Complex Social Systems: Modelling Agents, Learning and Games

# Modelling carbon tax policies' impacts across multiple economic regions

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20. December 2022

**Abstract**

Despite being major contributors to global warming and targets of climate policies, firms are seldom the subject of existing climate policy studies. Here, an agent-based model is presented to address how firms operate in a multi-region system where markets are regulated under different climate policy regimes. Manufacturer firms base their relocation decisions on game theory and conduct carbon abatement according to stochastically-determined marginal cost profiles. Preliminary findings suggest that carbon taxes do not play a dominant role in influencing firms' relocation decisions. Nevertheless, they successfully depress carbon emissions and reduce the variability of model outcomes. Such results, if consistent across the parameter space, would provide evidence in favour of using carbon taxes as an effective climate policy tool.

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# Contents

# 1 Introduction

Climate change necessitates the reformation of complex socioeconomic and technological systems not only rapidly, but also at all scales [1]. To limit the global average temperature to below $2°C$ above pre-industrial levels, as per the 2015 Paris Agreement, governmental intervention is needed to enforce sustained decarbonisation. In the field of climate-related policymaking, agent-based models (ABMs) are recognised as especially useful tools as their handling of agent heterogeneity, bounded rationality, and micro-level behaviours offer more nuanced insights than traditional climate policy studies [2, 3, 4]. Nonetheless, numerous authors have voiced that the full potential of ABMs has not yet been unlocked: most studies so far have focused on single policies and their adjustment [2, 5]. In contrast, less attention has been paid to interactions amongst different policies and the systems within which they are emplaced, across spatial and temporal scales that are transferrable to real regional or global contexts [6, 7].

Even within literature that does examine climate policy interactions on an inter-regional level, firms – if they are represented at all as agents – are conceived as but one of a number of agent types, and are always sited statically in a fixed region [5, 8, 9, 10]. This marginal treatment of firms as agents is wanting, given that industry-related greenhouse gas emissions are higher than those from other end-use sectors and continue to increase [11]. In fact, the relatively geographically-mobile cement, iron and steel, and chemicals industries alone account for a fifth of global carbon emissions [12].

In this work, we present a game-theoretic agent-based model to investigate how differing climate policies amongst countries (hereby generalised as "regions") influence firm-level microeconomic behaviour. The aggregation of firms' actions are in turn reflected not only in macroeconomic indicators such as market shares, sales prices, and technological adaptation, but more importantly also by the evolution of carbon emissions over time. To the authors' best knowledge, this is the first ABM that focuses on how individual companies, as agents, behave within a global system comprising multiple markets and climate policies. By simulating firms' profit-maximising strategies, the model aims to show how the *relative* level of ambition in the climate policies of different regions may lead to emergent phenomena relating to climate adaptation and economic productivity.

The ABM characterises different regions based on their level of development and market properties, and allows each region to set a carbon tax on its domestically-produced goods. In response, using game theory, manufacturers decide whether to invest in carbon abatement technologies or to relocate to another region, in addition to conducting their usual market operations. These interactions play out over a time window during which tax penalties for emissions gradually tighten over time, inducing increasingly severe market conditions for companies. To examine the transferability of the model to actual circumstances, real-world data was used to represent three macroeconomic regions corresponding to developed, transitioning, and developing countries.

# 2 Context and Related Work

In the field of environmental economics, the use of ABM [13] and game theory [14] is not new. However, instances of both being combined are limited, with many of those implemented being studies of energy and fuel markets [15, 16]. Given that our project centres the interactions of heterogeneous firms in a way that is inherently strategic and takes place over a protracted timeframe, the use of both methods seemed most appropriate. Game theory thus provides a theoretical backbone from which a global market setting is enacted, where firm agents learn and operate in an intertemporal setting.

Our model draws on ABM microeconomic and climate policy frameworks inspired by Dosi *et. al* [17] and Foramitti *et. al* [18] respectively. Although we mainly investigate the behaviours of the globally mobile manufacturer class of agents, we retain the distinction, used by Foramitti *et. al*, between them and "upstream" fossil fuel supplier agents which are globally immobile but provide manufacturers with needed inputs. This is because, within an evolutionary environment where regions' climate policies are continuously being updated, prior studies have highlighted how natural resource stocks play a key role in driving changes in market dominance [16]. To accurately reflect how different implementations of climate policies among regions influence global carbon emissions, it is therefore necessary to model not only human constructs such as a region's level of technoeconomic development, but also the physical realities of geography. Furthermore, while climate policies targeting emissions reductions can take various forms such as "cap-and-trade" or direct regulation, we limit our model to the use of carbon taxes, which is the most common market-based instrument in ABM climate policy literature [3]. These taxes are applied exclusively to manufacturers since we consider regulation only of *actual* emissions caused by fuel usage, as opposed to *embodied* emissions in fuels extracted by suppliers.

While game theory is often applied to the simulation of competitive and cooperative behaviour [19], as in the case of oligopolies, our model takes the neo-classical economic approach of concentrating on competition between firms. Our reason for this is two-fold: firstly, to enable broader generalisability of the model, since the nature of cooperative behaviour between firms varies heavily by industry [20]; secondly, to simplify modelling, since we primarily examine not inter-firm interactions but the consequences of differential climate policies on firms' actions. In addition, firms' interactions do not occur directly with one another but instead are mediated by markets. Consequently, as with other works studying climate governance and policy [16, 21, 22], we draw from game theory the concepts of the replicator equation and mixed strategies, but apply these instead to model companies' behaviours.

Our literature review points to several underserved aspects of climate policy modelling that are nonetheless of value. Following from this, the aims of our project are thus to

1. Develop an agent-based model where firms base their actions on game theoretical principles to operate in a multi-region, multi-market system within which multiple climate policies are active.
2. Investigate how different combinations of climate policies affect the distribution, evolution, and/or final values of carbon emissions and other macroeconomic indicators.
3. Conduct a sensitivity analysis to identify how the model's parameters influence its results, and consequently gain insight as to the importance of various factors influencing carbon emissions in reality.

# 3 Model Description

Figure 1 presents an overview of the structure of the model. The model is comprised of multiple economic regions, $i \in R = \{1, \ldots, n\}$, each with different properties characterising their markets and relative level of techno-economic development. Within each region are two industry sectors: fossil fuel "suppliers", and capital and consumer goods "manufacturers". We denote the fuel suppliers in economic region $i \in R$ by $s_i \in S_i$ and the manufacturers in economic region $i$ by $m_i \in M_i$. Most of their attributes have different values depending on the economic region $i \in R$ they are located in and the economic region $j \in R$ to which they sell their products to. To refer to these different values, the subscript index $i$ and the superscript index $j$ are used; each region-specific attribute can thus be understood as elements of vector-valued quantities of dimension $n$.

While suppliers are geographically immobile, being tied to the physical location where they extract and produce fuels, manufacturers have the option of relocating to other regions. In addition, manufacturers require fuel inputs to create goods, emit carbon while doing so, and are subject to a carbon tax specific to the region they are located in. All suppliers and manufacturers have access to all regions, which each host its own fuel and goods markets open to all sellers. However, should companies sell outside of their domestic markets, they also have to bear the cost of import tax imposed by the region their buyers are located in.

