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French Optimal and Robust Trade Policies Under Carbon Footprint Reduction Constraint and Uncertainties

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Abstract

To respect their pledge to fulfill the 2015 Paris Agreement on climate change, many countries have designed so-called Nationally Determined Contributions. One lever to reduce national greenhouse gases emissions is to change the trade policy of the country, in order to import more from the current and future least carbon-intensive economies. However, future carbon intensities reductions are uncertain, leading to the production of emissions scenarios by several institutes. A fitting trade policy is then classically obtained for each of such scenarios. By contrast with such perfect foresight (anticipative) approach, we propose to take into account all the possible futures simultaneously, in order to determine a "robust-to-uncertainty" trade policy. Using a two-stage stochastic optimization framework between 2015 and 2030, we study the French case and we outline a method to design a robust trade policy in a highly uncertain and constrained context. This optimal policy is then compared to optimal-by-scenario policies and to current French imports.

Keywords. Optimal trade policy, Stochastic optimization, Import shares, Nationally Determined Contribution, Carbon footprint, France

1 Introduction

The goal of the first French "Stratégie Nationale Bas Carbone" (SNBC1) was to decrease by 40% territorial greenhouse gases between 1990 and 2030. This strategy did not take into account the carbon footprint from imported emissions, that is, emissions that take place abroad in order to product goods or services consumed in France. Carbon footprint equates indeed to the sum of non-exported territorial emissions and imported emissions. France seeks now to control its carbon footprint, and not only its territorial emissions.

In this context, the French government turned to the "Haut Conseil pour le Climat" (HCC) in 2020 with the following question: "What is the carbon footprint of goods that we import and how to reduce it efficiently?". In its report (Le Quéré et al. [2020]), the HCC highlights that imported emissions amounted up to half of the French carbon footprint in 2015. This observation is supported by evidence provided by an OFCE report (Maillet [2020]). Reducing carbon footprint seems possible, among other solutions, by controlling trade partners; fostering imports from economies with low carbon intensities is a possible lever.

In this paper, we transpose the objectives of SNBC1 in reduction of carbon footprint, instead of territorial emissions, and seek to determine an optimal trade policy for France, under constraints and uncertainty, be they ecological or economic. Constraints emerge from realism purposes, notably from the satisfaction of the French demand of imported goods and services, and from the carbon footprint reduction goal. Uncertainty arises from the trajectories of decarbonization of economies, *i.e.* from the fulfilling of their Nationally

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Determined Contributions (NDCs). Taking this uncertainty into account is crucial when it comes to add robustness to an optimal trade policy. This robustness, when compared to optimal perfect foresight trade policies obtained through deterministic optimization, is the key result of our study.

To our knowledge, there is no literature considering optimal trade policy regarding environmental criteria and using import shares as (direct or indirect) decision variables. Most literature dealing with optimal trade policy seems to fit into the context of specific aspects of neoclassical economics, *e.g.* oligopoly, monopolistic competition and heterogeneous firms, or comparative advantage (*e.g.* Haaland and Venables [2016], Eaton and Grossman [1986], Bhagwati and Srinivasan [1976], Costinot et al. [2020], or Costinot et al. [2015]). Otherwise, most optimization problems under carbon footprint constraints deal with technical systems, especially energy production ones (*e.g.* Pękala et al. [2010]).

The originality of our approach stems from the use of import shares as decision variables in a problem of carbon footprint reduction, and from our explicit stochastic optimization framework.

We now position our contribution with respect to the literature. Diagnoses of the carbon footprints of European countries have underlined the major part of indirect emissions. Similar studies have been done for Germany (Destatis [2019]), the UK (Wiedmann et al. [2008]) and France (Maillet [2020], Le Quéré et al. [2020]). They all emphasize the necessity of taking a consumer point of view to better account for the carbon footprint of consumed goods and in the determination of suitable public policies. Among possible solutions, the control of the carbon intensity of imported goods is highlighted for France in Le Quéré et al. [2020]. This approach is supported by previous research (Xu and Dietzenbacher [2014]) showing the growing role of imported emissions in carbon footprint of developed countries due to the structure of the value chain. It suggests to better keep track of the carbon impact of imports, and to use trade as a mitigation lever in public policies. Moran et al. [2020] looked at changes in the composition of imports as a consequence of carbon-friendly consumer spending choices. But they only considered individual consumer actions (though massively adopted), whereas our approach takes the point of view of a regulator aggregating at a national level a goal of *explicitly* controlling imported emissions. Thus, a certain interest for imports choices as a mitigation lever of carbon footprint has been shown both in the literature and by governments, but we did not find previous works effectively determining a trade policy based on a carbon target. In order to determine such policy, we write the optimization problem of a regulator subject to a carbon constraint and explicitly taking shares of French imports represented by each world region as decision variables.

