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&
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ASSESSING METHODS TO INTEGRATE THE PHYSICAL RISKS AND TRANSITION RISKS AND OPPORTUNITIES OF CLIMATE CHANGE INTO THE PRESIDENT'S MACROECONOMIC FORECAST

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SUMMARY

The Federal Government has broad exposure to the physical risks of climate change and the transition risks associated with the global shift away from carbon-intensive energy sources. At the same time, the shift to clean energy provides a generational opportunity to create new sources of economic growth. These transitional opportunities and challenges affect future output growth and other economic outcomes and are therefore relevant to the President's Budget. Building on nearly three years of work completed under Section 6(a) of Executive Order 14030 on Climate-Related Financial Risk, this paper presents a step-by-step methodology for quantifying these risks and opportunities into a macroeconomic forecasting framework with the goal of more accurately projecting near-term macroeconomic outcomes relevant to the President's Budget. For each step, we assess available tools, methodological tradeoffs, and directions for further research based on the current literature.

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1. Introduction

A growing body of literature documents how the effects of climate change, including rising temperatures, sea levels, and natural disaster frequency and intensity, affect macroeconomic outcomes such as productivity, labor supply, capital stocks, and overall economic output (e.g., Jay et al. 2023; Hsiang et al. 2023). Similarly, accumulating evidence demonstrates that transitioning to a clean energy system—one with net-zero emissions of greenhouse gases (GHGs)—will require a structural transformation of a scale, scope, and speed not previously seen, a process that is also likely to affect macroeconomic outcomes. Yet the U.S. Government's Budget forecast does not explicitly account for the macroeconomic effects of climate change nor the transition to a clean energy economy.[1] Accounting for these factors could have important policy implications since the macroeconomic forecast informs the Administration's policy proposals and the budgets that Agencies submit to the Office of Management and Budget (OMB).

To enhance the Government's ability to respond to the risks and opportunities arising from climate change and the clean energy transition, President Biden signed Executive Order (EO) 14030 on Climate-Related Financial Risk, directing work across the Federal Government to "advance consistent, clear, intelligible, comparable, and accurate disclosure of climate-related financial risk." Section 6(a) of the EO tasks the Council of Economic Advisers (CEA) and OMB to "identify the primary sources of Federal climate-related financial risk exposure and develop methodologies to quantify climate risk within the economic assumptions and the long-term budget projections of the President's Budget." This directive complements others within EO 14030, such as assessments of programmatic climate risk to the Federal Budget, as well as broader actions across the Federal Government to understand the economics consequences of climate change. Some of these efforts—for example, estimating the social cost of GHGs—consider how climate change impacts the economy and social welfare beyond what macroeconomic indicators capture. Because the scopes of these different measures are sufficiently distinct, care needs to be taken when considering how advances in estimating the effects of climate change on measures of social welfare more broadly may inform estimates of the effects of climate change on macroeconomic assumptions underpinning budget forecasts, and vice versa.

This paper builds on prior work responding to the EO by presenting a step-by-step approach to quantifying climate risks in a macroeconomic forecasting framework to inform the President's Budget. Each step in our approach features important decision points for those engaging in this work. We separate climate risk into two components: (1) the physical risks associated with the effects of climate change on economic outcomes and (2) the transition risks and opportunities associated with the effects of the clean energy transition. Quantifying the economic effects of

[1] Following the literature's convention, we refer to an economy with net-zero GHG emissions as a "clean energy economy". However, as illustrated in the United States' Long-Term Strategy, achieving net-zero GHG emissions across the economy will also require transitions independent of the production and use of energy (Department of State and Executive Office of the President 2021). In our approach, we address the transitions of both energy and non-energy sectors needed to achieve net-zero GHG emissions, as well as measures related to resiliency and adaptation.

physical risks requires estimating changes to environment and weather systems due to GHG emissions. Quantifying the economic effects of transition risks and opportunities requires accounting for both mitigation and adaptation actions as well as individuals' and firms' behavioral changes in the face of what potentially could be an historically swift structural transformation.[2]

This paper's contribution is twofold: (1) to identify key decision points in the process of accounting for climate change in macroeconomic forecasting; and (2) to assess available tools, methodological tradeoffs, and directions for further research based on the current literature. The literature has made considerable advances in recent years, and improvements in available tools allow us to more robustly account for the macroeconomic implications of physical risks and the transition to a clean energy economy. However, several areas remain where further research would be particularly useful for quantifying climate risk both in the context of the macroeconomic forecast for the President's Budget and more broadly:

- Most macroeconomic analyses draw on climate information at coarse spatial and temporal resolutions (e.g., national average annual temperature or precipitation). However, many of climate change's most consequential effects are driven by extreme events at a local or regional scale. Assessing these events will require a methodology that can tractably map from climate information at higher spatial and temporal resolutions to macroeconomic outcomes.

- The physical risks of climate change are most accurately reflected as a distribution of potential outcomes, with many of the effects concentrated in relatively unlikely, but potentially significant outcomes ("tail" events). This distribution of risks and effects motivates questions about how to adequately address physical risk in the context of central tendencies used for government budgeting. For decisionmaking purposes, budgeting currently relies on a single economic forecast, even as specific policies are shaped by broader macroeconomic analyses.

- Because weather patterns and shifts in energy supply and demand are already affecting macroeconomic indicators, research should assess the extent to which climate change and the risks and opportunities of transitioning to a clean energy economy are already captured by existing macroeconomic forecasts. Such research would help to avoid unintentionally double counting macroeconomic effects.

- Additional research is needed to account for the macroeconomic implications of the transition to a clean energy economy within sectors including industry and agriculture, as well as the macroeconomic effects of adaptation measures both private agents and governments have taken.

[2] In practice, physical risks interact with transition risks and opportunities. We follow the literature's convention by discussing these types of risks and opportunities separately, and anticipate that future research will better allow us to account for the macroeconomic implications of their interactions.

- Many studies find that the clean energy transition will necessitate net increases in investments in key sectors to build out capacity. However, the literature does not yet address the degree to which such additional investments might displace other economic activity. The degree of displacement will have important implications for macroeconomic forecasts.

Governments around the world, as well as multilateral institutions, private businesses, and academic institutions, are also working to answer these questions. The Fifth National Climate Assessment (2023), the work of a U.S. Government interagency process led by the U.S. Global Change Research Program, provides a comprehensive assessment of our current understanding of climate change's various physical risks and their influences on the domestic economy, and informs our discussion of modeling physical risks. The Congressional Budget Office likewise accounts for physical risks in its long-term macroeconomic outlook (Hernstadt and Dinan 2020). Multiple central banks, including the Federal Reserve, participate in the Network of Central Banks and Supervisors for Greening the Financial System (n.d.). Additionally, the Coalition of Finance Ministers for Climate Action (n.d.), which includes the Department of the Treasury, has produced multiple reports detailing climate risks' implications for key government functions and responsibilities, and how finance ministries can contribute to climate action. National governments—such as in Denmark (Danish Research Institute for Economic Analysis and Modelling n.d.), France (Pisani-Ferry and Mahfouz 2023), and the United Kingdom (Skidmore 2022)—are assessing transition risks and opportunities within the specific context of their own countries.

This paper begins with a brief overview of macroeconomic forecasting in the context of the Federal Budget. It then walks through the steps required to incorporate the effects of climate change and the transition to a clean energy economy into a macroeconomic forecast as well as key areas for future research.

2. Methodology Overview

Economic forecasts reflect our understanding of the present and future economic landscape, helping policymakers, investors, and the public make sense of economic data and inform expectations about the future.

The President's macroeconomic forecast serves two specific purposes. First, it provides a consistent basis for Agencies to make estimates of outlays and receipts for the Federal Budget. Second, the macroeconomic forecast is a policy statement, reflecting the President's best assessment of how the Administration's policies will affect future macroeconomic outcomes. As Box 1 outlines, however, the Budget's macroeconomic forecast is not a comprehensive measure of welfare, a stress test, or a statement about subnational economic conditions.

In previous white papers, we assessed the research on how to integrate climate change into a macroeconomic forecasting model. In CEA and OMB (2022), we broadly describe key challenges when incorporating climate into a macroeconomic forecasting model and the resources available to do so. In CEA and OMB (2023), we then identify several economic pathways by which physical risks and transition risks and opportunities can affect macroeconomic conditions and offer a conceptual framework to guide methodologies. This paper builds on that framework by developing a step-by-step methodology that contextualizes the literature, highlighting various points of consideration when integrating physical risks and transition risks and opportunities into a macroeconomic forecast, and posing questions for future research.

Box 1. Contextualizing the Budget's Macroeconomic Forecast

Consistent with section 6(a) of Executive Order 14030 (Executive Office of the President 2021), the methodological considerations discussed here focus specifically on quantifying climate risk within a macroeconomic forecast for a budgeting exercise. As discussed in Section 2, macroeconomic forecasts play a central role in fiscal policy. Nonetheless, this focus on macroeconomic forecasting cannot—and does not intend to—provide a comprehensive assessment of the macroeconomic effects of physical risks or transition risks and opportunities. The Federal Government relies on a much broader set of analyses than macroeconomic forecasts alone to inform its actions on climate, and the approaches considered here are not intended for other applications. We highlight three important limitations in scope when only analyzing effects on a macroeconomic forecast.

First, although macroeconomic forecasts play a critical role in the formulation of the U.S. Government's budget, they are not a comprehensive measure of welfare. Welfare measures are helpful guides in policymaking, and can provide important information in benefit-cost analyses, while economic measures, like gross domestic product (GDP), do not seek to correct for externalities and do not fully reflect nonmarket benefits, such as the value of improved health and well-being. Moreover, GDP currently does not link to natural capital accounting, and therefore does not fully capture changes to natural factor endowments. A macroeconomic forecast is unable to capture several important consequences of climate change and climate change policy (CEA and OMB 2023). On the physical side, GDP omits important nonmarket benefits of climate policy such as avoided human health impacts (Carleton et al. 2022), reduced social instabilities connected to climate change (Carleton and Hsiang 2016; Hsiang et al. 2017), and avoided degradation of ecosystem services (Drupp and Hänsel 2021; Hoel and Sterner 2007). The social cost of greenhouse gases aims to capture these broader benefits (Environmental Protection Agency (EPA) 2023a). Similarly, on the transition side, since macroeconomic variables do not reflect externalities, they cannot capture the welfare effects of the clean energy transition.

Second, macroeconomic forecasts for budgeting purposes generally reflect a central tendency, whereas policymaking often benefits from economic modeling that can consider a range of potential outcomes. Stress testing and "what if" analyses can provide useful context for understanding the scope of a policy's economic implications. The contrast between a central tendency and less likely outcomes is particularly acute for climate policy, given the potential relevance of extreme event scenarios for both physical and transition risks. Historical relationships of central tendency may therefore be less reliable indicators of future developments. Moreover, because economic dynamics can vary significantly with the state of the economy (e.g., in recessions versus expansions), our discussion's focus on forecasting central projections may not fully inform an integration of physical or transition risks into other macroeconomic modeling exercises. As CEA, OMB, and Department of the Treasury highlighted in a recent memo (2023), further enhancements in a number of research areas would considerably improve U.S. Government analytic capacity.

Third, a macroeconomic perspective can abstract from important variations across locations within the United States. For example, the Fifth National Climate Assessment notes that physical and transition risks vary significantly by location and socioeconomic status (Jay et al. 2023; Hsiang et al. 2023). Subnational analyses are particularly critical for State, Tribal, and local government decisionmaking, and can also help guide the development of Federal policies. Similarly, many Federal programs provide support to specific groups in need, and assessments that account for variation in impacts by socioeconomic status and related dimensions can ensure those programs are adequately targeted and funded. Executive Order 14030 also calls for the assessment of the Federal Government's climate-related financial risk exposure, leading to a range of analyses of Agency programs (e.g., OMB 2022; OMB 2023; OMB 2024). Programmatic and microeconomic assessments of climate-related financial risk provide an important complementary perspective to the macroeconomic forecasting we consider here.

Because our primary focus is the macroeconomic forecast used in the President's Budget, we predominantly consider a decadal horizon and anchor our discussion to a common approach to multiyear macroeconomic forecasts: the supply-side decomposition of the economy. As Table 1 illustrates, this decomposition breaks gross domestic product (GDP) into the product of its core components, including the working-age population, labor force participation rate, the average workweek, and labor productivity.[3] For the purposes of climate-energy-economic modeling, we group these elements into two components: measures related to labor supply (rows 1-4) and measures related to labor productivity (rows 5 and 6).[4] Labor productivity within the nonfarm business sector (row 5) itself can be decomposed into a component related to the capital stock and multifactor productivity. One of the advantages of a supply-side approach is that it anchors the forecast to longer-run trends (e.g., those related to population demographics) that, over the span of a decade or two, are roughly exogenous to many macroeconomic forces.[5] Because the supply-side decomposition of different components adds up to GDP, it offers a helpful way to estimate how changes to the underlying supply-side components lead to changes in projected GDP.

[3] Table 1 specifically reports trends in gross domestic output (GDO),the average of GDP and gross domestic income (GDI). In theory, GDP and GDI should be equal, and hence the same as GDO; in practice, GDP differs from GDI due to differences in underlying data sources. The conceptual decomposition presented in Table 1 also applies to GDP.
[4] The supply-side framework also has implications for other salient macroeconomic variables. For example, the unemployment rate is 1 minus the employed share of the labor force.
[5] The supply-side approach is not ubiquitous in macroeconomic forecasting. For example, as discussed in CEA and OMB (2023), Cambridge Econometrics' E3ME model relies on a demand-focused framework, and has been used in climate-energy-economic analyses.

Table 1. Supply-side Components of Actual and Potential Real Gross Domestic Output (GDO) Growth (%)

	Component	Growth Rate (percentage points)					
		1953:Q2 to 2019:Q4 (1)	1990:Q3 to 2001:Q1 (2)	2001:Q1 to 2007:Q4 (3)	2007:Q4 to 2019:Q4 (4)	2019:Q4 to 2023:Q3 (5)	2023:Q3 to 2034:Q4 (6)
1	Civilian noninstitutional population, age 16+	1.4	1.2	1.1	1.0	0.6	0.7
2	Labor force participation rate	0.1	0.1	–0.3	–0.3	–0.2	–0.1
3	Employed share of the labor force	0.0	0.1	0.1	0.1	0.0	0.0
4	Average weekly hours (nonfarm business)	–0.2	0.0	–0.2	–0.1	–0.2	0.0
5	Output per hour (productivity, nonfarm business)	2.1	2.4	2.4	1.5	1.3	1.7
6	Output per worker differential: GDO vs. nonfarm	–0.3	–0.3	–0.6	–0.4	0.4	–0.2
7	Sum: Actual real GDO	3.0	3.5	2.4	1.8	1.8	2.0

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Sources: Bureau of Labor Statistics; Bureau of Economic Analysis; Department of the Treasury; Office of Management and Budget; CEA calculations.
Note: GDP = gross domestic product. Gross domestic output (GDO) is the average of GDP and gross domestic income. Real GDO and real nonfarm business output are measured as the average of income- and product-side measures. The output-per-worker differential (row 6) is the difference between output-per-worker growth in the economy as a whole (GDO divided by household employment), and output-per-worker growth in the nonfarm business sector. All contributions are in percentage points at an annual rate. The forecast jumps off from data available on November 3, 2023. The total may not add up due to rounding. The periods 1953:Q2, 1990:Q3, 2001:Q1, 2007:Q4, and 2019:Q4 are all quarterly business-cycle peaks. Population, labor force, and household employment have been adjusted for discontinuities in the population series.
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Source: Table 2-3 of CEA (2024).

As outlined in Tables 2 and 3 from CEA and OMB (2023), large and growing literatures are building our understanding of how physical risks and transition risks and opportunities affect the supply-side components of GDP. These effects include direct responses to the physical risks of climate change as well as adaptive and mitigative actions due to technology, behavioral, or policy-induced changes. For example, the effects of climate-change-related events on migration and population growth would affect not only population but also labor force participation and the average workweek, while physical risk's effects on multifactor productivity would influence forecasts for labor productivity. Mitigative actions, like the development and deployment of clean technologies and infrastructure, will necessitate major investments in key sectors, which in turn will affect the capital stocks within the supply-side decomposition of GDP, and may lift labor productivity by boosting aggregate capital services per worker. Additionally, improvements in energy efficiency (Department of State and Executive Office of the President 2021) could translate to improvements in multifactor productivity.

In addition to the canonical components of the supply-side framework, we consider several complementary variables, including interest rates, inflation, residential investment, and international trade. Residential investment and international trade warrant separate consideration over a multiyear forecast window due to the structural changes arising from climate change and the transition to a clean energy economy. In particular, as we discuss below, these variables will be distinctly influenced by physical risk and the transition to a clean energy economy.