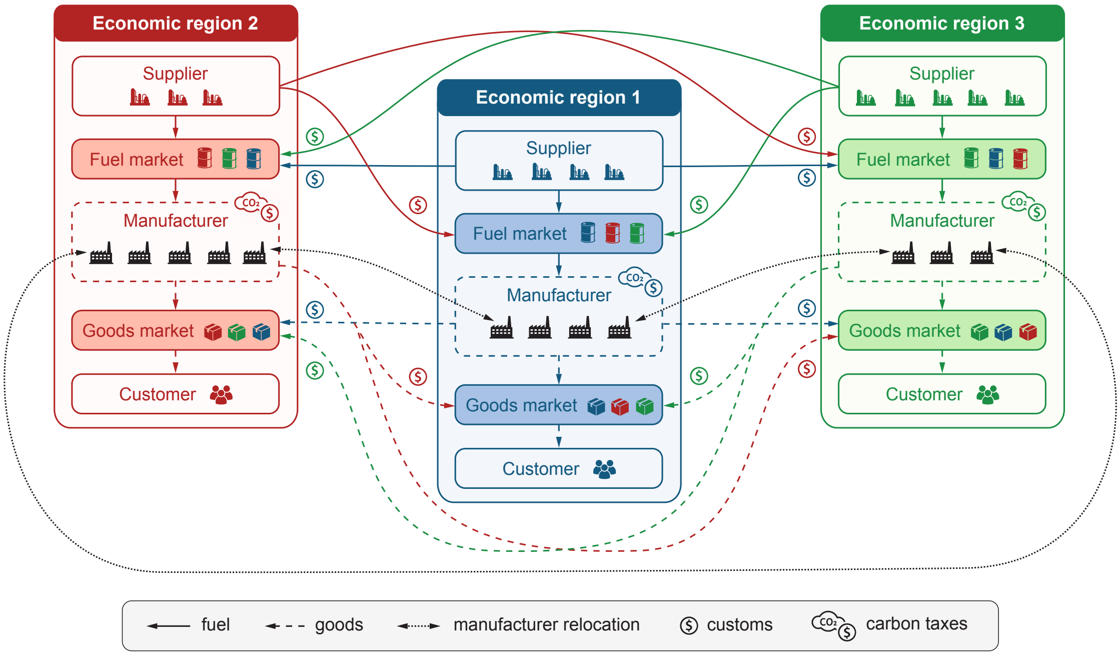


**Figure 1:** Multi-region ABM allowing for global trade. Each region has its own fuel/goods market to which all suppliers/manufacturers can sell their products. Manufacturers have to pay carbon taxes according to the policy of the host economic region proportional to their emissions. Moreover, manufacturers can relocate and adopt abatement options to reduce their emissions (not depicted).

## 3.1 Order of events

The economic evolution is induced by agents' actions at discrete time steps $t \in \{1, 2, \dots, T\}$, which can be thought of as representing months. At each time step, a sequence of interactions happen in the following order:

1. Each economic region updates its climate policy.
2. Manufacturers set their production goals and order fuels.
3. Suppliers set their production goals.
4. Suppliers produce fuels and sell them to manufacturers on the fuel markets.
5. Manufacturers produce goods and sell them to consumers on the goods markets.
6. Manufacturers evaluate and decide whether to relocate to another economic region.
7. Manufacturers decide whether to invest in abatement technology.
8. Manufacturers change towards more competitive fuel suppliers.

## 3.2 Implementation of climate policies

Each region regulates the emissions caused by fuel usage – as opposed to the emissions embodied in fossil fuels themselves – by levying a carbon tax on manufacturers sited within them. All regions' carbon taxes go into effect simultaneously after an initial start-up window that allows the model to reach a rough equilibrium, and then increase linearly with time until a specified final value is reached, whereby taxes are held constant. Although all firms in the same region pay the same tax per unit of emission released, $\sigma_i$, the total tax paid by each manufacturer is the product of the volume of goods produced, the prevailing tax rate, and their goods' per unit fuel intensity, $A_{m_i,t}$.

## 3.3 Production and price formation

The dynamics of fuel and goods production is modelled similarly as in [17] and [18] but generalised to the multi-market case, where commodities are produced for sale in the markets of each economic region. At the beginning of each time step $t$, every company $x_i \in S_i \cup M_i$ sets their production goals, $g^j_{x_i,t}$, for the market of each economic region. Their production goals are calculated from their expected demands, $\tilde{D}^j_{x_i,t}$, a buffer factor $I$ representing their desired inventory rate, and a subtraction of their leftover inventory from the previous time-step, $q^j_{x_i,t-1}$:

$$g^j_{x_i,t} = (1+I)\tilde{D}^j_{x_i,t} - q^j_{x_i,t-1}. \tag{1}$$

Manufacturers' expected demands $\tilde{D}^j_{m_i,t}$ are estimated by the demands of the last time-step $D^j_{m_i,t-1}$. In contrast, suppliers' expected demands are equal to their actual demands, and are calculated by summing the fuel orders of manufacturers in the current time step. While no constraints are placed on suppliers' extraction of fuels, manufacturers' production is limited by the availability of fuel resources. This is represented by dividing their inventory of fossil fuels $f_{m_i,t}$ by their fuel intensity $A_{m_i,t}$ and multiplying by the fraction of the corresponding sales market in the manufacturers' sales from the previous round $\phi^j_{m_i,t-1}$. In addition, manufacturers ration their fuels over the following $\tau$ time-steps to avoid sudden fuel shortages. Note that $A_{m_i,t}$ also measures a company's emissions intensity, since normalised units are implemented. Production is therefore computed as

$$\Delta q^j_{x_i,t} = \begin{cases} g^j_{s_i,t}, & \text{if } x = s \text{ (supplier)} \\ \min\Big(g^j_{m_i,t},\ \frac{f_{m_i,t}}{\tau \cdot A_{m_i,t}} \phi^j_{m_i,t-1}\Big), & \text{if } x = m \text{ (manufacturer).} \end{cases} \tag{2}$$

All companies produce and trade in the order of section 3.1. In each market, they offer their current inventory $q^j_{x_i,t}$, consisting of the sum of their latest production and their past inventory

$$q^j_{x_i,t} = q^j_{x_i,t-1} + \Delta q^j_{x_i,t}. \tag{3}$$

The prices at which the companies sell their products in each market $p^j_{x_i,t}$ must cover their production costs $B_{x_i,t}$ [1] and customs for exporting from economic region $i$ to economic region $j$, which we denote by $\rho^{ij}_x$. Suppliers and manufacturers incur separate customs tariffs; the $n \times n$ matrix $\rho_x$ of customs incurred by company $x$ thus comprises elements $\rho^{ij}_x$ and has zeroes on its diagonals, since customs do not apply for sales within domestic markets. Customs rates are also fixed over time so that the effects of changing emissions taxes can be more clearly identified.

As suggested in [18], fuel supplies become more scarce and difficult to extract as the reservoirs become empty, suppliers' production costs $B_{s_i,t}$ increase linearly by a factor $\zeta$ with every extracted unit of fossil fuel as

$$B_{s_i,t+1} = B_{s_i,t} + \zeta \sum_{j \in R} \Delta q^j_{s_i,t}. \tag{4}$$

In contrast to suppliers, manufacturers have to cover their emission costs, given by the prevailing carbon tax of their current economic region, $\sigma_{m_i}$, as well as their fuel costs, $c_{m_i}$. All companies also add an individual margin $\kappa^j_{x_i,t}$ to generate profits. Consequently, the sales price of a company's selling to economic region $j$ is defined as

$$p^j_{x_i,t} = \begin{cases} \big(1+\kappa^j_{s_i,t}\big)\big(1+\rho^{ij}_s\big) B_{s_i,t}, & \text{if } x = s \text{ (supplier)} \\ \big(1+\kappa^j_{m_i,t}\big)\big(1+\rho^{ij}_m\big)\big(B_{m_i,t} + A_{m_i,t}(\sigma_i + c_{m_i})\big), & \text{if } x = m \text{ (manufacturer).} \end{cases} \tag{5}$$

where $A_{m_i,t}$ again describes the manufacturers' fuel and emission intensity. The profit margin $\kappa^j_{x_i,t}$ reflects the dynamics of customer markets, where companies compete against each other to enlarge their market shares $\psi^j_{x_i,t}$. As modeled in [17] and [18], companies decide for a higher profit margin when they are successful, indicated by a growing market share. Conversely, they reduce their margins when their market shares are decreasing. This mechanism can be written as

[1] See appendix A.1 for a description of how $A_{m_i,t}$ and $B_{x_i,t}$ are generated.

$$\kappa^j_{x_i,t} = \kappa^j_{x_i,t-1}\left(1 + \vartheta\,\frac{\psi^j_{x_i,t-1} - \psi^j_{x_i,t-2}}{\psi^j_{x_i,t-2}}\right), \tag{6}$$

where the adaption speed is given by the factor $\vartheta$. Both equations (6) and (8) (described later) are reformulations of the generalised continuous-time replicator equation [19, 23] that guide companies' price-setting behaviours and the evolution of market shares respectively.