Since we are interested in establishing a long term trade policy, our optimization problem has to take into account not only present but also future carbon intensities of sourcing regions for French imports. These future intensities are widely considered to be uncertain, though countries have provided NDCs after the 21st Conference Of the Parties (COP) indicating a pledge for their future emissions. den Elzen et al. [2019] pointed out the uncertainty of major countries (and greenhouse gases emitters) meeting their NDCs. Benveniste et al. [2018] proposed a quantification of this uncertainty for every country, and assembled estimates of Gross Domestic Products (GDP) and emissions in 2030 and 2050 for all countries produced by the Organisation for Economic Co-operation and Development (OECD), the International Institute for Applied Systems Analysis (IIASA), the Potsdam Institute for Climate Impact Research (PIK) and the "Centre d'Études Prospectives et d'Informations Internationales" (CEPII). Thus we choose an optimization framework where this uncertainty appears explicitly. We will see that this approach leads to more robust trade policies than policies obtained under a perfect foresight approach, where the future emissions and GDPs are supposed known in advance.

This paper is organized as follows. In Section 2, we explicitly present our notations, then link them to the available data to finally formulate the stochastic optimization problem corresponding to least trade cost minimization under constraints and uncertainties. In Section 3, we display different numerical results; we compute optimal robust trade policies for 36 trading partners, also aggregated in 3 and 2 trading world regions; we discuss the interest of our stochastic approach. We conclude in Section 4.

2 Data and method

The problem studied here is the determination of an optimal French trade policy in order to follow the recommendation of the HCC in terms of carbon footprint reduction. This goal is a 40% decrease between 1990 and 2030. The framework used in this study is the so-called two-stage stochastic optimization (Shapiro et al. [2009]). The two stages correspond to the years 2015 and 2030. Decisions taken in the first stage (2015) are the import shares from each region. On the second stage, if the footprint target is not reached, France has to buy emissions quotas in order to cover the difference between its footprint and the target.

The random aspect of the problem is to be found in the French demand in 2030, in the carbon intensities of world economies in 2030 and in the price of the European carbon emission quotas in 2030.

The monetary amount of quotas France has to buy to cover an excess of carbon footprint over the reduction target is our penalization criterion. The estimation of the distribution of the random variables presented in the following of this section is based on the work of [Benveniste et al. \[2018\]](#). This study generates GDP and emission data for all countries in 2030 based on Nationally Determined Contributions announced by the countries on the occasion of Paris COP 21 and revised for COP 26.

2.1 GDP and greenhouse gases emissions in 2030

Data used in our study comes from the work of [Benveniste et al. \[2018\]](#). In the latter paper, the authors gather data and estimations of GDP and greenhouse gases (in CO_2eq) for every country, for the years 2015, 2030 and 2050. These data and estimations are furnished by 4 organisms: CEPII, IIASA, OECD and PIK. For future years, estimations of the distribution of emissions based on NDCs are proposed by each of these organisms, based on Nationally Determined Contributions given by the states themselves. When no NDC is given by a country, the organisms estimate themselves, as experts, the evolution of emissions of this country.

As a matter of fact, these estimations are done 5 times. Indeed, along with the IPCC reports it is commonly accepted, in the literature dealing with climate change and its attenuation, to consider 5 stylized (and standardized) possible versions of the world and its evolution: these are the *Shared Socioeconomic Pathways* (SSP). These SSPs account for the diversity of consequences of climate change and of climate policies. They are used by [Benveniste et al. \[2018\]](#) to build trajectories of greenhouse gases emissions associated with different sets of climate policies. 5 SSPs are considered: Sustainability (SSP1), Middle of the Road (SSP2), Regional Rivalries (SSP3), Inequalities (SSP4) and Fossil-fueled Development (SSP5). Uncertainty arises from NDCs, for example on the capacity of a country to meet its own NDC or on the reliability of the design of the NDC.

Thus [Benveniste et al. \[2018\]](#) build distributions of emissions for each country for each SSP and for each GDP data source. In our study, we take advantage of this work and build 20 scenarios of carbon intensities of world regions. A given scenario of ours is characterized by the choice of a tuple (SSP, GDP data source) — e.g. (SSP1, CEPII). For every region, we compute the mean of the distribution of emissions produced by [Benveniste et al. \[2018\]](#) for this region for this tuple (SSP, GDP data source). Finally, we divide this mean by the GDP of the region given by the selected GDP data source. This yields a carbon intensity of each region for this tuple (SSP, GDP data source).

Here below, we detail the mathematical formalization.

2.2 Notations for the decision problem

In order to write the two-stage optimization problem of a regulator — seeking to reach a carbon footprint target by modifying French trade policy, while minimizing the value of emissions quotas bought — we take the following notations, in which stage $t = 0$ refers to year 2015 and stage $t = 1$ refers to 2030.

As seen in §2.1, we use the estimations gathered by [Benveniste et al. \[2018\]](#) to derive 20 scenarios (one per couple SSP×organism furnishing data) in order to account for uncertainty arising from NDCs. We envision this set of scenarios to explore several possibilities of evolution of the variables presented below. More generally, *scenarios* are supposed to form a finite set \mathcal{S} , with the generic scenario being referred to as s , and having probability $\pi^s \geq 0$ (with $\sum_{s \in \mathcal{S}} \pi^s = 1$). In the equiprobable case, the probability of any scenario s is $\pi^s = 1/|\mathcal{S}|$, where $|\mathcal{S}|$ is the cardinality of the finite set \mathcal{S} of scenarios.

