Title: Distributional Impacts of Carbon Capture Technology

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Conflict of interest statement:

The authors whose names are listed above certify that they have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter of this proposal, including the energy industry business.

Background and motivation:

As part of his environmental agenda, President Biden has pledged to completely decarbonize the United States economy by 2050 and to achieve a carbon pollution-free power sector as early as 2035, all while ensuring that environmental justice is met (Biden - Harris Campaign, 2020). Environmental justice is defined by the Environmental Protection Agency (EPA) as ensuring that "all people regardless of race, color, national origin, or income" have "the same degree of protection from environmental and health hazards" (US EPA, 2021). Hence, understanding the distributional impacts of different paths towards clean electricity has become a key policy issue.

The US Congress is also taking steps towards decarbonizing the power sector. Thus, the House Energy and Commerce Committee introduced a new Bill in March 2021, the CLEAN Future Act H.R. 1512, requiring all electricity to come from clean sources by 2035. Fossil-fuel power plants, which in 2019 generated 63% of all electricity in the US (US Energy Information Administration, 2020), could still be considered "clean" in this legislative framework if they lower the carbon intensity of their emissions below a threshold—where carbon intensity is defined by the amount of carbon emissions associated with the generation of one megawatt-hour of electric energy. Retrofitting existing fossil-fuel power plants to satisfy the mandatory carbon intensity thresholds would require the use of carbon capture technology (Picciano et al., 2020). This requirement, together with tax credits for carbon capture at the federal and state level (Lonczak et al., 2021), indicates that the deployment of carbon capture technology might accelerate in the United States in the immediate future.

Carbon capture technology allows trapping CO_2 emissions before they are discharged into the atmosphere (Gonzales et al., 2020). In power plants—specifically those already in existence which would have to be retrofitted—CO_2 is captured post-combustion, by removing it from the exhaust of the combustion process. This captured CO_2 is then compressed into liquid form, and either stored into deep underground stable geological formations (such as depleted oil reservoirs), or used as an input in other industrial or manufacturing processes. Given this cycle, the whole process is referred to by the acronym CCUS (carbon capture, utilization, and storage).

Hence, CCUS is intended to eliminate CO_2 from combustion exhaust. However, this exhaust would still contain other harmful emissions resulting from combustion processes, such as fine particulate matter ($PM_{2.5}$) (European Environment Agency, 2020; Koornneef et al., 2010). Fine particulate matter can penetrate deeply into lung tissues and enter the bloodstream, causing a myriad of health problems that have been widely documented in the epidemiology literature (Anderson et al., 2012).

Therefore—unlike other clean energy sources like solar, wind, or nuclear—the effects of a large deployment of carbon capture technology on local air pollution are unclear. $PM_{2.5}$ emissions could decrease with carbon capture if fossil-fuel power plants with CCUS displace dirtier power plants. However, carbon capture could lead to *higher* $PM_{2.5}$ emissions in certain locations if fossil-fuel power plants with CCUS technology increase their generation and displace cleaner sources of energy.

In the United States, Black and socioeconomically disadvantaged communities have been and are more exposed to $PM_{2.5}$, given they disproportionally live closer to polluting facilities such as fossil-fuel power plants (Currie et al., 2020; Hsiang et al., 2019). As a result, these populations suffer a higher rate of negative health effects associated with $PM_{2.5}$ exposure (Bowe et al., 2019). Indeed, this

inequitable exposure to health hazards is what gave rise to the environmental justice movement during the 1980s (Banzhaf et al., 2019).

CCUS technology is seen as a key piece of the lowest-cost decarbonization path, one that minimizes societal and behavioral changes in the US and globally (Intergovernmental Panel on Climate Change, 2005). Compared to other more costly decarbonization paths, low-income communities would benefit from stable and non-rising energy prices, however, the overall welfare effects are ambiguous given the potential health impacts widely-deployed CCUS might bring with it. Hence, these two policy goals—reducing CO_2 emissions in a cost-effective way and decreasing local air pollutants that cause environmental injustices—might lead to trade-offs that are not yet well understood.

Research questions:

In the context described above, our project asks:

In the path towards decarbonization, how does carbon capture technology impact (1) energy prices and (2) the exposure of disadvantaged communities to local pollutants?