### 3.4 Manufactured goods markets

The goods markets are designed such that demand gradually shifts towards more competitive producers. Since all manufacturers can sell their products to any regional market, each manufacturer has different values of its attributes for each economic region indexed by superscript $j$. One such important market specific attribute is the competitiveness, $k^j_{m_i,t}$, of a company, which is determined by a company's sales price $p^j_{m_i,t}$ and the unfilled demand from last round $l^j_{m_i,t-1}$ (c.f. equation (14)) according to

$$k^j_{m_i,t} = -p^j_{m_i,t} - l^j_{m_i,t-1}. \tag{7}$$

The first term is motivated by the inverse relationship between competitiveness and sales price, while the second term accounts for customer losses when their demands from a past time step are not filled by the manufacturer. Competitiveness is then used to compute the evolution of the market shares as

$$\psi^j_{m_i,t} = \psi^j_{m_i,t-1}\left(1 - \chi_M\,\frac{k^j_{m_i,t} - \overline{k}^j_{M,t}}{\overline{k}^j_{M,t}}\right), \tag{8}$$

where $\chi_M$ controls how fast consumers shift towards more competitive manufacturers. The average level of competitiveness $\overline{k}^j_{M,t}$ within an economic region $j$ is given as

$$\overline{k}^j_{M,t} = \sum_{i\in R}\sum_{m_i\in M_i} k^j_{m_i,t}\;\psi^j_{m_i,t-1}. \tag{9}$$

Analogously, the average price for a given region $j$ is

$$\overline{p}^j_{M,t} = \sum_{i\in R}\sum_{m_i\in M_i} p^j_{m_i,t}\;\psi^j_{m_i,t}. \tag{10}$$

Total demands, $D^j_t$, are modelled as exponentially declining functions in the average price

$$D^j_t = D^j_0 \exp(-\mu\,\overline{p}^j_{M,t}), \tag{11}$$

where $\mu$ denotes the price sensitivity of demand. This relation signals how consumers tend to buy less of a good if its price rises. Demand can subsequently be allocated to the manufacturers with

$$D^j_{m_i,t} = D^j_t\;\psi^j_{m_i,t}. \tag{12}$$

Companies' actual sales in market $j$, denoted by $\hat{q}^j_{m_i,t}$ are then limited either by their demand or their inventory,

$$\hat{q}^j_{m_i,t} = \min\left(D^j_{m_i,t}, q^j_{m_i,t}\right). \tag{13}$$

Finally, if companies have produced and delivered too little for market $j$, they are left with an unfilled demand

$$l^j_{m_i,t} = D^j_{m_i,t} - \hat{q}^j_{m_i,t} \tag{14}$$

which enters as a competitiveness reduction factor in the next time step. After applying the above procedure to all manufacturers, the fraction of an individual manufacturer's goods sold to a given economic region $j$ is obtained from

$$\phi^j_{m_i,t} = \frac{\hat{q}^j_{m_i,t}}{\sum_{k\in R} \hat{q}^k_{m_i,t}}. \tag{15}$$

The operations of fossil fuel markets, which have many parallels with those of the manufactured goods markets, is described in A.2.

## 3.5 Relocations of manufacturers

The relocation of manufacturers can be cast within a game theoretic framework. Let $N^j_{M,t}$ denote the number of manufacturers in economic region $j$ at time step $t$. The manufacturer number change can be written in a generic Boltzmann-like equation as

$$\frac{\mathrm{d}}{\mathrm{d}t} N^j_{M,t} = \sum_{\substack{i\in R\\ i\neq j}} \big(w_{m_i}(j|i,t)N^j_{M,t} - w_{m_j}(i|j,t)N^i_{M,t}\big), \tag{16}$$

where the $w_{m_i}(j|i,t)$ terms are the transition rates at which a firm moves from region $i$ to region $j$ at time $t$. Since we are in an economic setting, firms imitate the behaviour of their (successful) competitors. Moreover, they are not allowed here to spontaneously relocate, as such movements would be arbitrary. Under these assumptions, the conditions shown in Helbing (section 12.2.4) [19] hold and the derivation of the game dynamical equations carries over. What is needed for the ABM implementation is the probability with which each manufacturer $m_i$ relocates to another economic region. This we choose to be

$$P_{m_i}(\text{relocate}|i,t) = \min\{\max_j(w_{m_i}(j|i,t)),\ \xi\}, \tag{17}$$

where $\xi$ is a model attribute that caps the probability with which a firm can relocate. This accounts for the possibility that manufacturers might refuse to move even if conditions are better elsewhere. We compute the transition rates by

$$w_{m_i}(j|i,t) = \frac{\gamma}{N_M/n} N^j_{M,t} \cdot \max\Big(\frac{E(j,t) - E_{m_i}(i,t)}{E(j,t)}, 0\Big) \qquad \forall j \neq i \tag{18}$$

in which $\gamma$ is a probability scaling factor, $N_M$ is the total number of manufacturers, and $E$ measures the "success" of a manufacturer in terms of profitability, i.e. the product of per unit profit margin $\kappa$ and demand $D$. Profitability is used as a catch-all metric for companies' success by suitably covering major reasons for firms' relocation decisions, such as business climates affected by tax legislation or firms' proximity to suppliers and customers [24], captured in this model by their incurred customs. Thus, the weighted average profitability for manufacturers in region $i$, selling to all regions $j \in R$, is

$$E(i,t) = (\overline{\kappa_{i,t} \cdot D_{i,t}}) = \sum_{j\in R} \sum_{m_i\in M_i} (\kappa^j_{m_i,t} D^j_{m_i,t}) \psi^j_{m_i,t} \tag{19}$$

while a manufacturer's current profitability, given that it is sited in region $i$, is

$$E_{m_i}(i,t) = \kappa_{m_i,t} D_{m_i,t} = \sum_{j\in R} \kappa^j_{m_i,t} D^j_{m_i,t}. \tag{20}$$

Note that $E(i,t)$ is not manufacturer-specific. From the game theoretic point of view, equation (18)'s maximisation term can be understood to measure a normalised *readiness* for a manufacturer to move from region $j$ from region $i$. Thus, $w_{m_i}(j|i,t)$ represents the companies' imitative processes as they evolve toward higher success rates. Should the manufacturer make the decision to relocate in (17), the choice of relocation destination is determined by the probability

$$P_{m_i}(j|i,t) = \frac{w_{m_i}(j|i,t)}{\sum_{j\neq i} w_{m_i}(j|i,t)}. \tag{21}$$

After the decision to relocate has been made, the company relocates after $t_{delay}$ time steps and is prevented from deciding whether to relocate from this new region for another $t_{stay}$ time steps. The use of probabilities in (17) and (21) allows companies to be modelled as having mixed instead of pure strategies.

### 3.6 Carbon abatement

Carbon abatement technologies can be adopted by manufacturers to reduce their emission intensities but increase their production costs. Each manufacturer $m$ has a different set of $N_\lambda$ such technological options, together with unique abatement cost factors $\epsilon^j = \epsilon_0 + y\epsilon_1^j$ that each characterise the costs of these technological options for the manufacturer in a given region $j$. Here, $\epsilon_0$ is the global base abatement cost factor while $\epsilon_1^j \sim Beta(\alpha^j, \beta^j)$, where $\alpha$ and $\beta$ are unique to each region. $y$ is a scaling factor for $\epsilon_1^j$.

The marginal abatement cost of each instance of technological adoption is defined as the ratio of extra cost $b_x$ per unit of production to a particular reduction in emissions $a_x$:

$$\omega_m^\lambda = \frac{b_x}{a_x}. \tag{22}$$

$a_x$ can be made constant with $a = \lambda/N_\lambda$, where $\lambda$ is the (maximum) abatement potential for the entire model, given as a factor of the original level of emissions. The marginal abatement cost can then be equivalently formulated as

$$\omega_i^\lambda = \epsilon^j \cdot a \cdot x \qquad x = 1, ..., N_\lambda \tag{23}$$

and $b_x$ back-calculated from the known values of $\omega_m^\lambda$ and $a_x$. Here, $x$ performs an indexing function and denotes how many technological adoptions a firm has adopted. Thus, as $x$ increases, both the marginal abatement cost and the extra cost per unit of production increase.