The world *regions* with which France trades constitute the finite set \mathcal{R} . The generic trading partner is referred to as r . We consider a set of 36 sourcing regions that gather 90% of the French imports in 2015, according to the French "Direction Générale des Douanes"¹.

Let I_0 be the vector of *French demand fractions*, that are *imported* by France from each world region $r \in \mathcal{R}$ at stage $t = 0$, constituting the first decision variable as

$$I_0 = \{I_0^r\}_{r \in \mathcal{R}} . \quad (1)$$

These decisions are taken at stage $t = 0$ (2015), hence the lower index in I_0 . Note that the region “France” appears in the vector I_0 in (1), so that the sum of the I_0 coefficients equates to 1. The fraction associated with the region France is blocked at its 2015 level: we do not account for the possibility of relocation, nor of offshoring.

Let C_1^s denote the vector of *carbon intensities* of the different world regions $r \in \mathcal{R}$ at stage $t = 1$ (2030), in the scenario s :

$$C_1^s = \{C_1^{r,s}\}_{r \in \mathcal{R}} . \quad (2)$$

¹https://lekiosque.finances.gouv.fr/site_fr/telechargement/telechargement_conjoncture.asp

These uncertainties are supposed to be revealed at stage $t = 1$, hence the lower index in C_1^s . The different scenarios $s \in \mathcal{S}$ allow to account for uncertainty in NDCs implementations.

Let $\bar{E}_1 = 249 \text{ MtCO}_2\text{eq}$ denote the 2030 carbon footprint target, which corresponds to a decrease of 40% from the French carbon footprint of 1990. Let D_1^s be the total French demand of importations at stage $t = 1$, which depends on the scenario s . Finally, we denote by Q_1^s the quantity of emissions quotas bought by France at stage $t = 1$ and by P_1^s its unitary price at stage $t = 1$, in the scenario s . France has to buy emissions quotas if its target \bar{E}_1 is not reached.

2.3 From data to ingredients for the decision problem

Estimates of the French GDP yield D_1^s , the value of the French demand of importations at stage $t = 1$ in scenario s . Imports are considered to represent the same part of D_1^s at $t = 1$ as at $t = 0$, that is, 30% according to INSEE. This is a strong hypothesis since this part has varied significantly in the past decades, but it enables to isolate the effects of the modification of the trade policy on carbon footprint. Denoting by $gdp_1^{FR,s}$ the French GDP in 2030 in scenario s , we thus set

$$D_1^s = 0.3 \times gdp_1^{FR,s} . \quad (3)$$

On the other hand, intensities $C_1^{r,s}$ are obtained by dividing, for each region r , the GDP by the greenhouse gases emissions. Denoting by $ghg_1^{r,s}$ the emissions of region r in 2030 in scenario s , $C_1^{r,s}$ is calculated as

$$C_1^{r,s} = \frac{ghg_1^{r,s}}{gdp_1^{r,s}} , \quad \forall (r, s) \in \mathcal{R} \times \mathcal{S} . \quad (4)$$

The price of a carbon quota is taken according to the conclusion of *Commission Quinet* (Quinet et al. [2019]) which determined a long term carbon price scenario to use in France. Thus, the price of carbon is fixed at 250€_{2018} per ton in 2030. This price is also in line with the approximate levels reached by the price of an emission allowance on the EU-ETS permits market on the long run due to cap restriction.

To strengthen the economic realism of the derived trade policies, we suppose that, for each world region $r \in \mathcal{R}$, the demand fraction I_0^r is bounded above by

$$\bar{I}_0^r = \delta \times I_0^{r,real} , \quad \forall r \in \mathcal{R} , \quad (5)$$

where $I_0^{r,real}$ is the real French import share from region r in 2015, and where the value of δ is set to 1.6 as explained below. The term δ limits the accessible variation in commercial exchanges between France and a region, by encompassing all possible costs of such variation that are not explicitly modeled in this study. These costs may arise from various reasons such as historical or geopolitical links between the region and France, geographical distance or transport costs. It also reflects the limit of each region in production of goods and services that it may export: France cannot possibly import more from a region than what it offers to export. Finally, the parameter δ may also be seen as one of relative sensitivity to the carbon constraint: an increased parameter increases the relative weight of the respect of the carbon constraint among the factors that determine French trade policies. The arbitrary value of $\delta = 1.6$ is the result of several tries. Lower values (< 1.4) contract indeed the set of admissible policies very close to the current policy. These values are relevant in worlds that do not care about carbon constraints. Since this study seeks precisely to measure the impact of caring about imported carbon content when trading, low values of δ are not suitable. Much higher δ values (> 1.8) yield trade policies where France exchanges with countries that could not realistically export that much goods, or, in some scenarios, where France leaves completely its historical partners. These high values make the carbon constraint prevail on other determinants of trade and, more importantly, on the production limits of sourcing regions. Thus, higher values are not relevant either, and we keep $\delta = 1.6$ which balances between a relative importance of the carbon constraint in the determination of trade policies, and realistic variations from the 2015 situation with a 15 years horizon.

