobs and fostering economic growth (see, for example, Walley and Whitehead, 1994; NERA, 2017; and Christian, 2021). In contrast, a recent paper based on a global survey of experts including senior officials from finance ministries and central banks, found that green projects are widely perceived capable to create more jobs, deliver higher short-term returns per dollar spent, and lead to increased long-term cost savings, by comparison with traditional fiscal stimulus (Hepburn et al., 2020).

[2] See also Helm (2020) and Agrawal et al., (2020).

This paper contributes to this debate. To our knowledge, it is the first study estimating directly the effect on GDP of money spent to foster the transition to a zero-carbon, nature-friendly world for a variety of green expenditure typologies. Although 'green' expenditure has historically tended to be defined as spending that helps reduce greenhouse gas emissions, we expand the definition to include examples of nature-based negative emissions technologies ("nature-based solutions" or NBSs) in the form of expenditure on biodiversity conservation and rewilding.[3] These are increasingly regarded by science as solutions that support the Earth's natural capabilities to sequester carbon and mitigate climate change. Moreover, these measures have been shown to be a vital complement of planetary climate and global temperature stabilization strategies (IPCC 2019; IPBES, 2019; Foley et al., 2020; Dasgupta et al., 2021).

Using a new international dataset, part of which was especially assembled for this analysis, we find that every dollar (private and public) spent on key carbon-neutral or carbon-sink activities—from zero-emission power plants to the protection of wildlife and ecosystems—can generate more than a dollar's worth of economic activity: the total increase in GDP is greater than the original increase in green spending. These economic effects appear significantly bigger and more long-lasting than 'non-eco-friendly' spending in alternative energy technologies or land/sea uses. Although green and non-ecofriendly expenditures are not always strictly comparable due to data limitations, the estimated multipliers associated with green spending are found to be generally larger than those associated with non-eco-friendly expenditure. In the case of renewable versus fossil fuel energy investments, where country and time samples are homogeneous and allow a formal statistical comparison, the difference between the associated multipliers emerge as non-zero with very high probability. The point estimates of the multipliers are 1.1-1.5 for renewable energy investment and 0.5-0.6 for fossil fuel energy investment, depending on horizon and specification.

These findings survive several robustness checks and lend support to existing bottom-up analyses (documented in the paper) that have found that, in general, stabilizing climate and reversing biodiversity loss are compatible with continuing economic advances. They also suggest that in crafting a post-COVID-19 recovery, investments in energy and land/sea use transitions are likely economically superior to those offered by supporting economic activities involving unsustainable ways to produce energy and food: the economy can recover more rapidly by building back better, while keeping many of the ecological improvements attained in 2020.

The empirical analysis borrows the concept of investment multiplier from the traditional macroeconomic literature to quantify the impact on GDP of green investment expenditures. The calculations are based on the estimates of factor-augmented panel vector-autoregressive models that deal with well-known technical issues in the recent

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[3] See Seddon et al. (2020) for a definition of NBSs.

literature on fiscal multipliers (along similar lines of Fragetta and Gasteiger, 2014; Caggiano et al., 2015; 2017; Amendola et al., 2020, among many others). First, the panel dimension allows exploiting data of many countries of which green and non-ecofriendly spending estimates are available. Second, augmenting the specification with factors extracted from many macroeconomic variables mitigates limited information concerns. This helps correct for the fact that there is likely important information that we do not explicitly include in our model, but that might have been used by economic agents in making their choices (see, e.g., Bernanke et al., 2005; Fragetta and Gasteiger, 2014; and Stock, Watson, 2005). Third, most specifications include forecasts of investments formed over the past year as an exogenous variable, to purge green and non-eco-friendly spending shocks from their anticipated component and mitigate the issue of shock foresight highlighted in the macro-fiscal literature (see, e.g., Forni and Gambetti, 2010, among others). The need of dealing with the issues of limited information and shock foresight stems from the problem of 'non-fundamentalness,' a potential source of bias deriving essentially from a misalignment between the information sets of economic agents and the econometrician.

The paper is organized as follows. Section II reviews current spending on clean energy and sustainable land uses and why a transition to net-zero emissions calls for more spending in these areas. Section III describes the data used in the estimation. Section IV presents the methodology employed to estimate spending multipliers. Section V reports the empirical results. Section VI illustrates the outcomes of robustness checks. Finally, Section VI draws policy implications and concludes.

II. WHY MORE IS NEEDED ON CLEAN ENERGY AND CONSERVATION

To date, world governments' collective US$14 trillion fiscal response to the economic damage of the COVID-19 pandemic has concentrated on measures to address the health emergency and support household and firms stranded by the lockdowns (IMF, 2021). As the immediate health crisis recedes, however, attention and funding will turn toward economic recovery, creating more opportunities to build back better. Accordingly, governments have been urged to make the post-coronavirus stimulus "green" to ensure that climate change agendas do not get sidetracked (Bozuwa et al. 2020; UN, 2020a; IMF, 2020). However, few governments have yet heeded this advice (VividEconomics, 2020), a decision likely driven, at least in part, by ongoing uncertainty about the jobs and growth implications of investing in more sustainable economies. In this context, a deeper understanding of the growth implications of green spending can help policymakers and advocates of a green recovery capitalize on opportunities where they exist.

This paper contributes to this debate by using, for the first time in the empirical economics literature, standard methods traditionally employed to estimate investment multipliers in order to quantify the impact on GDP of green stimulus measures. The analysis focuses on areas of economic activity which science identifies as having a high impact on sustainability and where spending on phasing-out of polluting processes and unsustainable practices is falling dramatically short relative to targets: (i) reducing emissions by increasing the use of clean energy; and (ii) supporting nature's carbon sinks by enhancing the quality and quantity of biodiversity conservation. Below we briefly discuss the importance of buttressing expenditure in these areas to enable green transitions.

Clean energy

Energy consumption contributes to around ¾ of all anthropogenic greenhouse gas emissions, as today energy enters virtually every sector of production from electricity, to agriculture, to transportation, to industry (WRI, 2020a). Cleaning energy consumption is thus considered key to reaching net-zero emissions by 2050 under most science-driven plans for climate stabilization (see, for example, Foley et al., 2020).

There are two categories of clean energy: renewable and non-renewable. Renewable energy is energy that is collected from renewable fuel resources, which are naturally replenished on a human timescale, including carbon-neutral sources like sunlight, wind, rain, tides, waves, and geothermal heat. The term often also encompasses biomass, but its carbon-neutral status is under debate. Nuclear energy—considered a "non-renewable" energy source because the material (uranium) used in nuclear power plants is not renewable on a human timescale—is another form of clean energy (see, e.g., IMF, 2019).[4] Indeed, nuclear energy ranks among the lowest carbon forms of energy generation, considering both direct emissions and its lifecycle impacts (IPCC, 2018) and has emerged as a credible cost competitor of both renewable and non-eco-friendly nonrenewable energy (IEA-OECD NEA, 2020). Reflecting these characteristics, research by both the Intergovernmental Panel on Climate Change and the International Energy Agency lists nuclear power among the key technologies capable and necessary to mitigate carbon emissions (IPCC, 2018; IEA, 2019b and 2020a).

Today, countries with the lowest carbon intensities like France and Sweden rely heavily on nuclear and/or hydroelectric energy as low-carbon sources for either baseload or flexible power. In fact, producing electricity exclusively with renewable sources under current technologies presents several significant technological challenges, since these sources

[4] Some have argued that because it produces radioactive waste, nuclear power should be excluded from any green spending concept. However, past IMF studies on green energy, including the recent 2019 Fiscal Monitor have included investment in nuclear power among sources of green energy because, like here, the definition of what constitutes 'green' energy has been based on the impact of the investment on gas emissions. See also Eyraud et al. (2011).

are intermittent, variable and unpredictable, depending on the weather and consequently having limited capacity factors (IEA, 2021). At the scale needed, storage of renewable energy is also currently not a viable option as the necessary technology is expensive and still developing although prices are falling fast (see Goldstein and Qvist, 2019; and, for recent storage cost estimates, Lazard Asset Management, 2020). Similarly, producing and adapting energy from hydrogen using renewables is not an immediate option. Although the idea of a future full of clean hydrogen is enjoying unprecedented political and business momentum, hydrogen continues to be used in the production of energy by burning fossil fuels with emissions equivalent to the CO_2 emissions of the United Kingdom and Indonesia combined (IEA, 2019).

In 2019, renewables (excluding large hydro) accounted for about one seventh of the share of global generation while nuclear energy accounted for about one-tenth (IRENA, 2019; IEA, 2019a). The overall share of clean energy is increasing slowly because of the large, established fossil fuel fleet and the decline in net terms of nuclear installed capacity.

Reflecting this, there is currently a big gulf between current green spending in these areas and what the science suggests as the target for global emissions by 2030: according to the base-case scenario in BloombergNEF's New Energy Outlook 2019, even limiting the increase in global temperatures this century to 2 degrees Celsius (as opposed to the IPCC, 2019-recommended 1.5°C)[5] would require the gross addition of some 2,836GW of new non-hydro renewable energy capacity by 2030—*double* of what is envisaged under current public and private sector targets—at an estimated cost of US$3.1 trillion over the decade. At the same time, nuclear capacity globally is estimated to have shrunk by a net 5GW in 2019, receiving an investment of a mere US$15 billion versus an investment of around US$282 billion for renewables over the same year (IEA, 2020a).

