Emissions Trading Schemes: Theoretical Modeling and Behavioral Investigation

by

Corina Haita

Submitted in partial fulfillment of the requirements for
the degree of Doctor of Philosophy
at
Central European University
Budapest, Hungary

Supervisor: Prof. Andrzej Baniak
Associate supervisor: Prof. Botond Kőszegi

Budapest, Hungary
January, 2014

CEU eTD Collection

© Copyright by Corina Haita.
All rights reserved.

CEU eTD Collection

Central European University
Department of economics

The undersigned hereby certify that they have read and recommend to the Department of Economics for acceptance the thesis entitled 'Emissions Trading Schemes: Theoretical Modeling and Behavioral Investigation' by Corina Haita.

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Chair of the thesis committee ....
Julius Horváth

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Advisor ....
Andrzej Baniak

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Associate Advisor ....
Botond Kőszegi

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Internal Examiner ....
Adam Szeidl

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

External Examiner ....
Peter Katuščák

CEU eTD Collection

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Internal Member ....
Andrea Canidio

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

External Member ....
Balázs Muraközy

I certify that I have read this dissertation and in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

External Member ....
Adam Szentpeteri

CEU eTD Collection

Central European University
Department of economics

Author: **Corina Haita**
Title: **Emissions Trading Schemes: Theoretical Modeling and Behavioral Investigation**
Degree: **Ph.D.**
Dated: Januarz 29, 2014

Hereby I testify that this thesis contains no material accepted for any other degree in any other institution and that it contains no material previously written and/or published by another person except where appropriate acknowledgement is made.

Signature of the author: ______________________
Corina Haita

CEU eTD Collection

Abstract

Emissions Trading Schemes (ETS) have become popular instruments for climate change mitigation since the ratification of the Kyoto Protocol in 1997. Their major appeal is that they require minimum of information on the side of the regulator while the efficient solution for achieving the environmental target is left in the care of market forces. This was firstly shown by the seminal paper of Montgomery (1972), who demonstrated that in a system of tradable pollution permits, market equilibrium coincides with the cost-effective solution and this is independent of how permits are initially allocated to the regulated polluters. The current thesis contributes to the literature on the functioning of the emissions markets, with a focus on the role of auctioning as a method of initial allocation of permits. In three rather independent chapters, the thesis explores the effect of various market frictions on the outcome of an ETS. Specifically, the first chapter aims at the theoretical understanding of the effectiveness of an ETS in which permits are allocated in an auction followed by a secondary market, and all the ETS-regulated firms exercise market power. Under these conditions the auction clearing price is below the secondary market price. In addition, the high emitters lose while the low emitters gain relative to the case when all firms take permits prices as given. However, if the polluters are not too different in terms of their permits needs, strategic behavior can result in a lower overall compliance cost than in the case of price-taking behavior. In the second chapter I investigate the effect of uncertainty and the role of the speculators on the compliance behavior and profits of risk-averse regulated polluters. Contrary to the policy discussion which often ignores the presence of a secondary market when permits are allocated in an auction, the model of this paper shows that when the auction takes place under uncertainty, there will always be trade in the after-market. Moreover, the model shows how firms take into account the possibility for trade when forming their bids in the auction. The model also demonstrates that, under the most realistic assumptions, the presence of the speculators adversely affects polluters profits, despite helping the regulator raise more revenue from selling permits. The third chapter searches for the behavioral bias of the sunk-cost fallacy in a

CEU eTD Collection

laboratory experiment, in which the alternative course of action is explicitly given and part of the initial investment can be recouped. Conditional on subjects understanding the experimental task, I find evidence of the manifestation of the bias, which, however, is independent of the size of the initial investment. Moreover, I find that the higher cognitive ability subjects are more likely to exhibit the bias. Given its design, the findings of the experiment bear implications for emissions permits trading behavior of the regulated firms who purchase permits in an auction.

CEU eTD Collection

Acknowledgements

I would like to thank my Ph.D advisors, Prof. Andrzej Baniak and Prof. Botond Kőszegi, who not only diligently guided me through the development of this thesis, but they were also very supportive and helpful regarding my after-PhD life. I am especially indebted to Prof. Kőszegi for becoming the Associate Advisor of my thesis at the time when I was struggling in darkness with the third chapter. Without his help, it is unlikely that this chapter would have ever been written.

At various points during the development of this thesis I benefited from suggestions and advice from several faculty members at the Central European University (CEU). In particular, I am very thankful to Andrea Canidio, Péter Kondor, Miklós Koren, Sergey Lychagin, Adam Seidl and Mirco Tonin.

I am very appreciative towards Nenad Kos, who, during my visit at Bocconi University in Milan, patiently read and discussed a draft which later became the second chapter of my thesis. These discussions also gave rise to an idea which was then developed into the first chapter of this thesis.

I am indebted to Daniela di Cagno and Paolo Crosetto for their logistic help in running the experiment of the third chapter in the CESARE laboratory at LUISS Guido Carli in Rome, and to Francesca Giardini, who assisted me with the first session of the experiment. I would also like to thank my colleagues at the International Center for Climate Governance in Venice, who served as pilot subjects.

I am thankful to the administrative staff of the Department of Economics at CEU for their professionalism, company and friendship during these years.

I would like to thank my fellow graduate students at the CEU who shared the pain of the PhD years. I am especially grateful to Anna Adamecz, Anikó Bíró, Péter Harasztosi, Cecília Hornok and Iryna Koshulap for their friendship and moral support.

I also want to thank Réka Futász, my academic writing advisor, who carefully read and corrected my style.

I am deeply grateful to George Soros for founding and financing the CEU, the place that changed my life and made the existence of this thesis possible.

Lastly, but not least, I want to thank Andreas Falah for bearing with me through the rush of the past year, for his kindness, love and faith in me.

All errors are mine.

CEU eTD Collection

Pentru mami

CEU eTD Collection

Contents

Abstract **v**

Acknowledgements **vii**

List of Tables **xii**

List of Figures **xiii**

Introduction **1**

1 Endogenous Market Power in an Emissions Trading Scheme with Auctioning **3**

1.1 Introduction 3
1.2 The Model 8
1.3 Price-taking Behavior 12
1.3.1 Secondary market trade 12
1.3.2 Initial allocation 13
1.4 Strategic Behavior 13
1.4.1 Secondary market trade 14
1.4.2 The auction 16
1.4.3 Equilibrium 18
1.5 Results and Discussion 19
1.5.1 Implications of strategic behavior 19
1.5.2 Comparisons 21
1.6 Conclusion 24
1.A Appendix 27
1.A.1 The Kuhn-Tucker conditions for the constrained problem 27
1.A.2 Strategic behavior with intercept and slope 28
1.A.3 The derivation of the net trade function for the strategic case . . 28
1.A.4 The derivation of the bidding schedules for the strategic case . . 29
1.A.5 The individual change in compliance cost 30

CEU eTD Collection

1.A.6 Proof of inequality (1.29) 31

2 Uncertainty and Speculators in an Emissions Trading Scheme **32**

2.1 Introduction 32

2.2 The Model 39

2.2.1 The players 39

2.2.2 The utilities 41

2.2.3 The markets 43

2.3 Equilibrium 44

2.3.1 Abatement and Secondary Market 45

2.3.2 Auction 47

2.3.3 Marginal Valuations 48

2.4 Numerical Comparative Statics 53

2.4.1 Individual valuations 53

2.4.2 Bid shading 55

2.4.3 Heterogeneity 56

2.4.4 The role of the speculators 60

2.5 Conclusions 62

2.A Appendix 64

2.A.1 Derivation of the bidding schedules 64

3 Sunk-Cost Fallacy with Partial Reversibility: An Experimental Investigation **65**

3.1 Introduction 65

3.2 Existing Literature 69

3.3 Experimental Design 73

3.3.1 Treatments and parameters 73

3.3.2 Procedure 75

3.4 Results 76

3.4.1 Consistent HL lottery choices 79

3.4.2 Cognitive ability 80

3.4.3 Economists versus non-Economists 82

3.4.4 The role of cognitive ability 83

3.4.5 Discussion 85

3.5 Applications 86

3.6 Conclusions 87

3.A Appendix 90

3.A.1 Tables 90

CEU eTD Collection

3.A.2 Instructions Screens 93
3.A.3 The Cognitive Quiz 101
3.A.4 Figures 102

Bibliography **104**

CEU eTD Collection

List of Tables

3.A.1 Experimental parameters 90
3.A.2 Descriptive statistics for the sample who invested 90
3.A.3 Decision variables: all sample 90
3.A.4 Averages for the subsample of consistent HL lottery choices 91
3.A.5 Averages of units used from the alternative asset by cognitive level . . 91
3.A.6 Non-parametric test of treatment differences by cognitive level 91
3.A.7 The effect of the cognitive ability 92

CEU eTD Collection

List of Figures

2.1 The sequence of decisions . . . 40

2.2 True individual valuation for the first permit ($\sigma^2 = 4$) . . . 54

2.3 Bid shading and expected price spread $N = 20$, $N_a = 10, \overline{E} = 100$, $\sigma^2 = 4$, $\epsilon = -3.1$, $\rho_f = 0.005$, $\gamma_f = 12$, $\alpha_f = 0.3$, $\theta_f = 10$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$) . . . 55

2.4 Equilibrium with heterogeneity in the abatement cost $\theta_f = f + 3$, $\epsilon = -3.81$, $\sigma^2 = 4$, $\gamma_f = 20$, $\alpha_f = 0.4$, $\rho_f = 0.004$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$ . . . 57

2.5 Equilibrium with heterogeneity in shock sensitivity $\alpha_f = f/50$, $\epsilon = -3.81$, $\sigma^2 = 4$, $\gamma_f = 20$, $\theta_f = 10$, $\rho_f = 0.05$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$ . . . 58

2.6 Equilibrium with heterogeneity in the expected BaU emissions $\gamma_f = 1.5(f + 15)$, $\epsilon = -3.81$, $\sigma^2 = 4$, $\theta_f = 10$, $\alpha_f = 0.4$, $\rho_f = 0.05$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$ . . . 59

2.7 The effect of the speculators: $\overline{E} = 200$, $N = 20$, $N_a = 10, \sigma^2 = 4$, $\gamma_f = 18$, $\theta_f = 10$, $\alpha_f = 0.3$, $\rho_f = 0.05$, $f = 1, \ldots, N$; $\rho_s = 0.001$, $\forall s = 1, \ldots, M$ . . . 60

2.8 Speculators' risk aversion $\overline{E} = 100$, $N = 20$, $N_a = 10$, $M = 5$, $\sigma^2 = 4$, $\epsilon = -3.81$, $\gamma_f = 10$, $\theta_f = 10$, $\alpha_f = 0.2$, $\rho_f = 0.3$, $f = 1, \ldots, N$ . . . 61

3.A.1 Introduction Screen . . . 93

3.A.2 Initial position Screen . . . 94

3.A.3 Investment Screen . . . 95

3.A.4 Financial position after investment Screen . . . 96

3.A.5 Trade 1 Screen . . . 97

3.A.6 Trade 2 Screen . . . 98

3.A.7 Profit Screen . . . 99

3.A.8 Holt and Laury risk aversion questions . . . 100

3.A.9 Distribution of units used from the alternative asset: All sample . . . 102

3.A.10 Distribution of the units used from the alternative asset by consistency of the answers to HL lotteries . . . 102

3.A.11 Distribution of the units used from the alternative asset by cognitive score . . . 103

3.A.12 Distribution of the units used from the alternative asset by field of studies 103

CEU eTD Collection

Introduction

This thesis consists of two theoretical chapters in Emissions Trading Schemes (ETSs) and one chapter which tests for the sunk cost fallacy with a laboratory experiment.

The first chapter contributes to the literature on market power in emissions permits markets, modeling an ETS in which polluters differ only with respect to their business-as-usual emissions. The polluters play a two-stage static complete information game in which their market power arises endogenously from the business-as-usual emissions. In the first stage the polluters bid in an auction for the distribution of the fixed supply of permits and in the second stage they trade these permits in a secondary market. For compliance, they can also engage in abatement activity at a quadratic cost. In equilibrium all polluters are successful in the auction, but in the secondary market the low emitters become net sellers and the high emitters are net buyers. In addition, the secondary market price is unambiguously above the auction clearing price. Consequently, the high emitters are worse off as a result of the strategic behavior. In addition, I find that the aggregate compliance cost increases in the heterogeneity of their business-as-usual emissions. However, there exists a threshold of the fixed supply of permits above which strategic behavior is compliance cost-saving for the polluters. Moreover, there are distributions of the business-as-usual emissions for which strategic behavior is compliance cost-saving for the polluters regardless of the level of the available supply of permits.

In the second chapter I develop a static game theoretical model of an ETS with auctioning, aiming at understanding the effect of the speculators on the auction outcome and polluters' profits. I assume that both the polluters and the speculators are risk averse and the polluters respond idiosyncratically to a common demand shock. The auction has a uniform price sealed-bid format to which only a subset of the polluters together with all the speculators submit bids. I derive polluters' endogenous valuations for permits and I find that they bid both for use and speculative reasons. Further, I conduct both analytical and numerical comparative statics with respect to the main

CEU eTD Collection

parameters of the model. It appears that, while all auction participants shade their bids, the presence of the speculators determines the polluters to bid closer to their true demands, thus increasing the auction clearing price towards its competitive value. At the extreme, where the speculators are risk neutral, their presence in the auction creates a trade-off between increasing regulator's revenue and hurting the profits of the auction-participating polluters.

The third chapter contributes to the literature attempting to document the sunk-cost fallacy in laboratory. I study the bias in a simple experimental setting, void of its previously acknowledged psychological roots. Under this design (i) the subjects have the possibility to partially recoup the investment in the initial course of action, (ii) the alternative course of action is made explicit and obvious and (iii) the associated returns of each course of action are deterministic. The sunk-cost fallacy hypothesis is not confirmed on the sample as a whole. However, I find evidence of its manifestation on subsamples for which I make the conjecture of having a better comprehension of the experimental task. Nevertheless, the bias appears to be independent of the size of the investment in the initial course of action. After controlling for mistakes in decisions and the effort put in the experimental task, I find that higher cognitive ability subjects are more prone to the bias. Finally, I argue that the previously acknowledged psychological drivers of the sunk-cost fallacy are not needed for the bias to manifest itself. Instead, I put forward the *realization utility* as the most likely underlying reason behind the manifestation of the sunk-cost fallacy under the current experimental design.

CEU eTD Collection

Chapter 1

Endogenous Market Power in an Emissions Trading Scheme with Auctioning

An earlier version of this paper was awarded the Best Student Paper Award at the Bratislava Economic Meeting 2012.

1.1 Introduction

During the last decades emissions trading schemes (ETS) have increased in popularity as policy tools for emissions reductions. Moreover, large ETSs like the European ETS (EU ETS) or the California ETS have commenced to implement auctioning as the method of initial allocation of permits. The main argument for implementing an ETS is the minimization of the social total cost of meeting the constraint on the total emissions target. Therefore, it is important to understand the nature of these markets, in particular when their functioning deviates from delivering the efficient outcome due to, for example, the exercise of market power by the players of the scheme. Such concerns have been raised in the literature both with regard to the trading of the emissions permits in the secondary market and to the auction for the initial allocation of permits. For example, in a paper assessing the effectiveness of the UK ETS, Smith & Swierzbinski (2007) put forth the possibility of the exercise of market power as an explanation for the substantial difference between the auction clearing price and the market price of the emissions permits when traded in the secondary market. Indeed, using a stylized model of a monopoly (a group of firms which coordinate their actions in the auction) with a competitive fringe, they are able to reproduce the market price of a permit

CEU eTD Collection

in the first year of the scheme following the auction.

In addition, in relation to the EU ETS, Ellerman et al. (2010) pointed out that, although the scheme covers more than 11,000 installations, many of them are owned by the same firm. Hence, it is conceivable that they obey the same strategies in the emissions markets. Moreover, using CITL data, Schleicher (2012) shows the uneven distribution of the emissions across the EU ETS entities: 84% of the installations in the EU ETS accounted for only 10% of the emissions generated within the scheme in 2011, which indicates a relatively concentrated market. Evidence of thin markets have also been observed at the initial allocation stage. During the first half of 2013, the number of bidders for the spot auction of the EU ETS was never larger than 20.[1] This is surprisingly low participation in the primary auction compared to the total number of the EU covered installations. Similarly, in the first four advanced auctions of California ETS for the sales of 2015 and 2016 vintage allowances, the Herfindahl - Hirschman Index was between 1198 and 3159. This signals conditions for a concentrated primary market.

Motivated by the above-mentioned anecdotal evidence, the aim of this paper is to understand the consequences of the exercise of market power in an ETS in which polluters[2] act strategically both in the auction, where permits are initially distributed, and in the secondary market, where the polluters trade the permits among themselves. Precisely, I model the initial allocation stage as a sealed-bid uniform price auction in which the participants simultaneously and independently submit bidding schedules to the regulatory agency who issues the permits. The latter clears the auction by equating the aggregate demand with the fixed supply of permits and distributes the permits to the polluters according to their bids and the market clearing price. Subsequently, the emitters trade their permit endowments in a secondary market. Hence, in the two-stage static complete information model of emissions trading developed in this paper, the initial allocation is endogenous. This allows to assess the effect triggered by the anticipated exercise of market power in the secondary market over the bidding strategy at the initial allocation stage.

Theoretical concerns about market power in emissions markets are not new in the literature. This literature was initiated by the seminal paper of Hahn (1984), whose model was later extended by Westskog (1996) and continued with Maeda (2003). In particular, Hahn (1984) found that the cost effective solution is achieved only if the firm with market power is initially endowed with the number of permits that it holds in equilibrium and that the permit price increases in the initial endowment of the dominant firm. Further, assuming a group of Cournot players as leaders in a leader-follower game with a price-taking fringe, Westskog (1996) recov-

[1] The results of the auctions are published on the European Energy Exchange platform (`www.eex.com`), which is the common auction platform chosen by the European Commission for auctioning the EU ETS allowances.

[2] The term "polluters" will be used interchangeably with the term "emitters" to denote the members of the ETS as players of the emissions markets.

CEU eTD Collection

ers the implications delivered by the seminal model. Finally, Maeda (2003) models two price makers, a net buyer and a net seller, with an infinite number of price-taking fringe emitters, and he derives conditions under which the two market makers can exercise effective market power. The paper finds that only the market maker with excess initial allocation of permits (the net seller) can influence the price above its competitive level, while the market maker with a deficit of permits (the net buyer) has no ability to exercise effective market power.

The common point of these previous studies is that both market power and the initial allocation of permits were decided exogenously. Specifically, they rely on the crucial assumption that one or several dominant firms have the ability to influence the price while the rest of the firms, i.e. the fringe, act as price takers. Hence, the discussion about inefficiency revolves around the initial allocation of permits. However, to the best of my knowledge, theoretical results on emissions markets in which on the one hand, market power arises endogenously and on the other hand, permits are distributed in an auction are missing. Therefore, the main question investigated in this paper is how the (anticipated) exercise of market power affects the overall effectiveness of the ETS. While inefficiency is expected from the outset, the aim of the current paper is to understand the direction of this inefficiency. More specifically, from the policy perspective it is relevant to understand who are the "winners" and the "losers" in an ETS where market power arises endogenously and the initial allocation of permits is conducted through an auction. In other words, it is interesting to characterize the polluters who can benefit from market power and, thus, have an incentive to behave strategically.