Proposed research methodology and data:

In order to provide an answer to our research question, we have to address three issues. First, we need to estimate to what extent CCUS would be deployed in a clean electricity scenario in 2035, and what energy sources CCUS would be displacing in a counterfactual scenario without this technology. Hence, we need to estimate the behavior of several actors (including energy generators, system operators, and end-users of electricity) that simultaneously make decisions given prices and technology available. Second, we have to evaluate to what extent changes in wholesale and retail energy prices resulting from the previous decision-making process are passed through to members of disadvantaged communities. Finally, we need to be able to translate local pollutants emissions into health impacts at a sufficiently detailed spatial level to evaluate which communities are being exposed to these pollutants.

Our proposed methodology addresses these three issues.

First, we will use a detailed power-sector model—the Engineering, Economic, and Environmental Electricity Simulation Tool (E4ST)—to characterize the power sector in 2035 under different sets of constraints (D. L. Shawhan et al., 2014). E4ST was originally developed by researchers at Resources for the Future and Cornell and Arizona State Universities (including one of the co-authors in this paper, Shawhan) and it is currently maintained and updated by developers at Resources for the Future (including Shawhan and two other co-authors in this paper, Funke and Witkin.)

E4ST solves a cost-minimization problem that simultaneously optimizes generator operation, investment, and retirement. To represent the joint decision-making of generation owners and system operators, the costs considered are generator variable costs, generator quasi-fixed costs, end-user consumer surplus losses, and investment costs. To do so, it uses data generated by the US Energy Information Administration (EIA), the US Environmental Protection Agency (EPA), the US National

Renewable Energy Laboratory (NREL), S&P Global/SNL, the transmission balancing authorities and regional reliability planning organizations, Energy Visuals Inc, hourly site-by-site wind and insolation data providers, and the North American Electric Reliability Corporation (Detailed descriptions of E4ST assumptions, algorithms, and data requirements are included in Mao et al. (2016), Shawhan et al. (2020), Shawhan et al. (2014), and Shawhan & Picciano (2019).)

E4ST incorporates CCUS technologies in particular by allowing existing coal power plants to be retrofitted with post-combustion carbon capture, and allowing new natural gas with carbon capture plants to be built in its simulations. CCUS projects in E4ST have the option of either selling their captured carbon for use in enhanced oil recovery, or paying for their carbon to be permanently sequestered in saline aquifers, with the choice of where and how their carbon gets used affecting both the project's revenue and carbon intensity. E4ST uses data from EPA's Integrated Planning Model for detailed transportation costs, storage costs, and storage capacity of different storage locations and options.

Specifically, we will model three potential sets of scenarios in year 2035 with E4ST:

(1) Baseline under current approved policies.

(2) Clean Energy Standard as proposed under the CLEAN Future Act, *without* carbon capture technology.

(3) Clean Energy Standard as proposed under the CLEAN Future Act, *with* carbon capture technology. Within this category, we will run several scenarios to account for the uncertainty about how CCUS would be incorporated in the CLEAN Future Act when it becomes law. Specifically, we will test different benchmarks of carbon intensity below which CCUS fossil-fuel plants could get clean energy credits, and different levels of tax incentives for CCUS technology. Comparing these scenarios will shed light on how parameters defined by policy could impact the distributional effects of carbon capture technology.

Among other outputs, E4ST will yield wholesale electricity prices and emissions of different pollutants, as well as grid operation and generator investment and retirement for each of these scenarios.

In the second step of our methodology, we will use the wholesale electricity prices resulting from the previous step as an input to evaluate the extent to which they are passed through to low-income households in each state. To do so, we will use an incidence model developed by one of the co-authors in this paper (Burtraw), and which is currently operated and updated by another co-author (Domeshek). This model has been previously used in the literature to measure incidence of different carbon policies (Gordon et al., 2015; Williams III et al., 2014b, 2014a). This model of household income and expenditure uses data on energy prices and quantities to estimate the share of consumer and producer surplus changes that accrue to households according to their position in the income distribution of each state. Hence, output from this model would let us compare the policy scenarios outlined above with respect to its progressivity, that is, the extent to which they lower costs proportionally more for low-income consumers. More details about the technical aspects of the model are described in Gordon et al. (2015).