Ecosystem conservation

Concerted efforts to mitigate greenhouse gas emissions from production in agriculture, fishery, and forestry are as important as clean energy in the quest for limiting increases in global temperatures. The IPCC's 2019 Special Report on Climate Change and Land estimates that the agri-food sector emits between 21-37 percent of greenhouse gases—a share expected to raise to 50 percent of all global emissions by 2050 absent policy action (IPCC, 2019; Willett et al., 2019). The sector is also widely indicated as the first cause of natural resources and biodiversity degradation, including its leading role as a driver of deforestation,

[5] As part of the Paris Agreement in 2015 countries agreed to a common goal of limiting the rise in global temperatures this century to "well below" 2 degrees Celsius, with an aim of keeping the increase at 1.5 degrees.

with large associated carbon releases (IPCC, 2019; IPBES, 2019; Willett et al., 2019; Batini, 2019; McElwee et al., 2020; Clark et al., 2020).[6]

The drivers behind such high emission record lie in developments in the agri-food sector of the past five or six decades, a sector that has become heavily industrialized and reliant on synthetic chemical applications, genetic modification, and deforestation to produce growing amounts of meat, dairy, and eggs, as well as fiber, timber, and biofuels (UNEP, 2020). At sea, high-tech techniques like sonar and equipment like supertrawlers with mechanized nets make it possible to exploit deeper waters at farther-flung locations and capture fish faster than they can reproduce, harming the oceans' ability to absorb carbon and destroying biodiversity (Batini, 2019 and 2021; FAO, 2020).

As in the case of energy, making food systems sustainable for a growing global population is technologically possible but involves a fundamental reconsideration of production and consumption. A more sustainable use of farmed land and fished sea allows to produce food without large-scale habitat disruption and loss of biological diversity, thereby protecting natural cycles on which food production itself relies. It also enables a more efficient use of land and seas, in a world where these serve both to produce food and sequester carbon, as less land and sea are needed if farming and fishing are repurposed away from the production of animal-based food which tends to be land-and sea-intensive and greenhouse gas emissions-intensive toward more plant-based food that allows to feed many more people with less resources and a fraction of greenhouse gas emissions. (FAO, 2017; Batini, 2019 and 2021; UNEP, 2020).

Nature conservation, through actions to protect, sustainably manage, and restore natural or modified ecosystems have emerged as "nature-based solutions" (NBS) to carbon sequestration. In addition, NBS are increasingly seen to hold the key to address the twin problems of climate change and biodiversity loss, if they are based on biodiverse ecosystems, and can also deliver broader societal and economic goals, such as improving health, providing jobs and reducing poverty (UN, 2020b; Waldron et al., 2020; McKinsey and Co., 2020a; Dasgupta et al., 2021). Crucially, NBS are widely indicated as the most effective and cheapest insurance against the emergence of new zoonotic diseases, like COVID-19, which have been associated primarily to human encroachment of wild habitats and the industrialization of animal farming for food (FAO, 2017; Andersen et al., 2020; OECD, 2020).

Like in the case of clean energy, the urgent need for action in this area has failed to generate a momentum and both government and private spending on agriculture remains heavily concentrated on promoting industrial agricultural methods; while spending on protecting land and sea remains minuscular and well below announced targets. A recent report by the World Bank, for example, indicates that countries producing two-thirds of the

[6] Estimates by the IPCC indicate that when all is accounted for, the agri-food sector is potentially responsible for well over a third of greenhouse gas emissions (IPCC, 2019).

world's agricultural output spent US$600 billion per year in agricultural financial support on average from 2014 to 2016 (Searchinger et al., 2020; UNEP-UNDP-FAO, 2021). Only a modest portion of programs support environmental objectives, and even fewer support the mitigation of climate change. Out of US$300 billion in direct spending, only 9 percent explicitly supports conservation, while another 12 percent supports research and technical assistance.

World financial efforts to conserve and restore nature fall correspondingly short of what is needed to protect nature supply at the global level (Dasgupta et al., 2021). Given that over half of 2019 global GDP was estimated to depend highly or moderately on ecosystems health (WEF, 2020), estimated financial flows into global biodiversity conservation are surprisingly small and inadequate.

A recent study (Paulson Institute-The Nature Conservancy-Cornell University, 2020) suggest that spending on a wide range of biodiversity-associated goods is currently (2019) between US$124 and US$143 billion, compared to a need of US$722-967 billion. Although the Paulson estimates represent only 0.1-0.2 percent of 2019 global GDP, it may still be a high-side estimate because much of the 'biodiversity-focused' spending analyzed in the study comes from countries who report the entirety of their environmental and agricultural budgets, and even their health budgets, as "biodiversity expenditure" (OECD, 2020a).[7] However, links between agricultural spending and biodiversity conservation are often tenuous and may even indicate investment in land use practices that are negative for biodiversity. An alternative is to take a more focused approach and address spending and spending needs only on items that have a strong and direct link with biodiversity conservation (Waldron et al., 2017). An example is the study of Waldron et al. (2020) into the policy proposal to expand protected areas to 30 percent of the Earth's surface. This study finds that the cost may be between US$103 billion and US$178 billion per year, depending on how the proposal is implemented, which represents 4-7 times more than the current level of investment of US$24.3 billion in protected areas.

III. Data on Green and Non-eco-friendly Spending

Data on greenhouse gas emissions and climate change, on installed renewable energy plants *capacity*, on levelized *cost* of energy (LCOE), and on levelized cost of electricity have

[7]Most biodiversity is found in lower-income tropical countries where international aid, given almost entirely by OECD countries, forms the majority of funding for biodiversity conservation. Average aid to biodiversity for 2013-17 was US$6.3 billion per year, representing just 0.01% of the OECD's GDP of US$47 billion (Turnhout et al., 2021).

become widely available through open sources. Conversely, data on *investments* in green or non-eco-friendly energy are not easy to come by as much of it relates to private finance. Similarly, data on spending on biodiversity conservation (a key indicator of green land use spending) and subsidies to non-eco-friendly agricultural practices are not readily available and need considerable manipulation of existing datasets. As a result, the datasets used in this paper have been assembled specifically for this project thanks to the help of various international energy agencies, universities, NGOs and multilateral development organizations. We discuss each set of data used below. For convenience we report data description distinguishing between 'green' and 'non-eco-friendly' spending and between 'energy' and 'land use' spending, in the following order: green energy spending data, including spending on supply and power investments on both renewables and non-renewables (subsection III.A); non-eco-friendly energy spending data including capital expenditure on the supply of fossil fuel and non-eco-friendly energy power investment (subsection III.B); green land use spending, mainly including spending on biodiversity conservation (subsection III.C); non-eco-friendly land use spending, mainly including subsidies to conventional industrial agriculture excluding green spending (subsection III.D).[8]

A. Green Energy Spending Data

Data on capital expenditure on clean renewable energy

Contrary to fossil fuels, most renewable energy (solar, wind, hydropower and other renewables, notably geothermal and marine power, biofuels and biogases) is directly obtained from readily available natural sources—solar, wind, geothermal[9] and marine[10] energy. In this sense, there is no such thing as investment in the 'supply' of these sources, contrary to fossil fuels which need to be detected (via exploration) dug up from underground deposits (via drilling either on land or on the seabed) and often refined involving substantial

[8] Note that spending on energy and land use differ because the former involves considerably more infrastructure spending, whereas the latter relies almost entirely on operational capital and smaller infrastructure/machinery investment, generally. Subsidies to land use/agriculture involve some support to the purchase of investment goods but also other categories of spending like price support, support for the purchase of seeds, insurance, etc. In addition, subsidies to land use (green or brown) tend to be spent by the public sector, which is not the case for spending on green or brown energy which is largely private.

[9] Geothermal energy is heat derived within the sub-surface of the earth. Water and/or steam carry the geothermal energy to the Earth's surface. Depending on its characteristics, geothermal energy can be used for heating and cooling purposes or be harnessed to generate clean electricity.

[10] Marine energy or marine power (also sometimes referred to as ocean energy, ocean power, or marine and hydrokinetic energy) refers to the energy carried by ocean waves, tides, salinity, and ocean temperature differences.

‘supply’ investments prior to being burnt for power generation. As a result, the investment made to generate clean renewable energy is all virtually directed at building (and operating) the infrastructure to transform the Earth’s natural energy into electricity. Some investment in renewables relates to repowering, that is spending for the refurbishment or upgrading of existing turbine system components with the latest and more advanced equipment.[11]

Our data on clean renewable energy comes from the IEA and consists of IEA estimates of capital spending on power generation using renewable sources by 11 countries or groups (Oceania Group merging Australia and New Zealand; Brazil; Canada; China; EA Group merging France, Germany and Italy; Indonesia; Japan; Korea; Mexico; Russia; and the USA) over the period 2000-2020. The investment data represent the total amount of investment costs in power generation incurred in any given year through the setup of solar wind, and other energy ‘farms’, as well as in networks for the transmission of electricity generated this way.[12] Investment in electricity networks includes investment in new infrastructure to accommodate new demand (increased connections and consumption), investment to replace ageing infrastructure and the investment required to integrate renewables in the power system and includes both transmission and distribution, and expenditure on digital equipment for the smart monitoring and operation of the grid (e.g. smart meters, automation and EV fast charging stations).[13] All these data exclude both financing and operational costs like for non-renewable clean energy below.

Data on capital expenditure in clean non-renewable energy (nuclear energy)

Data on capital expenditure on nuclear energy are rather homogenous and potentially go back several decades, as the world’s first nuclear power plant to produce usable electricity through atomic fission was built in the early 1950s. Despite this, up until a few years ago, the literature on the construction costs of nuclear power reactors looked solely to the development between 1970 and the end of the 1980s in the costs of construction in two countries (France and the United States), leaving out about three quarters of reactors built globally between 1960 and 2010 (see for example Grubler, 2010, and Berthélemy and

[11] The IEA indicates for example, in the case of wind farms, that by leveraging upon latest technological advances, repowering allows not only to “increment the nameplate capacity of an existing wind farm, but also to enhance load factors and to reduce operation and maintenance costs. This is mainly driven by larger turbines and increased hub heights that allow production of a greater amount of power with a smaller number of turbines” (IEA, 2020b).
[12] Investment estimates draw on IEA analysis on annual capacity additions and unit investment costs, partly derived from surveys with industry, IEA (2019a), S&P Global Platts (2020), BNEF (2020), IRENA (2020) and other organizations. More details can be found in IEA’s methodological annex to the IEA’s 2020 World Energy Report.
[13] Where possible, past investments in transmission and distribution assets, are based in publicly available data from utilities, regulators and other domestic entities.