Nonetheless, more recent studies have relaxed one or the other of the two assumptions. For example, Malueg & Yates (2009) and Lange (2012) have relaxed the assumption of exogenous market power allowing all firms to manipulate the permits price, but continued to have exogenous initial allocation of permits. Next, Montero (2009) discusses market power for the case in which permits are allocated in an auction, but continues to maintain the assumption of a dominant firm which exercises market power. Thus, relaxing the assumption of exogenous market power in a so-called bilateral oligopoly framework, Malueg & Yates (2009) make use of the supply function equilibria (SFE) *à la* Klemperer & Meyer (1989), focusing on linear strategies. They analyze both the case of full information and private information with respect to the abatement cost and find that private information attenuates the effect of the inefficiency driven by the exercise of market power, as compared to the case of full information. However, for the case of full information they find that strategic behavior always leads to a higher overall abatement cost, unless the initial allocations are such that no firm chooses to trade, in which case strategic behavior coincides with the cost-effective solution. In the same vein, Lange (2012), assuming endogenous market power in an emissions trading market, recovers the efficiency condition from Hahn's seminal paper: efficiency is reached if the players with market power (in this case all players) receive an initial allocation of permits equal to their efficient emissions level. Again, this paper assumes free allocation of the initial

CEU eTD Collection

permit endowment. Finally, Montero (2009) conducts a graphical analysis of the dominant firm's strategy in an uniform price auction for the distribution of the emissions permits. He concludes that the optimal strategy for the large firm is to bid an empty schedule and buy the permits from the fringe in the after-auction market. Note, however, that this paper continues to assume exogenous market power.

Hence, apart from investigating an important question related to the effect of market power in an ETS with auctioning, the model developed in this paper also contributes to filling the above-mentioned gap in the theoretical literature on market power in emissions trading. Precisely, my paper differs from the above-mentioned literature in two respects. First, I relax the assumption of exogenously assigned market power and I allow all emitters to exercise influence over the price to the extent that this is permitted by their characteristics, i.e. their parameters.[3] Second, the initial allocation is auctioning as opposed to being exogenously assigned according to a benchmarking rule (e.g. grandfathering). Hence, the auction implicitly gives rise to a new market which is missing from the earlier models, i.e. the primary market. Essentially, I augment the model of Malueg & Yates (2009) including a new decision stage, such that the initial distribution of permits is actioning rather than grandfathering. This approach raises the question of the propagation of the bidding strategies to the exercise of market power in the secondary market, as well as the effect of the anticipation of this behavior on the auction clearing price. Under this set-up it is clear that, unlike in the previous papers analyzing market power in an ETS, the initial endowment cannot be the soul source of market power, since it is in itself endogenous.

In the two-stage permits allocation model of this paper, the ETS covered entities (emitters) differ only with respect to their business-as-usual emissions. However, for tractability reasons and the desire of having a closed form solution in both stages of the game, two simplifying assumptions regarding the modeling of the abatement are necessary. First, instead of affecting the emissions intensity, in this model the abatement affects directly the overall amount of emissions. In other words, the abatement is modeled as end-of-pipe emissions reductions. Second, I assume that the quadratic abatement cost is the same for all firms. Both assumptions are crucial for obtaining a closed form solution of the model. Therefore, in my model, the source of market power, both in the primary and in the secondary market, is the business-as-usual emissions level.

I first solve the model for the benchmark case in which the polluters act in a competitive manner, i.e. the price-taking behavior case. Next, I analyze the solution of the strategic

[3] Weretka (2011) provides a general model of endogenous market power in bilateral trading, in an exchange economy with consumption. He sets up a model with two types of traders, consumers and producers characterized by utility and cost functions, respectively. He finds that the trading volume in the case of the exercise of endogenous market power is lower than the one obtained in the perfect competition case, leading to Pareto inefficiency. Moreover, the resulting price can be above or below its competitive counterpart, depending on the convexity of the utility and cost functions of the traders.

CEU eTD Collection

behavior game and I derive its implications regarding the relationship between the prices of the two markets, as well as the manner in which the inefficiency of the abatement burden is distributed among the scheme members. Finally, for the two cases of market behavior, I compare the total compliance costs, both at the individual and aggregate level. The equilibrium concept is Nash equilibrium in supply functions, focusing on the class of linear strategies.

As it can be anticipated, in order to exert influence over the price, the polluters shade their bids at the auctioning stage and depress the clearing price relative to the price-taking behavior case. In fact, I find that strategic behavior in both markets results in an unambiguously lower auction clearing price relative to the secondary market price of emissions permits. Intuitively, this result follows from the fact that in the primary auction all members of the scheme act as buyers such that their concerted action is able to depress the price, since on the supply side of the market there is no counteraction from the regulator. However, in the secondary market the same actors have opposing interests, acting both as buyers and sellers, such that their strategies "cancel out" making them unable to influence the price.

Next, I find that the large emitters can be worse-off when the permit markets are governed by strategic behavior. Because in absolute value the large emitters shade their bids more than the small emitters, the large emitters become net buyers and the low emitters sell their surplus of permits in the secondary market. In addition, the large emitters engage in more abatement relative to the price-taking behavior and relative to the low emitters. Therefore, potentially, some large emitters are hurt when all members of the ETS behave strategically. This is the case of those emitters for which the reduced price in the auction, as a result of the strategic behavior, does not outweigh the inefficiency in their abatement. However, it is also possible that each individual member of the ETS benefits from strategic behavior. For this it suffices that the largest emitter has low enough business-as-usual emissions.

At the aggregate level I find that strategic behavior can be cost-saving from the polluters' perspective. A necessary and sufficient condition for this is that the emissions cap of the scheme is above a certain threshold, which depends on the variance of the business-as-usual emissions. This implies that for a low enough variance of the distribution of the business-as-usual emissions it is possible that, from the point of view of the polluters, strategic behavior results in a lower total compliance cost than the price-taking behavior, regardless of the choice of the regulator concerning the fixed supply of permits. Because the emissions cap directly affects the auction clearing price, the larger the cap, the higher the compliance cost saving potential when firms bid strategically in the auction. This potential is even larger when firms are more similar because, in this case, the inefficiency in the distribution of the abatement burden is reduced, while the saving from permit purchase stays the same, since it does not depend on firms' business-as-usual emissions. These elements leave room for strategic behavior to pay off for the polluters. A similar result is missing from Malueg & Yates (2009), since

CEU eTD Collection

in their model the emitters do not have the opportunity of realizing cost savings at the initial allocation stage. Instead, in their model, strategic behavior is ineffective for the aggregate compliance cost, regardless of the choice of the emissions cap and regardless of the degree of heterogeneity among the emitters.

The next section sets out the model and discusses the underlying assumptions. In Section 1.3 I solve the model under the benchmark case in which polluters act as price-takers. Further, Section 1.4 solves the model for the case of strategic behavior and establishes the equilibrium of the emissions trading game. Section 1.5 discusses the implications of strategic behavior and compares the outcomes of the two types of market behavior. Finally, Section 1.6 concludes.

1.2 The Model

Consider an ETS with $N > 2$ emitters indexed by $i = 1, \dots, N$, who are required to comply with the environmental regulations, such that the total emissions in the scheme should not exceed a fixed emissions target. This target is equivalent to a fixed supply of emissions permits, $\overline{E}$, which is exogenously determined by the regulatory authority. The regulator distributes the permits to the polluters via a uniform price sealed-bid auction. Let $D_i \geq 0$ denote the number of permits earned by polluter i in the auction, such that $\sum_{i=1}^{N} D_i = \overline{E}$.[4] After the initial allocation is completed, the polluters can trade their permit endowments in a secondary market. Let t_i be the net purchase ($t_i > 0$) or net sale ($t_i < 0$) of permits by emitter i in the secondary market. For compliance the emitters also have the option of engaging in abatement activity at a quadratic cost,[5]

$$c(r_i) = \theta r_i^2, \tag{1.1}$$

where r_i is the amount of emissions reductions from the business-as-usual emissions level, $e_i > 0$. Thus, for any polluter i, the environmental constraint reads:

$$e_i = D_i + t_i + r_i \tag{1.2}$$

Several simplifying assumptions are embedded in equation (1.2) and the abatement cost function 1.1. First, while firms are assumed to be price-takers on their respective product markets, they also have the same emissions intensity. Therefore, the business-as-usual emissions level, e_i, can be regarded as a proxy for firms' output level, i.e. the emissions equivalent to the level of production which polluter i would produce as a solution to her profit maximization

[4] This implies that all permits are distributed in the auction.

[5] The choice of a particular functional form for the abatement cost function is imposed by the desire of having a complete close form solution of the game.

CEU eTD Collection

problem, given her technology and the market price of her final output, in the absence of the regulation. One could also assume that firms are asymmetric with respect to the emissions intensity and, at the same time, allow firms to manipulate their production decisions in order to comply with the regulations. Since such an approach does not allow for a closed-form solution of the auction game and one would have to resort to numerical simulations, it is left for further research. However, for the time being, the business-as-usual emissions level is the only dimension of heterogeneity among firms. Therefore, without any loss of generality, let $e_1 \geq e_2 \geq \cdots \geq e_N$ and $\bar{e}_k = \frac{1}{k}\sum_{i=1}^{k} e_i, \forall k = 1, \ldots, N$ be the average level of business-as-usual emissions of the k largest emitters in the scheme.

Second, in this paper e_i is assumed exogenous. Two alternative approaches could be considered for endogenizing e_i and, thus, implicitly include interaction with the output market. On the one hand, one could include interaction with the product market and maintain the assumption of price-taking behavior in this market. In this case firms would have the flexibility to reduce output in order to meet the environmental constraint, in addition to abatement and permits trading. However, this approach would only have quantitative implications to the model and complicate the notations, without any qualitative insights. On the other hand, in order to give firms the possibility to pass the cost of the environmental regulation to the output price, a certain competition structure should be assumed for the product market. Nonetheless, having ETS-regulated entities competing in the same product market has little realistic appeal. Most commonly, an ETS regulates different sectors and, while the contained firms compete for permits, they do not have a common output market. Nevertheless, one could imagine a sector-wise ETS in which firms also compete in the product market.

Third, the abatement is modeled as end-of-pipe emissions reduction (e.g. carbon capture-and-storage), since it is independent of the level of emissions. Hence, reducing emissions by 1 tonne of GHG costs the same for a high polluter as for a low polluter. This modeling approach to the abatement cost is also present in other papers (Maeda 2003, Montero 2009, Wirl 2009) and it has the advantage of allowing to identify the exact level of abatement undertaken by each firm. Note, however, that this formulation is equivalent to defining the abatement cost as a function of emissions and assuming that the marginal abatement cost is decreasing in the emissions level. Specifically, the insights of the model remain unchanged if one defines the abatement cost as a function of emissions.[6] However, in this case, the interpretation of e_i would change from the business-as-usual emissions to the achieved level of emissions after abatement.

The timing of the game is the following. In the first stage the polluters decide their bids in

[6]For example, one could define the abatement cost like in Malueg & Yates (2009): $c_i(e_i) = A_i - \lambda_i e_i + \theta e_i^2$, with $A_i > 0$ and $\lambda_i > 0$, where λ_i makes the difference between a low and a high marginal abatement cost firm. For this formulation of the problem the emissions constraint would then read: $e_i = D_i + t_i$.

CEU eTD Collection

the sealed-bid uniform price auction, choosing their bidding function $D_i(p_1)$, where p_1 is the auction price. In the second stage they decide how much to trade in the secondary market, choosing the supply (demand) schedules $t_i(p_2)$, where p_2 is the secondary market price. The decision criterion of polluter i is the minimization of the total emissions cost,[7]

$$C_i = \theta r_i^2 + p_2 t_i + p_1 D_i, \tag{1.3}$$

under the constraints:

$$\begin{aligned} & r_i \geq 0 \\ & t_i \geq -D_i \\ & e_i \leq D_i + r_i + t_i, \end{aligned} \tag{1.4}$$

The first constraint in (1.4) assures that the abatement is not negative, i.e. there is no possibility of disinvestment in emissions reductions, while the second constraint says that the polluter cannot sell in the secondary market more permits than it owns. The last constraint in (1.4) is the emissions budget constraint. Since, in optimum, this constraint bids, polluter's trading decision trivially determines her abatement. From this the level of abatement can then be substituted in (1.3) and (1.4), producing the following constrained decision criterion:

$$\begin{aligned} & \min_{D_i,\, t_i} C_i = \theta(e_i - D_i - t_i)^2 + p_2 t_i + p_1 D_i, \\ & e_i - D_i - t_i \geq 0 \\ & t_i \geq -D_i \end{aligned} \tag{1.5}$$

Before proceeding to finding the equilibrium, two important assumptions are in place in order to ensure that the game has solution. First, Assumption 1.1 introduces the scarcity of permits, which assures that there is a market for permits. In particular, this assumption guarantees that the first constraint in problem (1.5) is satisfied.

Assumption 1.1 *There is a market for permits, i.e. the total supply of permits is lower than the total business-as-usual emissions in the scheme:* $\overline{E} < \sum_{i=1}^{N} e_i$.

Second, due to the additive nature of the emissions constraint, the following assumption is sufficient in order for the second constraint in problem (1.5) to hold for all polluters in the scheme.

Assumption 1.2 *Given the assumed ordering of the business-as-usual emissions, the following must hold:* $e_N \geq \bar{e}_N - \dfrac{\overline{E}}{N}$, *where* $\bar{e}_N$ *is the average of all business-as-usual emissions in the scheme.*

[7]Note that $r_i \leq e_i$ should also hold. However, this is omitted, as it becomes redundant through the second and the third constraint.

CEU eTD Collection

Note that the inequality in Assumption 1.2 holds for any polluter $i = 1, \ldots, N$. In fact, this assumption puts a restriction only on the small emitters ($e_i < \bar{e}_N$), since the business-as-usual emissions of any large emitter ($e_i \geq \bar{e}_N$) satisfy the inequality in the assumption. The interpretation of Assumption 1.2 is that the smallest emitter is not too small, i.e. her business-as-usual emissions level is lower-bounded by the average deficit of permits in the scheme, or the distance from the average emissions of the smallest emitter is upper-bounded by the average number of permits in the scheme. Therefore, the variance of the business-as-usual emissions in the scheme can be driven down only by the small emitters. While this assumption might appear restrictive, it has a plausible realistic interpretation. For example, in the EU ETS, the definition of the installations covered by the scheme, which can be found in Annex 1 of the EU Directive, involves a threshold of minimum capacity, which implicitly defines a threshold for emissions (European Commission 2003). Similarly, in the ETS of the state of California, an entity becomes regulated if its emissions exceeded 25,000 metric tonnes in any year from 2008 to 2011.

If Assumption 1.2 does not hold, then there are polluters in the ETS which short sell permits, i.e. sell more permits in the secondary market than they own. However, since in this model there is only one round of trading, this case cannot be accommodated because polluters have to close their positions. Moreover, as it will be seen further for the case of strategic behavior, the violation of Assumption 1.2 leads to the situation in which the polluter abates more than her business-as-usual emissions. This would be equivalent with the emitter selling abatement. This case has a plausible interpretation in the context of the EU ETS where the emitters can gain credits (also called offsets) through Joint Implementation and Clean Development Mechanism projects,[8] which they can use for compliance against their own emission or sell in a secondary market. For these credits there is a separate market on which they are traded. Bringing this possibility into the discussion of this paper would imply that the market for these credits should be included into the model. However, the analysis of this mechanism is out of the scope of the paper.

With Assumptions 1.1 and 1.2 at hand, I further focus on the interior equilibrium of the game. (The corner solutions obtained from the Kuhn-Tucker conditions for the constrained problem (1.5) in the case of price-taking behavior are discussed in Appendix 1.A.1.) Thus, the cost function with constraits from (1.5) can now be written as an unconstrained cost function:

$$C_i = \theta(e_i - D_i - t_i)^2 + p_2 t_i + p_1 D_i, \tag{1.6}$$

[8]These credits are called Emission Reduction Units (ERUs) and Certified Emission Reduction units (CERs), respectively, and they are two of the three flexible mechanisms of the Kyoto Protocol, together with Emissions Trading, designed to help the so-called Annex I countries of this protocol to meet their greenhouse gas emissions targets.

CEU eTD Collection

This set-up allows to easily identify the direction of the inefficiency in the abatement levels, which is not characterized in Malueg & Yates (2009). Although they identify the non-cost effectiveness in abatement decisions coming from the strategic behavior of the polluters, they do not make any analyses concerning the direction of the distribution of the burden of the emissions reductions. In addition, my model incorporates the auction as the method of distribution of the initial endowment of permits, allowing, thus, to assess the propagation of the anticipated strategic behavior in the secondary market to the auction outcome.

This model builds on the fact that there is no reason to *a priori* assume that one emitter or the other has market power, but rather that all participating agents recognize their ability to influence prices. The equilibrium concept used for both markets is the SFE. Notice the bilateral nature of the trade in the secondary market, where there are both sellers and buyers among the polluters, as compared to the unilateral nature of the primary market. The former market structure was coined by Hendricks & McAfee (2010) as "bilateral oligopoly", while the latter is the dual problem encountered in the context of auctions in electricity markets *à la* Green (1999), Rudkevich (1999) and Rudkevich (2005).

As this is a sequential game, the solution method is backward induction, starting from the trading stage. As a benchmark, the price-taking behavior will be considered first. In what follows I shall use superscript c and s to refer to the price-taking and strategic behavior variables, respectively.

1.3 Price-taking Behavior

In this case, all polluters choose their trading volume and auction bids, taking prices as given.

1.3.1 Secondary market trade

The net-trade function for the price-taking case is obtained by minimizing (1.6) with respect to t_i. Hence, polluter i will submit the following net supply (demand) as a function of the market price

$$t_i^c(p_2^c) = e_i - D_i^c - \frac{1}{2\theta} p_2^c \tag{1.7}$$

The market mechanism then chooses p_2^c such that the excess demand is zero. Assuming that the whole supply of permits is distributed in the auction, i.e. $\sum_{i=1}^{N} D_i = \overline{E}$, this provides the secondary market clearing price:

$$p_2^c = 2\theta \left(\bar{e}_N - \frac{\overline{E}}{N} \right), \tag{1.8}$$

CEU eTD Collection

which is the usual result that in a frictionless market the price of permits equals the marginal cost of abatement in the scheme. Note that Assumption 1.1 ensures that p_2^c is positive. Substituting (1.8) in (1.7), the equilibrium trading volume is obtained:[9]

$$t_i^c = e_i - D_i^c - \bar{e}_N + \frac{\overline{E}}{N}. \tag{1.9}$$

Finally, equation (1.9) easily identifies the abatement level of each polluter i:

$$r_i^c = \bar{e}_N - \frac{\overline{E}}{N} = \frac{p_2^c}{2\theta}. \tag{1.10}$$

Again, by Assumption (1.1), the amount of abatement is positive for any polluter i. Note that the burden of abatement is equally split among the polluters as a result of the polluters having the same abatement cost function.