As reflected in our discussion above, this paper follows the literature's convention by separately considering the physical risks of climate change and the risks and opportunities of the clean energy transition. In practice, however, physical risk and the clean energy transition interact in many ways, such as adaptions to physical risks that bear on energy supply and demand. For example, climate-induced increases in temperature and water scarcity may further encourage the use of less water-intensive renewable sources, like wind, instead of emissions-producing thermal generation plants (Sanders 2015). An emerging literature is exploring how these interactions between climate events, adaptation to these events, and GHG mitigation affect economic outcomes (e.g., Barrage 2020; Colelli et al. 2022; Jeon 2023). This paper will not consider these interactions in detail, because the methodological approaches for capturing these dynamics in macroeconomic models is nascent, and this area should be revisited in future macroeconomic forecasting efforts.

This white paper offers a foundation for developing estimates of how physical risk and the transition to a clean energy economy will influence the U.S. macroeconomic outlook. In the next section, we present flexible step-by-step methodological frameworks for physical risks and transition risks and opportunities that encompass various options to harness the existing literature and available methods. For each step, we discuss points of consideration when selecting among options and highlight opportunities where research advances could further enhance our understanding of the macroeconomic implications of physical risks and transition risks and opportunities. In Box 2, we lay out "step zero": the extent to which the existing macroeconomic forecast accounts for physical risks and the transition to a clean energy economy.

Box 2. Physical Risks and Transition Risks and Opportunities in a Baseline Macroeconomic Forecast

A primary challenge to integrating physical risks and transition risks and opportunities into a macroeconomic forecast is determining the degree to which the forecast implicitly already incorporates these forces. Ideally, the macroeconomic forecast would be adjusted only to align its implicit assumptions with the macroeconomic forecasters' outlook on future physical risk, adaptation, and the transition to a clean energy economy.

Even if the physical risks of climate change have not been formally incorporated into a baseline forecast, the effects of climate change may be implicitly incorporated if GHG-driven changes in national environmental conditions are correlated with variables used to generate the baseline forecast. Depending on how the baseline forecast is generated and the channels being used to account for physical risk, determining the extent to which a baseline macroeconomic forecast includes the effects of climate change may be difficult.

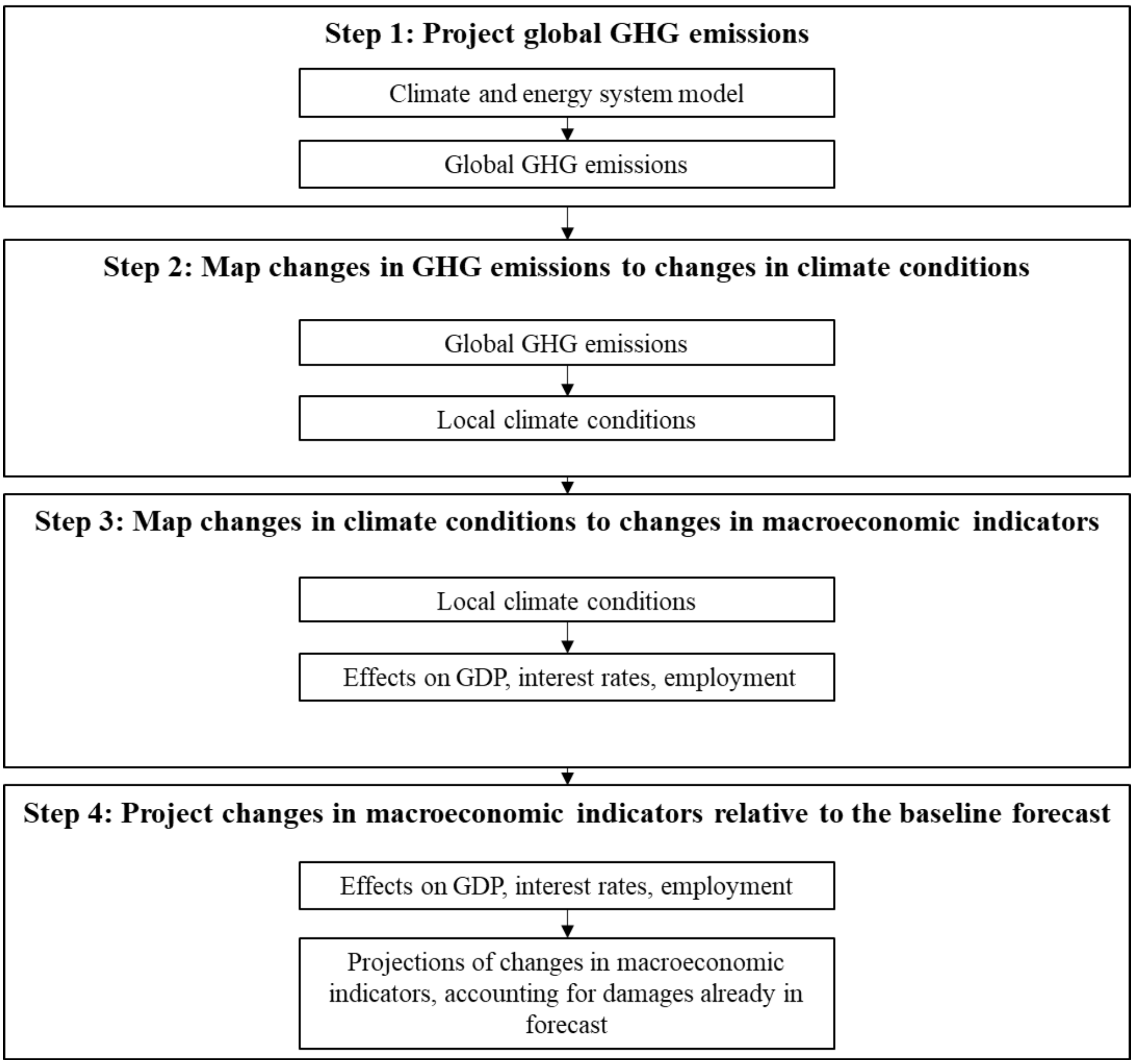
Regarding transition risks and opportunities, recent data already reflect shifts toward a less emissions-intensive economy. Consequently, even macroeconomic forecasts that do not explicitly take into account the effects of policies like the Inflation Reduction Act or other drivers of the transition to a clean energy economy still make implicit assumptions pertaining to the transition's pace, scope, and scale. These assumptions and their implications on the baseline macroeconomic forecast need to be accounted for to ensure that the adjustments to the macroeconomic forecast only reflect the differences between the scenario already captured in the baseline and the scenario consistent with the latest outlook on the clean energy transition.

3. Methodological Considerations

A. Physical Risk

We define the four iterative steps that are necessary to incorporate physical risk into a macroeconomic forecast as: (1) project global GHG emissions; (2) translate global GHG emissions to changes in local climate conditions; (3) map changes in climate conditions to changes in macroeconomic indicators; and finally, (4) project changes in macroeconomic indicators relative to the baseline macroeconomic forecast (Figure 1).

Figure 1. Physical Risk Approach Overview



Forecasters face important decision points in each of these steps, some of which have limited options. For some environmental conditions, the relationship between GHG emissions and the environmental condition is well established, but the relationship between that condition and a particular macroeconomic outcome is not. In other cases, there is confidence in the latter relationship, but the former is uncertain. And in yet other cases, neither relationship is well established.

In an ideal world, each study quantifying the relationship between a local[6] environmental condition and a macroeconomic outcome would account for adaptation, or how economic actors prepare for and respond to a new climate regime.[7] For example, a hotter climate will result in higher electricity consumption due to the increased use of air conditioners (Barreca et al. 2016; Rode et al. 2021). In order to provide estimates of local climate conditions' effects on macroeconomic variables, forecasters need to estimate functions that account for both ex ante and ex post adaptation (e.g., both increased installation of air conditioning in anticipation of warming and more frequent operation of air conditioning under realized warming) (Auffhammer 2018). As we detail later, a critique of recent econometric approaches based on year-to-year weather variation is that they may omit ex ante adaptation.

Uncertainties also exist at each step in the process. For instance, computational limitations, knowledge gaps, and inherent variability prevent many energy-earth system models from analyzing a full range of climate uncertainty. To generate a probability distribution of a given macroeconomic outcome and allow for reporting of both central projections and probabilistic scenarios, one needs probabilistic temperature projections—and changes in any correlated environmental conditions—for any given emissions trajectory from which one could sample interrelated uncertainties regarding climate and climate's macroeconomic effects.[8]

These limitations and uncertainties make providing a comprehensive and deterministic accounting of physical risks a challenge. Doing so would require quantifying relationships between every local environmental condition and every macroeconomic variable of interest—and accounting for adaptation. It is, however, instructive to elaborate on which relationships are supported by current evidence and which presently are difficult to quantify and are thus priorities for future research.

Step 1: Project global GHG emissions

We addressed the first methodological choice on the physical risk side—how to project global GHG emissions—in CEA and OMB (2023). The paper outlines several essential attributes for an energy system model in the context of macroeconomic forecasting, such as the ability to represent the particular U.S. climate policy approach, and then identifies five models that fit those attributes.

Step 2: Translate projections of GHG emissions to changes in local environmental conditions

[6] In this context, "local" refers to both national and subnational environmental conditions.
[7] See Auffhammer (2018) for a detailed discussion of adaptation.
[8] See for example, Rennert et al. (2021) and Rennert et al. (2022).

The second methodological choice is how to translate projections of GHG emissions to local environmental conditions, including extreme heat, flood and drought intensity, hurricane activity, wildfires, and sea level rise. Quantifying these effects onto U.S. macroeconomic forecasts requires specifying the link between GHG emissions and changes in the spatial pattern of these local environmental conditions. Spatial patterns matter for climate-macroeconomic forecasts: a hurricane that makes landfall over a city has different macroeconomic consequences than a hurricane that makes landfall on a sparsely populated area.

Many of the relationships between GHG emissions and local environmental conditions—including potential tipping points—remain uncertain or unknown. The Technical Summary of the Sixth Assessment Report of the Intergovernmental Panel on Climate Change provides detail on the state of these literatures (Arias et al. 2021, Table TS.5). Increases in air temperature and relative sea level across North American regions are consistently projected with high confidence. However, there is mixed confidence in forecasted trends of different precipitation-related impacts—floods, droughts, wildfire—with the direction of change unclear in some cases. Further, across most North American regions, there is low confidence in the local direction of change for wind speed, an indicator for hurricane activity, though there is evidence that the global proportion of tropical cyclones that reach very intense (Category 4 or 5) levels will increase (Knutson 2024).

For the local impacts that can be projected with greater confidence—air temperature and relative sea level rise—forecasters can more readily convert GHG emissions onto local conditions via a "downscaling method."[9] For example, Appendix A demonstrates a method for downscaling projections of global temperature to local temperature. For local impacts for which there is less confidence regarding the resulting spatial distribution of activity—including floods, droughts, and wildfire—forecasters need methodological approaches that account for such uncertainties. For example, forecasters can embed a hurricane model into a global circulation model (GCM) to produce a distribution of hurricane tracks under different GHG trajectories accounting for geophysical uncertainty (Seneviratne et al. 2021; Meiler et al. 2023). Likewise, forecasters could couple a hydrological model with surface and subsurface water flows with a GCM to produce a distribution of forecasted drought, flood, or wildfire conditions across the United States (Seneviratne et al. 2021). These forecasts can then serve as inputs into a stochastic macroeconomic forecast. Ideally, this setup would provide explicit estimates of the distribution of potential changes in the frequency and intensity of various extreme events, which are often the drivers of economic effects, especially on relatively short timescales.

Step 3: Map changes in local environmental conditions to macroeconomic indicators

The third methodological choice is how to map changes in local environmental conditions to macroeconomic indicators. Here, the literature takes two broad approaches. The first, referred to as the "top-down" approach, uses statistical and modeling techniques to estimate the effect of changes in environmental conditions on key macroeconomic indicators such as GDP. These statistical studies leverage large environmental and socioeconomic data, together with the latest

[9] See Carleton et al. (2022) Supplementary Information for a discussion of temperature downscaling.

econometric estimators, and benefit from at least two advantages.[10] First, data coverage across space and time allows researchers to isolate year-to-year variations in an environmental condition to obtain the arguably exogenous effect of the condition without confounding differences across location. For example, rather than attribute GDP per capita differences between hot and cold locations uniquely to their temperature difference—a measurement likely to be confounded because the locations also differ in other ways—researchers can instead compare the GDP per capita for a given location over time between hotter or colder years. Second, the large datasets these studies use enable the estimation of the potentially nonlinear relationship between environmental conditions and outcomes. There are however limitations to what these empirical analyses can provide. For example, as discussed in the next section, these approaches tend to treat adaptation incompletely and generally do not provide insight on the mechanisms through which an environmental condition affects GDP and other macroeconomic outcomes, which are often necessary for macroeconomic forecasting applications.

The second approach, referred to as the "bottom-up" approach, integrates the local effects of climate change into a particular structural representation of the economy. Table 2 from CEA and OMB (2023) broadly discusses these pathways and the U.S. Government's analytical capacity to use them in a macroeconomic forecasting exercise from a supply-side decomposition perspective. The bottom-up approach employs structural models that allow for climate effects to be embedded within key economic relationships, simultaneously yielding aggregate projections and providing scope and granularity to explore different mechanisms. There are also limitations to these bottom-up approaches. Structural macroeconomic models still may not easily capture hard-to-measure impacts, and may instead focus on pathways that are well understood and quantifiable (CEA and OMB 2023). They may as a result miss potentially significant channels that allow for the propagation of physical risks' effects, including those important for understanding macroeconomic effects of climate change (e.g., Kompas et al. 2018; Dellink et al. 2019). See Box 3 for a discussion of different types of bottom-up macroeconomic models that are applicable to the integration of physical risk into macroeconomic forecasts. While these approaches differ in their formulation of agents' decisionmaking and how they aggregate in equilibrium to the macroeconomy, they all feature the main supply-side components of output growth in their architectures, which may be informed by the discussion below of integrating physical risks into bottom-up approaches.

A number of important questions surround how to interpret and aggregate these literatures in the context of macroeconomic forecasting. This section first discusses an application of the top-down approach on the most studied and reproduced relationship in this literature: the relationship between local temperature and GDP per capita. We then discuss top-down approaches to estimating the relationships between other environmental conditions and GDP. Finally, we discuss bottom-up approaches to establishing relationships between local environmental conditions and other macroeconomic variables, including supply-side components of GDP.

[10] For reviews, see Hsiang (2016) and Auffhammer (2018).

Box 3. Types of "Bottom-up" Structural Macroeconomic Models Pertinent to Climate-Macroeconomic Modeling

Integrated assessment models (IAMs) combine a growth model with a climate module to represent how emissions from economic activity alter the global climate and how that in turn affects economic activity. Economists and climate scientists use several types of these models to forecast how climate change will affect macroeconomic measures and vice versa, including DICE (Nordhaus 2017), FUND (Anthoff and Tol n.d.), PAGE (Moore et al. 2018), and RICE (Nordhaus 2017). Highly detailed technology-rich IAMs such as the Global Change Analysis Model (Joint Global Change Research Institute n.d. a) have the ability to model the energy transition but lack the geographic detail needed to robustly quantify climate risk. Until recently, these models were deterministic and often did not have rich regional interactions or sectoral representations. Following recommendations from the National Academies of Sciences, Engineering, and Medicine (2017), more recent IAMS improve the characterization of uncertainty and have more detailed sectoral representations of physical risk, including DSCIM (EPA 2023a) and GIVE (EPA 2023a).