Escobar-Rangel, 2015). More recently, data has been produced to map historical reactor-specific overnight construction cost (OCC) data covering the full cost history for existing reactors in the Canada, France, Germany, Japan, India, South Korea and the United States, encompassing about two-thirds of all reactors built globally (Lovering, Yip and Nordhaus, 2016).[14]

The data used here extends the Lovering et al. (2016) dataset to 2017 and to include China. It was assembled specifically for this project by the OECD's Nuclear Energy Agency in collaboration with the World Nuclear Association and the International Atomic Energy Agency. Like in Lovering et al (2016), the data is measured looking at the real OCC of completed plants because it is both the dominant component of lifetime costs for nuclear power, and the cost component that varies most over time and between countries. The metric OCC includes the costs of the direct engineering, procurement, and construction (EPC) services that the vendors and the architect-engineer team are contracted to provide, as well as the indirect owner's costs, which include land, site preparation, project management, training, contingencies, and commissioning costs. The OCC excludes financing charges known as 'interest during construction.' The data, originally compiled in local currency units, have been converted to constant 2010 US dollars, using the nominal average market exchange rate of the year 2010 for comparability. Cost data are adjusted for inflation to constant 2010 values using the GDP deflator for each country. Lastly, the plant level data are aggregated at the country/year level based on the construction duration and assuming costs are spread homogenously across this construction period.

B. Non-Eco-Friendly Energy Spending Data

Like for green spending on energy (Subsection III.A), for non-eco-friendly spending on energy we use data from the IEA. The data record annual total capital spending on fossil fuels by 11 countries or groups (Oceania Group merging Australia and New Zealand; Brazil; Canada; China; EA Group merging France, Germany and Italy; Indonesia; Japan; Korea; Mexico; Russia; and the USA) over the period 2000-2020. Like for green energy spending

[14] OCC should not be confused with another popular measure of "cost" namely the Levelized Cost of Electricity (LCOE). It is the total cost to build and operate a power plant over its lifetime divided by the total electricity output dispatched from the plant over that period, hence typically cost per megawatt hour. It takes into account the financing costs of the capital component (not just the 'overnight' cost). This other metric reflects the 'total average cost per KWh' but does not reflect the total cost of electricity/services provided. Importantly, note that when comparing nuclear and renewables such as solar and wind, system costs should also be considered, as discussed in recent studies from the OECD-NEA (2019) and MITEI (2018) because when the share of wind/solar grows above approximately 1/3 of the electricity mix, the system costs grows exponentially and outweigh the advantage of cheap solar/wind.

sectors, the investment data for oil, gas and coal represent the total amount of investment costs incurred in any given year.[15]

In the case of upstream oil and gas investment, global spending estimates are based on announced investment activities of companies representing over three-quarters of global oil and gas production. Data on spending estimates for the oil refining sector are calculated based on project-level information on new refineries and upgrading projects in over 100 countries. Data on investment estimates for the midstream sectors such as oil and gas pipelines and shipping transport correspond to data by the IEA for demand, supply and trade for oil and gas products in line with the new methodology of the World Energy Model, used to produce the projections in the IEA's annual World Energy Outlook (IEA, 2020).

For the power generation sectors, this investment is allocated evenly between the year in which the project for a new plant reaches financial close, or begins construction, to the year in which it starts producing. For upstream oil and gas, and liquefied natural gas (LNG) projects, data on investment mirrors capital expenditure sustained over time as production from a new source increases, or expenditure made to ensure that energy production from an existing asset is sustained (IEA, 2020b).

Data on investment in electricity reflect annual capital expenditure to replace old assets or on new power plants and network assets. Here as well, expenditure is apportioned evenly to every year from the year that a final investment decision is made on an asset until the year the asset turns operational. In this sense, 2019 capital expenditure embeds also spending on assets that may not yet be operational but that will become operational in the future.[16] Like for spending on clean energy, investment in electricity networks includes transmission and distribution. Similarly to data on clean energy, these data exclude both financing and operational costs.

C. Green Land Use Spending Data

Ideally, an analysis on the economic impact of spending on green land use activities should encompass spending on sustainable agriculture and spending on ecosystem conservation. If

[15] Investment estimates reflect IEA analysis on annual capacity additions and unit investment costs, derived in part from surveys with industry, IEA (2019), S&P Global Platts (2020), BNEF (2020), IRENA (2019) and other organizations.
[16] The way the IEA measures investment across various energy sectors varies reflecting differences in the availability of data and the nature of expenditures. More details can be found in the World Energy Investment 2020 Methodology Annex.

possible, both should cover activities at sea, beyond terrestrial ones. In practice, (public and private) spending on sustainable farming remains negligible relative to spending on conventional (i.e. industrially mechanized, fossil fuel-energized and chemically driven) agriculture: in 2019, conventional agriculture still dominated 98 percent of food production globally (Batini, 2021). In addition, although sustainable farming has traditionally characterized all farming prior to the introduction of industrial farming methods following WWII, public subsidies to farming have actually coincided with the post-WWII industrial revolution of agriculture and are aimed primarily at sustaining industrial unsustainable practices by prizing productivity and profitability with little or no consideration for quality or human, animal or planetary health. On the contrary, efforts to redirect public agricultural support toward sustainable, regenerative farming—like organic farming—are very recent and in best cases extremely timid (Batini 2019 and 2021). It follows that data on spending on sustainable agriculture, when they exist and are not insignificant, do not go back much in time. The brevity of time series also affects potentially useful sources like green financing by the International Fund for Agricultural Development, which, potentially interest many countries but has started to be classified based on its 'greenness' only since 2018 (see IFAD, 2019). Data on spending on sustainable fishing activities, like regenerative ocean farming does not go far either, even if these activities go back for hundreds of years or even millennia, implying that this area of spending is equally impossible to analyze empirically (Batini and Smith, 2021).

Reflecting these constraints, we focus on what we consider to be the most reliable set of available data on spending in green (*aka* sustainable) land use activity, namely data on spending on biodiversity conservation. There is no standardized definition of what constitutes "biodiversity spending," a situation that has led countries to report, under the 'biodiversity' flag, a heterogeneous mix of items that can include the entire government budgets for agriculture, health, and environmental control including urban waste disposal. However, Miller et al. (2012) and Waldron et al (2013, 2017) define a subset of "strict" spending that directly conserves biodiversity (e.g. funding for a nature reserve). They then compiled the most complete and consistent long time series of biodiversity spending produced to date, applying a forensic examination of data from the four main sources of funding from 1992 to 2008: domestic governments, international aid (including donations from private foundations), long-term endowment-based systems such as conservation trust funds, and self-funding arrangements such as when tourism revenue to a national park is recycled to subsidize the park's running costs. Simultaneously, they used their definitions to extract this strict spending from biodiversity expenditure totals. The advantages of the "strict" dataset are that it has a consistent definition, greatly reducing the heterogeneity in what might be reported as "biodiversity spending", and that it avoids an inherent contradiction in the more loosely defined spending data—that spending on agriculture, for example, will often fund processes hostile to the conservation of biodiversity, as well as a subset of initiatives that aim to mitigate those processes. For these reasons, we focused on the strict dataset.

The specific data requirement for the multiplier calculation is that there should be a reasonably accurate year-by-year record of spending in each country. Data on aid-based expenditure is usually available for each individual year, but precise annual time series are far more difficult to assemble for the other sources of spending. We therefore focused on assembling a dataset of countries where reasonable annual expenditure estimates of total strict-sense expenditure could be sourced. In practice, this usually meant focusing on a number of countries where the relatively accurate data on aid was the dominant source of funding. The final sample of 16 countries for biodiversity-spending multiplier analysis is Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Ghana, Guatemala, Malawi, Mozambique, Niger, Senegal, Sierra Leone, Madagascar, Tanzania and Uganda. The final time period over which a time series was compiled was 1994-2008 (omitting 1992 and 1993 because of zeroes in those years for some countries).

D. Non-Eco-Friendly Land Use Spending Data

For non-eco-friendly spending, we focus on agricultural subsidies to conventional agriculture based on an elaboration of OECD producer support estimates (PSE) data assembled by Searchinger et al. in 2020 for the World Bank Group. In particular, we focus on the difference between all subsidies and the small percent of these that can be classified as 'green' in that is earmarked as explicitly supporting conservation and/or research and technical assistance items that tend to be weakly associated with sustainability priorities. This means that we consider 'non-eco-friendly' land use spending, spending via agricultural support directed at increasing the quantity and productivity via use of chemical inputs, greater mechanization or greater reliance on fossil fuels. These subsidies typically include (i) input subsidies—payments made to reduce the costs mostly of physical inputs such as chemicals, fertilizer, and machinery, although the OECD also applies the term to transfers reducing the cost of various on-farm services and capital investments; (ii) market price support, that is support which increases gross revenue to farmers as a result of higher prices due to market barriers created by government policies (that in turn require price-fixing strategies and import barriers); (iii) production payments, namely forms of agricultural support that are paid directly to farmers and can take many different forms; (iv) coupled payments, i.e. payments that are based in some way on the type, quantity, or amount of production, which typically is not related nor conditioned to sustainability goals; and also (v) decoupled payments, that is payments to farmers that do not depend on current or future production. For example, they can be payments based on past production.