When a company moves to another economic region, the set of carbon abatement options available to it changes to reflect the developmental conditions of its new economic region. This is reflected by the new $\epsilon_1^j$ value the manufacturer adopts in its new location, which in turn redefines $\omega_m^\lambda$ for each of its *remaining* technological options that have yet to be adopted.

At each time step, companies examine the next possible carbon abatement option with the lowest $\omega_m^\lambda$. It decides whether to implement this abatement option by comparing the marginal costs of abatement to the sum of the price of emissions $\sigma_{i,t}$ and fuels $c_{m,t}$, which can be seen as the marginal damage costs of releasing one unit of emission. To model firms' risk attitude towards technological investment, a profitability target $\eta$ is added to this condition:

$$\omega_m^\lambda(1+\eta) < \sigma_{i,t} + c_{m,t}. \tag{24}$$

# 4 Numerical Simulation and Results

## 4.1 Implementation

The model code was programmed in Python 3 using the AgentPy [25] and SALib [26] open-source libraries for ABM and sensitivity analysis respectively. We consider seven different policy scenarios for $n = 3$ regions designed as aggregates of developed, transitioning, or developing countries, as classified by the United Nations [27]. To characterise each region, appropriate metrics were chosen and data collected so as to impute values for region-specific parameters. Appendix A.3 provides details on these values and their sources. For each scenario, detailed in Table 1, the model is run 100 times. Every variable is declared as either static or variable in each run, with the latter sampled uniformly from a predefined range.

**Table 1:** Scenarios for different combinations of carbon tax policies amongst the $n = 3$ modelled regions. The low, medium, and high tax levels correspond to final per unit-good emissions taxes of numerical value 2.0, 4.0, and 6.0 respectively.

| **Scenario** | **Region** | | |
|---|---|---|---|
| | **Developed** | **Transitioning** | **Developing** |
| Non-existent climate policy *(all_no_tax)* | None | None | None |
| Uniformly weak policy *(all_low_tax)* | Low | Low | Low |
| Uniformly standard policy *(all_medium_tax)* | Medium | Medium | Medium |
| Uniformly ambitious policy *(all_high_tax)* | High | High | High |
| Developing region pioneers *(low_medium_high)* | Low | Medium | High |
| Developed region pioneers *(high_medium_low)* | High | Medium | Low |
| Foreseeable future *(high_low_low)* | High | Low | Low |

## 4.2 Timescale

Each run consists of 200 time steps, where each time step approximates a month. Consequently, an initial window of 50 time steps is allowed for the model to equilibrate, following which each region's climate policy is introduced linearly over the next 100 time steps. The model is then run for another 50 time steps, with all climate policies held constant.

## 4.3 Model Evaluation Metrics

To measure the effectiveness of combinations of carbon tax policies across regions, cumulative regional and global carbon emissions are tracked across time as $\sum_{j\in R}\sum_{m_i\in M_i} A_{m_i,t}\Delta q^j_{m_i,t}$ and $\sum_{i\in R}\sum_{j\in R}\sum_{m_i\in M_i} A_{m_i,t}\Delta q^j_{m_i,t}$ for all scenarios described in Table 1.

In addition, we calculate several other quantities to understand how carbon taxes affect firms and their behaviours. For one, the average number of abatement technologies adopted by firms in each region measures how effectively different regions' climate policies incentivise green innovation. We also track the evolution of the number of manufacturers in each region, as well as regional fuel and goods sales, to understand firms' spatial movements and how those change markets' outputs. The average goods price and market shares for each region are also analysed in the sensitivity analysis in section 5.1.

## 4.4 Results

Figure 2 shows the aggregated results of all runs of selected scenarios in Table 1 (the results for all simulated scenarios can be found in A.4). Each curve in the regional emissions plots represents a region's average emissions at a given time step, with the shaded area around the curve corresponding to its 95% confidence interval. The two vertical markers indicate when carbon taxes are introduced and when they stabilise respectively.

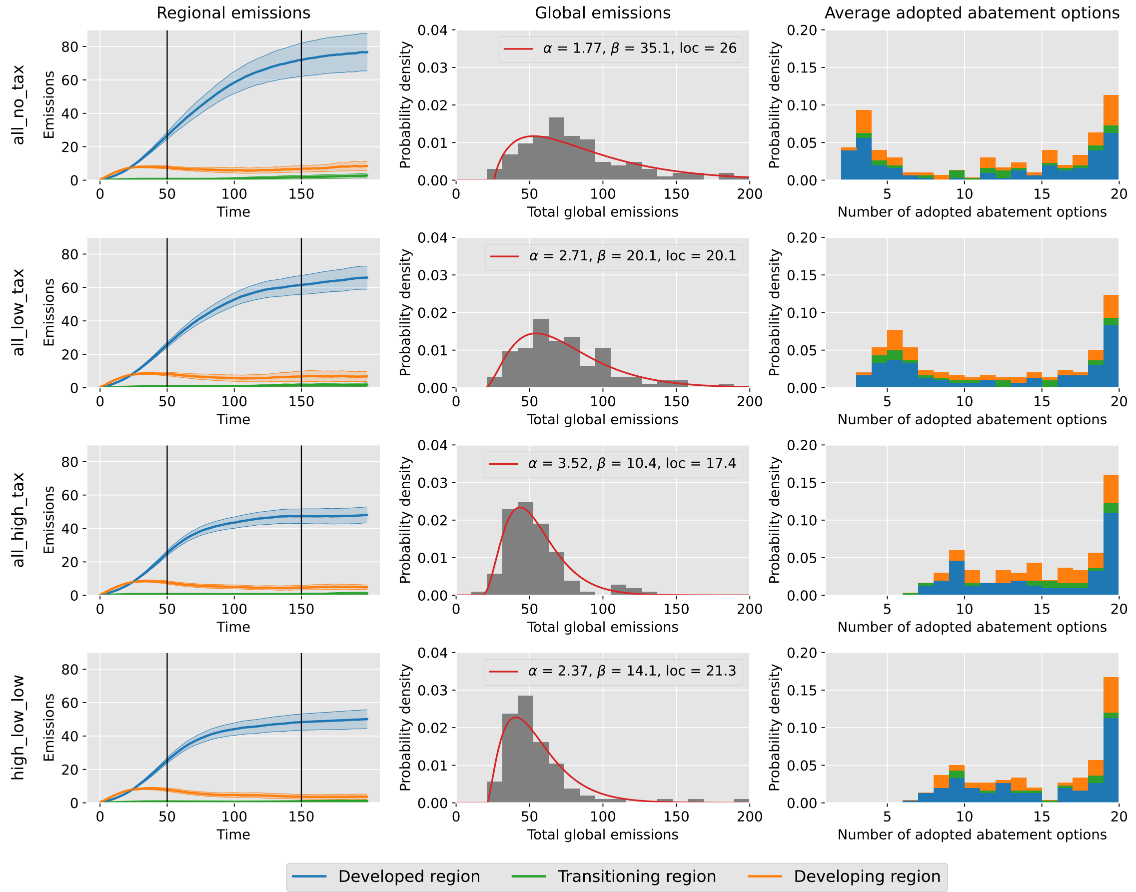


**Figure 2:** Comparison of regional emissions, global emissions, and average number of abatement options adopted per region between different scenarios for 100 runs. The histograms of global emissions are fitted in red by gamma distributions characterised by the indicated parameter values.

The central column of histograms depicts the distribution of global cumulative emissions at the last time step for all scenario runs. A gamma fit for the histogram has also been overlain on each scenario's plot, with the values for its shape parameter $\alpha$, rate (*i.e.* inverse scale) parameter $\beta$, and location displayed.

