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Regulation at the source? Comparing upstream and downstream climate policies

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ABSTRACT

Climate policies can be applied either upstream, where fossil fuels are extracted, or downstream, where emissions are generated. Specific policy instruments can be defined for either level, and can take the form of a price signal such as through a tax, or a quantity limit such as through direct regulation or a permit market. In this study, we present an agent-based model to compare the performance of these different instruments and regulation levels. Since policy coverage is often limited, i.e. not all firms being under the regulator's control, we also examine the impact of incomplete coverage on relative policy performance. Our analysis shows that only upstream regulation leads to an increase in fossil fuel prices, which is benefitial under limited coverage as it also affects firms not directly affected by the policy instruments; that prices under quantity-based regulation can decline after an initial peak, stabilizing at a lower level than under the tax; and that direct regulation is more efficient when applied upstream.

1. Introduction

The combustion of fossil fuels is the primary cause of global carbon emissions. To meet the target of limiting global warming to 1.5°°C, the use of coal, oil, and gas needs to be largely phased out within the next three decades (Masson-Delmotte et al., 2018). Regulatory measures can be applied at different levels in the system: upstream, which is where carbon first enters the economy through either extraction or imports of fossil fuels; midstream, where these fuels are refined and transported; or downstream, where the actual emissions take place through the combustion of fossil fuels (Goulder and Schein, 2013).

On both the upstream and downstream level, policy makers can either apply a market-based mechanism – e.g. through a carbon tax or a permit trading system – or regulate the production levels of firms directly – e.g. through a quota on the extraction, import, or use of fossil fuels. Applied to the downstream level, market-based mechanisms have the advantage that the regulator requires no perfect information about firms' abatement costs to achieve an efficient outcome (Perman et al., 2003). Foramitti et al. (2021) further show that a tax could be preferable to a permit market, as the unstable price of permits may favor emission-intensive producers and create windfall profits.

While climate policy has mostly been applied downstream, recent studies have called for more attention to the upstream level (Collins and Mendelevitch, 2015). According to Lazarus and van Asselt (2018), upstream policies could reduce the overall costs of mitigation as they 'widen the mitigation cost curve', prevent carbon lock-ins (Seto et al., 2016), and increase the political pressure for climate action. Sinn (2012) suggests that upstream policy could prevent a 'green paradox', where the anticipation of downstream policies could lead to higher upstream production levels. And Piggot et al. (2018) argue that supply restrictions could be effective even if not all fuel-producing countries participate.

Another important issue is the risk of 'carbon leakage', i.e. a situation where the emission reduction in a covered sector causes a rise of emissions elsewhere. While the existence of such leakage is undisputed, its magnitude is debated (Collins and Mendelevitch, 2015). The study of Erickson and Lazarus (2018) suggests that upstream policies address

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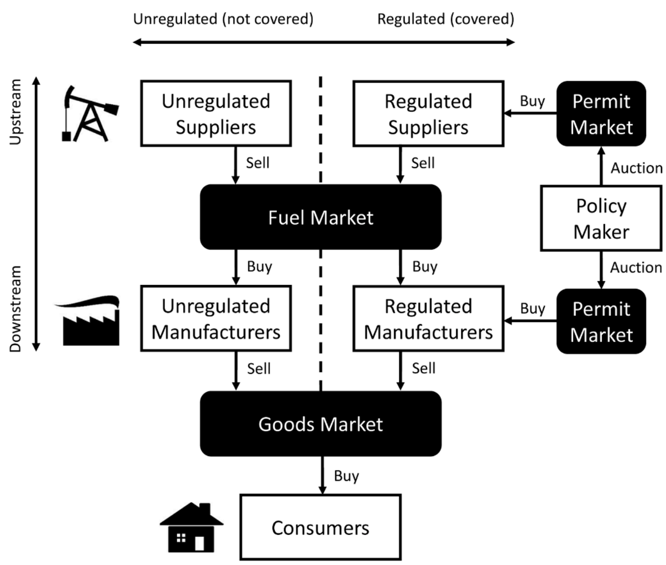


Fig. 1. Overview of agents (white) and markets (black).

carbon leakage better as supply restrictions can lead to higher prices that will decrease demand outside the regulators jurisdiction. Fæhn et al. (2017), in contrast, find for the case of Norway that upstream regulation would lead to higher leakage as domestic fuels could easily be substituted.

The models that are used for such comparisons of downstream and upstream regulation are mostly based on the assumptions of rational and representative agents with perfect knowledge. The real economy, in contrast, is a complex system characterized by unpredictable events, boundedly rational behavior, and heterogeneity (Arthur, 1999; Kirman, 2006; Mullainathan and Thaler, 2000). Another limiting assumption in many models is that policies are evaluated upon a single measure of costs.[1] The above-mentioned study of Fæhn et al. (2017) even combines welfare costs on the downstream with costs of foregone profits on the upstream into a single measure.

Here we present an agent-based model (ABM) to compare the relative performance of different policy instruments and regulation levels for the reduction of emissions. ABMs are increasingly applied to the analysis of climate policy (Castro et al., 2020), but have not yet been used for the comparative analysis of upstream and downstream regulation. The method allows for the exploration of economic dynamics based on the continuous interaction of individual agents that have to make decisions under limited information about future prices and demand (Farmer and Foley, 2009). Furthermore, ABMs can take into account heterogeneous technological options and behavior among firms.

We compare seven different scenarios, which include no policy, a carbon tax, a permit market, and direct regulation through a uniform quota, with each of the policy scenarios being applied for either extraction (upstream) or emissions (downstream). The aim is to understand how these scenarios compare under bounded rationality, heterogeneity, and dynamic markets. In the second part of the paper, firms in the model are separated between covered and not covered, with only the former being under the regulators control. This distinction is implemented to explore the possibility of carbon leakage, i.e. to compare the performance of the instruments when a share of companies does not have to obey national climate regulations.

Our model builds upon Foramitti et al. (2021). It consists of fossil fuel suppliers, manufacturers of final goods, and consumers. The firms in the model are heterogeneous in terms of their production factors and trading behavior. Over time, they change their production level based on expected demand and adapt their mark-up based on experienced success. They submit market orders for fuels and permits, and adapt their trading prices based on experience. Downstream manufacturers further adopt less emission-intensive technology based on the costs of regulation and fossil fuels.

The approach of this study is exploratory. Our model is not calibrated to a particular country or period, and instead looks at general dynamics under a wide range of parameter values and evaluation criteria. In this way, we identify potential drawbacks of each policy and discuss the underlying causal mechanisms. This puts our study in line with the approach of 'reflexive possibilistic modeling' (Edmonds and Aodha, 2019), which suggests to use ABMs for "identifying some of the possible ways a policy can go wrong (or indeed go right)".

The remainder of this article is organized as follows. Section 2 provides a detailed description of the model. Section 3 introduces the numerical experiment and the evaluation criteria of our analysis. Section 4 presents and discusses simulation results. Section 5 provides concluding remarks.

2. Model description

An overview of the model structure is given in Fig. 1. The model is made up of two industry sectors. One consists of 'suppliers' (S) of fossil fuels, which can represent coal mines, oil wells, or distributors that import fossil fuels. The other consists of 'manufacturers' (M), which use fuels in order to create goods and emit carbon as a byproduct. Firms in both sectors are separated into regulated and unregulated firms, with the latter not being covered by the regulator's policies and emission target. The following subsections provide a detailed description of the model.

2.1. Policy scenarios

The policy maker's aim is to reduce overall emissions to the target level e^*. We test three policy instruments to reach this target: a carbon tax, permit trading, and direct regulation through a uniform quota. Each of these are applied either upstream, where the regulator will regard the emissions embodied in fuels, or downstream, where the regulator will regard the actual emissions caused by the use of fuels. We compare these policies against a baseline scenario without any policy intervention. The three distinct instruments work as follows:

1. Under carbon taxation, an emission price p^e_t is set directly by the policy maker at the beginning of each round. All covered firms in the target sector have to pay the same price. The quantity of emissions is not defined directly, but is an outcome of market dynamics.
2. Under permit trading, the policy maker each round auctions a limited amount of permits u^*_t to the targeted sector, as described in Section 2.4. Firms have to submit a permit for each unit of (embodied or actual) emissions they cause. This regulates quantity directly, while the emission price is a result of trading dynamics.[2]
3. Under direct regulation, the policy maker sets a uniform quota that imposes a maximum emission limit $e^{\sigma}_{i,t}$ on a covered firm i. Similar to permit trading, this creates a direct quantity limit, although with a different allocation, and without firms having to pay for their share. This particular quota affects all covered firms equally (see Appendix A.1), and thus does not favor more efficient firms.

