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Low Carbon Economy and Energy Finance: Stochastic Models and Methods

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Abstract

In this doctoral thesis, three problems about environment protection are studied. The thesis develops two research fields: the electric vehicles and the electricity market. These two strands are closely related. In the first part, dedicated to electric vehicles, two decision-making models are studied. The first decision-making problem aims at identifying the optimal time at which a representative citizen decides to purchase an electric vehicle. He minimizes a cost functional depending on three main components. The first component is the opportunity cost of driving a fossil-fueled vehicle compared to an electric one for an average distance. The second is the cost occurring in the case of traffic bans (due to air pollution). The third component is the purchase cost of the car lowered by an incentive granted by policymaker.

In the second decision-making problem, a bilevel model is developed. A policymaker identifies the optimal incentive to distribute to a population of fossil-fuelled vehicles owners to incentivize the purchase of an electric vehicle. Vehicles owners differs from each other in terms of average distance travelled and disposable income. The Policymaker minimizes a cost function made by three elements: the direct costs of the incentives, the social costs of air pollution in terms of mortality and health care and the traffic bans cost. Fossil-fueled vehicles owners decide whether to accept the incentive offered by the policymaker. They minimize an individual cost function depending on the cost of the electric vehicle, the disposable income, the incentive offered by the policymaker, on private traffic bans costs and the average opportunity cost of driving a fossil-fuelled vehicle compared to an electric one.

In the second part of the thesis, dedicated to the electricity and environmental markets, a bilevel model is studied. A policymaker determines the optimal number of allowances to maximize the total electricity generation during a finite time horizon. He fixes a minimum percentage of electricity generated from renewable sources, and fixing, at the same time, a minimal blackout risk.. At the second level, two representative electricity producers, given the number of permits decided at the first level, decide the optimal level and the type (conventional or non-conventional) of capacity to install considering the energy demand electric meeting and a budget constraint.

We show that the policymaker has two main tools to lead the fossil-fuelled vehicle owner to purchase an electric vehicle: traffic bans rule and incentive. The incentive, from the policymaker point of view, represents a direct cost while imposing a traffic ban involves an indirect cost, not directly observable, such as, for example, a GDP slowdown. Identifying an efficient environmental policy is a hard task. As for the electric vehicles adoption, the policymaker deals with many factors such as his environmental awareness, his budget, the available income of his citizens, and the air pollution concentration.

As for the electricity market, we show that the ETS does not provide the policymaker an effective control to power producers to reduce emissions and to drive them to substitute conventional plants with renewables. In some cases, the ETS mechanism introduces an opposite incentive, that is one encouraging higher emissions than would obtain under a business as usual settings. Moreover, we show that the weakness of ETS does not depend much on the way the electricity market setting. In all the cases, it turns out that under a business as usual setting both emissions, RES penetration and electricity prices outperforms (from joint environmental and economic points of view) those resulting under an ETS.

Abstract (Italian Version)

In questa tesi di dottorato, vengono studiati tre problemi legati all'ambiente e, in particolare, al miglioramento della qualità dell'aria. La tesi si sviluppa attorno a due filoni di ricerca: i veicoli elettrici e il mercato elettrico. Come si vedrà nel corso della tesi, questi due filoni sono strettamenti collegati.

Nella prima parte della tesi, dedicata i veicoli elettrici, vengono studiati due modelli decisionali. Il primo è volto ad identificare il tempo ottimo in cui un cittadino decide di acquistare un'automobile elettrica minimizzando un funzionale di costo che dipende dal costo opportunità di guidare per una distanza media un veicolo inquinante rispetto ad uno elettrico, dal costo che egli deve sostenere nel caso in cui la circolazione stradale sia interrotta per un eccesso di polveri sottili ed, infine, dal costo di acquisto dell'autovettura al netto di un incentivo fornito dal policymaker. Nel secondo lavoro, viene sviluppato un modello a due livelli in cui un policymaker vorrebbe identificare l'incentivo ottimo da distribuire ad una popolazione di possessori di veicoli inquinanti, per incentivare una percentuale degli stessi all'acquisto di un'automobile elettrica. Gli automobilisti sono eterogenei tra loro per distanza media percorsa e reddito. Il policymaker minimizza una funzione di costo che tiene conto di tre elementi: i costi diretti derivante dagli incentivi, i costi sociali dell'inquinamento in termini di rischio di mortalità e ricoveri ospedalieri e del costo degli arresti del traffico. I possessori di veicoli inquinanti, a loro volta, decidono se accettare o meno l'incentivo offerto minimizzando una funzione di costo che dipende dal costo del veicolo elettrico, dal reddito disponibile, dall'incentivo del policymaker, dai costi associati ai periodi di arresto della circolazione e dal costo opportunità medio di guidare un veicolo inquinante rispetto ad uno elettrico.

Nella seconda parte della tesi, decidata al mercato dei permessi di emissione, viene studiato un modello a due livelli in cui il policymaker determina il numero ottimo di permessi di emissione tali da massimizzare la quantità di energia elettrica prodotta. Egli vorrebbe imporre che una percentuale mimina di energia elettrica venga prodotta da fonti rinnovabili e, allo stesso tempo, ridurre al minimo il rischio di blackout del sistema elettrico. Al secondo livello vengono studiate le decisioni di due produttori di energia elettrica che, basandosi sulla decisione del primo livello (numero di permessi), debbono decidere quanta e di che tipo (convenzionale o non-convenzionale) capacità installare per poter soddisfare la domanda di energia elettrica considerando un vincolo di bilancio.

I risultati mostrano che un policymaker ha a sua disposizione due strumenti principali per incentivare l'acquisto di un'automobile elettrica: gli arresti del traffico e gli incentivi. Dal punto di vista del policymaker, gli incentivi rappresentano un costo diretto mentre gli arresti del traffico producono un costo non direttamente osservabile come, ad esempio, la riduzione del prodotto interno lordo. Pertanto, identificare una politica ambientale efficente è un compito arduo. Per quanto riguarda l'adozione dei veicoli elettrici, il policymaker deve tener conto di diversi fattori quali la propria attenzione all'ambiente, il suo budget di spesa, la concentrazione degli inquinanti e le caretteristiche dei suoi cittadini, in particolare il loro reddito disponibile per gli acquisti.

Per quanto riguarda il mercato elettrico, si è mostrato come il meccanismo degli ETS non si configuri come uno strumento capace né di ridurre le emissioni del settore energetico né di indirizzare i produttori di energia elettrica all'utilizzo di di fonti rinnovabili. Si è visto come, in alcuni casi, il meccanismo degli ETS incoraggi l'aumento delle emissioni in misura maggiore di quelle che si avrebbero senza tale meccanismo. Questi risultati non dipendono dalla struttura che caratterizza il mercato elettrico. In particolare, nelle strutture di mercato analizzate (competitivo e cooperativo), si è dimostrato come le emissioni, l'utilizzo di fonti rinnovabili ed il prezzo dell'elettricità risultino migliori, sia da punto di vista ambientale che economico, nel caso di assenza del meccanismo degli ETS rispetto al caso in cui il meccanismo degli ETS sia attivato.

Contents

Chapter 1

Introduction

1.1 Motivation

This thesis presents three decision problems about environmental protection. In particular the main focus is on policies aiming at reducing air pollution and emissions. This is a major public concern. Among others, (Health Organization, 2019) cites asthma crisis, cardiovascular system alterations, tumors, premature deaths as consequences on human health of the exposure to high air pollution concentration. Health effects are also accompanied by socio-economic costs in terms of increasing number of hospitalizations, mortality risk, just to name a few, as shown in (S. and J., 2020). One of the most harmful pollutant is the Particulate Matter 10, PM_{10}, which is due to natural pollution[1] and human activities, such as industries, domestic heating, fossil-fueled vehicles emissions and many others. The problem of the fossil-fueled vehicles is particularly felt in the urbanized area where fleet electrification can be seen as one of the possible solutions.

From the policymaker's point of view, a central point is understanding how to encourage his citizens to adopt an environmental friendly vehicle. In particular, policymaker should build an environmental strategy considering different aspects, such as his state's features in terms of charging infrastructure development, electricity load distribution and management, and cultural and economical features of people. Looking at his citizens, policymakers deals with two main possible policies to encourage the electric vehicles adoption, purchase-based and use-based policies.

Purchase-based policies are policies used to lower the electric vehicle purchase price (incentives, reduction in registration fee, and others). Use-based policies include, for example, infrastructures development, such as charging station, support for R&D (research and development) and others.

As for the electric vehicles adoption, this thesis focuses on two policymaker's instruments, one for each policy types. We consider incentives as example of purchase-based policy and traffic bans as example of use-based policy. Traffic bans refer to the possibility that, if the PM_{10} concentration exceeds a safety threshold for many days, the fossil-fueled vehicles cannot circulate for a (short) period of time to temporarily reduce PM_{10} concentration. This instrument is frequently used in the Northern Italy and its rules and application modes are supplied in agreement "New Program Agreement for the Coordinated and Joint Replacement of Measures to Improve Air Quality in the Po Valley".

Identifying an environmental strategy based on traffic bans and incentives is not an easy task for the policymaker. Traffic bans and incentive involve indirect and direct costs, respectively.

[1] Natural pollution refers to the pollution created by natural events, such as volcanic eruptions.

Moreover, he needs to look at the different features of his citizens. Those two facts are strongly correlated. If the PM_{10} concentration is high for significant periods of time, the environmental policy may depends on policymaker's budget. On the one hand, if the policymaker has a high budget, he may introduce an incentives scheme to encourage his citizens to purchase an electric vehicle so that he can permanently reduce the air pollution. On the other hand, of the policymaker cannot finance an incentive scheme, he can base his environmental strategy on traffic bans. A further problem is added because the decision to accept the incentive or not is entirely in the hands of his citizens while, on the contrary, they cannot escape traffic stops.

Moreover, the policymaker's reasoning cannot fail to take into consideration the cultural and socio-economic features of citizens, as, for example, distance travelled and wealth. An environmental policy that does not consider those two features may be ineffective. If both features are low, policymaker may construct the environmental policy through incentive scheme rather than traffic bans. On the opposite case, an environmental policy based on traffic bans may be the appropriate one.

Fleet electrification cannot be seen as the unique solution to improve the air quality. It has to be combined to a strong use of renewable in the electricity generation. The use of electric vehicles involves a higher electricity demand. To avoid blackout problems, the additional electricity demand has to be covered increasing the electricity generation and to prevent the environmental benefits of electric vehicles use being wiped out, the additional electricity should be generated from renewable sources. Though renewable sources have many advantages (unlimited resource availability, low generation costs), their uncertainty set up several problems in the electricity generation (predictability and variability).

As for the greenhouse gases emission reduction, several policymakers have introduced an Emission Trading System (ETS). This mechanism is cap-and-trade scheme based on the idea that each tons of CO_2 emissions has to be covered by an allowance. With this mechanism, policymakers want to reduce the greenhouse gas emissions keeping a sustainable and high level of economic growth and providing low electricity prices. Focusing on the electricity sector, the ETS scheme can be effective if the electricity producers generate energy switching to renewables sources. The use of renewable sources involves further problems. The uncertainty of renewables generation can causes a mismatching between energy demand and supply. The latter leads to blackouts in the electricity system with a general loss of wealth. Moreover, the use of renewables leads to a lower the electricity price which hinder producers' profits. The unpleasant situation can lead the electricity producers to keep substantial shares of pollutant technologies to sustain the electricity price. Additionally, the introduction of emissions-containing policies leads to additional cost factor that inevitably ends up shifting to final consumer prices. This thesis analyzes the problem of how a policymaker can control the energy-mix of the electricity sector acting on the quantity of allowances issued on the ETS.

1.2 Contributions

1.2.1 Chapter 2

This chapter considers a representative owner of a fossil-fueled vehicle deciding the time at which purchasing an electric vehicle. The decision is taken with the aim of minimizing the total expected costs accrued when driving the fossil-fueled vehicle for a given distance. The first cost is the opportunity of driving one unit distance with a traditional fossil-fueled vehicle instead of an electric one, whenever fossil fuel is more expensive than electricity. The cost difference between the two fuels is assumed to be stochastic and evolving as a (one-dimensional) Itô's diffusion. A second cost faced by the agent comes from the fact that traffic bans for fossil-fueled vehicles can happen at certain times chosen by the policymaker. We assume that those traffic stops happen at a given constant rate according to some criterion chosen by the policymaker. The introduction of the latter cost is strongly motivated by the real-world pollution's reduction policies applied, for example, in the Northern of Italy. The last cost incurred by the agent is the purchase cost of an electric vehicle, net of the possible incentive ensured by the policymaker.

With regards to the methodology, the agent's decision problem is modeled as an optimal stopping problem and solved by relying on a classical guess-and-verify approach, which is based on the construction of candidate value function and optimal stopping time whose actual optimality is then verified through a verification theorem. The approach of (Alvarez, 2001) on optimal stopping problems for one-dimensional regular diffusions is used and it is shown that the optimal adoption time is of barrier-type. Indeed, the fossil-fueled vehicle's owner should switch to an electric vehicle only when the opportunity cost is sufficiently large. In a case study, the opportunity cost is assumed to evolve as an Ornstein-Uhlenbeck process. The model is calibrated using real data from Italy and the study of the expected switching time with respect to frequency of traffic bans and incentive is shown. An interesting result is that incentives and the frequency of traffic bans on fossil-fueled transport can be effective tools in the hand of the policymaker to encourage the adoption of electric vehicles, and hence to reduce pollution.

1.2.2 Chapter 3

This chapter investigates how an environmental policy, based on incentives, encourages a population of fossil-fueled vehicle owners to switch to an electric vehicle. Individuals minimize a cost function that depends on the incentive granted by the policymaker. The policymaker, on his side, wishes to minimize a cost function including economic incentives, public health costs and traffic bans costs. PM_{10} concentration is modeled as a discrete mean-reverting process with a controlled long-term average. The latter, in fact, depends also on the percentage of fossil-fueled vehicle owner deciding to purchase an electric vehicle which is connected to the incentive granted by the policymaker. A second novelty is concerned with the construction of an analytical model to identify the expected number of traffic bans which depends on the PM_{10} concentration. The third novelty lies in the fact that we describe the different features of that population: each vehicle owner is seen as realizations of a bivariate random variable representing the disposable income and the distance traveled. Policymaker's cost function depends directly on the number of electric vehicles incentivized. Moreover, our is the first paper where social and traffic bans cost appear in the objective function of the policymaker. The social costs, including the healthcare costs and the mortality risk costs, depend on the long-run average of PM_{10} concentration, which, as stated before, is a function of the electric vehicle incentivized by the incentive. Similarly, also the traffic bans costs depend on the PM_{10} concentration. A relevant contribution of this chapter is concerned with the methodological treatment of the problem. Due to the different features in terms of disposable income and distance travelled and boolean decision type of the fossil-fueled vehicle owner, we are able to identify an incentive, shared by a percentage of fossil-fueled vehicle owners, that reduce the initial stochastic bilevel multifollower problem to a deterministic single level (constrained) optimization model. The steps are made assuming that the population of the fossil-fueled vehicle owners, at first, is described as a discrete population and then, for analytical treatment, it is assumed to be composed by a continuous number of individuals.

1.2.3 Chapter 4

This chapter contributes to the existing literature by investigating the optimal number of allowances to be issued and, by analyzing how an ETS affects the energy-mix decision and the profits of two electricity producers. The considered market structure is based on two large companies of electricity producers working in an energy-only electricity market. Besides, the two producers differ in their technology mix: one owns Renewables Energy Source (RES) and coal plants, the other producer owns RES and gas plants. At the upper level policymaker aiming at maximizing the total electricity generated, keeping blackout risk at a minimum and ensuring a minimum percentage of RES penetration. The model is developed adopting a stochastic programming method, where the random scenarios consist of realizations of three sources of uncertainty: coal and gas prices and daily electricity demand. As novelty, the trajectories of the three stochastic processes are obtained through a multivariate Markov Chain bootstrapping. Coal and gas plants have different emission rates, and this influences producers in their optimal decision as to how to expand their energy-mix (also called technology portfolio), under a given budget constraint. The electricity price is endogenously calculated by the intersection between stochastic electricity demand and supply. A novelty aspect is also that the allowances price is endogenously calculated and it is determined as a risk neutral expectation of the future payoff. Moreover, our model extends the literature since it includes both short and long-terms effects of an ETS scheme. In the short-term, the allowances price triggers the fuel switch decision and the actual emissions, while the long-term impact is captured by the optimal energy-mix decision.

To deal with the game between the two producing companies, at first a large grid of the possible solutions for the two players, including both Pareto efficient and inefficient ones, is considered. Then just two solutions are chosen among the Pareto efficient solutions. The first solution represents the situation of competition where the two companies minimize the difference between their expected net present profits. The second solution is more cooperative in the sense that the two companies maximize the summation of their expected profits (i.e. maximize the profit to the power sector).

1.3 Organization of the thesis

The thesis is divided into two main parts:

- The first part is dedicated to the electric vehicles adoption decision. Two decision method for the electric vehicle adoptions are provided. At first, a representative agent's decision is considered and, later the interactions between a policymaker and his citizens are analyzed.
- The second part is dedicated to the electricity sector. A decision method to reduce electricity sector emissions is provided. The second part considers the interactions between a policymaker and an oligopolistic electricity sector.

The thesis is organized in four chapter:

- Chapter 1 presents an overview of the research question and the methodologies used in the thesis.
- Chapter 2 presents real options model for the optimal adoption of an electric vehicle considering a policymaker promoting the abeyance of fossil-fueled vehicles through an incentive, and the representative fossil-fueled vehicle's owner decides the time at which buying an electric vehicle, while minimizing a certain expected cost. After determining the optimal switching time and the minimal cost function for a general diffusive opportunity cost, we specialize to the case of a mean-reverting process. Finally, the effect of traffic bans and incentive on the expected optimal switching time is studied with a simulated case study.

- Chapter 3 investigates through a bilevel model the interactions between a policymaker and a population of vehicle owners. The policymaker aims at minimizing a cost function deciding the optimal incentive to encourage the largest possible percentage of the fossil-fueled vehicle owners to purchase an electric vehicle. Fossil-fueled vehicle owners have to decide about purchasing or not an electric vehicle. Both policymaker and fossil-fueled vehicle owners care about PM_{10} concentration. In particular the policymaker can decide to impose a traffic ban if the PM_{10} concentration exceed the safety threshold for many consecutive days. These stops generate a cost to the owners of a fossil-fueled vehicle. The initial bilevel formulation is reduced to a single level problem and then we solve it analytically.

- Chapter 4 investigates the impact of ETS on the emissions and the energy-mix through a bilevel model where the policymaker interacts with an oligopolistic electricity market over a finite time horizon. At the upper level, the policymaker aims at maximizing a welfare function deciding the optimal number of allowances to be distributed to the electricity market. At the lower level, the electricity market, represented by two large companies, decide the optimal long-term capacity expansion between conventional and non-conventional technologies. The uncertainty is modeled through scenarios, obtained using Markov chain bootstrapping, made of coal and gas prices and electricity demand. The problem is solved considering a large set of efficient equilibrium solution between the two electricity producers.

Part I

Electric Vehicles

Chapter 2

Optimal Switch from a Fossil-Fueled to an Electric Vehicle

This chapter is based on the article: Falbo P., Ferrari G., Rizzini G., Schmeck M.D., *Optimal Switch from a Fossil-Fueled to an Electric Vehicle,* which is currently under review in Decisions in Economics and Finance.

2.1 Introduction

It is well known that air pollution is increasing each day for many reasons. The increase depends on the number of fossil-fueled vehicles on the road, industrial emissions, especially in energy sector (see (Canadell et al., 2007), (Huisingh et al., 2015a)), domestic heating, transportation system, and many others (cf. (Health Organization, 2019)). Several studies have shown the connection between air pollution and human health damages, such as acute inflammation of the respiratory tract, asthma crisis, alterations in the functioning of the cardiovascular system, tumors etc.; for reference, see, for example, (Gautam and Bolia, 2020) and (S. and J., 2020). Moreover, it is estimated that air pollution causes around 7 million premature deaths in 2016 worldwide (Health Organization, 2019).

Various studies identify road traffic emissions as one of the major contributors to air pollution in the urban area (see (Colvile et al., 2001), (Belis et al., 2013), (Karagulian et al., 2015)). This is confirmed also, for example, in (Gualtieri et al., 2020), (Liu et al., 2020) and (Chen et al., 2020), which affirm that the traffic restriction due to the lockdown actions have decreased air pollution. Numerous solutions to road traffic pollution have been conjectured and, among these, fleet electrification is seen as one of the most practical. In (Soret et al., 2014) it is shown how transportation fleet electrification could be a good solution for improving air quality with two study cases of Madrid and Barcelona cities. The reduction of pollutants' concentration through incentive policies for the adoption of electric vehicles is also confirmed in (Zhao and Heywood, 2017) and (Laberteaux and Hamza, 2018).

As many authors state (see, for example, (Abdul-Manan, 2015; Nichols et al., 2015)), the road transportation electrification cannot be seen as the unique solution to the pollution problem. The road fleet electrification needs to be accompanied by an environmental policy which induces the strong use of renewable in the electricity generation. A subsidies scheme can be a possible strategy to achieve the aim of using renewables in electricity generation, as shown in (Bigerna et al., 2019). It is shown in (Buekers et al., 2014) that, in terms of external costs, the economic benefit for a country adopting electric vehicles can be positive or negative depending on the country's energy generation mix. The authors show that countries with energy mix depending on renewable sources may profit in terms of avoided external costs, such as the reduction of healthcare and social costs due to air pollution. The same findings can be read in (Casals et al., 2016) and (Onat et al., 2015).

To achieve the goal of reducing emissions through vehicle fleet electrification, policymakers throughout the world face the enduring public policy problem of how to encourage the adoption of electric vehicles. Public policy actions can be divided into direct and indirect actions. The diffusion of direct and indirect actions varies across countries because of several factors that characterize each case; e.g., charging infrastructure development, electricity load distribution and management, and cultural and economical features of people (differentiated through their personal income, willingness to pay, perceived risk, as well as psychological aspects like moral values and behavior).

Direct interventions – also called purchase-based incentive policies – are used in order to lower the electric vehicle purchase price. They include financial incentives, reduction in registration fee, registration tax, and vehicle ownership tax. On the other hand, indirect actions – also called use-based incentive policies – include, for example, the implementation of infrastructures, such as charging station and support for R&D (research and development). For the EU area, a literature review on direct and indirect actions can be found in (Cansino et al., 2018), where the different policies adopted by member states are compared.

Our work. In this paper, we consider a representative owner of a fossil-fueled vehicle deciding the time at which purchasing an electric vehicle. The decision is taken with the aim of minimizing the total expected costs accrued when driving the fossil-fueled vehicle for a given distance. The first cost is the opportunity of driving one unit distance with a traditional fossil-fueled vehicle instead of an electric one, whenever fossil fuel is more expensive than electricity. The cost difference between the two fuels is assumed to be stochastic and evolving as a (one-dimensional) Itô's diffusion. A second cost faced by the agent comes from the fact that traffic bans for fossil-fueled vehicles can happen at certain times chosen by the policymaker. We assume that those traffic stops happen at a given constant rate according to some criterion chosen by the policymaker. The introduction of the latter cost is strongly motivated by the real-world pollution's reduction policies applied, for example, in the Northern of Italy. The last cost incurred by the agent is the purchase cost of an electric vehicle, net of the possible incentive ensured by the policymaker.

With regards to the methodology, we model the agent's decision problem as an optimal stopping problem and we solve it by relying on a classical guess-and-verify approach, which is based on the construction of candidate value function and optimal stopping time whose actual optimality is then verified through a verification theorem. In order to deal with our general diffusive setting, we employ the approach of (Alvarez, 2001) on optimal stopping problems for one-dimensional regular diffusions, and we show that the optimal adoption time is of barrier-type. Indeed, the fossil-fueled vehicle's owner should switch to an electric vehicle only when the opportunity cost is sufficiently large (i.e., when the price of fossil fuel is sufficiently higher than that of electricity).

In a case study, we take the opportunity cost evolving as an Ornstein-Uhlenbeck process. Using real data from Italy, we validate statistically the chosen dynamics of the opportunity cost process and we calibrate the model. We then apply the decision model to study the dependency of the optimal switching time with respect to the various model's parameters. Moreover, we present the study of the expected switching time with respect to frequency of traffic bans and incentive. In particular, we show that economic incentives and the frequency of traffic bans on fossil-fueled transport can be effective tools in the hand of the policymaker to encourage the adoption of electric vehicles, and hence to reduce pollution.

Related literature. Several papers consider the decision of switching to an electric vehicle for a representative consumer/vehicle owner using a real options approach. In (Moon and Lee, 2019) it is investigated the decision of a consumer that aims at purchasing an electric vehicle by taking into account the total cost of ownership. The latter depends on fuel price uncertainty (modeled through a discrete binomial model) and technological advancements. Data are taken from the Korean market and the authors illustrate that, even without incentives, electric vehicles are more cost-effective than fossil-fueled ones. Moreover, the authors show that, when the uncertainty in fuel price decreases, people willingness to purchase an electric vehicle increases. (Agaton et al., 2019) presents an investment problem for a transportation operator deciding whether to purchase a fossil-fueled jeeps or electric jeeps fleet, by considering a governmental incentive and diesel price uncertainty. The latter follows geometric Brownian dynamics. The authors show that, considering the current Philippines' market structure, the optimal decision is to purchase a fleet of electric jeeps immediately. Moreover, it is suggested to governments to increase the incentive, the implementation of public charging stations, and the use renewable sources for electricity generation. A decision problem for a consumer who minimizes her transport expenditures is addressed in (He et al., 2017). The representative consumer wishes to optimally replace her old fossil-fueled vehicle by an hybrid electric vehicle. To this purpose, she considers government's incentives for the replacement and fossil fuel price uncertainty (modeled as a geometric Brownian motion). The authors show that incentives, uncertainty in fossil fuel price and distance traveled affect the replacement time. Moreover, when fuel price increases, the effect of incentive is attenuated, while a decrease in fuel price volatility reduces the replacement time.

Among the works taking instead the point of view of a company producing cars or of a policymaker, we refer to (Nishihara, 2010), (Kang et al., 2018), (Yamashita et al., 2013), and (Ansaripoor and Oliveira, 2018). In (Nishihara, 2010) the authors consider an automaker's whose cash-flows are modeled through a geometric Brownian motion. The automaker aims at promoting an hybrid vehicle, with the option to change the promotion to an electric vehicle in a future time. (Kang et al., 2018) investigates the decision of a manufacturer deciding the optimal time at which launch a new vehicle segment or to redesign the existing one under market uncertainty, which is modeled through gas price and regulatory standards. The decisions refer to the optimal timing and the choice of vehicles engine-type, which can be gas, electric and hybrid. In (Yamashita et al., 2013) it is investigated the development of plug-in electric vehicles' market by considering fuel price uncertainty and the availability of charging infrastructure. The policymaker has to determine the optimal incentive policy that can be used either to reduce the electric vehicle net purchase price or to build new charging infrastructures. The authors show that an increase in fuel price leads to a decrease in the incentive's effectiveness and to an increase in the electric vehicles' adoption. Finally, (Ansaripoor and Oliveira, 2018) studies the use of flexible lease contracts to determine the optimal number of vehicles to be leased minimizing simultaneously the risk (Recursive Expected Conditional Value at Risk) and the costs. The firm has to decide which type of engine among fossil-fueled, hybrids, and electric has to be used. Uncertainty is about CO_2 prices, fuel prices, distance traveled, fuel consumption, and technological aspects. The authors show that, when considering the technological change of electric vehicles, electric vehicles are the preferred technology for leasing.

Our work contributes to the literature employing a real options approach for the adoption of electric vehicles. In particular, differently to the existing works, we are able to accommodate in our model the possibly general and mean-reverting behavior of the opportunity cost, as well as the costs incurred by the representative agent because of the environmental policies employed by the policymaker in the form of traffic bans for fossil-fueled vehicles. To the best of our knowledge, the presence of these modeling features appear here for the first time within the literature on electric vehicles' optimal adoption problem.

The rest of the chapter is organized as follows. Section 2.2 formulates the problem within a general diffusive setting and presents its solution. Section 2.3 is devoted to the case study in which the opportunity cost process follows a mean-reverting dynamics and parameters' calibration. Section 2.4 shows theoretical and numerical sensitivity results. Section 2.5 provides a numerical simulation of the expected optimal switching time. Finally, Section 2.6 collects concluding remarks on policy implications, while Appendix .A recaps some mathematical details related to one-dimensional regular diffusions and Appendix .B presents the proof the main theorem

2.2 Problem formulation and Solution

2.2.1 Problem Formulation

We consider a fossil-fueled vehicle owner that aims, over an infinite time horizon, to manage her mobility costs. Buying an electric vehicle, she receives a fixed amount of money by a policymaker that wants to boost the adoption of green transport in order to reduce air pollutants' concentration. The fossil-fueled vehicle owner drives for an average distance of ℓ (per unit of time) and her aim is to determine the time at which to adopt an electric vehicle, while minimizing a certain cost functional. The latter is composed by different types of costs. The first involves the running stochastic opportunity cost per unit distance $\{X_t\}_{t\geq 0}$ of driving a fossil-fueled vehicle instead of an electric one. The second is the cost c associated to each traffic ban for fossil-fueled vehicles occurring at some random time[1]. The policymaker, for environmental reasons, imposes traffic bans at certain exogenous (random) times.[2] The third is the sunk purchase cost of the electric vehicle, I, net of the financial incentive, k, ensured by the policymaker. We assume, as natural, that $I > k > 0$.

With this specification, the total expected cost incurred up to the switching time τ

$$\mathbb{E}\left[\int_0^\tau e^{-\rho t}\ell X_t dt + \int_0^\tau e^{-\rho t} c dN_t + e^{-\rho\tau}(I-k)\right]. \tag{2.1}$$

Here, ρ is a personal discount factor and $\{N_t\}_{t\geq 0}$ is a counting process of the traffic bans. The expectation is taken with respect to the joint law of the process X and N, defined on some common complete filtered probability space $(\Omega, \mathcal{F}, \mathbb{F} := (\mathcal{F}_t)_t, \mathbb{P})$. Moreover, we assume that

[1] In many Italian cities, air pollution has spiked above the safety threshold of $50\frac{\mu g}{m^3}$ for many consecutive days during each year. Therefore, several cities have introduced restrictions on driving such as a ban on fossil-fueled vehicles. This happens, for example, in Northen Italy.

Air pollution is typically worst in Northern Italy, where densely populated cities, industry and farming create emissions and mountains trap it in low-lying plains. In the Italian context, we refer to the Temporary Limitations of 1st Level to Road Traffic of the document New Program Agreement for the Coordinated and Joint Adoption of Measures to Improve Air Quality in the Po Valley signed in Bologna on June 9th, 2017 by Italian Minister Galletti and the presidents of the regions of Po Basin (Emilia Romagna, Veneto, Lombardy and Piedmont) and adopted by Lombardy region with D.G.R. Number X/6675 of July 06th, 2017. See (Regione Lombardia, 2017).

[2] In the reality, both decision of imposing a traffic ban and its length consider also the forecasted weather conditions since windy or rain days can make the PM_{10} concentration fall over. In this chapter, we do not consider weather conditions assuming that each traffic ban has an average length of 2 days.

no anticipation is allowed and that any decision is taken with respect to (w.r.t.) the flow of information $\mathbb{F}$; that is, we let τ be an $\mathbb{F}$-stopping time.

Assuming that the process $\{N_t\}_{t\geq 0}$ is an homogeneous Poisson process with constant intensity λ, independent from $\{X_t\}_{t\geq 0}$, and noting that the compensated Poisson process $\{N_t - \lambda t\}_{t\geq 0}$ is a martingale, by the Optional Sampling Theorem (see, e.g., Theorem 3.22 in Chapter 1 of (Karatzas and Shreve, 1991)), we have (up to a standard localization procedure)

$$\mathbb{E}\left[\int_0^\tau ce^{-\rho t}dN_t\right] = \mathbb{E}\left[\int_0^\tau ce^{-\rho t}\lambda dt\right].$$

Hence, the cost functional (2.1) equivalently rewrites

$$\mathbb{E}\left[\left(\int_0^\tau e^{-\rho t}\ell X_t dt + \int_0^\tau e^{-\rho t}\lambda c dt\right) + e^{-\rho\tau}\left(I-k\right)\right], \tag{2.2}$$

where we see that the fossil-fueled vehicle owner faces now a running cost λc associated to an average number λ of traffic bans per unit of time. Notice that in Equation (2.2) we do not consider any vehicle maintenance costs since those must be paid both for an electric and a fossil-fueled vehicle, and they can be supposed of similar value.

Then, the fossil-fueled vehicle owner aims at finding when to switch to an electric vehicle so that her total costs are minimized; that is, she aims at solving

$$\inf_{\tau\geq 0}\mathbb{E}\left[\int_0^\tau e^{-\rho t}\ell X_t dt + \int_0^\tau e^{-\rho t}\lambda c dt + e^{-\rho\tau}\left(I-k\right)\right]. \tag{2.3}$$

From Equation (2.3) we see that the decision of the fossil-fueled vehicle owner should only depend on the evolution of the process $\{X_t\}_{t\geq 0}$; that is, on the opportunity cost of driving one unit distance with a fossil-fueled vehicle instead of an electric one (in the sequel, we shall also write "the unit distance opportunity cost").