The rightmost column shows the average number of abatement options firms in each region have adopted, for all 100 runs. In the simulation, $N_\lambda = 20$ and is thus the maximum number of abatement technologies a firm can adopt.

Figure 3 visualises manufacturer relocations, fuel sales, and goods sales of each region, together with their confidence intervals, for the same scenarios as in Figure 2. Again, full results are displayed in A.4.

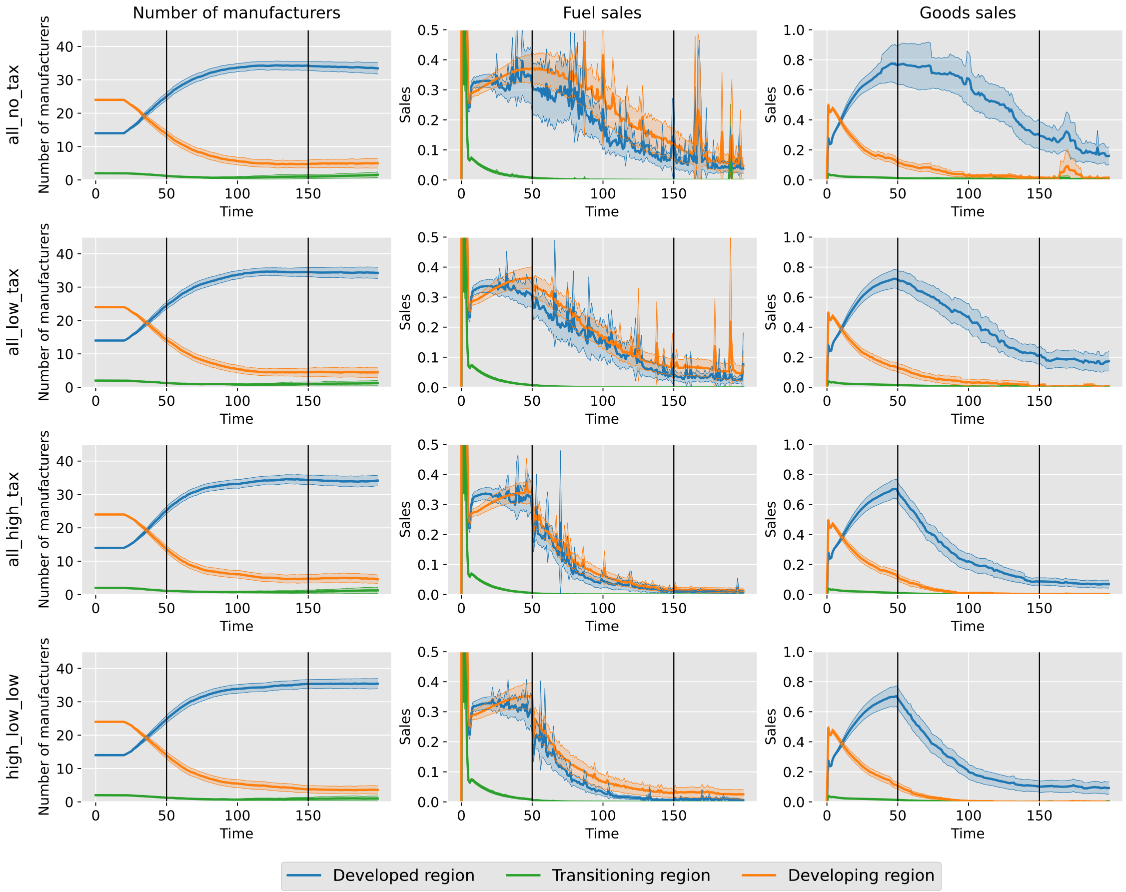


**Figure 3:** Comparison of averaged relocations of manufacturers, total fuel and goods sales from each economic region between different scenarios across 100 runs.

# 5 Discussion

Across all scenarios, the variance in outcomes shrinks the harsher the carbon tax. This is observed in both Figure 2 and 3 where the *all_no_tax* scenario gives the widest confidence intervals, while the *all_high_tax* scenario the lowest. Such results suggest that the increasing severity of carbon taxes serve to effectively constrain the outcome space of market operations. Consequently, more rapid drops in fuel and goods sales can be seen in scenarios with higher taxes. Furthermore, we observe that the climate policy of the developed region has the largest impact on global emissions; comparing the *all_high_tax* and *high_low_low* scenarios, the impact of carbon taxes in the developing and transitioning regions can be deduced to be limited since outcomes in both scenarios appear similar. This is likely due to the small number of manufacturers which remain in both these regions after enough time steps have elapsed.

Climate taxes also influence the distribution of the final cumulative global emissions, as seen in the gamma fits of Figure 2. In gamma distributions, skewness decreases as $\alpha$ grows [28]. Our simulations show that higher taxes increase right-skewedness of global emissions. Moreover, they generally also lead to a lower location value, which is the smallest value in a gamma distribution. Both of these patterns quantitatively illustrate that the effects of carbon taxes are robust even under stochasticity.

Figure 3 shows a consistent trend in manufacturers migrating to the developed region. We hypothesise that the lower marginal costs of investing in abatement technologies in the developed region, together with the region's larger domestic market and lower customs, are the primary factors behind this observation. Although such a result agrees with how multinational firms often expand into more lucrative markets in reality, its implications are unclear: optimistically, it could be interpreted that the impact of carbon taxes are not significant enough to observably damage a region's economic competitiveness. However, it could also be that our simulation's parameters were not tailored suitably enough to create such an effect.

## 5.1 Sensitivity Analysis

To quantify the influence of the variables on the model results, we perform a Sobol sensitivity analysis [29] for selected evaluation metrics listed in Table 2 and three parameters: the abatement potential ($\lambda/ld$), the maximum relocation probability ($\xi/xi$), and the relocation probability scaling factor ($\gamma/gamma$). The analysis decomposes the variance of a model's output into terms due to each input taken singularly and into terms due to the cooperative effects of groups of inputs, thereby describing the importance of each input. Here, we calculate the first order indices of each input to examine their individual effects and use Saltelli's extension of the Sobol sequence, which generates uniform samples over the parameter space [30]. Due to time constraints, only two scenarios, *all_no_tax* and *all_low_tax*, are analysed with the minimum recommended number of 5,000 generated samples.

**Table 2:** Evaluation metrics for the sensitivity analysis and their corresponding names used in the analyses pictured in Figure 4 and 5. $i = 1, 2, 3$ represent the developed, transitioning, and developing region respectively.

| **Evaluation metric** | **Programmed metric name** |
|---|---|
| Global emissions | sE_G |
| Emission of region $i$ | e_sum_i |
| Average goods price in region $i$ | aP_M_i |
| Market share of suppliers in region $i$ | psi_S_i |
| Market share of manufacturers in region $i$ | psi_M_i |
| Average number of adopted abatement options in region $i$ | aX_M_i |

The computed first order indices are plotted in Figure 4 and 5. The larger the index, the more significant the parameter; however, the existence of abnormal negative values point to imperfect results, which probably arise from the sample size being too small. Therefore, the subsequent interpretation mainly focuses on positive values.