[1] Common cost concepts include "change in GDP, change in consumption, change in welfare, energy system cost, and area under marginal abatement cost (MAC) curve" (Paltsev and Capros, 2013).

[2] Note that this model simplifies the permit trading to the interaction between the regulator and the firms to keep the complexity of the model manageable. The auctioning mechanism still captures two central aspects of permit trading. First, that permit prices are a result of firms' willingness to pay. And second, that firms with a higher willingness to pay receive a larger share of permits.

The stringency parameters of these policies ($p^e_t, u^*_t, e^\sigma_{i,t}$) are gradually increased until they reach the target e^*, as described in Appendix A.1. The coverage of the policies (i.e. the fraction of firms that are regulated) can further be limited, with the fraction of regulated firms given by the parameter φ. This can either represent a situation where only specific sectors are covered,[3] or one where firms share the market with foreign competitors that are outside the regulator's jurisdiction.

2.2. Order of events

The agents' actions follow discrete time-steps $t = 1, 2, \cdots, T$, which are meant to roughly represent months. Each round is characterized by the following chain of events:

1. The policy maker updates its climate policy.
2. Consumption good firms form their production goals and order fuels.
3. Fuel suppliers form their production goals.
4. If a permit market is in place, covered firms trade permits.
5. Suppliers produce fuels and sell them to manufacturers on the fuel market.
6. Manufacturers produce goods and sell them to consumers on the goods market.
7. Manufacturers decide whether to invest in abatement technology.
8. Manufacturers change towards more competitive fuel suppliers.

2.3. Production

At the beginning of each round t, every firm $i \in S \cup M$ (denoting both fuel suppliers $s \in S$ and manufacturers $m \in M$) sets their production goal $q^d_{i,t}$. Similar to Dosi et al. (2010), firms are demand-driven and myopic. This means that they base their goal on expected demand $\widetilde{D}_{i,t}$. They further add a desired inventory rate I and subtract the remaining inventory from last round $q_{i,t-1}$.

$$q^d_{i,t} = \widetilde{D}_{i,t} * (1 + I) - q_{i,t-1} \tag{1}$$

Firms production $q^p_{i,t}$ can be restrained by multiple factors. In case of direct regulation, by the quota $e^\sigma_{i,t}$. In case of permit trading, by their inventory of permits $u_{i,t}$. And for manufacturers, by their inventory of fossil fuels $f_{m,t}$. Manufacturers' restrictions further depend on their fuel intensity $A_{m,t}$, which describes the amount of fuel needed to produce one unit of output. Units are normalized so that the combustion of one unit of fuel leads to one unit of emissions, which means that $A_{m,t}$ also represents firms' emission intensity. Finally, firms also ration their use of permits and fuels over the following t^* rounds to avoid sudden shortages.

$$q^p_{i,t} = \begin{cases} min\left(q^d_{s,t}, e^\sigma_{s,t}, \dfrac{u_{s,t}}{t^*}\right) & \text{Suppliers} s \\ min\left(q^d_{m,t}, \dfrac{e^\sigma_{m,t}}{A_{m,t}}, \dfrac{u_{m,t}}{A_{m,t} * t^*}, \dfrac{f_{m,t}}{A_{m,t} * t^*}\right) & \text{Manufacturers} m \end{cases} \tag{2}$$

Firms produce and trade according to the order of events in Section 2.2. When they try to sell their goods at the respective market, they offer their current inventory $q_{i,t}$, which consists of both their latest production $q^p_{i,t}$ and past inventory $q_{i,t-1}$.

$$q_{i,t} = q^p_{i,t} + q_{i,t-1} \tag{3}$$

Suppliers' production costs $B_{s,t}$ increase by a factor β with every unit of fossil fuel they extract. This reflects that fuel supplies become more scarce and difficult to extract as reservoirs deplete.

$$B_{s,t+1} = B_{s,t} + \left(q^p_{s,t} * \beta\right) \tag{4}$$

Firms set their sales price $p_{i,t}$ to cover their production costs $B_{i,t}$ and their emission and fuel costs $c^e_{i,t}$. They further add a mark-up rate $\alpha_{i,t}$ to their costs per unit of production.

$$p_{i,t} = \left(B_{i,t} + c^e_{i,t}\right) * \left(1 + \alpha_{i,t}\right) \tag{5}$$

Firms emission and fuel costs $c^e_{i,t}$ are defined in Eq. (6), where $p^e_{i,t}$ relates to the price of emissions, $p^f_{i,t}$ refers to the price of fuels, and $A_{m,t}$ describes the manufacturers fuel and emission intensity. For suppliers, the price of emissions regards the embodied emissions of their fuels.

$$c^e_{i,t} = \begin{cases} p^e_{s,t} & \text{Suppliers} s \\ A_{m,t} * \left(p^e_{m,t} + p^f_{m,t}\right) & \text{Manufacturers} m \end{cases} \tag{6}$$

The mark-up rate $\alpha_{i,t}$ reflects the dynamics of a 'customer market' where firms compete against each other over their market share $\psi_{i,t}$. As described in Dosi et al. (2010), they set a higher profit margin when they are successful - meaning that their market share is growing - and reduce it when they are not. The magnitude of this adaptation is given by the factor ϑ.

$$\alpha_{i,t} = \alpha_{i,t-1} * \left(1 + \vartheta * \frac{\psi_{i,t-1} - \psi_{i,t-2}}{\psi_{i,t-2}}\right) \tag{7}$$

2.4. Permit market and quotas

There are two policy scenarios where the policy maker requires regulated firms j to submit permits for their production (see Section 2.1). One targets suppliers ($j \in S$), forcing them to submit an extraction permit for each unit of fossil fuel they introduce to the market. The other regulates manufacturers ($j \in M$), forcing them to submit an emission permit for each unit of fossil fuel they combust in their production process.

Permits are distributed at the beginning of each round through a discriminatory auction.[4] Every round, firms have to submit bids that are accepted by the regulator until u^*_t is reached or no more bids are left. Permits are then sold at the respective bid-price, and unsold permits are kept for next round's auction. Firms bidding volume is based on their desired amount of permits $u^d_{j,t}$, which depends on firms monthly production goal $q^d_{j,t}$, their rationing time t^*, and their existing inventory of permits $u_{j,t-1}$.

$$u^d_{j,t} = \begin{cases} \widetilde{D}_{s,t} * t^* - u_{s,t} & \text{Suppliers} s \\ \widetilde{D}_{m,t} * t^* * A_{m,t} - u_{m,t} & \text{Manufacturers} m \end{cases} \tag{8}$$

Firms have an idiosyncratic emission price $p^e_{j,t}$, which reflects how much they think a unit of emissions is worth and how much they are willing to pay for a permit at the auction. Depending on whether firms are able to trade their desired amount (success) or not (failure), they adapt their emission price based on the adaption rate μ_j for future rounds.[5]

$$p^e_{j,t+1} = \begin{cases} p^e_{j,t} - \mu_j * \left(1 + p^e_{j,t}\right) & \text{Success} \\ p^e_{j,t} + \mu_j * \left(1 + p^e_{j,t}\right) & \text{Failure} \end{cases} \tag{9}$$

[3] The European emission trading system, for example, only covers around 45% of European emissions (World Bank Group, 2019)

[4] A comparison of discriminatory pricing auctions with uniform pricing auctions and grandfathering (i.e. no auction) is presented in Foramitti et al. (2021).

[5] A factor 1 is added to Eq. (9) to avoid the permit price being locked-in if it is close to zero.