The process $\{X_t\}_{t\geq 0}$ is assumed to evolve according to the stochastic differential equation (SDE)

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t, \tag{2.4}$$

with initial condition $X_0 = x \in \mathcal{I}$, $\mathcal{I} := (\underline{x}, \overline{x})$, with $-\infty \leq \underline{x} < \overline{x} \leq +\infty$. Here, $\mu, \sigma : \mathcal{I} \to \mathbb{R}$ are Borel-measurable and such that

$$\sigma^2(x) > 0, \quad x \in \mathcal{I}, \tag{2.5}$$

and, $\forall x \in \mathcal{I}$, there exists $\varepsilon > 0$ (depending on x) such that

$$\int_{x-\varepsilon}^{x+\varepsilon} \frac{1 + |\mu(z)|}{\sigma^2(z)} dz < \infty. \tag{2.6}$$

Remark 1 (2.5) *expresses a nondegeneracy condition, while* (2.6) *is a local integrability condition.*

According to the results in Chapter 5 of (Karatzas and Shreve, 1991), SDE (2.4) admits a weak solution $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P}_x, W, X)$. Moreover, the stochastic basis is unique in the sense of probability law (see, e.g., (Karatzas and Shreve, 1991), Theorem 5.15 in Chapter V) and from now on, we will consider the stochastic basis $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P}_x, W, X)$ given and fixed. Moreover, in order to stress the dependency of X on its initial level x, we denote the solution associated to

(2.4) as $\{X_t^x\}_{t\geq 0}$. Finally, in the rest of the paper, we use the notation $\mathbb{E}\left[f\left(X_t^x\right)\right] = \mathbb{E}_x\left[f\left(X_t\right)\right]$, where $\mathbb{E}_x$ represents the expectation conditioned on $X_0 = x$.

Under the previous assumptions on μ and σ, the process $\{X_t^x\}_{t\geq 0}$ is a regular diffusion; that is, starting from x, it can reach any other $y \in \mathcal{I}$ in finite time with positive probability. In light with our subsequent application, we also assume that the boundary points $\underline{x}$ and $\overline{x}$ of the domain $\mathcal{I}$ are natural for X^x; that is, they cannot be reached in finite time with positive probability (see Chapter I of (Borodin and Salminen, 2002) for further details).

For future use, we also define $\mathcal{L}_X$ as the infinitesimal generator of the process X given by the second-order linear differential operator

$$\mathcal{L}_X = \frac{1}{2}\sigma^2\left(x\right)\frac{d^2}{dx^2} + \mu\left(x\right)\frac{d}{dx},$$

acting on two-times continuously differentiable functions. Moreover, we let $\psi_\rho(x)$ be the strictly increasing fundamental solution to $(\mathcal{L}_X u - \rho u) = 0$ and m' be the speed measure density of X (cf. Appendix .A for details).

Remark 2 *The assumptions on the process X made so far are satisfied in relevant cases, as in the case of Brownian motion with drift (i.e., $\mu\left(x\right) = \mu \in \mathbb{R}$ and $\sigma\left(x\right) = \sigma > 0$), and in the case of Ornstein-Uhlenbeck process (i.e., $\mu\left(x\right) = \theta\left(\mu - x\right)$, for some constants $\theta > 0$, $\mu \in \mathbb{R}$ and $\sigma\left(x\right) = \sigma > 0$). Those processes take values on $\mathcal{I} = \mathbb{R}$, so that $\underline{x} = -\infty$ and $\overline{x} = +\infty$.*

Since the value of the stopping functional (2.2) only depends on the law of the unit distance opportunity cost process X, given the underlying Markovian structure, we can define the value of the problem as

$$V\left(x\right) := \inf_{\tau\geq 0}\mathbb{E}_x\left[\int_0^\tau e^{-\rho t}\left(\ell X_t + \lambda c\right)dt + e^{-\rho\tau}\left(I - k\right)\right], \quad x \in \mathcal{I}, \tag{2.7}$$

where x represents the initial condition of process X, and the optimization is taken over the set of $\mathbb{F}$-stopping times.

The expectation in (2.7) can be clearly rewritten as

$$V\left(x\right) = \mathbb{E}_x\left[\int_0^\infty e^{-\rho t}\left(\ell X_t + \lambda c\right)dt\right] + \inf_{\tau\geq 0}\mathbb{E}_x\left[-\int_\tau^\infty e^{-\rho t}\left(\ell X_t + \lambda c\right)dt + e^{-\rho\tau}\left(I - k\right)\right],$$

where the first expectation above is the value of the option of never switching to an electric vehicle. Then, setting

$$\mathcal{U}\left(x\right) := \inf_{\tau\geq 0}\mathbb{E}_x\left[-\int_\tau^\infty e^{-\rho t}\left(\ell X_t + \lambda c\right)dt + e^{-\rho\tau}\left(I - k\right)\right]$$

and

$$\widehat{V}\left(x\right) := \mathbb{E}_x\left[\int_0^\infty e^{-\rho t}\left(\ell X_t + \lambda c\right)dt\right],$$

we have that

$$V\left(x\right) = \widehat{V}\left(x\right) + \mathcal{U}\left(x\right), \tag{2.8}$$

where, by the help of strong Markov property,

$$\mathcal{U}\left(x\right) = \inf_{\tau\geq 0}\mathbb{E}_x\left[e^{-\rho\tau}\left(\left(I - k\right) - \widehat{V}\left(X_\tau\right)\right)\right]. \tag{2.9}$$

In the rest of this paper we make the standing assumption that

$$\mathbb{E}_x\left[\int_0^\infty e^{-\rho t}|X_t|dt\right] < \infty \tag{2.10}$$

(so that $|V| < \infty$), and that

$$\lim_{x\to\underline{x}} \frac{\psi_\rho(x)\left(I-k-\widehat{V}\right)'(x) - \psi'_\rho(x)\left(I-k-\widehat{V}\right)(x)}{S'(x)} = 0. \tag{2.11}$$

Then, for any Borel-measurable function g we adopt the convention

$$e^{-\rho\tau}g\left(X^x_\tau\right) := \varliminf_{t\uparrow\infty} e^{-\rho t}g\left(X^x_t\right) \quad \text{on} \quad \{\tau = \infty\}. \tag{2.12}$$

The latter, in particular, ensures that the stopping cost $e^{-\rho\tau}(I-k-\widehat{V}(X^x_\tau))$ is well-defined on the event $\{\tau = \infty\}$.

Remark 3 *Notice that* (2.10) *has to be verified as a case by case basis. For example, it always holds true if X is a Brownian motion or an Ornstein-Uhlenbeck process. It is satisfied when $\rho > \mu$ if X is a geometric Brownian motion.*

From now on we focus on the optimal stopping problem (2.9) since it shares the same optimal strategy with V (cf. (2.7)), and since we can then obtain V from (2.8).

Remark 4 *In the case of finite time horizon, the optimal time τ^* will depend also on the time to maturity and it will change drastically the problem's solution (see, for example, (Peskir and Shiryaev, 2006) for further details). Qualitatively, we expect the same (w.r.t. the infinite time horizon case) results behaviors although the presence of the time to maturity constraint will reduce the optimal time.*

2.2.2 Problem Solution

We can reasonably expect that the agent would adopt an electric vehicle once the opportunity cost is sufficiently large. Hence, we can conjecture that there exists some critical level $x^* \in \overline{\mathbb{R}}$ such that $\tau^* = \inf\{t \geq 0 : X^x_t \geq x^*\}$ is optimal for (2.9) (hence for V). The following theorem provides the complete description of the problem's solution within the general setting described in the previous section. Its proof can be found in Appendix .B, where we follow the approach of (Alvarez, 2001).

Theorem 5 *We have the next three cases.*

(a) If

$$\lim_{x\to\underline{x}}(\ell x + \lambda c) < \rho(I-k) < \lim_{x\to\overline{x}}(\ell x + \lambda c) \tag{2.13}$$

then one has

$$\mathcal{U}(x) = \begin{cases} \left(I-k-\widehat{V}(x^*)\right)\frac{\psi_\rho(x)}{\psi_\rho(x^*)}, & \text{for} \quad x < x^*, \\ I-k-\widehat{V}(x), & \text{for} \quad x \geq x^*, \end{cases} \tag{2.14}$$

where x^* is the unique solution in $(\hat{x}, \infty)$, $\hat{x} := \frac{1}{\ell}(\rho(I-k) - \lambda c)$, to the integral equation

$$\int_{\underline{x}}^{x^*} \psi_\rho(y)\, m'(y)\big(\ell y + \lambda c - \rho(I-k)\big)dy = 0. \tag{2.15}$$

Moreover $\tau^* := \inf\{t \geq 0 : X_t^x \geq x^*\}$ *is optimal for* $\mathcal{U}$ *(hence for* V*).*

(b) If $\lim_{x\to\overline{x}} (\ell x + \lambda c) < \rho (I - k)$*, then it is never optimal to switch; i.e.* $\widehat{\mathcal{U}}(x) = 0$, $x \in \mathcal{I}$*, and* $\tau^* = +\infty$ $\mathbb{P}_x$*-a.s. (hence* $V(x) = \widehat{V}(x)$*).*

(c)If $\lim_{x\to\underline{x}} (\ell x + \lambda c) > \rho (I - k)$*, then it is optimal to switch immediately; i.e.* $\widehat{\mathcal{U}}(x) = I - k - \widehat{V}(x)$, $x \in \mathcal{I}$*, and* $\tau^* = 0$ $\mathbb{P}_x$*-a.s. (hence* $V(x) = I - k$*).*

2.3 Model's Analysis in a case study with mean-reverting dynamics

In this section we assume that in (2.4), one has $\mu(x) = a - bx$ for some constants $b > 0$, $a \in \mathbb{R}$ and $\sigma(x) = \sigma > 0$. This means that the unit distance opportunity cost is described by a mean-reverting process with dynamics

$$dX_t^x = (a - bX_t^x)\, dt + \sigma dW_t, \;\; X_0^x = x \in \mathbb{R}. \tag{2.16}$$

Here $\frac{a}{b}$ represents the mean-reversion level and b is the mean-reversion speed. The characteristic Equation (25) associated to (2.16) is

$$\frac{1}{2}\sigma^2 v''(x) + (a - bx)\, v'(x) - \rho v(x) = 0, \tag{2.17}$$

whose strictly increasing fundamental solutions is (cf. page 280 in (Jeanblanc et al., 2009)) is

$$\psi_\rho(x) = e^{\frac{(bx-a)^2}{2\sigma^2 b}} D_{-\frac{\rho}{b}} \left(-\frac{(bx-a)}{\sigma b} \sqrt{2b} \right), \tag{2.18}$$

where $D_\theta(\cdot)$ is the Cylinder function of order θ (Chapter VIII in (Borodin and Salminen, 2002)) defined as

$$D_\theta(y) := e^{-\frac{x^4}{4}} \frac{1}{\Gamma(-\theta)} \int_0^\infty t^{-\theta-1} e^{-\frac{t^2}{2} - yt} dt, \;\; \theta < 0, \tag{2.19}$$

and $\Gamma(\cdot)$ is the Euler's Gamma function.

Under the dynamics (2.16),

$$\widehat{V}(x) = \frac{a}{b}\frac{\ell}{\rho} + \left(x - \frac{a}{b}\right)\frac{\ell}{\rho + b} + \frac{\lambda c}{\rho}.$$

Moreover, the trigger level x^* can be completely characterized through the algebraic equation[3]

$$A^{OU}(x^*) = 0, \tag{2.20}$$

where

$$A^{OU}(x) := (x - \beta)\, \psi_\rho'(x) - \psi_\rho(x), \quad x \in \mathcal{I},$$

and

$$\beta := \left(I - k - \frac{a}{b}\frac{\ell}{\rho} - \frac{\lambda c}{\rho} \right) \frac{\rho + b}{\ell} + \frac{a}{b}. \tag{2.21}$$

Moreover, in this case $\underline{x} = -\infty$ and $\overline{x} = +\infty$, so that (2.13) holds. Finally, it can also be checked that (2.11) is satisfied.

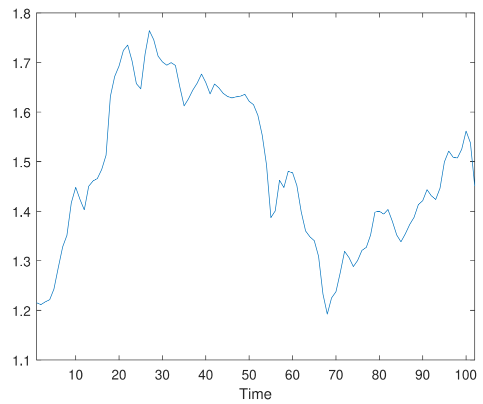
[3] As a matter of fact, (2.20) is equivalent to the integral equation (2.15) – see (33) and (37) in Appendix .B – and can be obtained via imposing the classical "smooth-pasting" and "smooth-fit" conditions.

2.3.1 Parameters estimation

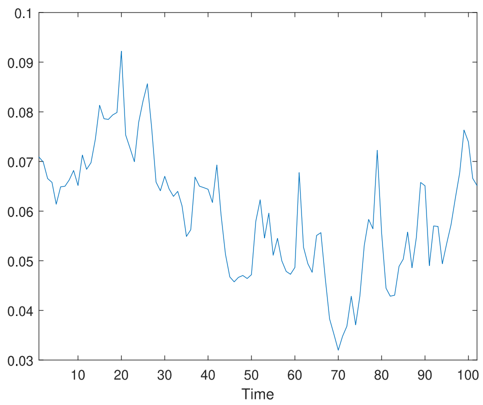
We now provide a calibration on Italian data of the previous mean-reverting model. We obtain the time series of the unit distance opportunity cost per kilometer X as

$$X_t = p_t^f \cdot h^f - p_t^e \cdot h^e, \tag{2.22}$$

where p_t^f represents the fuel price at time t, h^f is the fuel economy of a fossil-fueled vehicle, p_t^e represents the electricity price at time t and h^e is the fuel economy of an electric vehicle. The time series of p_t^f and p_t^e are plotted in Figure 2.1 while the time series $p_t^f \cdot h^f$ and $p_t^e \cdot h^e$ are plotted in Figure 2.2.



Fuel price time series, p_t^f measured in Euro per Liter.



Electricity price time series, p_t^e, measured in Euro per MWh.

Figure 2.1: Fuel and electricity prices time series.

The data for p_t^f and p_t^e refer to Italian markets considering monthly data form July 2010 to December 2018, published in (Italian Ministry of Economic Development, 2019) and (TERNA S.p.A., 2019). The average monthly gasoline price, p_t^f, is supplied by (Italian Ministry of Economic Development, 2019) and the average daily electricity price is supplied by (TERNA S.p.A., 2019). The average monthly electricity price, p_t^e, is calculated averaging the daily electricity prices. We set the fuel consumption of a fossil-fueled vehicle, h^f, at 0.076 liter/km and the fuel economy of an electric vehicle, h^e, at 0.20 kWh/km. Both parameters are taken as an average of technical values proposed by (Plötz et al., 2012) for different sizes of fossil-fueled and electric vehicles. The unit measure of X_t is euro per kilometer and, therefore, the distance is measured in kilometers. The time series of X_t is plotted in Figure 2.4. The graphs of auto-correlation and partial auto-correlation functions of X_t are shown in Figure 2.3. From the previous figures, we deduce that empirical data confirm the mean-reverting behavior of X_t assumed in (2.16). Annual parameters estimations are made by applying the Ordinary Least Squares method to an auto-regressive model of order one. The estimated mean-reversion level of X, $\frac{a}{b}$, is 0.1045, the estimated mean-reversion speed of X, b, is 0.5941 and the estimated volatility parameter of X, σ, is 0.090. Figure 2.4 shows a time trend. The estimated coefficient is of the order 10^{-5} and its associated p-value (0.2970) confirms that it is not statistically significant.

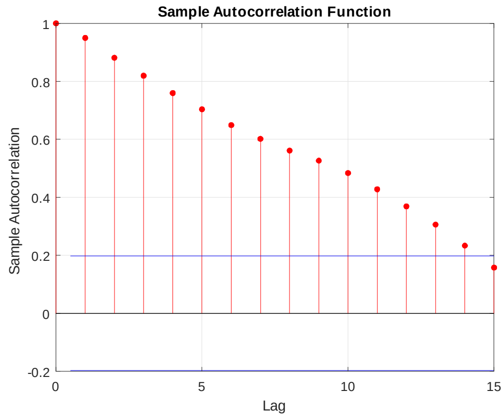
Figure 2.2: Representation of fuel and electricity prices time series in euro per kilometer.

Based on (Audimob, 2019), the fossil-fueled vehicle owner drives an average annual distance of 12000 kilometers. As explained in Section 2.2.1, the policymaker can decide to impose traffic bans to temporarily decrease the excess of pollutants in the air. In the Northern of Italy, for example, a traffic ban happens if the concentration of Particulate Matter 10, PM_{10}, exceeds a safety threshold of 50 $\frac{\mu g}{m^3}$ for 4 consecutive days, see (Regione Lombardia, 2017). In this work, we study the effect of the incentive on the electric vehicle adoption and we therefore assume that the policymaker imposes traffic bans at some random times which is described by a Poisson process. The intensity λ, which represents the expected number of traffic bans, has been estimated from the regions of the Northern of Italy. The decision of imposing a traffic ban differs across the regions (and the provinces) and it depends on many factors such as actual and forecast weather conditions. We consider four regions in Northern Italy: Lombardy, Veneto, Piedmont and Emilia Romagna. For each region, the parameter λ is estimated averaging the theoretical number of PM_{10} traffic bans that could have happened during the winter semesters $2017-2018$ and $2018-2019$. The data about PM_{10} concentration are provided by (Nazionale per la Protezione dell'Ambiente, 2018). Each day, the regional agency of (Nazionale per la Protezione dell'Ambiente, 2018) produces a bulletin indicating the so-called "day alert", which happens if the PM_{10} concentration exceeds the safety threshold.

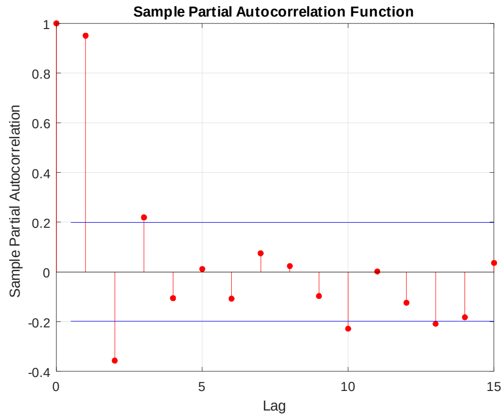
We calculate the theoretical PM_{10} traffic bans number counting, for each province, the number of times at which the PM_{10} concentration exceeds a threshold of 50 $\frac{\mu g}{m^3}$ for 4 consecutive days. Then, for each region, the frequency of PM_{10} traffic bans is calculated averaging the zonal frequencies of traffic bans. For Lombardy region, the annual average traffic bans is 7.2720. For Veneto region, the annual average number of traffic bans is is 7.4615. For Piedmont region, the annual average number of traffic bans is 6.4615. For Emilia Romagna region, the annual average number of traffic bans is 9.3300.[4]

We assume that fossil-fueled vehicle owner's annual discount rate is 5% and that she bears a fixed cost of 150€ for each traffic ban. The cost of each traffic ban represents the economic

[4]For Emilia Romagna region, in each zone, the daily PM_{10} concentration is represented by the worst daily concentration. In each zone of the other regions, the daily PM_{10} concentration is calculated averaging the 24 hours concentration.



Representation of the autocorrelation function for X_t.



Representation of the partial autocorrelation function for X_t.

Figure 2.3: Representation of autocorrelation and partial autocorrelation functions for X_t.

penalty that the fossil-fueled vehicle owner incurs looking for alternative transportation. The cost of each traffic ban includes the fossil-fueled vehicle owner' subjective price to many aspects, such as the time spent in the search, inconvenient of different transportation schedule, possible delay and ticket payment. According to (Statista, 2019), Nissan Leaf is the electric vehicle model most sold in the years 2017 and 2018 in Italy. Therefore, we set the purchase price, I, at 25000€, which is the average purchase cost of Nissan Leaf's vehicle type Acenta. According to the Italian Ministry of Economic Development's Decree of March 20$^{\text{th}}$, 2019, when a fossil-fueled vehicle owner decides to scrap a pollutant vehicle and to purchase an electric vehicle whose CO_2 emissions are less than 20 g/km, an incentive of 6000€ is granted. This is the case of Nissan Leaf Acenta which emits less than 20 gCO_2/km. The parameter values adopter in the analysis are shown in Table 2.1.

Table 2.1: Parameter Description and Estimation.

Parameter	Description	Value
ℓ	Distance driven	12000
$\frac{a}{b}$	Mean-reversion level of X	0.1045
b	Mean-reversion speed of X	0.5941
σ	Volatility coefficient of X	0.090
c	Subjective cost associated to one traffic ban	150
λ_L	Frequency of traffic bans in Lombardy case	7.2720
λ_V	Frequency of traffic bans in Veneto case	7.4615
λ_P	Frequency of traffic bans in Piedmont case	6.4615
λ_{ER}	Frequency of traffic ban in Emilia Romagna case	9.3300
I	Electric vehicle purchase cost	25000
k	Incentive offered by policymaker	6000
ρ	Subjective discount rate	0.05

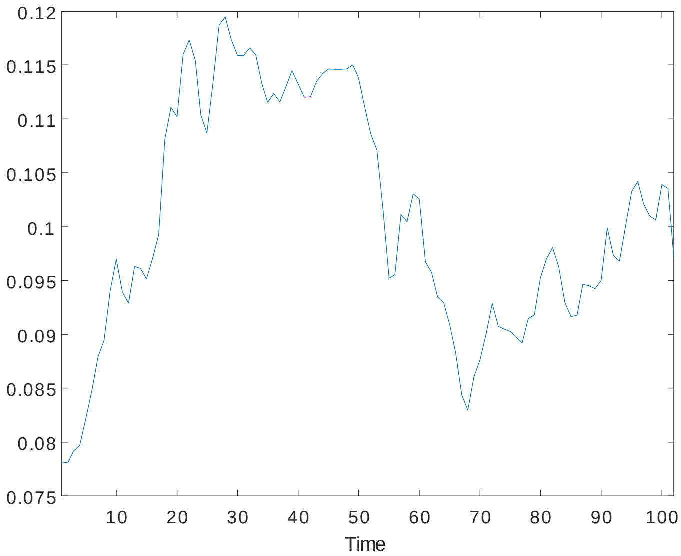


Figure 2.4: Unit distance opportunity cost time series. The data are considered with monthly frequency.

By using the previous parameters' value, Figure 2.5 provides an illustrative plot of the optimal switching rule. For the particular scenario presented, a new electric vehicle is bought after 3 years circa when the unit distance opportunity cost is around 0.18.

2.4 Comparative Statics

In this section we study both analytically and numerically the sensitivity of the decision threshold x^* as in (2.20) with respect to several key parameters. It is important to bear in mind that the optimal switching time is of the form $\tau^* = \inf\{t \geq 0 : X_t^x \geq x^*\}$ so that any monotonicity of x^* with respect to a certain parameter induces the same kind of monotonicity of τ^*.[5] For a given parameter $y \in \{\ell, \lambda, c, k\}$, we stress the dependency on y and (with a slight abuse of notation) we write (2.20) as

$$A^{OU}(x^*(y), y) := (x^*(y) - \beta(y))\, \psi'_\rho(x^*(y)) - \psi_\rho(x^*(y)) = 0.$$

Then, an application of the implicit-function theorem gives

$$\frac{\partial x^*(y)}{\partial y} = -\frac{A_y^{OU}(x^*(y), y)}{A_x^{OU}(x^*(y), y)}, \tag{2.23}$$

[5] Moreover, we notice that the sensitivity analysis of the decision time τ^* with respect to model's key parameters cannot be done both analytically and numerically. One can implement Monte Carlo simulation algorithms to analyze (only numerically) how the expected decision time $E_x[\tau^*]$ varies according to model's key parameters as in Section 2.5.

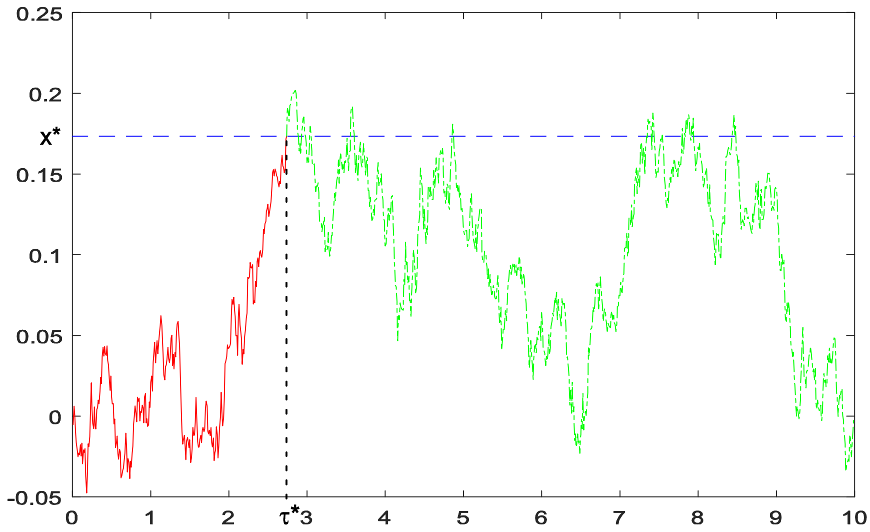


Figure 2.5: An illustration of the optimal switching rule.

upon noticing that, because $\psi_\rho'' > 0$ and $x^*(y) > \beta(y)$,

$$A_x^{OU}(x^*(y), y) = \frac{\partial A^{OU}}{\partial x}(x^*(y), y) = (x^*(y) - \beta(y))\psi_\rho''(x^*(y)) \neq 0.$$

Distance traveled

We start by studying the dependency of the optimal threshold x^* on the annual distance traveled, ℓ. By (2.23) with $y = \ell$ we have

$$\frac{\partial x^*(\ell)}{\partial \ell} = -\frac{A_\ell^{OU}(x^*(\ell), \ell)}{A_x^{OU}(x^*(\ell), \ell)}.$$

Because,

$$\frac{\partial \beta(\ell)}{\partial \ell} = -\frac{\rho + b}{\ell^2}\left(I - k - \frac{\lambda c}{\rho}\right),$$

we have

$$A_\ell^{OU}(x^*(\ell), \ell) = \psi_\rho'(x^*(\ell))\left(\frac{\rho + b}{\ell^2}\left(I - k - \frac{\lambda c}{\rho}\right)\right).$$

Using now that

$$A_x^{OU}(x^*(\ell), \ell) = (x^*(\ell) - \beta(\ell))\psi_\rho''(x^*(\ell)),$$

we get from (2.23)

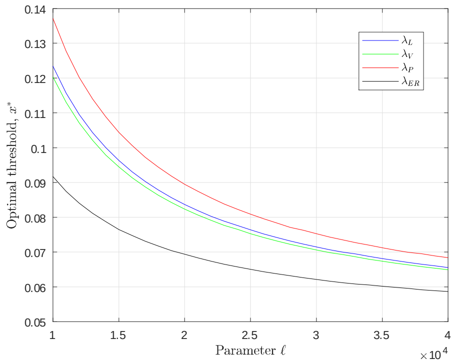
$$\frac{\partial x^*(\ell)}{\partial \ell} = -\frac{\psi_\rho'(x^*(\ell))\left(\frac{\rho+b}{\ell^2}\left(I - k - \frac{\lambda c}{\rho}\right)\right)}{(x^*(\ell) - \beta(\ell))\psi_\rho''(x^*(\ell))},$$

which, by (2.20), also reads as

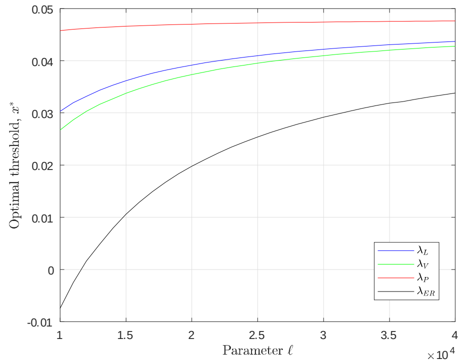
$$\frac{\partial x^*(\ell)}{\partial \ell} = -\frac{\left(\psi_\rho'(x^*(\ell))\right)^2\left(\frac{\rho+b}{\ell^2}\left(I-k-\frac{\lambda c}{\rho}\right)\right)}{\psi_\rho''(x^*(\ell))\,\psi_\rho(x^*(\ell))}.$$

We thus have

$$\frac{\partial x^*(\ell)}{\partial \ell} = \begin{cases} <0 & \text{if} \quad I-k-\frac{\lambda c}{\rho}>0 \\ >0 & \text{if} \quad I-k-\frac{\lambda c}{\rho}<0 \end{cases}. \tag{2.24}$$



Panel (a) Dependency of x^* w.r.t. the annual traveled distance, ℓ, when $I-k-\frac{\lambda c}{\rho}>0$.



Panel (b) Dependency of x^* w.r.t. the annual traveled distance, ℓ, when $I-k-\frac{\lambda c}{\rho}<0$.

Figure 2.6: Dependency of x^* w.r.t. the annual traveled distance, ℓ, for different choices of the parameter λ.

A numerical representation of (2.24) is presented in Figure 2.6.

The case $I-k-\frac{\lambda c}{\rho}>0$ is shown in Panel (a) of Figure 2.6. It represents the situation where the purchase cost, I, is not completely covered by the policymaker's incentive, k, and by the perpetual stream of benefit from avoided traffic bans, $\frac{\lambda c}{\rho}$. Because $k+\frac{\lambda c}{\rho}<I$, the initial investment cost I is more acceptable to the fossil-fueled vehicle owner if the distance traveled increases, as she can then recover the cost $I-k-\frac{\lambda c}{\rho}$ thanks to fuel saving per Kilometer. Under this condition, an increase in the distance traveled leads the fossil-fueled vehicle owner to adopt an electric vehicle sooner. The frequency of traffic bans influences the adoption decision: in the case of Emilia Romagna (black line in Figure 2.6) characterized by the highest number of traffic bans, the optimal threshold is the lowest (for any distance traveled ℓ). Conversely, for the red line (Piedmont) where traffic bans are less frequent.

The case $k+\frac{\lambda c}{\rho}>I$ is shown in Panel (b) of Figure 2.6. It represents the situation in which the purchase cost I is completely covered by the policymaker's incentive, k, and by the perpetual stream of benefit from avoided traffic bans, $\frac{\lambda c}{\rho}$. The increasing behavior of the optimal threshold x^* can be explained as follows. The fossil-fueled vehicle owner is subject to the risk that the initial advantage can be significantly eroded by driving costs if electricity costs more than fuel, i.e. if process X becomes negative for significant periods. Notice that negative values of process X means that driving one unit distance with an electric vehicle is more expensive than driving the same distance with a fossil-fueled vehicle. For the fossil-fueled vehicle owner, whose distance traveled is low, this risk is not perceived as relevant and, therefore, she agrees to purchase an electric vehicle at a low optimal threshold. Increasing the distance traveled, the risk of negative values of process X starts to be crucial in the purchase decision and she then protects herself by postponing the decision to purchase an electric vehicle and waiting for sufficiently large values of the opportunity cost X.

Frequency of traffic bans

We now move on by studying the dependency of the optimal threshold x^* on the frequency of traffic bans λ. Since

$$A_\lambda^{OU}\left(x^*\left(\lambda\right),\lambda\right) = \psi_\rho'\left(x^*(\lambda)\right)\cdot\frac{\partial\beta\left(\lambda\right)}{\partial\lambda} = \psi_\rho'\left(x^*(\lambda)\right)\left(\frac{c}{\rho}\frac{\rho+b}{\ell}\right),$$

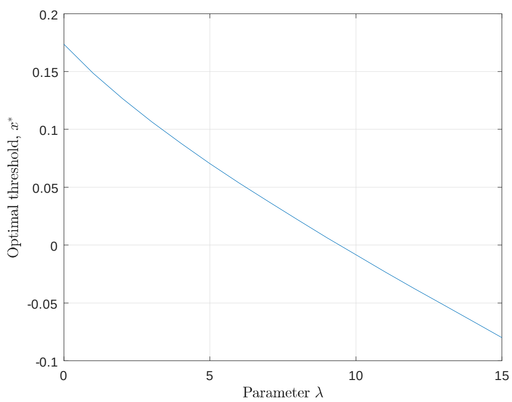
and

$$A_x^{OU}\left(x^*\left(\lambda\right),\lambda\right) = \frac{\psi_\rho\left(x^*\left(\lambda\right)\right)}{\psi_\rho'\left(x^*\left(\lambda\right)\right)}\psi_\rho''\left(x^*(\lambda)\right) > 0.$$

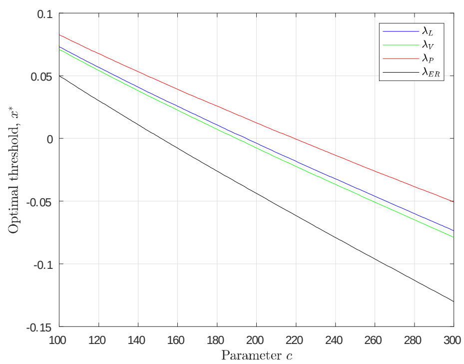
we have, by (2.23) for $y=\lambda$,

$$\frac{\partial x^*\left(\lambda\right)}{\partial\lambda} = -\frac{\left(\psi_\rho'\left(x^*\left(\lambda\right)\right)\right)^2\left(\frac{c}{\rho}\frac{\rho+b}{\ell}\right)}{\psi_\rho\left(x^*\left(\lambda\right)\right)\psi_\rho''\left(x^*\left(\lambda\right)\right)} < 0; \tag{2.25}$$

that is, an increase in the expected number of traffic bans leads to a decrease of the optimal threshold x^*. A numerical representation of (2.25) is shown in Panel (a) of Figure 2.7.