The data are in current prices and have been converted to US$ using OECD average yearly exchange rates. They cover 20 countries[17]—responsible for 2/3 of global agricultural production—for 22 years going back (1995-2016).[18]

IV. Methodology

A. Empirical Model

To compute multipliers for the various spending categories presented in Section III, we use panel vector-autoregressive (VAR) models.

The models take the following reduced form:

$$y_{i,t} = \rho_i + \gamma_t + A^1 y_{i,t-1} + \cdots + A^p y_{i,t-p} + B_i x_{i,t} + \varepsilon_{i,t}, \qquad (1)$$

where *t* denotes the time dimension, *i* denotes the country dimension and *p* the lag structure. The vector of endogenous variables is denoted by $y_{i,t}$; while $x_{i,t}$ denotes an exogenous variable included in some of the specifications (both are discussed in Subsection IV.B). Furthermore, A^1,…,A^p are the dynamic coefficients attached to the endogenous variables, B_i are the coefficients attached to the exogenous variable, ρ_i are country fixed effects, γ_t are time fixed effects and $\varepsilon_{i,t}$ is a vector of normally distributed residuals with mean zero and covariance matrix Σ_c.

Reformulating the model in vectorized form (ignoring country and time fixed effects and exogenous variables for simplicity) yields:

$$y = \acute{X}\beta + \varepsilon. \quad (2)$$

To estimate the coefficients β and the residual variance covariance matrix Σ, we adopt a Bayesian approach utilizing a traditional Normal-Wishart identification strategy that belongs to the families of conjugate priors, characterized by the fact that they produce distributions of the same families for the posterior.

We adopt Minnesota-type priors in line with a wide literature. The prior for β is assumed to be multivariate normal:

[17] These countries include Australia, Canada, Chile, China, Colombia, Iceland, Indonesia, Israel, Japan, Kazakhstan, Korea, Mexico, New Zealand, Norway, Russia, South Africa, Switzerland, Turkey, Ukraine, and the United States.

[18] More details on the methodology employed by the OECD to produce PSE data can be found here: http://www.oecd.org/agriculture/topics/agricultural-policy-monitoring-and-evaluation/documents/producer-support-estimates-manual.pdf

$$\beta \sim N(\beta_0, \Sigma_c \otimes \Phi_0). \qquad (3)$$

For β_0 we set values around 1 for own first lag coefficients, and 0 for further lags, cross-variable and exogenous coefficients. Φ_0 represents the variance for the parameters of one single equation in the panel VAR. Each of this variance is then scaled by the variable-specific variance contained in Σ_c. The prior variance on the coefficients assumes that the variance should be smaller on further lags. Such idea is extended to coefficients relating variables to past values of other variables. Given that little is known about exogenous variables, the variance on these terms is large.

The prior for Σ_c is an inverse Wishart:

$$\Sigma_c \sim IW(S_0, \alpha_0), \qquad (4)$$

where S_0 is a diagonal scale matrix for the prior with residual variance defined over the pooled sample of variables, α_0 is prior degrees of freedom defined as the minimum possible to obtain well-defined mean and variance. The posterior is represented by the kernel of a multivariate normal distribution for β (conditional on Σ_c) and an inverse Wishart distribution for Σ_c. Then, the joint posterior is used to derive the marginal distributions for β and Σ_c.

To recover structural shocks from estimated residuals, we apply a Cholesky identification scheme, assuming that the spending variables under investigation react with a lag to GDP, and that the latter reacts contemporaneously to each spending variable shock. In other words, we consider each spending variable under investigation as more exogenous than GDP. This choice is dictated by the fact that both types of green and non-eco-friendly spending examined in this paper are driven by multi-year strategies, and thus do not react mechanically to swings in the economic cycle within the same year. This feature contrasts with public spending items that may be strongly influenced by GDP and are the subject of classic empirical studies on fiscal multipliers. In fact, spending for the construction and installation of energy power-generating stations is mostly privately financed and tends to be preceded by years of feasibility studies, conditions monitoring and lengthy permit applications. Likewise, although often publicly financed, money spent on conservation or industrial agriculture follows arrangements dictated by long-term oriented donor strategies or structural agricultural policies. Hence, in none of these cases, contemporaneous output fluctuations are likely to be strong determinants of spending decisions.

For each of 10,000 draws from the posterior distribution,[19] we derive impulse responses for a time horizon of 5 years, saving the median response and the 16th and 84th percentile of their distribution as confidence bands. Given that the model requires the estimation of many parameters, for the sake of parsimony, we produce the baseline results

[19] Since we cannot derive analytical solutions for the impulse responses, we perform Monte Carlo simulation considering 20,000 parameters draw and discarding the first 10000 draw as burn-in.

with a uniform lag structure of one year and conduct robustness checks with a lag structure of two years in Section VI.

B. Data Coverage and Specification

Details on green and non-eco-friendly spending data are provided in Section III, while details on macroeconomic data are provided in the Appendix. Availability of green and non-eco-friendly spending data, as well as the rest of macroeconomic data dictates the year and country coverage ultimately used in the estimation, which requires balanced panel datasets. Table 1 summarizes the data coverage and sources. Annual data span over sample periods ranging from 1991 to 2019, depending on the spending component analyzed. Nuclear energy spending has the largest time coverage (27 years), while spending on green land use the shortest one (15 years).

At a minimum, the computation of the spending multipliers requires the inclusion of the relevant spending variable, $S_{i,t}$, and of GDP, $GDP_{i,t}$, in the vector of endogenous variables. To these two variables, we add a 1×4 vector of common factors, $F_{i,t}$, (as explained below) to control for a wide range of economic forces that may affect GDP. For the specifications related to investments in energy sources, we include also total investments net of energy investments, $I_{i,t}$, given that this is the direct non-energy counterpart of investment in the economy. In the specifications related to green and non-eco-friendly land use, we do not include total investments explicitly (but only as part of the extraction of common factors) because these two spending categories have a negligible investment component. In addition, their more limited coverage calls for an even more parsimonious specification. Therefore, the vector of endogenous variables reads as

$$y_{i,t} = [S_{i,t}, I_{i,t}, GDP_{i,t}, F_{i,t}], \tag{5}$$

except for the cases of green and non-eco-friendly land use, which exclude $I_{i,t}$.

To simplify the procedure related to the computation of spending multipliers, we divide all endogenous variables by the real potential GDP of the corresponding country. This way there is no need to take the logarithm of the variables and perform ex-post conversions of the estimated elasticities to dollar equivalents, avoiding potential biases. In fact, ex-post conversion requires the use of constant sample averages of the ratios of spending variables to GDP, which may instead vary over time, potentially biasing the size of the multipliers (for more details on this issue see, e.g., Gordon and Krenn, 2010 and Ramey and Zubairy, 2018, among others). For the baseline results we compute real potential GDP using the conventional HP filter, while in Section VI we present robustness checks with an alternative filter.

Table 1. Summary of Data Coverage and Sources

Spending Type	Time period	# of countries	Country list	Data sources
Renewable energy	2003-2019	9 + 2 groups	China, Japan, Korea, Canada, United States, Brazil, Indonesia, Mexico, Russia, Oceania group [Australia and New Zeland], EA group [France Germany and Italy]	IEA, IMF's WEO, Thomson Reuters Datastream
Nuclear energy	1991-2017	6	China, France, Japan, Korea, Canada, Usa	OECD-NEA, IMF's WEO, Thomson Reuters Datastream
Fossil fuel energy	2003-2019	9 + 2 groups	China, Japan, Korea, Canada, United States, Brazil, Indonesia, Mexico, Russia, Oceania group [Australia and New Zeland], EA group [France Germany and Italy]	IEA, IMF's WEO, Thomson Reuters Datastream
Green land use	1994-2008	16	BurkinaFaso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Ghana, Guatemala, Malawi, Mozambique, Niger, Senegal, Sierra Leone, Madagascar, Tanzania, Uganda	Waldron et al. 2018, IMF's WEO, Thomson Reuters Datastream
Non-eco-friendly land use	1997-2016	20	China, Japan, Korea, Canada, United States, Australia, Chile, Indonesia, Mexico, New Zealand, Russia, South Africa, Colombia, Iceland, Israel, Kazakhstan, Norway, Switzerland, Turkey, Ukraine	Searchinger et al. 2020, IMF's WEO, Thomson Reuters Datastream

As anticipated, to the basic set of endogenous variables, we add common factors, via principal components extracted from many macroeconomic times series. In fact, VAR models are characterized by a trade-off between parsimony and omission of relevant variables, which can give rise to "non-fundamentalness" of the identified shocks (see, e.g., Forni et al., 2009). "Non-fundamentalness" arises when current and past values of the observables do not contain enough information to recover structural vector autoregressive (SVAR) disturbances. In a nonfundamental system, structural shocks obtained via standard identification procedures may have little to do with the true disturbances, making SVAR evidence unreliable (see, e.g. Canova and Sahneh, 2018). Extracting information from a large set of macroeconomic variables mitigates the limited information problem because the principal components proxy the unobserved factors affecting most macroeconomic variables (see Fragetta and Gasteiger, 2014 for further details). Like Bernanke et al. (2005), we implement a two-step estimation procedure. As a first step, we extract four common factors. The Bai and Ng (2007) ICp2 information criterion selects 2 to 4 factors, depending on the country. Given that our approach constraints the number of factors to be the same for all countries in the panel, we utilize 4 factors uniformly for all countries. Depending on the country, factors explain between the 65,84% and the 89,95% of the informational dataset variance. The second step is adding the factors to our vector of endogenous variables.