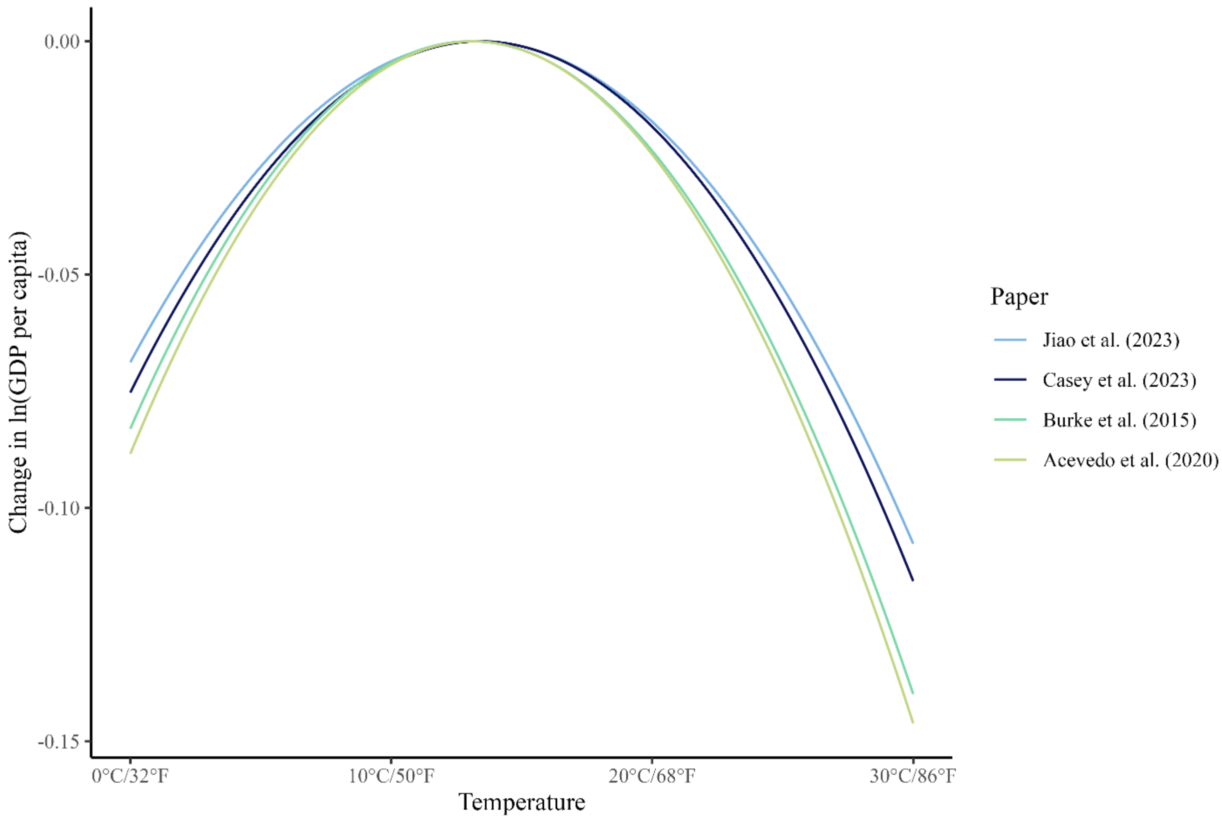
Computable general equilibrium (CGE) and dynamic stochastic general equilibrium (DSGE) models forecast how welfare-optimizing firms and consumers would behave in given economic environments. These agents could represent the entire macroeconomy or specific sectors or geographic regions that make up the macroeconomy. Table 4 from CEA and OMB (2023) discusses peer-reviewed multisector models commonly used by researchers to integrate climate effects. G-Cubed (McKibbin Software Group n.d.) is a hybrid CGE/DSGE model used in climate-macroeconomic modeling, and EPPA (MIT Joint Program on the Science and Policy of Global Change n.d.) and SAGE (Marten et al. 2024) exemplify CGE modeling.

Agent-based computational models (ABMs) are computer simulation models that follow the interactions and decisions of multiple heterogenous, and perhaps boundedly rational, agents. Since these types of models can provide more flexibility in modeling choices, it is becoming more common to integrate them into macroeconomic models (see Balint et al. 2017 for a survey). Lamperti et al. (2018) develop an ABM that allows for endogenous interaction between the macroeconomy and the climate while also allowing for heterogenous shocks to heterogenous agents and for sectoral spillovers.

Top-down approaches: Temperature and GDP per capita

Figure 2 presents the estimated relationship between the country-level real GDP per capita growth rate and population-weighted temperature for several top-down econometric papers.[11,12] Each paper finds a nonlinear relationship between country-level real GDP per capita growth and temperature. At annual average temperatures below approximately 13°C (55 °F), higher temperatures tend to raise per capita GDP growth; at temperatures above 13°C (55 °F), higher temperatures tend to lower per capita GDP growth (Burke et al. 2015).

Figure 2. Estimated GDP-Temperature Relationships



Sources: Burke et al. (2015); Acevedo et al. (2020); Jiao et al. (2023); Casey et al. (2023); CEA and OMB calculations.
Note: Estimated relationships between GDP per capita growth and contemporaneous temperature from published empirical studies. All studies include global coverage of countries. Figure shows relationship from Extended Data Table 1, Column 1 of Burke et al. (2015), Table 1, Column 5 of Acevedo et al. (2020) for 1950-2015 period; Table 4.1, Column 2 of Jiao et al. (2023), and Table 2, Column 4 of Casey et al. (2023).

[11] These papers were selected because they: (1) were published in a peer-reviewed journal in the last ten years; (2) report a statistical relationship between country-level temperature and real GDP growth that controls for potentially confounding factors across locations using panel data; and (3) offer access to replication materials. The papers use location-by-time panel (or longitudinal) data with statistical models that include location-specific fixed effects. This approach controls for time-invariant differences across locations that may be correlated with a location's average temperature and affect GDP growth rates.

[12] Some studies relate subnational temperature to GDP such as Kalkuhl and Wenz (2020). We omit Kalkuhl and Wenz (2020) because (1) their outcome is nominal, not real, GDP; and (2) their subnational regressions are not weighted by the number of subnational units, making their results hard to interpret as country-level effects.

In practice, applying this relationship into GDP per capita projections is a more complicated matter. As Appendix B details, an estimated contemporaneous relationship between temperature and GDP growth could be consistent with a one-time permanent increase in temperature either permanently lowering the level of GDP per capita (i.e., a "level" effect) or permanently lowering the growth rate of GDP per capita (i.e., a "growth" effect) (Dell et al. 2012; Casey et al. 2023; Newell et al. 2021; Nath et al. 2023; Tol 2024; Piontek et al. 2021). For GDP per capita projections, assuming temperature has a growth effect would lead to much larger GDP per capita losses than assuming temperature has only a level effect of comparable magnitude, with the divergence increasing over longer time horizons (see Appendix B).

Whether increasing temperature lowers GDP per capita levels or growth rates remains an open question. As Appendix B details, this question can be empirically assessed using a statistical model estimating lagged temperature effects on GDP per capita growth. If the sum of the lagged coefficients is zero, temperature has only a level effect; if the sum of the lagged coefficients is nonzero, temperature has an additional growth effect. Unfortunately, there are insufficient data to precisely estimate lagged temperature effects, especially over longer time horizons. While data limitations prevent clean empirical resolution of this question, it is unlikely to have much consequence over typical budget forecasting windows, which are often limited to ten years. More recently, Nath et al. (2023) advocate for a middle ground: detecting temperature as having a persistent effect on GDP per capita growth for ten years.

The debate between growth and levels aside, there are other limitations to the estimated relationship shown in Figure 2. First, such top-down relationships may not offer insights into how temperature affects specific underlying mechanisms such as supply-side components of GDP, like total factor productivity, labor force participation, or some other mechanism (Auffhammer 2018; Deschênes and Meng 2018; Pindyck 2021; Lontzek et al. 2015). Understanding such mechanisms is of particular importance for budgeting exercises: the various components of GDP that might be sensitive to temperature influence spending differently. For example, if temperature increases disproportionately reduce labor supply, rather than total factor productivity, higher temperatures could increase reliance on social safety net programs. As we discuss below, bottom-up approaches can provide insight on mechanisms. As the literature is still working toward a consensus understanding of the underlying mechanisms, a typical approach in current analyses is to assume that temperature increases' effects on GDP growth stem from changes in total factor productivity (e.g., Hernstadt and Dinan 2020).

Second, GHG emissions alter climate conditions over a long time horizon, with economic behavior likely responding to those expected changes over time. While changes in GDP per capita based on year-to-year temperature fluctuations provide plausibly exogenous temperature effects, they do not include responses to expected temperature change, which would capture adaptation (Deschênes and Greenstone 2007). By treating the future temperature path as unexpected—when in fact it is strongly trending—employing estimates from studies summarized in Figure 2 would omit the role of private adaptation and governments' adaptation policies.[13]

The issues articulated here for the temperature-GDP per capita relationship—growth versus level effect interpretation, underlying mechanisms, and assumptions about adaptation—are not unique to temperature effects. Small but growing literatures aim to assess the implications of other changes in local environmental conditions driven by GHG emissions on GDP per capita, as we now detail.

Top-down approaches: Other environmental conditions and GDP per capita

Hurricane activity's macroeconomic consequences are well documented. Studies have found links between hurricane activity and GDP per capita growth (Hsiang and Jina 2014; Strobl 2011) and businesses' survival rate (Basker and Miranda 2018). These empirical studies are complemented by structural studies that examine the economic mechanisms and welfare consequences underlying these impacts (Bakkensen and Barrage 2021; Fried 2022; Bilal and Rossi-Hansberg 2023).

However, outside of temperature and hurricane activity, the empirical relationships between GHG-driven local environmental conditions and GDP per capita are less well established. In the case of precipitation, one potential explanation is that it may not be a direct measure of local drought or flood conditions, due to natural hydrological features (e.g., river, lakes, aquifers) and human-made infrastructure (e.g., dams, irrigation canals, levees).

There is limited empirical understanding of wildfires' and sea level rise's macroeconomic impacts, though each poses risks of potential loss in capital stocks. Some recent studies link wildfire smoke to earnings and human health (Burke et al. 2021; Borgschulte et al. 2022; Heft-Neal et al. 2023). The relatively small extent of sea level rise to date has largely led to researchers using modeled and expected, rather than estimated, effects to the macroeconomy (Diaz 2016; Depsky et al. 2023).

Bottom up-approaches: Effects of local environmental conditions on macroeconomic outcomes

While GDP is a key macroeconomic indicator, macroeconomic forecasting often builds off GDP's supply-side components, such as labor productivity, labor force participation, and population. Indeed, the Federal Government largely relies on economic and statistical models of these supply-side components to assemble the macroeconomic forecast used in the President's Budget. However, as mentioned above, physical risk will also cause structural changes to some demand-side indicators including international trade flows and different types of investment, which warrant distinct consideration. As discussed in CEA and OMB (2023), once quantified, these pathways could be incorporated into one of the bottom-up models discussed in Box 3,

[13] Note that if the outcome is an optimized economic variable, like welfare, and there are no dynamics, the envelope theorem applies whereby the marginal impact of a temperature shock equals the marginal impact from a change in expected temperature (Deryugina and Hsiang 2017).

which can be aggregated to inform a projected effect onto GDP or a key component of GDP relative to a baseline (Roson and Sartori 2016; EPA 2021).[14]

Table 2 from CEA and OMB (2023) outlines physical risks' effects on key structural economic variables and the U.S. Government's analytical capacity to estimate these effects for the purposes of a macroeconomic forecasting exercise. The subsequent sections discuss the progress and current gaps to understanding the effects of climate change on these key macroeconomic variables—labor supply, productivity, capital services, and international trade—and consider how they can be incorporated into structural macroeconomic forecasting models.

Labor supply

Local environmental conditions can affect the labor supply components of a supply-side GDP decomposition through altered workweeks, labor force participation, population growth, and migration flows. Several studies examine the effects of temperature on the workweek. For the United States, Neidell et al. (2021) find that extreme temperatures reduce the workweek in industries with a high baseline temperature exposure. Somanathan et al. (2021) find absenteeism increases during hot days. Using data from several countries, Rode et al. (2022) find an inverted-U relationship where both extremely hot and cold days lead to fewer hours worked. The relationship between temperature and hours worked estimated in these studies can be used to inform labor supply forecasts in macroeconomic modeling of climate scenarios. Key challenges facing this literature include difficulties in modeling the flexibility some workers have in adjusting their workweek when experiencing extreme temperatures and incorporating adverse effects on hours dedicated to nonmarket work (e.g., housekeeping).

Climate change might also affect labor force participation through increased morbidity. The Fifth National Climate Assessment concluded that the changing climate is leading to higher incidence of severe and adverse health outcomes (Hayden et al. 2023). However, more work is needed to robustly identify the necessary statistical relationships and account for extreme weather events in addition to changes in temperatures (Ackerman and Stanton 2008).

Climate change's effect on migration is multifaceted, and may therefore be more difficult to incorporate into a macroeconomic forecasting model. Factors influencing decisions to migrate include the available resources at either location—and necessarily the extent to which climate change has depleted those resources—and the costs of avoiding relocation (Cattaneo and Peri 2016; Kaczan and Orgill-Meyer 2020; Hornbeck 2012). Several empirical studies evaluate how climate change alters migration patterns both into and out of the United States.[15] A large literature shows that climate-induced natural disasters and sea level rise have displaced

[14] In particular, EPA's Framework for Evaluating Damages and Impacts (FrEDI) estimates variables relating to the supply-side decomposition of GDP, such as work hours lost and property damages (EPA 2021).

[15] Notable examples include Hunter et al. (2013), Jessoe et al. (2018), and Nawrotzki and DeWaard (2016).

substantial numbers of people.[16] One challenge in this literature is the inherent tension in ascribing causal effects to unexpected climate shocks, when a complementary literature describes migration decisions as typically made in response to anticipated long-run changes (Mullins and Bharadwaj 2021).

Labor and agricultural productivity

Climate change's effects on both labor and agricultural productivity (e.g., crop output per acre) are well documented. Dell et al. (2012), De Lima et al. (2021), and Kjellstrom et al. (2009) find that higher temperatures lead to decreased labor productivity in climate-exposed industries. Interestingly, Basker and Miranda (2018), Hallegatte and Dumas (2009), and Okuyama (2003) find, however, that labor productivity can rise after severe storms, due to the adoption of more capital-intensive work processes implemented by surviving businesses when rebuilding.

Studies on agricultural productivity find that extreme climate events can adversely affect irrigation, crop health, water quality, worker health and safety, inputs supplied, prices, and output yields and quality (Bolster et al. 2023). Beach et al. (2015), Moore et al. (2017), and Baker et al. (2022) find that higher temperatures and GHG emissions lower agricultural yields. Costinot et al. (2016) find that the expected effects of climate change on agricultural productivity could reduce global crop values by one sixth.

Several structural studies leverage statistical relationships between climate change and labor and agricultural productivity to estimate climate change's macroeconomic effects (e.g., Dellink et al. 2019; Roson and Sartori 2016). Dellink et al. (2019) notably rely on statistical relationships between various climate change measures and various measures of productivity, including temperature's effect on labor productivity and extreme weather events' effect on crop yields. This approach allows for the propagation of different types of physical risk across different economic sectors and onto overall macroeconomic indicators.

Physical risks to labor and agricultural productivity are key channels by which climate can affect the macroeconomy, and are featured in each of the structural models cited by CEA and OMB (2023) on methodologies for forecasting the macroeconomic impacts of physical risk. Consequently, existing climate-macroeconomic modeling frameworks could readily leverage further advances in establishing robust empirical findings between physical risk and productivity.

Capital services

Climate change poses significant risks to physical capital, and changes to physical capital will, in turn, affect capital service flows into GDP. Key channels include capital destruction, financing costs and access to insurance, and lower capital productivity (perhaps through higher than expected depreciation or retirement). Each of these channels will influence investment and capital accumulation rates.

[16] See Deryugina et al. (2018) and DeWaard et al. (2020) for examples of hurricanes affecting migration patterns and Depsky et al. (2023), Desmet and Rossi-Hansberg (2021), and Hauer (2017) for examples of sea level rise affecting migration patterns.

Conceptually, the investment response to a climate event that destroys capital is ambiguous: investment growth could move above its prior trend, return to trend, or decline below the trend (Batten 2018). The economic literature has not reached consensus on how investment responds to natural disasters. For example, Hsiang and Jina (2014) and Otto et al. (2023) find evidence consistent with a below-trend recovery scenario following environmental disasters. Crespo Cuaresma et al. (2008) find that added growth can occur in research and development (R&D) in high-income countries and Cavallo et al. (2013) find a recovery to baseline trend following natural disasters. The response of investment to climate-change-induced capital destruction therefore needs to be carefully considered in any structural macroeconomic forecasting exercise.

A significant amount of capital is stored in housing, and climate change threatens to increase the physical risk to real estate. Bin et al. (2011) forecast significant losses to homes exposed to coastal sea level rise. First Street Foundation (2021) estimates that annual losses for properties in flood risk zones totaled $20 billion in 2021 and forecasts annual losses will rise to $32 billion by 2051. Furthermore, Hino and Burke (2021) and Bakkensen and Barrage (2021) find evidence that pricing for climate-exposed buildings does not fully account for climate risk, leading to less efficient resource allocation, particularly during recovery efforts.

Shifts in private and public borrowing costs due to climate risks will also influence investment recovery trends. Angeli et al. (2022) find that climate change can increase risk premiums, which could lead to increased financing costs for investors and lower demand for capital. Correa et al. (2023) find that corporate loan interest rates increase in response to climate-related natural disasters, while Dafermos et al. (2018) develop a structural model and find that climate change leads to increased defaults. Ascari et al. (2024) and Batten et al. (2020) suggest increased inflationary pressures from supply-chain constraints could alter interest rates. Changes to interest rates would not just affect private-sector borrowers; Barrage (2020) finds that shifts in public borrowing due to physical risk are important in determining optimal fiscal policy.

The increase in physical risk from more extreme events will also increase insurance costs (The President's Council of Advisors on Science and Technology 2023). Otto et al. (2023) find that better access to insurance can mitigate declines in GDP growth caused by hurricanes. However, insurance companies are likely to increase rates for homeowners in climate-exposed areas (Mulder and Kousky 2023). At the same time, public insurance programs, such as the National Flood Insurance Program, expect rising payouts as a result of future physical risk (OMB 2022). Shifts in private and public borrowing costs and access to insurance may influence how investment and capital accumulation respond to climate change and extreme weather events.