The third step of our methodology allows us to translate pollutant emissions in each of the scenarios considered into health effects of exposed populations. For this, we will use a reduced-complexity air-pollution model, InMAP (Tessum et al., 2017). InMAP—which has been used in the economics literature (Hernandez-Cortes & Meng, 2020; Mayfield et al., 2019; Shapiro & Walker, 2020)—presents

one key advantage with respect to other commonly-used models, such as AP3 (Muller, 2020): it uses a variable spatial resolution computational grid, which allows it to achieve a finely spatial resolution (down to a 1km-grid in populated areas) without requiring taxing computational times.

This high spatial resolution is key to explore disproportional impacts in disadvantaged communities. For instance, impact analysis performed using tools such as EPA's CO-Benefits Risk Assessment (COBRA), only provide impacts aggregated at the county level (US EPA, 2017). However, the distribution of population within a county is not homogenous. As environmental justice advocates have claimed, disadvantaged communities tend to live closer to pollution sources and hence be more exposed to its harmful effects, a fact that has been well documented in the literature as well (Banzhaf et al., 2019). As a result, county aggregates might mask significant heterogeneous effects of pollution on disadvantaged communities.

To run scenario simulations with InMAP, we will use data on emissions derived with E4ST (including emissions location and stack characteristics) as inputs. InMAP uses an air quality model to translate these emissions into annual-average ambient concentrations of primary and secondary $PM_{2.5}$ in each of the model grid cells (which, as indicated, can be as small as $1km^2$ in populated areas.) Then, it uses published estimates of the elasticities of mortality with respect to $PM_{2.5}$ concentration (Krewski et al., 2009; Lepeule et al., 2012) to derive mortality estimates. For this last step, we will also use population counts at the census-tract level provided by the Census and all-cause mortality rate data at the county level from the Centers for Disease Control and Prevention.

As a result of this analysis, we will be able to obtain pollution-related mortality at the census-tract level, which we will be able to link to socioeconomic demographics of population in that tract using Census data. We will then be able to evaluate different emissions scenarios in 2035 with and without deployment of carbon capture technology with respect to health impacts of disadvantaged communities.

Finally, and to connect the results from the different steps in our methodology, we will perform back-of-the-envelope calculations to estimate welfare changes for disadvantaged communities given estimated energy prices for different income brackets and health effects in each of the scenarios modelled.

Contribution to the literature:

Overall, this project will improve our understanding on the distributional impacts of a technology whose use might become widespread in the near future: carbon capture. We are able to do this contribution by using three state-of-the-art high-resolution models that let us, first, forecast the location and extent of carbon capture future deployment; second, evaluate the distributional effects of resulting energy prices on households with different levels of income; and finally, translate the resulting emissions into health outcomes at a high-resolution level.

Hence, this project contributes to the economics literature that investigates the distributional impacts of policies geared towards limiting carbon emissions, like cap-and-trade (Fowlie et al., 2012; Grainger & Ruangmas, 2018; Hernandez-Cortes & Meng, 2020; Shapiro & Walker, 2021), or of energy transitions more broadly (Mayfield et al., 2019). Fowlie et al. (2020) highlight the tensions that aroused

in the context of California when proposed climate change policy failed to consider local air pollution impacts. We contribute to this literature by analyzing the effects of a technology that effectively decouples carbon from other pollutants' emissions. We shed light on the welfare implications that the technology of choice to curb carbon emissions in the path towards decarbonization might cause from the lens of disadvantaged communities. Understanding these implications and tradeoffs is key to achieve the two-fold policy goal of decarbonizing the economy in a cost-effective manner while not harming the communities that historically have borne a disproportional impact of pollution exposure.

Project timeline:

We expect to have an initial working paper by the *end of July 2021,* and a final draft *by May 2022*. Specifically, we envision the following milestones:

- *By end of May 2021*: complete scenario modelling with E4ST and analysis of pollution-related mortality with InMAP, which are currently underway.
- *By end of June 2021*: preliminary analysis of results, including changes in wholesale prices at the state level.
- *By end of July 2021*: initial draft of working paper.
- *By end of May 2022*: final draft, including the sub-state modeling of distributional effects of energy prices.

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