Except for the specifications on green and non-eco-friendly land use, where the investment component is small, we add the forecast of total investments as an exogenous variable. Namely, this is the forecast of time-*t* total investment (gross capital formation), developed by the IMF's World Economic Outlook (for the renewable and non-eco-friendly energy spending specifications) a year before. The addition of this variable represents a way to purge the investment shocks from the change in the total investments already anticipated by economic agents in the past year, mitigating the problem of *shock foresight*, well known in the fiscal literature. Here, clearly the expectations refer not only to government, but also to private spending. The choice of controlling for *total* investments is dictated by the absence of comprehensive vintages of forecasts of investment in energy sources.

V. RESULTS

This section reports our baseline results. We discuss results by sector, starting with energy to then move to land use, and comparing output effects of green and non-eco-friendly spending. Two sets of results are shown in each case: the *impulse response functions* (IRFs) of spending (in alternative forms of energy or land use) on GDP, and the associated *cumulated spending multipliers* defined as the cumulative change in GDP divided by the cumulative change in spending on energy or land use, at various time horizons, following the approach proposed by Gordon and Krenn (2010) and Ramey and Zubairy (2018). As discussed in the previous section, having normalized the variables of interest by real potential GDP circumvents any concerns related to ex-post conversion. Thus, cumulated multipliers are computed simply as the ratio of discrete approximations of the integral of the median IRFs of real output and government purchases over a given time horizon.

Multiplier values should be interpreted in the standard way. For example, a value of the cumulated spending multiplier equal to 1.5 in the third year would indicate that, after three years from the occurrence of the spending shock, the cumulative increase in output, in dollar terms, is one and a half the size of the cumulative increase in green (or non-eco-friendly) expenditure. In this case, then, a change of, for example, US$100 in public or private investment in clean energy infrastructure or power generation will have an effect of more than US$100 (and precisely US$150) on the level of real GDP.

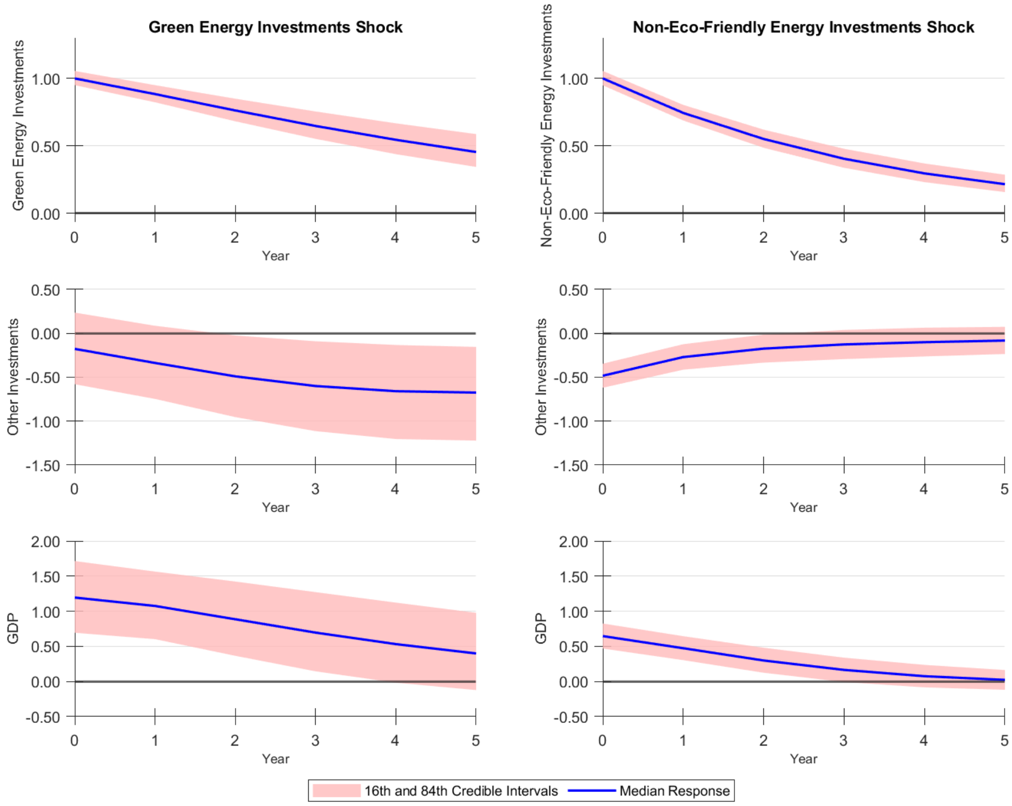
As first proposed by Keynes, the multiplier may be greater than one because a change in aggregate expenditures circles through the economy: firms investing in renewables pay workers and suppliers, workers and suppliers buy goods from other firms, those firms pay their workers and suppliers, workers spend on consumer goods generating further streams of income, and so on (Keynes, 1936). In this way, the original change in aggregate expenditures spurred by an increase in, say, private investment in clean energy is actually spent more than once. Note that Keynes' investment multiplier related interchangeably to public or private spending or the sum of these, and thus our multipliers are not fiscal spending multipliers but Keynesian investment multipliers, *lato sensu*.

A. Green Energy Versus Non-Eco-Friendly Energy Spending Multipliers

In this subsection we report impulse response functions (IRFs) and cumulated multipliers of spending on clean energy (renewable and non-renewable) versus spending on non-eco-friendly energy (fossil fuel energy generation). It is worth noting upfront that multipliers related to fossil fuel and renewable energy generation are fully comparable because their underlying data cover the same country and time sample. The data on nuclear energy spending cover a smaller set of countries and a larger number of years, therefore they are not strictly comparable.

Figure 1 shows the impulse response of GDP to a 1 percent shock to spending in renewable clean energy versus a similar shock in non-eco-friendly energy; the upper and lower borders of the pink area around the median (blue) line indicate the 16^{th} and 84^{th} credible intervals, as customary with Bayesian inference. The figure shows that a shock to spending on green renewable energy is more persistent than an equal-sized shock to fossil fuel energy spending, and the output response is much more persistent, hovering well above zero beyond the medium term (5 years), while the output response to a non-eco-friendly energy spending shock dies off completely after 5 years. Both shocks, in the transition, crowd out other investments to an extent.

Figure 1. Impulse Responses to Green (Renewable) and Non-Eco-Friendly (Non-Renewable) Energy Investment Spending



Note: Blue bold lines represent median responses. Shaded areas represent credible intervals delimited by the 16^{th} and the 84^{th} percentiles.

Based on the impulse response depicted in Figure 1, we can compute the corresponding multipliers (Table 2). Both at short and longer horizons the green renewable energy spending multiplier is systematically higher than the non-eco-friendly energy multiplier. Specifically, the impact multiplier for green renewable energy is 1.19. For non-eco-friendly energy, the impact multiplier is 0.65, suggesting that these kinds of expenditures tend to crowd out private investment or consumer spending that would have otherwise taken place to a larger extent.

Table 2. Cumulated Multipliers associated to Green (Renewable) and Non-Eco-Friendly (Non-Renewable) Energy Investment Spending

Horizon	Green (Renewable) Energy Investments Multiplier	Non-Eco-Friendly Energy Investments Multiplier
Impact	1.19*	0.65*
1 Year	1.20*	0.64*
2 Years	1.19*	0.62*
3 Years	1.17*	0.59*
4 Years	1.14*	0.55
5 Years	1.11	0.52

Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

Focusing on the impact multiplier, however, may be misleading because investments in energy can only be implemented over time and the economy may only respond gradually. The cumulative multiplier for green renewable energy spending falls only marginally over the years and plateaus to a 5-year value of 1.11, very close to the first-year effect. This may reflect the fact that renewables are built sequentially and the persistence of the multiplier as well as the fact that the composition of their investment vector typically includes different types of activities (construction itself, networks for transmission and distribution, smart meters, etc.). For non-eco-friendly energy spending, however, the multiplier becomes even smaller at year 5 (0.52). In other words, when an additional dollar of public or private money is spent to build more fossil fuel energy infrastructure and power generation plants, this expenditure crowds out some other component of GDP (investment, consumption, or net exports) by 48 cents in the medium run. When the same dollar is spent on solar, wind or geothermal, 11 cents are instead crowded in. In addition, while the green multiplier is statistically significant up until 4 years after the shock occurrence, the non-eco-friendly multiplier loses its significance after 3 years.[20]

A fair question is whether the difference between the two multipliers is statistically significant. Bayesian inference does not allow us to construct a test as in the frequentist approach. Therefore, we follow an approach compatible with Bayesian inference, in line with Caggiano et al. (2015) and Amendola et al. (2020). This approach, however, requires the multipliers to be computed within the same specification, which is feasible given the homogenous coverage for green (renewable) and non-eco-friendly (fossil fuel) investment data. Therefore, we re-estimate a VAR containing both investments in the vector of endogenous variable, with green investment ordered first and non-eco-friendly investment

[20] For the sake of simplicity, we prefer to use the terminology of statistical significance, in analogy to the frequentist approach to inference. However, the Bayesian approach formally leads to credible intervals around the estimates. We consider "significant" those multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

ordered second (the opposite ordering yield very similar results, reported in Section VI). Exploiting the 10,000 parameter draws from the posterior distribution, we compute empirical distributions of the differences between green and non-eco-friendly energy investment multipliers. This procedure allows us to compute the probability that the difference is greater than zero (Table 3). It turns out that, at all horizons, more than 90 percent of the distribution is located above zero, indicating that the difference between the two multipliers is positive with high probability. In addition, the merged specification yields higher median green energy investments multipliers, and lower median green energy investments multipliers, than the two separate specifications, making the point estimate of the difference between the two even higher.