A relatively common way to capture climate change's effects on capital productivity within a structural economic model is to adjust capital depreciation rates. Climate change can reduce capital available to workers for production, such as electricity transmission, distribution, and generation (Electric Power Research Institute 2022; Auffhammer et al. 2017; Rode et al. 2021) or roads and railways (Jay et al. 2023).[17] Caldecott et al. (2016) find that climate change has increased the incidence of capital stranding. Such outcomes have been explored in structural

[17] Also see Neumann et al. (2021); Parrado et al. (2020) and Fant et al. (2021).

models in the form of climate-induced acceleration of capital depreciation (Fankhauser and Tol 2005; Catalano et al. 2020). The effect of climate hazards on capital depreciation found in these studies could allow macroeconomic models to at least partially account for capital losses due to climate change.

International Trade

Climate change will also affect economic activity outside of the United States, including for the United States' trading partner and potentially affecting foreign demand for U.S. exports or increasing the cost of foreign imports into the United States. Extreme weather events are already disrupting transportation networks directly, raising trade costs and the prices of final goods. For instance, delays in shipping due to the recent droughts in the Panama Canal have already increased U.S. export prices of liquified natural gas (Energy Information Administration 2023) and various agricultural products (United States Department of Agriculture 2023). These effects can be empirically estimated using gravity equations that model trade flows' responses to local climate shocks, holding conditions elsewhere in the trade network fixed (Martínez-Martínez et al. 2023). Such an approach, however, overlooks the global nature of climate change, which alters environmental conditions simultaneously across the globe and can result in cascading impacts (Lawrence et al. 2020). Robustly capturing the effects of climate change requires accounting for trade responses to a global shock (e.g., Dingel et al. 2019).

The current literature suggests that the macroeconomic consequences of physical risks abroad over the next couple decades may not be large enough to have measurable effects on U.S. GDP. Estimates from Dellink et al. (2017) indicate that U.S. imports and exports would decline by roughly 0.2 percent by the early 2030s and by less than one percent by 2060, compared with a baseline without any climate-related effects. Other similar research has largely corroborated this finding.[18] Furthermore, Martínez-Martínez et al. (2023) find insignificant effects of temperature and extreme events on U.S. trade flows using reduced-form econometric approaches.

However, shifts in trade flows due to physical risk could affect production in specific economic sectors and other key economic measures, such as inflation, and these indirect effects could themselves have important consequences for GDP. Liefert et al. (2021) suggest that adverse effects of climate change in other countries could reduce agricultural exports from the United States.[19] McNulty and Jowitt (2021) find that climate change events could affect the extraction of raw minerals, which could introduce price shocks into supply chains that cascade to downstream

[18] For other studies on this topic, see Nordhaus (2011), Eboli et al. (2010), and Feyen et al. (2014). Countries in Southeast Asia, the Middle East, North Africa, and Sub-Saharan Africa are more likely to be adversely affected by climate change because they are more reliant on trade. The studies generally project a decline in world trade, compared with a counterfactual without climate change, which is mostly driven by large projected declines in developing countries closer to the equator where the effects of physical risk from climate change are expected to be more severe.

[19] The authors state that roughly 20 percent of U.S. agricultural production is sold abroad. They assess changes in U.S. agricultural products when purchasers abroad experience natural disasters that reduce their demand for exports. They consider natural disasters occurring in different countries sequentially and simultaneously and at different times.

producers and consumers. Izaguirre et al. (2021) find that climate risk can create congestion at ports, which also introduces higher transport costs that could be passed through to consumers.

At the same time, global trade flows could be altered by diminishing sea ice and the opening of Arctic sea routes. According to the National Intelligence Council (2021), the increased viability of Arctic sea routes could reduce trade times between Europe and China by 40 percent. To date, no studies have estimated the macroeconomic effects of these new routes, but Maurer and Yu (2008) find that the opening of the Panama Canal had significant effects on trade flows and welfare for the United States.

Step 4: Project changes in macroeconomic indicators relative to the baseline forecast

The fourth methodological step to account for physical risk is to project changes to macroeconomic indicators. As discussed in Box 2, accounting for the extent to which the baseline macroeconomic forecast already incorporates physical risk is important. For example, given that temperature affects GDP, that effect may already be indirectly included in GDP forecasts if temperature is correlated with any of the variables formally used to forecast GDP, such as labor market participation (Graff Zivin and Neidell 2014). The magnitude of the implicit effect varies depending on the approach taken to leverage historic economic data to generate the forecast. While this issue—referred to in econometrics as omitted variables bias—is not typically considered in forecasting exercises that prioritize forecast accuracy, it can pose a concern when trying to adjust a forecast with an externally estimated effect.

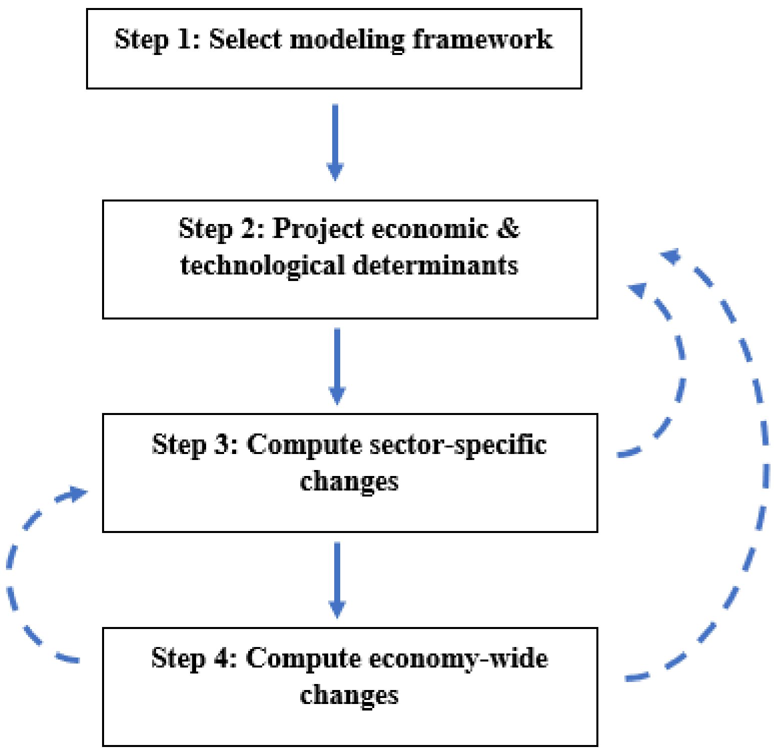
B. Transition Risks and Opportunities

Transitioning to a clean energy economy will require many sectors to transform. As these transformations manifest over time, the ways in which sectors interact with one another will themselves change. The macroeconomic consequences of this transition will depend on the pace, scope, and scale of these sectoral transformations—including the winding down of emissions-intensive business activity and capital, the winding up of clean alternatives, and a rise in adaptation activity to increase resilience to climate hazards—and how these changes affect economic activity across other sectors.

Accounting for the transition to a clean energy economy in a macroeconomic forecast is an inherently interdisciplinary exercise. Broadly, this accounting needs to address two questions: (1) how does the transition to a clean energy economy affect sector-level economic activity; and (2) how do these changes in sector-level economic activity affect the macroeconomy? As Figure 3 shows, we address these questions through four steps. Step 1, selecting a modeling framework, underscores how different modeling approaches influence the relationships the forecaster can capture. For example, a modeling framework that prioritizes cross-country dynamics may abstract from differences across sectors. Step 2 considers economic and technological determinants of key sectors' trajectories. Given the overall modeling framework and these determinants, Step 3 discusses how to compute sector-level changes in economic activity and assets. Lastly, Step 4 shows how these sector-level changes can be aggregated to determine economy-wide changes driven by the transition to a clean energy economy. While in many cases, the macroeconomic modeling may ultimately only require the outputs from Step 3—which would serve as inputs—we also address the preceding steps, each of which helps to shape the estimated macroeconomic effects of the transition. Additionally, as Figure 3 illustrates, there may be important channels of endogeneity, with the overall macroeconomic outlook influencing the transition to a clean energy economy.

Further research is needed to robustly account for the macroeconomic implications of the transition to a clean energy economy. While an extensive literature evaluates the effects arising from changes in the power, transportation, and buildings sectors, less attention has been paid to other prominent emissions-producing sectors, such as industry and agriculture; clean technology manufacturing and other upstream activities; and investments in energy efficiency that will help shape the pace, scope, and scale of the transition. [20] Similarly, limited literature addresses the macroeconomic effects of adaptation measures and other forms of climate resilience. [21] In the coming years, physical risks will warrant increases in adaptation investments, irrespective of the mitigation actions more typically associated with transition risks and opportunities. While the

Figure 3. Transition Risks and Opportunities Approach Overview



Note: Dashed lines reflect general-equilibrium channels that could be salient but may be hard to capture.

[20] For example, two recent multi-model studies of the Inflation Reduction Act's (IRA's) effects on emissions and energy have sector-specific discussions for only the electricity, transportation, and building sectors. Bistline et al. (2024) have an explicit "Industry and Other" category, while EPA's (2023) "Industry" category includes agriculture and forestry. EPA (2023b) notes that "the IRA industrial sector policies are represented the least of all sectors across the multi-sector modeling" (93).

[21] As Fried (2022) observes, the literature that applies to macroeconomic modeling to climate policy "focuses on aspects of climate change other than adaptation" (3306).

overarching approach we describe could accommodate a broader scope of mitigation and adaptation, doing so will remain challenging in practice absent further advances in research.

Step 1: Select a modeling framework

Models of the effects of the clean energy transition face tradeoffs between resolution and tractability. We highlight four dimensions of resolution for forecasters to consider: internal consistency, sectoral, spatial, and temporal. For expositional purposes, we discuss sector-level modeling independently of macroeconomic modeling, as illustrated by the distinctions made in Steps 3 and 4 of Figure 3. However, computational general equilibrium models and dynamic stochastic general equilibrium models with sufficient sectoral detail simultaneously generate sector-level and economy-wide projections. Our expositional framing still broadly applies to models that jointly project sectoral and macroeconomic trends, as such models typically nest sector-specific "blocks" of equations and also face tradeoffs on what economic relationships to prioritize modeling. Additionally, while for discussion purposes we consider using only a single model at any given step, in practice forecasters could employ a portfolio of models to leverage the advantages of different approaches. The various considerations we discuss below would apply to each of the models within the portfolio.

Internal consistency: Internal consistency reflects the degree to which the economic modeling of the transition to a clean energy economy rests on the same assumptions as the baseline macroeconomic forecast. For example, a forecaster could "plug" into their macroeconomic model estimates of the Inflation Reduction Act's (IRA's) fiscal and economic effects from government sources (e.g., Congressional Budget Office 2022) or academics (e.g., Bistline et al. 2023). If the baseline macroeconomic forecast's outlook aligns with that applied in the external study, integration can be straightforward. However, assessing the degree of forecast alignment can be challenging, and alignment may weaken over time as the macroeconomic outlook changes. In contrast, building up from estimates of sectoral activity over the transition to a clean energy economy can enable the forecaster to ensure those estimates account for their views of the broader macroeconomy.

Sectoral: The United States' Long-Term Strategy considers five broad sectors key to the transition to a clean energy economy: electricity, transportation, buildings, industry, and agriculture (including forestry and land use) (Department of State and Executive Office of the President 2021). The pace of each sector's transition may be influenced by both sector-specific factors and by interactions with other sectors.[22] In general, there is a modeling tradeoff between breadth and depth: models that can account for cross-sector interactions may be better able to model variables like prices, which are influenced by both supply and demand, but will often capture less detail within any individual sector. Single-sector models, on the other hand, can yield more detailed projections of that sector's supply and factor demand.

[22] For example, a shift in demand from internal combustion engine vehicles to electric vehicles (EVs) will increase demand for electricity generation, influencing electricity producers' decisions; meanwhile, expectations about electricity's future supply and price will influence the demand and production of EVs.

Spatial: Breadth-versus-depth tradeoffs are also prominent for the spatial dimension of analysis. The clean energy transition in the United States will likely be influenced by changes in activity in other countries.[23] Models that account for the pace, scope, and scale of the transitions to a clean energy economy across the world can better capture trajectories for domestic variables, like commodity prices, that are strongly influenced by international economic forces. However, using global analyses may make internal consistency more challenging if the macroeconomic forecaster does not have as developed an economic outlook outside of the United States as within it. Spatial detail at the subnational level may also be helpful for capturing transition dynamics. For example, the price and speed at which infrastructure necessary to support the clean energy transition can be built—such as for the transmission and delivery of electricity—may vary across areas. However, as in the multinational case, developing consistent subnational economic forecasts can be challenging.

Temporal: Resolution in the sectoral and spatial dimensions often must be determined jointly with resolution in the temporal dimension. Macroeconomic forecasts at decadal horizons are usually estimated at an annual or quarterly frequency—including the forecast underpinning the President's Budget—a far shorter time step than is typically applied in models used to project the transition to clean energy economy.[24] A shorter time step allows a model to better capture economically salient adjustment frictions and reactions to changes in economy-wide conditions but can increase computational burden and necessitate simplification across other dimensions to retain tractability.

The tradeoffs and decisions across the four dimensions of methodological resolution—internal consistency, sectoral, spatial, and temporal—vary with the nature of the macroeconomic forecast's context and application. We proceed with a maximal approach to provide a holistic view of the factors that could be taken into account when modeling the transition to a clean energy economy.

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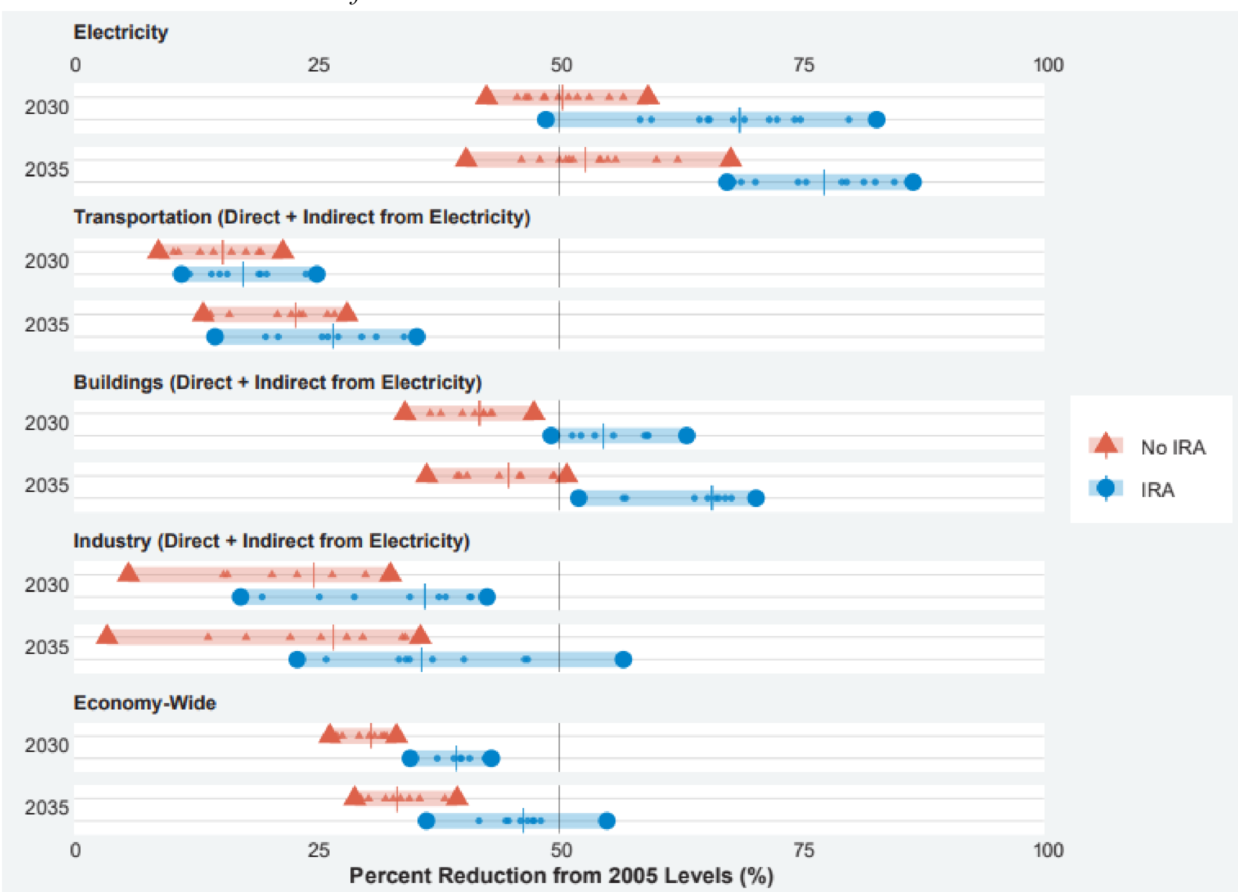
[23] For example, projected prices of clean technology inputs may be biased upwards if they only take into account changes in U.S. demand and biased downwards if they only take into account innovations from R&D spending within the United States.