1.3.2 Initial allocation

At this stage the initial allocation D_i^c is determined via a uniform price sealed-bid auction in which the total number $\overline{E}$ of permits is distributed to the members of the ETS. Thus, participants submit demand schedules $D_i^c(p_1^c)$ to a market mechanism which finds the clearing price at the point where the horizontal summation of these demand schedules equates the total supply of permits. Substituting (1.7) and (1.8) into the cost function (1.6) and minimizing the latter with respect to D_i^c, it obtains that the prices of the two markets are equal, i.e. $p_1^c = p_2^c$. This means that the polluters are indifferent between buying the permits at the auction and buying them in the secondary market. In this case, any permit allocation is efficient such that the regulator could simply allocate the permits randomly and let firms costlessly redistribute the permits in the secondary market.

1.4 Strategic Behavior

In the strategic case the polluters recognize and use their ability to influence the prices for permits, both in the primary (the auction) and the secondary market. However, the strategic behavior is exercised differently in the two markets. In the auction, which is the first stage of the game, all polluters are buyers and the supply of permits is fixed. Thus, all polluters form strategic demand schedules and the market power is unilateral, since the regulator is not an active player in this model. In the secondary market, which is the second stage of the game,

[9] Note the distinction between the trade function $t_i^c(p_2)$ given by (1.7) and the equilibrium trading volume t_i^c given by (1.9).

CEU eTD Collection

the polluters act both on the supply and on the demand side of the market for permits. This makes market power bilateral.

Thus, I define the strategic equilibrium of the emissions trading game as follows:

Definition 1.1 *A strategic equilibrium of the emissions trading game is a vector of quantities and prices* $((D_i^s)_N, p_1^s, (t_i^s)_N, p_2^s, (r_i^s)_N)$ *such that: (i) at the auctioning stage every polluter* i *minimizes* (1.6) *choosing* p_1^s *such that* $D_i(p_1^s) = \overline{E} - \sum_{j\neq i} D_j(p_1^s)$*; (ii) the auction clears:* $\sum_{i=1}^N D_i(p_1^s) = \overline{E}$*; (iii) at the secondary market stage every polluter* i *minimizes* (1.6) *choosing* p_2^s *such that* $t_i(p_2^s) = -\sum_{j\neq i} t_j(p_2^s)$ *taking the auction outcome as given; (iv) the secondary market clears:* $\sum_{i=1}^N t_i(p_2^s) = 0$ *and (v) the emissions constraint holds for every polluter* i*:* $r_i^s = e_i - D_i^s - t_i^s$.

For tractability and keeping the comparability with the price-taking case, I will further focus on the family of linear strategies in both markets. The solution method for finding both the strategic bids in the auction and the strategic net-trade functions in the secondary market is the standard one used in the SFE literature (Klemperer & Meyer 1989, Rudkevich 2005, Green 1999, Baldick et al. 2000)). Moreover, the uni-dimensionality and linearity assumed for the strategies solves the multiplicity of equilibria problem common to the SFE (Rudkevich 2005, Lange 2012). Again, the model is solved by backward induction.

Before turning to solving for the equilibrium of the emissions trading game under strategic behavior, one additional assumption is required in order to ensure that the first constraint in problem (1.5) is satisfied. For this, it suffices to tighten Assumption 1.1 as follows:

Assumption 1.3 *The total supply of permits is lower than one fraction of the total business-as-usual emissions in the scheme:* $\overline{E} \leq \dfrac{N(N-1)}{N(N-1)+1}\left(\sum_{i=1}^N e_i\right)$.

Note that this assumption encompasses Assumption 1.1, since $\frac{N(N-1)}{N(N-1)+1} < 1$. It implies that strategic behavior under the setup of this paper is feasible if the emissions cap is tight enough. However, when N becomes large, $\frac{N(N-1)}{N(N-1)+1}$ approaches 1 such that this assumption becomes similar to Assumption 1.1. Therefore, from this point of view, Assumption 1.3 is not very restrictive.

1.4.1 Secondary market trade

The competitive trade function in (1.7) shows that the polluters are heterogeneous only with respect to the intercept of this function, as a result of the assumption of symmetry in the abatement cost. Therefore, for the strategic behavior case, I will assume that polluters exercise market power by choosing the intercept of their net-trade function. One could also assume that the polluters use both the intercept and the slope of this function as their strategy.

CEU eTD Collection

However, due to the symmetry in the abatement cost, the slopes will be equal among polluters. Thus, allowing for "full" market power, i.e. choosing both the intercept and the slope of the net-trade function, would affect the results only quantitatively, without adding any qualitative insights. Moreover, the secondary market price will be the same, regardless of assuming that the polluters choose both the intercept and the slope, or only the intercept (see Appendix 1.A.2 for details).

Thus, let

$$t_i^s(p_2^s) = a_i - \frac{1}{2\theta}p_2^s, \tag{1.11}$$

be the net trade function of polluter i, where the intercept a_i is her strategy, chosen such that to minimize the compliance cost function (1.6), with p_2^s being given by the market clearing condition $\sum_{i=1}^{N} t_i^s(p_2^s) = 0$. In Appendix 1.A.3 it is shown that the net trade function is given by

$$t_i^s(p_2^s) = (e_i - D_i^s) + \frac{1}{N}\left(\left(\bar{e}_N - \frac{\overline{E}}{N}\right) - (e_i - D_i^s)\right) - \frac{1}{2\theta}p_2^s. \tag{1.12}$$

Hence, the intercept of the net trade function is composed of two terms: the deficit (surplus) of permits after the initial allocation, $(e_i - D_i)$, plus one fraction of the difference between the individual deficit (surplus) and the average deficit of permits in the scheme. The latter term represents player's deviation from her true demand (supply) in an attempt to manipulate the price (compare (1.12) with (1.7)). While the buyers pretend to be needing fewer permits for the same price in order to depress the equilibrium price, the sellers decrease their supply to drive up the price. The resulting secondary market equilibrium price for the strategic case reads:

$$p_2^s = 2\theta\left(\bar{e}_N - \frac{\overline{E}}{N}\right) \tag{1.13}$$

which, compared to (1.8) reveals that the secondary market equilibrium price is the same regardless of emitters' market behavior. Although my model assumes a specific functional form for the abatement cost function, Weretka (2011) shows that this result holds for any payoff function with constant second derivative. Intuitively, this is due to the fact that the strategic behavior on the side of the buyers and the sellers "cancels out," i.e. the buyers and the sellers have the same price impact. However, as Weretka (2011) shows, this result does not hold when the buyers' and the sellers' utility functions have different convexities. In this case the market would clear in the favor of the players with a flatter marginal utility.

Next, the trade of player i is given by

$$t_i^s = \frac{N-1}{N}\left((e_i - D_i^s) - \left(\bar{e}_N - \frac{\overline{E}}{N}\right)\right), \tag{1.14}$$

while its sign provides the trading position of player i as a net buyer, if positive, or as a

CEU eTD Collection

net seller, if negative. An emitter whose deficit of permits following the auction is below the average deficit of permits in the scheme is a net seller ($t_i^s < 0$). A net seller is also an emitter with surplus of permits after the auction, i.e. $e_i < D_i$ (to see this, the reader is also referred to Assumption 1.1). Conversely, a net buyer is an emitter whose deficit of permits is above the average deficit of permits in the scheme.

Finally, the abatement level of polluter i can also be calculated:

$$r_i^s = \frac{1}{N}\left(e_i - D_i^s\right) + \frac{N-1}{N} r_i^c \tag{1.15}$$

Equation (1.15) shows that the individual abatement in the strategic case is composed of two parts: one part is proportional to the individual deficit (surplus) of permits after the auction, and the second part is proportional to the efficient level of abatement.

1.4.2 The auction

At the auctioning stage, polluters' strategies consist of the bids they submit to the regulator in a uniform price sealed-bid auction. The polluters decide on their linear bidding schedules by choosing the price, acting as monopsonists on the residual supply of permits. The role of the regulator is that of a market mechanism, which clears the market by equating the fixed supply of permits with the total demand resulted from the aggregation of the individual demand schedules submitted by the polluters. Therefore, taking as given the equilibrium values for t_i^s and p_2^s, at this stage the objective function of a polluter is to minimize a quadratic function in $D_i^s(p_1^s)$:[10]

$$C_i^s(D_i^s(p_1^s)) = \frac{\theta}{N^2}(D_i^s(p_1^s))^2 - (\alpha_i - p_1)D_i^s(p_1^s), \tag{1.16}$$

with $\alpha_i = \frac{2\theta}{N^2}e_i + \frac{2\theta(\sum_{j=1}^N e_j - \overline{E})(N^2-1)}{N^3}$.

Hence, the coefficients of the linear terms in the C_i^s functions, α_i's, differ with respect to e_i. This implies that the equilibrium bids are asymmetric and the asymmetry consists of e_i. Consequently, polluters' valuations for permits increase in their business-as-usual emissions, i.e. $\partial\alpha_i/\partial e_i > 0$. Thus, e_i is responsible for bidders' aggressiveness at the auctioning stage. In order to find the strategic bids, the SFE concept is applied. This means that each bidder acts as a monopsonist on the upward-sloping residual supply, choosing the price to minimize the compliance cost given by (1.16). As it is usual in the literature,[11] I focus on the family of linear equilibria. In Appendix 1.A.4 it is shown that the optimal linear bid function of any

[10] The constant term has been discarded.

[11] See, for example, Green (1999), Baldick et al. (2000), Rudkevich (2005).

CEU eTD Collection

bidder i is the following piece-wise linear function[12]

$$D_i^s(p_1^s) = \begin{cases} \dfrac{N^2}{2\theta}\dfrac{N-2}{N-1}(\alpha_i - p_1^s), & \text{if } \alpha_i > p_1^s \\ 0, & \text{if } \alpha_i \leq p_1^s, \end{cases} \tag{1.17}$$

which is an affine function of p_1^s on its positive branch.[13]

As equation (1.17) shows, the parameter α_i represents bidder i's maximum willingness to pay for the first permit. This valuation decreases with the slackness of the environmental constraint ($\partial\alpha_i/\partial\overline{E} < 0$), but increases in the marginal abatement cost at the business-as-usual emission ($\partial\alpha_i/\partial\theta > 0$). Both results are intuitive. Finally, accounting for the relationship between α_i and e_i mentioned above, equation (1.17) shows that the higher the business-as-usual emissions e_i of polluter i, the more aggressive its bidding behavior in the primary auction.

Assuming that there exists a positive equilibrium price p_1^s, such that $\sum_{i=1}^N D_i^s(p_1^s) = \overline{E}$, then

$$p_1^s = \frac{1}{n}\sum_{i=1}^{n}\alpha_i - \frac{2\theta}{nN^2}\frac{N-1}{N-2}\overline{E}, \tag{1.18}$$

where $n \leq N$ is the number of polluters for which the demand is positive in the point where the fixed supply $\overline{E}$ crosses the total demand. In other words, n is the number of winning bidders, that is those polluters that have the strongest bids in the auction.

Recall that bidding aggressiveness only differs with respect to the business-as-usual emissions, e_i. Therefore, it is clear that the distribution of the permits will start from the most aggressive to the least aggressive bidder, i.e. from the largest to the smallest emitter. Thus, given the assumed ordering of the polluters relative to e_i, the bidders indexed from 1 to n are the bidders successful in the auction and those indexed from $n+1, \ldots, N$ have zero initial endowments of permits. Formally, the last successful bidder in the auction is given by

$$n = \sup\left\{ n \in \{1, 2, \ldots, N\} | e_n > \frac{\sum_{j=1}^n e_j}{n} - \frac{\overline{E}}{n}\frac{N-1}{N-2} \right\}. \tag{1.19}$$

Obviously, n may coincide with N and then all bidders are successful in the primary auction. In fact, due to Assumption 1.2, condition (1.19) holds for $n = N$. Therefore, the last winning bidder is the smallest polluter, which means that, indeed, all polluters are successful in the auction. The intuition behind this result is that Assumption 1.2 ensures that even the weakest bidder is strong enough because her distance from the average emitter is upper-bounded.

[12] Note that all firms biding an empty schedule also an equilibrium. However, this equilibrium is discarded from the analysis since it implies that the auction would be canceled.

[13] Note the factor $\frac{N-2}{N-1} < 1$ which captures the usual bid-shading property of the sealed-bid uniform price auction.

CEU eTD Collection

Consequently, substituting the auction clearing price given by (1.18) for $n = N$ into the bid schedule (1.17), the initial allocation of any bidder i is given by:

$$D_i^s = \frac{\overline{E}}{N} + \frac{N-2}{N-1}\left(e_i - \bar{e}_N\right). \tag{1.20}$$

Finally, accounting for the expression of α_i in equation (1.18), p_1^s is given by[14]

$$p_1^s = p_2^s - \frac{2\theta}{N^3(N-2)}\overline{E}. \tag{1.21}$$

1.4.3 Equilibrium

Plugging (1.20) in (1.14) the equilibrium net trade in the secondary market is obtained as

$$t_i^s = \frac{1}{N}\left(e_i - \bar{e}_N\right). \tag{1.22}$$

Thus, those polluters with the business-as-usual emissions higher than the average emissions, $\bar{e}_N$, are net buyers in the secondary market and those with business-as-usual emissions below $\bar{e}_N$ are net sellers. In other words, the anticipation of the strategic behavior in the secondary market prevents the high emitters from acquiring the desired level of permits, and part of these permits is ripped off by the small emitters. Note that the average emitter is not trading. With this in place, the equilibrium abatement level of emitter i can also be calculated:

$$r_i^s = \bar{e}_N - \frac{\overline{E}}{N} + \frac{1}{N(N-1)}\left(e_i - \bar{e}_N\right) = r_i^c + \frac{1}{N(N-1)}\left(e_i - \bar{e}_N\right), \tag{1.23}$$

which shows that the abatement burden in the scheme is inefficiently distributed among polluters. In particular, the high emitters abate more compared to the first-best case, while the low emitters abate less.

At this stage, the strategic equilibrium of the emissions trading game can be formulated.

Proposition 1.1 *In an ETS with an uniform price auction as the method of initial allocation, in which all members of the scheme act strategically, the initial allocation profile is given by* (1.20), $i = 1, \ldots, N$, *the auction clearing price is given by* (1.21), *the net trade profile is given by* (1.22), *the secondary market equilibrium price is given by* (1.13) *and the abatement profile is given by* (1.23).

[14]Note that p_1^s is positive for any $N > 2$.

CEU eTD Collection

1.5 Results and Discussion

1.5.1 Implications of strategic behavior

In this section I discuss in more detail the consequences of the strategic behavior and its relation with the price-taking case. First, it is relevant to compare the prices of the two markets in order to asses the potential of gains from the price difference. Following (1.21), the following result can be established:

Result 1.1 *In an ETS with a uniform price auction as initial allocation method, polluters' strategic behavior both in the auction and in the secondary market leads to a spot market price above the auction clearing price, by the positive amount*

$$p_2^s - p_1^s = \frac{2\theta}{N^3(N-2)}\overline{E}.$$

The claim in Result 1.1 is intuitive. Since the regulator does not have any strategic role in this model, she does not counteract the polluters market power at the auction stage. Hence, this is a unilateral market in which all polluters act in the same direction, of depressing the clearing price. However, the secondary market is a bilateral market in which both the buyers and the sellers exercise market power. Therefore, since their interests diverge, there is less power for the players to drive the price in a given direction, such that the market clears at the competitive price level. Consequently, strategic behavior benefits the low emitters, who make profits from the price difference, and hurts the high emitters, who have to pay a higher price for supplementing their permits holdings. However, in the limit, as the number of polluters grows, the spread converges to zero, and they become indifferent between purchasing permits in the primary auction or in the secondary market. Hence, this approaches the situation of price-taking behavior.

Interestingly, the price difference increases both in the abatement cost parameter θ and in the total number of permits supplied $\overline{E}$. This result is due to the different rates at which the two prices increase in θ and decrease in $\overline{E}$. Specifically, p_2^s increases in θ at a higher rate than p_1^s does, and it decreases in $\overline{E}$ at a lower rate than p_1^s does, as a result of the direct versus indirect impact of these parameters on the two prices. In particular, $\overline{E}$ affects directly the auction price because the fixed supply of permits is taken into account in a direct manner when polluters decide their bids, since the purpose of the auction is that of distributing $\overline{E}$. Conversely, θ affects more the post-auction trading decisions and thus the secondary market price. This is because at this stage polluters have to close their positions by either trading permits or abating pollution. Therefore, the abatement cost directly affects their trading decisions. Note, however, that the price spread is independent of the business-as-usual emissions in the

CEU eTD Collection

scheme.

Empirical evidence also supports Result 1.1. For example, Smith & Swierzbinski (2007) found that the price of the auction in the UK ETS, which was conducted using a descending clock format, was considerably above the secondary market price of the allowances (17.79£/tonne of additional abatement while the price in the subsequent trading leveled at $2-4$£/emissions allowance). However, as opposed to the case modeled in this paper, in which the regulator sells permits, in the auction of the UK scheme, the regulatory body (the auctioneer) played the role of the buyer of abatement commitments from the polluters. Among other explanations for this price difference, the authors venture the possibility of market power. However, they use a model of collusion with a competitive fringe in order to mimic bidders' behavior at the auctioning stage and they find that this behavior predicts a price close to the observed price of the auction of abatement commitments.

Second, comparing r_i^s and r_i^c and combining equations (1.23) and (1.22), the direction of the inefficiency in the abatement level can be summarized in the following result:

Result 1.2 *The difference between the strategic level of abatement and its perfect competition counterpart is proportional to the trading position of the emitter:*

$$r_i^s - r_i^c = \frac{1}{N-1} t_i^s. \tag{1.24}$$

Hence, a net buyer ($t_i^s > 0$) will abate more than the efficient level r_i^c, when the polluters exercise market power. Conversely, a net seller ($t_i^s < 0$) will abate less than the efficient level. Thus, a non-competitive equilibrium will lead to the efficient level of abatement if and only if every polluter has no trading needs, that is her business-as-usual emissions coincide with the average level of the business-as-usual emissions in the scheme. Thus, equation (1.24) explicitly recovers the result identified by Lange (2012) in Proposition 3, using the relationship between the marginal abatement cost, the measure of market power and the permits' price.