Panel (a) Dependency of the optimal threshold x^* w.r.t. the frequency of traffic ban, λ.



Panel (b) Dependency of the optimal threshold x^* w.r.t. the subjective cost of one traffic ban, c, for different choices of parameter λ.

Figure 2.7: Dependency of x^* w.r.t. the frequency of traffic ban, λ, and the cost of one traffic ban, c.

If the frequency of traffic bans increases, the optimal threshold x^* decreases and the adoption time decreases as well. This can be explained by noticing that an increase in the frequency of traffic bans leads to two main effects: on the one hand, fossil-fueled vehicle owner's driving cost increases; on the other hand, the fossil-fueled vehicle owner cannot circulate during traffic ban periods. As a consequence, she accepts to purchase an electric vehicle at a lower optimal threshold (i.e. sooner) because the cost of driving an electric vehicle is then compensated by the savings derived from the avoided traffic bans.

Cost of one traffic ban

We here study the dependency of the optimal threshold x^* on the (subjective) cost associated to one traffic ban, c. Because

$$A_c^{OU}\left(x^*\left(c\right),c\right)=-\psi_\rho'\left(x^*\left(c\right)\right)\left(-\frac{\lambda}{\rho}\frac{\rho+b}{\ell}\right)=\psi_\rho'\left(x^*\left(c\right)\right)\frac{\lambda}{\rho}\frac{\rho+b}{\ell},$$

by (2.23)

$$\frac{\partial x^*\left(c\right)}{\partial c}=-\frac{A_c^{OU}\left(x^*\left(c\right),c\right)}{A_x^{OU}\left(x^*\left(c\right),c\right)}=-\frac{\left(\psi_\rho'\left(x^*\left(c\right)\right)\right)^2\left(\frac{\lambda}{\rho}\frac{\rho+b}{\ell}\right)}{\psi_\rho\left(x^*\left(c\right)\right)\psi_\rho''\left(x^*\left(c\right)\right)}<0. \tag{2.26}$$

That is, an increase in the marginal cost of traffic bans leads to a decrease the optimal threshold x^*. A numerical representation of (2.26) is shown in Panel (b) Figure 2.7.The more this cost increases, the earlier the fossil-fueled vehicle owner purchases an electric vehicle. In fact, the disadvantage associated to lower value of x^* is compensated by the saving derived from the avoided cost of traffic bans that she would incur still having a fossil-fueled vehicle. Of course, in the case of Emilia Romagna (black line in Panel (b) of Figure 2.7) – which is characterized by a greater frequency of traffic bans – the optimal threshold is reduced because of the larger traffic bans costs. The opposite holds true for the case of Piedmont (red line), where traffic bans are less frequent.

Incentive

We study the dependency of the optimal threshold x^* on the incentive granted by the policymaker, k. Since

$$A_k^{OU}\left(x^*\left(k\right),k\right)=\psi_\rho'(x^*(k))\left(\frac{\rho+b}{\ell}\right)>0,$$

we find by (2.23) and $A_x^{OU}\left(x^*\left(k\right),k\right)=\left(x^*\left(k\right)-\beta\left(k\right)\right)\psi_\rho''\left(x^*\left(k\right)\right)$ that

$$\frac{\partial x^*\left(k\right)}{\partial k}=-\frac{\left(\psi_\rho'(x^*\left(k\right))\right)^2\left(\frac{\rho+b}{\ell}\right)}{\psi_\rho\left(x^*\left(k\right)\right)\psi_\rho''\left(x^*\left(k\right)\right)}<0. \tag{2.27}$$

An increase in the incentive, k, leads to a decrease in the optimal threshold, x^*. A numerical representation of (2.27) is shown in Figure 2.8.

If the policymaker decides to increase the incentive to promote the electric vehicles adoption, the optimal threshold decreases. That is, the more the incentive increases, the earlier the fossil-fueled vehicle owner is motivated to purchase an electric vehicle. As one can notice traffic bans influence the adoption decision. In Emilia Romagna (black line in Figure 2.8), characterized by a high frequency of traffic bans, the optimal threshold is the lowest one (for any level of incentive) because of the large traffic bans' costs. The opposite happens for the red line (Piedmont), where traffic bans are less frequent.

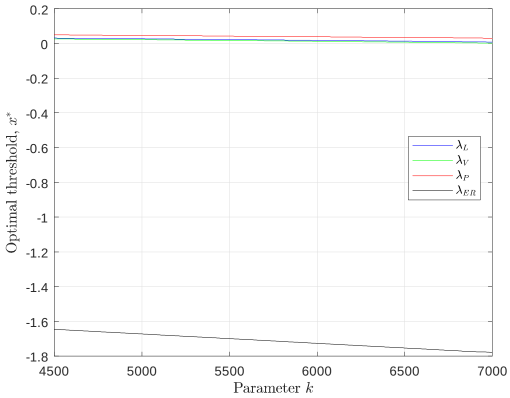


Figure 2.8: Dependency of x^* w.r.t. the incentive, k, for different choices of the parameter λ.

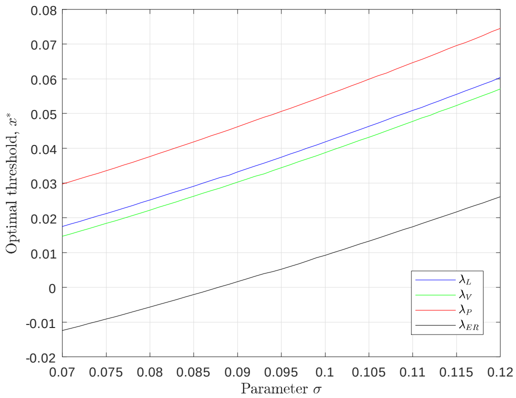


Figure 2.9: Dependency of x^* w.r.t. the volatility σ for different choices of the parameter λ.

Volatility coefficient

An important question concerns the dependency of the optimal trigger value (hence of the optimal switching time) with respect to the volatility parameter σ of the process X. Since the fundamental solution ψ_ρ also depends on σ (cf. (2.18)) the analysis of such a sensitivity is slightly more technical than the ones previously performed for ℓ, c, λ, and k. However, arguing as in the proof of Proposition 5.4 in Ferrari and Koch (2019) one can show the next result.

Proposition 6 *The mapping $\sigma \mapsto x^*(\sigma)$ is increasing.*

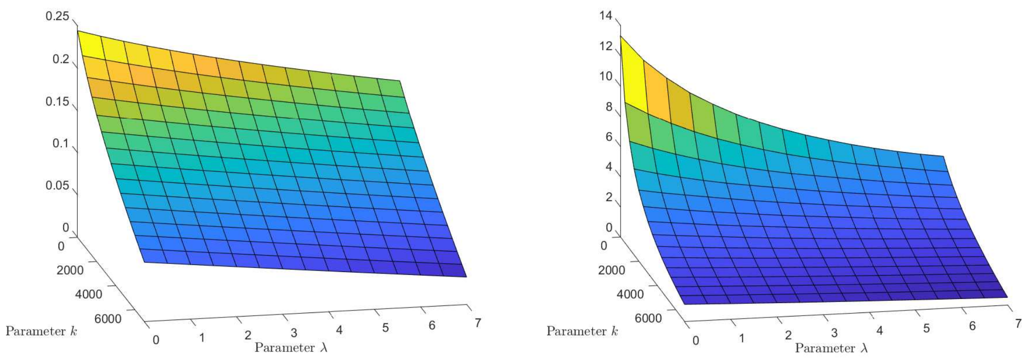
When the volatility coefficient σ increases, the fossil-fueled vehicle owner is subject to a risk that process X is negative for significant periods, i.e. that electricity costs more than fuel. Since waiting to invest is a protection against such risk, she best waits for sufficiently large values of the opportunity cost X. A drawing of the conclusion of Proposition 6 is presented in Figure 2.9.

2.5 Environmental policy implications: A simulation study

In this section, we analyze the expected optimal switching time as a function of the incentive and the frequency of traffic bans. This analysis is particularly relevant for policymakers for many reasons. First, it allows to identify a balanced policy mixing incentive and traffic bans to encourage the adoption of an electric vehicle. Moreover, it assesses if such policy reaches the desired impact within a prescribed period of time.
In Section 2.2.2, we proved that the optimal switching time is of the form $\tau^* = \inf\{t \geq 0 : X_t^x \geq x^*\}$. To conduct the subsequent analysis, we need to stress the dependency of τ^* on the frequency rate of traffic bans, λ, and the incentive, k, and, therefore, we write the expected optimal switching time as

$$\mathbb{E}_x \left[\tau^* (\lambda, k)\right], \tag{2.28}$$

for any given and fixed $x \in \mathcal{I}$. Observe that λ depends on the employed traffic ban rule, so $\mathbb{E}_x \left[\tau^* (\lambda, k)\right]$ can be seen as an outcome of two distinct policy instruments: the incentive, k, and the traffic bans rule.
The analysis of (2.28) is made through Monte Carlo simulation. We set $x = 0.02$ and we simulate 10000 trajectories of an Ornstein-Uhlenbeck process with coefficients a, b and σ as specified in Table 2.1. For a fossil-fueled vehicle owner, whose features are listed in Table 2.1, we consider a grid of possible combinations of k and λ. Then, for each possible combination (λ_i, k_i), the optimal threshold $x_i^* := x^* (\lambda_i, k_i)$ is calculated. For each simulated trajectory and for each optimal threshold, the associated optimal switching time, $\tau_i^* := \tau^* (\lambda_i, k_i)$, is then evaluated. Finally, the expected switching time is taken as an average of all the simulated switching times.



Panel (a) Dependency of the expected optimal switching threshold, $\mathbb{E}_x \left[x^* (\lambda, k)\right]$, w.r.t. the frequency of traffic ban, λ, and the incentive, k .

Panel (b) Dependency of the expected optimal switching time, $\mathbb{E}_x \left[\tau^* (\lambda, k)\right]$, w.r.t. the frequency of traffic ban, λ, and the incentive, k .

Figure 2.10: Dependency of $\mathbb{E}_x[x^*]$ and $\mathbb{E}_x[\tau^*]$ w.r.t. the frequency of traffic ban, λ, and the incentive, k.

The expected switching threshold as a function of λ and k is shown in Panel (a) of Figure 2.10. The expected optimal switching time as a function of λ and k is presented in Panel (b) of Figure 2.10. Notice that, as stated in Section 2.4, any monotonicity of $x^* (\lambda, k)$ is shared by its associated $\tau^* (\lambda, k)$, and therefore by $\mathbb{E}_x[\tau^* (\lambda, k)]$.

Panel (b) of Figure 2.10 shows that when both λ and k are null, the expected optimal switching time is the highest possible one. In particular, the fossil-fueled vehicle owner waits in average circa 13 years before switching to an electric vehicle. Such a large expected time can be understood by considering, firstly, that she does not incur any traffic ban and, secondly, that the policymaker does not grant any incentive. On the opposite case, when both λ and k are the greatest possible, the expected optimal switching time is around zero.
It is interesting to notice in Panel (b) of Figure 2.10 that the expected optimal switching time tends to (almost) flat out to a level below 2 (years) when the frequency of traffic bans exceeds $2-4$ per year and the incentive exceeds 3000€.
One also observes from Panel (b) of Figure 2.10 that incentives are more effective than traffic bans. Indeed, in order to see this, it is particularly useful to compare the upper-right and the lower-left corners of the surface in Panel (b) of Figure 2.10. The upper-right corner represents the effect of the maximum frequency of traffic bans in absence of incentives, while the lower-left corner represents the effect of the maximum incentive in absence of traffic bans. Clearly, the expected optimal switching time at the former is much higher.

Policymaker implications. It is relevant to observe that the two policy instruments, traffic bans and incentives, are different. Traffic bans produce temporary reduction of air pollution concentration and create an indirect cost such as, for example, a GDP slowdown. However, the key point that encourages the fossil-fueled vehicle owner to purchase an electric vehicle lies in the risk that many possible future traffic bans take place. Indeed, the rules[6] for imposing a traffic ban are usually adopted without fixing a deadline [7]. A light traffic ban rule (i.e. a traffic containment only after a long period of consecutive high PM_{10} concentration) should lead to a low frequency of traffic bans, and it is therefore proper of a policymaker that has a relatively low environmental concern. On the opposite case, an hard traffic ban rule is used when the policymaker is more interested in improving air quality or when the aim is to prevent the healthcare cost connected to air pollution. On the other hand, providing public incentives for the adoption of electric vehicles creates a direct cost for the policymaker and, as a consequence, such a policy could have a shorter lifetime with respect to the traffic bans rule. However, as shown in Panel (b) of Figure 2.10, incentives appear to be a more effective tool to lead fossil-fueled vehicle owners to switch to an electric vehicle sooner.
An environmental policy for the reduction of the air pollution can use traffic bans and incentive separately or jointly. The decision depends, essentially, on the policymaker environmental concern, as well as on the policymaker budget. The degree of use of those instruments depends, also, on the PM_{10} concentration in the study area. A final remark has to be done. Adopting an environmental policy, the policymaker has to bear in mind that the use of the incentive can be supposed more uncertain, since the decision to accept the incentive or not is entirely in the hands of the fossil-fueled vehicle owner. On the other hand, imposing traffic bans is only a decision of policymaker and the fossil-fueled vehicle owner has no other choice but to deal with.

2.6 Conclusions

In this work, we have provided a real options model for the problem of optimal adoption of an electric vehicle. We consider a fossil-fueled vehicle owner who has to determine the optimal time at which purchase an electric vehicle, while minimizing a cost functional that counts for the

[6] With the term "rule", we mean the number of the consecutive days at which the PM_{10} concentration exceeds the safety threshold of 50 $\frac{\mu g}{m^3}$.

[7] In this paper, traffic bans happen randomly but, in the reality, they are imposed following a given rule, as discusses in Section 2.3.

distance traveled, the possibility of being randomly stopped for some days, and the net purchase cost. The uncertainty is modeled through the unit distance opportunity cost of driving a fossil-fueled vehicle compared to an electric one. We have solved the resulting optimization problem in the case that the unit distance opportunity cost is modeled as a general one-dimensional Itô-diffusion and, later, we have provided a model calibration through real data and a detailed comparative statics by assuming a stochastic mean-reversion dynamics. In particular, both in the general case and in the case study, we have completely characterized the critical level of the unit distance opportunity cost triggering the optimal switch to an electric vehicle.

The problem analyzed in this work has provided important consequences both for the policymaker and for the fossil-fueled vehicle owner. A first result concerns the analysis of the parameters that influence the decision of purchasing an electric vehicle: the distance traveled, the subjective cost for each traffic ban, the frequency of traffic bans. With the exception of the driving distance, a change in those parameters implies a monotone response of the adoption time, for any choice of the other model's parameters. On the other hand, the monotonicity of the optimal switching time with respect to the distance traveled is different for different values of the other parameters. In particular, this depends also on how large is the cost of an electric vehicle, net of the incentive received from the policymaker and the saving arising from avoiding traffic bans.

The second result is that the policymaker has two main tools to lead the fossil-fueled vehicle owner to purchase an electric vehicle: traffic bans rule and incentive. The incentive, from the policymaker point of view, represents a direct cost while imposing a traffic ban involves an indirect cost which is not directly observable, such as, for example, a GDP slowdown. Moreover, the policymaker has to balance the two instruments: if the rule to impose traffic bans is tightening, the fossil-fueled vehicle owner is encouraged to switch to an electric vehicle also without granting incentives. If the rule to impose traffic bans is light, the policymaker may offer an incentive to encourage the fossil-fueled vehicle owner to switch to an electric vehicle. The decision on how combine the two is related to the policymaker's environmental awareness and the policymaker's budget. Future research can focus on the combination of other policies for pollutants reduction, such as, for example, encourage the use of renewable in the electricity production or increasing public transportation.

Chapter 3

Optimal Incentive in Electric Vehicle Adoption

This chapter is based on the article: Falbo P., Pelizzari C., Rizzini G., *Optimal Incentive in Electric Vehicle Adoption,* which is currently under review in Energy Economics

3.1 Introduction and literature review

From the 1980's, the world is subject to an increasing dome of pollution. The main responsible are industrial emissions, mostly in energy sector, (e.g. see Friedlingstein et al., 2010; Huisingh et al., 2015a), domestic heating, fossil-fueled transportation systems, natural pollution and many others, as discussed in (Health Organization, 2019). Policymakers around the world are challenged to build a long-term strategy to increase Gross Domestic Product, GDP, and, at the same time, to reduce the air pollution and its health effects. Many studies (e.g. see Straif et al., 2013; World Health Organization and Others, 2013) emphasize the strict connection between air pollution and human health damage. It has been estimated that air pollution is responsible, just to name a few, for asthma crisis, respiratory and cardiovascular diseases, tumors. Studies like (McGuire, 2016) and (Health Organization, 2016) have estimated that the death of 289,000 people in the high-income European regions. The report (Health Organization, 2016) says that, in 2016 worldwide, the air pollution has led to seven millions of premature deaths. As explained by (OECD et al., 2016), transportation sector counts for more than 20% on greenhouse gas. In particular, according to (Colvile et al., 2001), (Belis et al., 2013) and (Karagulian et al., 2015), in the urbanized area, fossil-fueled vehicles emissions are the major contributors to air pollution. The link between air pollution and road traffic is also confirmed by (e.g. see Gualtieri et al., 2020; Chen et al., 2020; Liu et al., 2020), which study the air pollution reduction occurred after the national lockdowns. Among all the substances produced by fossil-fueled vehicle the Particulate Matter 10, PM_{10},[1] is particularly dangerous substance. The exposure, in the medium-long term, leads to the onset of tumors as well explained in (Beelen et al., 2007) and (Pope III et al., 2002).

Many authors, (Abdul-Manan, 2015; Nichols et al., 2015), show that the use of electric vehicles can be an effective way to reduce PM_{10} concentration and its environmental and health damages. However, the use of electric vehicle is not sufficient to reduce air pollution for many reasons. The

[1] Considering the European legislation, UNI EN 12341/2014, PM_{10} is defined as the fraction of particles with aerodynamic diameter of 10 micrometers.

first is shown in (Soret et al., 2014), which finds that, in addition to the private fleet electrification, also heavy vehicles electrification must be fielded. Moreover, the use of the electric vehicles has to be combined with an environmental policy that induces the electricity producers to operate with renewable source (or green technologies) to generate electricity. (Buekers et al., 2014), (Casals et al., 2016) and (Onat et al., 2015) show that countries, whose generation mix is based on green technologies, avoid external costs in terms of air pollution effect with the use of the electric vehicles. A literature review on the electric vehicle adoption is presented in (Kumar and Alok, 2020). The authors cover many aspects both at citizens and government levels. At the citizens level, they focus on the total cost of ownership, battery cost, willingness to pay, rage anxiety, psychological characteristics, perceived risks and environmental benefits. At the government level, the main important aspects are the direct policies and indirect policies. As stated, policymaker can design an environmental policy that encourages its citizens to adopt electric vehicles. Those policies can be applied using direct or indirect actions. Direct actions aim at lowering the final purchase cost. Those actions may consist of an incentive, a reduction (partial or total) of the registration fee, registration tax, and vehicle ownership tax. Indirect actions aim at promoting the utility of the adoption of an electric vehicles, and can consist of reinforcing the charging infrastructure (i.e. charging stations), and supporting for the research and development, to name few. As a crucial point, each policymaker decides which type of actions is more effective according to the characteristics of his state/area such as, for example, charging infrastructure development, electricity generation mix, air quality. Moreover, policymaker needs also to consider cultural and economical features of the citizens of his area such as personal disposable income, willingness to pay, range anxiety, psychological aspects, and environmental benefits. (Bakker and Trip, 2013) states that policymaker has to also promote the knowledge (in terms of environmental benefits, costs, etc.) to its citizens about the electric vehicles to encourage their adoption. (Hardman, 2019) comparing the benefit of different direct and indirect action, confirms that a merit order of effectiveness of the actions cannot be determined since it depends on the specific features of the countries.

The direct and indirect actions implemented in the EU area are shown in the literature review of (Cansino et al., 2018). In many member states, a citizen purchasing an electric vehicle with a low emission factor, receives an economic incentive. The incentive varies in Europe according to the state. The registration fee has not to be paid in 8 states, while it has to be paid in 16 states in different amounts based on the vehicle's environmental impact. In the remaining states, the registration tax has to be paid independently of the vehicle's environmental impact. Many of the states employ the exemption of ownership tax to encourage the adoption of an electric vehicle. As for the indirect actions, (Cansino et al., 2018) cites the implementation of infrastructures and support for R&D. Regarding the infrastructures, all EU member States – with the exception of Belgium, Bulgaria, Cyprus, Croatia, Finland, Italy, Lithuania and Romania – have promoted electric vehicles' infrastructures through free public parking and development of charging stations.

Turning to R&D funding, the interventions can be divided into direct financing for the technological innovation of propulsion system and battery system. Educational actions aim at reducing citizens' concerns about electric vehicles and at stressing their beneficial effects. To achieve this goal, in Belgium, for example, retailers are obliged to expose the impact that fossil-fueled vehicles have on air quality.

In this paper, we focus our attention on a direct action that is the electric vehicle purchase cost reduction through incentive. Our findings confirm the studies of (Sierzchula et al., 2014), (Melton et al., 2017) and (Bunsen et al., 2018) who show a strong positive connection between financial incentives and the adoption of electric vehicle. Several other papers consider such interaction. (Zhu et al., 2019) propose a Stackelberg game in which three actors are considered:

Government, charging infrastructure investors and fossil-fueled vehicle owners. Government, maximizing a social welfare function, decides the total incentive amount to distribute to the charging infrastructure investors and fossil-fueled vehicle owners. Owners of the infrastructure construction maximize their profit deciding the number of new charging stations, while the fossil-fueled vehicle owners, maximizing their own utility, decide if purchase the electric vehicle. (Zaman and Zaccour, 2021) study a two-period game between strategic consumer and the government. On its hand, the government wants to minimize the total subsidy cost considering a car-replacement target level to reach. On his side, each strategic consumer wants to maximize his utility function deciding at which time to purchase a new vehicle. (Encarnação et al., 2018) investigate the possible incentive policy considering, simultaneously, government, citizens and companies with an evolutionary game theoretical approach. An interesting result underlines that the full adoption of electric vehicles needs a coordination between those three actors. In particular, it is shown that government regulation is necessary but not sufficient to reach a full electric vehicle adoption. (Li et al., 2019) consider a complex network evolutionary game to analyze the impact of different Government policies on automotive manufactures and heterogeneous consumers. With respect to the Government policy, automotive manufactures deal with tax subsidies, while consumers deal with purchase subsidies and fossil-fueled license plate restriction. Each consumer decides whatever to purchase an electric vehicle or a fossil-fueled one or do nothing. Each automotive manufacture has two possible strategies: produce electric vehicles or fossil-fueled ones. In (Deng et al., 2020) a Stackelberg problem is studied. In the upper level, a government has to minimize the total cost of subsidies and how to share it between consumers electric vehicle manufacture. In the lower level, the electric vehicle manufacture has to maximize the expected profit deciding the optimal production and the optimal selling price. Moreover, a constraint on the expected sale is considered by the Government. (Shao et al., 2017) present a model where a government maximizes a social welfare function determining the optimal subsidies or the optimal price discount rate considering a population of heterogeneous consumers and manufactures, when the latter have to decide the optimal pricing according to Government decision. Moreover, two different market structure are considered: monopoly and oligopoly.

Our contribution We contribute to the literature by investigating how an environmental policy, based on incentives, encourages a population of fossil-fueled vehicle owners to switch to an electric vehicle. Individuals minimize a cost function that depends on the incentive granted by the policymaker. The policymaker, on his side, wishes to minimize a cost function including economic incentives, public health costs and traffic bans costs. Our first novelty lies in the fact that we model the PM_{10} concentration as a discrete mean-reverting process with a controlled long-term average. The latter, in fact, depends also on the percentage of fossil-fueled vehicle owner deciding to purchase an electric vehicle which is connected to the incentive granted by the policymaker. The second novelty is concerned with the construction of an analytical model to identify the expected number of traffic bans which depends on the PM_{10} concentration. The third novelty lies in the fact that we describe the different features of that population: each vehicle owner is seen as realizations of a bivariate random variable representing the disposable income and the distance traveled. Policymaker's cost function depends directly on the number of electric vehicles incentivized. Moreover, our is the first paper where social and traffic bans cost appear in the objective function of the policymaker. The social costs, including the healthcare costs and the mortality risk costs, depend on the long-run average of PM_{10} concentration, which, as stated before, is a function of the electric vehicle incentivized by the incentive. Similarly, also the traffic bans costs depend on the PM_{10} concentration. A relevant contribution of this paper is concerned with the methodological treatment of the problem. Due to the different features in terms of disposable income and distance travelled and boolean decision type of the fossil-fueled vehicle owner, we are able to identify an incentive, shared by a percentage of fossil-fueled vehicle owners, that reduce the initial stochastic bilevel multifollower problem to a deterministic single level (constrained) optimization model. The steps are made assuming that the population of the fossil-fueled vehicle owners, at first, is described as a discrete population and then, for analytical treatment, it is assumed to be composed by a continuous number of individuals.

The rest of the chapter is organized as follows. Section 3.2 includes the an overview of the essential elements of our model, which is advanced in Section 3.3. Section 3.4 shows the steps to reduce the initial stochastic bilevel to a single-level constrained optimization model. In Section 3.5, we first provide a parameter estimation based on European data and then we illustrate an application of the model. Comments are provided on a baseline case, and on its extension obtained through comparative statics of some key parameters. Section 3.6 concludes the present analysis with some final remarks and possible extensions of the ongoing research. Appendix .C lists the main facts on AR(1) model, Appendix .D shows how to write analytically the expected number of traffic bans in terms of probability distribution.

3.2 Model Settings

3.2.1 Bilevel Optimization

We consider a policymaker and N vehicle owners over a finite discrete time horizon, $\{0, \dots, T\}$. The problem involves a hierarchical structure, and it is stated as a bilevel problem. At the upper level, the policymaker minimizes a social cost function deciding the incentive to encourage the owners of fossil-fueled vehicles to scrap their polluting vehicle and purchase an electric one (we will call it also switch decision). The lower level is populated by the decision problem of fossil-fueled vehicle owners. In this work, two main categories of vehicle owners are considered: electric vehicle owners and fossil-fueled vehicle owners.[2] The initial number of electric vehicles (i.e. at time 0) are αN and the fossil-fueled vehicles are $(1-\alpha)\,N$, with $\alpha \in [0,1]$. The previous numbers are assumed to be integer. Moreover, we characterize each fossil-fueled vehicle owner by specific distance traveled and disposable income. The fossil-fueled vehicle owners aim to minimize their individual cost function deciding whether to accept the incentive granted by the policymaker and switch to an electric one. For both policymaker and fossil-fueled vehicle owner the only time of decision is $t = 0$. The reaming times, $\{1, \dots, T\}$ are considered only to the purpose of calculating expectation of the possible traffic bans and the time dynamics of the pollution concentration. We label by $N\Delta\alpha$ the number of new electric vehicles purchased, and by $\Delta\alpha$ the percentage of new electric vehicles purchased at time $t = 0$. The essential elements of the problem are represented in Figure 3.1.

3.2.2 Concentration Dynamics of PM_{10}

Air pollution is made by many gaseous substances, such as carbon monoxide, CO, sulfur dioxide, SO_2, chlorofluorocarbons, CFCs, and nitrogen oxides, NO_x, particulate matter, PM, etc. In this paper, we focus on the major parameter of air quality, namely the Particulate Matter 10, PM_{10}. Hereinafter, the PM_{10} concentration will be measured in $\frac{\mu g}{m^3}$. To this purpose, we distinguish two components of the PM_{10} concentration: the background and the peak concentration. The background concentration is the average level of concentration due to many factors, such as

[2] For semplicity, we assume that the number of vehicles and the number of vehicles owners coincide.

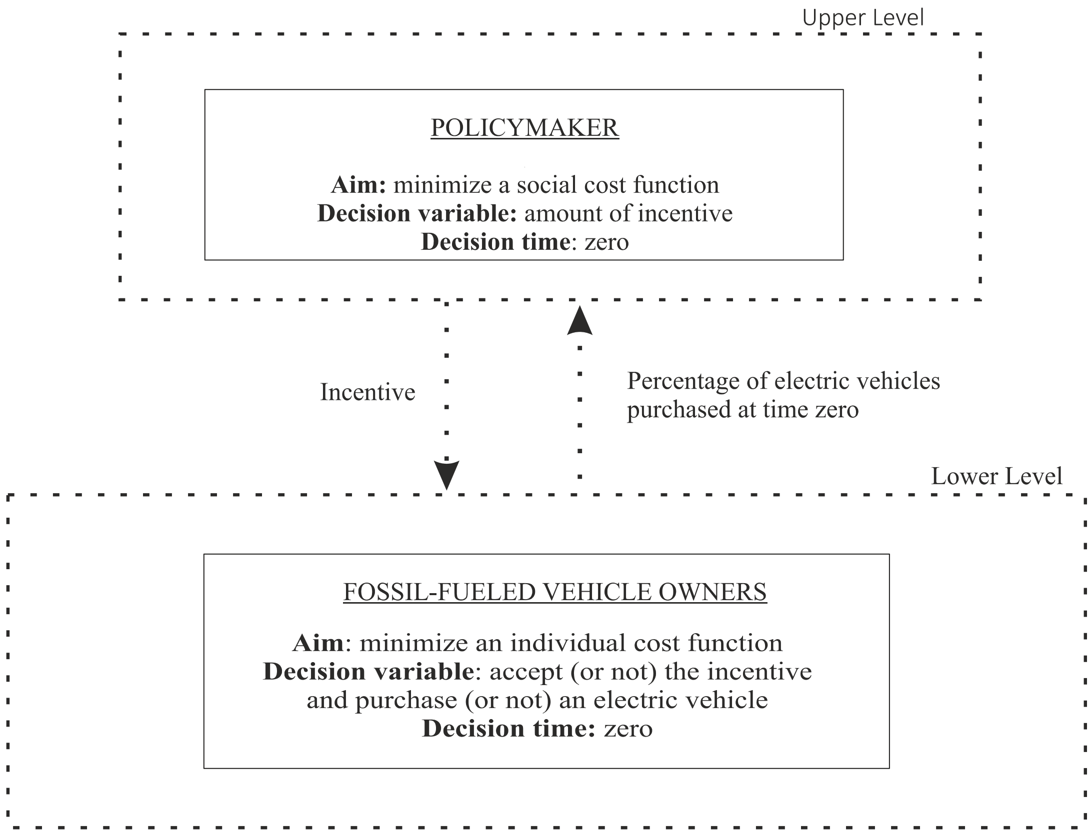


Figure 3.1: Representation of the problem.

natural pollution[3] and human activities, including the average level of road traffic. Deviations from the background level occur randomly and, when they reach high levels, they produce additional costs to the society. To bound the effect of such occasional peak concentration, a usual governmental intervention consists of imposing traffic bans. However, a more long-period policy, on the side of a policymaker, is to incentivize the purchase of electric vehicles to promote a consistent reduction of both background and the concentrations. The uncertainty is described by a probability space $(\Omega_H \times \Omega \times \Omega_X, \mathcal{F}, \mathbb{P}_H \times \mathbb{P} \times \mathbb{P}_X)$, where Ω_H is the sample space of the realizations of PM_{10} concentration, Ω is the sample space of the possible couples of distance traveled and disposable income characterizing each fossil-fueled vehicle owner, Ω_X is the sample space of the realizations of the unit distance opportunity cost. $\mathcal{F}$ is the σ-field of available information and $\mathbb{P}_H \times \mathbb{P} \times \mathbb{P}_X$ is the product probability measure. The use of product measure implies independence of PM_{10} concentration, traveled distance and disposable income and unit distance opportunity cost. The independence assumption between the trajectories of PM_{10} concentration and the couples of traveled distance and disposable income is supported noticing that each fossil-fueled vehicle owner drives the same distance for all times in $\{0, \ldots, T\}$, therefore, it can be seen as a fixed contribution to the PM_{10} concentration. This explains why the number of fossil-fueled vehicle owners appears in the constant term (i.e. the long-mean term) in Equation (3.1). The independence between the couples of traveled distance and disposable income and the unit distance opportunity cost is assumed since, for simplicity, we do not consider the effects on fuel and electricity prices due to the fleet electrification. The independence between PM_{10} concentration and unit distance opportunity cost is a reasonable as long as we do not assume any ETS scheme on the electricity market. We let the PM_{10} concentration dynamics, denoted by $\{H_t\}_{t\in\{0,\ldots,T\}}$, be

$$\begin{cases} H_t = \beta_0 + \beta_1(1 - \alpha - \Delta\alpha)N + \beta_2 H_{t-1} + \varepsilon_t, \\ H_0 = h_0. \end{cases} \tag{3.1}$$

This model is an autoregressive model of order one, AR(1), where the term $\beta_1(1 - \alpha - \Delta\alpha)N$ is the contribution of all fossil-fueled vehicles to PM_{10} concentration. In particular, β_1 refers to the PM_{10} concentration contribution of one fossil-fueled vehicle.[4] The ε_t are identical distributed and independent normal random variables with zero mean and variance σ_ε^2. The parameter β_0 is a fixed quantity. Finally, PM_{10} concentration at time zero is h_0. To ease interpretation, we rewrite put Equation (3.1) as a discrete time Ornstein–Uhlenbeck dynamics:

$$H_t - H_{t-1} = (1 - \beta_2)\left(\Phi(\Delta\alpha) - H_{t-1}\right) + \varepsilon_t, \text{ with } H_0 = h_0, \tag{3.2}$$

and

$$\Phi(\Delta\alpha) = \frac{\beta_0 + \beta_1(1 - \alpha - \Delta\alpha)N}{1 - \beta_2}. \tag{3.3}$$

The term $\Phi(\Delta\alpha)$ appearing in Equations (3.2) and (3.3) represents the long-run average of the PM_{10} concentration process and the quantity $1 - \beta_2$ is the mean-reversion speed of the process. Parameter $\Phi(\Delta\alpha)$ linearly depends on N and (negatively) on $\Delta\alpha$.