[24] E.g., the Global Change Analysis Model (Joint Global Change Research Institute n.d. a) and REgional Model of Investment and Development (Potsdam Institute for Climate Impact Research n.d.).

To illustrate the projections across currently available methods, we draw from recent intermodal comparison studies of the effects of the IRA on key economic sectors (EPA 2023b; Bistline et al. 2024). The effects estimated under these different modeling approaches would likely generate substantively different estimates of how the IRA affects the macroeconomic outlook. Figure 4 displays the estimated reductions to future carbon dioxide emissions due to the IRA by sector across ten multi-sector models (EPA 2023b). Two qualitative trends are consistent across the models: (1) the IRA will lead to lower emissions by 2035; and (2) the sector most affected through 2035 is electricity. Quantitative projections of sector-specific and aggregate changes in emissions vary across models, illustrating the implications arising from different model structures and assumptions about key inputs. The qualitative consistencies reflect particularly robust findings, since EPA (2023b) includes models that differ in scope and scenarios that are not harmonized. Multi-model studies like EPA (2023b) offer detailed information on the models' approaches and assumptions, allowing forecasters to compare across them and determine which type of modeling is most appropriate for their work.

Figure 4. Cross-Model Comparison of U.S. Carbon Dioxide Emissions Reductions under IRA and "No IRA" Scenarios from 2005 Levels



Source: Figure 1.3 of EPA (2023b).
Note: Each marker represents a different model estimate, with lines denoting the median estimate.

Step 2: Project economic and technological determinants

As noted above, some of the variation reflected in Figure 4 stems from different outlooks on the key factors that will shape the transition to a clean energy economy. We consider two groups of factors influencing the pace of the transition: (1) factors influencing the supply, price, and innovation of clean technologies; and (2) factors influencing the deployment of clean technologies. In practice, many of these factors are interdependent—for example, increases in the demand of a particular clean technology can affect its availability and price, as well as the price of other clean technologies.

The supply, price, and development of clean technologies

The pace of the transition to a clean energy economy will depend on expectations and realizations of changes in the cost of existing technologies, innovations leading to the availability of novel technologies, and the extent and characteristics of government policy related to the transition. To illustrate these concepts, we focus on the power sector.

Many existing clean energy technologies are likely to experience cost declines in the coming years that may not be accounted for in current forecasts. For example, between 2009 and 2023, the cost of solar photovoltaics fell 83 percent, while the cost of onshore wind power fell 63 percent (Lazard 2023). These cost declines exceeded expectations. In general, past forecasts of individual clean technologies have predominantly underestimated technological progress (Way et al. 2022).[25] As a range of models project a significant increase in demand for clean energy technologies, these technologies could move further along the experience curve and attain further cost reductions.

The degree to which existing clean energy technologies' prices will decline is subject to considerable uncertainty, as it depends on several forms of technological change, including applied R&D, learning-by-doing, and economies of scale.[26] Reduced-form approaches can offer tractable abstractions of these dynamics. For example, Way et al. (2022) consider a deterministic function for future technology prices known as Wright's Law, in which price declines are a power function of cumulative production.[27] This endogeneity between a technology's use and price is important to capture when evaluating the clean energy transition. A more holistic assessment of the dynamics driving experience curves could improve forecasting capabilities.[28]

In addition to improvements to existing technologies, the transition to a clean energy economy will require the development and deployment of new technologies. The International Energy

[25] For many clean energy technologies, improvements and cost reductions are spurred by repeat deployment and scale-up of manufacturing capacity (CEA 2022). As more producers enter the market, learning-by-doing dynamics can occur. These dynamics can be furthered by tax incentives that lower the cost of clean energy investment. An increased customer base allows producers to expand, allowing for economies of scale (CEA 2021; CEA 2023).
[26] Elia et al. (2021) survey the academic literature and find that most studies focus on just one factor in developing experience curves, and that even across the studies that account for multiple factors, many key considerations remain underexplored.
[27] Way et al. (2022) also examine Moore's Law, which assumes prices decline exponentially over time. The authors find that, when estimated from historical data on clean energy technologies, both laws perform similarly. The reliance of time as an explanatory variable may subject extrapolation under Moore's Law to elevated uncertainty.
[28] Existing methods are subject to large revisions; for example, wind industry experts surveyed in 2020 expected the cost of wind power in 2050 to be half what experts had projected just five years earlier (Wiser et al. 2021).

Agency (IEA) (2023a) estimates that about one third of global emissions reductions through 2050 will arise from technologies that are not yet developed enough to operate commercially at a mass scale. Achieving the necessary developments will require increased R&D on clean technologies across a variety of sectors. The Executive Office of the President (2022) identified a broad range of "game-changer" breakthroughs that could help propel the transition to a clean energy economy, ranging from net-zero concrete production to improvements in crop production that increase carbon sequestration.

At the macroeconomic level, the innovations that generate novel technologies are commonly abstracted into a composite measure of multifactor productivity growth. However, this approach may not reflect the developments that arise when sectors undergo structural change, as novel clean technologies may complement or substitute for other clean technologies.[29] Capturing these cross-technology dynamics would require jointly forecasting the individual products, increasing model complexity. Over short time horizons, technological breakthroughs could be assumed away, but such an assumption becomes more tenuous as the forecast horizon increases.

The representation of current and future policies, both domestic and international, is important for any macroeconomic forecasting exercise. Modeling policies poses two methodological choices. First, the forecaster must make assumptions about how government policies pertaining to the transition to a clean energy economy will change over time. Even if the macroeconomic forecast horizon itself is only a decade long, investment decisions in 10 years will themselves be influenced by the policy environment likely to be in place over the following years, requiring assumptions about subsequent policies or models that do not take into account the forward-looking nature of investment decisions.

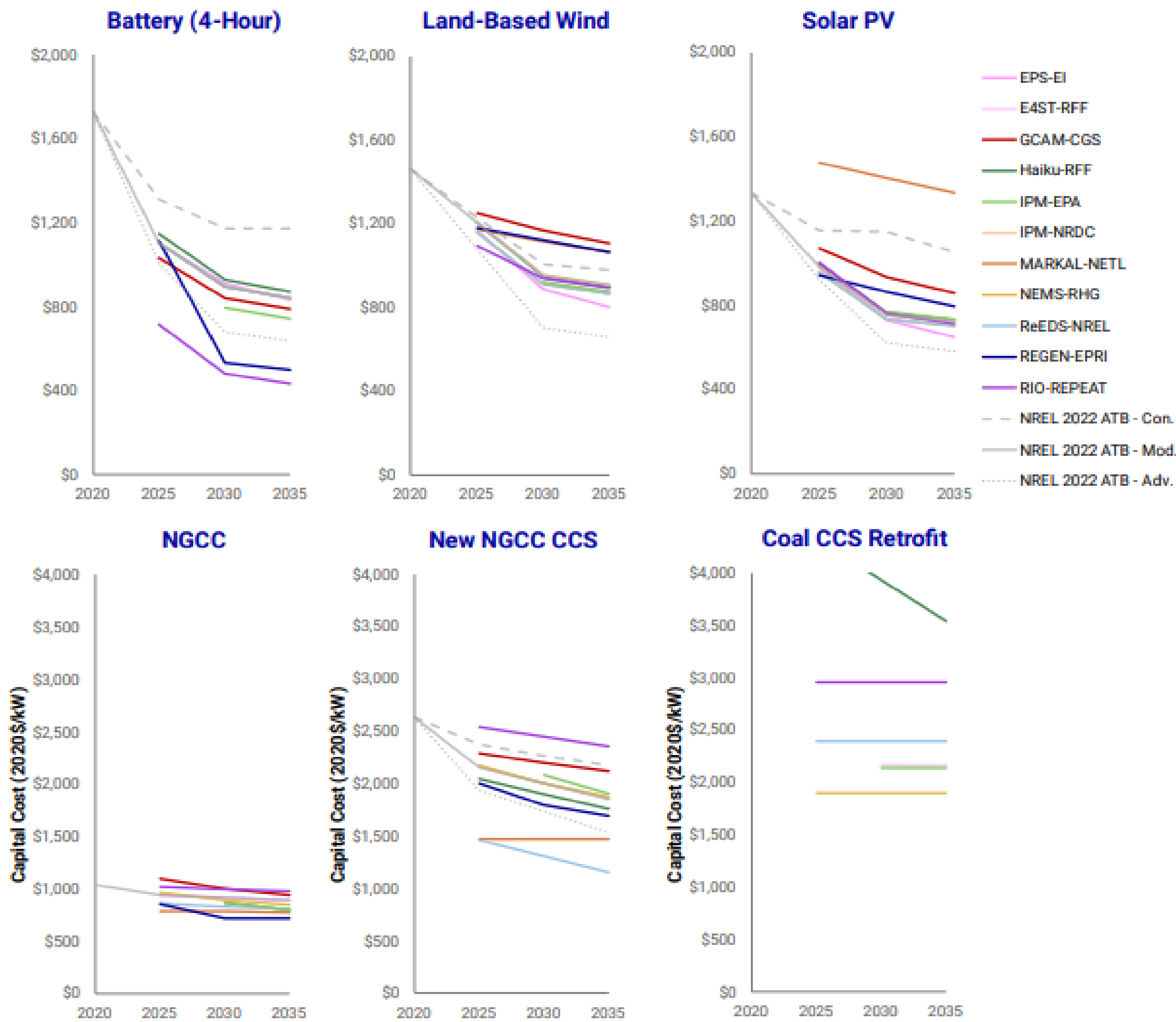
Second, the modeler must make assumptions about whether and how to account for variation in policy tools. Capturing any one country's suite of policies (including subnational policies in cases like the United States), let alone the breadth across countries, is difficult, and there is a need for a broad set of tools to model the economic implications of different types of policy (CEA et al. 2023).[30] As Bistline et al. (2023) note, different policies target different economic channels and tend to have different macroeconomic effects. For example, carbon taxes would make energy more expensive where energy remains reliant on carbon sources, deterring consumption in a way that a clean energy subsidy would not. Clean energy subsidies more directly target clean technologies' experience curves, leading to more rapid technology development than would be stimulated by carbon pricing (Bistline et al. 2023).

[29] On one hand, advances in linchpin technologies such as energy storage could enhance the commercial viability of a range of clean technologies, while alternatively, novel clean technologies could displace existing ones. For example, researchers are exploring the potential of using sodium-ion batteries as a substitute for the lithium-ion batteries typically used in EVs (Department of Energy 2023a).

[30] For example, the U.S. light-vehicle transportation sector has subsidies and tax incentives aimed at increasing demand and production of EVs, regulations on emissions standards across manufacturers, and taxes on gasoline.

Figure 5 illustrates the cost trajectories of the key power sources used in a multi-model study (Bistline et al. 2024). The estimated trends across the different models are qualitatively similar and point to growing cost reductions over time. Notably, even for relatively mature technologies like solar and wind, the cost projections vary, reflecting different assumptions about the availability of upstream technologies, supply constraints, and the effects of Federal, State, and local policies.

Figure 5. Capital Cost Assumptions for Key Power Sector Technologies over Time by Different Models



Source: Figure S3 of Bistline et al. (2024).
Note: Lines reflect different models' assumptions. Utility-scale solar photovoltaic (PV) costs are shown in terms of $/kW$_{AC}$ (kilowatts of adaptive current). NGCC: natural gas combined cycle. CCS: carbon capture and storage.

The deployment of clean technologies

The deployment of clean energy technologies is influenced by market frictions, characteristics of an economic market that inhibit participants from making ideal decisions. Because the clean energy transition reflects structural change, it is important to consider how frictions affect the use of both incumbent, emissions-producing technologies as well as newer clean technologies.

Frictions can relate to local and sectoral economic conditions (e.g., geographic mismatches between available workers and jobs), as well as broad macroeconomic conditions (e.g., strong economies have relatively few available workers). An internally consistent forecast would capture local and sectoral economic conditions, as well as broader macroeconomic ones, and reflect how macroeconomic changes influence the outlook for the transition to a clean energy economy. Existing models differ in their ability to capture various sources of frictions (CEA and OMB 2023), and the analysis of these frictions and their implications for the clean energy transition would benefit from further research (CEA et al. 2023).

We consider four key market frictions that will influence supply and demand of clean technologies and, hence, the broader transition: labor, capital, financial, and supply chain. Additionally, we discuss risks stemming from variation in natural conditions and climate change and adaptation measures in response to physical risk, which will also influence the transition to a clean energy economy.

Labor frictions: Along the transition to a clean energy economy, demand for certain types of labor to develop the technologies and related infrastructure and to deploy those technologies may exceed supply, with implications for wages, investments in human capital, and the pace of deployment. The temporal, sectoral, and spatial resolution applied in an estimation influences the types of labor frictions that can be captured. For example, modeling with five-year or longer time steps tends to abstract away from the short-term economic implications of labor frictions.[31] Reduced-form approaches, such as those that apply adjustment costs from changes in labor employed, are sometimes used in macroeconomic modeling to proxy for labor frictions (e.g., Bloom 2009; Christiano et al. 2015).

Capital frictions: Many models of the clean energy transition assume "irreversibility" frictions in what is often called the "putty-clay" model, under which capital deployed for a particular use cannot be repurposed (e.g., Joint Global Change Research Institution n.d. a; McKibbin Software Group n.d.). If capital allocated to support the extraction and use of carbon-based resources is irreversible, then it may not be easily reapplied or resold. Capital that is already applied to emissions-intensive activities curbs the clean energy transition by both producing emissions and reducing the scope for clean technologies to be deployed.

Frictions may also be present during the installation of new capital, particularly in the face of structural change. For example, a new overhead transmission line for electricity can take over a decade from planning through construction (IEA 2023b). Additional frictions in the deployment of clean energy can arise due to the need to connect new facilities to the grid, which may have different technical requirements than older systems (Department of Energy 2023b). Aggregate

[31] For example, it takes approximately three years for a worker to become fully trained as a wind turbine technician (Department of Energy n.d.). Modeling at quarterly or annual frequencies could capture differences between the supply and demand of wind turbine technicians. In general, worker shortages tend to lead to increased wages. Over the short term, the result is increased production costs, slowing deployment. However, increased wages also raise untrained workers' incentives to obtain training, ultimately boosting the number of technicians.

adjustment costs and other reduced-form approaches offer ways to estimate the effect of frictions to capital installation at the market level (e.g., Joint Global Change Research Institution n.d. a; McKibbin Software Group n.d.).

Financial frictions: The levelized cost of renewable electricity is more sensitive to financial conditions like interest rates than the levelized cost of carbon-based electricity (Bistline et al. 2023). Renewable energy developers have greater need for initial external sources of financing, as they incur a greater portion of their costs before revenues are generated, whereas ongoing operational expenses play a larger role for carbon-based energy sources (Bistline et al. 2023). Policy choices, such as when subsidies are provided relative to when installation or production occurs, may play an important role.[32] Modeling approaches with long time steps may not be able to capture the financial frictions arising from cashflow timing issues. Additionally, financial investors are increasingly seeking information related to companies' exposures to climate risk (Ilhan et al. 2023). Broader access to accurate and consistent information on risk exposures might realign credit and equity availability more closely to investors' preferences. In addition, the approaches taken to model the transition to a clean energy economy typically capture at most limited characteristics of the financial sector and associated frictions, a problem that macroeconomic modeling faces more generally (Pollitt and Mercure 2018).

Supply chain frictions: Supply chain frictions are relevant to the clean energy transition because of the increased demand for a resilient global supply chain of new products to build, maintain, and expand energy infrastructure. As a result, global resource constraints may arise over the short term (IEA 2022). At a high level, models with endogenous prices and deployment can capture the implications of any mismatches between supply and demand for clean technologies. But models differ in the extent to which they capture supply and demand constraints for key upstream inputs, such as rare earth metals (Bistline et al. 2024). Relatedly, upstream sectors themselves are subject to frictions, and different technologies' competitiveness may be affected by how well established their respective supply networks are.