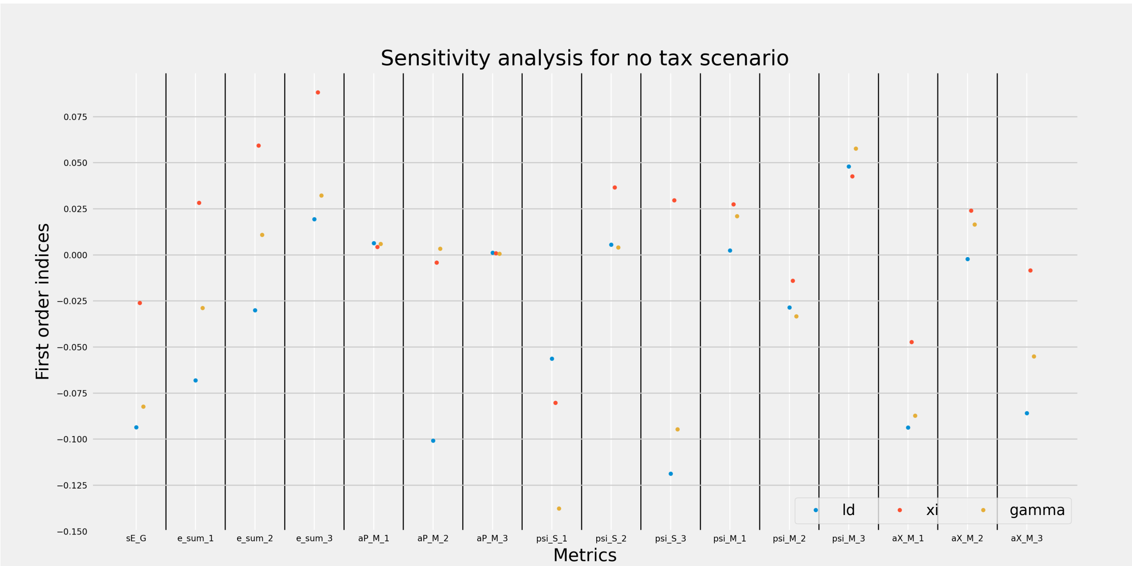


**Figure 4:** Visualisation of the first order indices of three parameters under the *all_no_tax* climate policy.

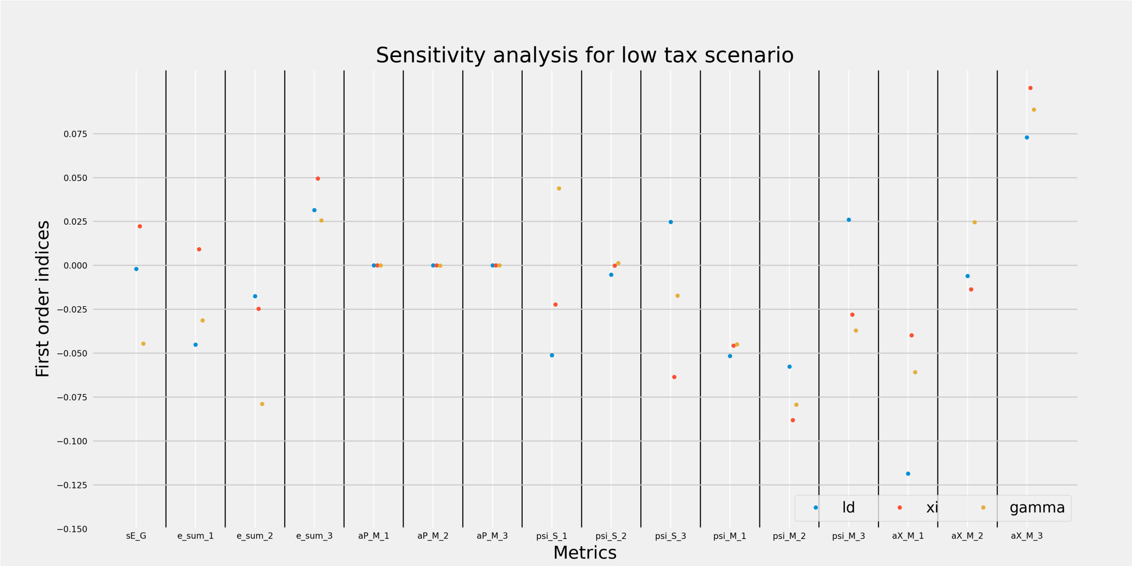


**Figure 5:** Visualisation of the first order indices of three parameters under the *all_low_tax* policy.

When no climate policy is adopted in all three regions, maximum relocation probability (*xi*) contributes most among the three investigated parameters to the variance of regional emissions. It is also the most critical parameter for the market share of suppliers in the transitioning region and developing region, as well as the market share of manufacturers in the developed region. These results align with our expectations, since the maximum relocation probability constrains the manufacturers' opportunities to relocate and affects their supplier preferences and production goals. All three parameters also influence the market share of manufacturers in the developing region. However, the sensitivity analysis does not offer much insight about how the three parameters influences regional average goods prices and the average number of adopted abatement options per region, which warrants further study. It is possible that the developing region shows the greatest sensitivity to parameter values because it is also the region which experiences the greatest out-migration of firms.

In comparison, when all three regions introduce low carbon tax policies, the relocation probability scaling factor (*gamma*) becomes the most critical parameter in determining the market share of suppliers in the developed region, while abatement potential (*ld*) becomes the most influential factor in the developing region. Although the effects of the three parameters on regional average goods prices are ambiguous, as in the *all_no_tax* scenario, the relocation probability scaling factor (*gamma*) has a noticeable impact on the average number of adopted abatement options in the developed region. In the developing region, all three parameters, but especially the maximum relocation probability (*xi*), are significant in determining the manufacturers' average number of adopted abatement options.

In summary, the model's maximum relocation probability (*xi*) is the most critical parameter amongst those analysed with respect to regional emissions and market shares. Although the relocation probability scaling factor (*gamma*) is less relevant, it still makes non-negligible contributions to the variance of regional market shares.

## 5.2 Outlook

This work presents an agent-based economic model capable of simulating multi-region climate policy scenarios with geographically mobile manufacturing firms. Leveraging the model's ability to reproduce the setting of a globalised economy comprised of heterogeneous regions and differing climate policies, our analysis was performed with initial conditions and parameter ranges considered to be approximately realistic. However, a next step would be to calibrate the model using more fine-grained data, such that the model dynamics can be compared with specific macroeconomic observations in today's global economy. For instance, the longer-term effects of implementing the recently-proposed European Union Carbon Border Adjustment Mechanism (CBAM) [31] on manufacturers could be studied by replicating such a measure with higher tariffs in our model.

Beyond calibration and verification, the model can be refined in several meaningful ways. One would be to enlarge the toolbox of climate policies covered to also include measures such as carbon emissions trading, imposition of carbon quotas, provision of subsidies for environmental technological innovations, or combinations thereof. Such policy mechanisms could be tested to understand not only their effectiveness and impact on the region which they are regulating, but also to investigate how these interact with policies in other regions to determine firms' behaviours. The role of suppliers could also be elevated by making them subject to climate regulation and allowing them to relocate as well.

In addition, to further build on our model's company-centric emphasis, firm entry and exit can be included. Presently, the model lacks such a mechanism and allows non-competitive firms to remain indefinitely in the market with a negligible market share. The threat of market exit or, conversely, the possibility of market dominance could place different evolutionary pressures on firms and influence their choices, such that patterns of firm relocation and innovation would possibly look very different with such an extension. Another major improvement would be to represent product/technology diffusion in our model, such that firms' efforts in carbon abatement have knock-on effects on their competitors' innovation as well, instead of only benefiting themselves. As Hötte [32] suggests, this is especially important for a model to give a fuller picture, since the performance of carbon taxes and other climate policies hinges significantly on technological diffusion barriers.

### 5.3 Conclusion

In this report, an agent-based model that simulates firms' market, relocation, and carbon abatement operations in a multi-region setting regulated by different combinations of carbon taxes was developed. The results of a three-region model simulating aggregates of developed, transitioning, and developing countries revealed that harsher carbon taxes are effective in curtailing global emissions, encouraging green innovation, and increasing the certainty of desired outcomes. However, modelling failed to produce any exodus of firms out of regions with higher taxes, as would usually be expected. This suggests that a further fine-tuning of model parameters would be necessary to better replicate real-world circumstances and generate results of more interest. A sensitivity analysis also subsequently revealed the criticality of parameters controlling manufacturers' relocation rates in controlling the model's outcomes. Although much room remains to improve the model and better explore its massive parameter space, the model offers a foundation to explore the underlooked question of how climate policy interfaces with firms' decision-making.

## 6 Individual Contributions

**Wen Yi Chan:** Mathematical modelling, Literature review, Analysis and writing. **Joel Huber:** Mathematical modelling, Implementation testing, Conceptual model visualisation, Project coordination. **Gaspard Krief:** Implementation testing, Visualisations, Proofreading. **Tianyi Liu:** Metrics design, Implementation testing, Data and result collection, Sensitivity analysis. **Pascal Troxler:** Implementation of mathematical model, Code architecture, Interactive dashboard.