Table 3. Cumulated Multipliers associated to Green (Renewable) and Non-Eco-Friendly (Non-Renewable) Energy Investment Spending—Merged specification

Horizon	[A] Green (Renewable) Energy Investments Multiplier	[B] Non-Eco-Friendly Energy Investments Multiplier	Prob [A]>[B]
Impact	1.40*	0.62*	0.92
1 Year	1.46*	0.58*	0.94
2 Years	1.49*	0.54*	0.94
3 Years	1.51*	0.51	0.93
4 Years	1.53*	0.48	0.92
5 Years	1.54	0.47	0.91

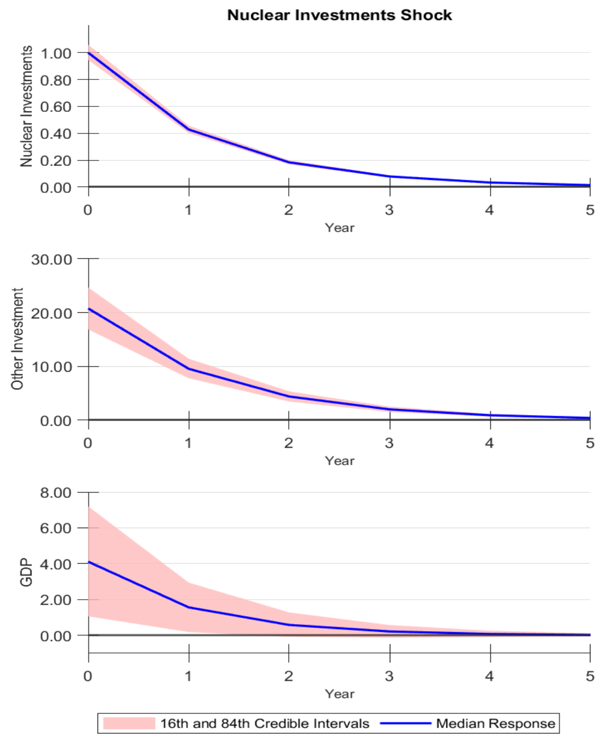
Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

These results are intuitive on three grounds. First, clean energy is more labor intensive than carbon-based fuels spending. In relation to spending within the fossil fuel industries, spending on clean energy—including the direct spending on specific projects plus the indirect spending of purchasing supplies—uses far more of its overall investment budget on hiring people, and relatively less on acquiring land (either on- or offshore), machines, and supplies and energy itself (Wiser et al., 2011; IRENA, 2016; Garrett-Peltier, 2017; WRI, 2020b). In addition to the jobs directly created in the renewable energy industry, growth in clean energy can create positive economic "ripple" effects. For example, both industries in the renewable energy supply chain and unrelated local businesses will benefit from increased household and business incomes (EPA, 2020; IEA, 2020c). Second, clean energy implies a higher domestic content. Considering direct plus indirect spending—clean energy spending relies much more on economic activities taking place within the domestic economy—such as retrofitting homes or upgrading the electrical grid system locally—and less on imports than spending within conventional fossil fuel sectors (IRENA, 2016; EPA, 2020). Third, clean-energy investments produce far more jobs at all pay levels—higher as well as lower-paying jobs—than the fossil fuel industry (E2-ACORE-CELI, 2020). For the United States, for example, Muro et al., (2019) find that workers in clean energy earn mean hourly wages that are between 10 and 20 percent above the national average; and their wages are more equitable, with workers at lower ends of the income spectrum earning up to US$10 more per hour than other jobs. At the same time, clean-energy investments also produce more jobs for a given dollar of expenditure due to the larger number of entry-level jobs relative to the fossil fuel industry. Jobs spread across three major industrial sectors (clean energy production, energy efficiency, and environmental management) and include all levels of skills including many electricians, carpenters, and plumbers. These considerations help rationalize the much stronger multiplier effect of clean spending than that of non-eco-friendly spending on the larger economy.

Figure 2 shows the impulse response of GDP to a 1 percent shock to spending in non-renewable clean energy (nuclear energy). The figure indicates that also in the case of nuclear energy, spending is more persistent than investment in non-eco-friendly energy. In addition, it has a crowding-in effect on other investments. This finding is consistent with the notion that nuclear investment tends to generate considerable employment at the local level (WNA, 2020). Table 4, reporting cumulated spending multipliers, indicates that spending on nuclear energy has a large output effect, about six times larger than the output effect associated with spending on fossil fuel energy. However, nuclear spending multipliers lose statistical significance after two years from the occurrence of the shocks.

Although nuclear spending multipliers are not strictly comparable to the other two sets of multipliers, its initially larger values may be linked to their nature. Relative to other forms of clean energy (e.g. solar and wind) investments in nuclear energy may lead to larger employment of both high- and lower-skilled resources for the construction of nuclear reactors relative to lighter energy producing infrastructure. In addition, while building and operating nuclear reactors tends to take time (5.1 years on average for large reactors of recent construction) spending is not sequential like in the case of renewables and tends to be more frontloaded, which could explain the stronger near-term impact and subsequent loss of statistical significance. This intuition is corroborated by findings in studies comparing a steady-state employment estimate for the generation of electricity using nuclear versus wind power, which indicate that investment in nuclear power produces about 25 percent more employment per unit of electricity than wind power (WNA, 2020). Moreover, research comparing pay across nuclear, wind and solar direct workforces in the United States in 2017 indicates that pay of nuclear workers is one-third higher than that in the wind and solar sectors, and that they were paid more than twice the mean for power sector workers (Oxford Economics, 2019). In the medium term, the nuclear energy spending multiplier is still larger than the renewable energy counterpart but, being not statistically significant, does not allow a clean-cut statistical comparison vis-à-vis multipliers from investment in other types of energy.

Figure 2. Impulse Responses to Nuclear Energy Investment Spending



Note: Blue bold lines represent median responses. Shaded areas represent credible intervals delimited by the 16th and the 84th percentiles.

Table 4. Cumulated Multipliers associated to Nuclear Energy Investment Spending

Horizon	Nuclear Energy Investments Multiplier
Impact	4.11*
1 Year	3.97*
2 Years	3.88
3 Years	3.83
4 Years	3.80
5 Years	3.78

Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

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B. Green Land Use Versus Non-Eco-Friendly Land Use Multipliers

Figure 3 plots the impulse response of GDP to a 1 percent shock to spending on ecosystem conservation (green land use spending) versus a shock of the same size to spending on subsidies to conventional agriculture (non-eco-friendly land use spending).

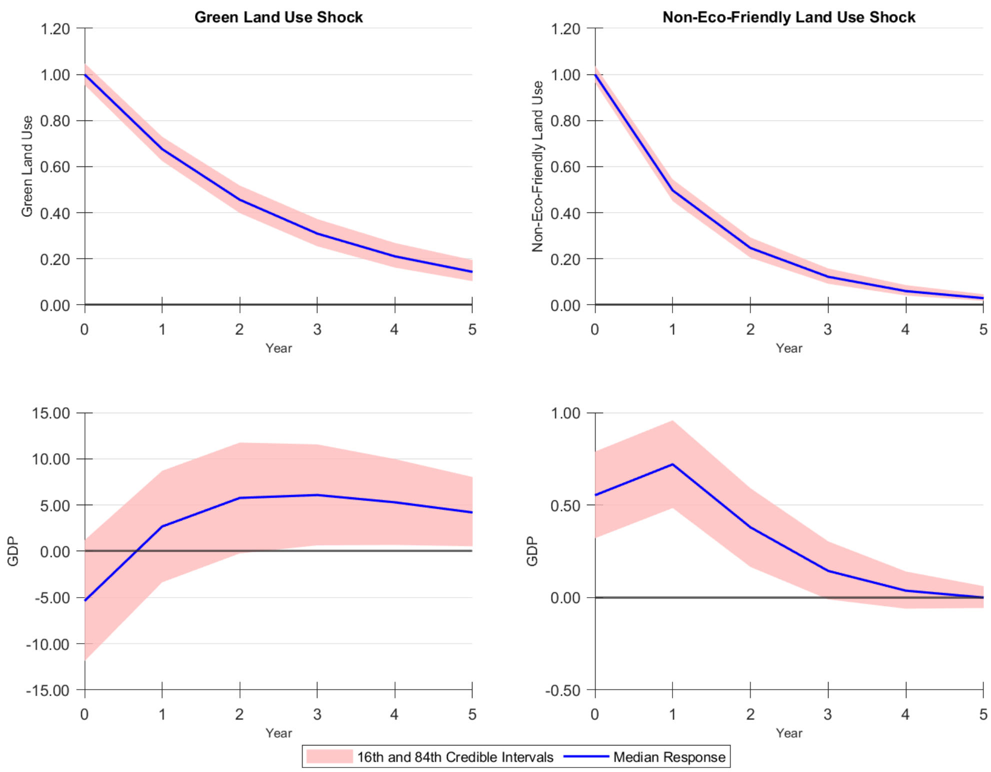
Interpreting differences in multipliers and impulse responses from spending in these two land use categories requires caution for two reasons. First the IRFs and associated multipliers have been estimated over different country and time samples, and in two separate econometric specifications, because of data coverage and availability constraints explained in Section 3. This is also the reason why a statistical test on their difference cannot be constructed. In addition, spending in conservation reflects a mix of public spending in wages, education, training and recreational programming (which are thus part of public consumption) and some public investment,[21] whereas spending on conventional agriculture here reflects primarily public transfers and subsidies to crop and animal producers in industrial farm systems. However, even coarse comparisons of average output effects of spending on sustainable versus unsustainable land uses can be informative, as a consensus is emerging that subsidies to unsustainable land use and conventional agriculture should be quickly redirected toward sustainable uses (see for example UNEP-UNDP-FAO, 2021). Getting a sense of the potential economic gains (or losses) of redressing land use subsidies to sustainable and land regenerative goals is key for policymaking and budgetary decisions.