In sum, it appears that, compared to the low emitters, the high emitters ($e_i \geq \bar{e}_N$) benefit less from strategic behavior. On the one hand, they have to abate more than the efficient level and, on the other hand, they purchase extra permits in the secondary market at a higher price than the auction clearing price. Although relative to the true demands all polluters shade their bids in the same proportion, in absolute value the large polluters are forced to shade their bids more compared to the small polluters. Thus, they cannot earn sufficiently many permits at the auction and they must buy the extra permits from the small players, at a higher price. At the same time, strategic behavior in the secondary market trade makes it unable to fully restore the efficient allocation of permits. Therefore, the large polluters have to abate more in order to meet their compliance needs. This inefficient distribution of the abatement burden in the scheme leads to a higher abatement cost for the large emitters.

CEU eTD Collection

However, as it will be seen next, some of the large polluters are still able to benefit from strategic behavior.

1.5.2 Comparisons

In this subsection I conduct comparisons between the strategic case and the price-taking case. First, I compare the total compliance cost both at the individual and scheme level and then I verify that strategic behavior leads to welfare loss.

Individual costs

Plugging the equilibrium values for the two cases into the cost function defined in (1.6), after some algebraic manipulations, the individual cost change when moving from price-taking to strategic behavior reads:

$$C_i^s - C_i^c = \frac{\theta}{(N-1)^2}(t_i^s)^2 - \frac{2\theta\overline{E}}{N^2(N-1)}t_i^s - \frac{2\theta\overline{E}^2}{(N-2)N^4} \tag{1.25}$$

Equation (1.25), together with Assumption 1.2, reveals that all net sellers ($t_i^s < 0$) and some of the net buyers (those who are relatively low-emitters), will benefit from strategic behavior, that is their total cost in the strategic behavior case is lower than the total cost in the price-taking case (the algebraic derivations can be found in Appendix 1.A.5). This result can be summarized as follows:

Result 1.3 *Strategic behavior benefits the low emitters ($e_i < \bar{e}_N$) and some high emitters ($e_i \geq \bar{e}_N$), namely those with low enough business-as-usual emissions, i.e. below the threshold given by* $\bar{e}_N + \frac{N-1}{N}\overline{E}\left[1 + \sqrt{1 + \frac{2}{N-2}}\right]$.

While for the low emitters this result is obvious, some of the high emitters can also benefit from strategic behavior because the resulted discounted auction price is enough to offset the secondary market expenses and the over-abatement for meeting their compliance needs. Moreover, the condition in Result 1.3 implies that, if the business-as-usual emissions of the largest emitter (e_1) are below $\bar{e}_N + \frac{N-1}{N}\overline{E}\left[1 + \sqrt{1 + \frac{2}{N-2}}\right]$,[15] then all polluters are individually better off acting strategically.

[15] Note that $\bar{e}_N + \frac{N-1}{N}\overline{E}\left[1 + \sqrt{1 + \frac{2}{N-2}}\right] \approx \bar{e}_N + 2\overline{E}$. Therefore, this condition is likely to hold in a real ETS.

CEU eTD Collection

Total costs

Summing up equations (1.6) for all polluters, with the equilibrium values from the strategic case, the total cost of compliance reads:

$$\sum_{i=1}^{N} C_i^s = \frac{\theta}{N(N-1)^2} Var(e) + \theta N \left(\bar{e}_N^2 - \frac{\overline{E}^2}{N^2} \right) - \frac{2\theta \overline{E}^2}{(N-2)N^3} \tag{1.26}$$

From (1.26) is it straightforward to see that:

Result 1.4 *The total cost of compliance with the environmental regulations when polluters act strategically is increasing in the variance of the business-as-usual emissions.*

To see the intuition behind Result 1.4, let us first note that neither the auction clearing price, p_1^s, nor the secondary market price, p_2^s, depend on the variance of the distribution of the business-as-usual emissions.[16] Hence, for two business-as-usual emissions distributions with the same mean and different variances, these prices will be the same. Therefore, despite the fact that higher variability in the business-as-usual emissions leads to higher inefficiencies in the primary market and, thus, higher trading volume in the secondary market, in aggregation the costs related to the inefficiencies on these markets are the same for the two different distributions, because prices are unchanged. However, it is in the abatement cost where the variance of the distribution of the business-as-usual emissions matters. Recall that, for two different distributions of the business-as-usual emissions having the same mean, the total abatement in the scheme is constant and equal to $\sum_{i=1}^{N} e_i - \overline{E}$. To simplify the reasoning, let us consider two polluters such that polluter 1 is the low emitter and polluter 2 is the high emitter, i.e. $e_1 < e_2$. Since the high emitter produces a higher level of abatement than the low emitter (see equation (1.23)), the total abatement cost of a low emitter is lower than the total abatement cost of a high emitter. Therefore, if we reduce the business-as-usual emissions of the low emitter by an amount ϵ and we increase the business-as-usual emissions of the high emitter by the same amount ϵ,[17] the aggregate level of abatement will stay the same, but the total cost of producing the given amount of abatement increases.

Next, adding up equations (1.25), the change in the compliance cost at the scheme level is:

$$\sum_{i=1}^{N} (C_i^s - C_i^c) = \frac{\theta}{N(N-1)^2} Var(e) - \frac{2\theta \overline{E}^2}{N^3(N-2)} \tag{1.27}$$

[16]This result is due to both the linearity of the net trade functions in the secondary market and of that of the bids in the primary auction.

[17]Note that this change in the business-as-usual emissions increases the variance of the distribution of the business-as-usual emissions, keeping their mean constant.

CEU eTD Collection

Equation (1.27) is the counterpart of Proposition 2 in Malueg & Yates (2009), which shows that the difference in the aggregate compliance costs between the strategic behavior and the price-taking behavior is proportional to the variation in the marginal abatement cost at the permits' endowment.[18] Therefore, they obtain that symmetry in permits endowment leads to the same total cost regardless of the market behavior of the polluters. This is due to the fact that in their model the initial allocation is free of charge, i.e. the first market is missing. Instead, in my model, in which there is a primary market for permits, the difference in the two costs is driven by the spread created between the prices of the two markets, as a result of the strategic behavior. Note, however, that if the variance of the business-as-usual stays constant while the number of polluters in the scheme grows, the difference in the two costs converges to zero. This is consistent with the intuition, since a high number of market participants leads to the competitive outcome.

Moreover, from equation (1.27), the following results can be established:

Result 1.5 *For every distribution of the business-as-usual emissions, there exists a threshold of the fixed supply of permits, $\overline{E} > \frac{N}{N-1}\sqrt{\frac{N-2}{2}Var(e)}$, above which strategic behavior is scheme-wise cost-saving for the polluters.*

Hence, the lower the variability of the business-as-usual emissions, the more likely for the strategic behavior to be cost-saving at the scheme level. The reason behind Result 1.5 is, again, the spread created between the auction price and the secondary market price, which becomes larger as the fixed supply of permits increases (see Result 1.1). Thus, for a given variance of the business-as-usual emissions there exists a threshold of the fixed supply above which the price gain is big enough to outweigh the inefficiencies resulted from strategic behavior. Hence, strategic behavior results in a lower compliance cost of the scheme relative to the price-taking behavior. A similar result is missing in Malueg & Yates (2009), since in their model the initial allocation is grandfathering rather than auctioning. Instead, in their model, the strategic behavior always leads to a higher aggregate abatement cost.

Note, however, that Assumptions 1.2 and 1.3 put a lower and an upper bound, respectively, on the fixed supply of permits in the scheme. Precisely,

$$N(\bar{e}_N - e_N) \leq \overline{E} \leq \frac{N^2(N-1)}{N(N-1)+1}\bar{e}_N, \tag{1.28}$$

where e_N is the business-as-usual emissions level of the emitter with the smallest business-as-usual emissions. Therefore, for the existence of a region of $\overline{E}$ in which the scheme as a whole

[18]In their model, the only source of heterogeneity among firms is the intercept of the marginal abatement cost.

CEU eTD Collection

is better-off acting strategically, it must be that:

$$\frac{N}{N-1}\sqrt{\frac{N-2}{2}Var(e)} \leq \frac{N^2(N-1)}{N(N-1)+1}\bar{e}_N \tag{1.29}$$

Indeed, in Appendix 1.A.6 it is shown that inequality (1.29) holds for any $N > 2$ and for any choice of e_i's, that is for any $Var(e)$. Therefore, as discussed before, for the strategic behavior to pay off from the point of view of the polluters, the available supply of permits has to be large enough in order to create a price spread (see Result 1.1) able to cancel out the effect of the inefficient allocation of the abatement burden in the scheme, which increases in the heterogeneity in the business-as-usual emissions. Finally, as a consequence of Result 1.5, note that if the variance of the business-as-usual emissions in the scheme is low enough, strategic behavior is compliance cost-saving for the polluters regardless of the choice of the cap by the regulator, within the limits described in (1.28).

Social welfare

Finally, let us also consider the regulator's revenue and define the social welfare of the scheme as the regulator's revenue from auctioning the permits, minus the total cost of compliance by the polluters. Therefore, making use of the equality $p_1^c = p_2^c = p_2^s$, if follows that the social loss from strategic behavior is given by

$$\Delta W = W^s - W^c = -\frac{\theta}{N(N-1)^2}Var(e) < 0, \tag{1.30}$$

Equation (1.30) confirms that market power results in social loss of welfare. This loss decreases with the number of polluters and increases in their heterogeneity and abatement cost. Since the price difference at the auction does not depend on polluters' heterogeneity, the regulator's revenue loss does not depend on the variance of their business-as-usual. Hence, this result reflects the findings with respect to the total compliance cost given by equation (1.27). It should be noted that the social welfare loss does not depend on the emissions cap. However, the regulator could choose the emissions cap to maximize the social welfare resulted from polluters' strategic behavior.

CEU eTD Collection

1.6 Conclusion

This paper developed a complete-information game of an ETS in which permits are distributed in two stages. First, the participants bid in an uniform price sealed-bid auction for the initial allocation of the permits and then they trade the permits in a secondary market. All polluters regulated by the scheme are allowed to exercise market power in the two markets for emissions permits. The market power arises endogenously from their business-as-usual emissions level, which is the sole source of heterogeneity in this model. The anticipation of the exercise of market power in the after-auction market influences the bidding strategies of the polluters when permits are initially allocated. Consequently, the abatement burden is distributed inefficiently: the high emitters abate more and the low emitters abate less in the strategic case than in the non-strategic first-best. While in the perfect competition case the secondary market is redundant as the permits can be efficiently allocated right in the auctioning stage, in the strategic case there exists trade at a price which is unambiguously above the auction clearing price.

The outcome of the game reveals that strategic behavior favors all net sellers (emitters with the business-as-usual emissions below the average) and some net buyers, namely those with the lowest business-as-usual emissions. At the individual level, the high emitters are disadvantaged as compared to the low emitters. First, they have to buy the deficit of permits in the secondary market at a higher price than the auction clearing price and, second, they abate more than in the perfect competition case. At the aggregate level, the higher the supply of permits, the more likely for the strategic behavior to be compliance cost-saving for the polluters. However, accounting for the regulator's revenue, the social welfare is undermined when polluters exercise market power and the loss of welfare is independent of the emissions cap. Finally, the model shows that there are ETSs for which strategic behavior is cost-saving for the polluters regardless of the choice of the regulator with respect to the fixed supply of permits. In particular, such an ETS is characterized by a low variance of the business-as-usual emissions in the scheme.

Despite its stylized nature, this analysis raises a few questions with regard to the ETSs in which initial allocation is auctioning (e.g. EU ETS , California ETS). First, given that the electricity producers have the highest needs for emissions, this model suggests that, given that they cannot pass-through the compliance cost, they might be the sector hurt if the active part of the market acts strategically. Second it appears that the permission of non-polluters to bid for permits in the auction, which, for example, is already stipulated in the auction regulations of the EU ETS, is well justified. Apart from the practical considerations of ensuring market liquidity, their presence may also have the role of enlarging the number of the market participants, avoiding thus the exercise of market power. Third, it is important that the regulator uses an auction format which gives firms the incentive to bid truthfully. Currently, both the EU and the Californian regulator use the uniform price auction that was also modeled in this paper and in which firms have the incentive to shade their bids.

Further steps and extensions of this model are worth considering. First, modeling heterogeneity in the abatement costs appears to be a more realistic approach than homogeneity, though it poses analytical difficulties. While I do not expect that this approach could change

CEU eTD Collection

the qualitative results of the model, it may, however, turn out to be important when resorting to quantitative evaluations of the effect of market power. Second, as in some ETSs the auction revenue is re-distributed to its members, it would be useful to investigate how this rule affects the outcome of the strategic behavior. Third, it is worth considering the regulator as a strategic player and model her decision on choosing the fixed supply of permits such that to maximize its revenue from the auction. Finally, a repeated game in which banking is also allowed seems to be a more realistic avenue, with the potential of changing the main qualitative results of the model.

CEU eTD Collection

1.A Appendix

1.A.1 The Kuhn-Tucker conditions for the constrained problem

In order to apply the standard Kuhn-Tucker conditions, I transform problem (1.5) into a maximization problem. I solve it for the second stage of the game, when polluters make secondary market trading decisions, under the assumption that they behave as price-takers. This reads:

$$\begin{aligned} &\max_{t_i} C_i = -\theta(e_i - D_i - t_i)^2 - p_2 t_i - p_1 D_i, \\ &- e_i + D_i + t_i \leq 0 \\ &- t_i - D_i \leq 0, \end{aligned} \tag{1.A.1}$$

where D_i is taken as given. Let λ_i and μ_i be the Lagrange multipliers associated with the first and the second constraint, respectively. Then, the Lagrange function is:

$$\mathcal{L}(t_i, \lambda_i, \mu_i) = -\theta(e_i - D_i - t_i)^2 - p_2 t_i - p_1 D_i + \lambda_i(e_i - D_i - t_i) + \mu_i(t_i + D_i)$$

and the necessary conditions for a maximum are:

$$\begin{cases} 2\theta(e_i - D_i - t_i) - p_2 - \lambda_i + \mu_i & = & 0 \\ e_i - D_i - t_i \geq 0; & \lambda_i \geq 0; & \lambda_i(e_i - D_i - t_i) = 0 \\ t_i + D_i \geq 0; & \mu_i \geq 0; & \mu_i(t_i + D_i) = 0 \end{cases} \tag{1.A.2}$$

Case 1: $\lambda_i > 0$ and $\mu_i > 0$.

This implies that $e_i - D_i - t_i = 0$ and $t_i = -D_i$. These provide $e_i = 0$. Thus, this is the case of a non-polluter. However, a non-polluter would not be part of the ETS, or she would be a speculator. Although introducing speculators into the model would be an interesting case to consider, I leave it for further research and I only focus here on polluters.

Case 2: $\lambda_i = 0$ and $\mu_i > 0$.

This amounts to $2\theta(e_i - D_i - t_i) - p_2 + \mu_i = 0$ and $t_i = -D_i$, from which it follows that $\mu_i = -2\theta e_i + p_2$. Since $\mu_i > 0$, then it must be that $2\theta e_i < p_2$. Hence, this is the case of a polluter whose marginal abatement cost at the level of her business-as-usual emissions is below the secondary market price. This type of ETS participant would sell in the secondary market all the permits she buys in the primary market ($t_i = -D_i$), and she would abate everything. While this may be a realistic case to consider, I leave these type of ETS participants out of the current analysis because, again, they resemble the case of a speculator.

Case 3: $\lambda_i > 0$ and $\mu_i = 0$.

This case obtains that $2\theta(e_i - D_i - t_i) - p_2 - \lambda_i = 0$ and $e_i - D_i - t_i = 0$. The latter equality is equivalent to the level of abatement being equal to 0. Further, this provides $\lambda_i = -p_2$. But, since $p_2 > 0$, this would imply that $\lambda_i < 0$, which is a contradiction.

Case 4: $\lambda_i = 0$ and $\mu_i = 0$.

CEU eTD Collection

This is the interior solution case in which both constraints are slack, resulting in

$$t_i = e_i - D_i - \frac{1}{2\theta} p_2.$$

This is the case considered throughout the paper.

1.A.2 Strategic behavior with intercept and slope

Let us focus on linear equilibria. Thus the net trade function for each trader i is given by $t_i^s(p_2) = a_i - b_i p_2$. Each polluter chooses the price to minimize her compliance cost function $C_i^s = \theta(e_i - D_i - t_i^s)^2 + p_2 t_i^s + p_1 D_i$ under the market clearing condition $t_i^s(p_2) + t_{-i}^s(p_2) = 0$, where $t_{-i}^s(p_2) = \sum_{j \neq i} t_j^s(p_2) = \sum_{i \neq j} a_j - (\sum_{i \neq j} b_j) p_2 = a_{-i} - b_{-i} p_2$. The first order condition with respect to p_2 reads: $2\theta(e_i - D_i - t_i^s)(t_{-i}^s(p_2))' + t_i^s(p_2) + p_2(-t_{-i}^s(p_2))' = 0$, and after grouping around p_2 it yields: $-2\theta(e_i - D_i - a_i)b_{-i} + a_i + (-2\theta b_i b_{-i} - b_i + b_{-i})p_2 = 0$, which has to hold for any p_2. Therefore, the following system of equations results, $\forall i$:

$$\begin{cases} -2\theta(e_i - D_i - a_i)b_{-i} + a_i & = & 0 \\ -2\theta b_i b_{-i} - b_i + b_{-i} & = & 0 \end{cases} \tag{1.A.3}$$

From the second equation of the system we have that $b_i = \dfrac{b_{-i}}{2\theta b_{-i} + 1}$, $\forall i$. As Rudkevich (1999) showed in Lemma 1, this system has a unique positive solution. Due to the polluters symmetry in the abatement cost, the solution of the system must be the symmetric one as well. Therefore,

$$b_i = \frac{N-2}{2\theta(N-1)}, \ \forall i.$$

Substituting it in the first equation of (1.A.3), the intercept of the net trade function is:

$$a_i = \frac{N-2}{N-1}(e_i - D_i), \ \forall i.$$

Finally, the net trade function for any polluter i is given by:

$$t_i = \frac{N-2}{N-1}\left(e_i - D_i - \frac{1}{2\theta} p_2\right)$$

The market clearing condition $\sum_{i=1}^N t_i = 0$, provides the equilibrium price $p_2 = 2\theta\left(\bar{e}_N - \frac{E}{N}\right)$.

1.A.3 The derivation of the net trade function for the strategic case

Using (1.11) and the market clearing condition, the secondary market price is given by

$$p_2^s = \frac{2\theta}{N} \sum_{i=1}^{N} a_i, \tag{1.A.4}$$

CEU eTD Collection

which substituted into (1.6) together with (1.11) and writing the first order condition with respect to a_i, it gives the reaction function of polluter i to the choice of the intercept by the other $(N-1)$ polluters:

$$a_i = \frac{1}{N^2-1}a_{-i} + \frac{N}{N+1}\left(e_i - D_i^s\right) \tag{1.A.5}$$

where $a_{-i} = \sum_{j=1, j\neq i}^{N} a_j$. Adding up equations (1.A.5) for all i it yields:

$$\sum_{i=1}^{N} a_i = \frac{N}{N+1}\left(\sum_{i=1}^{N} e_i - \overline{E}\right) + \frac{1}{N+1}\sum_{i=1}^{N} a_i,$$

from which it immediately follows that $\sum_{i=1}^{N} a_i = \sum_{i=1}^{N} e_i - \overline{E}$. Therefore, in equation (1.A.5), $\sum_{i=1}^{N} e_i - \overline{E} - a_i$ can be substituted for a_{-i} and it yields:

$$a_i = \frac{1}{N^2-1}\left(\sum_{i=1}^{N} e_i - \overline{E} - a_i\right) + \frac{N}{N+1}\left(e_i - D_i\right),$$

from which solving for a_i it produces

$$a_i = \frac{N-1}{N}(e_i - D_i^s) + \frac{1}{N^2}\left(\sum_{i=1}^{N} e_i - \overline{E}\right) = (e_i - D_i^s) + \frac{1}{N}\left(\left(\bar{e}_N - \frac{\overline{E}}{N}\right) - (e_i - D_i^s)\right) \tag{1.A.6}$$

Substituting (1.A.6) back into (1.11) the net trade function in (1.12) is obtained.