Physical risk and adaptation measures: The physical risks of climate change are interconnected with the risks and opportunities of the transition to a clean energy economy. For example, many energy technologies—such as hydroelectric power, hydrogen, and thermal generators—rely on water supply (Zamuda et al. 2023). Changes in precipitation patterns, droughts, and extreme heat would all influence such technologies' productivity and relative competitiveness. Risks of water scarcity and rising water temperatures, which would impede water's efficacy as a coolant, could spur further use of water-lean methods of power generation like wind and solar to enhance resilience to these physical risks (Sanders 2015).[33] Additionally, the rise in extreme weather events over recent years underscores the risks to electricity transmission infrastructure and networks, and extreme heat events and other climate hazards

[32] Many of the tax credit subsidies created or expanded by the IRA are transferable, which enables firms to exchange future subsidy payments for upfront financing from private intermediaries. This transferability makes the subsidy payments close but not equivalent to upfront support, given intermediation costs.
[33] As physical risks are multifaceted, increased resiliency against some risks will not necessarily increase resiliency against all risks. For example, shifts in wind and cloud coverage would affect the productivity of wind and solar generation, respectively, but have less of an effect on other means of electricity production.

influence electricity demand (Zamuda et al. 2023). Capturing the macroeconomic implications of how physical risks will influence the clean energy transition is a key area for future research.

In addition to their effects on clean energy technologies, physical risks may have macroeconomically significant effects on investment due to adaptation spending and other resilience measures.[34] These additional investments are unlikely to be reflected in either baseline macroeconomic forecasts or modeling exercises focused on mitigation. Structural modeling indicates that scenarios with higher severity of climate hazards have increased levels of adaptation investment (Fried 2022). Key areas for future research include expanding our understanding of: (1) existing adaptation actions; (2) the macroeconomic effects of those existing actions (e.g., increased investment); and (3) how the manner and degree of adaptation behaviors evolve over time, as economic decisionmakers increasingly account for the risks posed by climate hazards.

Step 3: Compute sector-specific changes

The next methodological choice is how to reflect the determinants of the transition to a clean energy economy in macroeconomic outcomes. In keeping with the broad macroeconomic framework discussed in Section 2, we consider two groups of economic outcomes: (1) capital investment and retirements; and (2) international trade.

To illustrate some of the dynamics in Steps 3 and 4, we rely on projections from the Global Change Analysis Model (GCAM).[35, 36] We rely on GCAM's Reference scenario to capture energy-system dynamics prior to the enactment of major mitigation policies, and detail this scenario in Appendix C. We contrast the trajectory under GCAM's Reference scenario with GCAM's Current Policies scenario, which captures the effects of major policies implemented worldwide. The differences between these two scenarios reflect the extent to which policies have altered the outlooks across the energy system around the world. We focus on differences in the projected trajectory of the U.S. energy system and their implications on the macroeconomic outlook.

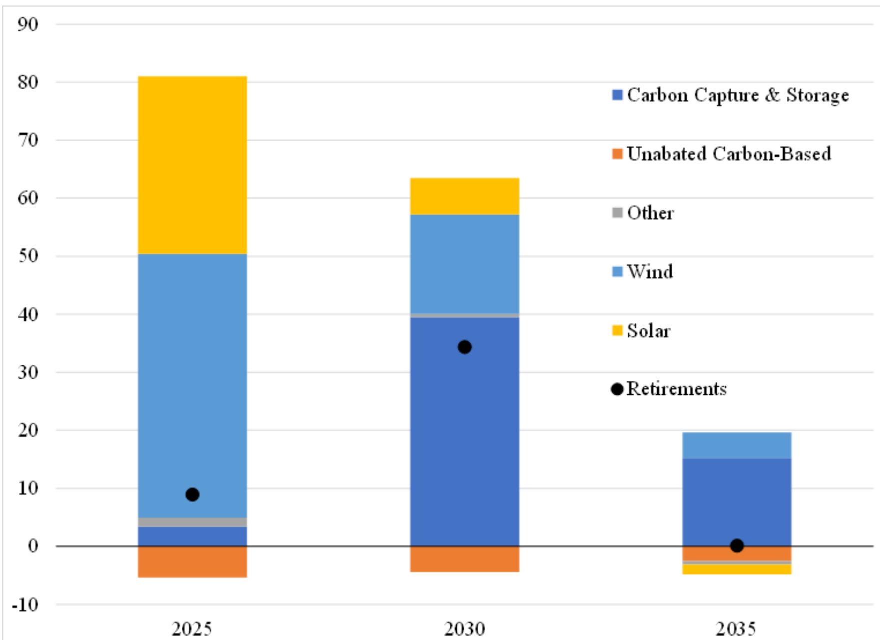
Capital investment and retirements

To capture effects on aggregate investment, we must account for both direct and indirect changes to investment. As in Step 2, we focus specifically on the power sector, for which GCAM provides dollar-based estimates.[37] Over the next decade, the power sector is poised to continue

[34] For example, increased investments in electricity transmission and distribution infrastructure will be necessary both to support the increased electrification of the economy (a mitigation action) and enhance resilience against the rising risks posed by extreme temperatures, wildfires, and other climate hazards (an adaptation action).
[35] We continue to rely on published multi-model projections to illustrate dynamics when we can do so. Otherwise, we rely on GCAM.
[36] As discussed in Appendix C, the latest version of GCAM endogenizes key macroeconomic variables, like GDP (Patel et al. 2023). Our GCAM results come from the preceding version, in which the macroeconomy is exogenous.
[37] Multi-model studies of the transition commonly focus on changes in sector emissions and metrics pertinent to particular sectors, rather than macroeconomic indicators. For example, EPA (2023b) considers changes in power capacity within the electricity sector and changes in EVs' share of new vehicle purchases for the transportation sector. Both metrics are correlated with changes in macroeconomic activity, but these metrics cannot be directly applied to a macroeconomic forecasting framework.

its transition to clean energy technologies. Increases in clean investment will likely displace investment that otherwise would have occurred for carbon-based power (Bistline et al. 2023). At the same time, infrastructure and equipment that is no longer economically competitive may be retired while it is still capable of operating; these instances reflect cases when the owner is financially better off by discontinuing operations (e.g., due to legal restrictions or because ongoing operating costs exceed revenues).[38] These "additional" capital retirements, beyond what occurs due to depreciation at a given point in time, directly lower the aggregate capital stock, reducing capital services and economic output, though retirements may also free up resources to fund new investments, which would reflect indirect increases in the aggregate capital stock.

Figure 6: Difference in Power Sector Investments & Retirements between GCAM Current Policies Scenario and GCAM Reference Scenario (Billions of 2023 USD)



Source: CEA and OMB calculations from GCAM results.
Note: Unabated Carbon-Based category includes plants fueled by coal, gas, or refined liquids that do not employ technologies to capture and store emissions

Figure 6 shows projected differences in power sector investments between GCAM's Current Policies and Reference scenarios. Power sector investments are persistently higher across the projection horizon under GCAM's Current Policies scenario than its Reference scenario. Through 2035, the difference between the two scenarios' investment projections declines as IRA provisions start to phase out. Combining over 2025, 2030, and 2035, the largest net additions to investment between GCAM's Reference and Current Policies scenarios are in wind, carbon capture and storage, and solar. In contrast, investment in unabated carbon-based power is persistently lower across GCAM's Current Policies scenario, though the decline in investment among these power sources is less than one tenth of the additional investment among cleaner

[38] Asset valuation frameworks can be helpful for anticipating the conditions under which different types of capital will continue to operate or be retired.

sources of power. Similarly, while capital retirements over the projection horizon are also higher under GCAM's Current Policies scenario, the projected additional investments are considerably larger.

Other major sectors' investment will also be directly influenced by the transition to a clean energy economy over the coming years, including fossil fuel extraction, vehicle manufacturing, the manufacturing of intermediate technologies and goods, heavy industry, and agriculture.[39] The net effects of the transition in these sectors will depend on changes in: (1) the total value of goods purchased; (2) the market share of U.S. production; and (3) the capital intensity of production. Estimating the macroeconomic effects of these sectors' transitions is a key area for further research.

The forecaster must also make assumptions about where new resources for clean technologies will originate. As Figure 6 suggests, the clean energy transition will require a net increase in investment over the coming years, not just a reallocation of investment that would have otherwise occurred. Consider two boundary scenarios. In one, the additional resources used by the power sector come from sources that would otherwise have been unused in the U.S. economy (e.g., idled properties and machines reactivated or imported from abroad). In the other boundary scenario, the rise in investment could fully displace activity elsewhere in the U.S. economy.[40] The literature gives only limited insight into the degree of resource displacement likely to occur along the transition to a clean energy economy, and in practice, the degree of resource displacement[41] likely falls between the boundary scenarios.[42] Economies with more underutilized resources than their peers are less susceptible to resource displacement,[43] and in fact, under some demand-oriented theories, economies typically operate with underutilized resources, implying that the clean energy transition will likely not lead to any resource displacement (Mercure et al. 2019).

History offers a few applicable insights into determining the degree of resource displacement. Previous economy-wide efforts to mitigate environmental and health effects of production—e.g.,

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[39] Fossil fuel prices will likely be altered by the transition to a clean energy economy, which in turn will affect investment incentives in the extraction and mining sectors. Additionally, the transition of the transportation sector will lead to a shift toward EV purchases, and domestic manufacturers will consequently need to shift their production toward EVs, as well. Similarly, the transition to a clean energy economy will require significant changes in the intermediary manufacturing sector due to the changes downstream. These changes may lead to investments in new plants devoted to EV production and clean intermediate technologies and less investment in plants that produce gasoline-fueled vehicles or equipment supporting emissions-intensive output.

[40] For example, at any given time, a fixed number of construction cranes are operational in the United States. Every construction crane allocated to building a power plant is one less crane that can be used to build houses, non-energy plants, or other structures.

[41] What we refer to as "resource displacement" has been referred to elsewhere (e.g., Mercure et al. 2019; Bistline et al. 2023) as a type of crowding out. As the phrase "crowd out" is conventionally used in fiscal contexts, we apply a distinct phrase to clarify that our focus is on factors of production.

[42] Bistline et al. (2023) note that it is in fact theoretically possible to have excess displacement, where the rise in investment actually spurs a temporary decline in GDP. This would require a sufficiently high elasticity of intertemporal substitution, which would spur a large shift into energy investment and away from non-energy capital. Such a shift would generate a rise in long-term capacity, at the expense of output in the near term.

[43] For example, Chodorow-Reich (2019) finds positive effects on employment from fiscal stimulus during the Great Recession in the United States.

to address causes of acid rain, to transition away from leaded gas—provide evidence on the effect of large-scale efforts to reduce emissions from the energy sector. The clean energy transition requires both building new clean infrastructure and retrofitting many existing assets swiftly across a range of sectors to address climate change, all while maintaining affordability and reliability and increasing resilience against physical risk. Correspondingly, policy responses to support the transition may differ in important ways from past efforts. For example, the literature pertaining to displacement from public infrastructure investment is not relevant for policies supporting the clean energy transition.[44] Studies examining large-scale changes in particular sectors (e.g., Ramey and Shapiro 2001) could be informative, but in using them it would be important to attend to differences in scale and scope. And though a separate literature assesses the extent to which R&D within the energy sector displaces the same activity outside the sector, the literature's current findings are mixed.[45] Furthermore, the literature's general findings may not be directly applicable to the primary drivers of the transition to a clean energy economy, particularly as its focus on emissions taxes does not directly relate to the United States' policy environment.[46] Clean energy subsidies and the emissions taxes researched in the R&D context target different groups of firms and, hence, likely generate different sectoral responses.[47] Studies that can quantify displacement from equipment and structures investment—and in response to subsidies rather than taxes—would more directly address the dynamics likely to arise in the U.S. economy due to the clean energy transition. Such questions would benefit from further investigation (CEA et al. 2023).

Another important decision around resource displacement regards the economic activity that will be displaced. A tractable assumption is "like for like" (e.g., equipment investment displaces

[44] Our assessment stems from three primary reasons. First, because the focus of the United States' clean energy policy is to induce private investment, companies generally need to expand if they want to receive increased benefits from such policies (e.g., the production credits and rebates on EV sales provide incentives for output, rather than input). In contrast, since a substantial share of Federal infrastructure is funded collaboratively between Federal, State, and local governments, strategic interactions may occur between different governments; for example, an additional Federal dollar of highway funding might entice a State government to spend less than it had originally planned on highways and instead spend on other services. Second, companies typically need to start investing and producing before they receive tax benefits from policies like the IRA. In contrast, public infrastructure investment can take a considerable time to manifest, and much of the money appropriated may not be spent until years after enactment. Third, unlike public infrastructure for highways and ports, the deployment of clean technology infrastructure in the United States is still in its early stages, meaning appropriately designed policies can mitigate coordination issues and send demand signals, which are more likely to spur sectoral investment by the private sector than offset it (Boushey 2023).

[45] Some studies find evidence of displacement from energy sector R&D, while others do not. For example, Popp (2004) estimates that energy sector R&D partially displaces R&D across other sectors, but the estimate is imprecise and statistically insignificant at the 10 percent confidence level. Popp and Newell (2012) find displacement within the energy sector but not into other sectors. Similarly, Noailly and Smeets (2015) find displacement between the fossil fuel and clean energy R&D, but do not test for cross-sector displacement. Conversely, Gray and Shadbegian (1998) and Hottenrott and Rexhäuser (2015) find empirical evidence of within-firm crowding out for environmental R&D, for example geared toward reducing pollution abatement costs.

[46] For example, the tax provisions in the IRA primarily support the production and consumption of clean energy technologies, rather than R&D (White House Office 2023).

[47] For example, the physical resources and worker expertise for R&D are likely more specialized than what is needed for equipment and structures investment, and this specialization might moderate the degree of displacement.

equipment investment).[48] However, broad reallocations could occur. In particular, the increase in demand for clean technology investment does not directly reduce investment demand elsewhere. An increase in aggregate investment demand could prompt businesses to increase the production of capital goods; that rise in investment demand would, all else being equal, push interest rates higher, increasing the supply of aggregate savings. Consequently, resource displacement may partly involve aggregate consumption, in order to support an increase in aggregate investment.[49] A key area for future research is to evaluate what sort of economic activity investments driving the clean energy transition will likely displace.

International trade

The transition to a clean energy economy will affect several sectors closely integrated with international markets. In particular, prices for many commodities related to the energy sector or clean technologies, such as petroleum products and critical minerals, are set globally. Relatedly, the United States is a prominent importer and exporter of fossil fuel commodities, which will likely be affected by the clean energy transition, as well as other equipment and inputs used in carbon-based and clean energy business activity. Additionally, as imports account for a significant share of the capital goods employed for U.S. investment, we consider how the transition's increased investment needs may influence imports.

Before proceeding, we note that U.S. imports and exports are prominent channels through which the national economy could be influenced by the policies employed by other countries, such as carbon border adjustment measures or clean technology subsidies. The effects of such policies on the U.S. economy would vary with the type of policy, its scope, and the country implementing it, among other factors.

Varvares (2023) characterizes the future trajectory of fossil fuel prices as one of the "deep uncertainties" surrounding the modeling and forecasting of the clean energy transition. Consider the price of oil. Standard economic theory suggests that the evolution of a price depends on whether the resource's supply or demand falls faster. Projected movements in supply and demand depend critically on assumptions about price elasticities, as well as the availability of clean energy alternatives, international dynamics, and supply-side frictions, as discussed in Step 1 and Step 2. Such assessments would need to be sector specific, to account for downstream industries currently reliant on oil byproducts. For oil in particular, international dynamics would include questions about who the marginal producer is and decisions that institutions like the Organization of the Petroleum Exporting Countries might make. Reduced-form time series techniques could leverage historical relationships to generate forecasts, but they may struggle to capture the ways in which the future might differ from the past because of the transition to a clean energy economy. The complexity of robust methods and less reliable nature of tractable methods make the future prices of fossil fuels during a clean energy transition deeply uncertain.

[48] The "like for like" assumption may be less applicable for measures related to energy efficiency or consumption, as many clean technologies have different energy footprints than other technologies.

[49] If resource displacement leads to less contemporaneous aggregate consumption than would have otherwise occurred, the relative decline would only be temporary. In this case, the foregone consumption stems from increased savings, which in turn yield gains in future wealth and aggregate productive capacity, boosting future consumption.

U.S. imports and exports may also be influenced by the transition to a clean energy economy. Over the decade leading up to 2023, fossil fuel energy products accounted for 13 percent of the value of goods exported and 9 percent of the value of goods imported on average.[50] As with fossil fuel prices, the outlook for net fossil fuel imports along the clean energy transition is uncertain.[51] Methods that account for cross-country flows can separately estimate gross imports and exports. If those detailed flows are not available, projections of domestic consumption and production of fossil fuels could still track changes in net imports and, hence, the direct effects on overall GDP.

Another critical import channel relates to investment. If aggregate investment is forecast to increase due to the transition to a clean energy economy (i.e., if resource displacement is not assumed to be complete), the additional investment will likely require additional imports. Over the decade ending in 2023, imports of capital goods and related parts, excluding the automotive sector, accounted for approximately 20 percent of private fixed investment. [52] More granular investment projections could account for variation in the capital composition of different sectors, including new sectors that are not reflected in existing data, the degree of sectoral expansion due to the transition to a clean energy economy, and the degree to which different forms of capital are likely to be imported.