The impulse responses in Figure 3 indicate that the effect of a shock to conservation spending is long-lasting, similarly to the shock to green spending in the energy sector, implying that for this sector too, the economic contribution of a stimulus can generate durable economic benefits, in addition to the mitigation and carbon-sink gains from preserving wildlife. By contrast, the effect of a spending shock to support industrial farming activities is considerably shorter-lived and completely dissipates after 5 years.

Table 5 reporting cumulated spending multipliers on green versus non-eco-friendly land use shows that, while green land use spending multipliers are not significantly different from zero on impact and over the first year's horizon, cumulated multipliers at horizons greater than one year are large and grow over time. This suggests that spending to sustain natural ecosystems exerts powerful positive ripple effects on the economies that practice it: for every dollar spent in conservation, almost seven more are generated in the larger economy in the medium term, a result in line with findings in bottom-up analyses of local and regional impacts (see Sub-Section V.C).

[21]For example this includes the construction and the maintenance of infrastructure such as fences, boardwalks, observation platforms, and other durable machinery such as communication equipment and optical devices for distant viewing, vehicles or satellite monitoring and GPS tracking devices necessary to perform conservation services.

Figure 3. Impulse Responses to Green and Non-Eco-Friendly Spending for Land Use



Note: Blue bold lines represent median responses. Shaded areas represent credible intervals delimited by the 16th and the 84th percentiles.

Table 5. Cumulated Multipliers associated to Green and Non-Eco-Friendly Spending for Land Use

Horizon	Green Land Use Multiplier	Non-Eco-Friendly Land Use Multiplier
Impact	-5.36	0.55*
1 Year	-1.60	0.85*
2 Years	1.45*	0.95*
3 Years	3.75*	0.96*
4 Years	5.45*	0.95
5 Years	6.67*	0.94

Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

These high multipliers associated to green land use are expected and can be ascribed to three main determinants. First, the estimates are conducted on data from developing countries, which typically capture spending programs financed by donors. Given that these programs do not crowd out nor absorb, but rather supplement, domestic resources, they are naturally characterized by high multipliers. Second, as documented by Waldron et al. (2020) the conservation activity has a strong labor intensity. Much of the economic impact of conservation is in driving a visitor economy, with associated creation of opportunity and income in sectors such as hospitality and tourism in rural and coastal communities which, in developing countries, tend to have below average income and thus are more likely to have higher propensities to spend. Third, by limiting land available for agricultural expansion, conservation spending lifts the prices paid to rural producers (Waldron et al., 2020). More generally, protecting biodiversity helps underpin the ecosystem services upon which economic activity and lives depend like food production, fresh water, natural resources, the protection from extreme weather events. These activities all create jobs and an inspiration for innovation through biomimicry (Kennedy and Marting, 2016; OECD, 2020).

By contrast, the multipliers of spending to support industrial agricultural production are below one at every horizon. This reflects the high mechanization of industrial agriculture, the typically low value added associated with high costs of machinery, fossil fuel energy, and imported chemical inputs and foreign-patented GMO seeds, all of which tend to have low domestic content, given the high global market concentration of suppliers of all these inputs (FOLU, 2019; UNEP, 2020; UNEP-UNDP-FAO, 2021). While keeping in mind the caution on comparability made above, this finding is a potential indication that repurposing spending from unsustainable land uses toward more labor intensive and high-domestic content sustainable land uses may promise important economic gains and may hold the keys to a successful green recovery.

C. Comparison of Green Spending Multipliers to Sectoral Impact Studies

It is difficult to contextualize our novel multiplier estimates in pre-existing empirical literature. The most proximate comparators are input-output and bottom-up studies on the impact of spending on GDP or GVA in some of the energy and land use spending categories[22] examined here.[23] However, clean categories do not yet exist in input-output tables, and most available studies are based on *ad-hoc* assembled "synthetic" industries. This approach allows researchers to evaluate public and private spending in clean energy and

[22] Input/output models link various sectors of the economy—agriculture, construction, government, households, manufacturing, services and trade—and trace how spending flows among those various sectors. An input/output model also includes geographic linkages, and shows how spending flows at national, state and county levels.
[23] GDP and GVA multipliers differ in derivation. The GDP multiplier describes the total output generated as a result of $1 of output in the target industry; the GVA multipliers instead describes the additional value added generated in the economy by spending $1 of direct value added. Gross value added provides a dollar value for the amount of goods and services that have been produced in a country, *minus* the cost of all inputs and raw materials that are directly attributable to that production. It thus corresponds to the difference between gross and net output.

compare it to the effects of spending on fossil fuels, for example. Also, some of the available studies only focus on employment creation, glossing over GDP impacts altogether.

Existing bottom-up and input-output analyses reaffirm significant economic benefits of green spending:

- *Clean (renewable) energy*. Estimates of the job impact of spending in clean energy indicate that this may beat job creations from spending on fossil fuels by a ratio of 3:1 (Pollin et al., 2009; Garrett-Peltier, 2017; WRI, 2020b). Forecasts of the growth impact for the United States of the American Clean Energy and Security Act (ACESA) performed employing different macro econometric models confirmed conclusions from other models that a transition to a lower-carbon economy would have no significant effect on the U.S. economy's long-term growth trajectory (Pollin et al., 2009). These findings are even more notable given that all these models did leave out positive effects of higher employment, the economic benefits of a higher level of domestic content (and thus a reduced trade deficit), the possibilities for major technological breakthroughs and the economic benefits of reducing greenhouse gas emissions. Globally, a 2016 report by IRENA calculates that doubling the share of renewables in the global energy mix by 2030 would increase global GDP by up to 1.1 percent or US$ 1.3 trillion compared to business as usual. Most of these positive impacts on GDP are driven by the increased investment in renewable energy deployment, which triggers ripple effects throughout the economy (IRENA, 2016). More recently, research by McKinsey (2020b) focusing on a typical European country of 50 million to 70 million people found that every €1 spent in clean energy could generate some €2 to €3 of GVA.[24] This research indicates that the employment boost from this stimulus package would also be substantial: 1.1 million to 3.0 million new "job years" of employment.

- *Clean (non-renewable) energy*. In the case of nuclear energy spending, NEI (2014) calculated economic benefits associated with the construction of 23 nuclear plants (comprising 41 reactors) in the United States using IMPLAN's input/output model, widely used by U.S. government agencies. The data collected for these studies provide a snapshot of the economic impact of an average nuclear power plant, including economic value or output (based on the plant's electricity sales), jobs provided, and labor income.[25] "Multipliers" can be developed for any industry/business sector or geographic area in the model, and capture the ratio of the

[24] The analysis focuses on four broad categories of clean energy spending, namely: Industry (improve industrial energy efficiency; build carbon-capture-and-storage infrastructure); Buildings (retrofit houses for energy efficiency; install smart-building systems; Energy (reinforce the electricity-distribution grid; expand energy storage; accelerate build-out of wind and solar power; accelerate rollout of LED street lighting); Transport (expand electric-vehicle charging networks; create bus rapid transit and urban rail schemes; scale up electric-vehicle manufacturing; develop active-transport infrastructure).

[25] Labor income is a subset of the total economic value or output.

facility's total economic output or value to its direct economic output or value. Multipliers for a county are typically found to be smaller than for a larger area, such as the state in which the county is located, because some spending associated with an economic activity migrates from the small area into the larger area. At the local area level, multipliers are larger if the local area tends to produce the types of goods and services that the plant requires. Estimates from the analysis based on normalized averages from analyses of the economic and employment impact show that every dollar spent by the average reactor results in the creation of US$1.04 in the local community, US$1.18 in the state economy and US$1.87 in the U.S. economy.[26] These results are corroborated by findings in country case studies on nuclear investment indicating that nuclear spending has added more value in GVA terms than the value associated by similar expenditure in non-eco-friendly energy (see for example IAEA, 2009).

- *Green land use*. In line with findings reported here, the most comprehensive global assessment of the financial and economic impacts of conservation ever completed looks at the impacts of six different combined terrestrial and marine scenarios with varying tradeoffs between biodiversity protection and extractive uses. It found that protecting 30 percent of the world's land and ocean provides greater benefits than the *status quo*, both in terms of financial outcomes and non-monetary measures like ecosystem services (Waldron et al., 2020). The revenues associated with protected areas outweighed the costs by a factor of at least 5:1, a multiplier close to our aggregate top-down estimates. This is a conservative ratio because it does not include non-monetary economic benefits from ecosystem services such as climate change mitigation, food protection, clean water provision and soil conservation. The study also found that land use patterns that prioritize biodiversity more strongly require higher public expenditure, as expected, but they also yield greater financial and economic benefits, with the scale of the rewards being directly linked to the level of financial ambition.

VI. Robustness Analysis

In this section we present the results of robustness checks addressing issues commonly discussed in the fiscal multipliers literature, which may be applicable also to the analysis presented in this paper.

First, given that, relative to the number of observations available, the panel VAR model requires the estimation of a large number of parameters, we produce the baseline

[26] The estimates are calculated per megawatt of installed capacity and reflect a nominal 1,000-megawatt plant size. In practice, new nuclear plants are larger than 1,000 megawatts, so the economic benefits understate the benefits that new nuclear plants will produce.

results with a uniform lag structure of one year. Bearing in mind that the use of a long lag structure would not be feasible, as we would run out of degrees of freedom, we check whether results are robust to the use of a lag structure of two years.

Second, to facilitate the computation of the baseline multipliers, we divide the endogenous variables by the real potential GDP of the corresponding country. This avoids potential biases that could arise from using constant sample averages of the ratios of fiscal variables to GDP in the ex-post conversion of the estimated elasticities to dollar equivalents (see, e.g., Gordon and Krenn, 2010; and Ramey and Zubairy, 2018). In our baseline estimates, we compute real potential GDP using the conventional HP filter. However, given the uncertainty around estimates of a latent variable such as potential GDP, we check whether results are robust to the use of the filter by Mohr (2005), which virtually removes the pro-cyclical bias in end-of-sample trend estimates that may arise with the use of the HP filter.