2.4 Formulation of a stochastic optimization problem

We consider 20 scenarios, one per couple (SSP \times organism furnishing data), all equiprobables. With the notation in §2.2, this means that $|\mathcal{S}| = 20$ and that the probability of scenario s is $\pi^s = 1/|\mathcal{S}| = 1/20$.

First, we write the problem formulation in an extensive linear form, with recourse variables $\{Q_1^s\}_{s \in \mathcal{S}}$ in addition to the original decision variables I_0 in (1). Second, we write an equivalent problem in the original decision variables I_0 , having the property to be a convex program.

2.4.1 Extensive linear form (in initial and recourse decision variables)

With the notations in §2.2, we write the optimization problem of a regulator as

$$\min_{\{I_0^r\}_{r \in \mathcal{R}}, \{Q_1^s\}_{s \in \mathcal{S}}} \sum_{s \in \mathcal{S}} \pi^s P_1^s Q_1^s \quad (6a)$$

$$0 \leq Q_1^s, \quad \forall s \in \mathcal{S}, \quad (6b)$$

$$0 \leq I_0^r \leq \bar{I}_0^r, \quad \forall r \in \mathcal{R}, \quad (6c)$$

$$\sum_{r \in \mathcal{R}} I_0^r = 1, \quad (6d)$$

$$D_1^s \left(\sum_{r \in \mathcal{R}} I_0^r C_1^{r,s} \right) - Q_1^s \leq \bar{E}_1, \quad \forall s \in \mathcal{S}. \quad (6e)$$

In the optimization problem (6), the regulator seeks to minimize the expected cost (6a) of buying emissions quotas at stage $t = 1$ (2030), under constraints that we comment right now. Constraint (6b) is a constraint of nonnegativity of the quantity Q_1^s of emissions quotas. Constraint (6c) corresponds to the nonnegativity of the French demand fractions I_0^r and to a maximal variation of I_0^r from the 2015 situation ($t = 0$). This constraint of realism accounts for all the links between countries not explicitly taken into account in our study that also influence trade between France and these countries. This maximum is a fixed parameter detailed in (5): each region can export to France up to 1.6 times the part of French demand it represents at stage $t = 0$. Constraint (6d) accounts for the satisfaction of French demand. Constraint (6e) represents the achievement of the carbon footprint target \bar{E}_1 for all scenarios $s \in \mathcal{S}$, thanks to the possibility of recourse by means of additional emissions quotas Q_1^s . Finally, note the difference in available information when the two decision variables are determined. I_0 is deterministic; this reflects a decision taken at stage $t = 0$. On the contrary, the decision Q_1^s depends on the scenario s because it is a function of French demand and carbon intensities of regions at $t = 1$, which all depend on the scenario s .

2.4.2 Convex form (in initial decision variables)

In case the price P_1^s of emission quotas bought by France at stage $t = 1$ is nonnegative for any scenario, that is, when

$$P_1^s \geq 0, \quad \forall s \in \mathcal{S}, \quad (7)$$

another interesting formulation is possible. Using the form of the objective function in (6a) and the constraints (6e), it is easy to observe that the variable Q_1^s is, at the optimum in the optimization problem (6), fully determined as a function $\left(D_1^s \left(\sum_{r \in \mathcal{R}} I_0^r C_1^{r,s} - \bar{E}_1 \right) \right)_+$ of import shares, future French demand and future carbon intensities, where $x_+ = \max\{x, 0\}$. Thus, in this setting, the optimization problem (6) rewrites as

$$\min_{\{I_0^r\}_{r \in \mathcal{R}}} \sum_{s \in \mathcal{S}} \pi^s P_1^s \left(D_1^s \left(\sum_{r \in \mathcal{R}} I_0^r C_1^{r,s} - \bar{E}_1 \right) \right)_+ \quad (8a)$$

$$0 \leq I_0^r \leq \bar{I}_0^r, \quad \forall r \in \mathcal{R}, \quad (8b)$$

$$\sum_{r \in \mathcal{R}} I_0^r = 1. \quad (8c)$$

In this form, the objective function (8a) of problem (8) is clearly a convex function of the vector of import shares $\{I_0^r\}_{r \in \mathcal{R}}$ thanks to the polyhedral convex $(\dots)_+$ terms in (8a). Constraints (8b)–(8c) are linear and depend also only on variables $\{I_0^r\}_{r \in \mathcal{R}}$. Thus, this form places problem (8) in the framework of convex optimization, with the property that solutions are then expected to be (generally) inside their constraints domain (whereas solutions of linear programs lie on the border). Thanks to such convex formulation, we obtain robust solutions for the import shares $\{I_0^r\}_{r \in \mathcal{R}}$.

