Emission tax vs. permit trading under bounded rationality and dynamic markets[⋆]

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ABSTRACT

A price on emissions can be achieved through an emission tax or permit trading. The advantages and drawbacks of either instrument are debated. We present an agent-based model to compare their performance under bounded rationality and dynamic markets. It describes firms that face uncertainty about future demand and prices; use heuristic rules to decide production levels, trading prices, and technology adoption; and are heterogeneous in terms of production factors, abatement costs, and trading behavior. Using multiple evaluation criteria and a wide range of parameter values, we find that the main difference between the two policies lies in the fact that permit prices fall after successful abatement. This can lead to higher production levels under permit trading, but can also drive emission-efficient firms out of the market. Scarcity rents under permit trading can further create higher profit rates for firms, the extent of which is shown to depend on the mechanisms for market-clearing and initial allocation.

1. Introduction

To stay within 1.5°C of global warming, greenhouse-gas emissions need to be reduced to net zero in about three decades (Masson-Delmotte, Zhai, Pörtner, Roberts, Skea, Shukla, Pirani, Moufouma-Okia, Péan, Pidcock, Connors, Matthews, Chen, Zhou, Gomis, Lonnoy, Maycock, Tignor and Waterfield, 2018). Economists argue that an effective solution involves putting a price on emissions (Aldy, Krupnick, Newell, Parry and Pizer, 2010; Baranzini, van den Bergh, Carattini, Howarth, Padilla and Roca, 2017), likely as part of a policy package with additional measures (Mehling and Tvinnereim, 2018; Bouma, Verbraak, Dietz and Brouwer, 2019). Such a price could be achieved through either an emission tax, where firms are charged per unit of emissions, or through permit trading,[1] where firms receive a limited amount of emission permits which they can trade on a permit market. The former fixes the price of emissions, while the latter fixes the quantity and lets the market determine the price.

The relative advantages and drawbacks of either instrument have received much attention (e.g., Baumol and Oates, 1988; Pizer, 1997; Boyce, 2018). According to a review of the literature by Goulder and Schein (2013), the marginal incentives to reduce emissions are the same for both instruments, even if permits are allocated for free. They further conclude that both instruments have the same flexibility regarding the distribution of burdens between firms and consumers, rules for offsetting, and border adjustments. A fixed price can nevertheless help to prevent price volatility and reduce policy errors in the face of uncertainties, complementary policies, and international competition (Goulder and Schein, 2013). Tradable permits, on the other hand, have the advantage that they can respond automatically to uncertainties like technological change.

Assessing the actual performance of both instruments in reality is difficult – particularly in the context of climate change. Their effects are hard to separate from other factors that influence overall emission outputs (Mehling and Tvinnereim, 2018). Furthermore, current interventions are "modest and less ambitious than they could be" (Narassimhan,

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[1] In the context of climate change, the term 'carbon tax' is often used instead of emission tax. Permit trading is also known as emission trading, carbon market, or cap-and-trade, while permits are sometimes called 'allowances'.

Gallagher, Koester and Alejo, 2017). Real world cases are therefore not necessarily revelatory about performance under the stringent levels of regulation that the 1.5°C target would require.[2]

Traditional models used to study this issue have been criticized of being inadequate for the analysis of climate policies (Farmer, Hepburn, Mealy and Teytelboym, 2015), as they assume representative and rational behavior. In reality, the economy is a complex system that is subject to a continuous process of adaptation to often unpredictable changes (Arthur, 1999). Moreover, economic agents are heterogeneous in terms of their behavior and capabilities (Kirman, 2006). Finally, agents are 'boundedly rational' (Mullainathan and Thaler, 2000), meaning that they are unable to identify the optimal course of action to pursue their goals.

Agent-based models (ABMs) are particularly suited to address these three characteristics (Castro, Drews, Exadaktylos, Foramitti, Klein, Konc, Savin and van den Bergh, 2020), as they can simulate economic dynamics based on the continuous interaction of multiple agents with different information and decision rules (Farmer and Foley, 2009). There are already several ABM studies that look at the dynamics of permit trading (Matsumoto, 2008; Chappin and Dijkema, 2009; Zhang, Yu and Bi, 2010; Zhang, Zhang and Bi, 2011; Richstein, Chappin and de Vries, 2014; Tang, Wu, Yu and Bao, 2015, 2017; Yu and Zhu, 2017; Zhu, Duan, Wu and Wang, 2016; Zhu, Chen, Yu and Fan, 2018; Yu, Fan, Zhu and Eichhammer, 2020). Several others consider only emission taxes (Chen, Zhu, Fan and Cai, 2013; Gerst, Wang, Roventini, Fagiolo, Dosi, Howarth and Borsuk, 2013; Lee, Yao and Coker, 2014; Van Der Vooren and Brouillat, 2015; Monasterolo and Raberto, 2016; Li, 2017; Li and Strachan, 2017; Kraan, Kramer and Nikolic, 2018). However, the ABM method has not yet been employed for a comparative evaluation of both instruments.[3]

In this paper, we address this research gap and present an agent-based model to assess the performance of an emission tax and permit trading under bounded rationality, heterogeneity, and dynamic markets. We employ a novel approach that compares the performance of policies under equal effectiveness of emissions reduction, using a broad set of evaluation criteria: abatement costs for firms, emission prices, changes in profit rates and output, and financial impact on consumers. The model is exploratory, which means that it is not meant to predict real-world outcomes, but rather to identify general differences between the above-mentioned policies, as well as the causal dynamics that could explain these differences. Our aim is to test if, and under what conditions, the above-mentioned theoretical equivalence of tax and permit market holds in a dynamic and uncertain environment. To ensure robustness of our findings, we perform model analysis for a variety of decision rules and a wide range of parameter values.

Our model consists of a single sector where emitting firms face either an emission tax or a permit trading system and have to compete on a consumption goods market. The goods market is described by evolutionary replicator dynamics where demand gradually shifts towards more competitive firms. The permit market is formalized as a trading exchange, where firms adapt their trading prices based on experienced success or failure. Firms are heterogeneous in terms of production factors, abatement costs, and their behavior regarding permit trading and investment in abatement technology. Their decisions depend on heuristic expectation rules about future costs and demand. Over time, they change their production level based on expected demand, adapt their mark-up based on experienced success, and adopt less emission-intensive technology based on the experienced price per unit of emission due to either the tax or permit market.

The resulting model represents a synthesis of ideas and methods from environmental, behavioral, and evolutionary economics. It is inspired by three earlier ABM studies. The modeling of the consumption goods market is based on Dosi, Fagiolo and Roventini (2010), who simulate a demand-driven economy with endogenous growth, technological changes, and business cycles. The modeling of the permit trading market is adopted from Zhu et al. (2018), who explore the interaction of heterogeneous abatement and trading strategies on a permit market under constant production levels. The distinction between uniform and discriminatory pricing for permit auctions is inspired by Tang et al. (2017), whose model combines permit trading dynamics with the competition on a goods market for the case of the Chinese economy.

The remainder of this article is organized as follows. Section 2 explains the theoretical context of this study. Section 3 provides a detailed description of the model. Section 4 introduces the numerical setting and the different policy scenarios that are tested. Section 5 presents simulation results and a sensitivity analysis. Section 6 summarizes our findings and discusses limitations.

[2]The highest existing price of 139 USD/tCO2e in Sweden (World Bank Group, 2018), which does not even cover all sectors, is still far below the estimates of the IPCC that the carbon price would need to rise to a value between 245–14300 USD2010/tCO2e within the next three decades to reach the 1.5°target (Masson-Delmotte et al., 2018, p.152).

[3]One exception is Isley, Lempert, Popper and Vardavas (2015). Yet, its focus is on a very particular issue, namely how lobbying dynamics between firms and regulator can change policy stringency over time. Moreover, this study assumes the permit market to follow classic equilibrium features.