1.A.4 The derivation of the bidding schedules for the strategic case

Each bider i solves the following problem:

$$\min_{p_1^s}\left(\frac{\theta}{N^2}D_i^s(p_1^s)^2 - (\alpha_i - p_1^s)D_i^s(p_1^s)\right) \text{ such that } D_i^s(p_1^s) = \overline{E} - D_{-i}^s(p_1^s), \tag{1.A.7}$$

where $D_{-i}^s(p_1^s) = \sum_{j\neq i} D_j^s(p_1^s)$. This boils down to solving the following differential equation:

$$-\frac{2\theta}{N^2}D_i^s(p_1^s)(D_{-i}^s)'(p_1^s) + (\alpha_i - p_1^s)(D_{-i}^s)'(p_1^s) + D_i^s(p_1^s) = 0, \tag{1.A.8}$$

With linear bids of the form

$$D_i^s(p_1^s) = x_i - y_i p_1^s, \;\; x_i, y_i \geq 0, \tag{1.A.9}$$

if all the other polluters use the same linear strategies, that is $D_j^s(p_1^s) = x_j - y_j p_1^s$ for all $j \neq i$, then for each polluter i, equation (1.A.8) becomes:

$$\frac{2\theta}{N^2}x_i \sum_{j=1,\, j\neq i}^{N} y_j - \alpha_i \sum_{j=1,\, j\neq i}^{N} y_j + x_i - \left(\frac{2\theta}{N^2}y_i \sum_{j=1,\, j\neq i}^{N} y_j - \sum_{j=1,\, j\neq i}^{N} y_j + y_i\right)p_1^s = 0, \tag{1.A.10}$$

CEU eTD Collection

which has to hold for any p_1^s. Therefore, the following system of equations characterizes the parameters x_i and y_i:

$$\begin{cases} \dfrac{2\theta}{N^2} x_i \displaystyle\sum_{j=1,\, j\neq i}^{N} y_j - \alpha_i \sum_{j=1,\, j\neq i}^{N} y_j + x_i & = 0 \\ -\dfrac{2\theta}{N^2} y_i \displaystyle\sum_{j=1,\, j\neq i}^{N} y_j + \sum_{j=1,\, j\neq i}^{N} y_j - y_i & = 0. \end{cases} \tag{1.A.11}$$

Solving for $\sum_{j=1,\, j\neq i}^{N} y_j$ from the first equation of system (1.A.11) it yields:

$$\sum_{j=1,\, j\neq i}^{N} y_j = \frac{x_i}{\alpha_i - \frac{2\theta}{N^2} x_i}$$

Substituting this into the second equation of the system it provides $y_i \alpha_i = x_i$. Therefore,

$$\sum_{j=1,\, j\neq i}^{N} y_j = \frac{y_i}{1 - \frac{2\theta}{N^2} y_i}.$$

Because polluters are symmetric in the marginal abatement costs, it follows that $y_i = y_j = y, \forall i \neq j$. Thus, substituting and solving for y in the above equation, it obtains

$$y_i = \frac{N^2}{2\theta} \frac{N-2}{N-1}, \forall i.$$

Thus, substituting for x_i and y_i in (1.A.9), the bid function in (1.17) is obtained.

1.A.5 The individual change in compliance cost

The change in compliance cost favors the strategic behavior, i.e. $\Delta C_i < 0$, if and only if

$$\frac{N-1}{N^2}\overline{E}\left(1 - \sqrt{1 + \frac{2}{N-2}}\right) \leq t_i^s \leq \frac{N-1}{N^2}\overline{E}\left(1 + \sqrt{1 + \frac{2}{N-2}}\right). \tag{1.A.12}$$

Further, accounting for the value of t_i^s, the double inequality in (1.A.12) reduces to

$$\bar{e}_N - \frac{\overline{E}}{N} + \overline{E}\left(1 - \frac{N-1}{N}\sqrt{1 + \frac{2}{N-2}}\right) \leq e_i \leq \bar{e}_N - \frac{\overline{E}}{N} + \overline{E}\left(1 + \frac{N-1}{N}\sqrt{1 + \frac{2}{N-2}}\right) \tag{1.A.13}$$

Since $1 - \dfrac{N-1}{N}\sqrt{1 + \dfrac{2}{N-2}} < 0, \forall N > 2$ and by Assumption 1.2, $\bar{e}_N - \frac{\overline{E}}{N} \leq e_i, \forall i$ it follows that the first inequality in (1.A.13) holds for all i. This means that the double inequality in equation (1.A.12) captures all net sellers and some net buyers, namely those with low business-as-usual emissions (see the second inequality in equation (1.A.13)).

CEU eTD Collection

1.A.6 Proof of inequality (1.29)

Using the well-known identity $Var(e) = \frac{1}{N}\sum_{i=1}^{N} e_i^2 - \frac{1}{N^2}\left(\sum_{i=1}^{N} e_i\right)^2$ and eliminating the square root, after some algebraic manipulations, inequality (1.29) becomes:

$$\frac{N(N-2)}{2(N-1)^2}\sum_{i=1}^{N} e_i^2 < \left(\frac{N-2}{2(N-1)^2} + \frac{N^2(N-1)^2}{(1+N(N-1))^2}\right)\left(\sum_{i=1}^{N} e_i\right)^2$$

Since $e_i > 0$, $\forall i$, we have that $\sum_{i=1}^{N} e_i^2 < \left(\sum_{i=1}^{N} e_i\right)^2$. Therefore, for the above inequality to hold it suffices to show that

$$\frac{N(N-2)}{2(N-1)^2} < \left(\frac{N-2}{2(N-1)^2} + \frac{N^2(N-1)^2}{(1+N(N-1))^2}\right).$$

After some algebraic manipulations, this reduces to $N^3(N^2-2N-1) + N(6N-5) + 2 > 0$. It is now easy to see that each term of the left-hand side in the last inequality is positive for any $N \geq 3$. Thus, inequality (1.29) is proven.

CEU eTD Collection

Chapter 2

Uncertainty and Speculators in an Emissions Trading Scheme

2.1 Introduction

After the ratification of the Kyoto Protocol in 1997, emissions trading schemes (ETS), also known as cap-and-trade programs, have received considerable attention both from the policy makers and economists. ETSs are favored as market-based instruments for controlling pollution because they give flexibility to firms in complying with the given environmental goal by the means of free trade. Their major appeal is that the greenhouse gases (GHG) emissions mitigation goal is achieved with minimum cost for the society, since a competitive emissions market will direct the emissions reductions towards the most cost-effective emitters. Moreover, unlike in the case of designing a carbon tax, the regulator does not need to know detailed information about the compliance costs or the emissions needs of each installation regulated under a cap-and-trade program.

Such considerations have also been recognized by the European Union (EU) when adopting a cap-and-trade system as its policy pillar to combat climate change. The European Union Emission Trading Scheme (EU ETS) is currently the biggest cap-and-trade program in the world and it runs in trading phases. The first two phases of the scheme (2005-2007 and 2008-2012, respectively) were characterized by the discretionary nature entailed by the free permits allocation method, also called grandfathering.[1] However, Phase 3 of the scheme (2013-2020) came with significant changes regarding the institutional design of the scheme. Perhaps the most important change is the method of initial allocation, which will evolve progressively to full auctioning by the end of the trading phase. Moreover, while in Phases 1

[1] At least 95% and at least 90% of the allowances have been distributed for free in the first and second phases of the scheme, respectively.

CEU eTD Collection

and 2 of the scheme the permits were distributed only to the regulated installations, starting with Phase 3 also non-regulated firms[2] can purchase permits directly from the European Commission (EC) through the auctions organized periodically.[3] The non-regulated firms are typically authorized individuals, investment banks or credit institutions who seek to make profits by engaging in speculating activity in the emissions markets. Therefore, I will further refer to these type of firms as speculators.

Similarly, through Article 5 of its Climate Change chapter, the Air Resources Board (ARB) established the California Emissions Trading System, which has been in place from the beginning of 2013. California implemented auctioning as the method of allocating the permits right at the start of the schem in a considerably larger proportion than the EU did in its Phase 1. However, in order to participate in the auction, an entity has to be approved by ARB and has to comply with the financial regulatory requirements. As in the case of the EU auctions, non-regulated firms are also allowed to bid and acquire permits in the auction. However, the Californian ETS auctions are organized less frequently than in the EU ETS, i.e. at quarterly intervals.

The motivation of this paper is, thus, driven by the emergence of auctioning as a popular method of allocating the emissions permits in an ETS, together with the inclusion of the speculators, but also by the policy discussion regarding auctioning as alternative to grandfathering. First, the discussion about the auction design and the auction format often overlooked or explicitly disregarded the secondary market. For instance, Benz et al. (2008) argue that, with auctioning, the secondary market will become thin or illiquid because the allocation via auctioning will be close to efficiency. Therefore, the auction design proposed by the authors ignores the possibility for re-sale. Similarly, Demailly & Quirion (2006) do not take into account the existence of a secondary market under auction allocation when they discuss the potential for leakage in the European cement industry under different permit allocation rules. This approach to modeling ETSs is also present in the economics literature. Specifically, Subramanian et al. (2008) do not model the possibility for re-sale because they assume that firms are symmetric such that the auction distributes the permits efficiently. Hence, all these papers overlook the fact that as long as there are no institutional barriers to the existence of a secondary market, its mere existence influences bidders behavior and, thus, the auction outcome.

Second, most of the policy discussion on the optimal auction format also discarded the possibility for exercise of market power in an ETS, on the grounds of the existence of a large number of auction participants (Cramton & Kerr 2002, Benz et al. 2008, Neuhoff 2007). Nevertheless, it has been shown that in auctions of divisible goods in which all successful bidders

[2]For details, see *Article 18* in the Commission's Regulation (EU) No 1031/2010 of 12 November 2010.
[3]The EC has designated the EEX platform in Leipzig as the transitional common auction platform.

CEU eTD Collection

pay the same clearing price, they have an incentive to under-report their true demands, even if the number of auction participants is large (Wilson 1979, Milgrom 2004, Ausubel et al. 2013). This can result in severe under-pricing. Therefore, my model accounts for the potential of price manipulation in the auction. Third, some authors argued that an auction at the start of a trading phase should provide a price signal for the secondary market (Hepburn et al. 2006, Hofmann 2006),[4] but when an active secondary market is already in place, bidders will bid according to the existing permits price in the trading market (Hofmann 2006). Moreover, other views expressed that buying permits in the secondary market or in the auction would make little difference for the individual firms (Hepburn et al. 2006) or that a sealed bid auction format would avoid the separation between the auction and the secondary market (Neuhoff 2007). However, as the model of this paper shows, even without an established trading market, the regulated firms bid by taking into account the anticipated secondary market price, given that there exists possibility for re-sale. Furthermore, the prices of the two markets need not be equal and, in fact, it is unclear whether the secondary market price will be below or above the auction clearing price. Hence, the model shows a separation between the two markets.

Thus, the main contribution of this paper is that of building a formal model of an ETS in which the initial allocation is via auctioning, incorporating the secondary market and, at the same time, allowing for speculators to bid in the auction. To the best of my knowledge this is the first model of an ETS which investigates firms' bidding behavior under uncertainty and, at the same time, accounting for the secondary market. Hence, contrary to the concerns expressed in the policy literature, the model developed in this paper shows that as long as the aggregated business-as-usual (BaU) emissions exceed the emissions cap of the scheme, a secondary market for permits will always exist. Specifically, I show that the secondary market arises for three reasons. First, at the auctioning stage firms have imperfect information about their true emissions needs, such that they form their bids based on their *expectations* about these needs. Second, because I realistically assume that not all polluting firms are present in the auction, the primary market is thin.[5] Hence, the auction provides incentives for bid-shading. Moreover, because of the asymmetries in their characteristics (abatement costs, BaU emissions etc.), some firms shade their bids more than others. Third, firms are risk averse and respond idiosyncratically to the economy-wide uncertainty. This determines firms to shade their bids more than they would do so otherwise. All these lead to an inefficient allocation and the need for redistribution through the secondary market, after the uncertainty is resolved.

In addition, the literature on auction design for the distribution of emissions permits often

[4] This implies that the secondary market price will be a function of the auction clearing price.

[5] This assumption is grounded on the current experience both with the EU ETS and the California ETS, as it will be explained in more detail in Section 2.2.

CEU eTD Collection

makes the analogy between auctions of permits and auctions of T-Bills (Neuhoff 2007, Holt et al. 2007, Matthes & Neuhoff 2007). The model of this paper allows to understand how an emissions permit is valued by the bidders compared to a T-Bill or other financial instruments, which are issued in an auction with the possibility for re-sale in a secondary market. By contrasting the derived endogenous valuations for permits of a polluter and a speculator, one can readily see that while a speculator takes into account only the re-sale value of the permit, much like an investor does with a bond, a polluter also accounts for its use value for compliance. Precisely, in a polluter's valuation for the first permit one can identify a component which is a function of the re-sale value of the permit (the speculative component) and a component which relates to the use of the permit in the process of production (the use component). Moreover, while the re-sale price of a bond does not bear any or little uncertainty, as it will be seen, this need not be the case for an emissions permit.

Hence, this modeling exercise aims at understanding the effect of the auction and the inclusion of the speculators on polluters' compliance behavior and on the outcome of the ETS. Although auctioning is by and large defended against free allocation,[6] it still raises several questions, especially if it takes place in an environment governed by uncertainty or potential for price manipulation. Under these circumstances, wealth redistribution will still occur, raising questions such as: who are the predicted "winners" in an ETS with auctioning; what is the role of uncertainty; or how does the presence of the speculators in the markets for permits influence their outcomes and the polluters profits.

In order to achieve these aims I develop a static, two-stage game in complete information which mimics the design of an ETS with auctioning as the method of initial allocation of permits. The game incorporates two types of players, the regulated firms (the polluters), who need to hold one permit for each unit of pollution released in the atmosphere, and the non-regulated firms (the speculators),[7] who engage in the permits markets for the purpose of gaining profits from the price difference. In the first stage, a subset of the polluters[8] together with the speculators participate in the auction for the distribution of the fixed supply of permits and in the second stage they decide on their secondary market trade and, in the case of the polluters, the abatement (emissions reductions) levels.

The auction is modeled as a uniform price sealed-bid auction[9] of a perfectly divisible asset, whereby the bidders submit demand schedules and receive permits according to their bids, at the price where the aggregate demand equates the total supply. In this model, as in reality, the supply of permits is fixed and exogenous, established based on geological and meteorological

[6]See Cramton & Kerr (2002) and Benz et al. (2008) for arguments defending auctioning.

[7]The idea of speculators acting in the permits market is also exploited by Colla et al. (2005) in a context of free allocation with two rounds of trade.

[8]Details about this subset will be provided in Section 2.2.

[9]This is the auction format used both by the EU and the California ETS.

CEU eTD Collection

considerations.[10] Therefore, in the framework of this paper the regulator does not play any strategic role in the sense that she does not make any decision, except for conducting and clearing the auction at the initial allocation stage. The secondary market trade is modeled as a Walrasian exchange in which all polluters and the speculators participate.

The underlying assumption of the model is that firms face uncertainty at the auctioning stage. This uncertainty takes the form of a common shock to polluters' BaU emissions. However, the uncertainty is realized after the initial allocation of permits is completed, such that the secondary market trade and abatement decisions take place after firms learn their true emissions needs. The polluters respond to the uncertainty in an idiosyncratic manner and the response can be positive or negative, such that a polluter can be either a pro-cyclical or a counter-cyclical firm. The polluters are also heterogeneous with respect to their expected BaU emissions, i.e. the emissions the firm would expect to release if her output demand conditions stayed unchanged and there was no environmental regulation.

In this model all agents are assumed to be risk averse and the risk aversion is captured by constant absolute risk aversion (CARA) utility functions of profits. The risk averse behavior of firms when taking decisions under uncertainty is defended by several authors (Sandmo 1971, Leland 1972). Moreover, the assumption about the risk aversion of agents acting in the emissions permits markets is also supported by empirical evidence. Specifically, Chevallier et al. (2009) find that the investors in the EU ETS exhibited higher risk aversion than on comparable equity markets during the period of their study from October, 2006 to November, 2007. Other authors assume risk averse polluters when studying the behavior of the European carbon price (Aatola et al. 2013) or when comparing taxes and permits as regulatory market instruments (Baldursson & von der Fehr 2004). Regarding the speculators, their behavior in my model can be related to the auction with re-sale literature *à la* Kyle (1989), Vargas (2003), Keloharju et al. (2005), in which a risky asset is traded before its liquidation value is realized. In this literature, the speculators are typically assumed to be risk averse. Vargas (2003) also brings evidence that traders in the Argentinean uniform price T-Bills auctions exhibit risk-averse bidding behavior. Finally, the closest to my paper, Colla et al. (2005) build a model of repeated trading of permits, in which both polluters and speculators are present, and they assume all agents to be risk averse with CARA utility functions of profits.

The main results of the paper can be summarized as follows. First, I find that a polluter's true valuation for the first permit increases in her risk aversion and in the volatility of the common shock if her response to the common shock has the same direction as that of the ETS as a whole. In addition, the higher the abatement cost and the expected BaU emissions, the more the firm is willing to pay for the first permit at the auctioning stage. Hence, a polluter

[10]For example, the EU ETS cap for 2013 is just slightly below 2.04 billion permits and it will decrease until 2020, such that "[...]the overall global annual mean surface temperature increase should not exceed 2 degrees Celsius above pre-industrial levels" (Directive 2009/29/EC of the European Parliament).

CEU eTD Collection

will be more aggressive at the auctioning stage if she expects high demand for permits in the secondary market or good conditions for her output market. Moreover, depending on its characteristics, a polluter can both over-value and under-value a permit relative to its expected re-sale price. By contrast, a speculator values the first permit exactly at its expected re-sale price in the secondary market. However, the presence of the speculators increases the competitiveness of the auction, determining the polluters to bid closer to their true demands. Consequently, the auction clearing price approaches its competitive value. Second, numerical comparative statics show that, contrary to the conventional wisdom favoring the participation of the speculators in the permits markets because they enhance market liquidity, I find that, under the most realistic assumptions, the participation of the speculators hurts polluters' profits. This is due to the fact that the presence of the speculators in the auction has two effects. On the one hand, it leads to an increase in the auction clearing price and, on the other hand, it decreases polluters' permits purchases. While the latter effect may have a positive impact on the polluters by preventing them to over-buy permits, thus insuring them in the case of a negative shock, the former will generally hurt polluter's profits. Thus, the overall effect on their profits depends on the relative change in prices and polluters' initial endowments when the speculators enter the market.