3 Numerical results

Here, we solve numerically the optimization problem (8). For this purpose, we keep, for each country, the mean of its emissions and GDP in 2030 given by the 4 organisms (OECD, IIASA, PIK, and CEPII) for

each SSP. This yields 20 equiprobable scenarios (4 organisms \times 5 SSPs), that are input data for the convex optimization problem (8).

Once obtained the optimal solution $\{I_0^r\}_{r \in \mathcal{R}}$ — that we coin “robust optimal policy” (more evocative than stochastic optimal policy) or “robust (stochastic) optimal policy” — we compare its performances with other pre-determined policies:

- the current trade policy;
- the 20 “perfect foresight policies” that are solutions of problem (6) when all the probabilities π^s , in the family $\{\pi^s\}_{s \in \mathcal{S}}$, are set to zero except for one scenario.

Let us be more specific regarding this last case. Consider a single scenario $\bar{s} \in \mathcal{S}$ (for instance, scenario SSP1 estimated by IIASA). The perfect foresight policy associated with scenario \bar{s} solves the following deterministic program:

$$\min_{\{I_0^r\}_{r \in \mathcal{R}}, Q_1^{\bar{s}}} P_1^{\bar{s}} Q_1^{\bar{s}} \quad (9a)$$

$$0 \leq Q_1^{\bar{s}}, \quad (9b)$$

$$0 \leq I_0^r \leq \bar{I}_0^r, \quad \forall r \in \mathcal{R}, \quad (9c)$$

$$\sum_{r \in \mathcal{R}} I_0^r = 1, \quad (9d)$$

$$D_1^{\bar{s}} \left(\sum_{r \in \mathcal{R}} I_0^r C_1^{r, \bar{s}} \right) - Q_1^{\bar{s}} \leq \bar{E}_1. \quad (9e)$$

This is problem (6) with $\pi^{\bar{s}} = 1$ (e.g. $\pi^{\text{IIASA-SSP1}} = 1$) and all other $\pi^s = 0$, that is, we optimize thinking that the future will be scenario \bar{s} for sure. These perfect foresight policies are solution of deterministic optimization problems, as the scenario is known in advance at stage $t = 0$, that are linear programs; as a consequence, they yield “corners” solutions, that are less robust to hazard. Indeed, resulting import shares are closely associated with the scenario they are optimized for. For pessimistic scenarios, this gives policies concentrated in few countries, thus closely associating the success of this policy — in reaching the carbon footprint target — to the successful implementation of NDCs of these few countries. Other scenarios may be very optimistic as they feature the completion of NDCs for countries that, in most other scenarios, fail to reduce their emissions. Optimistic scenarios yield optimal policies that rely, at least partially, on such countries. Thus resulting policies may also be considerably stretched between all world regions. In a policy approach, the latter optimistic case is more detrimental. Indeed, if France imports from fewer countries than in the current situation, and estimates that, in the end, these partners might not sufficiently reduce their emissions — leading to supplementary needs for emissions quotas — France may decide to help them, if the (social) cost of helping is lower than the final cost of supplementary emissions quotas and climate related damages. On the contrary, such recourse is not an option when the decided trade policy has substantially diversified regions of imports. This policy trap – bad trade policy choice and no possible recourse – exists because of the cherry picking of the optimal solution when deterministic optimization along a particular scenario is done. The robust (stochastic) optimal policy, that we advocate for, avoids this issue by taking all scenarios into account altogether.

3.1 Results for 2 aggregate regions

To better perceive the robustness of decarbonization policies obtained through stochastic optimization, we present a 2D case in Figure 1, where only 2 regions, apart from France, are considered: Europe and the rest of the world. It can easily be seen that all the deterministic optimal solutions saturate some constraints — they are all near corners — but the robust (stochastic) optimal solution is not in a corner of the admissible polygon (a segment, here), which makes it more robust to hazard. The current situation is clearly distinct from any of the presented optimal policies (deterministic or stochastic), but not that far from the robust (stochastic) optimal policy. In the robust (stochastic) optimal solution, the European import share is increased from 70% to roughly 80% compared to the current situation. This reflects that, even when uncertainty is accounted for, European economies are significantly more decarbonized than those from the rest of the world. However, this general trend does not apply to all scenarios, and this is why there exist deterministic optimal solutions with a decreased European share when compared to the current situation: these solutions are optimal in scenarios where the trend is not verified. In any case, the robust (stochastic) optimal policy leads to a more balanced, more robust trade policy.

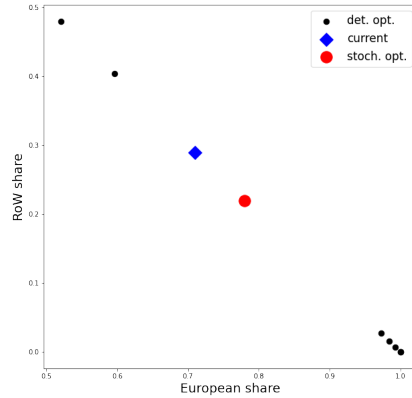


Figure 1: Scatter plot of robust (stochastic) optimal policy, current policy and the 20 perfect foresight policies (2 aggregate regions)