Hence, firms that want to buy permits increase their emission price until they receive their desired amount of permits. If their trades are successful (i.e. they received their desired amount of permits), they reduce the bidding price in the hope to spend less on future bids.[6]

Under direct regulation, firms do not have to pay for permits, but still have an incentive to charge consumers an emission price if there is more demand than they are allowed to produce. In other words, if firms are not allowed to increase production in reaction to high demand, they raise prices instead. This represents a scarcity rent (Kalkuhl and Brecha, 2013). They thus apply the same adaption as in Eq. 9, with their conditions of success being defined as follows:

$$\widetilde{D}_{i,t} \leq \begin{cases} e^{\sigma}_{s,t} & \text{Suppliers} s \\ e^{\sigma}_{m,t} * A_{m,t} & \text{Manufacturers} m \end{cases} \tag{10}$$

2.5. Consumption good market

The goods market follows the same evolutionary dynamic as in Foramitti et al. (2021), following Dosi et al. (2010), where demand gradually moves towards more competitive producers. Competitiveness $k_{m,t}$ is given by a firm's sales price $p_{m,t}$ and unfilled demand from last round $l^{g}_{m,t-1}$ (Eq. (17)). The first term implies that a firm's competitiveness falls with increasing sales prices. The second term ensures that firms lose customers when they are unable to fulfill their demand.

$$k_{m,t} = -p_{m,t} - l_{m,t-1} \tag{11}$$

These factors of competitiveness define the evolution of firms' market shares ψ_m, where χ denotes how fast consumers shift towards more competitive firms.

$$\psi_{m,t} = \psi_{m,t-1} * \left(1 - \chi^{M} * \frac{k_{m,t} - \overline{k}_t}{\overline{k}_t}\right) \tag{12}$$

The average competitiveness $\overline{k}_t$ is given by the weighted competitiveness of each firm, using the last rounds market shares $\psi_{m,t-1}$ as weights.

$$\overline{k}_t = \sum_{m \in M} \psi_{m,t-1} * k_{m,t} \tag{13}$$

The level of total demand follows a simple declining curve that depends on the average price $\overline{p}^{g}_{t}$. This means that consumers tend to buy less of the good if the overall price rises. The price sensitivity of demand is given by the factor γ.

$$D^{g}_{t} = D_0 * e^{-\gamma * \overline{p}^{g}_{t}} \tag{14}$$

This total demand for goods is then allocated according to firms' market shares:

$$D_{m,t} = \psi_{m,t} * D^{g}_{t} \tag{15}$$

Firms actual sales $q^{*}_{m,t}$ are then either limited by their demand or their inventory:

$$q^{*}_{m,t} = \min\left(D_{m,t}, q_{m,t}\right) \tag{16}$$

If firms have produced too little, they are left with a certain amount of unfilled demand $l_{m,t}$ that will translate into reduced competitiveness in the following round:

$$l_{m,t} = D_{m,t} - q^{*}_{m,t} \tag{17}$$

2.6. Fossil fuel market

The fossil fuel market is organized through an order-based system. Manufacturers calculate their desired amount of fuels $f^{d}_{m,t}$ in the same way as their desired amount of permits in Eq. 8:

$$f^{d}_{m,t} = \widetilde{D}_{m,t} * t^{*} * A_{m,t} - f_{m,t} \tag{18}$$

Each manufacturer m has a preference $d_{m,s,t} \in [0, 1]$ for each supplier s that defines what percentage of their desired fuels they will order from it. A supplier's demand $D_{s,t}$ thus becomes the sum of these orders:

$$D_{s,t} = \sum_{m \in M} f^{d}_{m,t} * d_{m,s,t} \tag{19}$$

Suppliers try to produce enough to meet this demand, as described in Section 2.3. Their sales and unfilled demand are calculated like on the consumption good market (Eqs. (16) and (17)). If there is unfilled demand, it will be reduced from all orders in an equal share. Each firms' market share $\psi_{s,t}$ is defined as their share in total sales:

$$\psi_{s,t} = \frac{q^{*}_{s,t}}{\sum_{s \in S} q^{*}_{s,t}} \tag{20}$$

At the end of each round, manufacturers adapt their list of preferred suppliers. Similar to the change of demand on the consumption good market, each supplier's competitiveness $k_{s,t}$ is calculated as in Eq. (11). The preferences $d_{m,s,t}$ of each manufacturer then change based on the replicator dynamics in Eq. (12) with the adaption speed χ^{S}.

2.7. Abatement

As in Foramitti et al. (2021), manufacturers can decide to adopt a new technology that will reduce their emission intensity and increase their production costs. These technological options could represent the installation of more emission-efficient machines, a shift from fossil fuels to renewables as an energy source (e.g., electricity), or new production routines that reduce fossil fuel dependency.

Each firm has a different set of possible technological options x that allow for a particular reduction in emissions a_x at an extra cost b_x per unit of production. The marginal abatement costs of this technological step, i.e. the additional production costs of emitting one unit less, are defined as:

$$c^{\lambda}_{m} = \frac{b_x}{a_x} \tag{21}$$

Every round, firms examine the next possible technological option x with the lowest c^{λ}_{m}. A technological improvement is implemented by comparing the marginal costs of abatement to the sum of the price of emissions $p^{e}_{m,t}$ and fuels $p^{f}_{m,t}$, which can be seen as the marginal damage costs of causing one unit of emission.[7] Since technological investment is a long-term decision involving uncertainty about future cost of abatement, firms add an idiosyncratic profitability target η_m to this condition to reflect their different risk attitude.

$$c^{\lambda}_{m} * (1 + \eta_m) < p^{e}_{m,t} + p^{f}_{m,t} \tag{22}$$

Under permit trading, a manufacturer decides to invest in technological improvements once the sum of the price of emissions and fuels is higher than the cost of abatement. This reduces their emission intensity, which in turn affects their demand and trading price for permits in the next round. Manufacturer's trading and abatement behavior thus reflects a balance between the cost of permits and the cost of abatement options.

[6] If firms have more permits then they want or if they manage to buy all available permits, they will treat that round as successful.

[7] The cost of fuels is covered here, which is not the case in textbook treatments of abatement costs.

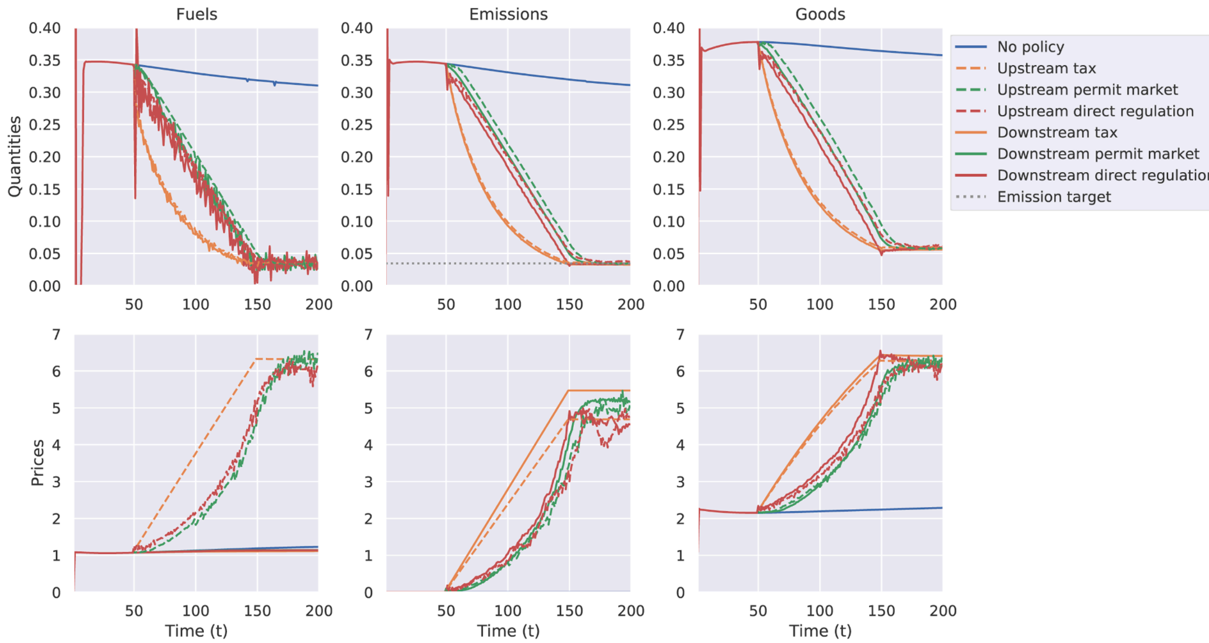


Fig. 2. Quantity and price dynamics for a single run under full coverage.