In terms of policy, these results suggest that the permission of the speculators to bid in the auction may not be welcomed from the polluters' perspective. Allowing them to participate in the auction increases its competitiveness and lifts up the clearing price. While this has obvious benefits for the auctioneer's revenue, it adversely affects the polluters, who have to pay more for their initial endowments and, generally, it increases their compliance costs. Therefore, an alternative measure for increasing auction competitiveness and government revenue is to ensure and facilitate the access to the auction of the small bidders. This can also be achieved by organizing frequent auctions which would encourage the participation of otherwise cash-constrained bidders. However, both the polluters and the regulator could benefit from the presence of the speculators if some auction revenue redistribution rule was in place. Nevertheless, this would affect polluters' bidding behavior and this situation is beyond the scope of this paper.

To the best of my knowledge, this paper is the first attempt to explicitly model an auction followed by a secondary market for the distribution of the emissions permits in an ETS. Moreover, in this framework I account for possible frictions in these markets and I allow for several levels of heterogeneity among firms. Nevertheless, my paper relates in several ways to other studies that model markets for emissions permits.

First, Subramanian et al. (2008) develop a model in which permits are distributed in a uniform price auction, but they omit the secondary market even under the assumption of firms heterogeneity. Although firms do not bid truthfully in their model, which has the effect of

CEU eTD Collection

halving the revenue to the regulator, the fact that they do not consider the existence of a secondary market, leads to efficient allocation in the auction. However, their restriction to the non-existence of the secondary market is unrealistic. Moreover, as my model shows, since the possibility for trade in the after-market is part of the information set of the polluters, this considerably affects their bidding behavior. Similarly to my model, the authors assume complete information, but they do not incorporate uncertainty. Furthermore, while I focus on the permits markets by assuming that all firms are price takers on their respective output markets, Subramanian et al. (2008) include the output market in two scenarios, local monopoly and Cournot competition, respectively. Due to the assumed competition structure on the output market, in both scenarios they find that dirtier firms invest less in abatement than cleaner firms, because in their model the emissions cap acts as a production capacity constraint. By contrast, in my model, where all firms are price takers on the output markets, the abatement level is determined by the usual equality between the permits' price and the marginal abatement cost. This result is due to the existence of the secondary market. Therefore, in my model, firms with a higher marginal abatement cost abate less than those who can abate cheaper. Altogether and individually, the level of abatement decreases in the emissions cap. Instead, Subramanian et al. (2008) find that the optimal level of emissions reductions increases in the fixed supply of permits. Finally, while my model assumes that firms are asymmetric throughout, in their two-firm asymmetric auction game, Subramanian et al. (2008) claim a linear equilibrium in which they impose symmetric intercepts equal to the fixed supply of permits. By contrast, I derive the asymmetric unique linear equilibrium for an auction game with more than two firms, without imposing any restriction.

The closest paper to mine is Colla et al. (2005). The authors build a model with two rounds of trading in which they incorporate two types of risk averse traders, firms and speculators, of total measure equal to unity. Hence, their markets are competitive. Rather than considering auctioning as the method of allocating permits, their model assumes free initial allocation and thus only the polluting firms are endowed with permits initially. Therefore, in the first trading round the speculators buy the permits from the polluters and unwind their positions in the second trading round. The trading rounds are separated by the realization of a common productivity shock, which affects all the polluting firms identically. In their model polluters are homogeneous and therefore, the equilibrium is symmetric. Quite the opposite, my model allows for heterogeneity in several dimensions, including different levels of risk aversion and idiosyncratic responses to the common shock. In addition, the sequence of decisions is different in the two models. Colla et al. (2005) has firms commit to investment decisions (abatement) before they learn the shock to their productivity. In my model firms benefit from more flexibility for compliance after the shock is realized, since the abatement decisions are taken in the absence of uncertainty. Assuming that polluters commit to abatement investment before they know the realization of the shock would decrease their valuation for permits

CEU eTD Collection

in the auction because permits and abatement investment are strategic complements in my model, as they are in the most realistic case. It is also for this reason that, in my model, the secondary market price is independent of the presence of the speculators on this market.

Colla et al. (2005) show that the price of the first round of trade increases in the number of speculators if and only if they are less risk averse than the polluting firms. By contrast, since in my model the first market is a unilateral market (the auction), its price increases with the number of speculators regardless of the relationship between their risk aversion and that of the polluters. Interestingly, Colla et al. (2005) find that the spread between the price of the second trading round and that of the first trading round is positive. Thus, in their model the speculators will always have an incentive to engage in the markets for permits. However, this is not always true in my model, in which the speculators are only in the position of gambling on the secondary market price. Similarly to Colla et al. (2005), but using numerical comparative statics rather than analytical ones, I find that the price of the first market decreases with the speculators' risk aversion, although the nature of this market is different in the two papers, i.e bilateral and competitive in Colla et al. (2005) and unilateral and strategic in my model.

In terms of methodology, my paper borrows from the finance literature on market microstructure along the lines of Kyle (1989), and it can also be integrated into the auction of divisible goods literature *à la* Wang & Zender (2002). However, it does depart from this literature because here I consider asymmetric equilibrium. Therefore, results on the supply function equilibrium in the electricity markets such as Green (1999), Rudkevich (1999), Rudkevich (2005) and Baldick et al. (2000) provide the basis for the methodological framework in solving for the asymmetric equilibrium at the auctioning stage.

The paper continues as follows. Section 2.2 outlines the elements of the model and its assumptions. In Section 2.3 I solve the model and discuss the results. Since the model cannot be fully solved analytically, Section 2.4 includes numerical comparative statics. Section 2.5 concludes.

CEU eTD Collection

2.2 The Model

2.2.1 The players

Assume an ETS which regulates $N > 2$ polluters. During the regulation period each polluter f has stochastic BaU emissions e_f given by:

$$e_f = \gamma_f + \alpha_f \epsilon, \tag{2.1}$$

where ϵ is a common shock which affects all the polluting firms and it is normally distributed with mean zero and variance σ^2. Hence, the parameter $\gamma_f > 0$ is the level of the expected BaU emissions while α_f is polluter's idiosyncratic sensitivity to the common shock. The BaU emissions can be interpreted in terms of demand for firm's final output. Thus, assuming exogenous BaU emissions is equivalent to assuming that firms are price takers on their respective output markets.

The sensitivity parameter α_f can be positive or negative, depending on how the firm's product demand moves relative to the common shock. Under the normality assumption firm f believes that her output demand is a normally distributed random variable with mean γ_f and variance $\alpha_f^2\sigma^2$. In order to ensure a negligible probability of e_f being negative, I will maintain the following assumption:

Assumption 2.1 *For each polluter $f = 1, \ldots, N$, $\Phi\left(\frac{\gamma_f}{\alpha_f \sigma_f}\right) \to 1$, where Φ is the cumulative distribution function of the standard normal distribution.*

In addition to the polluting firms, there is also a finite number $M > 2$ of speculators who participate in the markets for permits with the only purpose of making profits from the price difference. A speculator will be denoted by s.

The firms are engaged in a sequence of decisions as described by Figure 2.1. First they learn the emissions cap $\overline{E}$ auctioned by the regulator and decide to participate in the auction. For the time being, I assume that both the emissions cap and the decision to participate in the auction are exogenous.[11] Next, the auction is conducted following a sealed-bid uniform price format. If a firm $j \in \{f, s\}$ participates in the auction, then she submits a demand

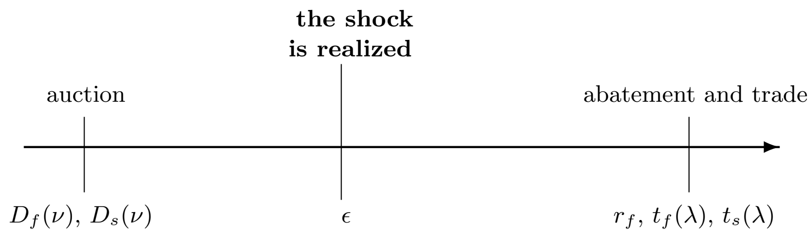


Figure 2.1: The sequence of decisions

schedule $D_j(\nu)$ representing the number of permits she would like to purchase at any price ν. The regulator collects all the individual demands to form the aggregated demand and computes the clearing price ν^* as the point where the aggregated demand equates the fixed

[11]In practice, the emissions cap is decided based on geological and meteorological forecasts related to the global temperature. A polluter's decision to participate in the auction may be based on cash constraints or acceptance as a member of the auction platform.

CEU eTD Collection

supply $\overline{E}$. At this stage each bidder receives the initial allocation of permits according to her bidding schedule and the auction clearing price. However, when firms bid for their initial endowment of permits, they face uncertainty incorporated in the common demand shock ϵ. This uncertainty is resolved after the initial allocation for permits is completed.

Having learned their true BaU emissions, in the second stage firms can trade the permits in a secondary market to unwind their position, in the case of the speculators, or to achieve compliance, in the case of the polluters.[12] Hence, the secondary market has the role of correcting the misallocations from the first stage, when the real needs for permits were unknown. I denote the price of the secondary market by λ and the supply (demand) on this market by $t_j(\lambda)$. In order to ensure that the probability of the secondary market price being negative is negligible, I will maintain the following assumption:

Assumption 2.2 $\Phi\left(\frac{\sum_N^{f=1}\gamma_f - \overline{E}}{\sigma\sum_N^{f=1}\alpha_f}\right) \to 1$, *where* Φ *is the cumulative distribution function of the standard normal distribution.*

Finally, for compliance, the polluters can also engage in abatement (emissions reduction) activity at a quadratic cost $\theta_f r_f^2$, where r_f denotes firm's f emissions reductions from the BaU level e_f. The interpretation of the abatement cost in the context of this model is that of end-of-pipe abatement (e.g. a filter which reduces the emissions at the end of the product line, CO_2 capture and storage facilities or investment in green projects generating certificates which can be used against the discharged emissions). Note that I model the abatement decision after the final allocation of permits is known and the uncertainty is resolved. In this case the abatement investment cycle is relatively fast and firms have the possibility to adapt their investment after the permits markets' outcomes are realized. One variant of the timing of this game is when abatement decisions take place under uncertainty, i.e. before the auction is conducted. This would reflect the long term abatement decisions at a lower frequency than the auction. This approach is, in fact, closer to the reality of an ETS in which several auctions are conducted during one calendar year. However, this would complicate the analytical tractability of the model and it is left for further research.

2.2.2 The utilities

Polluters

In this model permits are not bankable, i.e. they bear no value at the end of the trading period. Therefore, a polluter will close her position by trading the surplus or deficit of permits on the secondary market, accounting for the abatement decisions such that she complies with the

[12] Penalties for non-compliance are excluded from the model. Most emissions trading schemes have prohibitively high penalties such that non-compliance is deterred.

CEU eTD Collection

regulations. Hence, her net supply (demand) in the secondary market is given by the total amount of emissions discharged less the amount of permits purchased in the auction and less her level of emissions reductions:

$$t_f = e_f - D_f - r_f, \tag{2.2}$$

Thus, a positive t_f indicates a net buyer, while a negative t_f implies a net seller. Obviously, if $t_f = 0$, the firm does not participate in the secondary market. Therefore, any expenditure for permits in the secondary market by one firm represents revenue for another firm. Note that the only tradable instrument in this model is the emissions permit issued by the regulator such that no firm can sell more permits than she holds.

At this point the profit function of polluter f can be formulated as follows:

$$\Pi_f = -\lambda(e_f - D_f - r_f) - \theta_f r_f^2 - \nu D_f, \tag{2.3}$$

Hence, a polluter derives profit from the revenue (expenses) of selling (purchasing) permits in the secondary market, minus the abatement cost and minus expenses on purchasing permits in the auction. In addition, I assume that all polluters are risk averse with a CARA utility function of profits. Letting $\rho_f > 0$ be the constant absolute risk aversion coefficient, each polluting firm f maximizes the following utility function:

$$U_f(\Pi_f) = -\exp(-\rho_f \Pi_f). \tag{2.4}$$

Speculators

Recall that the speculators engage in the markets for permits with the purpose of making profits from the price difference. In essence, the behavior of the speculators in this model can be related to the auction with re-sale literature, where the re-sale price of the auctioned asset is uncertain. Therefore, they can be regarded as bidders for an asset, which has the random post-auction value given by the secondary market equilibrium price. Hence, the profit of any speculator s is given by the revenue from selling the permits in the secondary market, minus the expenses of buying them in the auction:

$$\Pi_s = -\nu D_s + \lambda D_s, \tag{2.5}$$

Similarly to the polluters, each speculator s maximizes a CARA utility function of profits,

$$U_s(\Pi_s) = -\exp(-\rho_S \Pi_s), \tag{2.6}$$

where $\rho_s > 0$ is her coefficient of risk aversion.

CEU eTD Collection

2.2.3 The markets

Primary market

As already noted, the initial distribution of permits takes place through a primary market which has the form of a sealed-bid uniform price auction. While I assume complete information in both stages of the game, I model this market as a strategic market. The latter assumption is supported by several facts. First, there is evidence that despite the large number of regulated entities under various ETSs, only a finite number of them participate in the auctions for the initial distribution of permits.[13] For example, under the EU ETS, during the first half of 2013, the number of bidders in the EU auctions was never larger than 21.[14] This is a surprisingly low number compared to the total number of installations covered by the scheme, which is around 12,000 installations. Similarly, in the first three quarterly auctions organized by the Air Resource Board within the Californian ETS, there were on average only 85 participants out of the total of around 600 installations. Presumably, the low participation in the primary auction is due to reasons such as cash constraints, lack of know-how, acceptance by the auctioneer to participate in the auction,[15] transaction fees etc.

Second, it has been established both theoretically and empirically that in uniform price auctions there is an incentive for demand reduction, even when the number of bidders is large. For instance, Milgrom (2004) argues that even when bidders are small relative to the market, there can be Nash equilibria in which prices settle far below the competitive price, unlike in the case of two-sided markets. This result has been firstly pointed out by Wilson (1979) who showed that the uniform price auction can have equilibria which result in significant reduction of the revenue to the auctioneer, both with risk neutral and risk averse bidders and regardless of the number of bidders. Hence, bidders have incentive to under-report their demands. Moreover, Ausubel et al. (2013) emphasize that when bidder's marginal utility is decreasing, the seller will not be able to extract the whole surplus, even when the number of bidders approaches infinity. Hence, as long as the auctioneer does not act strategically (one-sided market), the bidders have the power to influence the price.

Third, as Ellerman et al. (2010) pointed out, many of the regulated installations belong to business groups. Hence, as long as business groups are allowed to bid in the auction,[16] this will considerably reduce the number of the actual bidders, and it will increase their power to manipulate the price. Lastly but not least, modeling the auction as a strategic market does

[13]Modeling firms' entry decision in the auction is an interesting avenue, which, however, is left for future research.

[14]Based on EEX Exchange market data: www.eex.com

[15]For example, a firm who wants to participate in an auction has to register as a member of the exchange conducting the auction, or has to make a liability proof in the form of a bid guarantee.

[16]This is the case of the EU ETS (see the EU ETS Directive).

CEU eTD Collection

not reduce the generality of the problem. Letting the number of bidders grow large, one can always recover the competitive equilibrium. Therefore, accounting for the bid shading in fact ensures the generality of the equilibrium.

Therefore, in the spirit of the arguments discussed above, I assume that only a subset of the regulated firms bid in the primary market for permits distribution. Let this subset be composed of firms indexed from 1 to N_a, with $N_a < N$. Recall that the M speculators are also present in this market. Finally, I assume that the $N_a + M$ bidders present in the auction shade their bids in order to influence the auction clearing price.

Secondary market

The secondary market, on the other hand, is a large market. Given that polluters have to comply with the environmental regulations, the rest of $N - N_a$ polluters enter the secondary market as buyers, together with the unsuccessful bidders in the primary auction. Thus, this market will be thicker than the primary market and it is, therefore, modeled as a competitive market. The arguments are as follows. The transaction possibilities in a secondary market for emissions permits are more varied than on the primary market, and the ETS operators can access it via many routes. For example, the ETS operators can trade directly to each other or use intermediaries like banks and specialized traders. Therefore, firms' constraints on engaging in permits' exchanges are lower than in the case of the primary auction, and the transactions do not necessarily take place through an organized exchange. Thus, from this point of view one will expect a higher participation in the secondary market.

Moreover, as compared to the primary market, this is a bilateral market. With a finite number of players and quadratic utility functions, it has been shown that such markets do not create incentive for strategic behavior (Malueg & Yates 2009). The reason is that, due to the bilateral character of the market, the strategies of buyers and sellers cancel out leaving the equilibrium price unchanged relative to its competitive value. Hence, I model this market as a Walrasian market, which clears at price λ^*, such that the excess demand is zero.

2.3 Equilibrium

The problem of each polluter is to find the optimal combination of abatement and permits holding to achieve the environmental compliance, while the speculators only need to decide on their bids in the auction, since the secondary market trade only serves to unwind their positions. I assume that the permits and abatement are perfectly divisible and, therefore, the utility functions are differentiable with respect to each decision variable. Hence, I only consider continuous strategies and I solve the model by backward induction.

CEU eTD Collection

2.3.1 Abatement and Secondary Market

At this stage the uncertainty is resolved, such that maximizing the CARA utility function is equivalent to maximizing the profit function itself. Hence each polluter f decides on her abatement level r_f, given her initial allocation, such that to maximize her profit function given by (2.3) under the constraint $0 \leq r_f \leq e_f$. The constraint ensures that the abatement is not negative and it is not larger than the actual BaU emissions. The Kuhn-Tucker conditions provide the following optimal level of abatement:

$$r_f = \begin{cases} \dfrac{\lambda}{2\theta_f}, & \text{if} \quad 2\theta_f e_f \geq \lambda \\ e_f, & \text{if} \quad 2\theta_f e_f < \lambda \end{cases}, \forall f. \tag{2.7}$$

Hence, a firm for which the marginal abatement cost at the optimal emissions level is above the secondary market price will abate only up to the point where the marginal abatement cost equals the secondary market price, that is $r_f = \dfrac{\lambda}{2\theta_f}$. This is the supply of emissions reduction, which increases in the value of the permits in the secondary market and decreases in the slope of the marginal abatement cost.[17] Conversely, a firm for which the marginal abatement cost is below the secondary market price will choose to abate the whole amount of necessary emissions, i.e. $r_f = e_f$.