Step 4: Compute economy-wide changes

The final methodological choice is how to map sector-specific macroeconomic effects to economy-wide changes. In keeping with the supply-side framework described in Section 2, we characterize the clean energy transition's macroeconomic implications by evaluating its effects on aggregate capital, aggregate labor, and aggregate multifactor productivity. Given the pervasive nature of energy throughout the economy, we also discuss the transition's implications for price inflation.

Aggregate capital

The transition to a clean energy economy will affect the trajectory of aggregate capital through its effects on changes in aggregate investment and capital retirements. The aggregate capital trajectory, in turn, affects labor productivity. The standard perpetual-inventory model allows for the investments generated by the clean energy transition to be incorporated into the aggregate capital stock. In contrast, at least two approaches could be taken with the additional capital retirements: (1) measure direct reductions to the aggregate capital stock, similar to the treatment of capital losses during natural disasters; or (2) adjust capital depreciation rates upward to

[50] Over the decade to 2023, goods exports accounted for 8 percent of U.S. GDP, while goods imports amounted to 12 percent of U.S. GDP, on average. Data come from the Bureau of Economic Analysis' National Income and Product Accounts and International Transactions Accounts.
[51] If domestic demand declines faster than domestic supply, producers can still export to consumers abroad. Similarly, if domestic supply declines faster than domestic demand, consumers can still import from producers abroad.
[52] Data come from the Bureau of Economic Analysis' National Income and Product Accounts and International Transactions Accounts.

achieve the same fall in the aggregate capital stock.[53] Assuming direct reductions implies that the retirements are unexpected, whereas adjusting depreciation rates implies anticipation, a distinction that affects the treatment of other macroeconomic conditions. For example, anticipated changes to depreciation rates would also be priced into capital rental rates, whereas unanticipated direct reductions would not affect these rates ex ante. Fundamentally, the appropriate choice depends on which conceptual premise aligns most closely with the forecaster's views of how much the current economy will respond to future dynamics related to the transition to a clean energy economy.

Given changes to the aggregate capital stock, changes to labor productivity can be projected through the flow of capital services. Assuming competitive pricing, rental rates on capital reflect their marginal productivity. Accordingly, the changes in the capital stock, alongside rental rates, offer a measure of productivity growth. Since rental rates vary by capital type, the projected changes to the aggregate capital stock could be decomposed (e.g., among nonresidential structures, equipment, and intellectual property). This approach would be particularly important if additional capital retirements were being accounted for by changes in depreciation rates, which should also be reflected in capital rental rates.

Using this general framework, we can illustrate the aggregate effects of additional investment spurred by the transition to a clean energy economy and the implications of different assumptions on resource displacement. To measure changes in sector-level activity, we rely on the differences in power sector investment and capital retirement projections across GCAM's Current Policies and Reference scenarios shown in Figure 6. For our baseline macroeconomic forecast, we use the forecast underpinning the FY25 President's Budget.[54] To account for changes in capital services, we assume that additional capital retirements are unexpected[55] and that depreciation and capital rental rates are unchanged by additional power sector investments.[56] We apply the "like for like" assumption described above so that new equipment investment displaces other equipment investment and new structures investment displaces other structures investment. Given these assumptions, Figure 7 illustrates the implications on real GDP of displacement rates of 25 percent, 50 percent, and 75 percent, holding all else about the forecast

[53] Valuation methodologies that leverage asset pricing techniques can be particularly useful in projecting economic depreciation.

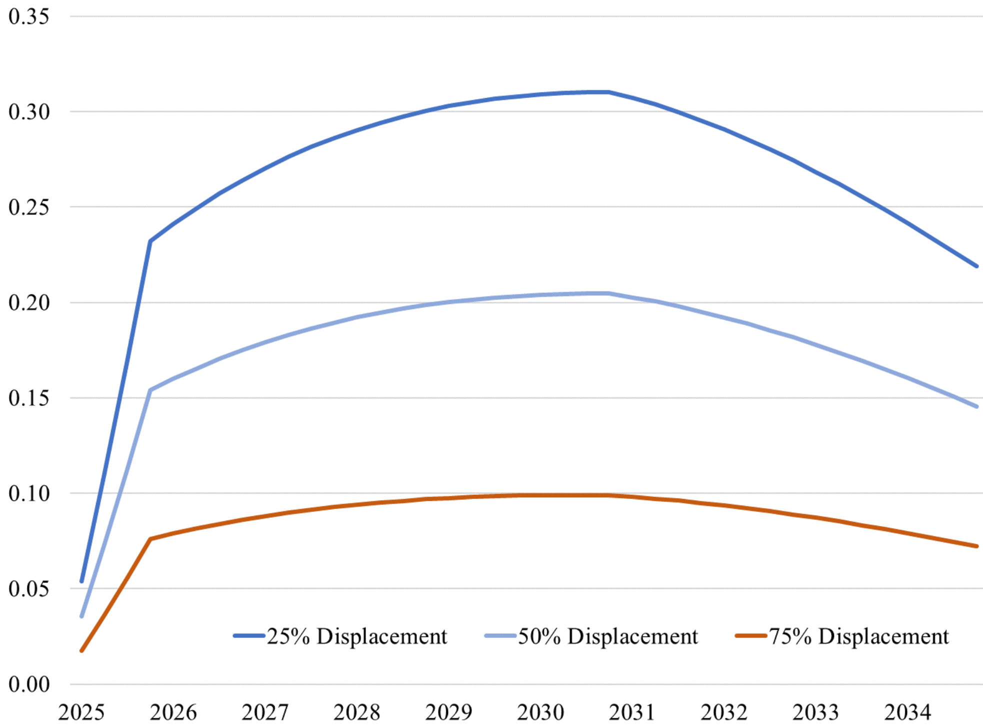
[54] The macroeconomic forecast used in the FY25 President's Budget does not explicitly account for the macroeconomic effects of the transition to a clean energy economy. We assume that its investment trajectories are consistent with GCAM's Reference scenario from 2025 onward.

[55] In practice, retirements due to changes in economic competitiveness are often planned, and hence, the assumption that such retirements are unexpected is a simplification for tractability.

[56] We assume further that power sector investments and capital retirements are allocated in line with the current distribution of private sector investment and capital across the utilities sector. We allocate power sector investments equally between nonresidential structures and non-computer equipment and allocate 75 percent of additional retirements to nonresidential structures and the remaining 25 percent to non-computer equipment.

equal. Clearly, assumptions around resource displacement have significant implications for the macroeconomic forecast.

Figure 7. Sensitivity of Projected Power Investment Contribution to GDP (%) under Different Assumptions on Resource Displacement



Source: CEA and OMB calculations from GCAM projections.
Note: These projections only focus on changes in the aggregate capital stock driven by the power sector, and do not provide comprehensive estimates of the clean energy transition's effects on the macroeconomy. The graphed trends reflect the net changes to power sector investment and capital retirement, as well as the assumed displacement of investment across other sectors.

Aggregate labor

As noted in Section 2, changes in aggregate labor can arise from changes in the population, labor force participation, the share of the labor force employed, and average hours worked. All else being equal, the expansion in investment needed to build out the clean energy economy would likely lead to an expansion in key sectors' labor demand while the transition is underway. In periods of economic slack, such as when the unemployment rate is elevated, expansions in labor demand can be satisfied by increased hiring, raising aggregate labor. However, if labor markets are already forecast to be operating at full employment, increasing aggregate labor can be challenging, particularly over the sustained period necessary to support the transition to a clean energy economy. Consequently, when the economy is already forecast to be running at full employment, it is more likely that the build-out needed to drive the transition to a clean energy economy will lead to a reallocation of labor across sectors, rather than an increase in aggregate labor.

Still, some evidence suggests that the deployment of clean technologies can boost local employment. From the perspective of a macroeconomic forecast, what matters is whether those local increases in labor activity represent increases in aggregate labor or the geographical movement of workers toward new job opportunities. For the power sector, local-level evidence indicates that the construction of power plants and similar technologies does have broad positive economic effects, such as creating indirectly supported jobs (e.g., Kline and Moretti 2014; National Renewable Energy Laboratory n.d.). Additionally, analysis by the Department of Energy (2023c) shows that employment growth in the energy sector outpaced the economy-wide average in 2022, with expansions in every state and across a range of sectors.[57] This growth aligns with broad evidence that geographical spillovers and agglomeration effects can spur sustained changes in regional business activity (CEA 2021).

The aggregate effects of positive local spillovers may be particularly large for investments spurred by U.S. clean energy policies. For example, analysis of clean technology manufacturing investments following the IRA's enactment show that planned activity occurs disproportionately in communities with relatively few economic opportunities (Van Nostrand and Feiveson 2023; Van Nostrand and Ashenfarb 2023).[58] Similarly, Parilla et al. (2024) find that over 2021 and 2022, 28 percent of clean energy investments were in employment-distressed counties, well above the shares for overall nonresidential private fixed investment (7 percent) and nonresidential private fixed investment in structures (10 percent).[59] These data suggest the buildout of a clean energy economy expands employment opportunities where they are scarce. The extent to which these positions draw local residents into the labor force, as opposed to drawing in workers from other areas, depends on factors like the positions' skill needs and broad labor market frictions. But, if investments in such places can support increased labor force participation across local residents, they could boost aggregate labor supply. Quantifying these clean technology investments' effects on labor markets and the pass-through of changes in local labor markets to aggregates is a question for further research.

Aggregate multifactor productivity

Within the context of our high-level, supply-side framework (Section 2), aggregate multifactor productivity reflects how effective the economy is at combining capital and labor to produce output. The transition to a clean energy economy could affect aggregate multifactor productivity through several channels. Here, we qualitatively discuss effects stemming from the expansion in clean technology R&D and investment, as well as the ways in which changes in energy costs could affect productivity across the economy.

As discussed, the development of novel technologies to propel the clean energy transition could expand the economy's innovation capacity. If there are tradeoffs in the allocation of resources between R&D and consumption or residential investment, then aggregate multifactor

[57] Note that these statements about employment in the energy sector reflect net effects. Similar to the investment trends in Figure 6, employment growth is not likely to be uniform within energy subsectors. As Figure 6 illustrates a net expansion in investment, on net most energy subsectors and localities will likely experience increases in employment over the coming years.
[58] While it is too soon to attribute the geographical siting of these planned investments to the IRA, these outcomes are consistent with the IRA's place-based initiatives, including those tied to Justice40 (White House Office n.d.).
[59] Parilla et al. (2024) classify a county as employment-distressed if: (1) its employment rate across 25–54-year-olds is at least 5 percentage points below the national average; and (2) median household income is less than $75,000.

productivity in the business sector increases. If instead the resources displace R&D spending across the rest of the economy, innovations may be effectively reallocated across sectors, with no net effect on aggregate multifactor productivity. While some research (e.g., Acemoglu et al. 2012) finds that a reallocation toward clean technologies can have a temporary net negative effect on aggregate multifactor productivity, the policy environment can have considerable influence on the timing of productivity gains and tradeoffs between productivity in the energy and non-energy sectors (Pisani-Ferry and Mahfouz 2023; Acemoglu et al. 2012).[60]

The energy transition may also indirectly affect productivity outside the energy sector if it affects energy prices. Empirical analyses have shown sustained economic gains from energy price reductions (Stern and Enflo 2013; Fiszbein et al. 2022).[61] Analyses of energy price shocks, however, suggest different effects over shorter periods. For example, use of energy saving technologies in the United States rose following oil price shocks in the 1970s (Hassler et al. 2021), and European businesses defied many expectations over the winter of 2022, when they were broadly able to continue to operate despite a sharp increase in energy prices (Zeniewski et al. 2023).[62] How applicable these results are to the upcoming energy transition is unclear, as their focus on energy price shocks contrasts with the widely anticipated shift toward clean energy sources.

The clean energy transition is a good example of why aggregate multifactor productivity is often referred to as "a measure of our ignorance" (e.g., Abramovitz 1956). We are not aware of frameworks that could quantify the changes in aggregate multifactor productivity across the channels described above, much less their combined effects. Such frameworks are a promising direction for future research.

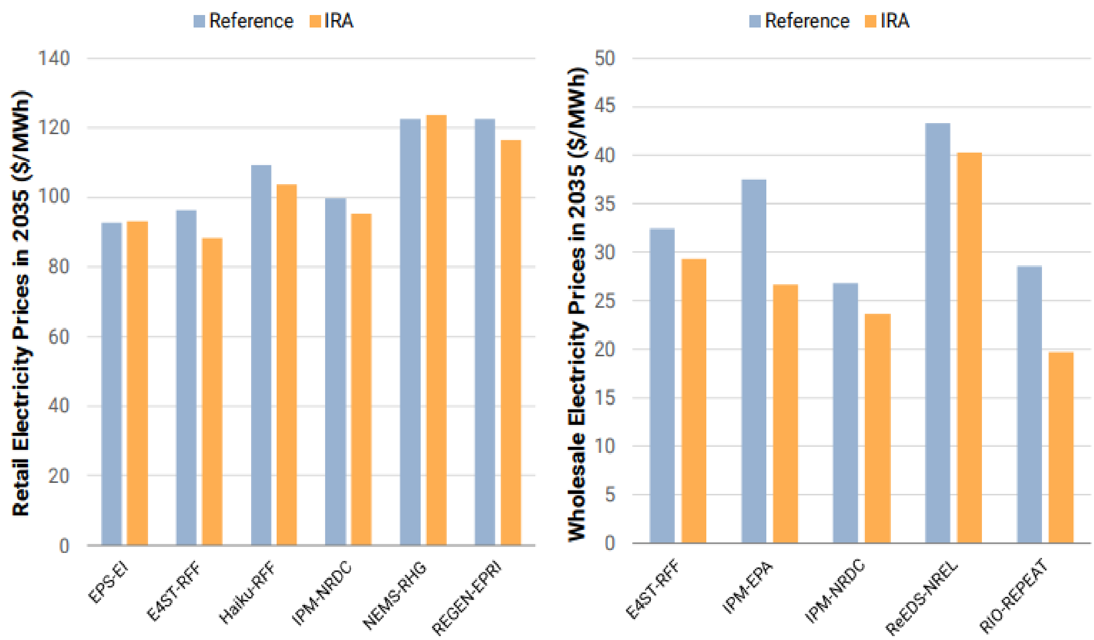
Inflation

Over the long run, inflation should tend to be stable around its target rate due to effective monetary policy. But across shorter intervals, the transition to a clean energy economy could affect overall price growth due to changes in the cost and demand for energy and the rise in investment demand.

[60] Acemoglu et al. (2012), for example, find that subsidies to R&D innovations help to accelerate the transition to a clean energy economy and that a swift transition is less costly overall than a long one.
[61] Additionally, producing and running artificial intelligence technologies is extremely energy intensive (Lin and Voas 2023); cheaper access to power could catalyze growth in the sector, which could in turn potentially unlock productivity gains in the overall economy.
[62] As Zeniewski et al. (2023) note, policy measures, including fiscal support, helped to mitigate the disruptions causing spiked energy prices. Business-driven responses included supply chain adjustments and shifts in fuel sourcing.

The transition to a clean energy economy will lead to two notable changes regarding energy prices. First, electricity will be increasingly generated from clean sources, in part due to subsidies provided by policies. Second, as the broad economy becomes more electrified, electricity will account for a greater share of total energy consumption. Figure 8 shows that various models project a decrease in wholesale electricity prices in 2035 due to the IRA. While projected changes to retail electricity prices are more varied, nearly all models show a decline in residential retail prices over time and the multi-sector studies show consumers benefit on net due to less reliance on non-electricity energy sources (Bistline et al. 2024).

Figure 8. Projections of Electricity Prices in Scenarios with and without IRA across Different Models



Source: Figure S17 of Bistline et al. (2024).
Note: Bars correspond to different models.

Additionally, the investment spurred by the transition to a clean energy economy and the potential for resource displacement might generate short-term changes to price dynamics. If supply constraints impede the ability of markets of clean technologies and related products to absorb increased demand, the imbalance would put temporary upward pressure on those products' prices to better align supply and demand. Given the sustained duration over which the transition will boost investment demand for clean technologies, these temporary upward pressures due to frictions might persist for longer. However, the broad implications of these upward pressures are ambiguous. The anticipated nature of the sustained duration of the transition would allow suppliers to preemptively act and expand to meet the future increase in demand. Additionally, changes in monetary policy can help ensure that overall inflation remains at its target rate. Consequently, within the context of a multiyear, central-tendency macroeconomic forecast, the trajectory of inflation is likely to be unchanged by the increased investments due to the clean energy transition.