3. Numerical experiment

In our experiment, we simulate a setting of 30 upstream and 30 downstream firms over the time-span of 200 rounds. The model initiates over 50 rounds, then a climate policy is linearly introduced over the following 100 rounds,[8] followed by 50 more rounds where the policy is held at a constant level. The policies are compared under the same level of effectiveness, i.e. their stringency is set so that they all meet the emission target e^*. The permit markets reach this target automatically, while the emission tax and quota are calibrated.

We repeat this experiment 64,000 times to look at a wide range of different parameter combinations, which are described in Appendix A.1. The code for the simulation is written in Python 3 and available on GitHub.[9] The parameter variation is based on the sampling scheme of Saltelli et al. (2010) and operationalized through the Python package SALib (Herman and Usher, 2017). The same package is used to calculate Sobol sensitivity indices (Sobol, 2001), which are presented in Appendix A.3.

The baseline and the six policy scenarios are compared between two distinct settings (see Section 2.1). In the first setting, all firms are regulated by the climate policy (full coverage, Section 4.1). In the second, only a fraction of firms is regulated and the rest is outside the regulator's jurisdiction (limited coverage, Section 4.2).

To analyze and compare the relative impact of each instrument, we consider five different evaluation criteria. Each criterion regards the state of the model at the last ten rounds of the simulation, and describes how well a given policy performs relative to the other six scenarios. Their mathematical definition can be found in Appendix A.2. The criteria are as follows:

1. *Technology adoption:* The share of abatement[10] that is achieved through the adoption of more emission-efficient technology (technological abatement).
2. *Compositional change:* The share of abatement that is achieved through a restructuring of the sector that gives emission-intensive firms a lower market-share.
3. *Production decline:* The share of abatement that is achieved through a reduction of firms' production levels.
4. *Sales price:* The average sales price $p_{t,m}$ of downstream manufacturers.
5. *Consumer impact:* The average financial burden on consumers, assuming that policy revenue is recycled and given back to consumers. Calculated as the average sales price minus the policy revenue per good.

Since policies are compared with the same effectiveness, the first three criteria can be seen as different formulations of efficiency. High technology adoption and compositional change regard the emission-efficiency of the economy (i.e. average emissions per unit of production), while a low production decline represents an efficient economy in regard to economic output. The other two criteria - sales price and consumer impact - are desirable to be low in regard to the equity impacts and political feasibility of the policy.

In addition, we control for the following six indicators in our model. These help us to identify the causal link between a certain policy and its performance along the evaluation criteria. Their exact definition is also given in Appendix A.2. The indicators are as follows:

1. *Emissions:* The overall emissions of the downstream sector.
2. *Emission price:* The average emission price $p^e_{t,j}$ of regulated firms.

3-4 *Profit shares:* The amount of profits in the downstream and upstream sector.

5-6 *Market concentrations:* The distribution of market shares in the downstream and upstream sector.

[8] This means that the policy is strengthened over time along a linear path over 100 rounds to avoid extreme changes in the economy from one round to another. This is in line with climate policy design in countries like Argentina, Canada, and South Africa (World Bank Group, 2019).

[9] Link to the repository: https://github.com/JoelForamitti/UvsD_ABM

[10] As derived in Appendix A.2, abatement is decomposed into three contributing factors. This results in three shares which sum up to the total amount of abatement that is equal among the policy scenarios (as they reach the same emission target).

4. Results and discussion

Results are presented in two parts. In Section 4.1, we explore the case of full coverage, meaning that all firms in the target sector are covered by the climate policy. This demonstrates the differences between the policies when no carbon leakage is possible, e.g. in a closed economy with full coverage, or under a global agreement between connected economies. In Section 4.2, we consider the contrasting case of limited coverage. In both parts, there is one sub-section that shows dynamic results over time for a single run of the model, and a second one that presents average results over multiple runs and varied parameters. A sensitivity analysis can be found in Appendix A.3.

4.1. Full coverage

4.1.1. Single run dynamics

Fig. 2 shows the quantity and price dynamics over time for a single run, using mid-point parameter values from Table Appendix A.2 . We can see that all policies, while following different paths, end up leading to a similar reduction of fuels, emissions, and sales, as well as a similar increase in goods prices. The model thus demonstrates that, under full coverage, a reduction of emissions will lead to a similar change in prices independent of the policy instrument and whether it is applied upstream or downstream.

One key difference between the two regulation levels is that upstream policies lead to an increase in fuel prices, while downstream regulation leads to a price close to or even below that under no policy. This is because when downstream regulation reduces the amount of emissions, it automatically also reduces the demand for fossil fuels. This is good for climate mitigation, in the sense that it reduces the profits that can be made from selling fossil fuels, but it is also problematic in the sense that firms who are not covered by the downstream policy could get easy access to cheap fuels, which can lead to carbon leakage (see Section 4.2).

Fig. 2 further shows that quantity-based regulation (i.e. permit trading and direct regulation) displays a dynamic where prices stabilize at a lower level than the tax or even decline after an initial peak (henceforth referred to as 'overshoot-decline dynamic'). This dynamic has been identified as a key difference between downstream tax and permit trading in Foramitti et al. (2021), and can be explained by the fact that successful abatement makes production more emission-efficient, which in turn leads to less demand for emissions and fuels, and thus lower emission and fuel prices.

Finally, upstream regulation tends to reach the same abatement with a lower emission price, particularly in the case of taxation. This is because upstream regulation creates higher profit rates as firms set their mark-up as a percentage of their costs per unit of production. Downstream firms then have to pay this additional mark-up for every unit of fuel, to which they than also apply their own mark-up rate. This means that an upstream policy can apply the same pressure as a downstream policy with a lower emission price.

4.1.2. Average results over multiple runs

In Fig. 3, the evaluation measures and additional indicators are presented as average results over all parameter combinations tested. As mentioned in Section 3, the six policy scenarios are compared under equal effectiveness, i.e. the levels of stringency are set so that all policies reach the same emission target. Like already observed for a single run, production decline and sales price increase are fairly similar (Fig. 3).

Fig. 3 further shows that technology adoption tends to be slightly higher for quantity-based policies. This happens due to the unstable emission prices seen in Section 4.2.1, which leads to a temporary price levels above that of the carbon tax until enough technological improvements have taken place to drive the price down again. This, in turn, results in lower scarcity of goods, and thus lower sales prices. Regarding compositional change on the goods market, both tax policies perform best. This is because the unstable prices of quantity-based regulation can create a competitive advantage for less emission-efficient producers. The consistent and usually higher price of the tax thus creates a stronger advantage for emission-efficient firms.

As the uniform quota does not favor more emission-efficient producers, compositional change and market concentration are very small for direct regulation on the downstream level. However, the policy does not lead to a stronger production decline as the quota increases scarcity and stimulates more technology adoption, thus increasing emission-efficiency.

While other types of quotas could increase the efficiency of quotas on the downstream level, our scenario demonstrates that the inefficient selection (i.e. low compositional change) of direct regulation is not a disadvantage when applied upstream. On the contrary, compositional change and market concentration are slightly higher than under upstream permit trading. This is because the less efficient selection of upstream firms through the quota can lead to higher fuel prices and thus create a stronger selective effect (i.e. high compositional change) downstream.

Since there is no policy revenue under direct regulation, the quota creates particularly high profit rates and consumer impacts. In that sense, direct regulation is very similar to a permit system where permits are allocated for free, only that firms have no influence on the distribution of permits. The tax, due to its higher price, causes higher mark-ups and thus more profits than the permit market in its target sector.[11] Finally, consumer impacts are lower for both tax and permit trading if these are applied downstream, as the higher emission price (see Section 4.2.1) leads to more policy revenue which is then recycled back to the consumers.