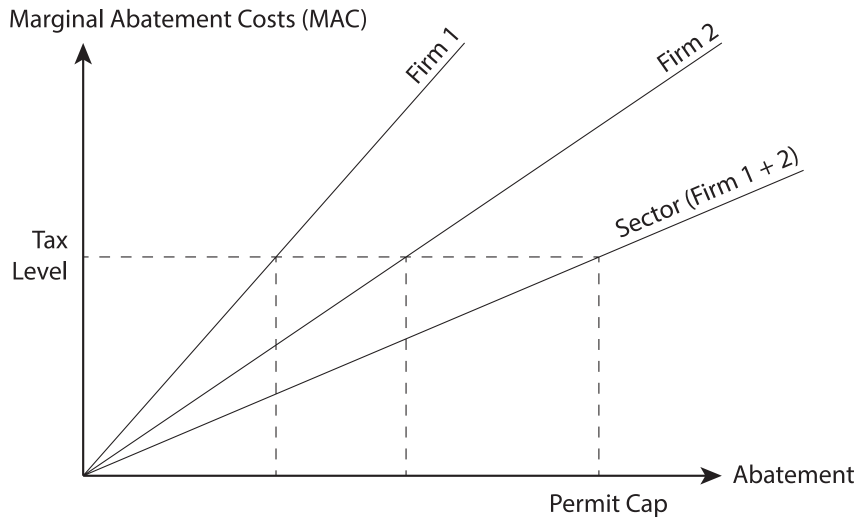


Figure 1: Equivalence of emission tax and permit trading illustrated for a sector consisting of two emitting firms

2. Background

Conventional economic models of environmental policies assign a central role to the notion of abatement (e.g. Baumol and Oates, 1988; Perman, Ma, McGilvray and Common, 2003). This refers to an action that results in the reduction of emissions, usually framed as the implementation of a new technology or production routine. Each possible measure is then evaluated on the basis of its costs. Sorted from lowest to highest, these measures can be arranged into an abatement cost curve. At every level of abatement, this curve shows the costs of reducing one more unit of emission, also called the marginal cost of abatement (MAC). Accordingly, a policy is deemed efficient, i.e. leading to the least-cost solution, if the MAC is equalized between firms. Otherwise there exists at least one firm that could reduce emissions and one that could increase them so that total abatement costs would be reduced.

Within this theory, an emission tax and permit trading are both efficient. This is illustrated for the case of two firms in Figure 1. Under a tax, firms abate until their MAC is equal to the tax level. The tax is set at the level necessary to reach the emission target. Under permit trading, the regulator distributes as many permits as are allowed within the emission target. Firms trade these permits until their MAC is equal to the permit price. This price clears at the same level as the tax, as this is where the industry-wide MAC curve meets the emission target. Regardless of whether the government auctions permits or distributes them for free, the same price should be expected. The performance of the two instruments is therefore considered to be identical (for a mathematical proof, see Perman et al., 2003, Appendix 7.1).

This view of abatement does not take into account that changes in emissions result not just from improvements in production processes, but also from structural changes in the economy, as well as adjustments of economic output. Many models try to solve this by assuming that all these changes, as well as their costs, are included in the MAC curve (e.g. Pezzey and Jotzo, 2012; Branger and Quirion, 2014), essentially assuming them to be given and exogenous. However, knowledge about the costs of technological abatement alone is not enough to determine what price will relate to which abatement level. It is important to understand the effect of a policy on the trading behavior of firms on the goods market as well as on demand.

Real firms are further “boundedly rational", meaning that they are unable to identify their best path of action because of limited information as well as limited time and capacity to evaluate that information (Simon, 1952). They therefore use simple rules (‘heuristics’) to make decisions about production and trade as they face uncertainty regarding future demand and costs. According to Dosi, Napoletano, Roventini, Stiglitz and Treibich (2020), “in complex, evolving economies characterized by pervasive uncertainty and perpetual structural change, heuristics may provide a more accurate and robust tool for inference and action than more sophisticated forecasting techniques”. In regard to climate policy, this applies to abatement behavior, where empirical research has shown that uncertainty creates barriers to cost-effective investment decisions (Venmans, 2016).

Moreover, it is widely accepted that heterogeneity can contribute to explaining economic outcomes and should therefore be given serious attention in economic models. Kirman (2006) argues that “heterogeneity will persist since agents will only slowly learn to adapt and that in the meantime the environment will change”. While the classic theory of environmental economics addresses some degree of heterogeneity by taking different technological abatement costs into account, it overlooks that firms can also be heterogeneous in terms of other production factors, trading behavior, and investment decisions.

Finally, there is no single factor that can be used to rank policies. As there is no consensus on how to estimate damage costs from climate change (Pindyck, 2017), many scholars suggest using a measure of cost-effectiveness, i.e. how to achieve a predefined target under least costs (Boyce, 2018). However, one can find distinct elaborations of this in the literature (Paltsev and Capros, 2013). Costs from technological improvements (abatement costs) do not tell us about costs to firms (profit losses), costs to the overall economy (changes in overall output and sales), and the costs to consumers (changes in sales prices).

These considerations motivate the model design and analysis described in the following sections, where we introduce heterogeneous agents with heuristic decision rules; continuous interaction on a goods and permit market; a novel decomposition of abatement into contributing factors; as well as multiple evaluation criteria to take different types of costs into account.

3. Model Description

The model consists of a single economic sector of N emitting producers. Their actions follow discrete rounds $t = 1, 2, \dots, T$. We further distinguish multiple regulation periods $y = 10, 20, \dots, T$.[4] Each round is characterized by the following chain of events:

1. In the first round of a regulation period ($t = y$), the regulator updates their climate policy.
2. Firms form demand expectations, set a production goal, and adapt their mark-up rate.
3. If permit trading is active, firms exchange permits and adjust their trading price.
4. Firms produce goods and try to sell them at the goods market.
5. Firms decide whether to adopt less emission-intensive technology.

Most variables are constant per round t. One exception is the trading procedure in Step 3, which is repeated until no more trades are possible. This means that trading volumes and prices can adapt multiple times within a single round.

3.1. Expectations and goals

At the beginning of every round t, each firm $j = 1, \dots, N$ decides on its desired output level and profit rate. Following Dosi et al. (2010), we assume that firms set the desired production level $g^d_{j,t}$ to meet their expectations for demand $\tilde{D}_{j,t}$. All firms use the same heuristic rule to calculate their expectations from experience. This is done by one of the following three rules, the latter two being based on the study of Anufriev, Hommes and Philipse (2013):

$$\tilde{D}_{j,t} = \begin{cases} D_{j,t-1} & \text{Myopic} \\ D_{j,t-1} + \mu_2 * (D_{j,t-1} - D_{j,t-2}) & \text{Trend following} \\ \mu_3 * D_{j,t-1} + (1 - \mu_3) * g^d_{j,t-1} & \text{Adaptive} \end{cases} \tag{1}$$

Firms have an inventory of goods $g^I_{j,t}$, which is increased through production and decreased through sales. Firms want this inventory to be slightly larger than estimated demand as an insurance against expectation or prediction errors. Their production goal therefore depends on their desired inventory share I^d and current inventory:

$$g^d_{j,t} = \tilde{D}_{j,t} * (1 + I^d) - g^I_{j,t} \tag{2}$$

Next, firms set their mark-up rate $m_{j,t}$, which they adapt from round to round based on the rate of change of their market share s_j. The magnitude of this adaptation is given by factor υ:

$$m_{j,t} = m_{j,t-1} * \left(1 + \upsilon * \frac{s_{j,t-1} - s_{j,t-2}}{s_{j,t-2}}\right) \tag{3}$$

[4] A regulation period represents the time-span of a year, consisting of ten rounds which can roughly be seen as months.

This represents the context of a "customer market", where firms compete against each other in terms of their shares of demand in the sector (Dosi et al., 2010). It describes a process where firms set a higher profit margin when their market share is growing and reduce it when their share is falling.

3.2. Regulation of emissions

The emission level $e_{j,t}$ of a firm j at time t is given by the product of its emission intensity $A_{j,t}$ per unit of output and its total output $g^p_{j,t}$:

$$e_{j,t} = A_{j,t} * g^p_{j,t} \tag{4}$$

Both an emission tax and permit trading effectively create a price $p^e_{j,t}$ per unit of emission for every firm. In case of an emission tax, this price is set directly by the regulator at the beginning of each regulation period and is equal for all firms. Under permit trading, this price reflects the trading price $p^u_{j,t}$ on the permit market and can differ among firms:

$$p^e_{j,t} = \begin{cases} 0 & \text{No policy} \\ p^{tax}_t & \text{Emission tax} \\ p^u_{j,t} & \text{Permit trading} \end{cases} \tag{5}$$

Permit trading works as follows. Firms have to submit a permit for each unit of emission, and are not allowed to continue production if they run out of permits. If permits are not used before the end of a regulation period, they expire.[5] At the beginning of each regulation period ($t = y$), the regulator distributes e^{cap}_t new permits among the firms. There are two different methods for this initial allocation, reflecting the most common practices of permit trading in the real world (Narassimhan et al., 2017):

1. **Grandfathering:** Permits are handed out for free based on firms' performance on variable z in the past regulation period. There are two different ways to achieve this (Böhringer and Lange, 2005):
   (a) Emission-based updating, where the share of permits each firm receives equals its share in total emissions, meaning that $z = e$.
   (b) Volume-based updating, where the share of permits each firm receives equals its share in total production, meaning that $z = g^p$.