# A Appendix

## A.1 Generation of firms' fuel intensity and production cost values

Different fuel intensity and production cost values are assigned to all suppliers and manufacturers to generate heterogeneous firm agents. Each region confers a unique baseline fuel intensity, $A_0$, and an initial production cost, $B_0$ to the firms that are initially sited in it. Firms then determine their individual $A_{m_i,t}$ and $B_{x_i,t}$ values by adding a heterogeneity factor, $\Delta C$, to the baseline value:

$$C = C_0 + \Delta C. \tag{A.25}$$

Here, $C$ can represent either fuel intensity or production cost values. $\Delta C$ is calculated by drawing a value randomly from the region-specific heterogeneity range $\Delta C_0$, and then scaling it by a factor $\sim Uniform(-0.5, 0.5)$ such that the mean $A_{m_i,t}$ and $B_{x_i,t}$ values remain at $A_0$ and $B_0$.

## A.2 Fossil fuel markets

As in [18], the fossil fuel markets operate according to an order-based system. Manufacturers calculate their desired amount of fuels as

$$\tilde{f}_{m_i,t} = A_{m_i,t}\, \tau \sum_{j\in R} g^j_{m_i,t} - f_{m_i,t}, \tag{A.26}$$

which depends on the sum of their production goals for all markets weighted by the fuel intensity $A_{m_i,t}$ and the forecasting factor $\tau$, which denotes a fixed number of time steps. Each manufacturer $m_i \in M_i$ has a preference $d_{m_i,s,t} \in [0,1]$ for each supplier $s \in S = \bigcup_{i\in R} S_i$. This defines what fraction of their fuel demand is ordered from each supplier. A supplier's demand $D^i_{s,t}$ for region $i$ is thus given by the sum of these orders,

$$D^i_{s,t} = \sum_{m_i\in M_i} \tilde{f}_{m_i,t} d_{m_i,s,t}. \tag{A.27}$$

The suppliers' sales and unfilled demand are calculated the same way as for the manufacturers participating in consumption good markets. In particular, equations (13) and (14), with $m_i \to s_i$ are applied to compute the actual sales and unfilled demand of each supplier in economic region $i$. If there is unfilled demand, it will be reduced from all orders by an equal share.

Each company's market share $\psi^i_{s,t}$ is then given by their share in total sales in market $i$ as

$$\psi^i_{s,t} = \frac{\hat{q}^i_{s,t}}{\sum_{s\in S} \hat{q}^i_{s,t}}. \tag{A.28}$$

At the end of each round, manufacturers adapt their list of preferred suppliers. For this, each supplier's competitiveness $k^i_s$ is calculated as in (7) for the manufactured goods markets. Equation 8 is likewise applied to suppliers. The preferences $d_{m_i,s}$ of each manufacturer for a certain supplier $s$ then changes as

$$d_{m_i,s,t} = d_{m_i,s,t-1} \cdot \exp\left(\chi_S \frac{k^i_{s,t} - \overline{k}^i_{S,t}}{\overline{k}^i_{S,t}}\right), \tag{A.29}$$

where $\chi_S$ is the adaption speed by which manufacturers change towards more competitive suppliers and $\overline{k}^i_{S,t}$ is the average supplier competitiveness in market $i$. Moreover, the fraction of fuels sold through the fuel market in economic region $i$ can be obtained by applying (15) to each supplier.

The per-unit good fuel cost of a manufacturer, $c_{m_i}$, is calculated as its total cost of buying fuels from its suppliers divided by the volume of fuels bought. Again, $\hat{q}^{m_i}_{s_j,t}$ is the actual volume of fuels supplier $s_j$ sells to manufacturer $m_i$.

$$c_{m_i} = \frac{\sum_{j \in R} \sum_{s_j \in S_j} p^i_{s_j,t} \hat{q}^{m_i}_{s_j,t}}{\sum_{j \in R} \sum_{s_j \in S_j} \hat{q}^{m_i}_{s_j,t}} \tag{A.30}$$

## A.3 Parameter values

**Table 3:** Values of fixed model parameters. For region-specific parameters, matrix element values correspond to a single region each. These values are estimated using the specified metrics. The metric data is collected from [33, 34, 35, 36]. For the matrix representing the abatement $\beta$-distribution parameters, the first rows contains the Beta distribution $\alpha$ values for each region and the second the corresponding $\beta$ values.

| **Parameter** | **Symbol** | **Value** | **Metric** |
|---|---|---|---|
| *Global* | | | |
| Number of economic regions | $n$ | 3 | |
| Simulation length | $T$ | 200 | |
| Policy implementation duration | $T^*$ | 100 | |
| Initialisation length | $T_0$ | 50 | |
| Desired inventory rate | $I$ | 0.1 | |
| Initial margin of supplier | $\kappa_0$ | 0.1 | |
| Initial margin of manufacturer | $\kappa_0$ | 0.1 | |
| Time steps before relocation | $t_{delay}$ | 5 | |
| Time steps after relocation | $t_{stay}$ | 15 | |
| Base abatement cost factor | $\epsilon_0$ | 15 | |
| Number of abatement options | $N_\lambda$ | 20 | |
| Abatement cost adjustment factor | $y$ | 5 | |
| *Region-Specific* | | | |
| Initial number of suppliers | $N_{S_0}$ | $[12 \quad 6 \quad 22]$ | Oil production |
| Initial number of manufacturers | $N_{M_0}$ | $[14 \quad 2 \quad 24]$ | Manufacturing output |
| Maximum demand | $D_0$ | $[2.0 \quad 0.4 \quad 1.0]$ | GDP |
| Initial fuel intensity | $A_0$ | $[0.8 \quad 1.2 \quad 1.0]$ | Emission intensity |
| Initial fuel intensity heterogeneity | $\Delta A_0$ | $[(0.1, 0.3) \quad (0.1, 0.3) \quad (0.1, 0.5)]$ | |
| Initial production costs | $B_0$ | $[1.2 \quad 0.8 \quad 1.0]$ | Overall manufacturing cost |
| Initial production heterogeneity | $\Delta B_0$ | $[(0.1, 0.3) \quad (0.1, 0.3) \quad (0.1, 0.5)]$ | |
| Customs for fuel | $\rho_S$ | $[0.2 \quad 0.4 \quad 0.7]$ | Average tariff rate |
| Customs for goods | $\rho_M$ | $[0.2 \quad 0.4 \quad 0.7]$ | Average tariff rate |
| Abatement $\beta$-distr. parameters | $\beta$ | $\begin{bmatrix} 3-\sqrt{2} & 4 & 3+\sqrt{2} \\ 3+\sqrt{2} & 4 & 3-\sqrt{2} \end{bmatrix}$ | Marginal abatement cost |

**Table 4:** For each iteration of the model run, values are sampled uniformly from the ranges of the variable model parameters presented here.

| **Parameter** | **Symbol** | **Min. Value** | **Max. Value** |
|---|---|---|---|
| Supplier market share adaption rate | $\chi_S$ | 0.1 | 0.5 |
| Manufacturer market share adaption rate | $\chi_M$ | 0.1 | 0.5 |
| Supply cost increase | $\zeta$ | 0.01 | 0.02 |
| Profit margin adaptation rate | $\vartheta$ | 0.1 | 0.5 |
| Forecasting factor | $\tau$ | 3 | 10 |
| Price sensitivity of demand | $\mu$ | 0.4 | 0.5 |
| Relocation probability scaling factor | $\gamma$ | 0.005 | 0.0035 |
| Maximum relocation probability | $\xi$ | 0.8 | 1 |
| Abatement potential | $\lambda$ | 0.5 | 0.9 |
| Profitability target | $\eta$ | 0.1 | 0.5 |