4.2. Limited coverage

In the following subsections, we assume that only a fraction φ (see Table Appendix A.2 in Appendix A.1) of firms on the market are covered by the respective climate policy. This allows for the possibility of carbon leakage, i.e. that the climate regulation in the covered sector causes emissions to increase elsewhere.

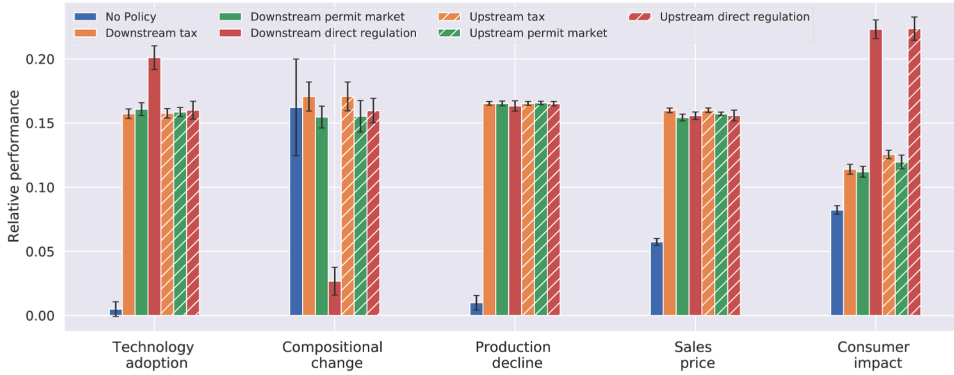
4.2.1. Single run dynamics

In Fig. 4, we can see the emissions over time, separated between embodied (upstream) and caused emissions (downstream), as well as between covered and total (covered plus not covered) emissions. We see that regulation on one level affects outcomes on the other only weakly, i.e. reaching the local target downstream reduces upstream extraction only by a small amount, and vice versa.

Emissions under quantity-based regulation fluctuate strongly as they mirror the fluctuation in emission prices. This is because the competition between firms that are covered and those who are not causes emission prices to change fast over time. Under the full coverage setting, emission price changes only affected firms' demand because of differences in emission intensity and changes in overall demand. Under limited coverage, in contrast, there is an additional dynamic as covered firms can loose market shares to firms that are not regulated.

Total emissions appear slightly lower for upstream regulation. This is because of the fuel price increase that only happens under upstream regulation, as discussed in Section 4.1.1. Under limited coverage, fuel price changes affect all firms (both covered and not covered), and thus also incentivizes emission reduction outside the reach of the regulator. Downstream regulation, in contrast, only creates such incentives for covered firms.

[11] In Foramitti et al. (2021), it has been shown that permit trading can create higher profit rates than a tax because firms could receive permits at a low price and make profit by selling them to competitors. This is not the case in current model because permit trading has been simplified so that permits are only auctioned and not traded between firms.



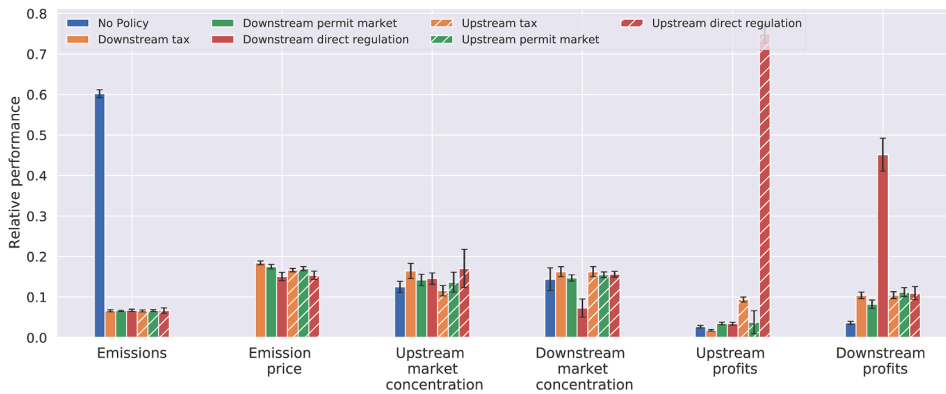


Fig. 3. Policy evaluation criteria (top panel) and additional indicators (bottom panel) under full coverage. Values indicate the performance of each scenario relative to the others (see Appendix A.2). Error bars report standard deviations.

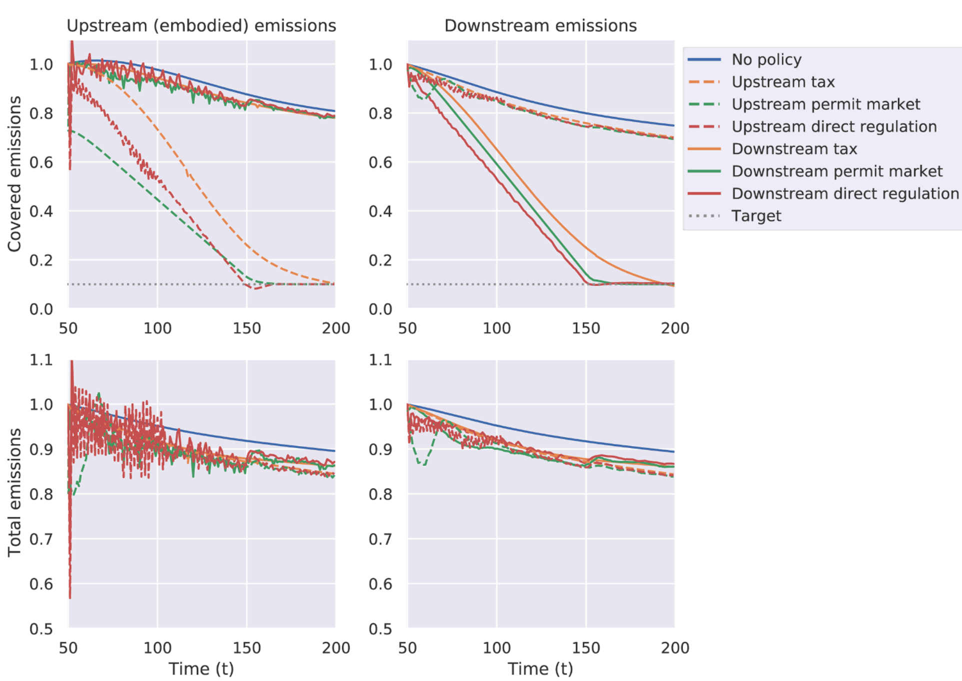


Fig. 4. Emissions over time under limited coverage. Note: The y-axis describes the percentage of emissions relative to the emission level before the introduction of the policy.