   At the beginning of each regulation period, firms receive the following number of permits that is added to their inventory $u_{j,t}$:

$$u_{j,t} = \frac{\overline{z}_{j,t}}{\sum_{i=1}^{N} \overline{z}_{i,t}} * e^{cap}_t \tag{6}$$

$$\overline{z}_{j,t} = \sum_{l=t-11}^{t-1} z_{j,l} \tag{7}$$

2. **Auction:** In the first trading round of a regulation period, firms submit their bids as described below. Like in Tang et al. (2017), the best bids are successively accepted until e^{cap}_t is reached. The permits are either sold at the price of the last successful bid (uniform pricing) or every bid is accepted at its respective bid-price (discriminatory pricing).[6]

Permits are subsequently traded between firms. Each round t, firms try to obtain the number of permits they expect to need until the end of the regulation period. They calculate their desired trading volume $u^d_{j,t}$ based on their production

[5] Permit markets can further include options of price floors and price ceilings, as well as offsetting mechanisms (Narassimhan et al., 2017), which can cause the emission target to be watered down. Here, we abstain from such complications and focus on a simple version of permit trading that reliably meets its target.

[6] If there are not enough bids, the remaining permits are grandfathered.

Table 1
Adaptive factors for the permit trading price $p^u_{j,t}$.

If trade is a ...	Bid	Ask
Success	$1-\delta_j$	$1+\delta_j$
Failure	$1+\delta_j$	$1-\delta_j$

goal $g^d_{j,t}$, the number of rounds left until the end of the regulation period t^*, their emission intensity $A_{j,t}$, and the amount of permits $u_{j,t}$ they already own:

$$u^d_{j,t} = g^d_{j,t} * A_{j,t} * t^* - u_{j,t} \tag{8}$$

Firms submit a market-order for the desired amount $u^d_{j,t}$ at their trading price $p^u_{j,t} = p^u_{j,t-1}$ from last round. This order becomes a bid to buy if $u^d_{j,t} > 0$ and an ask to sell if < 0. If there is no auction for initial allocation, trade is based on a double auction similar to Zhu et al. (2018). The highest bidder and the lowest asker are iteratively matched until there is no possible match left. The trading price is set using one of two following methods:

1. **Uniform pricing**: The last successful ask price becomes the trading price for all matched orders, like in Zhu et al. (2018).
2. **Discriminatory pricing**: The trading price is set for every trade individually at the mid-point between the ask and bid price, like in Nicolaisen, Petrov and Tesfatsion (2001).

Each firm has their own emission trading price $p^u_{j,t}$, which evolves gradually upon experience, similar to Zhu et al. (2018).[7] Depending on whether they were able to trade their desired amount (success) or not (failure) at the auction, they adapt the price by an idiosyncratic percentage δ_j. This is shown in Eq. 9, with the sign given in Table 1.

$$p^u_{j,t} = p^u_{j,t} * \left(1 \pm \delta_j\right) \tag{9}$$

After the trading exchange is cleared, firms adjust their trading volume (Eq. 8) and their price (Eq. 9), submit new market orders, and the trading exchange clears the market again. This procedure repeats until either no bids or no asks are left, which means that no more trades are possible in this round. Firms then keep their remaining permits to be used in the next round ($u_{j,t+1} = u_{j,t}$).

Hence, firms adjust their trading price until they receive their desired number of permits. If they want to buy, they adjust it upwards, and if they want to sell, they adjust it downwards. If their trades are successful, they do the opposite in the hope to spend less on future bids or earn more on future asks. As the supply of permits is limited, this creates a scarcity effect that drives permit prices up as long as there is unfulfilled demand. As a result, prices converge to a value that balances permit supply and demand over time.

The market-price p^u_t of each round reflects the ask price of the last successful trade. If no trade takes place, it reflects the lowest ask price. If there are also no selling orders, it reflects the highest bid price.

3.3. Production

Firms try to meet their production goal $g^d_{j,t}$. Under a tax there is no quantity restriction, while under permit trading they are constrained by the amount of permits they own. In order to not have a sudden drop of production to zero towards the end of the regulation period, they ration their permits over the remaining rounds t^* of the given period in case they will not be able to buy new ones. Their production for round t is given as:

$$g^p_{j,t} = \min\left(g^d_{j,t}, \frac{u_{j,t}}{A_{j,t} * t^*}\right) \tag{10}$$

Firms production output $g^p_{j,t}$ is then added to their current inventory $g^I_{j,t}$. Firms also set their sales price $p^g_{j,t}$, which depends on their emission intensity $A_{j,t}$, emission price $p^e_{j,t}$, production costs per unit of output $B_{j,t}$, and mark-up $m_{j,t}$

[7] The initial emission price at the beginning of the simulation is equal for all firms and given by the parameter p^u_0.

(see Eq. 3).

$$p^g_{j,t} = \left(A_{j,t} * p^e_{j,t} + B_{j,t}\right) * \left(1 + m_{j,t}\right) \tag{11}$$

Under an emission tax, the emission price $p^e_{j,t}$ is equal to the tax level $p^{tax}_{j,t}$, while under permit trading it is a result of past trading outcomes. This means that firms learn about the trading price of permits on the market, include this price in their sales price, and pass it on to consumers.[8] This can create profits for firms beyond their mark-up, which can be seen as a 'scarcity rent' (Kalkuhl and Brecha, 2013) caused by the limited availability of permits.

3.4. The goods market

The goods market is identical to the one described in Dosi et al. (2010), where buyers are represented at an aggregate level. Due to imperfect information and heterogeneity on the market, it takes time for consumers to discover and shift to products they prefer. Therefore, demand gradually moves towards more competitive products that are either cheaper or better supplied. The competitiveness (or fitness) of each firm j is defined as follows:

$$f_{j,t} = -\omega_1 * p^g_{j,t} - \omega_2 * l_{j,t-1} \tag{12}$$

The first term describes that a firms' fitness falls with increasing sales prices. The second term describes that firms lose customers when they are unable to fulfill their demand. $l_{j,t-1}$ signifies the unfulfilled demand of that particular firm in the previous round (Eq. 19). ω_1 and ω_2 denote relative weights associated with the two terms (i.e. $\omega_1 + \omega_2 = 1$). These factors of competitiveness define the evolution of firms' market shares s_j, with χ denoting how fast consumers shift towards more competitive firms:

$$s_{j,t} = s_{j,t-1} * \left(1 - \chi * \frac{f_{j,t} - \overline{f}_t}{\overline{f}_t}\right) \tag{13}$$

The average fitness $\overline{f}_t$ is given by the weighted average of each firm, using the last rounds market shares $s_{j,t-1}$ as weights:

$$\overline{f}_t = \sum_{j=1}^{N} s_{j,t-1} * f_{j,t} \tag{14}$$

Total demand D_t is then allocated according to firms' market shares:

$$D_{j,t} = s_{j,t} * D_t \tag{15}$$

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 factor γ.

$$D_t = D_0 * e^{-\gamma * \overline{p}^g_t} \tag{16}$$

The average price of goods $\overline{p}^g_t$ is weighted by firms' market shares:

$$\overline{p}^g_t = \sum_{j=1}^{F} s_{j,t} * p^g_{j,t} \tag{17}$$

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

$$q^s_{j,t} = \min(D_{j,t}, g^I_{j,t}) \tag{18}$$

[8] This has for example been observed in the initial phase of the European emission trading system, where firms like the German electricity producer RWE charged consumers for emission permits at their market price, even though they had received them for free. (Goeree, Palmer, Holt, Shobe and Burtraw, 2010)

If firms have produced too little, either because of false demand expectations or output restrictions due to a limited number of emission permits, they are left with a certain amount of unfulfilled demand $l_{j,t}$ that will translate into reduced competitiveness in the following round.

$$l_{j,t} = D_{j,t} - q^s_{j,t} \tag{19}$$

Goods are assumed to be non-perishable, meaning that firms keep their remaining inventory $q^I_{j,t}$ for the following round.

$$q^I_{j,t+1} = q^I_{j,t} - q^s_{j,t} \tag{20}$$

3.5. Technological improvements

In accordance with the abatement cost curve discussed in Section 2, firms can decide to adopt a new technology that will reduce their emission intensity and increase their production costs. In line with the literature on abatement investments (Chao and Wilson, 1993; Xepapadeas, 2001), we assume these to be irreversible. If emission prices change in the future (e.g., because permit prices drop), certain investments will turn out to be unprofitable as paying the lower price for regulation would be better for the company than to use the new technology.