3.2 Results for 3 aggregate regions

Going on, we simplify the original problem with 36 countries to only 3 big world regions: Europe, America and Asia. We then represent, in \mathbb{R}^3 , the import shares for the robust (stochastic) optimal policy, the current policy and the 20 perfect foresight policies. In Figure 2, we can see that the 20 “deterministic optimal solutions” (perfect foresight) are spread wider in $[0, 1]^3$ because they lie on corners of the polygon of feasible solutions, as optimal solutions of a linear program. This explains the robustness of the robust (stochastic) optimal policy: the spread of the deterministic optima reveals the diversity of possible futures. Note that, as explained above, some perfect foresight solutions increase the balance between import shares for all 3 regions, even though it appears that, in most scenarios (namely all scenarios except the few these optima are optimized for), Asian and American emissions tend to be significantly higher than European ones. Thus, the "wisest" option may not necessarily be to balance between regions. We insist therefore on the fact that perfectly adapting to only one future may be detrimental if another future is in fact realized, whereas the robust (stochastic) optimal policy balances all of these possible futures.

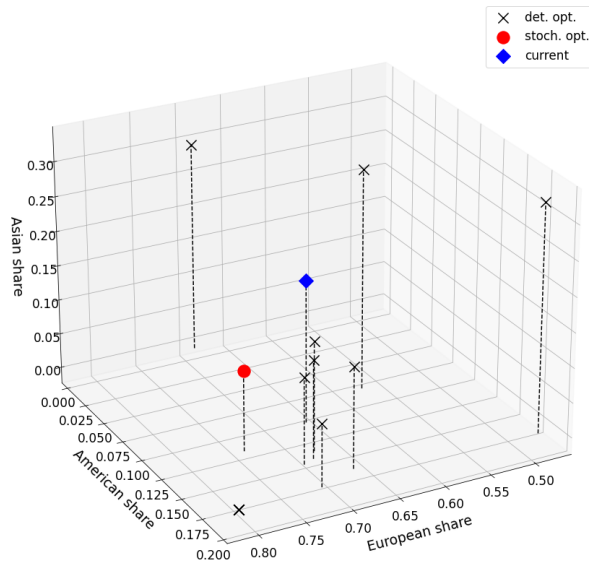


Figure 2: Scatter plot of robust (stochastic) optimal policy, current policy and the 20 perfect foresight policies (3 aggregate regions)

3.3 Results for 36 world regions

Results with 36 world regions illustrate how the robust (stochastic) optimal policy is more robust to randomness than other pre-determined policies. On the one hand, the optimal policies for a deterministic problem fare better than the optimal solution of the stochastic problem for the particular futures they were designed for. On the other hand, they are also less robust to randomness: their frequencies of necessary recourse to additional carbon quotas — *i.e.* of failure to meet the carbon footprint target (event $Q_1 > 0$) — are significantly greater than what is obtained with the optimal solution of the stochastic problem (Figure 3). In every scenario, the ratio between necessary emissions permits and imported carbon footprint amounts at least to 50%, whatever the policy is. However, this ratio is systematically the lowest for the robust (stochastic) optimal policy. Thus, this policy leads not only to the lowest probability of having to buy emissions permits (Figure 3) and the most on the left distribution of final carbon footprint, but also to the lowest relative importance of emission permits in the meeting of the carbon footprint target.

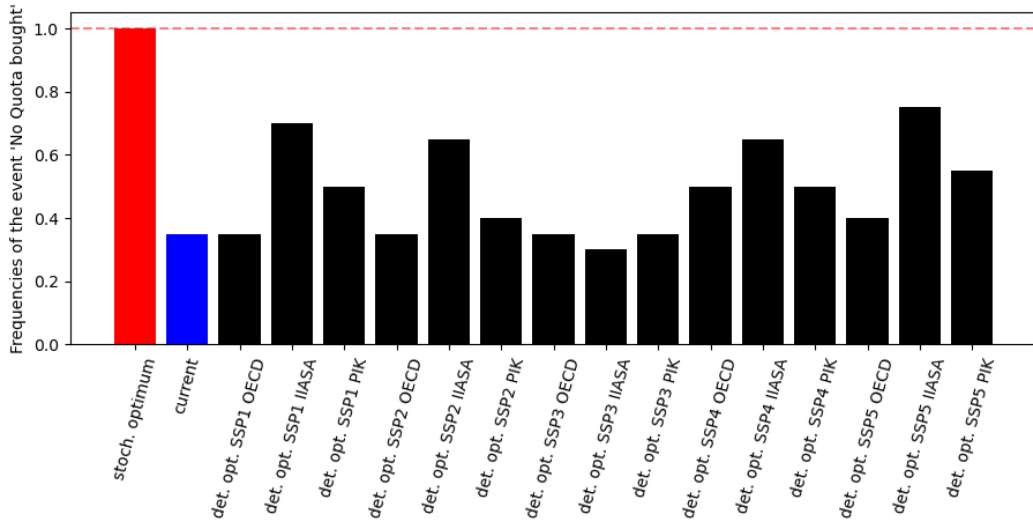


Figure 3: Comparison of frequencies of the event "No necessary supplementary quota" (*i.e.* $Q_1 = 0$) for the robust (stochastic) optimal policy, the current and mean policy and the 20 perfect foresight policies