Tables 6-8 report the green and non-eco-friendly multipliers obtained by making these modifications to the baseline estimation procedure. All conclusions drawn from the baseline estimates survive the changes. While green (renewable) energy investment multipliers are slightly higher under the alternative specifications, non-eco-friendly energy investment multipliers are virtually unaffected (Table 6).

Table 6. Robustness Checks on Cumulated Multipliers Associated to Green (Renewable) and Non-Eco-Friendly (Non-Renewable) Energy Investment Spending

	Lag structure of 2 years	
Horizon	Green Energy Investments Multiplier	Non-Eco-Friendly Energy Investments Multiplier
Impact	1.28*	0.66*
1 Year	1.43*	0.66*
2 Years	1.48*	0.65*
3 Years	1.46*	0.62
4 Years	1.41	0.60
5 Years	1.35	0.58
	Alternative measure of potential GDP	
Horizon	Green Energy Investments Multiplier	Non-Eco-Friendly Energy Investments Multiplier
Impact	1.73*	0.65*
1 Year	1.68*	0.65*
2 Years	1.61*	0.64*
3 Years	1.53*	0.61
4 Years	1.45	0.58
5 Years	1.39	0.55

Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

Table 7. Robustness Checks on Cumulated Multipliers Associated to Nuclear Energy Investment Spending

Horizon	Nuclear Energy Investments Multiplier
Lag structure of 2 years	
Impact	4.38*
1 Year	4.23*
2 Years	4.10
3 Years	4.01
4 Years	3.95
5 Years	3.92
Alternative measure of potential GDP	
Impact	3.26*
1 Year	3.17*
2 Years	3.12
3 Years	3.09
4 Years	3.07
5 Years	3.06

Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

Table 8. Robustness Checks on Cumulated Multipliers Associated to Green and Non-Eco-Friendly Spending for Land Use

Horizon	Green Land Use Multiplier	Non-Eco-Friendly Land Use Multiplier
Lag structure of 2 years		
Impact	-3.38	0.19*
1 Year	-1.77	0.22
2 Years	0.93	0.25
3 Years	3.59*	0.27
4 Years	5.60*	0.28
5 Years	6.85*	0.30
Alternative measure of potential GDP		
Impact	-5.18	0.42*
1 Year	-1.97	0.55*
2 Years	0.81	0.62*
3 Years	3.02*	0.66*
4 Years	4.70*	0.67
5 Years	5.98*	0.67

Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

Relative to the baseline results, nuclear energy investment multipliers are somewhat higher with a lag structure of two years and slightly lower with the alternative measure of potential GDP, but the overall dynamic and statistical significance is very similar (Table 7). Finally, the multipliers associated with green spending for land use under the alternative specifications are comparable to those obtained under the baseline model. In contrast, non-eco-friendly land use spending multiplier become smaller and quickly lose statistical significance with a lag structure of two years (Table 8).

In Subsection V.A, we also reported multipliers of green (renewable) and non-eco-friendly (fossil fuel) investment computed within the same specification, to calculate the probability that their difference is greater than zero. This implied estimating a VAR containing both investments in the vector of endogenous variables and the order used was green investment first and non-eco-friendly investment second. Therefore, it seems worth checking whether inverting the order of the two investments in the vector of endogenous variables changes the results significantly. It turns out that it does not (Table 9). In this case, the probability of green energy investments multipliers being larger than non-eco-friendly investments multipliers is somewhat lower, but still ranges between about 80 and 90 percent, depending on the horizon, leaving the bottom line of the analysis unaltered.

Table 9. Robustness Check on Cumulated Multipliers associated to Green (Renewable) and Non-Eco-Friendly (Non-Renewable) Energy Investment Spending—Merged Specification and Alternative Variables Ordering

Horizon	[A] Green (Renewable) Energy Investments Multiplier	[B] Non-Eco-Friendly Energy Investments Multiplier	Prob [A]>[B]
Impact	1.12*	0.68*	0.79
1 Year	1.23*	0.65*	0.84
2 Years	1.31*	0.62*	0.87
3 Years	1.36*	0.59	0.87
4 Years	1.40*	0.57	0.86
5 Years	1.44	0.55	0.86

Note: * denotes multipliers with credible intervals, delimited by the 16th and the 84th percentiles, that exclude zero.

VII. CONCLUSIONS AND POLICY IMPLICATIONS

The post-COVID-19 economic recovery stimulus packages provide a unique opportunity to build a more resilient and sustainable future and advance the much-needed transition. Building back better, many argue, promises recovery results in economic growth, while at the same time strengthening resilience against future climate related shocks and mitigating climate change itself.

In this paper we have assembled a new international dataset documenting expenditure in green and non-eco-friendly energy and land use—the two main sources of anthropogenic pressure on Earth's planetary boundaries—from a variety of institutional and academic sources. We used these data to estimate spending multipliers by employing a well-known estimation methods. To our knowledge this is the first study to estimate output multipliers of renewable and non-renewable (nuclear) energy investments, and on those associated with fossil fuel energy, conservation and industrial agriculture.

We find that investing on clean energy, like solar, wind or nuclear ends up producing more GDP than it initially demands. By contrast, spending on non-eco-friendly energy generation, is found to crowd out other forms of domestic spending to a larger extent. These findings can be rationalized by noting that, compared with fossil fuel technologies, which are typically mechanized and capital intensive, the renewable energy industry is more labor intensive. This feature is highlighted in sector studies documented in the paper, showing that more jobs are created for each unit of electricity generated from renewable sources than from fossil fuels.

Similarly, our findings on ecosystem conservation spending show that it is associated to large economic gains. In contrast, spending to support unsustainable land uses—in our case highly mechanized and imported-input-dependent industrial crop and animal agriculture—returns less than the initial expenditure.

All our estimates are robust to different econometric specifications and may underestimate the economic gains from investing in green energy and land use. In fact, they do not account for the current or future GDP impact of climate change and biodiversity loss, nor for the public health implications of non-ecofriendly spending, both of which are non-negligible and are on the rise globally (see, for example, Burke, Hsiang and Miguel, 2015; OECD, 2020).

The overarching conclusion from this study is that gearing post-COVID economic stimuli to investments that favor decarbonization and carbon-capture through nature-based solutions is not just good for the planet: it also promises to be the cheapest and shortest route back to a prosperous global economy.

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APPENDIX

A. Data

A.1 Endogenous Variables

Our variables of interest are gross domestic product and, depending on the specification, total investments, renewable energy investments, non-eco-friendly energy investments, nuclear energy investments, green land use spending, non-eco-friendly land use spending.

Data on clean renewable energy and non-eco-friendly energy investments come from the International Energy Agency. Data on nuclear energy investments were assembled specifically for this project by the OECD's Nuclear Energy Agency in collaboration with the World Nuclear Association and the International Atomic Energy Agency. Green land use spending data were updated starting from the work of Waldron et al (2013, 2017). Non-eco-friendly land use spending data are based on an elaboration of OECD producer support estimates (PSE) and assembled by Searchinger et al. in 2020 for the World Bank Group. Gross domestic product and total investments are downloaded from the IMF's World Economic Outlook database.

All series are transformed in real terms using the implicit GDP price deflator. Then, they are normalized by diving by real potential GDP.

The time span and the set of countries included in the analysis depend on the availability of data. Specifically:

- for clean renewable energy and non-eco-friendly energy investments specifications, dataset includes China, Japan, Korea, Canada, United States, Brazil, Indonesia, Mexico, Russia, Oceania group (Australia and New Zealand) and EA group (France, Germany and Italy), for a time span that goes from 2003 to 2019;

- for nuclear energy investments specification dataset includes China, France, Japan, Korea, Canada and United States, for a time span that goes from 1991 to 2017;

- for green land use spending specification dataset includes Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Ghana, Guatemala, Malawi, Mozambique, Niger, Senegal, Sierra Leone, Madagascar, Tanzania and Uganda, for a time span that goes from 1994 to 2008;

- for non-eco-friendly land use spending specification dataset includes China, Japan, Korea, Canada, United States, Australia, Chile, Indonesia, Mexico, New Zealand, Russia, South Africa, Colombia, Iceland, Israel, Kazakhstan, Norway, Switzerland, Turkey and Ukraine, for a time span that goes from 1997 to 2016.

A.2 Exogenous Variables

Regarding specifications that include clean renewable energy investments, non-eco-friendly energy investments and nuclear energy investments, we use as exogenous variables the forecast of the total investments made at time *t-1* for time *t*, provided by IMF's World Economic Outlook.

A.3. Informational Dataset

The informational dataset used to extract common factors consists of 12 series for each country downloaded from IMF's World Economic Outlook and Thomson Reuters Datastream Economics databases. The choice of the time series to include in the informational dataset is dictated by their availability for all countries and for all periods included in the analysis.

The following variables were downloaded for each country considered:

- National Account: Government Consumption Expenditure; Total Government Revenue; Export of Goods and Services; Imports of Goods and Services; Final Consumption Expenditure of Households; Gross National Saving.

- Output: Industrial Production Index (not available for Green Land Use Dataset); Change in Inventories.

- Employment: Employees Domestic Concept.

- Exchange rates: Real Effective Exchange Rates (not available for Green Land Use Dataset).

- Money and credit quantity aggregates: Broad Money or Money Supply M0, M1, M2, M3 (depending on the availability).

- Price indexes: Consumer Price Index.

Where appropriate we transform variables to guarantee stationarity tested by the Phillips and Perron (1986) and Kwiatkowski et al. (1992) tests.