As described in Zhu et al. (2018), each firm has an idiosyncratic list of possible technological options ($i = 1, \ldots, \alpha_{steps}$) that allow for a particular reduction in emissions a_i at an extra cost b_i per unit of production. The marginal abatement costs of this technological step, i.e. the added production costs of emitting one unit less, are defined as:

$$c^\alpha_i = \frac{b_i}{a_i} \tag{21}$$

Every round, firms examine the next possible technological option i with the lowest c^α_i. As derived in Appendix A.1, a technological improvement is desirable when its marginal costs of abatement c^α_i is lower than the emission price $p^e_{j,t}$. Related uncertainty about the costs for a firm due to the tax or permit system function as a barrier to investments (Venmans, 2016). In the present model, we capture firms' reaction to this uncertainty in a simplified manner through a minimum profitability target η_j. This factor is heterogenous among firms, reflecting their different attitude towards risks: while some firms neglect uncertainty and invest in new technology once it becomes profitable under existing conditions, others require a profit margin large enough to compensate them in case the regulation price falls in future rounds. This leads to the following condition for investments:

$$c^\alpha_i * (1 + \eta_j) < p^e_{j,t} \tag{22}$$

If the condition in Eq. 22 is true, firms decide to adopt a new technology. This decision becomes effective in the next month and results in an update of a firm's abatement and production technology, as shown in Eq. 23. This assumes that abatement has a long-term effect on firms variable production factors, reflecting that production capital has a long lifetime, while part of the investments in abatement comes in the form of proprietary knowledge that does not depreciate. While this is a simplification, it captures many characteristics of real world cases, for example that firms assume higher production costs to pay back investments over time, or face higher production costs because the new technology requires more expensive resources or maintenance (e.g. because of a fuel switch).

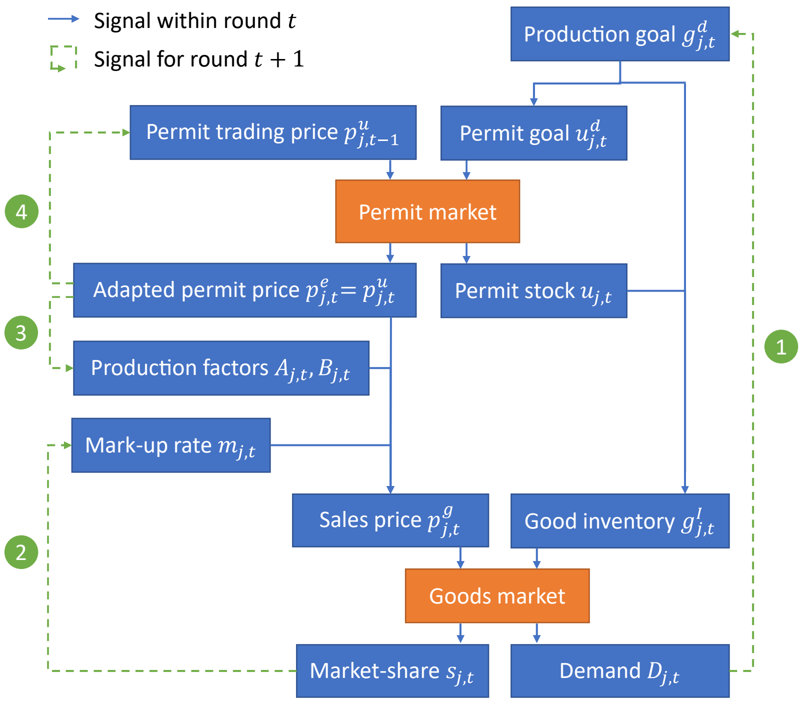
$$\begin{aligned} A_{j,t+1} &= A_{j,t} - a_i \\ B_{j,t+1} &= B_{j,t} + b_i \end{aligned} \tag{23}$$

3.6. Summary

Figure 2 provides an overview of the most important causal relations within the model for the case of a permit market. Every round follows the flowchart from top to bottom along the blue arrows. The green arrows represent signals that will have an influence in the following round. From this, one can see that there are four main dynamics within the model:

1. Past demand forms future production goals.
2. Changes in market shares influence future mark-up.
3. Past permit trading outcomes drive future trading prices.
4. Emission prices cause technological improvements.

Figure 2: Overview of model variables and their causal relations under permit trading.



4. Numerical Experiment

We simulate a time-span of 300 rounds (30 regulation periods of one year), reflecting the time-frame until 2050 given by the IPCC (Masson-Delmotte et al., 2018). The code is written in Python 3 and is available on GitHub[9]. The model is not calibrated for a specific application. Instead, 19 out of 25 parameter values are varied to cover a wide range of possible cases and to test robustness of the results to different behavioral and technological assumptions. All parameters in the model and their possible ranges are given in Table 2.

For the sensitivity analysis to deliver robust outcomes, we use a large sample of 190,000 distinct parameter combinations that are varied according to the sampling scheme of Saltelli, Annoni, Azzini, Campolongo, Ratto and Tarantola (2010). Abatement costs α, initial production factors A_0, B_0, the permit trading behavior δ, and the profitability target η can be heterogeneous among firms with a difference between them up to 40%. For each of these parameters, a random variation from the base value is drawn for every firm j at the beginning of each run, taken from a uniform distribution:

$$x_j = x * (\Delta x * \mathcal{U}(0,1)) \ \dots \ x = \{A_0, B_0, \alpha, \delta, \eta\} \tag{24}$$

Firms have $i = 1, \dots, \alpha_{steps}$ technological options, each with an abatement potential of $a = \alpha_{pot}/\alpha_{steps}$ and a marginal abatement cost of $c^\alpha_i = b_i/a = \alpha_{costs} * a * i$. An example of a resulting abatement cost curve, using average parameter values, is given in Figure 3.

We explore five different policy scenarios under these parameter ranges (bold denotes shortcut names used in discussing the results):

1. **No policy**
2. Permit trading with initial allocation through emission-based **Grandfathering (E)**

[9] https://github.com/JoelForamitti/TvsP_ABM

Table 2
Value ranges of model parameters.

Parameter	Symbol	Values (min-max)	
Number of rounds	T	300	
Number of firms	N	30	50
Emission target[a]	e^*	0.1	0.2
Initial production factors	A_0, B_0	1	
- Heterogeneity	$\Delta A_0, \Delta B_0$	0	40%
Maximum demand	D_0	1	
Price sensitivity of demand	γ	0.1	0.5
Initial mark-up [b]	m_0	0.2	0.4
Mark-up adaptation rate [c]	ϑ	0.04	0.2
Market share adaptation rate [b]	χ	0.025	0.15
Market share weight difference [c]	ω_1/ω_2	0.2	5
Initial permit trading price	p_0^u	0.01	
Desired inventory share	I^d	0.1	
Permit price adaption rate	δ	0.05	0.3
- Heterogeneity	$\Delta\delta$	0	40%
Abatement potential [d]	α_{pot}	0.17	0.87
Number of abatement options	α_{steps}	20	
Abatement cost factor	α_{costs}	1	10
- Heterogeneity	$\Delta\alpha_{costs}$	0	40%
Profitability target	η	0	0.4
- Heterogeneity	$\Delta\eta$	0	40%
Auction mode [e]	ψ	1	2
Expectation mode [f]	μ_1	1	3
- Trend factor [g]	μ_2	0.5	1
- Adaptive factor [g]	μ_3	0.25	0.75

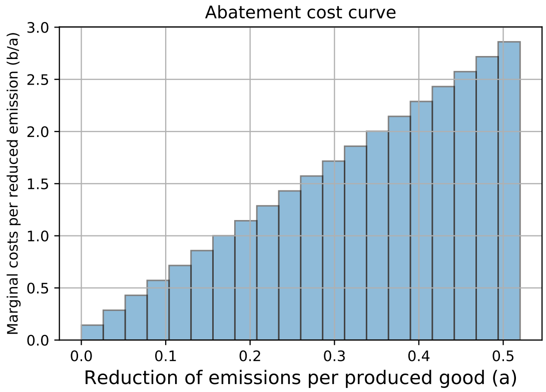
Notes:
[a] Roughly reflect the projected industrial emission reduction of 73% - 91% of the IPCC scenarios (Masson-Delmotte et al., 2018, Table 4.1.).
[b] Taken from Isley et al. (2015) (adapted for different time-scale).
[c] Dosi et al. (2010) use $\vartheta = 0.04$ and $\omega_1/\omega_2 = 1$.
[d] Reflecting the context of different emitting sectors whose potential has been calculated by McKinsey & Company (2009), i.e. power, petroleum and gas, cement, iron and steel, chemicals, transport, buildings, waste, agriculture, and other industries.
[e] Values are integers, reflecting options in section 3.2.
[f] Values are integers, reflecting options in Eq. 1.
[g] Taken from Anufriev et al. (2013).