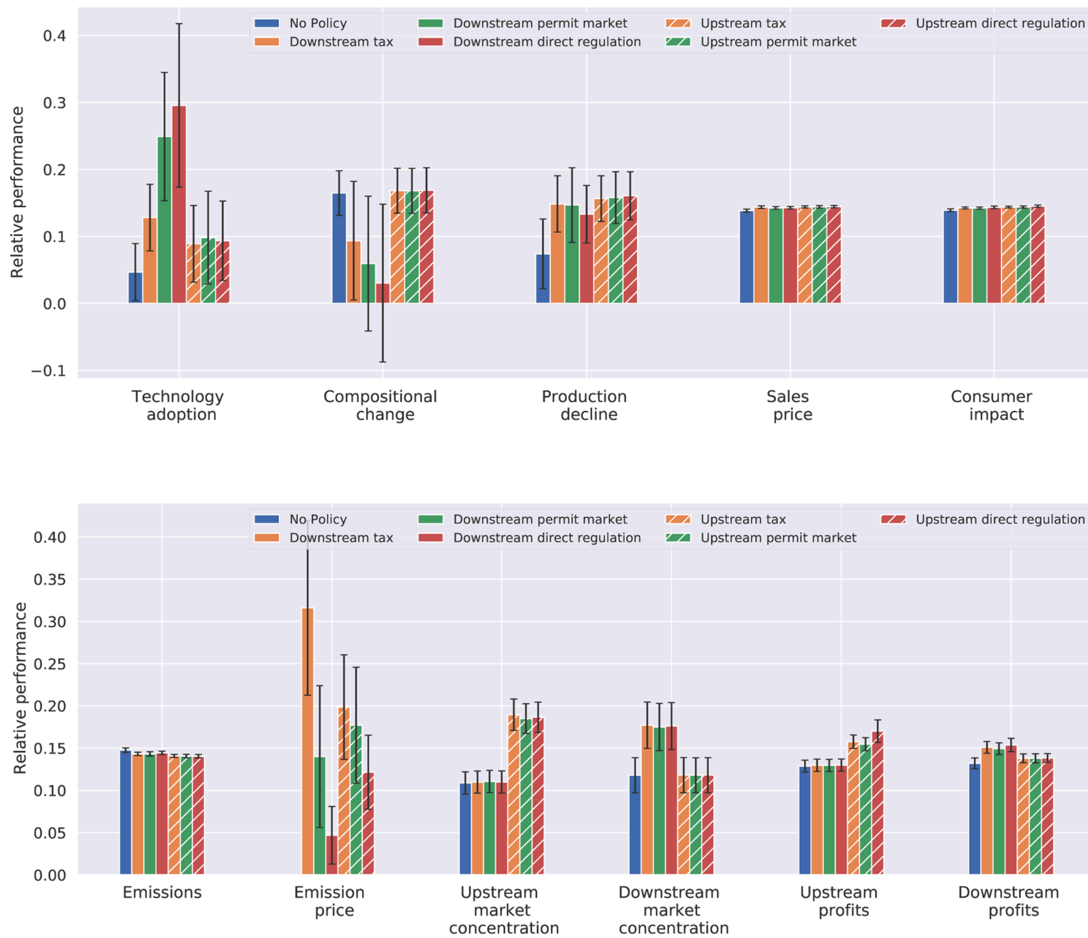


Fig. 5. Policy evaluation criteria (top panel) and additional indicators (bottom panel) under limited coverage. Values indicate the performance of each scenario relative to the others (see Appendix A.2). Error bars report standard deviations.

4.2.2. *Average results over multiple runs*

Fig. 5 presents the same evaluation measures and additional indicators as in Section 4.1.2, but this time for the setting of limited coverage. Note that these measures regard all firms (covered and not covered). In line with the discussion above, we can observe that upstream regulation leads to slightly less emissions and more compositional change, as the increase in fuel prices affects all firms downstream (i.e. even those that are not within the regulator's reach).

We can further see that quantity-based regulation leads to more technology adoption when applied downstream. This is due to the same 'overshoot-decline' dynamic introduced in Section 4.1.1. The reason that this dynamic does not appear here for upstream regulation is that fuel suppliers cannot innovate, while the policy impacts are diffused with the unregulated fuel supply sector (i.e. overall fuel prices fluctuate less because only part of the fuel suppliers are affected) before it reaches downstream firms.

Market concentration is increased by policies only within their regulation level, i.e. upstream policies increase upstream market concentration and downstream policies downstream market concentration. This can be understood through the competition between firms. As firms in the regulated sector become less competitive in comparison to unregulated firms, their market shares will shrink and the overall market concentration will increase; and succesful firms will apply higher profit rates.

Due to this competitive effect, the emission price necessary to reach the target is very low. Essentially, under limited coverage, a policy mainly reduces emissions by driving covered firms out of the market. Small changes in the emission price can thus have a strong competitive effect, which can be seen in the high standard deviation for the emission price in Fig. 5.

5. Conclusions

This study presented an agent-based model to compare the performance of upstream and downstream regulation for climate change mitigation, considering the instruments of taxation, permit trading, and direct regulation through a uniform quota. The model takes into account heterogeneous agents using heuristic decision rules on constantly changing markets, as well as the difference between full and limited coverage. Results were presented for multiple runs with a wide variation of parameter values, and evaluated upon multiple measures.

In our analysis, we compare the performance of each policy and regulation level under an equal level of effectiveness. This suggests that none of the tested instruments can be ruled out as an adequate instrument to reduce emissions. However, we do identify several dynamics that lead to relevant differences between the policies.

In line with Foramitti et al. (2021), we show that quantity-based regulation can lead to an overshoot in prices followed by a decline after successful abatement. In comparison to a tax, this dynamic can lead to a higher level of technological adoption and production costs, while compositional change towards emission-efficient firms is smaller as a low emission price can make such firms less competitive.

A key difference that is found between the two regulation levels is that downstream policies reduce the demand for fuels, which means that only upstream policies lead to an increase in fuel prices. This can be both beneficial and detrimental for the success of climate policy. On the one hand, it can reduce the profits that can be made from selling fossil fuels, on the other it allows firms who are not covered by the downstream policy to buy fuels at a cheap price - increasing the risk of carbon leakage.

We further demonstrate that the level of regulation matters particularly for direct regulation. Applying a uniform quota downstream creates little abatement through compositional change as it does not advantage more emission-efficient firms. However, when applied upstream, this inefficient selection leads to an increase in fuel prices, which can only strengthen the shift towards more emission-efficient firms further downstream.

These insights complement the results from traditional models like Erickson and Lazarus (2018) and Fæhn et al. (2017) by identifying potential policy dynamics that are overlooked under the assumptions of rational and representative behavior and economic equilibrium. Further dynamics could be identified under additional assumptions, and calibration towards particular cases would be necessary to test their likelihood. The flexible structure and open-source nature of our model makes it very suitable for such extensions.

Some suggestions for future research are to account for different fuel types and trading strategies, emissions from fossil fuel extraction, agent learning (Yu et al., 2020), and additional abatement options like end-of-the-pipe technologies. Further features like heterogeneous consumers, inter-sectoral interactions, finance, and labor markets, could allow for an assessment of impacts on additional criteria like economic stability and equity.

CRediT authorship contribution statement

Joël Foramitti: Conceptualization, Software, Writing – original draft. **Ivan Savin:** Conceptualization, Supervision, Writing – review & editing. **Jeroen C.J.M. van den Bergh:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

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Appendix A

A1. Parameter values

This section presents the parameter values used in our numerical experiment. Table Appendix A.1 presents the fixed parameters, which are being held constant throughout the whole simulation. Table Appendix A.2 presents variable parameters, which are varied for each of the 64,000 simulation runs based on the sampling scheme of Saltelli et al. (2010).

There are further three policy parameters p_t^e, u_t^*, and σ_t, which are gradually changed over the policy implementation period T^*, with their final values calibrated to reach the emission target e^*. In the first round of permit trading, the amount of permits u_t^* is multiplied by t^* to avoid extreme fluctuations in the initial rounds. Under direct regulation, the individual quotas of each firm are calculated based on their emissions before the start of the policy:

$$e_{i,t}^{\sigma} = \sigma_t * e_{i,T_0-1} \tag{A.1}$$

Firms technological abatement options are calculated as follows. Firms have $i = 1, \cdots, N_\lambda$ technological options, each with an abatement potential of $a = \lambda / N_\lambda$ and a marginal abatement cost of $c_i^\lambda = b_i / a = \theta * a * i$. This means that firms' marginal abatement costs will linearly increase with every abatement step that they take.

