**Intro**

**Background 1:**

* Energy substitution towards cleaner energy coupled with higher energy efficiency should be the main goal of environmental policy to solve climate externality (Rezai and Var Der Ploeg 2017, IPCC 2016).
* Empirical evidence on energy usage in industrial contexts, which accounts for 37 % of world greenhouse gas emissions (Worell et al. 2009), is not well captured by standard production theory.
* In this context, policies such as carbon taxes might not be optimal to incentivize substitution towards cleaner energy.
  + Carbon taxes puts a price on polluting energy inputs like fossil fuels that reflects relative emission intensity of each input.

**Background 2:**

* In developing countries like India, use of coal is much more prevalent than in developed countries. In fact, the cleanest energy source that can readily be used in industrial contexts is natural gas, which pollutes even less than electricity.
* Moreover, natural gas technologies tends to be associated with higher energy efficiency than other fossil fuels 🡪 results of directed technical change where R&D efforts are directed towards the cleaner energy input (examples: electric arc furnaces in steelmaking )
* In this context, may be optimal to subsidize natural gas rather than tax it or tax it at a lower rate than implied by a carbon tax while simultaneously heavily taxing coal and oil to incentivize its adoption until deep decarbonization of the electricity grid.
  + Switching towards natural gas was responsible for a decrease in CO2 by nearly half between 1990 and 2014 in Germany (Rehfeldt et al. 2020), and a similar story is present in many developed countries.

**Overview of contribution**

* I provide novel empirical evidence on plant’s usage of energy inputs in the Indian manufacturing context:
  1. Mix of energy inputs and presence of corner solutions that vary even within narrowly defined industries.
  2. Presence of Switching between energy inputs across years.
  3. How 1 and 2 are related to productivity and energy efficiency.
* I build a production model where the choice of energy inputs can be very flexible, and I estimate the model in the Indian manufacturing context. The same analysis can be done in any regions of the world but with different policy implications.
* I solve an optimal policy problem in the presence of a climate externality and focus on two aspects of the optimal policy:
  1. Relative tax rate on different polluting inputs and how it departs from a carbon tax.
  2. Optimal price-discrimination across location to incentivize usage of natural gas in India.

**Literature**

*Fuel Switching*

Large literature by environmental engineers that study energy transition in industrial context (Wiertzema et al. 2018, Luh et al. 2020, Lechtenböhmer et al., 2016):

* My model tries to capture overarching features of this literature through what I call “energy tasks”, but in an abstract way which allows me to aggregate across different industrial processes.

Empirical literature on fuel switching:

* My approach can be viewed as combining the line of research popularized by Joskow and Mishkin (1977) that study fuel substitution as a discrete choice with conditional logit and the line of research popularized by Atkinson and Halvorsen (1976) who estimate fuel substitution from continuous fuel demand implied by a translog profit function

*Optimal Policy*

* Departure from Golosov et al. (2014) who show that a carbon tax is optimal solution to the climate externality under strong assumptions on production structure 🡪 fully flexible fuel substitution in an aggregate CES production function

*Green technological change*

* I contribute to this literature by empirically confirming earlier claims that greener technologies also tend to be more productive. My model directly embeds that

*Automation*

* Due to the many theoretical parallels between energy substitution and automation (where labor is substituted for capital), I contributed to this literature by showing identification and estimation of recent automation models (Acemoglu and Restrepo 2021) using plant-level data.

**Empirical Evidence**

**Data**

* ASI panel 2008-2016 🡪 all manufacturing plants with at least 100 workers and a sample of plants with less than 100 workers
* All manufacturing industries (however, evidence may be presented for a single industry only to highlight that these patterns are happening within industries)

**Fuel mix and corner solutions**

* Graph that compares Canadian plants with Indian plants in cement manufacturing 🡪 says a lot

**Fuel switching**

* Define switching as adding a fuel to last period’s mix (descriptive stats like how many plants do that?)

**Switching/mixing and productivity**

In a single table, show:

* Number of fuels in mix and productivity
* Switching and productivity
* Natural gas and productivity
* Natural gas and energy efficiency (higher energy efficiency may mean higher productivity so those are related).

**Model**

**Production for a single plant**

* Energy-tasks within a standard CES in capital, labor, intermediates and
  + Focus on intuition (ex of energy tasks like oil for transportation, electricity for heating the building, coal for industrial heating and where substitution is at the task-level)

**Implication of energy tasks**

* More productive fuels decrease fuel quantity needed to produce a unit of energy. When tasks are perfect complement, more productive fuels decrease total energy consumed (more energy efficient).fu

**Full model – definition**

* Monopolistic competition (show inverse demand)
* Show dynamic problem where plants can pay fixed cost to add a fuel to the mix.
* Show that only choice of F\_{t+1} is dynamic, everything else is static.

**Timeline of production**

* Helps building intuition. Show when government announces tax (i.e. after plant observe its productivity draw for each fuel in F\_t but before it chooses F\_{t+1})

**Identification and estimation**

**Main identification challenge**

* Show that the Gamma\_f’s are basically fuel-augmenting productivity terms but since E is unobserved, I cannot separate the scale of all fuel-augmenting productivity from the

**Main identification solution**

* Using Grieco et al. 2016, I can uniquely recover E up to production function parameters. I can use their method to recover all production function parameters using the fact that I observe expenditures (Pe\*E = sum\_f p\_f e\_f) but not E or Pe separately 🡪 recovers tfp z, production function parameters and E up to scale normalization across all plants 🡪 recovers fuel-augmenting productivities \Gamma\_f up to scale normalization across all plants

**Identification of fuel-specific productivity distribution**

* Once I observe fuel-augmenting productivity terms, I can use an algorithm to simulate these fuel-augmenting productivity terms using distributional assumptions, and use simulate GMM to recover the parameters of the fuel-specific productivity distributions

**Preliminary results**

* Show some preliminary results of PFE and