3. Permit trading with initial allocation through volume-based **Grandfathering (V)**
4. Permit trading with initial allocation through **Auction**
5. Emission **Tax**

All four policies are introduced gradually in ten linear steps within the first ten regulation periods of the simulation run, as shown in Figure 4. This is meant to avoid fluctuations from extreme and sudden changes and to reflect a politically more feasible scenario. For permit trading, this means that emissions are capped to e^* in ten equal steps from the amount of emissions in the first regulation period e_0. Similarly, the tax p^{tax} is gradually introduced and increased until it reaches the final tax level p^{e^*}.

The aim of this study is to compare the policy scenarios under an identical level of effectiveness. The final tax level p^{e^*} is therefore calibrated by repeating the simulation with different levels until the necessary stringency is found that reaches the same emission target as the permit market. This assumes that the regulator has perfect information about the market. However, the tax would arguably follow a similar implementation curve if the regulator would use a pre-defined rule (like discussed in Boyce, 2018) to gradually adjust the tax until the target is reached.

Figure 3: Example of an abatement cost curve.



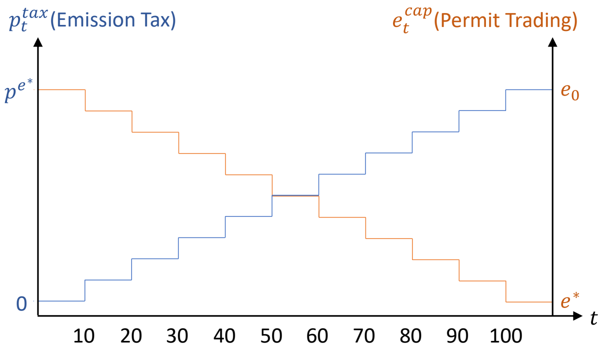


Figure 4: Gradual implementation of climate policies until round 100.

5. Results and Discussion

5.1. Model dynamics in a single run

We first present the results of a single run to understand the dynamics of the model, using average values for all given parameter ranges in Table 2, as well as uniform-price auctioning and myopic expectations. Figure 5 shows the evolution of market shares throughout the simulation. All firms start with the same market share $1/N$, after which more competitive firms gradually claim a bigger share of the market. In the baseline scenario, this is caused by the heterogeneity of firms' production costs and their competitive pricing behavior. This dynamic is further influenced by emission prices and technological changes under the policy scenarios.

Figure 6 shows the overall abatement, i.e. the reduction of monthly emissions relative to the beginning of the simulation, and its decomposition. As derived in Appendix A.2, abatement efforts are decomposed into the following three components:

1. A compositional change within the sector due to a shift from high- to low-emission firms.
2. A change in emission-intensity due to adoption of low-emission technology.
3. A change of overall production of the sector due to a reduction of output.

An efficient policy would have the highest possible abatement from compositional change, as this does not create extra costs in contrast to technological improvements. On the other hand, a reduction of output is the only factor without an abatement limit and can compensate the limited potential of the other two factors.

The tax level p_t^{tax} and average market price of permits p_t^u for different auctioning mechanisms is shown in Figure 7. One can observe similar dynamics as observed in Zhu et al. (2018). The permit price first overshoots the equilibrium price and then gradually declines. This is because the market price will keep rising until supply and demand of permits

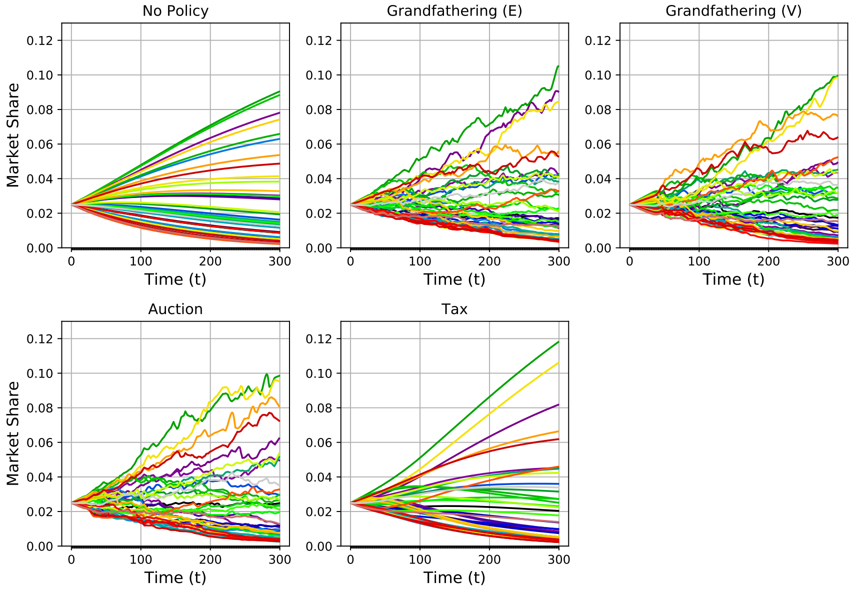


Figure 5: The evolution of market shares over time.

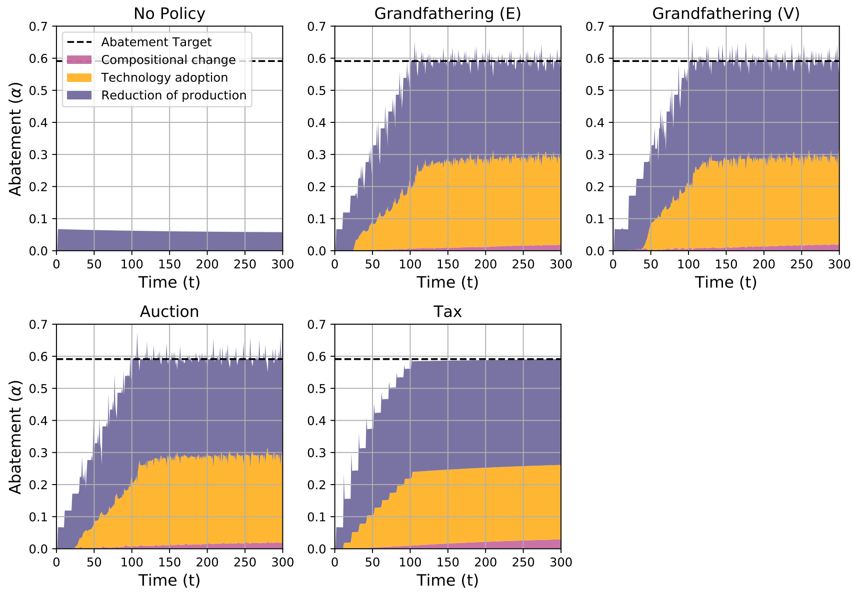


Figure 6: Decomposition of abatement over time.

are in balance, but once the price is high enough to trigger technological adoption, permits will become less scarce and their price will go down. Furthermore, the discriminatory-pricing mechanism clearly leads to a higher price under both auction and grandfathering.