A2. Performance criteria

The definition $Y_{n,z}$ of each measure n and scenario z is given in Table Appendix A.3. The policy evaluation criteria ($n = 0 - 5$) and additional indicators ($n = 6 - 11$) are described in Section 3). They are calculated as a sum of the upstream ($j \in S$) or downstream ($j \in M$) sectors activity in the last ten rounds of the simulation, as given by the function S:

$$S(y_{j,t}) = \sum_{t=T-10}^{T} \sum_{j=1}^{N_j} y_{x,t} \tag{A.2}$$

The relative measures $C_{n,z}$ that are shown in Section 4ww describe the results for each scenario z and measure n in relation to the other scenarios as given in Eq. Appendix A.3. This means that the eleven measures describe relative performance between the scenarios and sum up to 1.

$$C_{n,z} = \frac{Y_{n,z}}{\sum_{z=1}^{6} |Y_{n,z}|} \tag{A.3}$$

The first three criteria critera are based on the decomposition of downstream abatement as put forward in Foramitti et al. (2021, Appendix 2). A manufacturers' change in emissions from round 0 to round t can be decomposed into changes in production level and changes in emission-intensity, using the functions $\overline{x}_t = (x_t + x_0)/2$ and $\Delta x_t = x_t - x_0$.

$$\begin{aligned} \Delta e_{m,t} &= e_{m,t} - e_{m,0} \\ &= q_{m,t} * A_{m,t} - q_{m,0} * A_{m,0} \\ &= \Delta q_{j,t} * A_{m,0} + \Delta A_{m,t} * q_{j,0} + \Delta q_{m,t} * \Delta A_{m,t} \\ &= \Delta q_{m,t} * \overline{A}_{m,t} + \Delta A_{m,t} * \overline{q}_{m,t} \end{aligned} \tag{A.4}$$

The change in production $\Delta q_{m,t}$ can further be decomposed further into contributions from a shift of relative shares of production $\rho_m = q_{m,t} / Q_t$ within the sector and a decline in total production $Q_t = \sum_{m=1}^{N_m} q_{m,t}$.

$$\begin{aligned}\Delta q_{m,t} &= \rho_{m,t} * Q_t - \rho_{m,0} * Q_0 \\ &= \Delta\rho_{m,t} * Q_t + \Delta Q_t * \rho_{m,t} + \Delta\rho_{m,t}\Delta Q_t \\ &= \Delta\rho_{m,t} * \overline{Q}_t + \Delta Q_t * \overline{\rho}_{m,t}\end{aligned} \tag{A.5}$$

Consumer impact describes average sales price minus the regulators' revenue per unit of goods sold. The revenue $R_{i,t}$ from each firm is given by either the tax or permit payments of each round:

$$R_{i,t} = \begin{cases} 0 & \cdots \text{No policy or direct regulation} \\ e_{i,t} * p_t^e & \cdots \text{Tax} \\ p_{i,t}^u * u_{i,t}^t & \cdots \text{Permit trading} \end{cases} \tag{A.6}$$

Finally, the profit $\pi_{i,t}$ in criterion 10 and 11 describes the sum of revenue from sales minus the sum of expenses for production, fuels, and regulation.

$$\pi_{i,t} = q_{i,t}^* * p_{i,t} - q_{i,t} * B_{i,t} - R_{i,t} - \begin{cases} 0 & \cdots \text{Suppliers} \\ e_{m,t} * A_{m,t} & \cdots \text{Manufacturers} \end{cases} \tag{A.7}$$

A3. Sensitivity analysis

To understand the sensitivity of the results towards each parameter, we perform a Sobol sensitivity analysis (Saltelli et al., 2010; Sobol, 2001) for each measure and varied parameter. The calculated first-order Sobol Sensitivity Indices are presented in Fig. Appendix A.1 and Appendix A.2 for full and limited coverage. Extensive data on the average evaluation measures over different values for each parameter can further be found in the supplementary material. Here we provide a summary of some of the more pronounced sensitivities.

Let us first regard full coverage. A higher heterogeneity of the production factors ($\Delta A_0, \Delta B_0$) makes the compositional change towards more emission-efficient firms less sensitive to price fluctuations, which reduces the difference between the tax scenarios and quantity-based regulation. Consumer impact is further increased in the tax and permit market scenarios, while it is decreased under direct regulation.

Another relevant factor is the emission price adaption rate (μ), which decreases technology adoption for the tax scenarios, and increases it for downstream direct regulation. This regards the 'overshoot-decline' dynamic of quantity-based regulation, which explained the lower technology adoption of the tax scenarios in Section 4. The magnitude of this dynamics is reduced when firms adapt their prices more slowly, i.e. if the emission price adaption rate is low.

Technology adoption is also affected by the profitability target (η), although the effect is small. A high value of this parameter leads to lower adoption under the tax scenarios and the upstream permit market. Downstream direct regulation, in contrast, shows an increase of adoption and a decrease of compositional change. Consumer impact is further decreased for all revenue-based instruments (i.e. tax and permit market).

Downstream market adaption speed (χ^M), while having only a small effect, increases technology adoption and compositional change in all scenarios except the downstream quota. Consumer impact is further increased for all revenue-based instruments. The upstream speed (χ^S) increases technology adoption for tax and permit market, while decreasing it for direct regulation. It also decreases production decline for tax and permit scenarios, while increasing it under upstream direct regulation.

The mark-up adaption rate (ϑ) reduces technology adoption for downstream policies and increases it for upstream policies, while generally increasing compositional change in all policy scenarios and leading to less production decline for quantity-based regulation. The heterogeneity of the abatement cost factor ($\Delta\theta$) increases compositional change for both tax scenarios as well as for downstream direct regulation.

Many parameters are particularly sensitive under downstream direct regulation. Increased technology adoption and decreased compositional change with high abatement cost factor (θ) and demand sensitivity (γ). Lower sales price and production decline are found for low heterogeneity (ΔA_0, ΔB_0) as well as high abatement potential (λ), permit price adaption rate (μ), and mark-up adaption rate (ϑ).

Further sensitivities that are similar for all scenarios are found for the demand response to prices (γ), which decreases the sales prices, the production cost increase (β), which decreases sales price and production decline, and the abatement cost factor (θ), which reduces consumer impact (except for direct regulation).

Regarding the limited coverage setting, the coverage factor (φ) is also shown to affect the results (see, e.g. pp. 63-64 in the supplementary material). This sensitivity appears in particular for upstream regulation and for the measures of consumer impact and sales price. However, no simple linear relationship is found between the parameter values and the evaluation measures. A more detailed analysis of this relationship is left for future research.

Other sensitivities that do not appear under full coverage are found for the upstream production cost increase (β) and the mark-up adaption rate (ϑ), but also do not show a clear relationship. This is likely because the price increase of fuels from unregulated suppliers plays a key effect in the results discussed in Section 4.2, with different levels of upstream production cost and mark-up increases also affecting competitive dynamics.

Table Appendix A.1
Values of fixed model parameters.

Parameter	Symbol	Value
Simulation length	T	200
Policy implementation period	T^*	100
Initialization length	T_0	50
Number of firms in each sector	N_m, N_s	30
Number of abatement options	N_λ	20
Initial production factors	A_0, B_0	1
Maximum demand	D_0	1
Desired inventory rate	I	1
Emission target	e^*	0.1
Initial mark-up	m_0	0.1
Initial emission price	p_0^e	0.1

Table Appendix A.2
Value ranges of variable model parameters.

Parameter	Symbol	Minimum value	Maximum value
Abatement cost factor	θ	15	20
Forecasting factor	t^*	3	10
Abatement potential	λ	0.5	0.9
Fraction of covered firms[a]	φ	0.3	0.7
Profitability target	η	0.1	0.5
Price sensitivity of demand	γ	0.4	0.5
Mark-up adaptation rate	ϑ	0.1	0.5
Market share adaptation rates	χ^M, χ^S	0.1	0.5
Emission price adaption rate	μ	0.05	0.1
Heterogeneity factors	$\Delta A_0, \Delta B_0, \Delta\theta, \Delta\mu, \Delta\eta$	0.1	0.5
Upstream production cost increase	β	0.01	0.1

Notes: [a] The fraction φ is set to 1 in Section 4.1 (full coverage) and only varied in Section 4.2 (limited coverage).

Table Appendix A.3
Definition of policy evaluation criteria and additional indicators.

n	Criteria	$Y_{n,z}$
1	Technology adoption	$S(\Delta A_m * \overline{q}_m)$
2	Compositional change	$S(\Delta\rho_m * \overline{A}_{m,t})$
3	Production decline	$S(\Delta Q_t * \overline{\rho}_{m,t} * \overline{A}_{m,t})$
4	Sales price	$S(q_{m,t} - l^g_{m,t})$
5	Consumer impact	$S(s_{m,t} * p^g_{m,t})/10 - S(R)/S(q_{m,t} - l^g_{m,t})$
6	Emissions	$S(e_{m,t})$
7	Emission price	$S(e_{j,t} * p^e_{j,t})$
8	Upstream profit rate	$S((\pi_{s,t}))/S((q^*_{s,t}))$
9	Downstream profit rate	$S((\pi_{m,t}))/S((q^*_{m,t}))$
10	Upstream Market concentration	$S((\psi_{s,t})^2)$
11	Downstream Market concentration	$S((\psi_{m,t})^2)$

Notes: $S()$ and R are given in Eqs. Appendix A.2 and Appendix A.6.