3.2.3 PM_{10} Concentration Peaks and Traffic Bans

The European Union most important directive for air quality is directive 2008/50/EC. Through this directive, European Union identifies the degree and duration of exposure to pollutants of

[3] Natural pollution refers to the pollution created by natural events, such as volcanic eruptions.

[4] We assume that fossil-fueled vehicles have the same contribution factor and electric vehicles have no impact on PM_{10} contribution. The latter hypothesis is supported by empirical data, at least for small size electric vehicles as shown, for example, in (Cavallaro et al., 2018).

citizens and imposes an air quality target to be fulfilled. The Italian Government adopted legislative decree no. 155/2010 following such a directive. The European Union identifies a safety threshold for average annual and daily PM_{10} concentration not to be exceeded. The annual safety threshold is set to $40\frac{\mu g}{m^3}$, whereas the average daily one is set to $50\frac{\mu g}{m^3}$. Moreover, the daily safety threshold must not be exceeded more than 35 times per year. The problem of air pollution (and its health consequences) is particularly felt in Northern Italy, where densely populated cities, industries and farming activities create emissions that mountains trap it in low-lying plains. Therefore, the governors of Italian regions Emilia-Romagna, Veneto, Lombardy, and Piedmont signed an agreement with the Italian Minister of the Environment and the Protection of Land and Sea in 2017. The agreement "New Program Agreement for the Coordinated and Joint Replacement of Measures to Improve Air Quality in the Po Valley", introduces many restrictions on driving, heating systems and open flames during the winter season. The document allows policymakers to temporarily stop the circulation of polluting vehicles (traffic ban) to reduce the PM_{10} concentration. The rest of this section is devoted to explain how this mechanism works. A policymaker imposes a traffic ban if, for a number of τ consecutive days, the PM_{10} concentration has been greater than or equal to the daily safety threshold of $50\frac{\mu g}{m^3}$. The decision also considers the forecasted weather conditions because windy or rain days can make the PM_{10} concentration fall over. Moreover, the document provides a hierarchical set of decisions for the stop of fossil-fueled vehicles: they can be temporally or totally stopped based on classes of lower and lower emission factors.

Our Methodology In our model, two simplifications apply. The assumption of a unique contribution factor aggregates the fossil-fueled vehicles into a single class, which is not allowed to circulate during a traffic ban period. Moreover, forecasted weather conditions and seasonality of climate are not taken into account by policymaker in traffic ban decisions. A traffic ban is adopted if, for τ consecutive days, the PM_{10} concentration has been greater than or equal to the safety threshold, labeled by c. Let $TB(\Delta\alpha, t, \tau, T)$ be the number of traffic bans imposed in the time horizon $\{t, \dots, T\}$. Notice that $TB(\Delta\alpha, t, \tau, T)$ depends on $\Delta\alpha$ and on the aforementioned number of consecutive days, τ. To fix ideas, let us consider the consecutive times $\{t, \dots, t+\tau-1\}$. A policymaker can impose the traffic ban $TB(\Delta\alpha, t, \tau, t+\tau-1)$ if

$$\mathbb{I}_{\left\{\sum_{k=t}^{t+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha)\geq c\}}=\tau\right\}} = 1, \tag{3.4}$$

where we write $H_k(\Delta\alpha)$ to stress the dependency of the PM_{10} concentration in Equation (3.1) on $\Delta\alpha$. According to Equation (3.4), the expected number of traffic bans in the time horizon $\{0, \dots, T\}$ is calculated as

$$TB(\Delta\alpha, 0, \tau, T) = E^{\mathbb{P}_H}\left[\sum_{i=0}^{T-\tau}\left(\mathbb{I}_{\left\{\sum_{k=t}^{t+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha)\geq c\}}=\tau\right\}}\right)\right]. \tag{3.5}$$

The calculation of the previous expected value is detailed in the Appendix (.D). Figure 3.2 shows the mechanism for imposing a traffic ban as expressed in Equation (3.4) setting $\tau = 4$ and starting from $t = 1$.

3.3 Bilevel Formulation

As briefly discussed in Section 3.2.1, the interaction between the policymaker and vehicle owners is modeled through a stochastic bilevel model. The upper level problem represents a social

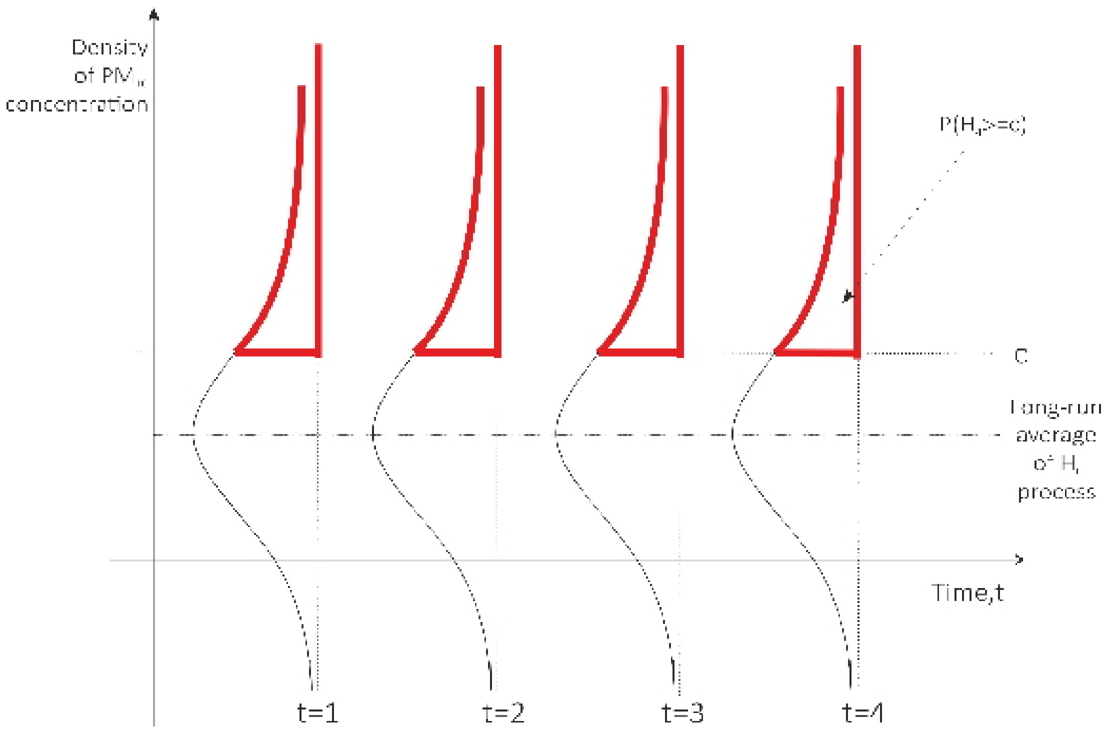


Figure 3.2: Graphical representation of the traffic ban mechanism with $\tau = 4$ and starting time $t = 1$.

cost minimization performed by the policymaker. He identifies the optimal incentive to offer to fossil-fueled vehicle owners to replace their polluting vehicles with an electric ones. The policymaker, while minimizing its objective function, has to consider that each of the $N(1-\alpha)$ fossil-fueled vehicle owners is characterized by a specific disposable income and distance traveled. The lower-level problem represents the optimal scrap decision made by each fossil-fueled vehicle owner when minimizing an individual cost function. For the i-th fossil-fueled vehicle owner, his decision variable is represented by a boolean variable, labeled by η_i: each fossil-fueled vehicle owner can only decide to scrap his polluting vehicle or not and, consequently, purchase an electric vehicle or not. Once all fossil-fueled vehicle owners have taken their decisions, the lower-level decision variables are aggregated as follows:

$$\Delta\alpha = \frac{1}{N} \sum_{i=1}^{N(1-\alpha)} \eta_i. \tag{3.6}$$

The aggregate variable, $\Delta\alpha$, represents the percentage of fossil-fueled vehicle owners deciding to scrap their polluting vehicle and to purchase an electric vehicle. As said above, the time of decision is $t = 0$. After that decision, the total electric vehicles are $N(\alpha + \Delta\alpha)$. The relevant variable in the policymaker is $\Delta\alpha$. The bilevel problem can be stated as in the following;

$$\min_{x,\Delta\alpha} \quad N \cdot \Delta\alpha \cdot x + SC(\Delta\alpha) + LGDP\,(\Delta\alpha) \tag{3.7}$$

$$\text{s.t.} \quad x_{\min} \leq x \leq x_{\max}, \tag{3.8}$$

$$\Delta\alpha = \frac{1}{N} \sum_{i=1}^{N(1-\alpha)} \eta_i, \tag{3.9}$$

$$\min_{\eta_i} f_i(\eta_i), \quad i = 1, \dots, N(1-\alpha), \tag{3.10}$$

$$\text{s.t.} \quad \eta_i \in \{0, 1\}, \tag{3.11}$$

where

$$f_i(\eta_i) = (1-\eta_i)\left(L_i \cdot k^+ + TB\,(\Delta\alpha_0, 0, \tau, T) \cdot c_{stop}\right) + \eta_i \left(L_i \cdot k^- + I - \Gamma_i - x\right). \tag{3.12}$$

The next subsections are devoted to examine the elements of the bilevel problem of Equations (3.7) - (3.11).

3.3.1 Upper level

The upper level objective function (3.7) is the policymaker total expected social cost. The first term is the total cost of the incentive accepted by $N \cdot \Delta\alpha$ fossil-fueled vehicle owners deciding to scrap their polluting vehicle and purchase an electric ones. The second term, $SC(\Delta\alpha)$, measures the impact on the average social costs of an increment of the PM_{10} concentration in terms of hospitalizations and mortality risk. It is defined as

$$SC\,(\Delta\alpha) = (hc + mr) \cdot \Phi\,(\Delta\alpha) \cdot T \cdot N, \tag{3.13}$$

where hc and mr are the unit damage costs for two core endpoints, respectively hospital admissions (e.g. for respiratory and cardiovascular morbidity) and mortality risk, due to the exposure to PM_{10}. Unit damage costs, hc and mr, represent the annual cost per capita due to $1\frac{\mu g}{m^3}$ of the PM_{10} concentration and it is expressed as $€/\mu g/m^3/cap/yr$ while the term $\Phi\,(\Delta\alpha)$ modeled in Equation (3.3) represents the long-run average of the PM_{10} concentration process. The third term, $LGDP\left(\Delta\alpha\right)$, is the social cost in term of GDP loss associated with traffic bans. It is defined as

$$LGDP\left(\Delta\alpha\right) = prl \cdot n_B \cdot TB\left(\Delta\alpha, 0, \tau, T\right), \tag{3.14}$$

where prl is the GDP loss due to one day of traffic ban, n_B is the length (in days) of a traffic ban and $TB\left(\Delta\alpha, 0, \tau, T\right)$ is the expected number of traffic bans over the time horizon $\{0, \ldots, T\}$ calculated as in Equation (3.5).

Overall, the objective function in the upper level is the combination of three terms depending on $\Delta\alpha$: the cost of the incentives increases with $\Delta\alpha$, the social costs and the GDP losses decrease with $\Delta\alpha$. However, $\Delta\alpha$ depends in a non-linear way with respect to the incentive, x, as we will see in the lower level of this model. This makes the optimization problem non-linear. Constraint (3.8) states minimum and maximum values for the incentive. Constraint (3.9) reports the lower level aggregate variable introduced in Equation (3.6), i.e. the percentage of fossil-fueled vehicles owners deciding to scrap their polluting vehicle and purchase an electric one.

3.3.2 Lower level

The lower level problem is included in Equations (3.10) and (3.11). Each fossil-fueled vehicle owner minimizes, in the objective function (3.10), his individual total cost deciding either purchase (or not) an electric vehicle. The decision is, therefore, of boolean type: keeping the polluting vehicle is labeled as $\eta = 0$, whereas the decision of adopting an electric vehicle is labeled as $\eta = 1$. Moreover, the first addend in Equation (3.12) reflects the total costs incurred by each fossil-fueled vehicle owner when deciding to keep their polluting vehicle. On the other hand, the second addend in Equation (3.12) expresses the total costs incurred by each fossil-fueled vehicle owner when deciding to accept the incentive and purchase an electric vehicle. As it will often recur in this chapter, we introduce the terms $E\left[X_t^+\right]$ and $E\left[X_t^-\right]$ and we finish the section analyzing separately the two addends of Equation (3.12).

The choice of buying an electric vehicles depends also on the electricity and fuel prices in terms of time varying opportunity cost. We construct the unit distance opportunity cost of driving a fossil-fueled vehicle instead of an electric one time series as in Chapter 2:

$$X_t = h^f p_t^f - h^e p_t^e, \tag{3.15}$$

where p_t^f is the gasoline price at time t, h^f is the fuel economy of a fossil-fueled vehicle, p_t^e is the electricity price at time t and h^e represents the fuel economy of an electric vehicle.

Each fossil-fueled vehicle owner's decision is based on expectation conditioned on the informations available on the decision time. In our model, the decision time for each fossil-fueled vehicle owner is only $t = 0$, where the informations are included in the poorest σ-algebra, $\mathcal{G} = \{\Omega, \emptyset\}$. We work out the following quantities

$$E\left[X_t^+\right] = E\left[\max\left(X_t, 0\right)\right], \quad E\left[X_t^-\right] = E\left[\min\left(X_t, 0\right)\right].$$

The term $E\left[X_t^+\right]$ is the opportunity cost of driving one unit of distance with a fossil-fueled vehicle instead of covering the same distance with an electric one, when driving a fossil-fueled vehicle is more expensive than driving an electric one. The term $E\left[X_t^-\right]$ represents the opportunity cost of driving one unit of distance with an electric vehicle instead of covering the same distance with a fossil-fueled one, when driving an electric vehicle is more expensive than driving a fossil-fueled one.

No-switch decision

If $\eta_i = 0$, the individual cost function, labeled by Λ_i^0, includes the fuel-opportunity driving costs and the traffic ban costs:

$$\Lambda_i^0 = L_i \cdot E\left[X_t^+\right] + TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop}, \;\; i = 1, \ldots, N\left(1-\alpha\right). \tag{3.16}$$

The term $L_i \cdot E\left[X_t^+\right]$ is the opportunity cost of driving L_i units of distance with a fossil-fueled vehicle instead of covering the same distance with an electric one, when driving a fossil-fueled vehicle is more expensive than driving an electric one. It is calculated as the product of the individual distance traveled, L_i, and the expected opportunity cost of driving one unit of distance, $E\left[X_t^+\right]$.

The term $TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop}$ is the expected cost of traffic bans. It is calculated as the product between the expected number of traffic bans in the time horizon $\{0, \ldots, T\}$ that each individual expects, the average length (in days) of one traffic ban, n_B, and the daily private cost of each traffic ban, c_{stop}. Moreover, we assume that the fossil-fueled vehicle owners estimate the expected number of traffic bans using Equation (3.5) and anticipating that the percentage of people adopting the switch decision will be $\Delta\alpha_0$. The daily private cost of each traffic ban, c_{stop}, represents the daily economic penalty that each fossil-fueled vehicle owner bears looking for alternative transportation system with the associated inconvenient of different transportation schedule, possible delay and ticket payment. The term c_{stop} expresses the same average cost among all the fossil-fueled vehicle owners population. We left as future work the generalization of the electric vehicle purchase model where each fossil-fueled vehicle owner is characterized by a specific daily private cost of each traffic ban.

Switch decision

If $\eta_i = 1$, the individual cost function, labeled by Λ_i^1, includes the electric-opportunity driving costs and the electric vehicle net purchase cost, that is

$$\Lambda_i^1 = L_i \cdot E\left[X_t^-\right] + I - \Gamma_i - x, \;\; i = 1, \ldots, N\left(1-\alpha\right). \tag{3.17}$$

Interpretation of the term $L_i \cdot E\left[X_t^-\right]$ is immediate: it is the opportunity cost of driving L_i (in kilometers) with an electric vehicle instead of covering the same distance with a fossil-fueled one, under the hypothesis that driving an electric vehicle is more expensive than driving a fossil-fueled one. The term $I - \Gamma_i - x$ is the electric vehicle net purchase cost. It is composed of three terms: the electric vehicle purchase cost, I, the i-th individual disposable income, Γ_i, and the incentive granted by the policymaker, x.

3.4 Reduction of the bilevel problem to a single level problem

As briefly discussed in the introduction, we now investigate the main modeling contribution of our analysis: the reduction of the stochastic bilevel problem to a single level constrained problem. The main advantage of this approach lies in the fact that we obtain a closed-form solution to the optimization problem. We can immediately state that the original stochastic bilevel problem can be reduced to the following single-level problem:

$$\min_y \; N \cdot \Delta\alpha(y) \cdot y + (hc + mr) \cdot \Phi(\Delta\alpha(y)) \cdot T \cdot N + prl \cdot n_B \cdot TB(\Delta\alpha(y), 0, \tau, T) \tag{3.18}$$

$$\text{s.t.} \;\; x_{\min} \leq y \leq x_{\max}, \tag{3.19}$$

$$\Delta\alpha(y) = 1 - \alpha - \left(\int_0^{\ell_{\max}(y)} \int_0^{\gamma(\ell,y)} f_{\Gamma,L}(\gamma,\ell)\, d\ell d\gamma \right) (1-\alpha). \tag{3.20}$$

The following sections are devoted to explaining and show such transformation.

3.4.1 Comparing the Costs of Switch and No-Switch

Up to this point, we dealt with a population composed of a discrete number of fossil-fueled vehicle owners. For analytical treatment, we reformulate the problem in a continuous setting, where a fossil-fueled vehicle owner is identified as a realization of an absolutely continuous bivariate random variable (Γ, L), i.e. $\omega = (\gamma, \ell) \in \Omega$, with $\mathbb{P}$ the probability distribution of (Γ, L) and $f_{\Gamma,L}(\gamma,\ell)$ its probability density function. To fix ideas, one can interpret the probability density function $f_{\Gamma,L}(\gamma,\ell)$ in a discrete setting as the proportion of fossil-fueled vehicle owners with a disposable income equal to γ and a traveled distance equal to ℓ. This last assumption introduces an equivalence between the subscript i and ω in Equations (3.17) and (3.16). In particular we let:

$$\Lambda^0_\omega(x) = \ell \cdot E\left[X_t^+\right] + TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop}, \tag{3.21}$$

$$\Lambda^1_\omega(x) = \ell \cdot E\left[X_t^-\right] + I - \gamma - x. \tag{3.22}$$

The cost function $\Lambda^1_\omega(x)$ depends negatively on the incentive because the net purchase cost, $I - \gamma - x$, decreases as the incentive, x, increases. Drawing the functions $\Lambda^1_\omega(x)$ and $\Lambda^0_\omega(x)$ in the plane (x, Λ_ω), one can notice that there exists a unique incentive value that makes those functions equal. We refer to this value as "ω-th indifference incentive" and it is shown in Figure 3.3. The indifference incentive makes the fossil-fueled vehicle owner indifferent between the choice of scrapping their polluting vehicle and purchasing an electric vehicle and the choice of keeping their fossil-fueled one.

To prevent trivial cases where the decision of purchasing is made even with an incentive equal to zero, it is necessary that

$$\Lambda^1_\omega(0) > \Lambda^0_\omega(0). \tag{3.23}$$

The value of the ω-th indifference incentive is calculated by equating Equations (3.21) and (3.22). It is defined by

$$y_\omega = I - \gamma - TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop} - \ell\left(E\left[X_t^+\right] - E\left[X_t^-\right]\right), \tag{3.24}$$

that is

$$y_\omega = I - \gamma - TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop} - \ell \cdot E\left[X_t\right],$$

where, in the last step, we write $E[X] = E\left[X_t^+\right] - E\left[X_t^-\right]$. According to Equation (3.24), it is possible to define a decision variable equivalent to η_i:

$$\eta_{y_\omega} = \begin{cases} 0 & \text{if} \quad x < y_\omega \\ 1 & \text{if} \quad x \geq y_\omega \end{cases} \tag{3.25}$$

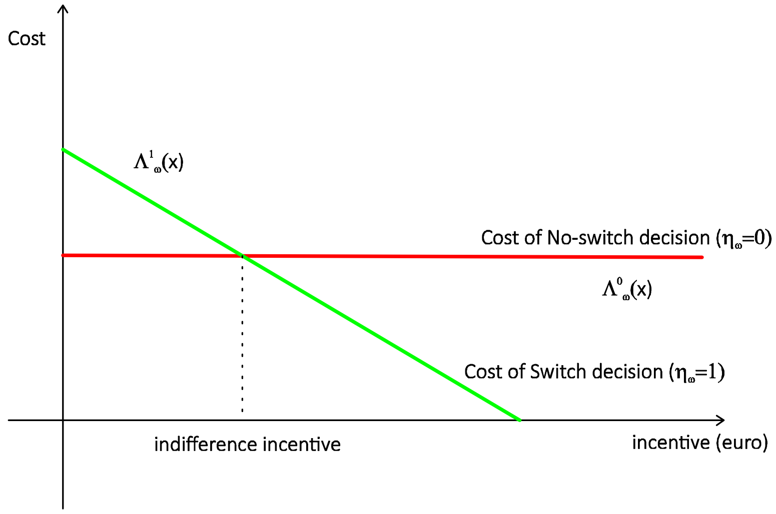


Figure 3.3: Representation of the ω-th fossil-fueled vehicle owner cost functions and the associated indifference incentive.

which depends on the ω-th indifference incentive. The interpretation follows. Each fossil-fueled vehicle owner decides to scrap their polluting vehicle and purchase an electric one if and only if the incentive granted by policymaker, x, is greater than or equal to the indifference incentive. Using Equation (3.25), it is possible, for all fossil-fueled vehicle owners, to model a new cost function that depends on their indifference incentive. For the ω-th fossil-fueled vehicle owner, the new cost function is a stepwise function defined as

$$\Lambda_{y_\omega}(x) = \begin{cases} \ell \cdot E\left[X_t^+\right] + TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop}, & \text{if} \quad x < y_\omega \\ \ell \cdot E\left[X_t^-\right] + I - \gamma - x, & \text{if} \quad x \geq y_\omega \end{cases} . \tag{3.26}$$

A representation of the ω-th cost function in terms of the indifference incentive, as in Equation (3.26), is shown in Figure 3.4.

The indifference incentive, y_ω, varies according to Equation (3.24), which depends on each fossil-fueled vehicle owner distance traveled and disposable income. Therefore, the indifference incentive y_ω is a function of the bivariate random variable (Γ, L) We notice that the same value of incentive, labeled by y, may be associated with fossil-fueled vehicle owners characterized by different disposable income or distance traveled. We now introduce the following set

$$B_y = \left\{(\ell, \gamma) \in \mathbb{R}_+^2 \cup \{0\} : \gamma = I - TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop} - y - \ell \cdot E\left[X_t\right]\right\}, \tag{3.27}$$

which is the set of all fossil-fueled vehicle owners with an indifference incentive equal to y. Given y, B_y identifies an equivalence class of decision makers. For them, the decision is

$$\eta_y = \begin{cases} 0 & \text{if} \quad x < y \\ 1 & \text{if} \quad x \geq y \end{cases} .$$

In the same spirit of Equation (3.26), the cost function of fossil-fueled vehicle owners with an indifference incentive equal to y is defined as

$$\Lambda_y(x) = \begin{cases} \ell \cdot E\left[X_t^+\right] + TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop}, & \text{if} \quad x < y \\ \ell \cdot E\left[X_t^-\right] + I - \gamma - x, & \text{if} \quad x \geq y \end{cases} , \tag{3.28}$$

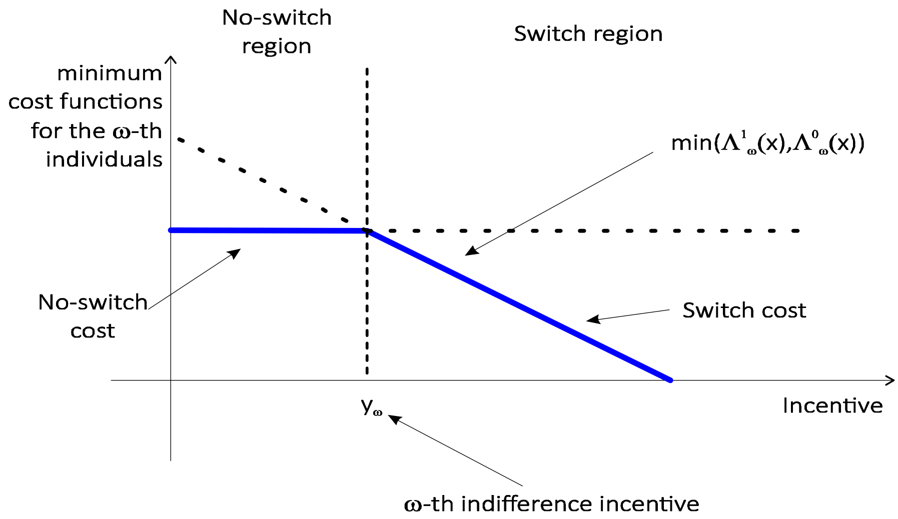


Figure 3.4: Representation of the ω-th cost functions $\Lambda_{y_\omega}(x)$ in terms of the ω-th indifference incentive.

where each step of Equation (3.28) is characterized by a specific intercept determined by the realizations of the bivariate random variable (Γ, L).

3.4.2 Partition of the Sample Space Ω

In our setting, the introduction of set B_y and the use of probability theory allow us to analytically reduce the initial bilevel problem to a single level problem. The sample space of fossil-fueled vehicles owners, discussed in Section 3.2.2, is partitioned according to set B_y, which, in turn, depends on the value of the indifference incentive. The sample space of fossil-fueled vehicle owners, Ω, can be divided into two disjoint sets: the set of fossil-fueled vehicle owners that have to decide whether to purchase an electric vehicle and the set of fossil-fueled vehicle owner that decide to keep their polluting vehicle when the policymaker's incentives is set to y. The latter is denoted as "no-switch set" and it is labeled by NS_y while the former is denoted as "decision set" and it is labeled by S_y. We notice that the measures of sets NS_y and S_y depend on B_y and on the probability measure $\mathbb{P}$.

No-Switch Set

The no-switch set, NS_y, is defined as

$$NS_y = \left\{(\ell, \gamma) \in \mathbb{R}_+^2 \cup \{0\} : \gamma < I - TB\left(\Delta\alpha_0, 0, \tau, T\right) \cdot n_B \cdot c_{stop} - y - \ell \cdot E\left[X_t\right]\right\}. \quad (3.29)$$

Set NS_y is populated by those elementary events consisting of fossil-fueled vehicle owners, characterized by a couple (ℓ, γ), that, when the incentive is set to y, cannot purchase an electric vehicle either because they have a low disposable income or because their distance traveled is not so high to compensate the purchase of a new vehicle. The measure of NS_y, $\mathbb{P}(NS_y)$, is calculated through a joint cumulative distribution function using the density function of the bivariate random variable (Γ, L), $f_{\Gamma,L}(\gamma, \ell)$:

$$\begin{aligned}\mathbb{P}(NS_y) &= \mathbb{P}\left(\left\{(\ell,\gamma) \in \mathbb{R}_+^2 \cup \{0\} : \gamma < I - TB(\Delta\alpha_0, 0, \tau, T) \cdot n_B \cdot c_{stop} - y - \ell \cdot E[X_t]\right\}\right) \\ &= \int_0^{\ell_{\max}(y)} \int_0^{\gamma(\ell,y)} f_{\Gamma,L}(\gamma,\ell)\, d\gamma d\ell,\end{aligned} \tag{3.30}$$

where $\ell_{\max}(y)$ is the upper bound of integration of the first integral,

$$\ell_{\max}(y) = \frac{I - TB(\Delta\alpha_0, 0, \tau, T) \cdot n_B \cdot c_{stop} - y}{E[X_t]}, \tag{3.31}$$

and $\gamma(\ell, y)$ is the upper bound integration of the second integral. The function $\gamma(\ell, y)$ depends on the the indifference incentive y and on the values taken by the random variable L and it is defined as

$$\gamma(\ell, y) = I - TB(\Delta\alpha_0, 0, \tau, T) \cdot n_B \cdot c_{stop} - y - \ell \cdot E[X_t]. \tag{3.32}$$

Decision set

The decision set, S_y, is the complementary of the no-adoption set with respect to Ω. Set S_y can be analytically defined in the following way:

$$S_y = \left\{(\ell,\gamma) \in \mathbb{R}_+^2 \{0\} : \gamma \geq I - TB(\Delta\alpha_0, 0, \tau, T) \cdot n_B \cdot c_{stop} - y - \ell \cdot E[X_t]\right\}. \tag{3.33}$$

As done for the no-adoption set, the measure of S_y, $\mathbb{P}(S_y)$, is calculated through a joint cumulative distribution function using the density function of the bivariate random variable (Γ, L), $f_{\Gamma,L}(\gamma, \ell)$:

$$\begin{aligned}\mathbb{P}(S_y) &= \mathbb{P}\left(\left\{(\ell,\gamma) \in \mathbb{R}_+^2 \{0\} : \gamma \geq I - TB(\Delta\alpha_0, 0, \tau, T) \cdot n_B \cdot c_{stop} - y - \ell \cdot E[X_t]\right\}\right) \\ &= 1 - \int_0^{\ell_{\max}(y)} \int_0^{\gamma(\ell,y)} f_{\Gamma,L}(\gamma,\ell)\, d\gamma d\ell,\end{aligned} \tag{3.34}$$

with $\ell_{\max}(y)$ and $\gamma(\ell, y)$ are expressed as in Equations (3.31) and (3.32), respectively. In the discrete case, $\mathbb{P}(S_y)$ is the percentage of fossil-fueled vehicle owners deciding to purchase an electric vehicle depending on the indifference incentive.

A representation of the partition of the sample space Ω through B_y, the indifference set is shown in Figure 3.5.

When a positive α percentage of electric vehicles is considered, using Equations (3.30) and (3.34), the general formulation of $\Delta\alpha$ is

$$\Delta\alpha = 1 - \alpha - \left(\int_0^{\ell_{\max}(y)} \int_0^{\gamma(\ell,y)} f_{\Gamma,L}(\gamma,\ell)\, d\gamma d\ell\right)(1-\alpha).$$

3.5 Model Application

In this section, we apply the model in Equations (3.18)-(3.20) assuming a population of one million of citizens, i.e. $N = 1000000$, with a ratio of vehicles to citizens equal to $1:1$ and a time horizon of 365 days. Such settings describe approximately the case of an industrialized and densely populated area like the province of Brescia in Italy.

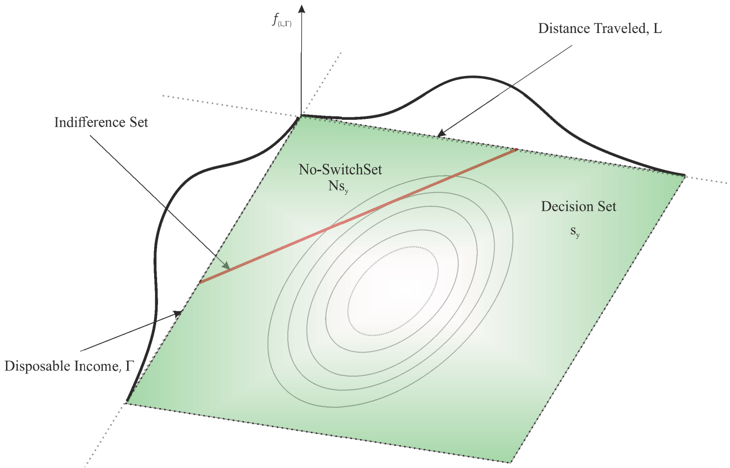


Figure 3.5: Graphical representation of the partitioned sample space Ω into the no-switch set, NS_y and the decision set, S_y with respect to the indifference set B_y.

3.5.1 Parameters Estimation

$\mathbf{PM_{10}}$ concentration

The percentage of electric vehicle owner, α, is estimated from Italian data supplied by (Club d'Italia, 2018) for 2018 and it is 0.005%. We approximate the previous percentage to zero so we set $\alpha = 0$. The parameters of PM_{10} concentration in Equation (3.1) are estimated from Italy with daily frequency from January 1st, 2018 to December 31st, 2018. The data are supplied by (Environment Agency, 2018). In particular, (Environment Agency, 2018) collects the data from measurement stations. Based on Article 5 of 'Legislative Decree 155/2010' (2010), such measurements are divided in three categories: traffic, industrial and background. Traffic measurement stations are located in such a position that PM_{10} concentration is mainly influenced by road traffic emissions, industrial measurement stations are located in such a position that PM_{10} concentration is affected mainly from industry emissions while background measurement stations are located in such a position that PM_{10} concentration is not affected by well identified sources. We construct the PM_{10} concentration time series averaging, for each day, the PM_{10} concentration of all measurement stations types. This time series in plotted in Figure 3.6. The graphs of auto-correlation and partial auto-correlation functions are shown in Figure 3.7. Such a graphs show that the empirical data confirm the mean-reverting behavior of PM_{10} concentration assumed in (3.1). Based on Figure 3.7, an AR(3) model seems to be the most appropriate, confirmed also by the Bayesian information criterion (BIC). Our choice to describe the PM_{10} concentration time series as an AR(1) model is based on presuppositions. Using an AR(1) model assumption, we can derive explicitly the expected number of traffic bans in Equation (3.5) without using any simulation method. It means that the advantages of dealing with an AR(1) model are greater than the econometrics advantages, i.e. a best fit of the PM_{10} dynamics. Moreover, the econometric estimations based on an AR(1) model are significative.