Figure 7 also shows the result under an alternative parameter setting where the technological potential parameter α_{pot} is set to its maximum and abatement costs α_{costs} to its minimum. This either reflects a situation with fast and cheaply available technological improvements, or one with government subsidies that support the installment of low-emission technologies. Under such a setting, the price drops to a much lower level as the sector is able to become almost emission free and the demand for permits becomes low. In turn, this leads to lower sales prices and more

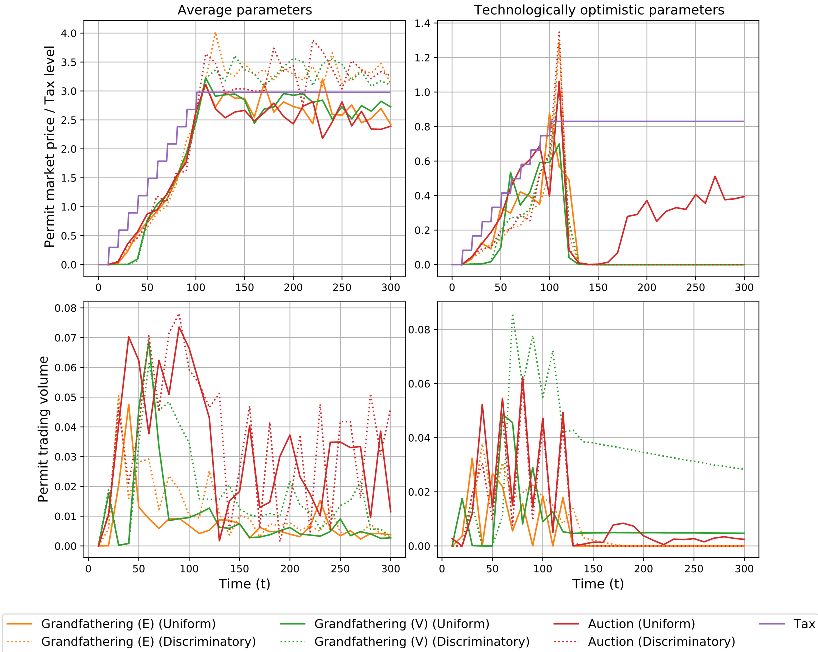


Figure 7: Dynamics of permit trading price and tax level (top panel), as well as permit trading volume (bottom panel). Values are averaged over one regulation period.

demand for goods.

This observation highlights an important difference between the emission tax and permit trading. The emission tax sets a price and then holds it constant. Under these conditions, a profitable technology will remain profitable over time. The permit market can also reach a high emission price that will trigger technological improvements. But if those improvements reduce emissions significantly, the price will drop, making those firms with new technologies less competitive.[10] As demonstrated in Figure 7, this can give rise to a cycle where more emitting firms regain a bigger market share, causing the sector to become more emission-intensive again, pushing the price back up, leading to new technological improvements, and so on.

The described pattern marks a potential inefficiency of permit trading, namely that it can drive firms out of the market after they have reduced their emissions, causing their more emission-efficient technology to become a stranded asset. This is connected to firms' bounded rationality. If firms would know in advance that the price would drop again in the future, then they would resist adopting better technology during periods of high emission prices. However, if all firms would be more careful with their investments, then the price would never go down because the emission intensity of the sector would stay constant. It is therefore difficult to imagine how optimal behavior would look like in this context, which is in line with the discussion of 'rational heuristics' by Dosi et al. (2020).

Figure 7 also presents the average amount of permits that is traded each round. The volumes are clearly higher in the auction scenario than under grandfathering, particularly in the first half of the simulation run. In all three scenarios, trading volume is reduced over time as the distribution of permits gets closer to a stationary state.

5.2. Policy evaluation of multiple runs

For the evaluation and comparison of policy performance, we look at results of multiple runs for all parameter combinations described in Section 4. We use ten criteria to evaluate the impact of each policy scenario, regarding the state of the sector at the last regulation period of the simulation. The mathematical formulation of these criteria is described in Appendix A.3. The criteria are as follows:

[10] This is driven by our assumption in Section 3.5. that abatement causes long-term changes both in emission intensity and variable production costs. Future extensions of this model could consider the effect of different forms of abatement.

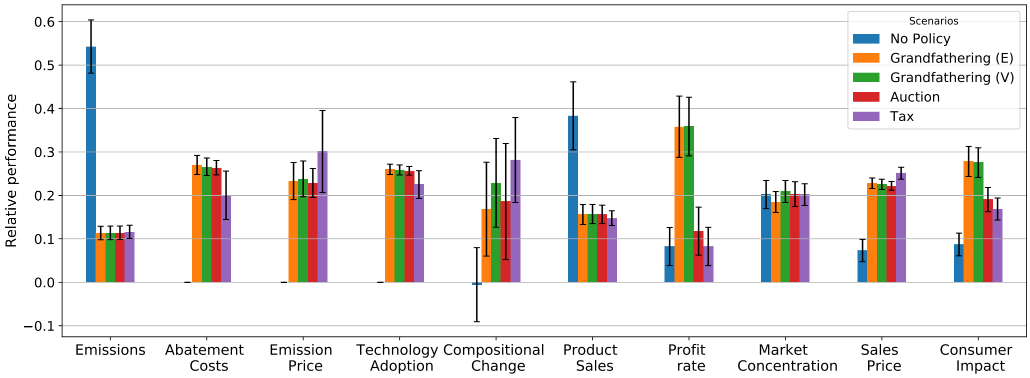


Figure 8: Averaged evaluation measures, as derived in Appendix A.3. Values indicate the performance of each scenario relative to the others (see Eq.32). Error bars report +/− standard deviation.

1. **Emissions:** Serves as a control to demonstrate that the policies are compared at almost identical effectiveness.
2. **Abatement costs:** What firms have to pay per unit of emission due to an increase in production costs from technological improvements.
3. **Emission price:** Depending on the policy, this reflects the level of the emission tax or the market price of permits.
4. **Technology adoption:** The share of abatement that is achieved through improved technological efficiency.
5. **Compositional change:** The share of abatement that is achieved by less emission-intensive firms having gained a higher market share.
6. **Product sales:** The amount of sold goods. This can be seen as the overall efficiency of the sector, taking into account the behavior of both firms and consumers.
7. **Profit rate:** How much profit firms make in relation to their production costs.
8. **Market concentration:** The distribution of market shares within the sector, operationalized through the Herfindahl-Hirschman Index.
9. **Sales price:** The average sales price for goods, reflecting the average financial burden on consumers.
10. **Consumer impact:** The average financial burden on consumers, assuming that they receive the recycled policy revenue. Calculated as the average sales price minus the policy revenue per good.

The results are presented in Figure 8. Let us first consider the difference between the different permit trading scenarios. All lead to a similar efficiency in terms of abatement costs, technology adoption, and product sales. Yet, there is more compositional change under grandfathering with a volume-based updating rule. This is because firms who already benefit from the climate policy and increase production get an additional benefit from being allocated a higher amount of permits in the next regulation period. This also causes a slightly higher market concentration than under emission-based updating.

As most permits are received for free under grandfathering, firms incur a large scarcity rent that generates a considerably high profit rate in comparison to the other scenarios. This, in turn, leads to a higher consumer impact, as the regulator receives no policy revenue that can be recycled to consumers. Our model thus suggests that the question between initial allocation through grandfathering or auction mainly is about the distribution of burdens between industry and consumers.

The discussion from here on will focus on comparing the tax and auction-based permit trading scenario. Their relative performance is shown in the first column of Table 3. The values are normalized to represent the percentage (from -100% to 100%) by which the tax performs higher than the auction on each respective measure, as defined in Appendix A.3.

The tax leads to lower abatement costs for the firms than the auction-based permit market, as it reaches the emission target through a lower abatement share of technology adoption and a higher share of compositional change and reduction of production. The latter is because the tax level (emission price) is higher than the permit price (in the

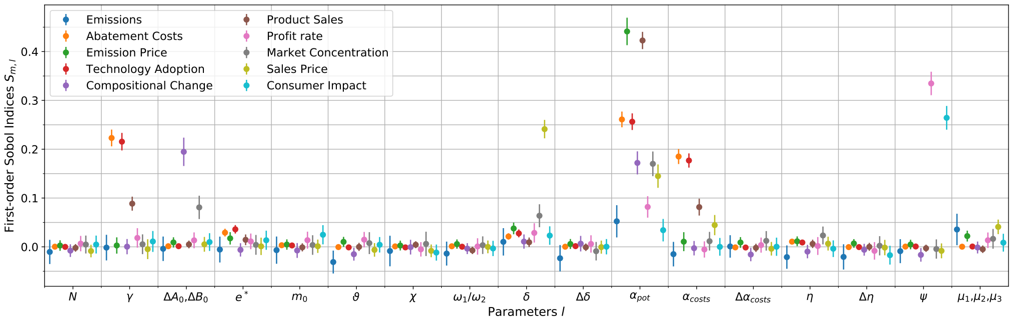


Figure 9: Sensitivity analysis of the comparative performance between tax and auction.

last regulation period of the simulation), leading to less demand. The reasons for the lower permit price were already discussed in Section 5.1. Permit prices rise fast to reflect the current scarcity and trigger technological adoption, which in turn reduces prices and weakens the incentive for compositional changes as it creates a competitive disadvantage for firms with a low emission-intensity.