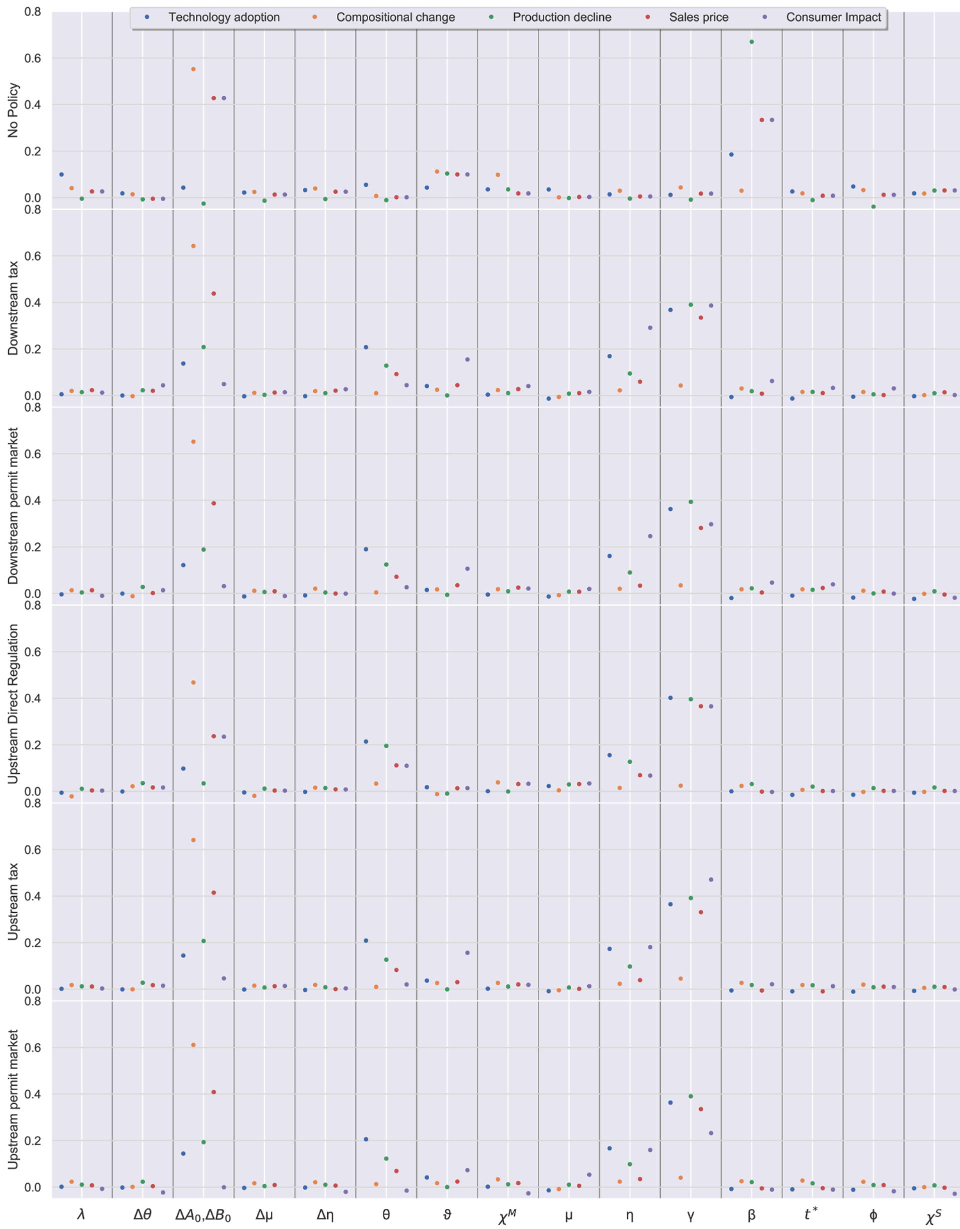

Fig. Appendix A.1. Sobol sensitivity indices for full coverage.

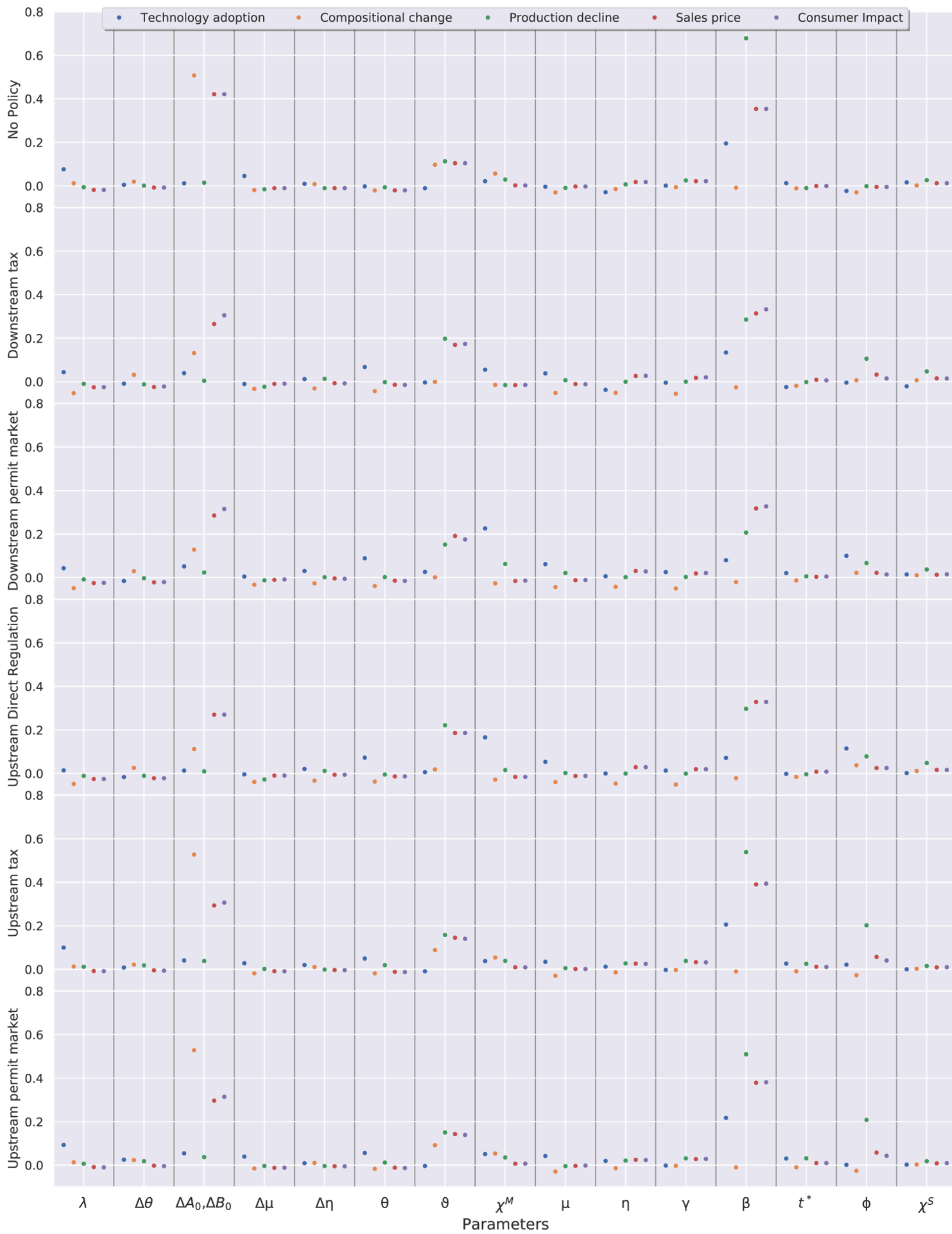

Fig. Appendix A.2. Sobol sensitivity indices for limited coverage.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.techfore.2021.121060

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