Parameters β_0, β_2 and σ_ε^2 in Equation (3.1) are estimated applying the Ordinary Least Squares method to an auto-regressive model of order one. The estimated values and the significance levels are reported in Table 3.1.

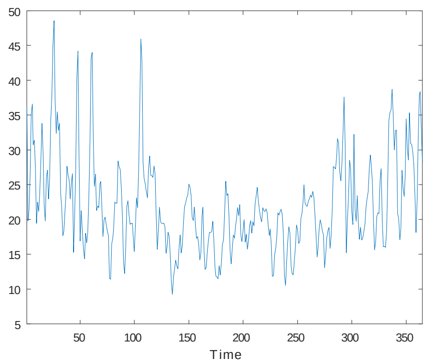


Figure 3.6: Average PM_10 concentration.

Parameter	Estimated value	Significance Level
β_0	3.94	$1,80735 \cdot 10^{-8}$
β_2	0.82	$1,35255 \cdot 10^{-91}$
σ_ε	3.85	-

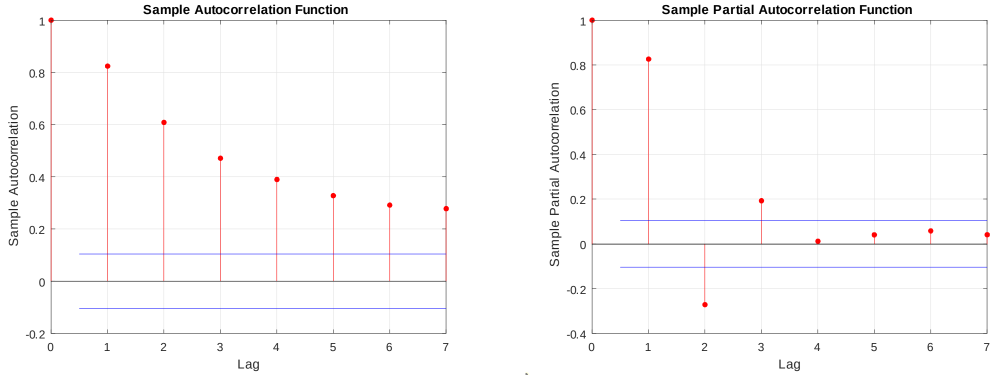
Table 3.1: Estimated values and significance levels of parameters of PM_{10} concentration.

We notice that the high statistical significance of the mean-reverting parameter. The PM_{10} concentration at time zero is set to $25\frac{\mu g}{m^3}$. The estimation of parameter β_1 in Equation (3.1) is delicate since it is not possible to measure directly the impact of a fossil-fueled vehicle in terms of PM_{10} concentration.

To estimate parameter β_1 value, we applied the model of the traffic bans in Equation (3.5) plugging the estimated values of β_0, β_2 and σ_ε of Equation (3.1) and assuming $\alpha = 0$ and $\Delta\alpha = 0.05$. We then calibrated the model adjusting the parameter β_1 until it produced an expected number of traffic bans similar to the observed traffic bans in the four Italian regions of Chapter 2. The value of β_1 resulting from this calibration is 0.00000367521. It is possible to see that the resulting traffic bans of model $TB\left(\Delta\alpha, 0, \tau, T\right)$ as in Equation (3.5) is 8.54, that is reasonably closed to that of the four regions.

Parameters in the upper level

The term $(mr + hc)$ of the social cost (per capita) in Equation (3.13) is set to $417,7446$ euro. It latter is obtained multiplying the Italian average social cost per capita taken from (S. and J., 2020), $1392,4821$ euro, by an adjustment factor of 30% that is based on empirical estimation in (Arpae, 2017). The term prl in Equation (3.14) is set to 28 millions euro while the average length of days of each traffic ban, n_b, is set to 2 days. The value of prl is estimated supposing that the each traffic ban reduces of 20% the daily GDP in the population (for example, the province of Brescia in Italy, in 2016 was around 35 bilions of euro obtained by multiplying the number of citizens (around one million) by the GDP pro capita in (ISTAT, 2018)). As for the boundary values of incentives, $x_{\min}$ and $x_{\max}$, we set $x_{\min} = 0$ and $x_{\max} = 6000$ euro. The choice of $x_{\max}$ is based on the Italian Ministry of Economic Development's Decree of March 20th, 2019. It states that an incentive of 6000 is granted if a fossil-fueled vehicle is scrapped and an electric vehicle,



Autocorrelation function for PM_{10} concentration.

Partial autocorrelation function for PM_{10} concentration.

Figure 3.7: Representations of the auto-correlation and partial auto-correlation functions for H_j.

with a CO_2 emissions rate less than 20 g/km, is purchased.

Parameters in the lower level

We assume that the daily individual economic penalty that the fossil-fueled vehicle owner incurs looking for alternative transportation during a traffic ban, c_{stop}, to 75 euros for each individual. Distance traveled and disposable income are assumed to be a continuous bivariate normal random variable with zero correlation. Although a strictly positive distribution, such as a bivariate lognormal random variable, would be a better option, the normality assumption is reasonable as long as the means of disposable income and distance traveled are significantly larger than its variance. The estimations of those means and standard deviations are based on data from (Enerdata, 2020) and (EUROSTAT, 2020) for the Europe from 2007 to 2017 with annual frequency. For the distance traveled, L, expressed in kilometers, the mean is $\mu_L = 12818$ and the standard deviation is $\sigma_L = 1479$. For the disposable income, Γ, expressed in euro, the mean is $\mu_\Gamma = 22318$ and $\sigma_\Gamma = 3048$. We calculate the quantities $\mu_L - 3 \cdot \sigma_L$, $\mu_L + 3 \cdot \sigma_L$ and $\mu_\Gamma - 3 \cdot \sigma_\Gamma$, $\mu_\Gamma + 3 \cdot \sigma_\Gamma$. We observe that those values are positive. Using the fact that $P(-3\sigma \leq Z \leq 3\sigma) \approx 0.99$ for any normal random variable Z, we state that the possible outcomes of both random variables, L and Γ, are positive with probability of 99%. The purchase cost, I, is set to 25000€ as in Chapter 2. Based on empirical data of Chapter 2, the estimated values are $\widehat{E\left[X_t^+\right]} = 0.1$ and $\widehat{E\left[X_t^-\right]} = 0$ and therefore $\widehat{E\left[X_t\right]} = 0.1$.

3.5.2 Analysis of the Results

In this section we study numerically the comparative statics of important outputs of the model with respect to several key parameters. The output considered will be: the incentive (x), the percentage of new electric vehicle purchased at time zero ($\Delta\alpha$), the policymaker's cost function and the expected traffic bans, (TB).

Sensitivity to parameter α We start commenting the comparative statics with respect to the percentage of electric vehicles at time zero, α. When the percentage of electric vehicles at time zero is the lowest one, $\alpha = 0$, the PM_{10} is at its highest level and it leads to the highest expected (previsional) number of expected traffic bans, as one can see in Panel (b) of Figure 3.9. The fossil-fueled vehicle owners bear the highest traffic bans costs, so the policymaker can offer a minimum amount of incentive. The percentage of new electric vehicle purchased, $\Delta\alpha^*$, is equal to 70%. As parameter α increases, the expected (previsional) number of traffic bans reduces. Under this circumstances, to encourage the fossil-fueled vehicle owners to purchase an electric vehicle, the policymaker has to set a higher level of incentive. An interesting case is that when parameter α is set from 50% on. In these cases, the expected (previsional) number of traffic bans is around zero and the policymaker fixes optimally the incentive at 2800 euro. Despite the incentive increases, the total cost for the policymaker is decreasing. This last effect can be explained noticing that there is a high presence of electric vehicles which leads to a low level of air pollution. The policymaker cost function is reduced because, on the one hand, there is a reduction in the direct cost of the incentive because few people decide to adopt an electric vehicle. On the other hand, both social and GDP losses costs are reduced because of a decrease in the PM_{10} concentration.

Sensitivity to parameter τ We now study the comparative statics with respect to the traffic stop rule (parameter τ, the number of consecutive days that triggers a traffic ban). We start observing that the number of expected (previsional) traffic bans is obviously decreasing with respect to an increase in parameter τ: increasing the required number of consecutive days to force a traffic ban, reduce the probability of such event. An illustration is shown in Panel (d) of Figure 3.9. When the expected (previsional) number of traffic ban decreases, the cost associated to the no-switch decision decreases and, therefore, the policymaker has to offer an increasing incentive to promote the electric vehicle adoption. We notice that policymaker's objective function is increasing with respect to parameter τ even if the optimal percentage of electric vehicle purchased, $\Delta\alpha^*$, is decreasing. The reasons are twofold. On one hand, the total cost of incentives increases because the fossil-fueled vehicle owners accept to switch to an electric vehicle with a higher incentive value. On the other hand, the social cost increases due to an increase in the PM_{10} concentration connected to a decreasing in the percentage of the new electric vehicle, $\Delta\alpha^*$. As general rule, it is possible to state that the policymaker has to define the stop rule carefully. A low value of τ leads to a higher expected number of traffic bans, that can be acceptable to a policymaker with relatively high environmental concern. On the opposite case, a high value of τ leads to a lower expected number of traffic bans that help to sustain the local GDP but, on the other hand, penalizes the citizens with higher social costs.

Sensitivity to parameter I As for the purchase cost I, one can notice that, when the electric vehicle purchase cost is relatively low, the optimal percentage of electric vehicle purchased is the highest one even if the incentive is set to zero. The obvious result can be commented observing in Panel (f) of Figure 3.8 the area of the no-switch set, which is modeled through Equations (3.31) and (3.32). Both $\ell_{\max}$ and $\gamma_{\max}$ depend on the incentive, x, and the purchase cost, I. Joint variations of those parameters modify the no-switch set area. In particular, it increases as long as

$$\frac{\Delta I}{\Delta x} > 1, \tag{3.35}$$

Condition (3.35) says that the area of the no-switch set increases if the variation in the purchase cost, I, is greater than the variation in the incentive, x. Observing the values of purchase cost and the incentive in Figure 3.8, one can immediately see that indeed condition (3.35) holds.

Decreasing the optimal percentage of electric vehicles leads to an increase of both social cost in the policymaker's objective function and in the number of optimal expected traffic bans as shown in Panel (e) and (f) of Figure 3.9, respectively.

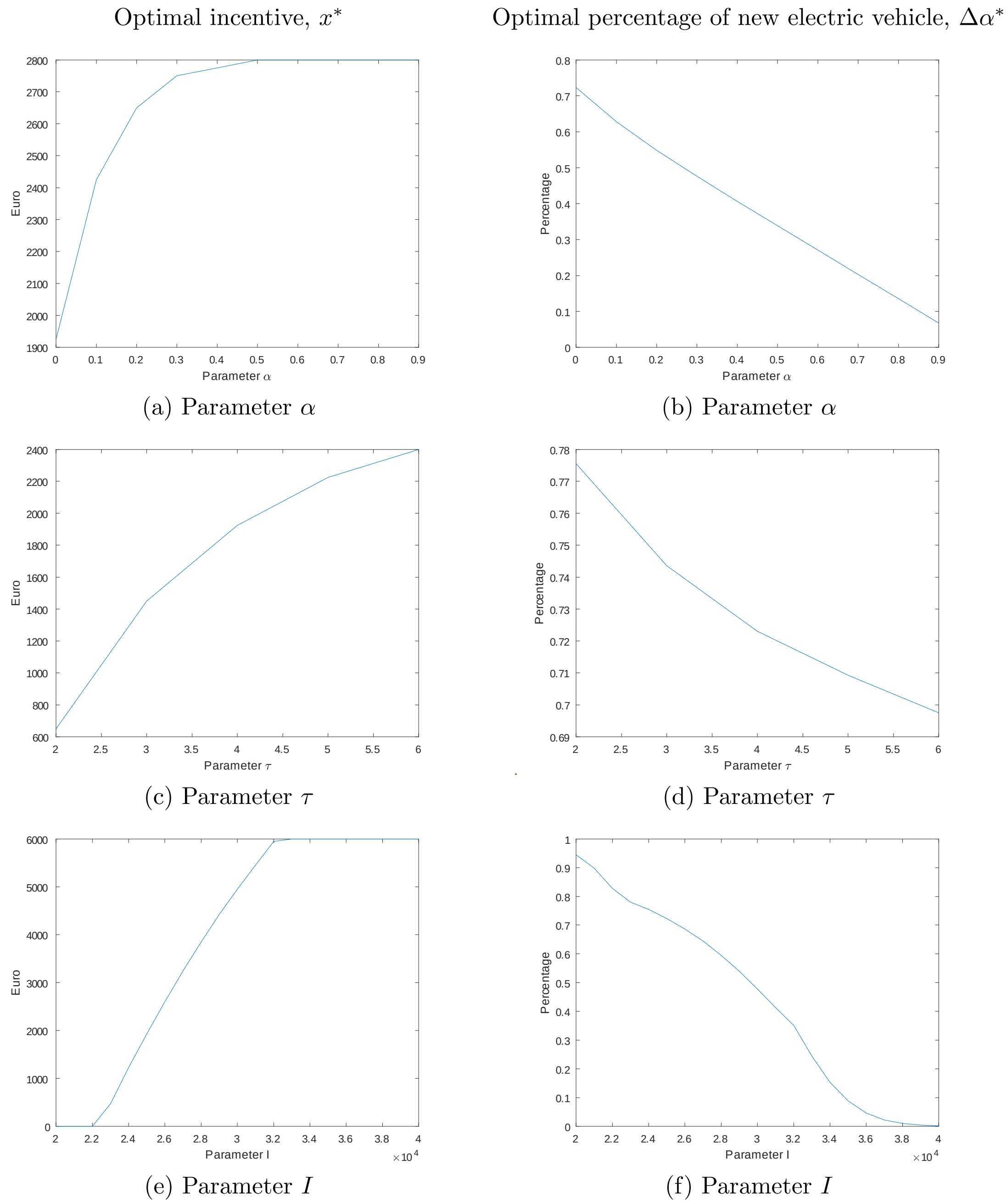
Sensitivity to average parameter μ_Γ We recall that this parameter is the average of the disposable income. We observe that as long as the fossil-fueled vehicle owners have on average a low disposable income, the policymaker offers the maximum level of incentive (i.e. 6000 euro) to encourage the electric vehicles adoption . Nevertheless only the 30% of the fossil-fueled vehicle owners decide to switch. This leads to increasing social costs. The low percentage of electric vehicle purchased is given by a combination of two contrasting effects. On one hand, an increase in the incentive leads to a reduction of the no-switch set area. On the other hand, when the mean of the random variable Γ increases, (i.e. owners are richer on average), the policymaker reduces the incentive, so both $\ell_{\max}$ and $\gamma\,(y,\ell)$ increase as well as the no-switch set area. At the same time, the distribution of (Γ, L) starts to move to West-South considering Figure 3.5. The latter movement happens with a higher speed than that of the no-switch area therefore the percentage of new electric vehicle increases. As a result, as we observe in Panel (a) of Figure 3.11, social costs reduce.

Sensitivity to volatility parameter σ_Γ We now move to study the comparative statics with respect to the volatility parameter of the disposable income, σ_Γ. We immediately notice that the optimal incentive has a parabolic behavior. The explanation is based on the similar arguments applied in the comparative statics with respect to the mean of the disposable income, μ_Γ. When the volatility parameter is low, the fossil-fueled vehicle owners have a disposable income closed to μ_Γ and even if the policymaker fixed a low incentive, only a small percentage of the fossil-fueled vehicle owners (those corresponding to the low income tail of the distribution of Γ) are collected in the no-switch set area, so the people deciding to switch is closed to one. Increasing the volatility parameters leads to two different effects. On the one hand, the policymaker needs to fix a higher level of incentive, which decreases the no-switch area, and on the other hand, the number of fossil-fueled vehicle owners represented by the low income tail of the distribution of Γ in the same area is decreasing as well. The combination of those effects leads to a significant decrease in the optimal percentage of electric vehicles. We notice that the maximum level of incentive is reached when σ_Γ is around 2500 and after that value, a surprising fact happens: the policymaker decides to reduce the incentive. This happens because of a trade-off problem for the policymaker. When the volatility parameter is less than 2500, few fossil-fueled vehicle owners accept to purchase an electric vehicle so the policymaker could increase the indifference incentive to promote the electric vehicle adoption. After that point, a higher levels of incentive combined with increasing percentage of people in the no-switch area leads to an increase in the cost of incentives. In this situation, the cost of incentives would increase with a higher rate with respect to the growth rate of the social costs. Policymaker is in front of a trade-off: keeping a higher level of incentive to increase the percentage of new electric vehicles and save money in terms of social cost or reduce the incentive with a reduction of the percentage of new electric vehicle adoption and increase the social cost. The policymaker chooses to reduce the incentives and left the social cost growing as against the cost of the incentive.

3.6 Conclusions

In this paper we have provided a bilevel model for the optimal public incentive policy to assist the switch decision of a population of fossil-fueled vehicle owners. The policymaker minimizes a cost function including the total cost of incentives, social costs (hospitalization costs and the cost associated to mortality risk) and the traffic bans costs (namely, the GDP slowdown). On their hand, fossil-fueled vehicle owner have to decide if to switch (or not) to an electric vehicle. They minimize an individual cost function depending on the random values of distance traveled yearly and personal income. To enhance the analytical treatment, we model these random variables as a continuous bivariate random variable, so that the initial bilevel problem is reduced to a single level problem. We have solved the resulting optimization problem. For an application the model has been calibrated through real data and a detailed comparative statics on some model's parameters.

The problem analyzed has provided important implications for the policymaker. As we have seen, many factor either exogenous or under the control of the policymaker influence the optimal incentive. The available income of the citizens has, as it could be expected, a strong influence on their decision. Moreover, the policymaker regulation can encourage the adoption of the electric vehicle using the traffic bans. Despite we do not optimize the traffic bans regulation, our model shows that the optimal incentive can be combined with alternatives stop rules. This extension is left as future research. Moreover, it would be interesting to model a switching decision within a dynamic setting, observing how the fossil-fueled vehicles owners' decision impact both on gasoline and electricity prices. In the same spirit, it significantly would be interesting to investigate how the alternative stop rules impact on the PM_{10} concentration.

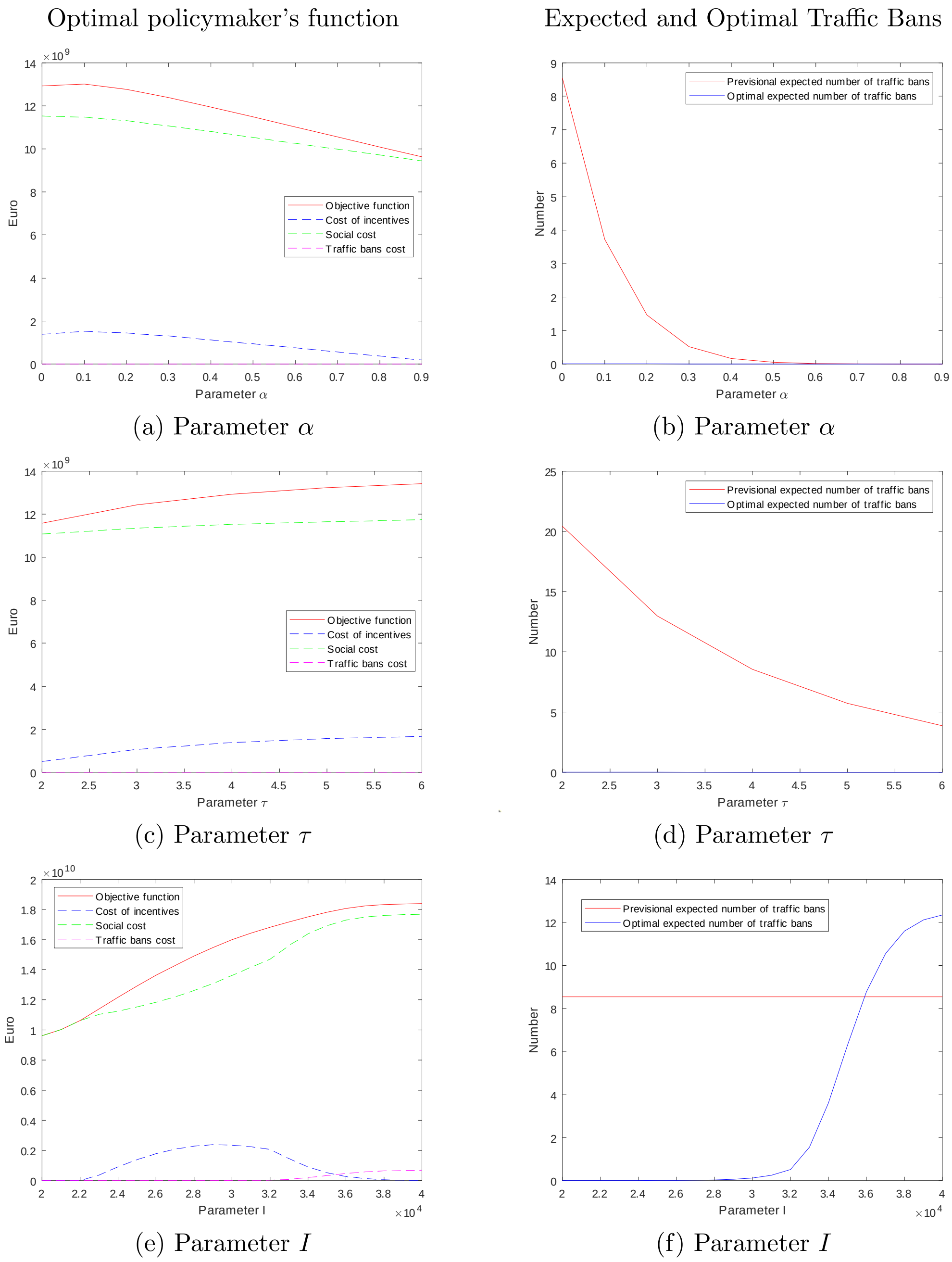


(a) Parameter α (b) Parameter α

(c) Parameter τ (d) Parameter τ

(e) Parameter I (f) Parameter I

Figure 3.8: Dependency of the optimal incentive, x and the optimal percentage of new electric vehicles, $\Delta\alpha$ w.r.t. parameters α, τ and I.

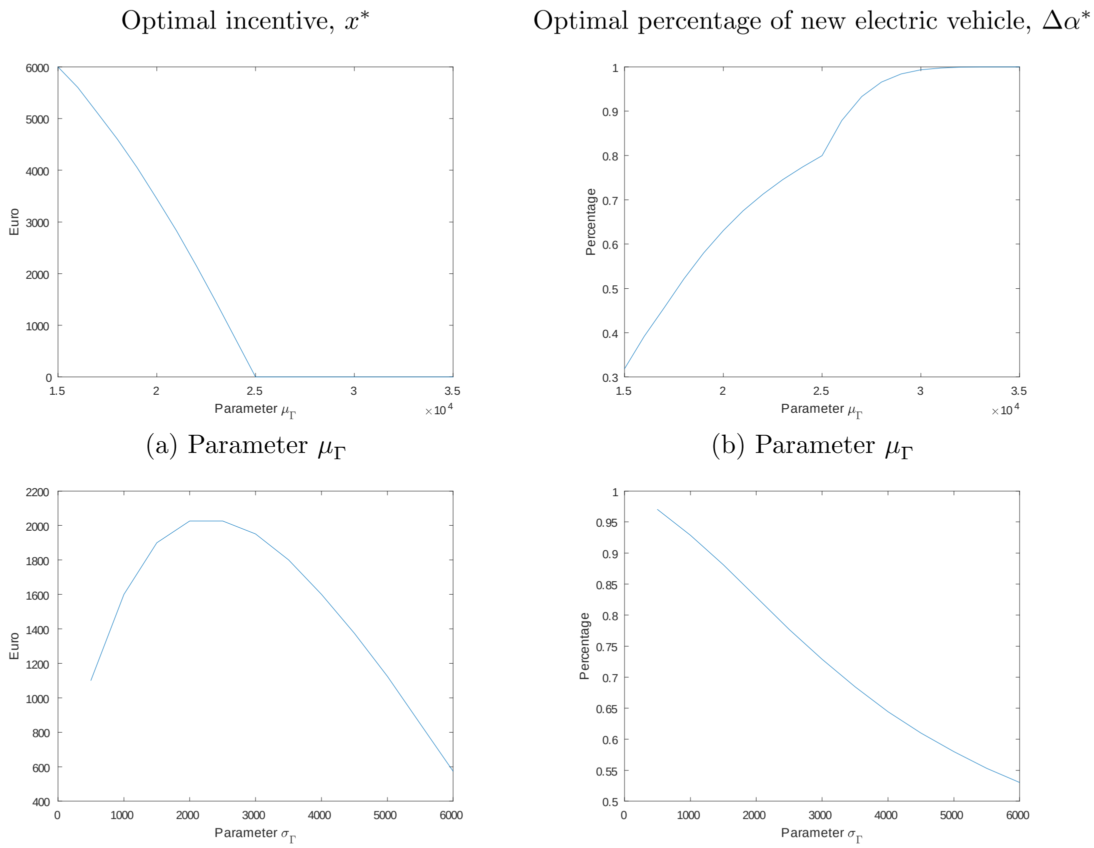


(a) Parameter α (b) Parameter α

(c) Parameter τ (d) Parameter τ

(e) Parameter I (f) Parameter I

Figure 3.9: Dependency of the policymaker's objective function and the expected traffic bans w.r.t. parameters α, τ and I.

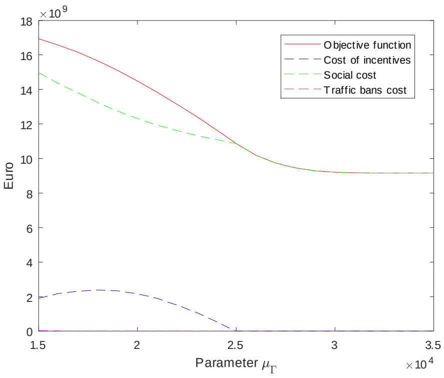


(a) Parameter μ_Γ (b) Parameter μ_Γ

(c) Parameter σ_Γ (d) Parameter σ_Γ

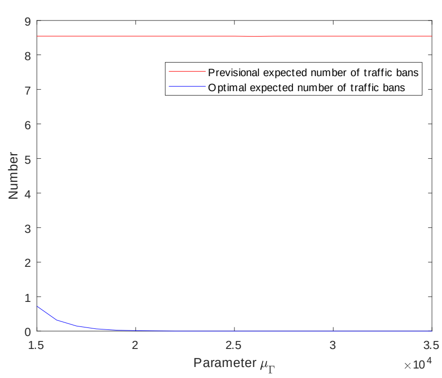
Figure 3.10: Dependency of the optimal incentive, x and the optimal percentage of new electric vehicles, $\Delta\alpha$ w.r.t. parameters μ_Γ and σ_Γ.

Optimal policymaker's function

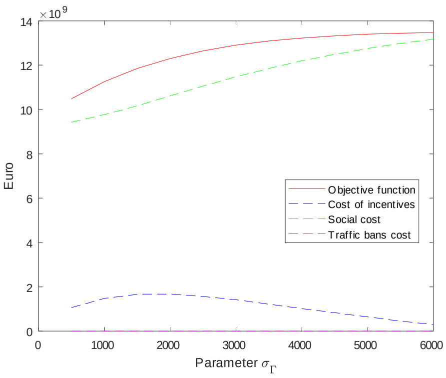


(a) Parameter μ_Γ

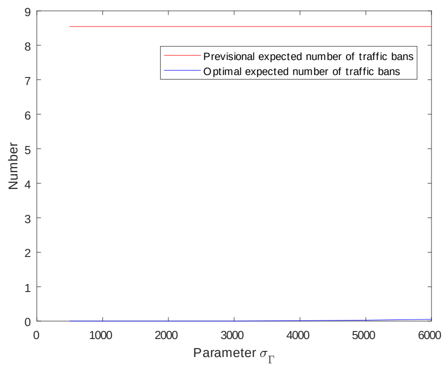
Expected and Optimal Traffic Bans



(b) Parameter μ_Γ



(c) Parameter σ_Γ



(d) Parameter σ_Γ

Figure 3.11: Dependency of the policymaker's objective function and the expected traffic bans w.r.t. parameters μ_Γ and σ_Γ,

Part II

II - Electricity Market

Chapter 4

ETS, Emissions and the Energy-Mix Problem

4.1 Introduction

Economic activities have led to a constant increase in concentrations of pollutants in the air. The sectors of energy and manufacturing are the major contributors among other sources of pollution (e.g. see Friedlingstein et al., 2010; Huisingh et al., 2015b) and (Birol, 2017) estimates that those sectors count for approximately 42% of CO_2 emissions worldwide.

Many studies (e.g. see Straif et al., 2013; World Health Organization and Others, 2013; Health Organization, 2019) emphasize the strict connection between air pollution and human health damage, in terms of increasing number of asthma crises, respiratory and cardiovascular diseases, and premature deaths.

In these circumstances, policymakers are called to seek a new perspective view of economic sustainability that allows, on the one hand, for the reduction of air pollution, and, on the other hand, for the maintenance of a sustainable level of gross domestic product.

The promotion of electric vehicles can be an effective way to reduce air pollution concentration (at least in the urbanized area) with a shrinking of environmental and health damages, although electric vehicles alone are not enough to permanently reduce air pollution, as discussed in (Abdul-Manan, 2015; Nichols et al., 2015) and (Nichols et al., 2015). The electric vehicles adoption has to be combined with an environmental policy that forces the electricity producers to generate electricity with green technologies, as studied in (e.g. see Buekers et al., 2014; Casals et al., 2016; Onat et al., 2015).

A major environmental tool adopted in many countries worldwide to cut Greenhouse Gas emissions in the electricity production system, is the Emission Trading System (ETS). The ETS scheme is made by a given number of emission certificates (or emissions allowances). Many studies such as (Demailly and Quirion, 2006), (Demailly and Quirion, 2008), (Grubb and Neuhoff, 2006), (Fabra and Reguant, 2014), (Fell et al., 2015) ensure that the electricity sector profited from ETS scheme. However, several criticisms have raised around ETSs through time. Most of them have been focusing on the grandfathering of the allowances and the windfall profit resulting to the polluting producers (at the cost of consumers). Other criticisms to the ETSs have been concerned with over-allocation of permits, high price volatility and in general for failing to meet their goals.

In Europe, ETS scheme, known as European Union Emissions Trading Scheme (EU ETS), has been introduced from January 2005 with Directive 2003/87/EC with the aim of reducing the

CO_2 emissions by 2050, see (European Commission, 2011).

The policymaker, on his hand, pursue a multiobjective policy which includes the reduction of greenhouse gas emissions, the maintenance of economic growth, which, however, has a polluting impact on the environment, and the maintenance of low electricity prices.

Electricity producers have three ways to reduce the cost of emission certificates that is (i) investing in green technologies plants, reducing production from polluting plants, (iii) stop the electricity generation, when the unit cost of producing (exacerbated by the costs of permits) is lower than the unit price of sale. The environmental aim of the policymaker would clearly benefit if electricity producers started to convert their plants into greener ones.

Building an environmental strategy, a policymaker may encounter various problems. The first problem concerns the uncertainty on electricity demand meeting. The second problem is related to the electricity price and the electricity producers' profit. As for the first question, the use of renewables by the electricity producers can causes the mismatch between demand and supply in the electricity sector. Mismatching problem is particularly felt by the policymaker since if blackouts happen frequently, cause a decrease in Gross Domestic Product. The second question is based on the fact that the use of renewables causes a fall in the electricity price and, therefore, in the electricity producers' profit. Therefore, to redress the latter situation, the electricity producers are likely to use conventional technology for the electricity generation.

In an ETS, a particularly delicate role is played by the policymaker, who is called upon to decide the number of emission permits. Emissions-containing policies based on the permit market have a further heavy limit since its introduction leads to additional cost factor that inevitably ends up shifting to final consumer prices.

In the existing literature, there are many studies that focus only on the policymaker or on the producers but there are few works that consider both agents simultaneously. For the policymaker's side, we mention, for example, (Venmans, 2016), (Duscha, 2018) and (Cadez and Czerny, 2016) in which different strategies to reduce green gas emissions are explained. For the electricity producers's side, we mention for example, (Brohé and Burniaux, 2015), (Bonenti et al., 2013), (Fagiani et al., 2014) and (Falbo et al., 2019) where the dependency of the investment decisions, the electricity generation and the profit of firms considering different sectors on allowances are shown.

To the best of our knowledge, there are few studies that analyze, through a bilevel structure, the interaction between policymaker and producers. (Lei and Wei, 2007) present an integer linear bilevel problem in which a policymaker, maximizing a welfare function, determines the number of allowances to be distributed to farms and sewage enterprises. The latter, maximizing their profit,.have to decide the number of allowances to be bought from the market.

In (Tao et al., 2014) a bilevel stochastic programming model is proposed. On the upper level, the policymaker, minimizing the total emissions, decides the optimal percentage of allowances to be distributed for free to a firm, ensuring a sustainable employment rate. On the lower level, the firm, maximizing a profit function, decides the amount of emission allowance purchased from the government, the amount of emission allowance purchased from the outside market and the amount of emission allowance repurchased by the government from the firm. The firm must respect several constraints including demand, employment capacity, and budget.