Ultimately, this leads to a higher sales price and lower product sales under the emission tax.[11] Yet, the consumer impact is still slightly lower under an emission tax than under the auction. Two reasons can be given for this. First, the trading dynamics of permits cause firms to charge a scarcity rent to consumers, which leads to a higher profit rate and shifts the distribution of burden towards consumers. And second, the lower price of emissions due to successful mitigation leads to less policy revenue in the auction compared to the emission tax, and thus less money can be recycled back to consumers.

5.3. Sensitivity analysis

Using the Python package *SALib* (Herman and Usher, 2017), we apply Saltelli's sampling scheme to the parameter ranges and perform a Sobol Sensitivity Analysis (Sobol, 2001; Saltelli, 2002; Saltelli et al., 2010) on the relative difference of performance between tax and auction (Table 3). Figure 9 presents the first-order Sobol indices regarding the relative performance between tax and auction. These measures indicate the percentage of the variance in Table 3 that can be attributed to the direct contribution of each parameter. Apart from six exceptions, most first-order indices are well below 0.1.

The relative performance of abatement through compositional changes displays sensitivity to the heterogeneity of the production factors ($\Delta A_0, \Delta B_0$). Table 3 shows that the tax performs better than the auction, but more so when heterogeneity is low. This makes sense as we have already identified the price fluctuations of permit markets to be the reason for worse performance on compositional changes. If heterogeneity is high, the signal to shift to low-emission producers is stronger than the price fluctuations, which reduces this disadvantage of the auction and makes it perform relatively better.

Many measures are sensitive to the abatement parameters α_{pot} and α_{costs}. This is caused by the drop in permit demand after successful abatement. As can be seen in Table 3, high technological potential of abatement leads the auction to have less compositional changes and more technological adoption in comparison to the emission tax. This dynamic further appears to be amplified by a high permit price adaption rate (δ), which increases technology adoption and decreases compositional change and the final sales price.

The profit rate and consumer impact are sensitive to the auctioning mode of the trading exchange (ψ). Discriminatory-pricing generates lower profit rates than uniform-pricing, which in turn leads to a lower consumer impact. This means that discriminatory-pricing is more costly for firms, as high-bidding firms have to pay a higher price than the rest of the sector.

We further find that the emission price and corresponding technology adoption are sensitive to the sensitivity of

[11] Note that our model does not take into account rebound effects, i.e. the recycled policy revenue does not lead to increased demand. Under such a rebound effect, the higher policy revenue of the tax could lead to higher performance on product sales.

demand (γ). Table 3 shows that under a low sensitivity of demand, the emission tax has less advantage on compositional change and reaches a similar share of abatement through technology adoption as the permit market.

Finally, many factors in the model do not have a strong influence on the difference between auction and tax. Firms investment behavior (captured by the factor η), for example, does not reinforce or weaken the sometimes unprofitable investment dynamics that were observed. Similarly, behavior on the consumer market (captured by the parameters ϑ, ω, and χ), the heterogeneity of abatement factors and trading behavior, and the number of firms, have almost no influence on the results.

6. Conclusion and Policy Implications

We have developed an agent-based model to compare an emission tax and a permit trading market under bounded rationality, heterogeneity, and dynamic markets. In the model, firms make heuristic choices about production levels, mark-up rates, trading prices, and the adoption of new technology. They further have to compete on a consumption goods market where consumers gradually shift towards cheaper available goods. The study includes a wide range of parameter values to reflect the context of different sectors, different technological cases, and different behavior. Results are provided as an average over 190,000 iterations and supported with a variance-based sensitivity analysis.

Our work builds upon the established models of Dosi et al. (2010), Tang et al. (2017), and Zhu et al. (2018), and presents four key innovations to the literature. First, we present the first study that employs an ABM to compare the performance of an emission tax and dynamic permit trading. Second, we evaluate the performance of different policies under equal effectiveness, thus allowing for a fair comparison on additional criteria. Third, we decompose abatement efforts into the contribution of technological improvements, compositional changes, and a reduction of overall production. And fourth, we provide a set of ten different evaluation criteria to take multiple dimensions of policy performance into account.

We find that the main difference between the two instruments lies in the fact that permit prices fall when abatement is successful and permits become less scarce. When there is a high potential to abate emissions through technological improvements, permit trading can lead to a fall in prices that can drive green firms out of the market and make their low-emission technology into a kind of stranded assets. At the same time, however, these low prices can also increase the demand, and hence production, in the respective sector. Scarcity rents (Kalkuhl and Brecha, 2013) caused by the demand for permits can further cause a higher profit rate for firms under permit trading, leading to a higher average impact on consumers than under an emission tax. This challenges the proposition of Goulder and Schein (2013) that the distribution of burdens between firms and consumers are the same for both instruments.

Regarding the different possible mechanisms for permit trading, our results suggest that grandfathering leads to more financial impact on consumers as windfall profits are stronger and no revenue can be gained from the policy to counteract the higher prices of goods caused by the scarcity of permits. We show that profit rates are lower under a discriminatory-pricing mechanism than under uniform-pricing. Moreover, we find that a volume-based updating rule for grandfathering creates an advantage for low-emission firms to grow their market share in comparison to an emission-based updating rule. These findings support the notion that the initial distribution of permits affects the performance of permit markets, which is confirmed by experimental studies (Goeree et al., 2010).

Overall, an emission tax and permit trading perform reasonably similar under the assumptions and parameter settings explored in the current study. Nevertheless, the model reveals two arguments that an emission tax might be preferable. First, overall abatement costs might be lower as a stable price creates a stronger structural shift towards low-emission producers and a lower demand in the emitting sector. And second, there is less uncertainty about the effects of an emission tax. Direct control over the price can avoid the possibility of low prices leading to contra-productive incentives, as well as high prices generating windfall profits for firms. The uncertainty about emission levels can further be resolved by adjusting the emission price gradually upwards until the emission target is met (Boyce, 2018).

To conclude, taking bounded rationality and dynamic markets into account reveals results that deviate from conventional analysis based on rational and representative agents. It is worth noting that it is the dynamic and uncertain nature of the system as a whole that is driving these results. Changes in the heuristic rules and associated parameters have only a small influence on the differential performance of the two instruments. Extensions of the model could test if this remains true under more sophisticated decision-rules, particularly regarding expectations, liquidity, and investments.

Several further aspects remain outside the scope of our model. As it is a single-sector model, it does not consider the role of macroeconomic mechanisms – such as public budget balance, income-spending links, rebound effects, and multisectoral interactions – on the relative performance of instruments. As the demand side is aggregated, we can neither judge distributional effects on consumers. And we do not take into account how political-economy factors, like lobbying, could affect the performance of policies. Other aspects that deserve more attention in the future are the role of cyclical patterns, the relevance of permit banking, and the calibration of the model towards specific real-world cases.

A. Appendix

A.1. Profitability of abatement

The theory described in Section 2 posits that a technological improvement is profitable when the marginal costs of abatement $c^{\alpha} = b/a$ is lower than the emission price $p^{e}_{j,t}$. In the model, this condition is identical to the condition that the sales price per output under adoption of that technology should be lower than without the adoption of that technology. This means that a firm would have a higher fitness under its current mark-up and emission price if the technology is adopted. This is shown in Eq. 25, which compares the sales price $p^{g}_{j,t}$ with and without the new technology:

$$\begin{gathered}\Big((A_{j,t} - a) * p^{e}_{j,t} + (B_{j,t} + b)\Big) * \left(1 + m_{j,t}\right) < \Big(A_{j,t} * p^{e}_{j,t} + B_{j,t}\Big) * \left(1 + m_{j,t}\right) \\ b/a < p^{e}_{j,t}\end{gathered} \tag{25}$$

A.2. Decomposition of abatement

A change in emissions from round 0 to round t can be decomposed into changes in production level and changes in emission-intensity.

$$\begin{aligned}\Delta e_{j,t} &= e_{j,t} - e_{j,0} \\ &= g^{p}_{j,t} * A_{j,t} - g^{p}_{j,0} * A_{j,0} \\ &= \Delta g^{p}_{j,t} * A_{j,0} + \Delta A_{j,t} * g^{p}_{j,0} + \Delta g^{p}_{j,t} * \Delta A_{j,t} \\ &= \Delta g^{p}_{j,t} * \overline{A}_{j,t} + \Delta A_{j,t} * \overline{g}^{p}_{j,t}\end{aligned} \tag{26}$$