4. Conclusion

Climate change poses a range of risks to the United States for the foreseeable future. At the same time, the clean energy transition is gaining pace in the country and is poised to advance further in the coming years. The Federal Government recognizes it is crucial to ensure it is prepared for the changes likely to arise due to physical risks and transition risks and opportunities (EO 14030). Such preparation calls for a whole-of-government approach and an interdisciplinary assessment that reflects the interrelationships among climate, energy systems, and the economy, along with other dimensions. This paper addresses one component of that assessment: the mechanisms through which physical risks and transition risks and opportunities will affect the macroeconomic assumptions underpinning budget forecasts. We develop a step-by-step methodological framework for accounting for physical risks and the clean energy transition in a macroeconomic forecast. In doing so, we leverage advances made in a range of fields and identify several key areas for future research. This paper's focus on the macroeconomic assumptions used in budget forecasts complements other efforts within EO 14030, such as assessments of programmatic climate risk to the Federal Budget, and broader actions across the Federal Government.

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APPENDIX

Appendix A: Additional Details on Downscaling

This Appendix presents an example of a procedure for downscaling global mean surface temperature (GMST) to population-weighted U.S. temperature. This methodology was developed by Rasmussen et al. (2016) and is used in Carleton et al. (2022) and Rode et al. (2021).[63]

The approach proceeds in two steps. In the first step, one can generate GMST anomaly, $\widetilde{GMST}$, based on climate models and climate model surrogates that emulate the full distribution of climate sensitivities.[64] GMST anomaly is relative to average GMST between 2001 and 2010.

In the second step, one can then estimate the relationship between GMST and annual average daily population-weighted continental U.S. temperature ($\widetilde{CONUS}$) as

$$\widetilde{CONUS}_{\tau,g,t} = \beta\, \widetilde{GMST}_{g,t} + \varepsilon_{\tau,g,t}, \tag{A.1}$$

where τ is a U.S. county, g is the climate model, and t is time in years. The coefficient estimated from this model, $\hat{\beta}$, can be used to downscale GMST to population-weighted U.S. temperature, which is used in the top-down econometric methods described in Appendix B.

[63] We are particularly grateful to Tamma Carleton for sharing methodology and code.
[64] The tails of the distribution of climate sensitives are completed using emulated data.

Appendix B: Approaches for Physical Risk Projections

This Appendix begins with theory showing how temperature can affect GDP levels and growth rates. It then shows how these two effects can be separately estimated empirically if there were no data limitations and how they have been estimated in practice to date. We then show how to project GDP in a macroeconomic forecast based on these two effects. While we focus on the temperature-GDP relationship, the issues raised here are not unique to the relationship. They can arise for the effects from other greenhouse gas–driven changes in local environmental variables (e.g., hurricane activity, drought/flood intensity, etc.) or for other macroeconomic variables (e.g., interest rates, employment, etc.).

1. Theory

To show how temperature can affect GDP levels and growth rates, we reproduce the theoretical framework in Dell et al. (2012), which follows the derivation in Bond et al. (2010). Consider the following single factor economy in country i and year t:

$$Y_{i,t} = e^{\theta T_{i,t}} A_{i,t} L_{i,t}, \qquad \text{(A.1)}$$

where Y is aggregate output, L measures population, and A measures labor productivity. The exponential functional form allows the parameter θ to have a percentage effect on output level for a unit change in temperature $T_{i,t}$. Furthermore, we assume that the growth rate in productivity takes the form

$$\Delta \ln(A_{i,t}) = g_i + \gamma T_{i,t}, \qquad \text{(A.2)}$$

where $\Delta \ln(A_{i,t}) = \ln(A_{i,t}) - \ln(A_{i,t-1}), g_i$ is the country's baseline growth rate and γ is the effect of a unit change in temperature on the growth rate. Rewriting equation (A.1) as per capita output, $y_{i,t} = \frac{Y_{i,t}}{L_{i,t}}$, taking first differences of logs, and inserting equation (A.2) yields

$$\Delta \ln(y_{i,t}) = (\theta + \gamma) T_{i,t} - \theta T_{i,t-1} + g_{i.} \qquad \text{(A.3)}$$

Now, consider the same object rewritten as

$$\Delta \ln(y_{i,t}) = \beta_0 T_{i,t} + \beta_1 T_{i,t-1} + g_i. \qquad \text{(A.4)}$$

A regression of the GDP per capita growth rate on only contemporaneous temperature produces a coefficient that combines both growth and level effects and is thus unable to separate the two effects. Distinguishing growth and level effects of temperature requires a regression of growth rate of GDP per capita on contemporaneous and lagged temperatures. In that regression, the coefficient on current temperature reveals the sum of the growth and level effects, $\beta_0 = (\theta + \gamma)$, and the coefficient on lagged temperature reveals the level effect of temperature, $\beta_1 = -\theta$. The sum of the coefficients on contemporaneous and lagged temperatures reveals the growth effect of temperature, $\beta_0 + \beta_1 = \gamma$.

The same reasoning applies to models where past temperature has time varying effects on productivity growth. One can write a generalized version of equation A.2 from $t = 0$ to some $t = p$:

$$\Delta\ln(A_{i,t}) = g_i + \gamma_0 T_{i,t} + \gamma_1 T_{i,t-1} + \gamma_2 T_{i,t-2} + \cdots + \gamma_p T_{i,t-p}, \tag{A.5}$$

such that one can estimate the regression

$$\Delta\ln(y_{i,t}) = \sum_{j=0}^{p} \beta_j T_{i,t-j} + g_i, \tag{A.5}$$

where the cumulative growth effect is revealed by the sum of current and lagged coefficients on temperature, or $\sum_{j=0}^{p} \beta_j = \sum_{j=0}^{p} \gamma_j$.

2. Estimation

In practice, most researchers use country-by-year data to estimate some variant of equation A.3:

$$\Delta\ln\left(y_{i,t}\right) = \beta_1 T_{i,t} + \beta_2 T_{i,t}^2 + \lambda_1 P_{i,t} + \lambda_2 P_{i,t}^2 + \mu_i + \upsilon_t + \varepsilon_{i,t}. \tag{A.6}$$

Compared with equation A.3., equation A.6 allows a quadratic relationship between temperature and GDP per capita growth and includes controls for population-weighted quadratic precipitation $P_{i,t}$, country-specific fixed effects μ_i (which includes any country-specific time invariant determinant of growth, including g_i), and year-specific fixed effects υ_t to capture annual shocks common to all countries. Estimation of equation A.6, by omitting lagged temperature terms, cannot differentiate between whether a contemporaneous temperature shock has a growth or level effect. Even if lagged temperature terms are included, they are often imprecisely estimated such that a researcher may not have statistical support for the absence or presence of growth effects (e.g., Burke et al. 2015). Whether there are level or growth effects matters for the approach to projecting GDP per capita, which we discuss in the next section in the context of a macroeconomic forecast.

Growth and level effects can be also be estimated structurally with computable general equilibrium models.[65]

3. Projection

Assuming the regression specification in equation A.6, define $h\left(T_{i,t}\right) = \beta_1 T_{i,t} + \beta_2 T_{i,t}^2$. Next, define the difference between projected temperature in future year t and the last year of historical data—2023 for expositional purposes—as $\Delta_{i,t} = h\left(T_{i,t}\right) - h\left(T_{i,2023}\right)$.

[65] Applying a structural model may necessitate interpolating between values presented in a given paper. For example, Kompas et al. (2018) show the annual percent change in U.S. GDP due to climate change at 1°C, 2°C, 3°C, and 4°C warming relative to 1986–2005 (Table 2). One can fit a linear model to interpolate these estimates for additional temperature values.

Under the assumption that temperature has a level effect on GDP per capita, one can interpret $\Delta_{i,t}$ as a temperature-dependent version of the constant level effect structural parameter θ. Projected GDP per capita can then expressed as

$$y_{i,t} = \left(1 + \Delta_{i,t}\right) y_{i,t}^{F}, \tag{A.7}$$

where $y_{i,t}^{F}$ denotes the baseline macroeconomic forecast.

If, alternatively, one assumes that temperature has a growth effect on GDP per capita, one can interpret $\Delta_{i,t}$ as a temperature-dependent version of the constant growth effect structural parameter γ.[66] Projected GDP per capita can then be expressed as

$$y_{i,t} = y_{i,t-1} * (1 + g_{i,t}^{F} + \Delta_{i,t}), \tag{A.8}$$

where g_i remains the country's baseline growth rate but includes: (1) an F superscript to clarify that it is the baseline growth rate in a macroeconomic forecast; and (2) a t subscript, given that the forecast may vary from year to year. The initial value of $y_{i,t-1}$ is the last year of available data.

[66] Note that this expression differs from its analog in Burke et al. (2015) (see Supplementary Materials equation 20), who calculate $\Delta_{i,t}$ with reference to average temperature over the previous 30 years, rather than end-of-history temperature.

Appendix C: Details on the Global Change Analysis Model

To augment the results from multi-model studies, we illustrate different macroeconomically relevant characteristics of the transition to a clean energy economy using the Global Change Analysis Model (GCAM), as recommended in CEA and OMB (2023). GCAM is developed by the Joint Global Change Research Institution (JGCRI), in collaboration between the University of Maryland and the Pacific Northwest National Laboratory (PNNL). This Appendix provides a brief description of GCAM, contextualizes it with respect to the discussion in Section 3B, and summarizes the two GCAM scenarios used to illustrate transition dynamics in Section 3B.

1. GCAM background

GCAM is an open-source, global, multi-sector dynamics model.[67] It includes an energy-economy model that integrates regional information on land, population, and current technology; the supply and demand of various resources (energy sources, water, crops, livestock, forests); and a climate module that tracks GHG emissions. GCAM's economic module begins with external projections of population, labor force participation, labor productivity growth rates, and GDP. It then produces estimates of commodity prices, commodity production, power-sector investment, energy use, land use, water use, and GHG emissions for each of its regions.

Within the framework outlined in Step 1 of Section 3B, GCAM captures many important attributes of the clean energy transition and factors influencing it. For example, its multi-sector nature enables it to capture dynamics across energy, transportation, industry, and agriculture (including forestry and land use). It is global in scale, covering 32 separate regions, including one for the United States.[68] However, its five-year time step limits the degree to which the model can capture macroeconomically relevant frictions. Additionally, in the version employed to generate our projections, the macroeconomy is exogenously determined. More recently, JGCRI released a new version of GCAM with an endogenous macroeconomy (Patel et al. 2023).

GCAM also accounts for many of the key determinants influencing the pace, scale, and scope of the clean energy transition (Step 2 of Section 3B). GCAM captures both improvements to existing clean technologies and the availability of relatively novel technologies (e.g., carbon capture and storage), though both sets of features are externally determined. GCAM is flexible enough to account for nonprice policies, as well as price policies, an important attribute when accounting for the policies applied in the United States. Regarding frictions, GCAM applies capital irreversibilities and can therefore project capital retirements stemming from changes in economic competitiveness. Other frictions, such as labor and financial frictions, are not explicitly accounted for but may be indirectly captured through the model's calibration process.

2. GCAM's Reference and Current Policies scenarios

This analysis uses two scenarios: the "GCAM Reference" and the "GCAM Current Policies" scenarios. The GCAM Reference scenario assumes no new major domestic climate policies after

[67] For more details, see JGCRI (n.d. a) for GCAM's technical documentation.
[68] An extended version of GCAM, GCAM-USA (JGCRI n.d. b), allows the generation of state-level projections within the global GCAM model.

2015 (GCAM's calibration date) and no explicit international climate policy in any year. It includes post-2015 changes in Corporate Average Fuel Economy standards, state-level light-duty and freight-electric vehicle targets and mandates, and clean energy tax credits for 2020. It also includes a planned coal-fired electricity generation phaseout and no new construction of unabated coal or nuclear plants. The incorporation of these post-2015 policies helps bring the Reference scenario closer to a counterfactual without major recently enacted U.S. policies like the IRA. Consequently, the differences between GCAM's Current Policies and Reference scenarios more closely resemble the differences presented in recent multi-model studies examining the effects of the IRA (e.g., EPA 2023b; Bistline et al. 2024).

The GCAM Current Policies scenario incorporates major policy developments after 2015. For the United States, those developments include the IRA, the Bipartisan Infrastructure Law,[69] and 2023–2026 Light-Duty Vehicle Standards. Importantly, this scenario only includes legislation or final regulations and therefore does not reflect fully the Biden-Harris Administration's regulatory agenda.[70] Like GCAM's Reference scenario, the Current Policies scenario assumes a planned phaseout of coal-fired electricity generation and no new construction of unabated coal or nuclear plants. Outside of the United States, other countries' climate policies are based on their Nationally Determined Contributions starting in 2020. Box C.1 lists the IRA provisions modeled.

Box C.1 IRA Policies Included in the GCAM Current Policies Scenario

Electricity Sector

- Section 13101 – Production tax credit (PTC) extension
- Section 13102 – Investment tax credit (ITC) extension
- Section 13015 – PTC for existing nuclear
- Section 13302 – Residential clean energy credit
- Section 13701 – New clean electricity PTC
- Section 13702 – New clean electricity ITC
- Section 50144 – Energy community reinvestment financing
- Section 13104 – 45Q: extension of credits for captured CO_2

Transportation Sector

- Sections 13201/13202 – Extension of incentives for biofuels
- Section 13203 – Sustainable aviation biofuels
- Section 13401 – Clean vehicle credit
- Section 13403 – Commercial clean vehicle credit
- Section 13404 – Alternative refueling property credit
- Section 13704 – Clean fuel PTC

[69] Bipartisan Infrastructure Law provisions include Federal investments supporting charging infrastructure for EVs and investments for school and transit bus electrification.

[70] For example, it does not account for the proposed revisions to the Section 111 regulation of GHG emissions from electricity-generating units. Additionally, the Current Policies scenario was established prior to the finalization of the post-2026 Light- and Heavy-Duty Vehicle emissions standards.

Buildings Sector

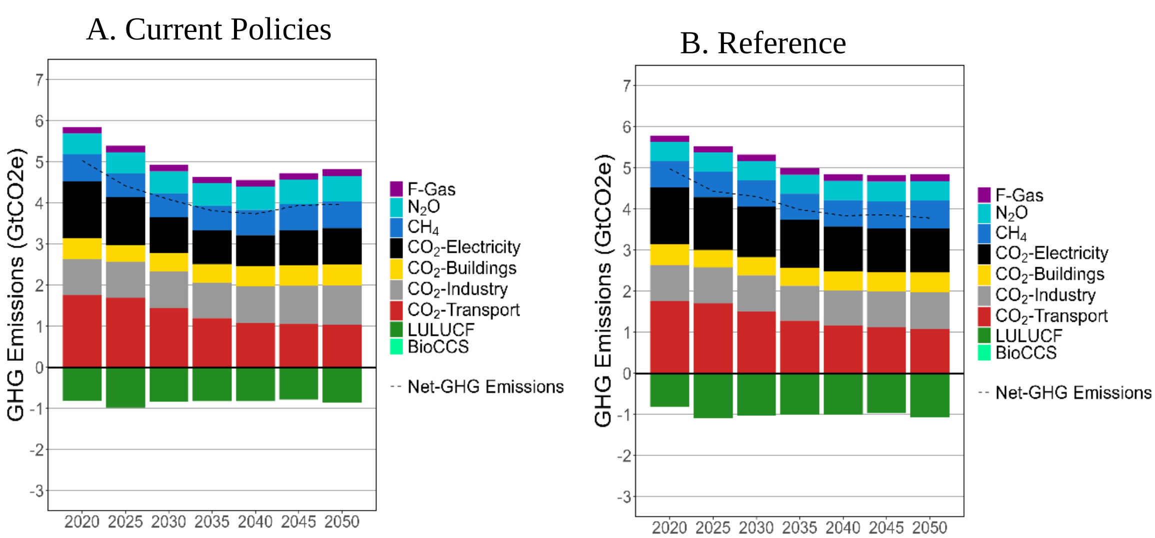
- Section 13304 – Energy efficient home credit
- Section 50121 – Home energy efficiency credit

Industry and Other Sectors

- Section 13204 – 45V: production credits for clean hydrogen
- Section 21001 – Additional agricultural conservation investments
- Section 60113 – Methane emissions reduction program

Figure C.1 shows the trajectories in US GHG emissions for the two scenarios through 2050. Current Policies results in a 36 percent reduction in GHG emissions in 2030, compared with 2005, in line with estimates from other modeling studies (e.g., EPA 2023b). GHG emissions start to increase again post-2035 in Current Policies, as some of the IRA's provisions start to expire. The Reference scenario results in a 33 percent reduction in U.S. GHG emissions from 2005, in part reflecting the assumptions of planned coal power plant phaseout, no new unabated coal-fired power plants, and existing state-level light duty and freight EV targets and mandates. While the IRA provisions were not modeled separately, the largest reductions in U.S. GHG emissions from 2020 through 2035 are in the electricity sector (41 percent decline), followed by transport (32 percent decline) and buildings (11 percent decline).[71]

Figure C.1. Projected GHG Emissions in the United States under Different GCAM Scenarios



Source: Pacific Northwest National Laboratory
Note: LULUCCF: Land Use, Land Use Change, and Forestry. BioCCS: Bio-energy Carbon Capture and Storage.

[71] Percent changes reflect internal calculations by PNNL.