For convenience, in what follows I assume that the BaU emissions and the abatement cost of all firms are such that they operate in the region where the marginal abatement cost at BaU is above the secondary market price. If there are firms with the marginal abatement cost below the secondary market price, they should not be motivated to participate in the auction. However, if they do participate, then they do it for pure speculative reasons. Exactly because they can abate all the BaU emissions, they will not be buyers in the secondary market, either. Thus, I consider this group of firms as being assimilated into the group of speculators. Therefore, I maintain that the optimal level of abatement for each polluter f is given by:

$$r_f = \frac{\lambda}{2\theta_f} \tag{2.8}$$

Further, recall that the secondary trade takes place after the initial endowment is completed through the auction and after the uncertainty is realized. Thus, taking D_f and ϵ as given and using (2.8) in (2.2), the demand (supply) of firm f reads:

$$t_f(\lambda) = e_f - D_f - \frac{1}{2\theta_f}\lambda, \ \forall \lambda. \tag{2.9}$$

[17] Note that a positive price in the secondary market assures positive levels of abatement.

CEU eTD Collection

Note that for $D_f = 0$, equation (2.9) gives the demand function for the $N - N_a$ firms which do not participate in the action, as well as for the unsuccessful bidders.

At this stage, the speculators have to close their positions by selling all permits earned at the auctioning stage, since at the end of the game any permit held has zero value. Therefore, the supply of permits by each speculator s is:

$$t_s(\lambda) = -D_s, \ \forall\lambda \tag{2.10}$$

Proposition 2.1 *If the entire supply of permits is distributed in the auction, then*

$$\lambda^* = \frac{\sum_{f=1}^{N} e_f - \overline{E}}{\sum_{f=1}^{N} \frac{1}{2\theta_f}}. \tag{2.11}$$

clears the secondary, i.e. $\sum_{f=1}^{N} t_f(\lambda^*) + \sum_{s=1}^{M} t_s(\lambda^*) = 0,$

Assumption 2.2 ensures that λ^* is positive. Note that the secondary market price is not affected by the presence or the characteristics of the speculators. This is intuitive since speculators do not need permits for production and the secondary market is competitive. However, as expected, λ^* is increasing in the abatement cost and decreasing in the total supply of permits. Consequently, as equation (2.7) shows, the amount of abatement decreases in the number of available permits. This result is in contrast with both Subramanian et al. (2008) and Colla et al. (2005), who find that the abatement investment increases in the number of permits issued by the regulator. While their results are somewhat counter-intuitive, the explanation stands in the fact that both papers model the permits and the abatement as strategic complements. Thus, an increase in the available permits is seen as an expansion of firms' production capacities such that abatement becomes more attractive. By contrast, in my model the permits and the abatement are strategic substitutes.

Accounting for (2.1), the secondary market price can be broken down into a deterministic and a stochastic component, respectively:

$$\lambda^* = \bar{\lambda}^* + \Omega\epsilon, \tag{2.12}$$

where $\bar{\lambda}^* = \frac{\sum_{f=1}^{N} \gamma_f - \overline{E}}{\sum_{N}^{i=1} \frac{1}{2\theta_f}}$ is the expected secondary market price and $\Omega = \frac{\sum_{f=1}^{N} \alpha_f}{\sum_{N}^{i=1} \frac{1}{2\theta_f}}$ is the sensitivity of the secondary market price to the economy-wide uncertainty, ϵ. Again, Assumption 2.2 ensures that the expected secondary market price is positive. Hence, there is a secondary market for permits, in expectations. Moreover, as ϵ is normally distributed, it follows that λ^* is also normally distributed with mean $\bar{\lambda}^*$ and variance $\Omega^2\sigma^2$.

The sensitivity of the secondary market price to the overall uncertainty is, in essence, the polluters' aggregate response to this uncertainty. Note that Ω is positive if most polluters

CEU eTD Collection

have a large positive response to the overall uncertainty, i.e. $\sum_{f=1}^{N} \alpha_f > 0$, and negative otherwise. Therefore, if most firms are pro-cyclical ($\Omega > 0$), i.e. their demand follows the economic cycles, for a positive shock to the economy ($\epsilon > 0$) they would like to produce more since their demand is boosted. Consequently, the demand for permits increases, resulting in a higher secondary market price. Conversely, if most firms are counter-cyclical ($\Omega < 0$), the positive shock is actually bad news for the firms and they are not willing to buy any more permits. Instead, they would like to sell the available permits, thus increasing the supply in the secondary market and depressing the permits' price. However, the latter case is less realistic since most regulated industries are pro-cyclical.

2.3.2 Auction

At this stage the regulator issues the permits via a sealed-bid uniform price auction. In a sealed-bid uniform price auction, the bidders simultaneously submit their individual demand schedules and pay the same clearing price for all the permits they win. The clearing price is determined such that the aggregated quantity demanded equals the available supply. In this model, when firms submit their bidding schedules to the regulator (the auctioneer of permits), their BaU emissions, as well as the price of the emissions permits in the secondary market, are uncertain. Consequently, the equilibrium price of the secondary market, λ^*, can be interpreted as the post-auction value of a permit.

Recall that only the polluters $f = 1, \ldots, N_a$, $N_a < N$ participate in the auction along with the M speculators. Thus, in order to decide their bids, these firms have to form expectations with respect to their utility functions of profits defined by (2.4) and (2.6), respectively. Following Marin & Rahi (1999), it turns out that maximizing the expected value of the ex-ante utility of profit in the case of a polluter, is equivalent to maximizing the following objective function:

$$\widehat{U}_f(D_f(\nu), \nu) = -\frac{1}{2}\kappa_f \Omega^2 D_f^2(\nu) + \left(\bar{\lambda}^* - \kappa_f \Omega B_f - \nu\right) D_f(\nu), \; f = 1, \ldots, N_a \tag{2.13}$$

where,

$$A_f = \frac{\Omega^2}{4\theta_f} - \Omega\alpha_f \; ; \; B_f = -\alpha_f \bar{\lambda}^* - \Omega\gamma_f + \frac{1}{2\theta_f}\Omega\bar{\lambda}^* \text{ and } \kappa_f = \frac{\sigma^2 \rho_f}{1 + 2\sigma^2 \rho_f A_f} \tag{2.14}$$

Equation (2.13) is a mean-variance derived utility function, in which the parameter κ_f captures the disutility of the firm from bearing the uncertainty at this stage of the game. It should be noted that the higher the uncertainty or the higher the risk aversion, the larger the disutility: $\partial\kappa_f/\partial\sigma^2 > 0$ and $\partial\kappa_f/\partial\rho_f > 0$. However, in order for the ex-ante utility function of the polluter to be well-defined, the following additional assumption is required:

CEU eTD Collection

Assumption 2.3 *For any polluter f, the following holds:* $1 + 2\rho_f \sigma^2 A_f > 0$

Note that Assumption 2.3 also ensures that κ_f is positive. This assumption can be easily interpreted if one substitutes for A_f from (2.14). Thus, the condition from the assumption becomes $\Omega\alpha_f < \dfrac{1}{2\sigma^2\rho_f} + \dfrac{\Omega^2}{4\theta_f}$. Therefore, if most firms are pro-cyclical ($\Omega > 0$), Assumption 2.3 implies an upper positive bound on firm f's sensitivity. Conversely, if the individual sensitivities result in aggregate counter-cyclicality ($\Omega < 0$), then it puts a lower negative bound on firm f's sensitivity. This is to say that firms can be neither too pro-cyclical nor too counter-cyclical.

Further, maximizing the ex-ante utility of a speculator is equivalent to maximizing the following:

$$\widehat{U}_s(D_s(\nu), \nu) = -\frac{\sigma^2\rho_s\Omega^2}{2} D_s^2(\nu) + \left(\bar{\lambda}^* - \nu\right) D_s(\nu) \;\; s = 1, \ldots, M \tag{2.15}$$

One could argue that not only are the speculators less risk averse than the polluters, but they are rather risk neutral. Note that this case is already included in the model and it is obtained by making $\rho_s = 0$ in (2.15). Hence, instead of maximizing a mean-variance utility function, a risk neutral speculator would simply maximize the expected profit $\left(\bar{\lambda}^* - \nu\right) D_s(\nu)$. This implies that if a risk neutral speculator bids competitively, it is enough for the prices of the two markets to be equalized in expectation and this speculator captures the whole market. However, in this model all bidders are assumed to shade their bids; therefore making the speculators explicitly risk neutral does not change the results of the model. Moreover, risk neutrality can be recovered from the model at any time by making $\rho_s = 0$.

2.3.3 Marginal Valuations

The objective function in (2.13) reveals two interesting facts. First, the quadratic term in D_f is the result of the risk aversion of the polluter relative to the uncertainty governing her decision process. Second, we are facing the problem of a uniform price auction with heterogeneous bidders. Thus, they have heterogenous valuations, but each winning bidder pays the same unit price. In fact, taking the first derivative with respect to D_f in (2.13) one can recover the true marginal valuation for permits of an auction-participating polluter, where B_f was substituted from (2.14):

$$v_f(D_f) = \bar{\lambda}^* \left(1 + \kappa_f \Omega \left(\alpha_f - \frac{\Omega}{2\theta_f}\right)\right) + \kappa_f \Omega^2 \gamma_f - \kappa_f \Omega^2 D_f, \;\; f = 1, \ldots, N_a \tag{2.16}$$

Hence, polluter's marginal valuation decreases in the number of permits. Moreover, the valuations are endogenous since there is a re-sale opportunity, which is reflected in the constant term on the right-hand side of equation (2.16). This result was anticipated by Hofmann

CEU eTD Collection

(2006), who argues that the existence of the secondary market will influence bidding behavior of the auction participants. Moreover, the author maintains that no order will be made at the (expected) secondary market price. Equation (2.16) supports this view. However, this is not the case for a speculator, as her marginal valuation reads:

$$v_s(D_s) = \bar{\lambda}^* - \sigma^2 \rho_s \Omega^2 D_s \;\; s = 1, \ldots, M. \tag{2.17}$$

Thus, a speculator's true valuation for the first permit is independent of her risk aversion or the shock volatility, reflecting the fact that the shock does not directly affect her activity. Instead, she values the first permit at its expected re-sale price, $\bar{\lambda}^*$. However, the slope of her valuation function does depend on her risk aversion and the volatility of the shock to the polluter's output market demand.

The endogenously derived valuations for permits characterize firms' bidding aggressiveness. The intercepts of the marginal valuation functions in (2.16) and (2.17) represent the maximum willingness to pay for the first permit of a polluter and a speculator, respectively. While in the case of the speculators this is exactly equal to the value of a permit in the re-sale market and it is, thus, independent of their risk aversion, for the polluters this is altered by the dual nature of a permit: an asset for speculation and an instrument for compliance. In fact, considering the marginal valuations for permits given by (2.16) and (2.17), the following proposition describes the difference between a speculator and a polluter in valuing the first permit.

Proposition 2.2 *(i) A speculator values the first permit at its re-sale value* $\bar{\lambda}^*$.

(ii) A polluter's valuation for the first permit includes a speculative component equal to $\bar{\lambda}^* \left(1 + \kappa_f \Omega \left(\alpha_f - \frac{\Omega}{2\theta_f}\right)\right)$*, which depends on the expected secondary market price, and a use component,* $\kappa_f \Omega^2 \gamma_f$*, which reflects the role of the permit as a compliance instrument.*

Contrasting (i) and (ii) allows to understand how an emissions permit differs from other financial instruments such as bonds or securities. While it is safe to assume that a speculator in this model regards the emissions permit as a security with a random liquidation value, a polluter's valuation for the first permit depends on her fundamentals. Precisely, a permit is regarded both as a speculation asset and as an input in the process of production. Naturally, its value increases in the expected needs for permits given by γ_f, but it is unclear how the polluter would bet on the price of the permit in the secondary market. This, again, depends on polluter's characteristics. These results are summarized in the following propositions.

Proposition 2.3 *A polluter's maximum willingness to pay for the first permit increases in:*

(i) the expected BaU emissions, γ_f

(ii) her risk aversion, ρ_f*, and in the overall uncertainty,* σ^2*, if and only if one of the*

CEU eTD Collection

following conditions holds: (i) $\Omega > 0$ and $\alpha_f > \bar{\alpha}_f$, or (ii) $\Omega < 0$ and $\alpha_f < \bar{\alpha}_f$, where $\bar{\alpha}_f = \frac{\Omega}{2\theta_f \bar{\lambda}^*}\left(\bar{\lambda}^* - 2\theta_f\gamma_f\right)$.

Proof: The proposition follows directly from (2.16) by taking the first derivative of the intercept of the valuation function with respect to γ_f and κ_f, respectively, recalling that κ_f increases in ρ_f and σ^2.

While the intuition behind the first result of Proposition 2.3 is simple, the second result requires more discussion. If a firm's response to the shock is in the same direction as that of the aggregate sensitivity (Ω), then high risk aversion and large uncertainty induces her to prefer securing more permits in the auction. Consider the case in which the aggregate sensitivity implies that the regulated sector is mostly pro-cyclical ($\Omega > 0$). Thus, in the case of an ex-post positive shock to the economy ($\epsilon > 0$), the secondary market price increases relative to its expected value. If, in addition, the firm is pro-cyclical (α_f is positive), then her BaU emissions are larger than expected. Therefore, ex-ante the firm prefers to secure the needed permits in the auction and avoid paying a higher price in the secondary market. Recall that firms operate in the region where the marginal abatement cost at the expected BaU is larger than the secondary market price, i.e. $\bar{\lambda}^* - 2\theta_f\gamma_f < 0$. Therefore, result (ii) says that the polluter does not need to be pro-cyclical for her valuation for permits to increase in her risk aversion or shock volatility. However, the counter-cyclicality should be low enough for the firm to act towards securing permits at the auctioning stage.

Next, since a polluter's marginal valuation takes into account the secondary market price for permits through its speculative component, it is interesting to see in which conditions the polluter over-values or under-value the first permit relative to its expected re-sale value, $\bar{\lambda}^*$. The following proposition provides these conditions. Under the same conditions a polluter will also value the first permit more (less) than any speculator does.

Proposition 2.4 *A polluter will over-(under-)value the first permit relative to $\bar{\lambda}^*$, and consequently will value it more (less) than a speculator does, if and only if one of the following conditions hold: (i) $\Omega > 0$ and $\alpha_f > \bar{\alpha}_f$, or (ii) $\Omega < 0$ and $\alpha_f < \bar{\alpha}_f$, where $\bar{\alpha}_f = \Omega\frac{\bar{\lambda}^* - 2\theta_f\gamma_f}{2\theta_f\bar{\lambda}^*}$.*

Proof: The proposition follows directly from (2.16) by comparing its intercept with $\bar{\lambda}^*$.

Thus, in an ETS in which all polluters are pro-cyclical (the most realistic case) or all polluters are counter-cyclical (the least realistic case), the speculators always have a smaller bidding power for the first permit than the polluters. This is because the polluters prefer to secure their permits needs right at the auction and, possibly sell some of them in the after-market. However, their final gains in permits at the auction depend on the relative bid shading, since neither the polluters, nor the speculators bid truthfully for the first permit, as shall be seen in the next section.

CEU eTD Collection

Finally, it is relevant to understand polluter's speculative behavior. Proposition 2.5 establishes the monotonicity of the true valuation function with respect to the expected secondary marker price.

Proposition 2.5 *A polluter's valuation for the first permit increases in* $\bar{\lambda}^*$ *if and only if* $\alpha_f \Omega \sigma^2 \rho_f < 1$.

Proof: The result follows directly from (2.16) by taking the first derivative with respect to λ^*, using the definitions of κ_f and A_f and accounting for Assumption 2.3.

Note that the condition in Proposition 2.5 is more likely to hold the less risk averse the polluter is (small ρ_f) or the smaller her sensitivity to uncertainty (small α_f). Such characteristics increase her speculative side. Since the expected secondary market price decreases in $\overline{E}$, a consequence of Proposition 2.5 is that, given the assumptions of the model, the influence of the environmental constraint on polluter's speculative bidding is independent of firm's fundamentals γ_f or θ_f, and it only depends on the individual and aggregate risk-taking behavior through α_f, ρ_f and Ω.

Equilibrium Bids

The bidding strategies are based on the endogenously derived individual marginal valuations, which are assumed to be common knowledge, as is the perfectly inelastic supply, $\overline{E}$. Following Green (1999), I focus on the class of linear bidding strategies and I assume that all polluters participating in the auction have positive valuations for the first permit.[18] If some firms had negative valuations, they would not participate in the auction and, given the common knowledge assumption of this model, they would be disregarded by all the other participants at this stage. However, they would be present in the secondary market as buyers.

In Appendix 2.A.1 it is shown that the demand schedule for any bidder $j \in \{f, s\}$ is an affine function of ν. Precisely, the demand schedules are kinked function with the kink at the point where the price equals firm's true valuation for the first permit. For a polluter this reads

$$D_f(\nu) = \begin{cases} y_f\left(\bar{\lambda}^* - \kappa_f \Omega B_f - \nu\right), & \text{if } \bar{\lambda}^* - 2\Omega\kappa_f B_f > \nu \\ 0, & \text{if } \bar{\lambda}^* - 2\Omega\kappa_f B_f \leq \nu \end{cases} \tag{2.18}$$

and for a speculator we have

$$D_s(\nu) = \begin{cases} y_s\left(\bar{\lambda}^* - \nu\right), & \text{if } \bar{\lambda}^* > \nu \\ 0, & \text{if } \bar{\lambda}^* \leq \nu, \end{cases} \tag{2.19}$$

where the slopes y_f, $f = 1, \ldots, N_a$ and y_s, $s = 1, \ldots, M$ are solutions to the system of

[18] Note that this is true for all speculators.

CEU eTD Collection

equations given by (2.A.4), in Appendix 2.A.1, which cannot be solved analytically. However, Rudkevich (1999) shows that this system of equations has exactly one non-negative solution. This information is enough to conclude that the auction has a unique linear equilibrium in the form of the piecewise affine functions given by (2.18) and (2.19).

It should be noted again that the case of risk neutral speculators is nested in the model for $\rho_s = 0$. Thus, maintaining the strategic bidding assumption, a risk neutral speculator would not be able to equalize the prices of the two markets. In his case, the bid function of a speculator would continue to be given by (2.19), but her bid shading factor y_s would be simply given by the sum of the bid shading factors of the other $N_a + M - 1$ bidders. Only if all firms, including the polluters, were risk neutral, strategic bidding would lead to all bidders submitting empty schedules and the auction would be canceled.

Clearing Price

The auctioneer aggregates the individual demands and calculates the auction clearing price as the point in which the aggregated demand equates the fixed supply of permits. The aggregated demand is the horizontal summation of the piecewise functions given by (2.18) and (2.19), so it is itself a piecewise function. Therefore, some bidders receive zero permits in the auction if their maximum willingness to pay for the first permit is below the clearing price. This price is defined as the highest price for which the aggregate excess demand is non-negative:

Definition 2.1 *Let ν^* be the price at which the auction clears. Then, ν^* is defined as:*

$$\max\{\nu \geq 0 | \sum_{f=1}^{N_a} D_f(\nu) + \sum_{s=1}^{M} D_s(\nu) \geq \overline{E}\}, \text{ if } \{\nu \geq 0 | \sum_{f=1}^{N_a} D_f(\nu) + \sum_{s=1}^{M} D_s \geq \overline{E}\} \neq \emptyset \quad (2.20)$$

and zero otherwise.