In mathematical terms, this follows a similar procedure as in Griliches and Regev (1995), with mean values being defined as follows:

$$\overline{x}_t = \frac{x_t + x_0}{2} \tag{27}$$

In a similar manner, the change in production $\Delta g^{p}_{j,t}$ can be decomposed further into contributions from a shift of relative shares of production $\rho_j = g^{p}_{j,t}/Q_t$ within the sector and a decline in total production $Q_t = \sum_{j=1}^{N} g^{p}_{j,t}$.

$$\begin{aligned}\Delta g^{p}_{j,t} &= \rho_{j,t} * Q_t - \rho_{j,0} * Q_0 \\ &= \Delta \rho_{j,t} * Q_t + \Delta Q_t * \rho_{j,t} + \Delta \rho_{j,t} \Delta Q_t \\ &= \Delta \rho_{j,t} * \overline{Q}_t + \Delta Q_t * \overline{\rho}_{j,t}\end{aligned} \tag{28}$$

This leads to a decomposition into three terms of abatement:

$$\begin{aligned}\alpha_t &= -\sum_{j=1}^{N} \Delta e_{j,t} \\ &= -\sum_{j=1}^{N} \left(\Delta A_{j,t} * \overline{q}_{j,t}\right) - \overline{Q}_t \sum_{j=1}^{N} \left(\Delta \rho_{j,t} * \overline{A}_{j,t}\right) - \Delta Q_t \sum_{j=1}^{N} \left(\overline{\rho}_{j,t} * \overline{A}_{j,t}\right)\end{aligned} \tag{29}$$

The three terms can be interpreted as follows:

1. A change in emission-intensity due to adoption of low-emission technology.
2. A compositional change within the sector due to a shift from high- to low-emission firms.
3. A change of overall production of the sector due to a reduction of output.

A.3. Definition of performance criteria

The performance criteria $Y_{m,z}$ are applied to each criteria m and scenario z. The definition of the individual measures is given in Table 4. They are calculated as a sum of the whole sectors activity in the last regulation period of the simulation, as given by the function S:

$$S(y_{j,t}) = \sum_{t=T-10}^{T} \sum_{j=1}^{N} y_{j,t} \tag{30}$$

Market concentration is captured by the Herfindahl–Hirschman Index. Technology adoption and compositional change correspond to the decomposition of abatement from Appendix A.2. Consumer impact describes average sales price minus the regulators' revenue per good. This represents how much a consumer has to pay on average for the good if the policy revenue is recycled by the regulator and handed to the consumers in equal amounts. The revenue R in the last regulation period of the simulation is given by either the sum of tax payments, or by the sum of firms' trades X_t at the initial auction of permits:

$$R = \begin{cases} 0 & \ldots \text{No policy or grandfathering} \\ \sum_{t=T-10}^{T} \sum_{j=1}^{N} e_{j,t} * p_t^{tax} & \ldots \text{Emission tax} \\ \sum_{x \in X_t} p_{j,x}^{u} * u_{j,x}^{t} & \ldots \text{Auction} \end{cases} \tag{31}$$

The relative evaluation measures $M_{m,z}$ shown in Figure 8 describe the results for each scenario z in relation to the other scenarios as given in Eq. 32.

$$M_{m,z} = \frac{Y_{m,z}}{\sum_{z=1}^{4} |Y_{m,z}|} \tag{32}$$

The comparative values between tax and auction used in Table 3 and for the sensitivity analysis in Figure 9 are given in Eq. 33. The definition of this average is chosen to avoid a division by zero and results in a range from -100% to 100%.

$$M^* = \frac{Y_{m,tax} - Y_{m,auction}}{|Y_{m,tax}| + |Y_{m,auction}|} * 100 \tag{33}$$

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Table 3
Performance of tax relative to auction.

Measures	Overall Results	Auction Pricing-Mode		Technological Potential		Heterogeneity		Demand Sensitivity		Permit Price Adaption Rate	
		Discr.	Unif.	Low	High	Low	High	Low	High	Low	High
Emissions	1.03 (2.58)	1.03 (2.59)	1.03 (2.57)	1.36 (3.82)	0.7 (1.12)	1.03 (2.55)	1.04 (2.61)	1.09 (3.15)	0.97 (2.0)	0.84 (1.57)	1.22 (3.52)
Abatement Costs	-15.1 (312.19)	-15.1 (313.25)	-15.09 (311.12)	-7.08 (201.34)	-23.12 (294.49)	-15.08 (318.71)	-15.12 (305.67)	-7.74 (148.65)	-22.46 (367.45)	-12.94 (213.33)	-17.26 (401.7)
Emission Price	11.88 (271.77)	11.89 (269.37)	11.88 (274.17)	3.31 (47.46)	20.46 (349.05)	11.08 (234.33)	12.68 (307.94)	11.16 (342.61)	12.6 (199.9)	9.57 (205.04)	14.19 (327.81)
Technology Adoption	-7.07 (84.55)	-7.06 (84.75)	-7.07 (84.35)	-2.93 (54.93)	-11.2 (79.95)	-7.3 (84.14)	-6.83 (84.86)	-3.3 (39.78)	-10.83 (100.95)	-5.77 (54.99)	-8.37 (110.73)
Compositional Change	17.41 (837.25)	17.31 (823.63)	17.51 (850.86)	8.04 (420.19)	26.78 (1078.78)	27.19 (1334.49)	7.63 (148.75)	15.26 (802.1)	19.56 (863.13)	13.17 (566.15)	21.65 (1072.46)
Product Sales	-2.72 (24.59)	-2.72 (24.61)	-2.71 (24.58)	0.19 (12.2)	-5.63 (20.08)	-2.9 (25.24)	-2.54 (23.88)	-1.43 (22.79)	-4.01 (23.08)	-2.26 (15.93)	-3.17 (32.85)
Profit Rate	-17.64 (414.44)	-5.83 (250.19)	-29.45 (299.63)	-22.57 (564.84)	-12.71 (215.39)	-18.22 (427.33)	-17.07 (400.9)	-19.47 (529.23)	-15.81 (292.98)	-15.09 (246.49)	-20.19 (569.4)
Market Concentration	-0.08 (91.47)	-0.07 (91.9)	-0.08 (91.03)	-3.39 (81.09)	3.23 (79.91)	-2.13 (61.05)	1.97 (113.49)	-0.62 (119.06)	0.46 (63.29)	1.85 (42.46)	-2.01 (133.03)
Sales Price	6.09 (15.65)	6.1 (15.69)	6.09 (15.62)	4.81 (12.52)	7.38 (15.5)	6.18 (15.43)	6.01 (15.86)	6.04 (18.61)	6.15 (12.69)	4.4 (10.97)	7.78 (14.62)
Consumer Impact	-5.98 (54.89)	-2.19 (40.3)	-9.77 (40.72)	-6.98 (84.23)	-4.99 (23.58)	-6.08 (56.42)	-5.88 (53.35)	-6.29 (80.93)	-5.68 (28.67)	-5.17 (32.34)	-6.8 (76.11)

Notes: Values refer to percentages between -100% and 100%, as derived in Appendix A.3. Positive values mean that this measure is higher under a tax. Variance is given in brackets. Discr. and Unif. refer to Discriminatory and Uniform. Low and high refer to values below or above the average values in Table 2.

Table 4
Definition of performance criteria

m	**Measure**	$Y_{m,z}$
1	Emissions	$S(e_{j,t})$
2	Abatement costs	$S\left(g^{p}_{j,t} * (B_{j,t} - B_{j,0})\right) / S(e_{j,t})$
3	Emission price	$\sum_{t=T-10}^{T} p^{tax}_{t} or \sum_{t=T-10}^{T} p^{u}_{t}$
4	Technology adoption	$S\left(-\Delta A_{j,t} * \overline{q}_{j,t}\right)$
5	Compositional change	$S\left(-\overline{Q}_{t} * \Delta \rho_{j,t} * \overline{A}_{j,t}\right)$
6	Product sales	$S\left(g^{s}_{j,t}\right)$
7	Profit rate	$S\left(g^{s}_{j,t} * (p^{g}_{j,t} - c^{p}_{j,t})\right) / S\left(g^{p}_{j,t} * c^{p}_{j,t}\right)$
8	Market concentration	$S\left((s_{j,t})^{2}\right)$
9	Sales price	$S\left(s_{j,t} * p^{g}_{j,t}\right) / 10$
10	Consumer impact	$S\left(s_{j,t} * p^{g}_{j,t}\right) / 10 - R / S\left(g^{s}_{j,t}\right)$

Notes: $S()$ and R are given in Eqs. 30 and 31, $c^{p}_{j,t}$ refers to a firms' average production costs per unit of output.