We look at the actual import shares in the 36 regions framework (Figure 4), as they currently amount to 90% of French imports (French "Direction Générale des Douanes" data). The robust (stochastic) optimal solution is characterised by higher shares devoted to European countries, notably Germany, Spain and the UK. It is also noteworthy that the robust optimum policy leads to zero imports from China, Belgium, or Poland, for instance. This notable difference with the current policy is explained by the projections of the carbon intensities of these countries (see Figure 5 in Appendix A). Indeed, the robust (stochastic) optimal policy concentrates on the countries that have the lowest carbon intensities across the different SSPs. This entails the disappearance of China and Poland — that have clearly higher carbon intensities — while we observe a significant increase of import shares from Germany, Italy, the United States, Spain, Netherlands, the United Kingdom, or even Switzerland. All those latter countries have the relatively lowest carbon intensities under uncertainty. In particular, Japan and Switzerland do not display GHG emissions uncertainty, as experts are very confident in these countries implementing successfully their NDCs (see Benveniste et al. [2018] for an explanation). Note that Belgium, that has a slightly higher carbon intensity distribution, also drops almost to zero like Poland and China. As emissions distributions of countries may clearly be separated in different classes, the robust (stochastic) optimal policy concentrates imports in regions belonging to the class of low emissions countries, as these countries are more carbon-efficient in all considered futures.

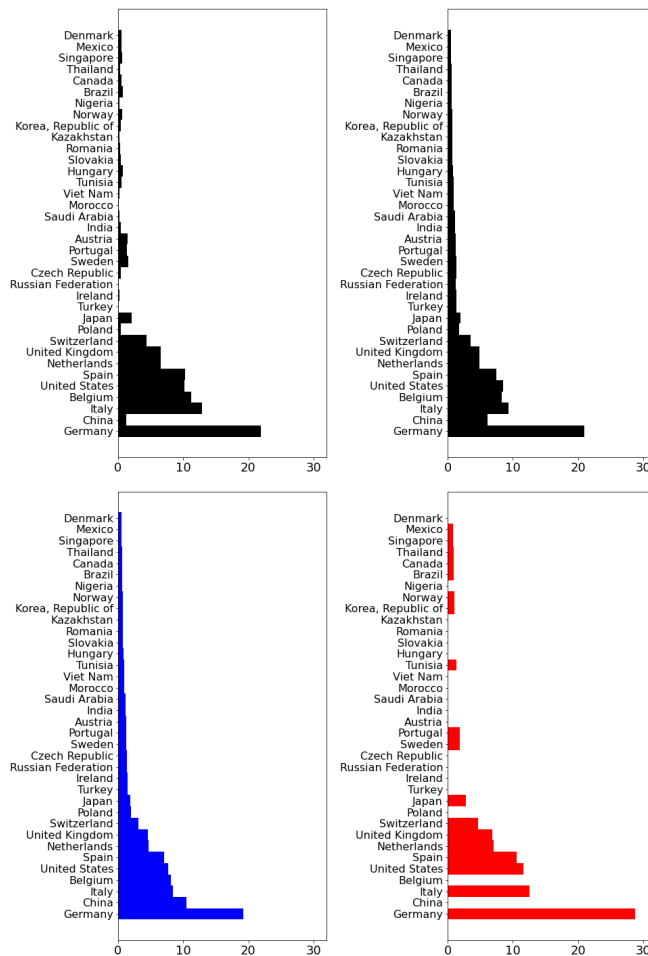


Figure 4: Import shares from the current 36 biggest suppliers of France in the current policy (bottom left in blue), robust (stochastic) optimal policy (bottom right in red) and a selection of 2 (among 20) perfect foresight policies (upper, in black)

4 Conclusion and discussion

Using import shares as decision variables — and aiming to minimize the volume of carbon quotas bought by France in 2030 — we have seen, in this study, that an explicitly stochastic optimization approach would lead to a more robust trade policy than any deterministic one. When tested in various scenarios, the former policy is less likely than the latter to miss the carbon footprint target — i.e. to necessitate the buying of emissions permits — and, when it does, fewer permits are required. On the contrary, perfect foresight (that is, anticipative) policies built to be optimal in a certain version of the future behave better in this version than the robust solution, but worse in all other futures. The greater robustness of our stochastic optimal policy advocates for the diffusion of stochastic optimization frameworks when dealing with scenarios of future, rather than optimizing according to each scenario.

It appears, in Figure 4, that the current French policy is relatively close to the robust (stochastic) optimal policy. This may be explained by the fact that France imports essentially from the European Union — which is composed of countries that have, on the whole, lower carbon intensities of production than the rest of the world. The distributions of GHG emissions provided for these countries by IIASA, CEPII, OECD and PIK have also generally lower spread. It reflects the relative confidence of the experts in, at least, the design of their NDCs and, perhaps, in their strategies to fulfill their NDCs. These lower centers and lower spreads of distributions may explain why countries (mostly non-European) that represented low shares of French total imports (namely less than 1%) or countries subject to debate between experts (such as Belgium) disappear in the robust (stochastic) optimal policy (Figure 4).