## A.4 Multi-run results for all scenarios

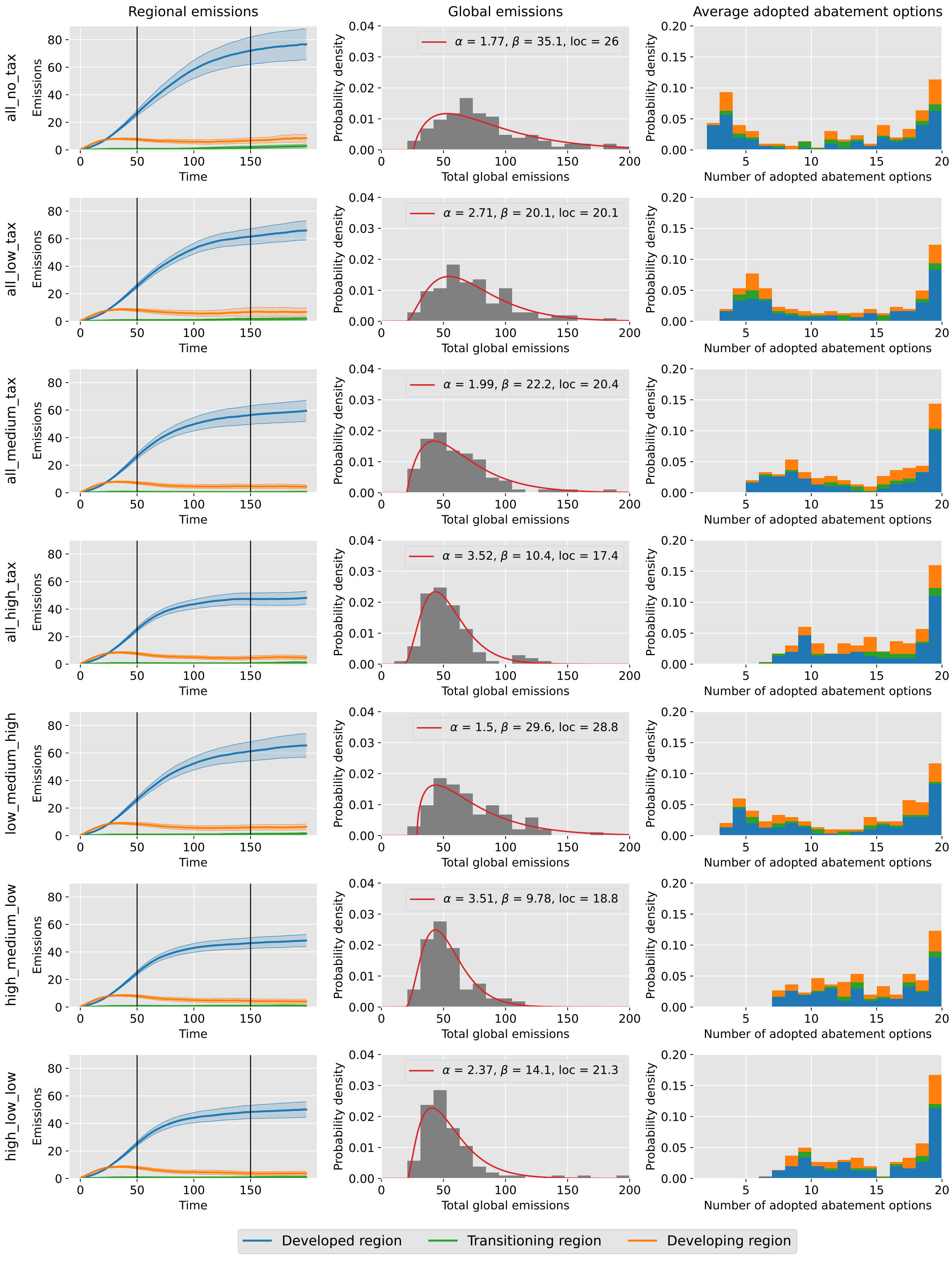


**Figure 6:** Comparison of regional emissions, global emissions, and average number of abatement options adopted per region for all scenarios across 100 runs. The histograms of global emissions are fitted in red by gamma distributions characterised by the indicated parameter values.

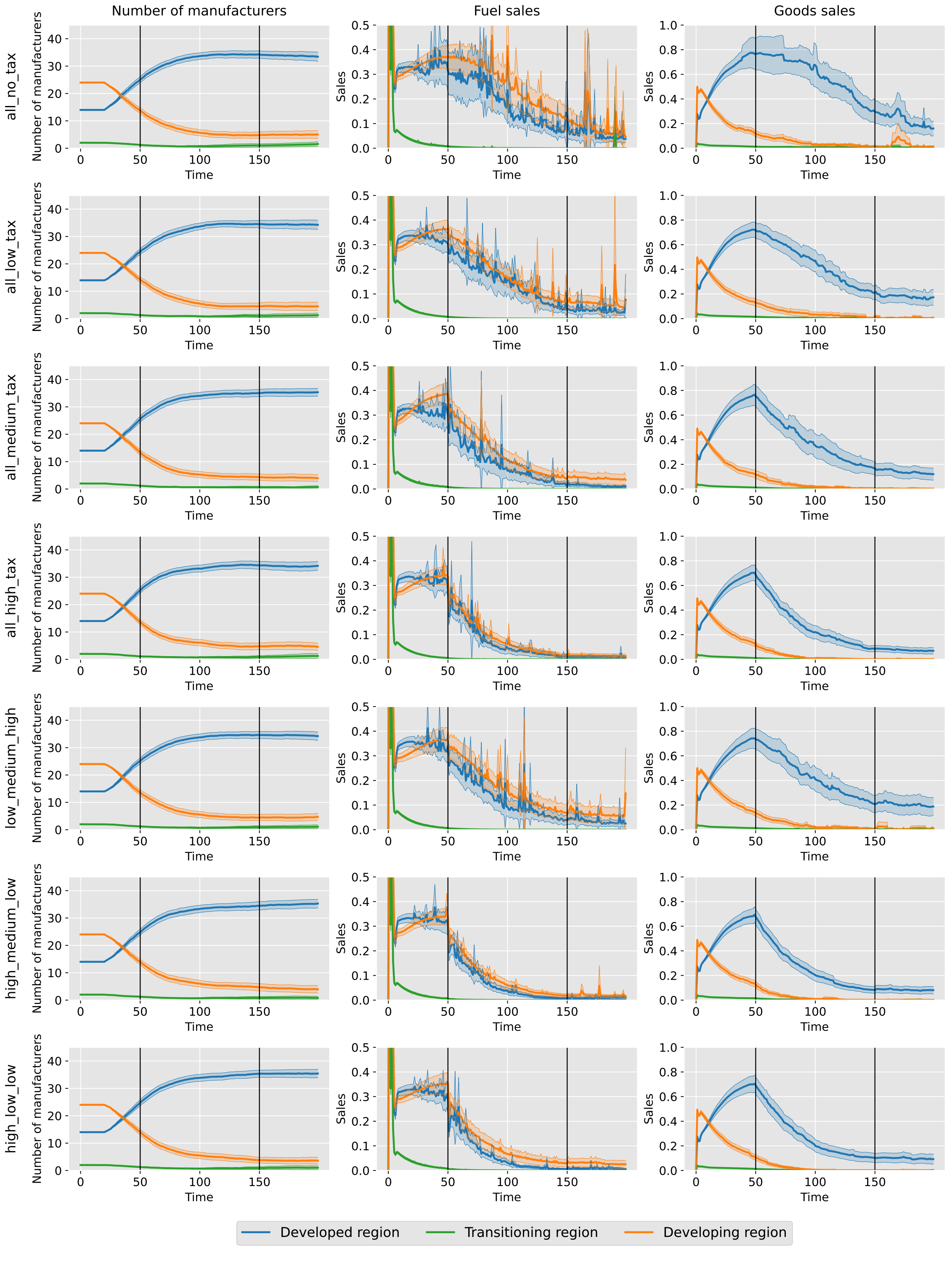


**Figure 7:** Visualisation of the averaged relocations of manufacturers, total fuel sales to each economic region, and goods sold for all scenarios across 100 runs.

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