More recently, (Tao, 2017) presents a bilevel model for the iron and steel production. On the upper level, the policymaker would like to keep the CO_2 concentration below a certain threshold value and would like to improve the infrastructure network through the sale of a part of the emission certificates through either the free distribution of allowances or the purchase of allowances. The iron and steel producer would like to maximize its profit through the optimal amount of steel. In addition, in order not to incur penalties, the manufacturer would like the emissions from the production process to be lower than the sum of the emission certificates he holds. (Hong et al., 2017) presents a bilevel model where a policymaker, maximizing a social function, determines the optimal number of allowances to allocate to firms, who, maximizing their profit, decide the production level to meet the policymaker's emissions reduction target.

(Feng et al., 2020) describes a bilevel problem. At the upper level, the policymaker decides the carbon price to minimize the carbon intensity and maximize the revenues considering the electricity demand and an electricity price range. At the lower level, many electricity producers with different conventional technologies, maximizing their profits, decide the fuel purchase and the carbon trading.

We contribute to the existing literature by investigating the optimal number of allowances to be issued and, by analyzing how an ETS affects the energy-mix decision and the profits of two electricity producers. We consider a market structure with two large companies of electricity producers working in an energy-only electricity market. Besides, the two producers differ in their technology mix: one owns Renewables Energy Source (RES) and coal plants, the other producer owns RES and gas plants. At the upper level policymaker aiming at maximizing the total electricity generated, keeping blackout risk at a minimum and ensuring a minimum percentage of RES penetration. The model is developed adopting a stochastic programming method, where the random scenarios consist of realizations of three sources of uncertainty: coal and gas prices and daily electricity demand. As novelty, the trajectories of the three stochastic processes are obtained through a multivariate Markov Chain bootstrapping. Coal and gas plants have different emission rates, and this influences producers in their optimal decision as to how to expand their energy-mix (also called technology portfolio), under a given budget constraint. The electricity price is endogenously calculated by the intersection between stochastic electricity demand and supply. A novelty aspect is also that the allowances price is endogenously calculated and it is determined as a risk neutral expectation of the future payoff. Moreover, our model extends the literature since it includes both short and long-terms effects of an ETS scheme. In the short-term, the allowances price triggers the fuel switch decision and the actual emissions, while the long-term impact is captured by the optimal energy-mix decision.

To deal with the game between the two producing companies, we first develop a large grid of the possible solutions for the two players, including both Pareto efficient and inefficient ones. Then we focus on just two solutions chosen among the Pareto efficient solutions. The first solution represents the situation of competition where the two companies minimize the difference between their expected net present profits. The second solution is more cooperative in the sense that the two companies maximize the summation of their expected profits (i.e. maximize the profit to the power sector).

The rest of the chapter is organized as follows. Section 4.2 presents the general setting of our model, Section 4.3 presents the bilevel structure of the problem and the two market settings. In Section 4.4, a case study application is analyzed. Section 4.5 concludes.

4.2 Model

4.2.1 General Settings

We consider a policymaker and an oligopolistic energy-only[1] electricity market, where only two large (representative) electricity producers act. Policymaker and electricity producers interact over a discrete finite time horizon $\{0, \dots, T\}$. Electricity can be generated using non-conventional (also referred as "green" or "renewables"), namely wind, and/or conventional (also referred as "polluting") technologies, namely coal and gas.

[1] The electricity producers are paid for the amount of electricity generated, and the decision of keeping capacity available is not remunerated.

We label the existing non-conventional and conventional generation capacities for the coal based producer by Q_{rc}, Q_c. The analogous variables for the gas based producer are labeled by Q_{rg}, Q_g.

At any time t, the electricity generated by the four possible plants are labeled by $q_{k,t}$ with $k \in \{rc, rg, c, g\}$ while the electricity generation on the period $\{1, \ldots, T\}$ by four possible plants is labeled by q_k with $k \in \{rc, rg, c, g\}$.

Electricity producers generate air pollution expressed in tonnes of CO_2e[2]. We denote by h_t the tonnes of CO_2e emitted at time t by the two producers:

$$h_t = \sum_{k \in \{c,g\}} q_{k,t} \cdot e_k, \tag{4.1}$$

where e_k the emission factor of conventional technology k measured in tonnes per MWh of electricity generated. The cumulative tonnes of CO_2e at time t is denoted by H_t and it is defined as

$$H_t = \sum_{j=1}^{t} h_j = \sum_{j=1}^{t} \sum_{k \in \{c,g\}} q_{k,j} \cdot e_k. \tag{4.2}$$

At time $t = 0$, the policymaker determines the number of allowances, labeled by H, issued for free to the electricity producers through the maximization of a welfare function given by the total amount of electricity produced. Moreover, he fixes a minimum percentage of electricity generated from renewable sources, and, at the same time, a minimal blackout risk. At time $t = 0$, electricity producers decide the optimal long-term expansion of their capacities, through the maximization of a profit function considering a budget and a safety margin constraints. The long-term capacity expansion for the coal based producer are labeled by ΔQ_{rc} and ΔQ_c respectively for non-conventional and conventional technologies. Similarly, the long-term capacity expansion for the gas based producer are labeled by ΔQ_{rg} and ΔQ_g.

To make the notation simpler, we label the total resulting capacity (existing and long-term expansion) for the k-th technology by Q_k^+ as

$$Q_k^+ := Q_k + \Delta Q_k, \quad k \in \{rc, rg, c, g\}.$$

As assumption, negative long-term expansion capacities are not allowed, i.e. the existing technology plants cannot be dismantled, while the new installed plants are immediately available and operational. Moreover, after time $t = 0$, no new capacity is installed. Once the long-term capacity expansions are decided, at each intermediate time t, $t \in \{1, \ldots, T\}$, each producer decides only electricity generation based on his total (existing and long-term expansion) capacity, the electricity demand and the generation costs, which changes randomly at every time t. Tables 4.1 and 4.2 summarize the notation for existing and long-term expansion capacity of all technologies and producers.

4.2.2 Uncertainty

In this work, the uncertainty is represented by three stochastic processes representing the coal and gas prices and the daily electricity demand. We denote by $\{P_{c,t}\}_{t \in \{0,...,T\}}$ the stochastic process of daily coal price, by $\{P_{g,t}\}_{t \in \{0,...,T\}}$ the stochastic process of gas price and by $\{D_t\}_{t \in \{0,...,T\}}$ the stochastic process of the electricity demand. For future use in Section 4.2.2, we consider also

[2] Electricity generation from conventional technologies produces greenhouse gases: CO_2 (carbon dioxide), N_2O (nitrogen oxide), $PFCs$ (perfluorocarbons). In this paper, we will indicate, indifferently, the previous greenhouse gases as CO_2e.

	Conventional Capacity	
Producer	Existing	Long-term expansion
Coal based producer	Q_c	ΔQ_c
Gas based producer	Q_g	ΔQ_g

Table 4.1: Existing and long-term expansion capacity of conventional technologies for electricity producers.

	Non-conventional	
Producer	Existing	Long-term expansion
Coal based producer	Q_{rc}	ΔQ_{rc}
Gas based producer	Q_{rg}	ΔQ_{rg}

Table 4.2: Existing and long-term expansion capacity of non-conventional technologies for electricity producers.

a sequence of independent random variables, $\{Z_t\}_{t\in\{0....,T\}}$. All of them considered with daily frequency. The probability space is $(\Omega, \mathcal{F}, \mathbb{P})$, where Ω is the product sample space $\Omega_b \times \Omega_z$, $\mathcal{F}$ is the σ-field, and $\mathbb{P}$ is the product probability $\mathbb{P}_b \times \mathbb{P}_z$.

In particular, Ω_b and $\mathbb{P}_b$ are the sample space of realizations of the triplet $\{P_{c,t}, P_{g,t}, D_t\}_{t\in\{0....,T\}}$ and its probability measure, respectively while Ω_z and $\mathbb{P}_z$ are the sample space of the possible realizations of $\{Z_t\}_{t\in\{0....,T\}}$ and its probability measure, respectively. With the use of product measures, we state that the triplet $\{P_{c,t}, P_{g,t}, D_t\}_{t\in\{0....,T\}}$ is independent of the random variable Z_t at any time in $\{0, \ldots, T\}$.

Forecasted Emissions

Electricity producers are actually interested in predict the expected cumulative emissions at final time T. This prediction is crucial due to its influence on the allowances price. The latter is crucial to determine the fuel switch on the power market. The starting point of the mechanism lies in the prediction on the future emissions. We assume that the forecasted emissions can be modeled as follows:

$$\widehat{h_t} = h_a + \alpha \cdot t + \sigma Z_t, \tag{4.3}$$

where h_a is a base of CO_2e daily emissions, $\alpha > 0$ is a drift coefficient, $\sigma > 0$ is the volatility parameter and $\{Z_t\}_{t\in\{0,...,T\}}$ is a stochastic process of independent normal random variables, each of them with mean μ and variance 1. The cumulative forecasted emissions at time t, $\widehat{H_t}$, are calculated as

$$\widehat{H_t} = \sum_{j=0}^{t} \widehat{h_t} = h_a\,(t+1) + \alpha \sum_{j=0}^{t} j + \sigma \sum_{j=0}^{t} Z_j.$$

The normality assumption is reasonable as long as the mean of the forecasted cumulative emissions is significantly larger than its variance. In a continuous setting, the normality assumption in the forecasted cumulative emission dynamics can be also found, for example, in (Carmona et al., 2013).

At each time $t \in \{0. \ldots, T\}$, based on the effective cumulative daily emissions H_t (as in Equation (4.2)), electricity producers forecast the cumulative daily emissions from that time on. With a slight abuse of notation, we denote the latter by $\widehat{H_T}|H_t$. Based on Equation (4.3), the forecasted cumulative emissions at time T, conditional on the information at the beginning of each time t, $\widehat{H_T}|H_t$, are calculated as

$$\widehat{H_T}|H_t = H_t + (T-t)\, h_a + \alpha \sum_{j=t+1}^{T} j + \sigma \sum_{j=t+1}^{T} Z_j. \tag{4.4}$$

Based on Equation (4.4), at each time t, $\widehat{H_T}|H_t$ is modeled as a normal random variable with mean

$$\mu_{\widehat{H_T}|H_t} = H_t + (T-t)\, h_a + \alpha \sum_{j=t+1}^{T} j, \tag{4.5}$$

and variance

$$\sigma^2_{\widehat{H_T}|H_t} = (T-t)\cdot \sigma^2. \tag{4.6}$$

The proofs of Equations (4.5) and (4.6) are shown in Appendix .E.

4.2.3 Merit Order Curve, Relevant Events, Allowances and Electricity Prices

Electricity producers face two different spot markets: the electricity market and the allowances market. The electricity market is energy-only and characterized by uniform auction system and merit order: each producers offers all his capacity at the marginal cost. The electricity price at time t, denoted by $p_{e,t}$, is calculated as an equilibrium price based on the intersection between electricity demand and supply. For clarity's sake, we introduce the allowances price at time t as $p_{a,t}$ while Section 4.2.3 will be devoted to illustrate its analytical formulation. As standing hypothesis, in our model, we neglect (i) intermediate banking and borrowing of certificates, (ii) profits and losses resulting from the sales/buying of the certificates and we let technology life equal to T.

Merit Order Curve

Electricity producers, facing a stochastic and price inelastic daily electricity demand, determine the electricity supply curve through merit order. Merit order ranks the available technologies based on ascending order of marginal costs of generation. Non-conventional technologies represent the first step of the supply curve since their marginal generation costs, labeled by $c_{vnc,t}$, are extremely low and, for simplicity, set to zero. The other steps are filled by conventional technologies. Under an ETS scheme, the marginal electricity generation cost considers the raw material of the technology (coal or gas) price and the allowances price, which, in turns, depends on technologies' carbon intensities. Coal and gas marginal generation costs at time t are labeled by $c_{vc,t}$ and $c_{vg,t}$, respectively. They are calculated as follows

$$c_{vc,t} = p_{c,t}\cdot m_c + p_{a,t}\cdot m_{EUA,c}, \tag{4.7}$$

$$c_{vg,t} = p_{g,t}\cdot m_g + p_{a,t}\cdot m_{EUA,g}, \tag{4.8}$$

where m_c and m_g are the coal and gas efficiency factors, respectively, and $m_{EUA,c}$ and $m_{EUA,g}$ are the CO_2e equivalent emission factors for coal and gas, respectively.

The introduction of an ETS scheme leads also to a short-run namely fuel switch decision. Fuel switch decision occurs on the power market comparing the marginal costs of the conventional technologies. It $c_{vg,t} < c_{vc,t}$, there is fuel switch and the merit order curve is wind, gas and coal.

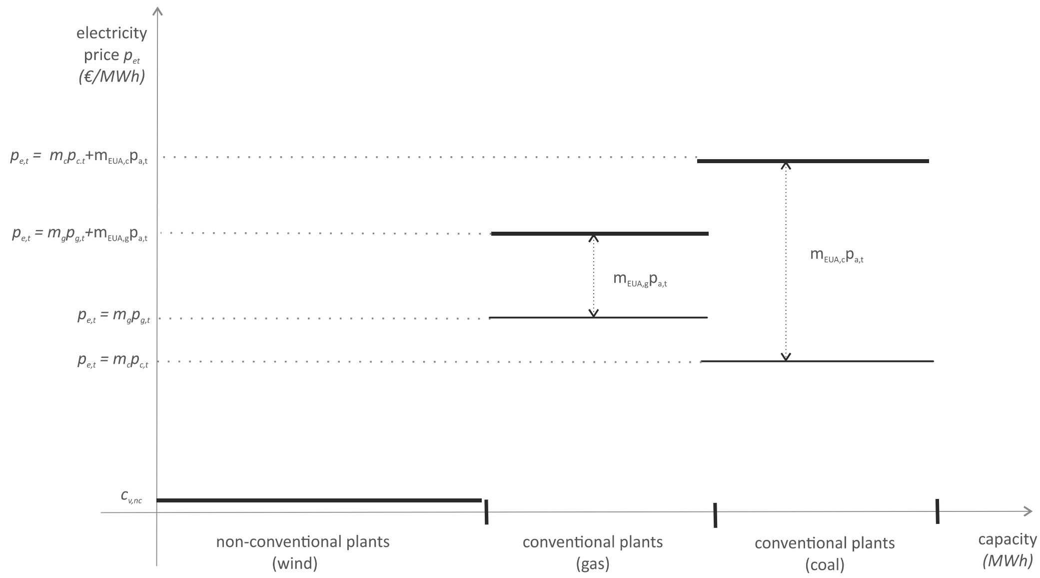


Figure 4.1: Graphical representation of the merit order curve in the case of fuel switch.

A representation on how merit order curve changes in fuel switch case is shown in Figure 4.1, where the finest lines represent coal and gas prices without an ETS scheme.

If $c_{vc,t} < c_{vg,t}$ no-fuel switch occurs and the merit order curve is wind, coal and gas. A representation of the merit order curve in no-fuel switch case is shown in Figure 4.2 where the finest lines represent coal and gas prices without an ETS scheme.

Since the electricity demand at every time t is stochastic and the supply curve depends on random values of the coal, gas and allowances prices, the electricity prices are also stochastic.

It is possible to partition the sample space Ω into five events depending on the the electricity demand and coal and gas prices. The label and the description of the five events are summarized in Table 4.3. The rest of the section is devoted to the explication of these events.

Events in Ω	Regime	Demand Level	Description
$A_{1,t}$	-	Low	$D_t \leq 24 \cdot \left(Q_{rc}^+ + Q_{rg}^+\right)$
$A_{2,t}$	No-Fuel Switch	Average	$24 \cdot \left(Q_{rc}^+ + Q_{rg}^+\right) \leq D_t \leq 24 \cdot \left(Q_{rc}^+ + Q_{rg}^+ + Q_c^+\right)$
$A_{3,t}$	Fuel Switch	Average	$24 \cdot \left(Q_{rc}^+ + Q_{rg}^+\right) \leq D_t \leq 24 \cdot \left(Q_{rc}^+ + Q_{rg}^+ + Q_g^+\right)$
$A_{4,t}$	No-Fuel Switch	High	$D_t > 24 \cdot \left(Q_{rc}^+ + Q_{rg}^+ + Q_c^+\right)$
$A_{5,t}$	Fuel Switch	High	$D_t > 24 \cdot \left(Q_{rc}^+ + Q_{rg}^+ + Q_g^+\right)$

Table 4.3: Representation of the partition of the sample space based on electricity demand, coal and gas prices.

The event $A_{1,t}$ occurs if the electricity demand is entirely satisfied by plants equipped with non-conventional technologies. Event $A_{2,t}$ occurs if fuel switch does not happen and the electricity demand is entirely (or partially) satisfied by coal technology. Event $A_{3,t}$ occurs if fuel switch happens and the electricity demand is entirely (or partially) satisfied by gas technology. Event $A_{4,t}$ occurs if, under the no-fuel switch regime, the electricity demand is entirely (or partially) satisfied by gas technology. Event $A_{5,t}$ occurs if, under fuel switch regime, and the electricity demand is entirely (or partially) satisfied by coal technology.

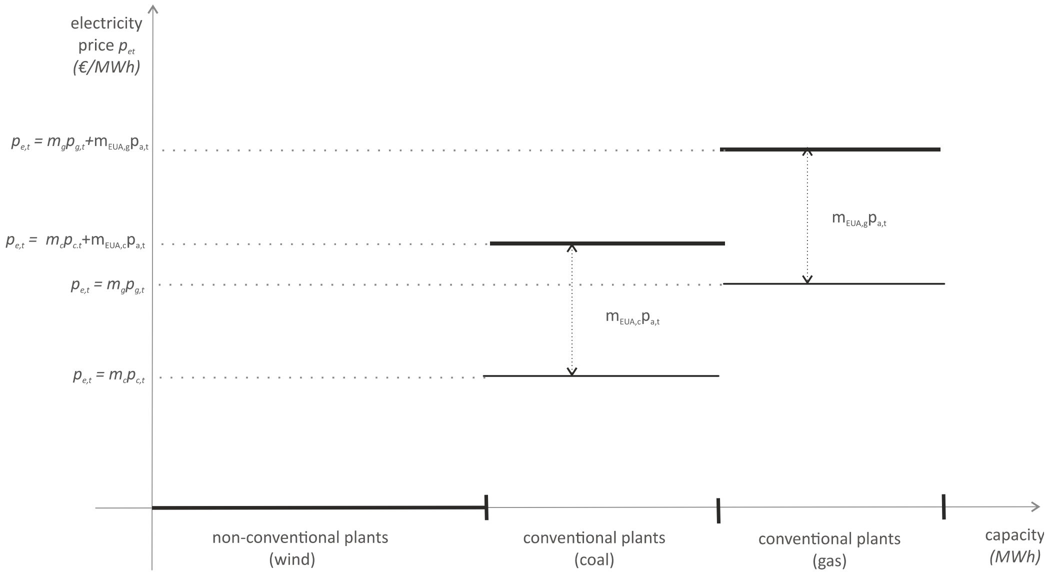


Figure 4.2: Graphical representation of the merit order curve in the case of no-fuel switch.

Allowances Price

The allowance price, $p_{a,t}$, is calculated as an expectation, as in (Hinz and Novikov, 2010). The allowance price at the beginning of time t is

$$p_{a,t} = F \cdot \mathbb{E}\left(1_{(H,+\infty)}\left(\widehat{H_T}|H_t\right)\right) \cdot e^{-r(T-t)} = F \cdot \mathbb{P}\left(\left(\widehat{H_T}|H_t\right) > H\right) \cdot e^{-r(T-t)}, \tag{4.9}$$

where F is the fine that the producers have to pay if the emissions at time T exceed the total number of allowances, r is the continuously compounded interest rate and $\mathbb{P}\left(\left(\widehat{H_T}|H_t\right) > H\right)$ represents the probability that the expected cumulative emissions exceed the cap, H. Notice that the approach of (Hinz and Novikov, 2010) does not consider the fact that it is more convenient purchasing an allowance than investing in a non-conventional technology plant. Our model considers this aspect since the allowance is distributed for free.

Electricity Price and Relevant Events

In this section, we show how the electricity price changes according to the different events of Ω discussed in Section 4.2.3 and collected in Table 4.3.

In the event $A_{1,t}$, at time t, electricity demand is completely satisfied by the non-conventional technology plants. In this event, the electricity producers do not generate CO_2e. The electricity price is equal to the marginal production of the renewables:

$$p_{e,t}|A_{1,t} = 0. \tag{4.10}$$

In the event $A_{2,t}$, at time t, the second step of the electricity supply curve is based on coal technology. Electricity demand exceeds the non-conventional plants capacity and it has to be partially (or completely) covered using coal plant capacity:

$$p_{e,t}|A_{2,t} = p_{c,t} \cdot m_c + p_{a,t} \cdot m_{EUA,c}. \tag{4.11}$$

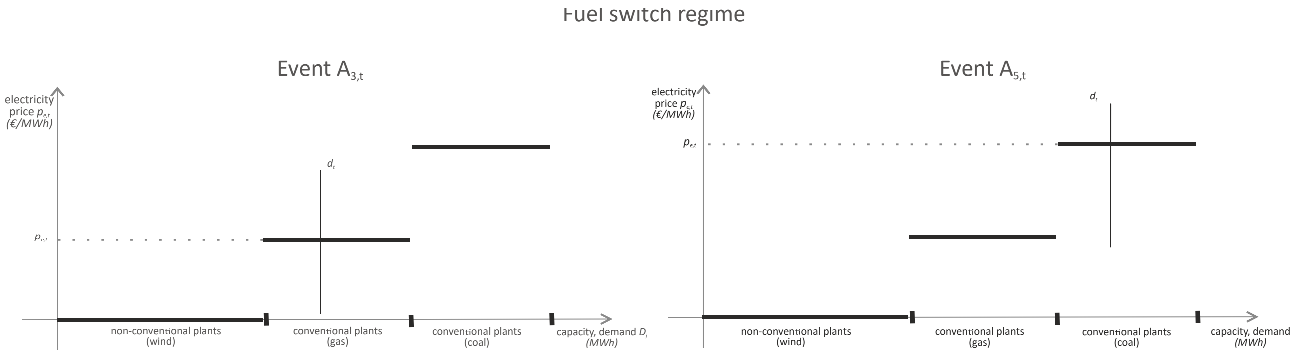


Figure 4.3: Graphical representation of the electricity price for events $A_{3,t}$ and $A_{5,t}$.

In the event $A_{3,t}$, no-fuel switch occurs and gas is the marginal technology, then

$$p_{e,t}|A_{3,t} = p_{g,t} \cdot m_g + p_{a,t} \cdot m_{EUA,g}. \tag{4.12}$$

In the event $A_{4,t}$, we are in the fuel switch regime and gas is the marginal technology, so

$$p_{e,t}|A_{4,t} = p_{g,t} \cdot m_g + p_{a,t} \cdot m_{EUA,g}. \tag{4.13}$$

In the event $A_{5,t}$, fuel switch occurs and coal is the marginal technology, therefore

$$p_{e,t}|A_{5,t} = p_{c,t} \cdot m_c + p_{a,t} \cdot m_{EUA,c}. \tag{4.14}$$

Table 4.4 summarizes the values of the electricity price for a general time t.

Events in Ω	Regime	Demand Level	Electricity price, $p_{e,t}$
$A_{1,t}$	-	Low	0
$A_{2,t}$	No-Fuel Switch	Average	$p_{c,t} \cdot m_c + p_{a,t} \cdot m_{EUA,c}$
$A_{3,t}$	Fuel Switch	Average	$p_{g,t} \cdot m_g + p_{a,t} \cdot m_{EUA,g}$
$A_{4,t}$	No-Fuel Switch	High	$p_{g,t} \cdot m_g + p_{a,t} \cdot m_{EUA,g}$
$A_{5,t}$	Fuel Switch	High	$p_{c,t} \cdot m_c + p_{a,t} \cdot m_{EUA,c}$

Table 4.4: Electricity price according to relevant events.

Electricity prices in Table 4.4 are shown in Figures 4.3 and 4.4.

4.2.4 Electricity Producers Profit Functions

As discussed in Section (4.2.1), the electricity producers optimize an individual profit function. The revenues can be divided in two categories: the revenues from the electricity generated by non-conventional technology and the revenues from the electricity generated by conventional technologies (coal and gas). The latter is modeled as a clean and dark spread option for electricity producer by coal and gas, respectively. The clean (dark) spread option measures the profitability of electricity generated by gas (coal) technology based on its variable cost and the electricity price. At any time t, each electricity producer gains only if the electricity price is greater than the marginal cost of the technology used to produce one MWh of electricity. We label the clean and dark spread option at time t by $SO_{t,c}$ and $SO_{t,g}$, respectively. The former is $SO_{t,c} = \max(0; p_{e,t} - c_{vc,t})$ and the latter is $SO_{t,g} = \max(0; p_{e,t} - c_{vg,t})$.

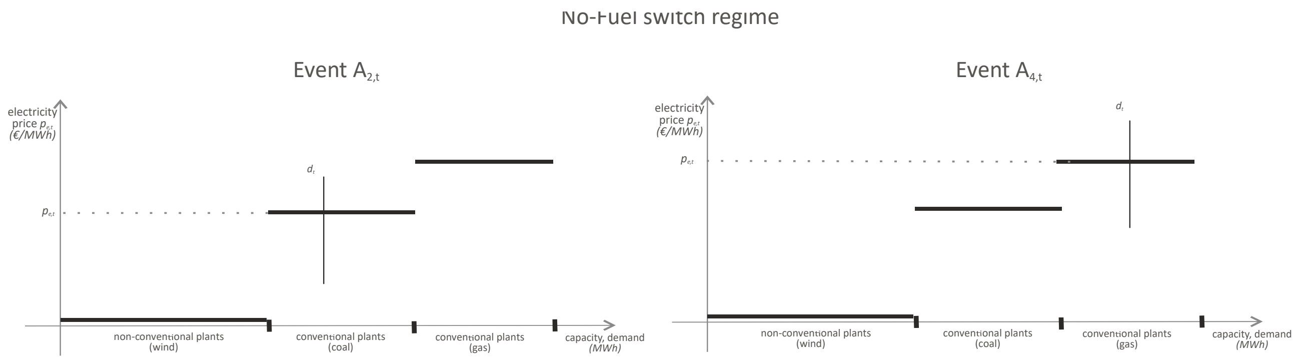


Figure 4.4: Graphical representation of the electricity price for events $A_{2,t}$ and $A_{4,t}$.

Electricity producers face also costs which reflect the sum of depreciation, operation, and maintenance costs of the plants from time $t-1$ to t. We assume that the existing plants, Q_{rc}, Q_{rg}, Q_c, Q_g, have been already amortized so that the cost term refers only to the long-term expansion capacity. We label cost terms by B_c and B_g for the electricity producer based on coal and gas, respectively. The former is $B_c = a\left(\sum_{k\in\{rc,c\}} \widetilde{b_k}\Delta Q_k\right)$ and the latter is $B_g = a\left(\sum_{k\in\{rg,g\}} \widetilde{b_k}\Delta Q_k\right)$, where the term a is the depreciation factor and $\widetilde{b_k}$ is transformation factors for each technology, which includes an average derating coefficient for non-conventional technology.

We notice that the long-term capacity expansion decision of each producer impacts on the other in terms of covered demand, electricity generation and profit. For this reason, we write each electricity producer's profit function depending on the long-term expansion decisions of both producers. We label the profit functions by $\pi_{c,t}(\Delta Q_{rg}, \Delta Q_{rc}, \Delta Q_g, \Delta Q_c)$ and $\pi_{g,t}(\Delta Q_{rg}, \Delta Q_{rc}, \Delta Q_g, \Delta Q_c)$ for the coal based and gas based producer, respectively. The profit functions are defined as

$$\pi_{c,t}(\Delta Q_{rg}, \Delta Q_{rc}, \Delta Q_g, \Delta Q_c) = q_{rc,t} \cdot p_{e,t} + q_{c,t} \cdot SO_{c,t} - B_c, \tag{4.15}$$

$$\pi_{g,t}(\Delta Q_{rg}, \Delta Q_{rc}, \Delta Q_g, \Delta Q_c) = q_{rg,t} \cdot p_{e,t} + q_{g,t} \cdot SO_{g,t} - B_g. \tag{4.16}$$

The first term in Equations (4.15) and (4.16) express the revenues of electricity produced through non-conventional plants from time $t-1$ to t, $q_{rc,t}$ and $q_{rg,t}$, respectively, sold at price $p_{e,t}$. The second terms are the dark (in Equation (4.15)) and clean (in Equation (4.16)) spread option associated to electricity produced through conventional plants from time $t-1$ to t, $q_{c,t}$ and $q_{g,t}$, respectively. The last term represents the cost component. We notice that the electricity generation at time t by the k-th technology is

$$q_{k,t} = \begin{cases} \min\left(24 \cdot Q_k^+, D_{resid,t}\right) & \text{if } k \text{ is the marginal technology,} \\ 24 \cdot Q_k^+ & \text{if } k \text{ is not the marginal technology,} \end{cases}$$

where $D_{resid,t}$ is the electricity demand not already covered at time t. The last part of this section is devoted to analyzing electricity producers profit functions and electricity generations according to the relevant event summarizes in Table 4.3.

Fuel-switch case When event $A_{1,t}$ happens, electricity demand is fully satisfied by non-conventional plants and, according to Table 4.3, the electricity price is equal to zero, as explained in Section 4.2.3. Electricity producers profits and electricity generated are listed in Table 4.5. Table 4.6 shows the electricity generation for each type of technology.

Event $A_{1,t}$ (Low demand)		
Producer	Profit (Euro)	Electricity generated (MWh)
Coal based producer	$-B_c$	$D_t \cdot \left(\frac{Q_{rc}^+}{Q_{rc}^+ + Q_{rg}^+}\right)$
Gas based producer	$-B_g$	$D_t \cdot \left(\frac{Q_{rg}^+}{Q_{rc}^+ + Q_{rg}^+}\right)$

Table 4.5: Profits and electricity generated in the event $A_{1,t}$.

Event $A_{1,t}$ (Low demand)		
Producer	Non-conventional techn., (MWh)	Conventional techn., (MWh)
Coal based producer	$D_t \cdot \left(\frac{Q_{rc}^+}{Q_{rc}^+ + Q_{rg}^+}\right)$	0
Gas based producer	$D_t \cdot \left(\frac{Q_{rc}^+}{Q_{rc}^+ + Q_{rg}^+}\right)$	0

Table 4.6: Electricity generation for each type of technology in the case of event $A_{1,t}$.

In the event $A_{3,t}$, fuel switch occurs and the electricity is sold at $p_{e,t}|A_{3,t} = p_{g,t} \cdot m_g + p_{a,t} \cdot m_{EUA,g}$. Both the spread options are zero. There is no demand for producing electricity with coal. The gas based producer generates electricity at zero profit since his plants are marginal. Producers profits and electricity generated are listed in Table 4.7. Table 4.8 shows the electricity generation for each type of technology.

Event $A_{3,t}$ (Fuel switch and average demand)		
Producer	Profit (Euro)	Electricity generated (MWh)
Coal based producer	$24 \cdot Q_{rc}^+ \cdot p_{e,t}|A_{3,t} - B_c$	$24 \cdot Q_{rc}^+$
Gas based producer	$24 \cdot Q_{rg}^+ \cdot p_{e,t}|A_{3,t} - B_g$	$D_t - 24 \cdot Q_{rc}^+$

Table 4.7: Profits and electricity generated in the event $A_{3,t}$.

In the event $A_{5,t}$, fuel switch occurs and gas is the marginal technology and the electricity price is $p_{e,t}|A_{5,t} = p_{c,t} \cdot m_c + p_{a,t} \cdot m_{EUA,c}$. The coal based producer has no gain on conventional generation since it is marginal. On the opposite case, the gas based producer obtains a positive profit for each MWh from his gas plants (his spark spread option is in the money because $p_{e,t}|A_{5,t} > c_{vg,t}$). Electricity producers profits and electricity generated are listed in Table 4.9. Table 4.10 shows the electricity generation for each type of technology.

No-fuel switch cases. In the case of event $A_{2,t}$, coal plants are activated to satisfy the remaining electricity demand and the electricity price is equal to the coal marginal generation cost: $p_{e,t}|A_{2,t} = p_{c,t} \cdot m_c + p_{a,t} \cdot m_{EUA,c}$. Electricity producers profits and electricity generated are listed in Table 4.11. Table 4.12 shows the electricity generation for each type of technology.

In the case of $A_{4,t}$, no-switch occurs and gas is the marginal technology. The electricity price is $p_{e,t}|A_{4,t} = p_{g,t} \cdot m_g + p_{a,t} \cdot m_{EUA,g}$. Producers profits and electricity generated are listed in Table 4.13. Table 4.14 shows the electricity generation for each type of technology.

Event $A_{3,t}$ (Fuel switch and average demand)

Producer	Non-conventional techn., (MWh)	Conventional techn., (MWh)
Coal based producer	$24 \cdot Q_{rc}^{+}$	0
Gas based producer	$24 \cdot Q_{rg}^{+}$	$D_t - 24 \cdot \left(Q_{rc}^{+} + Q_{rg}^{+}\right)$

Table 4.8: Electricity generation for each type of technology in the event $A_{3,t}$.

Event $A_{5,t}$ (Fuel switch and high demand)

Producer	Profit (Euro)	Electricity generated (MWh)
Coal based producer	$24 \cdot Q_{rg}^{+} \cdot p_{e,t} \vert A_{5,t} - B_c$	$D_t - 24 \cdot \left(Q_{rg}^{+} + Q_{g}^{+}\right)$
Gas based producer	$24 \cdot Q_{rg}^{+} \cdot p_{e,t} \vert A_{5,t} + 24 \cdot Q_{g}^{+} \left(p_{e,t} \vert A_{5,t} - c_{vg,t}\right) - B_g$	$24 \cdot \left(Q_{rg}^{+} + Q_{g}^{+}\right)$

Table 4.9: Profits and electricity generated in the event $A_{5,t}$.