It is noteworthy that trade policies are often determined through border tariffs, and not directly import shares. The method we propose could be coupled with a general equilibrium calculation to derive the

optimal border tariffs associated with these import shares. Perhaps the trade policy could also be influenced by non-tariff measures, such as suggested in [Ederington and Ruta \[2016\]](#). Finally, the economic realism of this study is obviously debatable: a real trade policy has to respect WTO agreements and, more generally, to fit in a complex geopolitical and economic context. Still, the objective is to encourage the use of explicitly stochastic frameworks to make decision-making more robust, rather than to yield an effective French optimal trade policy.

A Distributions of carbon intensity for 10 biggest sourcing regions (except China)

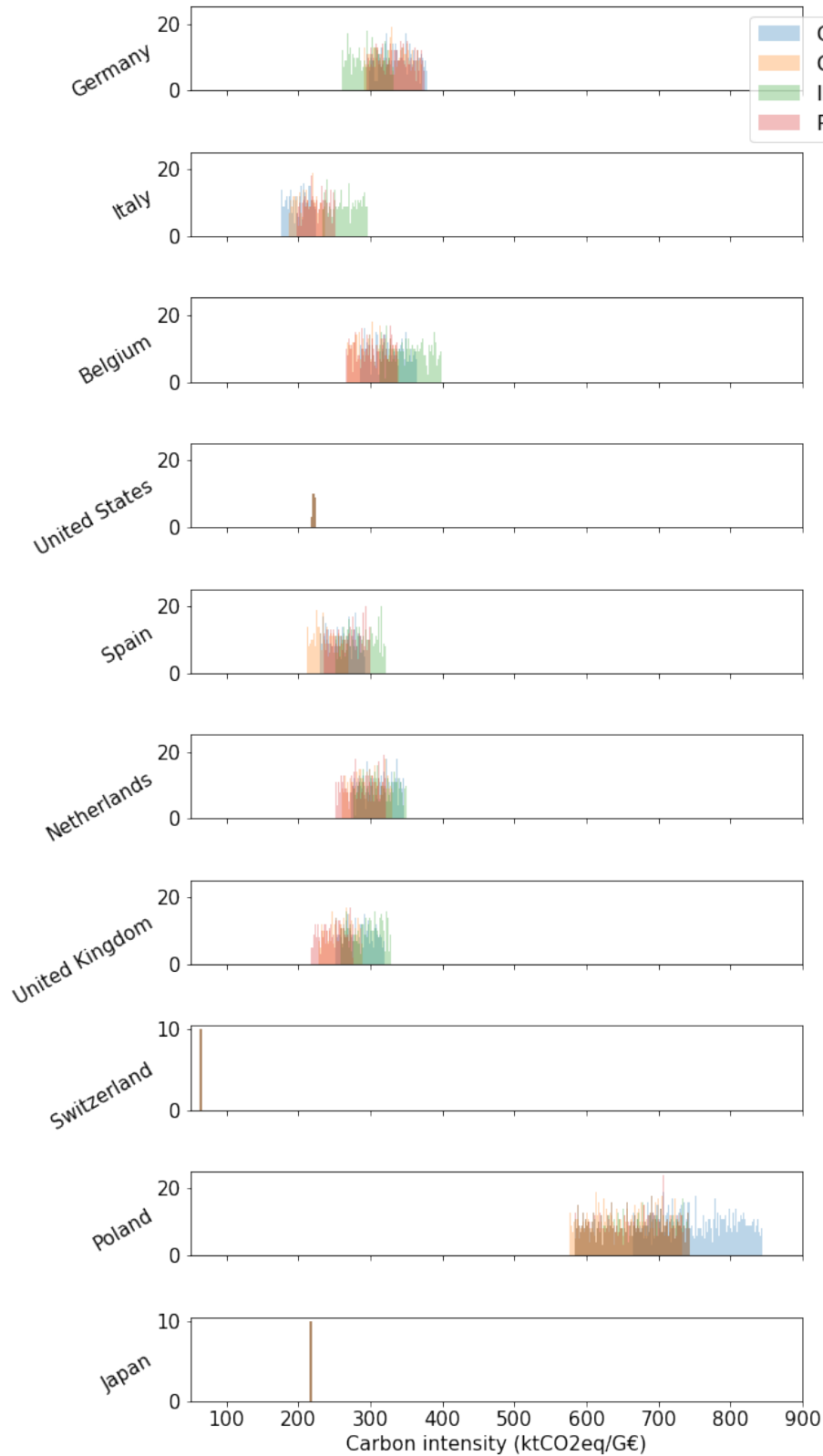


Figure 5: Carbon intensity (in 2030) distributions of the 10 biggest (in 2015) sourcing regions (except China) for the 4 organisms (CEPII, IIASA, OECD and PIK), averaged over the 5 SSPs.

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