4.3 Bilevel Formulation

The interaction between the policymaker and the electricity producers is modeled through a stochastic bilevel model. At the upper level problem, the policymaker maximizes a social welfare function. His decision variable is the optimal number of allowances to freely distribute to the electricity producers. The first level decision is structured as follows

$$\max_{H,\Delta Q_k} E^{\mathbb{P}} \left[\sum_{k\in\{rc,rg,c,g\}} \sum_{t=1}^{T} q_{k,t} \right] \tag{4.17a}$$

$$\text{s.t.}\mathbb{P}\left(\frac{\sum_{k\in\{rc,rg\}} \sum_{t=1}^{T} q_{k,t}}{\sum_{k\in\{rc,rg,c,g\}} \sum_{t=1}^{T} q_{k,t}} \geq \xi \right) \geq \alpha_1, \tag{4.17b}$$

$$\mathbb{P}\left(D_t \leq \sum_{k\in\{rc,rg,c,g\}} q_{k,t}, \ \ \forall t \right) \geq \alpha_2, \tag{4.17c}$$

$$H \geq 0 \tag{4.17d}$$

The upper level objective function (4.17a) represents the expected total electricity production over the time period $\{1, \ldots, T\}$ that can be seen as a proxy of Gross Domestic Product, (e.g. see Ferguson et al., 2000; Yoo, 2006; Hirsh and Koomey, 2015).Through constraint (4.17b), policymaker wants to improve RES penetration in the electricity market, imposing that at least a minimum percentage of total electricity production, ξ, has been produced by non-conventional technology. Since the electricity generated is stochastic, the RES penetration constraint is expressed in terms of probability and ξ and α_1 depend on the policymaker's environmental concern. Constraint (4.17c) is a probabilistic constraint ensuring that the electricity demand at each time t is covered by electricity generated at each time t at least with probability α_2. Constraint (4.17d) is the nonnegative constraint on the number of emissions allowances.

Event $A_{5,t}$ (Fuel switch and high demand)

Producer	Non-conventional techn., (MWh)	Conventional techn., (MWh)
Coal based producer	$24 \cdot Q_{rc}^{+}$	$D_t - 24 \cdot \left(Q_{rc}^{+} + Q_{rg}^{+} + Q_{g}^{+}\right)$
Gas based producer	$24 \cdot Q_{rg}^{+}$	$24 \cdot Q_{g}^{+}$

Table 4.10: Electricity generation for each type of technology in the event $A_{5,t}$.

Event $A_{2,t}$ (No fuel switch and average demand)

Producer	Profit (Euro)	Electricity generated (MWh)
Coal based producer	$24 \cdot Q_{rc}^{+} \cdot p_{e,t}\vert A_{2,t} - B_c$	$D_t - 24 \cdot Q_{rg}^{+}$
Gas based producer	$24 \cdot Q_{rg}^{+} \cdot p_{e,t}\vert A_{2,t} - B_g$	$24 \cdot Q_{rg}^{+}$

Table 4.11: Profits and electricity generated in the case of event $A_{2,t}$.

At the lower level, the electricity producers optimize simultaneously the long-term energy-mix considering the expected profit as their objective functions and the following constraints:

$$\max_{\Delta Q_{rc}, \Delta Q_c} E^{\mathbb{P}} \left[\sum_{t=1}^{T} e^{-r \cdot t} \pi_{c,t} \left(\Delta Q_{rc}, \Delta Q_c, \Delta Q_{rg}, \Delta Q_g \right) \right] \tag{4.18a}$$

$$\text{s.t.} \Delta Q_{rc} \cdot b_{rc} + \Delta Q_c \cdot b_c \leq M_c, \tag{4.18b}$$

$$24 \cdot (\Delta Q_{rc} + \Delta Q_c) \geq \beta \cdot \mathbb{E}\left[D_t\right], \tag{4.18c}$$

$$\Delta Q_{rc}, \Delta Q_c \geq 0. \tag{4.18d}$$

$$\max_{\Delta Q_{rg}, \Delta Q_g} E^{\mathbb{P}} \left[\sum_{t=1}^{T} e^{-r \cdot t} \pi_{g,t} \left(\Delta Q_{rc}, \Delta Q_c, \Delta Q_{rg}, \Delta Q_g \right) \right] \tag{4.19a}$$

$$\text{s.t.} \Delta Q_{rg} \cdot b_{rg} + \Delta Q_g \cdot b_g \leq M_g, \tag{4.19b}$$

$$24 \cdot (\Delta Q_{rg} + \Delta Q_g) \geq \beta \cdot \mathbb{E}\left[D_t\right], \tag{4.19c}$$

$$\Delta Q_{rg}, \Delta Q_g \geq 0. \tag{4.19d}$$

Equations (4.18a) and (4.19a) are the lower level objective functions. The latter are the electricity producers' expected profit over the time horizon $\{1, \ldots, T\}$, whose main features are detailed in Section 4.2.4. Constraints (4.18b) and (4.19b) are the budget constraints imposing that the cost associated of new capacity plants (green and polluting) do not to exceed the boundary value M_c and M_g. The coefficients b_{rc}, b_{rg} and b_c, b_g are the unit cost for non-conventional, b_{rc}, b_{rg}, and conventional technologies, b_c, b_g, respectively. Constraints (4.18c) and (4.19c) impose that the capacities installed by each producer cover, at least, a minimum share, β, of the electricity demand. The Constraints (4.18d) and (4.19d) are the nonnegative constraint for the new expansion capacity.

4.3.1 Efficient Frontier and Producers' Decision Methods

In this section, we first present how we identify an efficient frontier of the long-term capacity expansions to the two producers for any fixed value of H (the decision variable of the upper level).

Event $A_{2,t}$ (No fuel switch and average demand)

Producer	Non-conventional techn., (MWh)	Conventional techn., (MWh)
Coal based producer	$24 \cdot Q_{rc}^{+}$	$D_t - 24 \cdot \left(Q_{rc}^{+} + Q_{rg}^{+}\right)$
Gas based producer	$24 \cdot Q_{rg}^{+}$	0

Table 4.12: Electricity generation for each type of technology in the event $A_{2,t}$.

Event $A_{4,t}$ (No fuel switch and high demand)

Producer	Profit	Total electricity generated (MWh)
Coal based producer	$24 \cdot Q_{rc}^{+} \cdot p_{e,t} \vert A_{5,t} + 24 \cdot Q_{c}^{+} \cdot (p_{e,t} \vert A_{4,t} - c_{vc,t}) - B_c$	$24 \cdot (Q_{rc}^{+} + Q_{c}^{+})$
Gas based producer	$24 \cdot Q_{rg}^{+} \cdot p_{e,t} \vert A_{5,t} - B_g$	$D_t - 24 \cdot (Q_{rc}^{+} + Q_{c}^{+})$

Table 4.13: Profits and electricity generated in the case of event $A_{4,t}$.

As starting point of this section, we label the set of the combinations of capacity for the electricity producers by $\Pi(S_i)$ where $S_i := \Delta Q_{rc,i}, \Delta Q_{c,i}, \Delta Q_{rg,i}, \Delta Q_{g,i}$ with $i = 1, \dots, N$, represents its elements and N is the total number of combinations of long-term capacity expansion. For clarity, we label the expected profit resulting for each combination, respectively for the coal and gas based producers:

$$EP_{c,i} := E^{\mathbb{P}}\left[\sum_{t=1}^{T} e^{-r\cdot t}\pi_{c,t}(S_i)\right] \text{ and } EP_{g,i} := E^{\mathbb{P}}\left[\sum_{t=1}^{T} e^{-r\cdot t}\pi_{g,t}(S_i)\right]$$

For each combination in $\Pi(S_i)$, we define an efficiency ratio, $ER_i(S_i)$, as

$$ER_i(S_i) = \frac{EP_{c,i}}{\max(EP_{c,i} - EP_{g,i})}. \tag{4.20}$$

The efficiency ratio, $ER_i(S_i)$, in Equation (4.20) represents the slope of the line connecting the origin of the axes of the plane (EP_g, EP_c) with each capacity combination. We obtain a frontier, labeled by $EF(S_i)$, composed of the solutions satisfying the Pareto rule optimality. A combination S_i is Pareto optimal if a player cannot improve his expected profit without reducing the expected profit of the other. A representation of the efficient frontier is shown in Figure 4.5.

Once the efficient frontier is constructed, we select from the latter particular combinations with two different criteria. The first criterion minimizes the difference of the expected profits between the two producers:

$$S_i \in \arg\min(|EP_{g,i} - EP_{c,i}|), \quad \text{on } EF(S_i). \tag{4.21}$$

The second criterion maximizes the sum of the expected profit of the two producers:

$$S_i \in \arg\max(EP_{c,i} + EP_{g,i}), \quad \text{on } EF(S_i). \tag{4.22}$$

In other words, this second criterion maximizes the expected profit of the electricity sector. So its output should approximate a real world energy sector where the producers cooperate, i.e. a colluding market. On the contrary, the criterion in Equation (4.21) should better approximate a real world market where oligopolist producers compete, balancing their profits expectations, at the cost of eventually obtaining jointly a lower expected profit. The latter decision criterion represents a competing market.

Event $A_{4,t}$ (No fuel switch and high demand)		
Producer	Non-conventional techn., (MWh)	Conventional techn., (MWh)
Coal based producer	$24 \cdot Q^+_{rc}$	$24 \cdot Q^+_c$
Gas based producer	$24 \cdot Q^+_{rg}$	$D_t - 24 \cdot \left(Q^+_{rc} + Q^+_{rg} + Q^+_c\right)$

Table 4.14: Electricity generation for each type of technology in the case of event $A_{4,t}$.

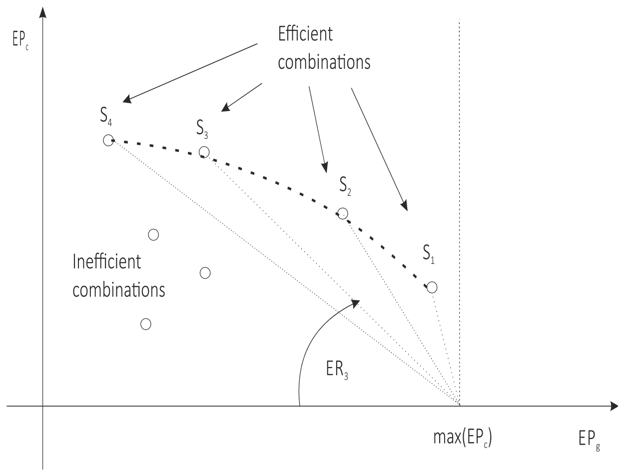


Figure 4.5: Representation of efficient frontier.

4.4 Numerical Application

In this section, we present an application of the model in Equations (3.7) - (4.19d). At first, we present the results on the entire efficient frontier and, then, we focus on the optimal combinations according to Equations (4.21) and (4.22) in Section 4.3. The model is solved numerically using grids for the number of allowances and long-term expansion capacities within a time period of one year. At first, we generate 500 scenarios of 365 daily values of gas and coal prices and electricity demand, $(p_{g,t}, p_{c,t}, d_t)$, that will be used as source of uncertainty for each capacity expansion combinations. The solution scheme is the following:

1. Iterate cap, $H_j,\ \ j = 1, \dots, J$.
2. Iterate capacity expansion combinations, $S_i = (\Delta Q_{rc,i}, \Delta Q_{c,i}, \Delta Q_{rg,i}, \Delta Q_{g,i})$, $i = 1, \dots, N$.
   (a) Calculate the expected profits for each producers associated to i-th capacity expansion combination, $EP_{c,i}$ and $EP_{g,i}$, $i = 1, \dots, N$, over the scenarios generated.
   (b) Check if the i-th capacity expansion combination is feasible.
3. Construct the efficient frontier for each H_j.
4. Select the long-term capacity expansion combinations S^*_i on H_j based on Equations (4.21) and (4.22).
5. Select the optimal cap value, H^*, according to Problem (4.17).

4.4.1 Setting of Parameters and Scenario Generation

The grid for the total yearly cap H is shown in Table 4.15, so $J = 20$ possible values.

Values of yearly cap H	
20.000.000	120.000.000
30.000.000	130.000.000
40.000.000	140.000.000
50.000.000	150.000.000
60.000.000	160.000.000
70.000.000	170.000.000
80.000.000	180.000.000
90.000.000	190.000.000
100.000.000	210.000.000
110.000.000	230.000.000

Table 4.15: Grid values for H.

The percentage ξ of Equation (3.9) is set to 40% and 80% in view of (European Parliament and Council of European Union, 2018) and (European Parliament, 2020), respectively, while the parameter α_1 is set to 90%. As for the no blackout constraint, we set the parameter α_2 to 1% to ensure that, with a probability of 99%, the electricity generated covers the daily electricity demand.

We fix the fine F to 100 euro per tons of CO_2e as required by (European Parliament and Council of European Union, 2003) and the annual compounded interest rate r to 2%. We set the conventional existing capacity, Q_c and Q_g, for both electricity producers to 3000 MW while the existing capacity for non-conventional technology, Q_{rc} and Q_{rg}, is set to zero. For each technology, we restrict the solution space to a grid of possible long-term capacity expansion (measured in MW) as $1000, 2500$, 5000, 7500, 10000, 13000, 18000. The overall solution space of the lower level is therefore the combinations of those grid values of the long-term capacity expansion. So we have that $N = 2041$ possible combinations.

To compute coal and gas marginal costs, we set the parameter m_c and m_g, the coal and gas efficiency factors respectively, to $0,470$ and 1. According to (Lazard, 2018), the CO_2e equivalent emission factors for coal and gas, $m_{EUA,c}$ and $m_{EUA,g}$, are set to 0.85 and 0.46, respectively. Both parameters are measures in tons per MWh.

As for the electricity producers constraints, we assume that each of them has a budget constraint of $10 \cdot 10^{10}$ euro. The depreciation factor b is set to 5% per year while the unit investment cost, b_k, are based on (Lazard, 2018) and their settings are listed in Table 4.16.

Conversion factor	Value	Unit of Measure
Coal Technology, b_c	5188714	Euro per MW
Wind Technology, b_{rc}, b_{rg}	2457812	Euro per MW
Gas Technology, b_g	1058225	Euro per MW

Table 4.16: Unit investment cost setting for each type of technology.

We assume that the non-conventional technology is subject to a derating risk due to weather volatility. We set the annual average derating coefficient to 15%. As for the expected emissions dynamics in Equation (4.4), we set $\sigma = 1502549$, $\alpha = 0$, and $h_a = 100000$.

4.4.2 Scenarios Generation

The original time series of the daily electricity demand is provided by (TERNA S.p.A., 2018). The time series refers to Italian data from January 1st, 2014 to December 31st, 2018. The unit measure is MWh. The time series of the daily coal prices is provided by (Reuters Eikon, 2018b) from January 1st, 2014 to December 31st, 2018. The unit measure is Dollars per 1000 Metric Tonne. We transform its currency multiplying the latter time series by the time series of the exchange rate provided by (Reuters Eikon, 2018a). For the time series of the daily gas price is used Italian PSV Natural Gas Futures time series provided by (Reuters Eikon, 2018c) from January 1st, 2014 to December 31st, 2018. The unit measures is euro.

The possible realizations of the triplet of coal, gas prices and electricity demand, $(P_{c,t}, P_{g,t}, D_t)$, are obtained through a multivariate Markov chain bootstrapping, based on the idea in (Cerqueti et al., 2017, 2019). This method is particularly sophisticated since it allows to bootstrap and simulate time series whose interrelationships arise in a non-parametric way. We generate 500 trajectories of 1300 daily values, i.e. around 3.5-year long scenarios. According to (Cerqueti et al., 2017, 2019), based on a cluster analysis (with Euclidean distance and Ward aggregation method), the state space of the three variables has been partitioned according to Table 4.17.

Component	State	Lag
Coal price	8	5
Gas price	8	5
Electricity demand	8	5

Table 4.17: Partition of the state space of coal and gas prices and electricity demand.

In absence of some reduction method, the corresponding (full) Markov transition probability matrix would consist of $35{\cdot}10^{13}$ rows. This is the number of resulting by the possible combinations of the states at time lags t and $t-1$ and 512 combinations of the states in $t+1$.

Thanks to the inter-dependence among the three variables, the method of (Cerqueti et al., 2017, 2019) leverages, among other things, on the fact that many combinations have never been observed in the historical observations. The resulting empirical transition probability matrix consists of 1083 rows (57 are the observed ones), each representative of trajectories of three-valued process observed on a time window of 5 days and 181 columns. An example of the original and a bootstrapped time series for coal and gas prices and electricity demand are shown in Figure 4.6.

To show the quality of the bootstrapping, that the original time series can be considered as a realization of the same stochastic process, we calculate the distribution of several statistics. If the quality of the bootstrapping is high, any statistic of the original time series would be contained in the main body distribution. For simplicity, we plot the distribution of the mean value of the three variables in Figure 4.18.

4.4.3 Results

In this section, we first comment some key aspects associated to the efficient frontier of each level of cap. We report the results of the electricity generation, the electricity producers' expected net present value, the cumulative electricity sector emissions and the electricity price. We show the results using boxplots, where the red mark indicates the median, the bottom and top edges of the box indicate the 25^{th} and 75^{th} percentiles, respectively. Those results are shown in Figures 4.8 and 4.9.

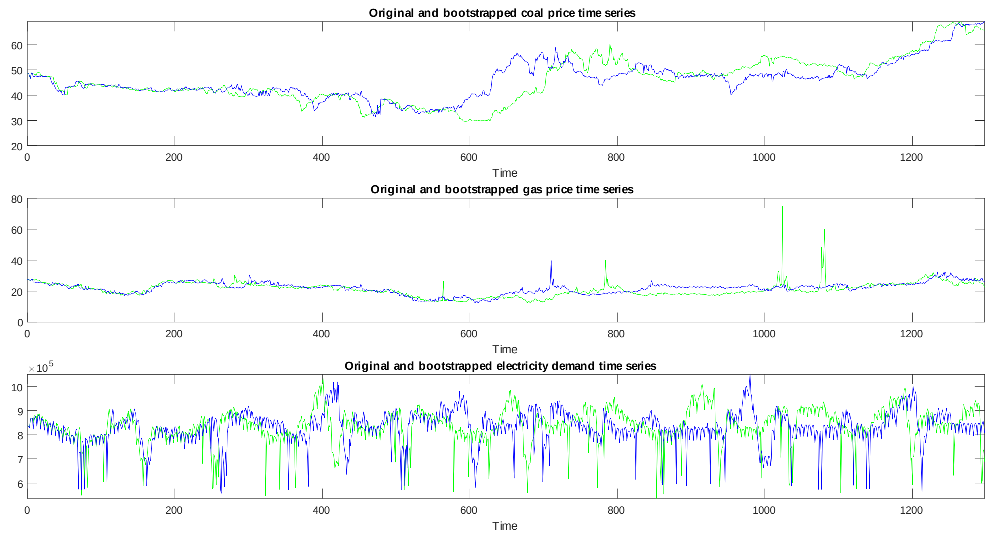


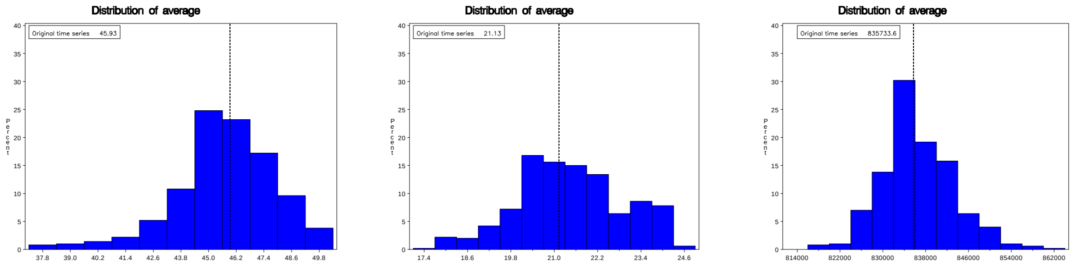
Figure 4.6: Original (green) and one bootstrapped (blue) time series for coal and gas prices and electricity demand.

Long-term capacity expansions ΔQ_{rc}, ΔQ_c and electricity production q_{rc}, q_c

Under ETS scheme. When the cap is strict, the electricity market works under fuel switch regime and the coal is the marginal technology. The coal based producer installs both conventional and no-conventional capacity for two different reasons. On the one hand, he installs conventional capacity to cover the remaining (after non-conventional capacity and gas capacity) electricity demand. On the other hand, he install non-conventional capacity to increase his profit (the non-conventional generation is done at zero cost). The last sentence is confirmed noticing that the non-conventional generation q_{rc} is higher than the conventional one, q_c. When the cap is intermediate, i.e. $H \in \{70.000.000, \dots, 110.000.000\}$, the allowances price decreases and the fuel switch regime happens with lower frequency. In this case, he decides to increase his generation by conventional technology because he can leverage on the fact that the other producers install more conventional capacity to not meet a blackout in the electricity market. Decisions can be seen this fact from the median (red line) of boxplots in Figures 4.8 and 4.9.

Business-As-Usual. When the cap is large, i.e for H_i from 170.000.000 on, the allowances price goes to zero. We liken this situation as the Business-As-Usual situation, where no ETS scheme is applied. Coal based producer decides to install less conventional expansion capacity than non-conventional one. The reason is clear: noticing that the non-conventional generation cost is zero, producer uses the conventional generation to keep the electricity price relatively high. With such electricity price, he can increase his profits covering the largest possible part of the electricity demand with non-conventional technology plants installed.

Long-term capacity expansions ΔQ_{rg}, ΔQ_g and electricity production q_{rg}, q_g



Panel (a) Panel (b) Panel (c)

Table 4.18: Orginal value and distribution of the first moment of the coal (Panel (a)) and gas (Panel (b)) prices and electricity demand (Panel (c)) bootstrapped time series.

Under ETS scheme. When the cap is low, gas based producer works under fuel switch regime. He decide to install less conventional capacity than non-conventional one to increase his profit. In these circumstances, coal is the marginal technology. Gas based producer covers a large part of electricity demand with non-conventional technology (which has the highest profit margin). He decides to install a small amount of conventional technology capacity since he can leverage on the fact that the other producers install more conventional capacity to not meet a blackout in the electricity market.

When the cap increases, gas based producer decides to install more conventional capacity and low non-conventional one. In this case, coal based producer leads him to install more conventional capacity to keep the electricity high and covering the unmeet demand.

Starting from cap value of $H = 70.000.000$ on, gas based producer installs more non-conventional capacity than conventional one. This happens for two reasons. On the one hand, gas is the marginal technology, he installs conventional capacity to cover the remaining electricity demand and on the other hand, he install non-conventional capacity to increase his profits.

Business-As-Usual. When the cap is large, i.e for H from 170.000.000 on, the allowances price goes to zero, which is the same as in the Business-As-Usual situation, where no ETS scheme is applied. In line with the other producer decision, gas based producer decides to install less conventional expansion capacity than non-conventional one. Producer uses the conventional generation to keep the electricity price high so he can increase his profits, and, at the same time, covering the main part of the electricity demand with non-conventional technology plants.

Emissions

Under ETS scheme. The electricity market emissions dynamics reflects the producers' decision. As long as they install (and use) conventional capacity, the emissions will increase. The length of the boxplots reveals that when the cap is low, the efficient combinations are the ones with a high capacity of conventional technology. For $H \in \{70.000.000, \ldots, 110.000.000\}$, both emissions and boxplots length increase. The increasing in the boxplots length is explained noticing that these boxplots represent an intermediate situation where the producers balance their capacity decisions between conventional and non-conventional technology. It means that, in the efficient frontier, are also considered capacity expansion combinations with a high level of non-conventional technology. The increasing emissions features is explained noticing that even if combinations with a high level of non-conventional technology are candidate to be chosen (i.e. they are Pareto optimal), both producers decide to install conventional capacity and generate electricity with that ones.

Business-As-Usual. From values of cap of 170.000.000 on, both emissions and boxplots length decrease. The reason lies in the fact that the efficient frontier is mainly constructed by combinations of capacity expansion with a high level of non conventional technology. At this stage, emissions are not zero since producers generate electricity by conventional technology in order to keep the electricity price high enough to increase revenues.

Electricity Price

Under ETS scheme. The electricity price dynamics depends on producers' decisions and electricity demand. Electricity price attains its maximum when the cap is stringent. In this situation, as for the emissions, the length of the boxplots reveal that the efficient combinations are the ones with a high level of conventional technology.

For $H \in \{120.000.000, \ldots, 160.000.000\}$, we notice two facts: electricity price decreases and boxplots lengths increase. Decrease in the electricity is explained arguing that electricity producers decide to use a large part of non-conventional technology to generate electricity. Increase in boxplots length are correlated to the variability of the combinations of capacity expansion stored in the efficient frontier. The reason of higher boxplots lengths is connected to fuel switch mechanism. Increasing the cap, the efficient frontier incorporate more combinations that capture (and allow the producers to deal with) the frequent possible changes from fuel switch to no-fuel switch regimes.

Business-As-Usual. From values of cap of 170.000.000 on, the length of electricity price boxplots decrease. The reason lies in the fact that the efficient frontier is mainly constructed by combinations of capacity expansion with a high capacity of non-conventional technology and it explains the decreasing boxplots length. Electricity price touches its minimum (around 20 euros per MWh) which, surprisingly, is not around zero. Producers generate electricity by conventional technology to keep the electricity price high enough to increase their profits.

Producers' Expected Profits

Under ETS scheme. We notice that both expected net profits for the electricity producers boxplots are decreasing as the cap increases. We notice that the coal based producer's profit is lower than the gas based producer's one. This is connected to the fuel switch regime and the capacity expansion decision. When the cap is strict, the electricity market works under fuel switch regime and the coal is the marginal technology. Coal based producer gains only from the generation by non-conventional technology (since coal is the marginal technology) while the other producer gains from both technologies (conventional and non-conventional). When the cap increases, the situation changes due to possible switching from fuel to no-fuel switch regimes. In this case, to keep the electricity price high, gas based producer decides to install more conventional capacity and low capacity of non-convetional one, while the coal based producer install more conventional capacity. This leads to a lower expected net present value since each additional unit of coal technology capacity costs more than an additional unit of gas technology capacity.

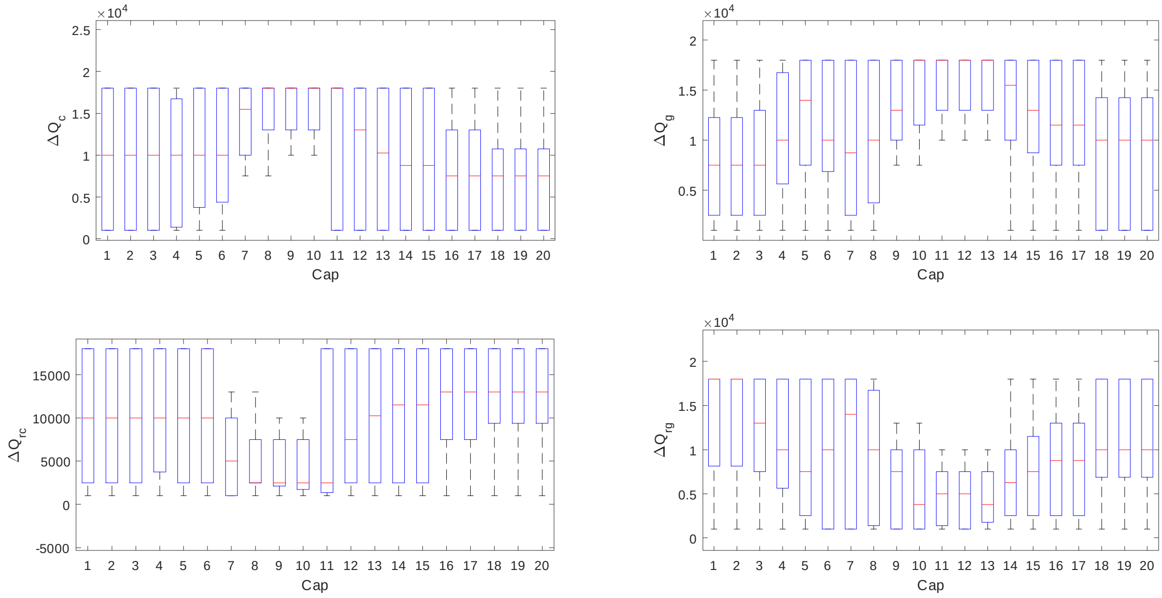


Figure 4.7: Boxplots of the long-term capacity expansion for each electricity producer.

Business-As-Usual. In this case, the expected profits are very low. This happens because of the strong use of non-conventional technology in the electricity generation. Coal based producer is subject to higher risk that his expected net present value becomes negative. This happens for two reasons. On the one hand, because of the lower electricity price and on the other hand because of the high cost that the coal based producer bears for each additional unit of coal capacity w.r.t. to the cost that gas based producer bears for each additional unit of gas capacity.

We now move to study the dependency of the energy-mix and the expected net present values with respect to the market setting discussed in Section (4.3) and the minimum RES penetration, ξ, of Equation (3.9).

Under competing market hypothesis, the expected net present values of the two producers are similar. As one can immediately notice from Figure 4.10, coal based producer defines a strategy based on larger installation of non-conventional capacity rather than conventional one. The reason is clearest: he wants to increase his revenues by selling the electricity generated by non-conventional technology leveraging to the electricity price determined by gas based producer. When the cap is between 70.000.000 and 110.000.000, fuel switch does not happen frequently and, in these cases, gas based producer does the same game did by the other producer with a stringent cap.

Under colluding market hypothesis, for small values of H, gas based producer installs few conventional capacity and high level of non-conventional capacity. The reasons is the following. When the cap is strict, coal is the marginal technology. Gas based producers leaves the other to install conventional capacity (to keep the electricity price higher) so the former can increase his profit.

For caps into the intervals 70.000.000 and 110.000.000, the situation slightly changes. Fuel switch regime does not happens frequently and, when it does not happen, gas is the marginal

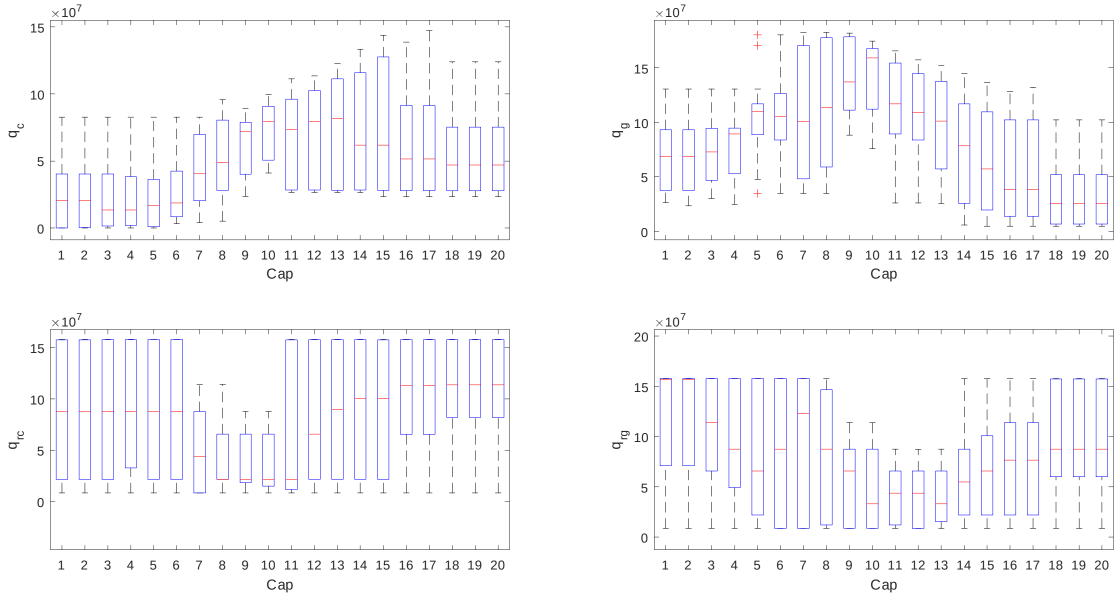


Figure 4.8: Boxplot of the electricity generation for each type of technology in period $\{1, \ldots, T\}$.

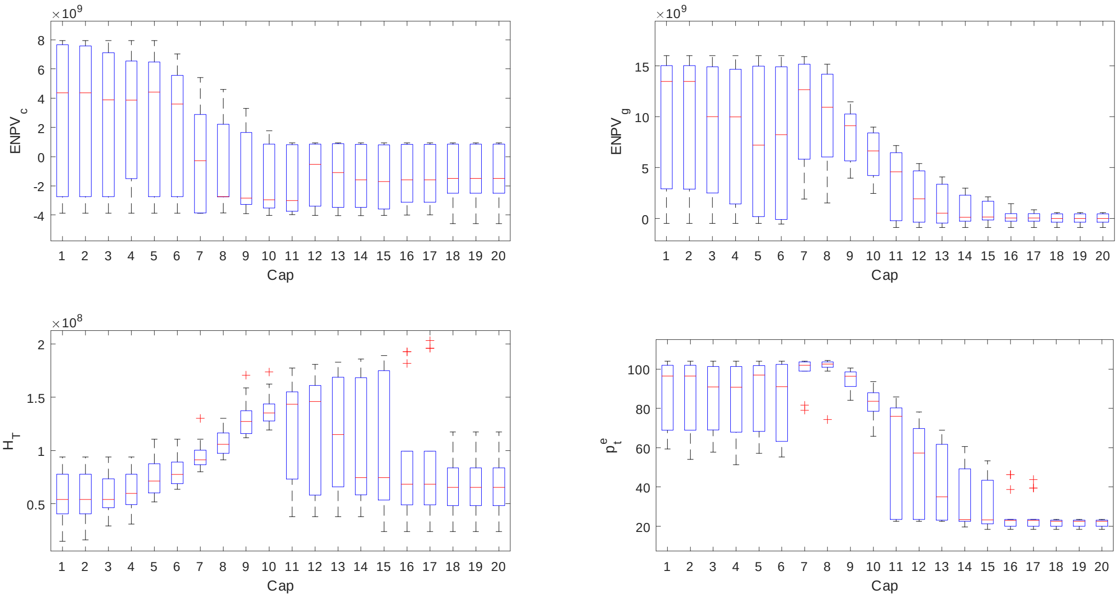


Figure 4.9: Boxplots of the expected net present value of the electricity producers, the cumulate emissions and the electricity price.

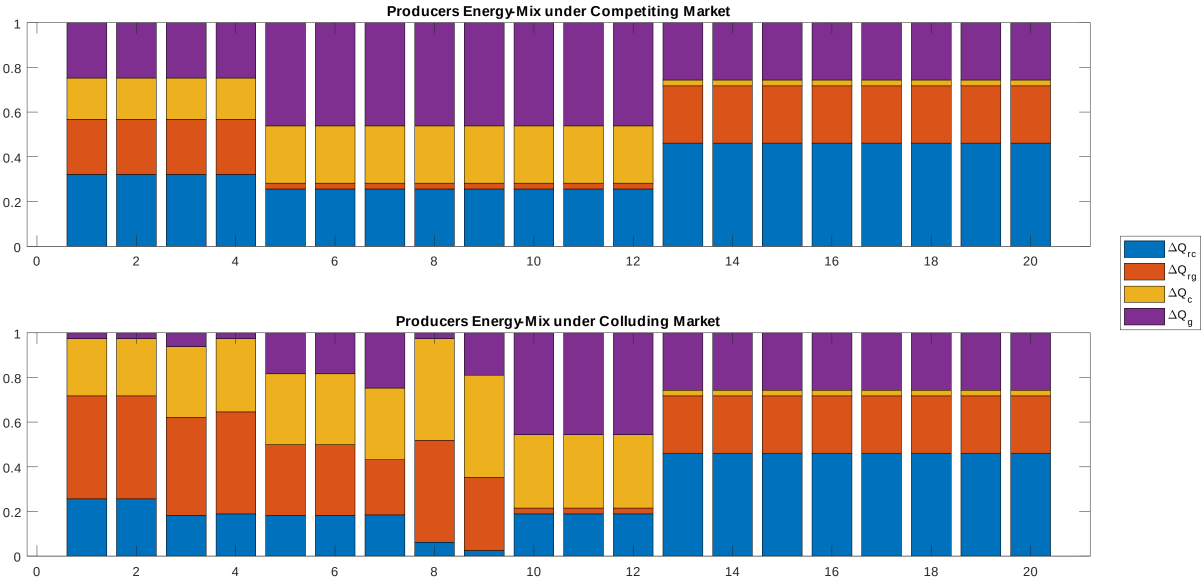


Figure 4.10: Long-term capacity expansion decision under competiting and colluding market.

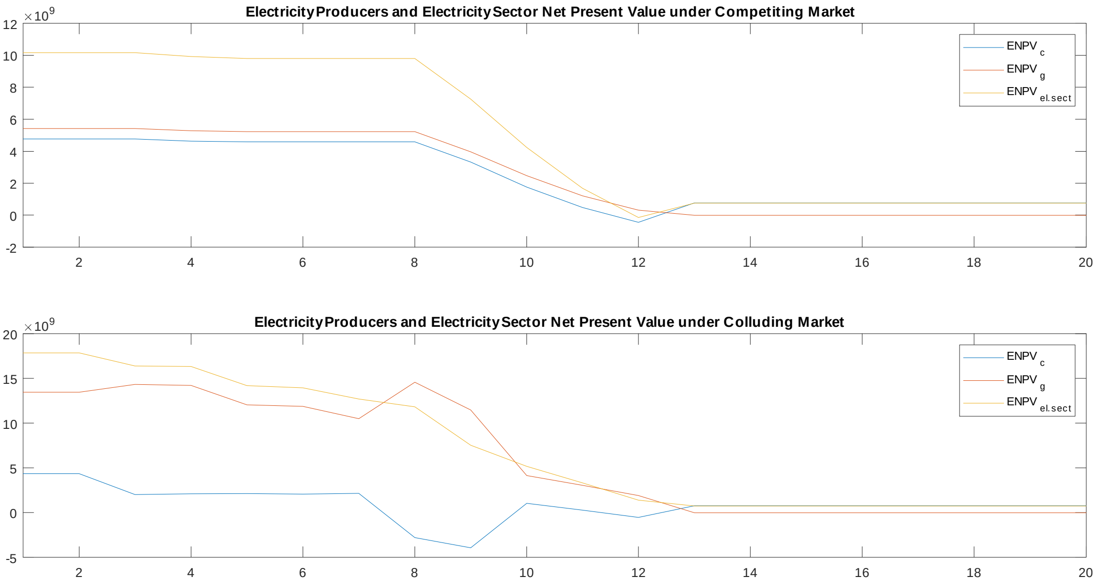


Figure 4.11: Expected net present values of the electricity producers and the entire electricity market under competiting and colluding market.

technology. Therefore, coal based producer leaves the other producer to install conventional capacity so the former can increase his profit. We observe, not surprisingly, that the colluding market setting leads to a higher profit for the electricity sector than the competitive market setting.

When the allowances price is zero, i.e. in BAU scenario, in both market settings, we notice that both producers install more capacity of non-conventional technology than the conventional one. In this case, gas is the marginal technology. On his hand, gas based producer installs many capacity of conventional technology to cover the electricity demand. Coal based producer decides to install many capacity of non-conventional technology to cover the largest possible part of the demand greatly increasing his profit. This explains also why in business-as-usual scenario the expected net profit of coal based producer is higher than the gas based's one.

A common situation to all decision criterion is that, for each level of ξ chosen (40% or 80%), the optimal solution for the policymaker (and, therefore, the optimal solution of the bilevel problem) is to impose a large cap. This means that the optimal solution is not to impose any ETS scheme. This conclusion is in line with the theoretical result obtained in a monopolistic setting in (Falbo et al., 2019).

Moreover, we observe that when ξ is set to 40%, the optimal number of allowances is such that its price is either it is very high or it is zero. It means that, when the policymaker has a low environmental awareness, the electricity producers can decide either to use conventional plants and pay the fine at the end of the period or to generate electricity with non-conventional technology.

When the policymaker has a high environmental awareness, i.e. $\xi = 80\%$, the optimal number of allowances depends on the electricity market setting. When the electricity producer works under competition, the optimal number of allowances is such that its price is zero as if in a business-as-usual condition. In a colluding market, the optimal number of allowances is such that its price is either it is very high or it is zero. It means that, the electricity producers can decide either to use conventional plants and pay the fine at the end of the period or to generate electricity with non-conventional technology depending only on economic convenience.

4.5 Conclusions

In this paper, we investigate a bilevel problem with a policymaker and two electricity producers. The policymaker's aim is at maximizing a welfare function deciding of regulating optimally an ETS scheme acting on the number of allowances issued to power producers working in an energy-only electricity market. The electricity producers decide how to expand their generation technology portfolio, under budget and safety-margin constraints. Moreover, the policymaker fixed two constraints to blackout risk at a minimum and to ensure a minimum percentage of RES penetration. To analyze the impact of the market structure, we first fix a large grid of the possible energy-mix solutions, including both Pareto efficient and inefficient ones. Then we focus on just combinations chosen among the efficient solutions according to two different decision criteria. The first is the energy-mix such that the two companies act as competitor. The second is more cooperative in the sense that the two companies work in a colluding market.

A first major result is the ETS shows weak to provide an effective incentive to power producers to reduce emissions and to drive them to substitute conventional plants with renewables. In some cases, it even introduces an opposite incentive, that is one encouraging higher emissions than would obtain under a business as usual settings. It turns out that the ETS does not provide the policymaker an effective control for its objectives. Indeed, increasing the cap leads to conflicting effects: on the one side, an excess of allowances reduces their price, as well as those of electricity, and makes coal technology preferred to gas. The immediate consequence is that fuel switch occurs less frequently and emissions increase. Moreover, the investment in polluting technologies (especially coal) keeps also high, at the cost of the investment in renewables, to sustain emissions and keep the allowance price higher. Indeed, this situation has been commonly observed in Europe in the last decade. However, when the cap is strict, the probability of exceeding the cap increases along with that of the allowances price. In this situation, the gas technology is preferred to coal, so fuel switch occurs frequently. Moreover, since fewer emissions are required to exceed the cap, investment in renewables are not strongly penalized. However, the price of electricity in this case raises to very high levels, which is an unwanted externality to the policy maker. Another relevant result of the analysis is that the weakness of ETS does not depend much on the way the competition between the two producers solves in favour of one of the two, or in a more balanced way. Of course, the profit distribution between the two producers can differ much from one solution or another. What does not really change much is the overall result (i.e. sector wide) in terms of total emissions and of ratio renewables/polluting technologies in the energy-mix, which are the conclusive goal for an ETS. In all the cases, it turns out that under a business as usual setting both emissions, RES penetration and electricity prices outperforms (from joint environmental and economic points of view) those resulting under an ETS.

Appendices

.A Facts on the underlying diffusion

Here we collect some properties of the process X. We refer the reader to Ch. II in Borodin and Salminen (2002) for further details. For some reference point $\tilde{x} \in \mathcal{I}$, we introduce the derivative of the scale function of $\{X_t^x\}_{t \geq 0}$ as

$$S'(x) := \exp\left\{-\int_{\tilde{x}}^{x} \frac{2\mu(y)}{\sigma^2(y)} dy\right\}, \quad x \in \mathcal{I}. \tag{23}$$

Moreover, we introduce the speed measure density of $\{X_t^x\}_{t \geq 0}$ as

$$m'(x) := \frac{2}{\sigma^2(x) S'(x)}, \quad x \in \mathcal{I}. \tag{24}$$

For a given parameter $\rho > 0$ (representing in the model the subjective discount factor of the fossil-fueled vehicle owner) we introduce the functions ψ_ρ and φ_ρ as the fundamental solutions to the ordinary differential equation (ODE)

$$(\mathcal{L}_X - \rho) u(x) = 0, \ \ x \in \mathcal{I}. \tag{25}$$

The function ψ_ρ can be chosen to be strictly increasing, while φ_ρ strictly decreasing; both ψ_ρ and φ_ρ are strictly positive. The Wronskian between ψ_ρ and φ_ρ (normalized by the scale function density) is the positive constant

$$W := \frac{\psi_\rho'(x)\varphi_\rho(x) - \psi_\rho(x)\varphi_\rho'(x)}{S'(x)} > 0, \quad x \in \mathcal{I}.$$

For future use, note that, by the linear independence of ψ_ρ and φ_ρ, any solution to (25) can be written as

$$u(x) = A\psi_\rho(x) + B\varphi_\rho(x), \ \ x \in \mathcal{I},$$

for some suitable parameters A and B.

We now recall additional properties of the fundamental solution to (25) ψ_ρ and φ_ρ. The fact that $\underline{x}$ and $\overline{x}$ are assumed to be natural (i.e. unattainable) translate into the analytic conditions:

$$\lim_{x \downarrow \underline{x}} \psi(x) = 0, \ \ \lim_{x \downarrow \underline{x}} \varphi(x) = +\infty, \ \ \lim_{x \uparrow \overline{x}} \psi(x) = +\infty, \ \ \lim_{x \uparrow \overline{x}} \varphi(x) = 0, \tag{26}$$

$$\lim_{x \downarrow \underline{x}} \frac{\psi'(x)}{S'(x)} = 0, \ \ \lim_{x \downarrow \underline{x}} \frac{\varphi'(x)}{S'(x)} = -\infty, \ \ \lim_{x \uparrow \overline{x}} \frac{\psi'(x)}{S'(x)} = +\infty, \ \ \lim_{x \uparrow \overline{x}} \frac{\varphi'(x)}{S'(x)} = 0. \tag{27}$$

Furthermore, for any $\underline{x} < \alpha < \beta < \bar{x}$, one has

$$\frac{\psi_\rho'(\beta)}{S'(\beta)} - \frac{\psi_\rho'(\alpha)}{S'(\alpha)} = \rho \int_\alpha^\beta \psi_\rho(y) m'(y) dy, \tag{28}$$

and

$$\frac{\varphi_\rho'(\beta)}{S'(\beta)} - \frac{\varphi_\rho'(\alpha)}{S'(\alpha)} = \rho \int_\alpha^\beta \varphi_\rho(y) m'(y) dy. \tag{29}$$

Finally, it is also worth noticing the probabilistic representation of the fundamental solutions ψ_ρ and φ_ρ in terms of the Laplace transform of hitting times. Letting $\tau_y := \inf\{t \geq 0 : X_t = y\}$, $x, y \in \mathcal{I}$, then

$$\mathbb{E}_x\left[e^{-\rho\tau_y}\right] = \begin{cases} \dfrac{\psi_\rho(x)}{\psi_\rho(y)} & \text{for} \quad x < y, \\ \dfrac{\varphi_\rho(x)}{\varphi_\rho(y)} & \text{for} \quad x > y. \end{cases} \tag{30}$$

.B Proof of Theorem 4 of Chapter 2

Proof. We here prove Theorem 5 by following arguments and techniques as those in Alvarez (2001), among others.

Step 1. We start with the most relevant case in which $\lim_{x\to\underline{x}}(\ell x+\lambda c)<\rho(I-k)<\lim_{x\to\overline{x}}(\ell x+\lambda c)$. As already discussed, since $x\mapsto \ell x+\lambda c$ is increasing, we expect that the optimal switching rule is of the form $\tau^*=\inf\{t\geq 0: X_t^x\geq x^*\}$, for some $x^*\in\mathcal{I}$ to be found. This guess leads to the candidate value function $\widehat{\mathcal{U}}$ given by

$$\widehat{\mathcal{U}}(x):=\begin{cases}\left(I-k-\widehat{V}(x^*)\right)\mathbb{E}_x\left[e^{-\rho\tau^*}\right], & \text{for}\quad x<x^*,\\ I-k-\widehat{V}(x), & \text{for}\quad x\geq x^*.\end{cases}\tag{31}$$

Exploiting the probabilistic representation of $\mathbb{E}_x\left[e^{-\rho\tau^*}\right]$ as in (30), we can write

$$\widehat{\mathcal{U}}(x)=\begin{cases}\left(I-k-\widehat{V}(x^*)\right)\frac{\psi_\rho(x)}{\psi_\rho(x^*)}, & \text{for}\quad x<x^*,\\ I-k-\widehat{V}(x), & \text{for}\quad x\geq x^*.\end{cases}\tag{32}$$

Notice that $\widehat{\mathcal{U}}$ is already continuous at x^* by construction. In order to determine a candidate for the threshold x^*, we impose that $\widehat{\mathcal{U}}$ is C^1 at $x=x^*$; i.e. $\widehat{\mathcal{U}}'(x^*-)=\widehat{\mathcal{U}}'(x^*+)$, which in turn leads to

$$-\left(I-k-\widehat{V}(x^*)\right)\psi_\rho'(x^*)+\left(I-k-\widehat{V}\right)'(x^*)\,\psi_\rho(x^*)=0.$$

Dividing the latter by $S'(x)$ (cf. (23)) we find

$$\frac{\left(I-k-\widehat{V}\right)'(x^*)\,\psi_\rho(x^*)}{S'(x^*)}-\frac{\left(I-k-\widehat{V}(x^*)\right)\psi_\rho'(x^*)}{S'(x^*)}=0.\tag{33}$$

Letting $A:\mathcal{I}\to\mathbb{R}$ be such that

$$A(x):=\frac{\psi_\rho(x)\left(I-k-\widehat{V}\right)'(x)-\left(I-k-\widehat{V}(x)\right)\psi_\rho'(x)}{S'(x)}\tag{34}$$

we have that (33) is equivalent to $A(x^*)=0$.

Using the fact that S' solves $(\mathcal{L}_X S')(x)=0$, and the fact that ψ_ρ solves (25), some algebra shows that

$$A'(x)=\psi_\rho(x)\,m'(x)\,(\mathcal{L}_X-\rho)\left(I-k-\widehat{V}\right)(x).$$

Thanks to (2.11), we have that $\lim_{x\to\underline{x}}A(x)=0$; hence, by the fundamental theorem of calculus, for any $x\in\mathcal{I}$, we have

$$A(x)=\int_{\underline{x}}^{x}\psi_\rho(y)\,m'(y)\,(\mathcal{L}_X-\rho)\left(I-k-\widehat{V}\right)(y)\,dy.\tag{35}$$

Since $(\mathcal{L}_X-\rho)\,\widehat{V}(x)=-(\ell x+\lambda c)$, we can write from (35)

$$A(x)=\int_{\underline{x}}^{x}\psi_\rho(y)\,m'(y)\,(-\rho(I-k)+\ell y+\lambda c)\,dy,\quad x\in\mathcal{I}.\tag{36}$$

Because it must be $A(x^*) = 0$, then we obtain the equation for x^*

$$\int_{\underline{x}}^{x^*} \psi_\rho(y)\, m'(y)\, (-\rho(I-k) + \ell y + \lambda c)\, dy = 0. \tag{37}$$

Step 2. We now show that there exists a unique x^* solving (37) such that $x^* > \hat{x}$ with

$$\hat{x} := \frac{1}{\ell}\left(\rho(I-k) - \lambda c\right).$$

With reference to (36), observe that $A(\hat{x}) < 0$ because $y \mapsto (-\rho(I-k) + \ell x + \lambda c)$ is increasing and null in $\hat{x}$. Using again (36) one finds

$$A'(x) = \psi_\rho(x)\, m'(x)\, (-\rho(I-k) + \ell x + \lambda c)$$

and we observe that $A'(x) > 0\ \forall x > \hat{x}$ and $A'(x) < 0\ \forall x < \hat{x}$.

Moreover, given $x > \hat{x} + \delta$, for some $\delta > 0$, the integral mean-value theorem and (35) give for some $\xi \in (\hat{x} + \delta, x)$

$$\begin{aligned}
A(x) &= \int_{\underline{x}}^{x} \psi_\rho(y)\, m'(y)\, (-\rho(I-k) + \ell y + \lambda c)\, dy \\
&= \int_{\underline{x}}^{\hat{x}+\delta} \psi_\rho(y)\, m'(y)\, (-\rho(I-k) + \ell y + \lambda c)\, dy + \int_{\hat{x}+\delta}^{x} \psi_\rho(y)\, m'(y)\, (-\rho(I-k) + \ell y + \lambda c)\, dy \\
&= \int_{\underline{x}}^{\hat{x}+\delta} \psi_\rho(y)\, m'(y)\, (-\rho(I-k) + \ell y - \lambda c)\, dy + \left(\frac{-\rho(I-k) + \ell\xi + \lambda c}{\rho}\right) \int_{\hat{x}+\delta}^{x} \rho\psi_\rho(y)\, m'(y)\, dy \\
&= \int_{\underline{x}}^{\hat{x}+\delta} \psi_\rho(y)\, m'(y)\, (-\rho(I-k) + \ell y + \lambda c)\, dy + \left(\frac{-\rho(I-k) + \ell\xi + \lambda c}{\rho}\right)\left(\frac{\psi'_\rho(x)}{S'(x)} - \frac{\psi'_\rho(\hat{x}+\delta)}{S'(\hat{x}+\delta)}\right).
\end{aligned}$$

Since $-\rho(I-k) + \ell(\hat{x}+\delta) + \lambda c > 0$ and $\lim_{x\uparrow\overline{x}} \frac{\psi'_\rho(x)}{S'(x)} = +\infty$, we have that $\lim_{x\uparrow\overline{x}} A(x) = +\infty$. This fact, together with $A(\hat{x}) < 0$ and $A'(x) > 0\ \forall x > \hat{x}$, leads to the existence of a unique $x^* > \hat{x}$ such that $A(x^*) = 0$; that is, satisfying (36).

Step 3. We now prove that the C^1-function $\widehat{\mathcal{U}}$ of (2.14) is such that

$$(a)\ \ (\mathcal{L}_X - \rho)\widehat{\mathcal{U}}(x) = 0 \ \text{ on } \ x < x^* \qquad \text{and} \qquad (b)\ \ \widehat{\mathcal{U}}(x) = I - k - \widehat{V}(x) \ \text{ on } \ x \geq x^*,$$

as well as

(c) $\widehat{\mathcal{U}}(x) \leq I - k - \widehat{V}(x) \qquad \forall x < x^*$,

(d) $(\mathcal{L}_X - \rho)\widehat{\mathcal{U}}(x) \geq 0 \qquad \forall x > x^*$.

Since (a) and (b) above are verified by construction, it thus remains to prove (c) and (d).

Proof of (c). Given (2.14) it is enough to show

$$\frac{I - k - \widehat{V}(x^*)}{\psi_\rho(x^*)} \leq \frac{I - k - \widehat{V}(x)}{\psi_\rho(x)}, \quad \forall x < x^*. \tag{38}$$

First of all, we notice that x^* is such that

$$\frac{d}{dy}\left(\frac{I-k-\widehat{V}(y)}{\psi_\rho(y)}\right)\bigg|_{y=x^*}=0 \tag{39}$$

because

$$\begin{aligned}\frac{d}{dy}\left(\frac{I-k-\widehat{V}}{\psi_\rho(y)}\right)\bigg|_{y=x^*} &= \frac{\left(I-k-\widehat{V}\right)'(y)\,\psi_\rho(y)-\left(I-k-\widehat{V}\right)(y)\,\psi_\rho'(y)}{\left(\psi_\rho(y)\right)^2}\Bigg|_{y=x^*}\\ &= A(y)\cdot\frac{W\cdot S'(y)}{\left(\psi_\rho(y)\right)^2}\bigg|_{y=x^*}=0,\end{aligned}$$

due to (39). Moreover, by (35),

$$\frac{d^2}{dy^2}\left(\frac{I-k-\widehat{V}}{\psi_\rho}\right)(y)\bigg|_{y=x^*}=\left[A(y)\cdot\left(\frac{W\cdot S'(y)}{\left(\psi_\rho(y)\right)^2}\right)'+A'(y)\cdot\frac{W\cdot S'(y)}{\left(\psi_\rho(y)\right)^2}\right]\Bigg|_{y=x^*}.$$

Now, since $A(x^*)=0$, using again (35) and the fact that $x^*>\hat{x}$ we have

$$\begin{aligned}&\frac{d^2}{dy^2}\left(\frac{I-k-\widehat{V}}{\psi_\rho}\right)(y)\bigg|_{y=x^*}=A'(x^*)\cdot\frac{W\cdot S'(x^*)}{\left(\psi_\rho(x^*)\right)^2}\\ =&\frac{W\cdot S'(x^*)}{\left(\psi_\rho(x^*)\right)^2}\cdot\frac{d}{dy}\left[\int_{\underline{x}}^{y}\psi_\rho(z)\,m'(z)\left(-\rho(I-k)+\ell z+\lambda c\right)dz\right]\Bigg|_{y=x^*}\\ &=\psi_\rho(x^*)\,m'(x^*)\left(-\rho(I-k)+\ell x^*+\lambda c\right)>0.\end{aligned}$$

This proves that the function $\frac{I-k-\widehat{V}(x)}{\psi_\rho(x)}$ attains a minimum at $x=x^*$ and thus gives (38).

Proof of (d). For any $x>x^*$ we have

$$(\mathcal{L}_X-\rho)\widehat{\mathcal{U}}(x)=(\mathcal{L}_X-\rho)\left(I-k-\widehat{V}\right)(x)=-\rho(I-k)+\ell x+\lambda c>0,$$

where in the second equality we use $(\mathcal{L}_X-\rho)\,\widehat{V}(x)=-(\ell x+\lambda c)$ and for the last inequality we use the fact that $x^*>\hat{x}$.

Step 4. The final verification of the optimality of $\widehat{\mathcal{U}}$ and of $\tau^*=\inf\{t\geq 0: X_t^x\geq x^*\}$ follows by a standard application of Itô's formula (up to a localization argument) and the use of inequalities (a)-(d) above. We refer to Peskir and Shiryaev (2006) for proofs in related settings.

Step 5. The proof of the fact that $\widehat{\mathcal{U}}=0$ and $\widehat{\mathcal{U}}=I-k-\widehat{V}$ in the other two cases easily follows by noticing that $V(x)=\inf_{\tau\geq 0}\mathbb{E}_x\left[\int_0^\tau e^{-\rho t}\left(\ell X_t+\lambda c-\rho(I-k)\right)dt\right]+(I-k)$ and (2.8). ■

.C Facts on the PM$_{10}$ Concentration

Based on Equation (3.1), the PM$_{10}$ concentration $H_t(\Delta\alpha)$, which is written with the explicit dependence on $\Delta\alpha$, is a normal random variable with mean $\frac{\beta_0+\beta_1(1-\alpha-\Delta\alpha)N}{1-\beta_2}$ and variance $\frac{\sigma_\varepsilon^2}{1-\beta_2^2}$, so

$$H_t(\Delta\alpha) \sim \mathcal{N}\left(\frac{\beta_0 + \beta_1(1-\alpha-\Delta\alpha)N}{1-\beta_2}, \frac{\sigma_\varepsilon^2}{1-\beta_2^2}\right), \quad t \in \{1, \ldots, T\}.$$

The expected value at time $t \in \{1, \ldots, T\}$ conditioned on the information available at time 0 is

$$\begin{aligned} E\left(H_t(\Delta\alpha) \,|H_0 = h_0\right) &= \left(\beta_0 + \beta_1(1-\alpha-\Delta\alpha)N\right) \cdot \sum_{k=0}^{t-1} \beta_2^k + \beta_2^t \cdot h_0 \\ &= \frac{\left(\beta_0 + \beta_1(1-\alpha-\Delta\alpha)N\right)\left(1-\beta_2^t\right)}{1-\beta_2} + \beta_2^t \cdot h_0. \end{aligned}$$

The variance at time $t \in \{1, \ldots, T\}$ conditioned on the information available at time 0 is

$$var\left(H_t(\Delta\alpha) \,|H_0 = h_0\right) = \sigma_\varepsilon^2 \cdot \sum_{k=0}^{t-1} \beta_2^{2k} = \sigma_\varepsilon^2 \cdot \left(\frac{1-\beta_2^{2t}}{1-\beta_2^2}\right).$$

The covariance of the PM_{10} concentration between times $t \in \{1, \ldots, T\}$ and $t+h > t$ conditioned on the information available at time 0 is

$$cov\left(H_t(\Delta\alpha), H_{t+h}(\Delta\alpha) \,|H_0(\Delta\alpha) = h_0\right) = \beta_2^h \cdot var\left(H_t(\Delta\alpha) \,|H_0(\Delta\alpha) = h_0\right).$$

.D Explicit Formula for the Expected Number of Traffic Bans

We show how to obtain a closed-form formula for calculate the expected number of traffic bans in Equation (3.5), which we recall here:

$$TB(\Delta\alpha, 0, \tau, T) = E^{\mathbb{P}_H}\left[\sum_{t=0}^{T-\tau+1}\left(\mathbb{I}_{\left\{\sum_{k=t}^{i+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha) \geq c\}} = \tau\right\}}\right)\right].$$

We can write the last expression in Equation (3.5) as

$$\sum_{t=0}^{T-\tau+1} E^{\mathbb{P}_H}\left[\left(\mathbb{I}_{\left\{\sum_{k=t}^{i+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha) \geq c\}} = \tau\right\}}\right)\right], \tag{40}$$

because of linearity of expectations. Given that, in general for a probability $\tilde{\mathbb{P}}$, $E^{\tilde{\mathbb{P}}}[\mathbb{I}_A] = \tilde{\mathbb{P}}(A)$, we have

$$\sum_{t=0}^{T-\tau+1} E^{\mathbb{P}_H}\left[\left(\mathbb{I}_{\left\{\sum_{k=t}^{i+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha) \geq c\}} = \tau\right\}}\right)\right] = \sum_{t=0}^{T-\tau} \mathbb{P}_H\left(\left\{\sum_{k=t}^{i+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha) \geq c\}} = \tau\right\}\right).$$

Let us focus on

$$\mathbb{P}_H\left(\left\{\sum_{k=t}^{i+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha) \geq c\}} = \tau\right\}\right). \tag{41}$$

We observe that the previous probability is equivalent to the following:

$$\mathbb{P}_H\left(\{H_t(\Delta\alpha) \geq c\} \cap \{H_{t+1}(\Delta\alpha) \geq c\} \cap \cdots \cap \{H_{t+\tau-1}(\Delta\alpha) \geq c\}\right),$$

that is the probability that τ indicator functions are jointly equal to 1. In other words, the event measured by the previous probability is the PM_{10} concentration at time t, $H_t(\Delta\alpha)$, above the safety threshold c for all times in the interval $\{t, \ldots, t+\tau-1\}$. Now, let us introduce the Gaussian multivariate random variable $(H_t, H_{t+1}, \ldots, H_{t+\tau-1})$[3]Then, the previous probability can be written as

$$\mathbb{P}_H\left(\left\{\sum_{k=t}^{i+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha)\geq c\}} = \tau\right\}\right) = \mathbb{P}_H\left(\{H_t(\Delta\alpha) \geq c\} \cap \{H_{t+1}(\Delta\alpha) \geq c\} \cap \cdots \cap \{H_{t+\tau-1}(\Delta\alpha) \geq c\}\right) \tag{42}$$

$$= \int_c^\infty \int_c^\infty \cdots \int_c^\infty f_{H_t,H_{t+1},\ldots,H_{t+\tau}}(h_t, h_{t+1}, \ldots, h_{t+\tau-1})\, dh_t dh_{t+1} \cdots dh_{t+\tau-1},$$

where $f_{H_t,H_{t+1},\ldots,H_{t+\tau}}(h_t, h_{t+1}, \ldots, h_{t+\tau-1})$ is the probability density function of $(H_t, H_{t+1}, \ldots, H_{t+\tau-1})$, characterized by the conditional (at time zero) autocovariance function in Appendix (.C). Using Equation (42), it is possible to write Equation (40) in integral terms as

$$\sum_{t=0}^{T-\tau+1} \mathbb{P}_H\left(\left\{\sum_{k=t}^{j+\tau-1} \mathbb{I}_{\{H_k(\Delta\alpha)\geq c\}} = \tau\right\}\right) =$$

$$= \sum_{t=0}^{T-\tau+1} \mathbb{P}_H\left(\{H_t(\Delta\alpha) \geq c\} \cap \{H_{t+1}(\Delta\alpha) \geq c\} \cap \cdots \cap \{H_{t+\tau-1}(\Delta\alpha) \geq c\}\right)$$
$$= \sum_{i=0}^{T-\tau+1} \left(\int_c^\infty \int_c^\infty \cdots \int_c^\infty f_{H_t,H_{t+1},\ldots,H_{t+\tau}}(h_t, h_{t+1}, \ldots, h_{t+\tau-1})\, dh_t dh_{t+1} \cdots dh_{t+\tau-1}\right).$$

.E Mean and Variance of Forecasted Cumulative Emissions

The forecasted cumulative emission is expressed in Equation (), that is written again here for clarity

$$\widehat{H_t} = \sum_{j=0}^{t} \widehat{h}_t = h_a(t+1) + \alpha \sum_{j=0}^{t} j + \sigma \sum_{j=0}^{t} Z_j,$$

and this section is devoted to prove that the conditional (at time t) expected value and variance of $\widehat{H_t}$ are those in Equations () and (). We start with the expected value. We use the linearity property of the expected value operator, the measurability of $\widehat{H_t}$ w.r.t. the σ-algebra $\mathcal{F}_t$ and the

[3]We omit for semplicity the dependency of H_j on $\Delta\alpha$.

fact that Z_j is a zero mean random variable.

$$\begin{aligned}
E\left[\widehat{H_T}|H_t\right] &= E\left[\widehat{H_T}|\mathcal{F}_t\right] \\
&= E\left[h_a(T+1)+\alpha\sum_{j=0}^{T}j+\sigma\sum_{j=0}^{T}Z_j|\mathcal{F}_t\right] \\
&= E\left[h_a(t+1)+\alpha\sum_{j=0}^{t}j+\sigma\sum_{j=0}^{t}Z_j|\mathcal{F}_t\right]+E\left[h_a(T-t)+\alpha\sum_{j=t+1}^{T}j+\sigma\sum_{j=t+1}^{T}Z_j|\mathcal{F}_t\right] \\
&= h_a(t+1)+\alpha\sum_{j=0}^{t}j+\sigma\sum_{j=0}^{t}Z_j+E\left[h_a(T-t)+\alpha\sum_{j=t+1}^{T}j|\mathcal{F}_t\right] \\
&= H_t+(T-t)\,h_a+\alpha\sum_{j=t+1}^{T}j.
\end{aligned}$$

We move to the conditional variance. We notice that the only remaining term is the stochastic term Z_t because the other terms, either are deterministic or measurable w.r.t. the σ-algebra $\mathcal{F}_t$.

$$\begin{aligned}
var\left[\widehat{H_T}|H_t\right] &= var\left[\widehat{H_T}|\mathcal{F}_t\right] \\
&= var\left[h_a(T+1)+\alpha\sum_{j=0}^{T}j+\sigma\sum_{j=0}^{T}Z_j|\mathcal{F}_t\right] \\
&= var\left[h_a(T-t)+\alpha\sum_{j=t+1}^{T}j+\sigma\sum_{j=t+1}^{T}Z_j|\mathcal{F}_t\right] \\
&= \sigma^2 var\left[\sum_{j=t+1}^{T}Z_j|\mathcal{F}_t\right]=\sigma^2(T-t)\,.
\end{aligned}$$

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