Thus, without a price floor condition, the auction clearing price reads:

$$\nu^* = \bar{\lambda}^* - \frac{\overline{E}}{\sum_{f=1}^{n} y_f + \sum_{s=1}^{m} y_s} - \frac{\Omega \sum_{f=1}^{n} y_f \kappa_f B_f}{\sum_{f=1}^{n} y_f + \sum_{s=1}^{m} y_s} \quad (2.21)$$

where, without any loss of generality, I assume that $f = 1, \ldots, n$ with $n \leq N_a$ and $s = 1, \ldots, m$ with $s \leq M$ are the polluters and speculators, respectively for which the clearing price is below their true valuations for the first permit (see equations (2.18) and (2.19)). These are the successful bidders. Hence, the initial endowment of an auction participant is given by

$$D_j^* = \max\{0, \, D_j(\nu^*)\}, \; j = 1, \ldots, n, 1, \ldots, m \quad (2.22)$$

CEU eTD Collection

where ν^* is defined in (2.21).

From equation (2.21) the following proposition can be established:

Proposition 2.6 *In an ETS with auctioning, risk averse market participants and limited auction participation by the regulated firms, there exists a spread between the auction clearing price and the expected secondary market price of permits give by*

$$\bar{\lambda}^* - \nu^* = \frac{\overline{E} + \Omega \sum_{f=1}^{n} y_f \kappa_f B_f}{\sum_{f=1}^{n} y_f + \sum_{s=1}^{m} y_s} \tag{2.23}$$

However, the sign of this spread is undecided and it depends on the characteristics of the polluters who are successful in the auction, on the aggregate shock sensitivity of all polluters and on the number of permits issues by the regulator. Proposition 2.6 indicates that the speculators can influence the sign of the expected price spread only to the extent that they can affect the polluters' bid shading factors y_f's. Nevertheless, they can directly influence the magnitude of this spread through their own bid shading factors y_s's (see the denominator on the right side of (2.23)).

2.4 Numerical Comparative Statics

As it has already been seen, it is difficult to obtain unambiguous predictions of the model via analytical manipulations. Moreover, the system of equations in (2.A.4) cannot be solved analytically. Therefore, in order to obtain the complete outcome of the emissions trading game as well as to conduct more clear-cut compartive statics, one must resort to numerical examples. Thus, in this section I assess the predictions of the model, by judiciously choosing the values of the parameters such that to meet Assumptions 2.1-2.3.

2.4.1 Individual valuations

Figure 2.2 shows the true valuation for the first permit of an individual polluter, as a function of the main parameters of the model, for different values of the permits supply, $\overline{E}$. Although the valuations are generally non-monotonic in model parameters, it turns out that for reasonable choices of the parameters there are portions on which the valuations are monotonic as shown in the figure. Thus, I fix the parameters at the values $\gamma_f = 20$, $\alpha_f = 0.4$, $\rho_f = 0.05$, $\theta_f = 10$ and in each picture of Figure 2.2 I vary each of these parameters in turn in order to obtain the monotonicity of the valuation. In addition, for each valuation constructed this way I vary the supply of permits to show that the more relaxed the environmental constraint, the lower the true valuation for the first permit. The upper-left picture of the figure shows

CEU eTD Collection

that the higher the slope of marginal abatement cost, θ_f, the more value the firm attaches to the first permit at the auctioning stage. This is intuitive since, in this model, permits and emissions reductions are substitutes. However, the valuation is convex, implying that the willingness to pay increases faster for higher marginal abatement costs. Also, the valuation increases faster for lower levels of permits supply, reflecting the tightness of the environmental constraint.

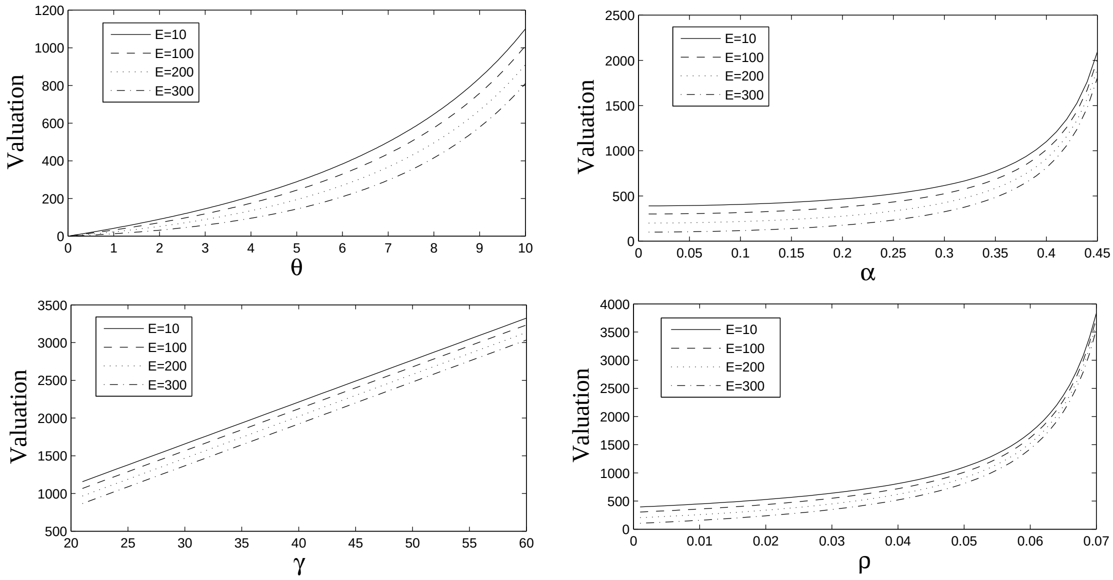


Figure 2.2: True individual valuation for the first permit ($\sigma^2 = 4$)

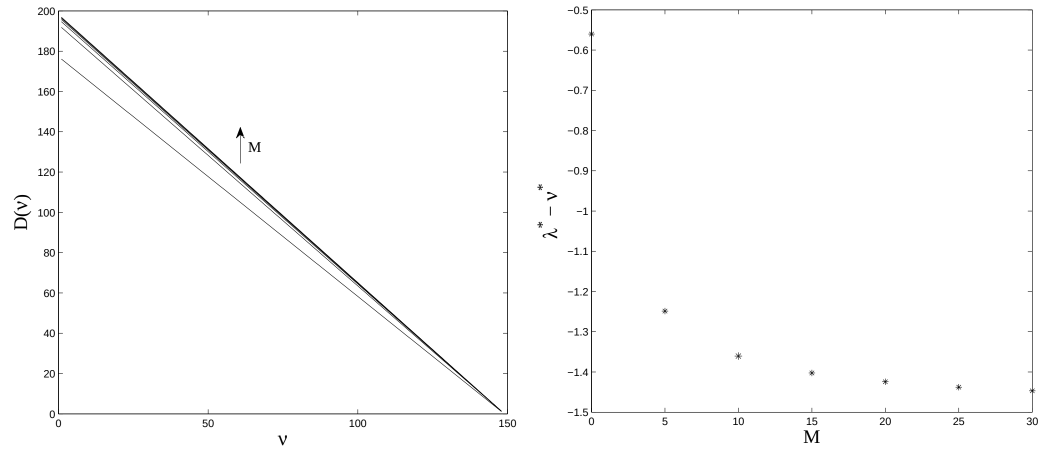
The upper-right picture shows the monotonicity of the individual valuation with respect to firm's sensitivity to the overall shock. The firm is willing to pay more for the first permit as she is more responsive to the shock because higher pro-cyclicality amplifies her permit needs in case of a positive shock. However, if her sensitivity exceeds some threshold (for the case illustrated in the figure this threshold is α_f=0.5), her valuation turns negative, such that she would not submit a bid. This is due to the fact that her shock sensitivity exacerbates her risk aversion such that the firm is not willing to take the risk of a negative shock and remain with permits inventories, which she would not be able to re-sale in the secondary market.

Further, the lower-left picture of Figure 2.2 illustrates the result in Proposition 2.3 with respect to the expected BaU emissions. The relationship is linear. Finally, the lower-right picture of the figure shows how the individual valuation of a polluter varies with her coefficient of risk aversion. As Proposition 2.3 anticipated, the valuation increases as the firm becomes more risk averse. Moreover, polluter's aggressiveness increases more sharply at higher levels of risk aversion.

CEU eTD Collection

2.4.2 Bid shading

Proposition 2.6 shows that the spread between the prices of the two markets depends on the slopes of the bidding functions. Therefore, the left picture of Figure 2.3 shows how the polluters' bidding function changes with the number of the speculators present in the auction. In other words, the left picture shows how the speculators affect polluters bidding strategies, while the right picture of the figure shows how they affect the expected price spread.



Poluters bidding functions

Expected price spread

Figure 2.3: Bid shading and expected price spread
$N = 20$, $N_a = 10, \overline{E} = 100$, $\sigma^2 = 4$, $\epsilon = -3.1$,
$\rho_f = 0.005$, $\gamma_f = 12$, $\alpha_f = 0.3$, $\theta_f = 10$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$)

The highest line in the left picture of Figure 2.3 depicts the true demand function, i.e. the demand the polluters would submit if they acted competitively. Any demand schedule below this line is characterized by bid-shading. Hence, it can be noticed that the polluters shade their bids more as the number of the speculators decreases. Conversely, they approach truthful bidding as more speculators enter the market. Next, consistent with theory, the polluters increasingly shade their bids with the number of units bid. This can be seen from the way the demand schedules diverge from each other as the quantity demanded increases. However, for larger number of speculators, the gap between the true demand and the actual bids decreases for each permit. Since the bids approach the true demands, the auction clearing price increases. This, together with the fact that the secondary market price is unaffected by the speculators, implies that the expected spread between the two market prices decreases. This is shown in the right picture of the figure. In conclusion, the larger the number of the speculators in the market, the less profitable the permit speculation activity. This result shows that with free-entry in the auction, of speculators or other polluters, the problem of market power in a uniform price auction for emissions permits can be self-correcting. However, this

CEU eTD Collection

possibility is postponed for future research.

2.4.3 Heterogeneity

In this section I analyze the outcome of the ETS allowing for firms' heterogeneity. Thus, I allow for variation in each of the main parameters in turn, holding the shock constant while considering a low (the empty circles) and a high (the filled circles) environmental constraint, respectively. Thus, in Figures 2.4 to 2.6, on the horizontal axes I order the firms as follows. Indices from 1 to 10 represent the polluters who participate in the primary auction; firms from 11 to 20 are the polluters who do not participate in the auction, while the last five firms from 21 to 25 denote the speculators. Hence, in terms of the notations of the model, we have $N = 20$, $N_a = 10$ and $M = 5$.

Abatement cost

Figure 2.4 shows the case in which firms differ only with respect to the marginal abatement cost, according to the correspondence $\theta_f = f + 3$, $f = 1, \ldots, 20$. As anticipated, high-abatement cost firms value the first permit more than the low-abatement cost firms, but their valuations decrease with the loosening of the environmental constraint (upper-left picture in the figure). This is also true for the speculators, since a looser environmental constraint means a lower expected secondary market price. In turn, the lower valuations reflect the lower auction clearing price. However, as the number of permits increases, all firms receive more permits in the auction (upper-right picture) and firms with higher valuations receive more permits. Interestingly, the variation in permit allocation decreases with the fixed supply of permits (the empty circles curve is steeper than the filled circles curve). This is because the scarcity of permits makes the high cost firms bid more aggressively.

CEU eTD Collection

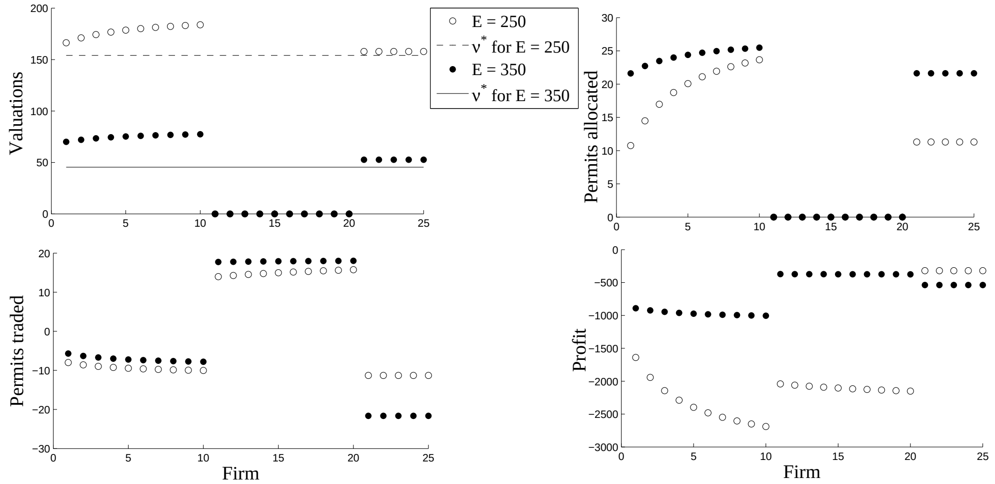


Figure 2.4: Equilibrium with heterogeneity in the abatement cost
$\theta_f = f + 3$, $\epsilon = -3.81$, $\sigma^2 = 4$,
$\gamma_f = 20$, $\alpha_f = 0.4$, $\rho_f = 0.004$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$

The lower left picture of Figure 2.4 depicts firms' net positions in the secondary market.[19] Negative values represent net sales while positive values are net purchases of permits. First, the polluters who do not participate in the auction purchase more permits the higher their abatement cost. Second, by construction, the speculators sell their full endowments. Third, among the auction-participating polluters the high cost ones sell more than the low cost firms, regardless of the emissions cap. This is due to their higher bidding aggressiveness coupled with the negative shock received by the economy. Interestingly, the increase in the emissions cap decreases the trade position as sellers of the polluters who participate in the auction. This indicates that a looser environmental constraint leads to a more efficient allocation of permits in the auction. This follows from the fact that the speculative component in the polluter valuation function decreases with the loosening of the environmental constraint through the expected secondary market price (see equation (2.16)). For this situation most of the trade takes place between the speculators and the polluters who do not participate in the auction. In this case the speculators act as a cushion for those polluters who do not participate in the auction.

Finally, the lower-right picture of Figure 2.4 shows firms' profits. While all polluters gain from the relaxation of the environmental constraint, the opposite holds for the speculators. However, the high-cost polluters have lower profits than the low-cost polluters, and the auction-participating polluters have lower profits than those who buy the permits only in the secondary market, although in the case illustrated in the figure, the latter have higher marginal abatement costs. This result is primarily due to the negative shock received by the

[19] For convenience, I represent the valuations of the auction non-participating polluters (indexed from 11 to 20) as being equal to zero.

CEU eTD Collection

economy in the example considered in the figure. The opposite is true if the economy experiences a positive shock, in which case the secondary market price is above its expected value (case not shown) and thus, the risk taken by the polluters who participate in the auction pays off. While the increase in the supply of permits depresses both the secondary market price and the auction clearing price, the change in the speculators' profits depends on the change of the spread of the two prices relative to the change in their permits inventories, brought about by looser environmental constraint. For the case illustrated in Figure 2.4 the increase in the price spread is lower than the decrease in the permits endowment, such that the combined effect is that of depressing speculators' profits.

Shock sensitivity

Figure 2.5 illustrates the equilibrium of the game when polluters differ only with respect to the their sensitivity to the overall shock, i.e. heterogeneity in α_f. Without any loss of generality, I assume that firms with higher index exhibit higher sensitivity according to $\alpha_f = f/50$. Again, the loosening of the environmental constraint decreases firms' valuations and, consequently, the auction clearing price (upper-left picture). Interestingly, with a tighter environmental constraint polluters' initial allocations are more dispersed (the filled circles curve in the upper-right picture is flatter than the empty circles curve). The result is primarily driven by the speculative motive of the polluters which is stronger in the case of a scarce supply of permits, translated in larger expected gains in the secondary market. One consequence of the strong speculative bidding of the polluters is that the pure speculators earn zero permits in the auction.

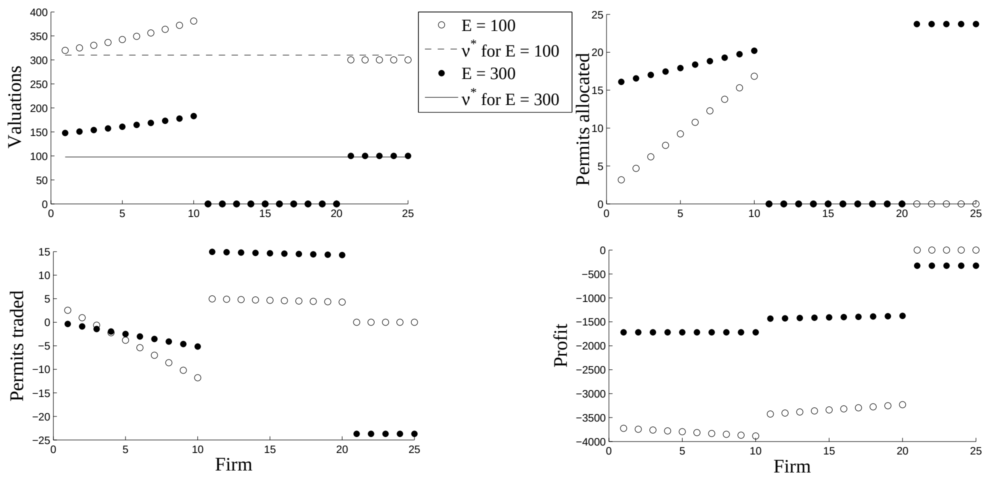


Figure 2.5: Equilibrium with heterogeneity in shock sensitivity
$\alpha_f = f/50$, $\epsilon = -3.81$, $\sigma^2 = 4$,
$\gamma_f = 20$, $\theta_f = 10$, $\rho_f = 0.05$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$

CEU eTD Collection

Note from equation (2.16) that the speculative component in polluters' valuation function also depends on the sensitivity to the global shock. Thus, they also use the permits market to hedge against the risk they face in their output markets, which is exacerbated by the sensitivity to uncertainty. The speculative bidding of the polluters is then reflected in their trading positions (lower-left picture) in the secondary market: high sensitive firms (more aggressive bidders) re-sell more permits. However, as the lower-right picture of the figure shows, they gain less profits than the low sensitive polluters because there is higher heterogeneity in the initial permits allocation than in their trading positions.

Expected BaU

Finally, Figure 2.6 shows the outcome of the ETS game when the polluters differ in their expected BaU emissions γ_f. Again, without any loss of generality I assume that, in expectations, low-indexed polluters are small emitters and high-indexed polluters are high emitters: $\gamma_f = 1.5(f + 15)$.

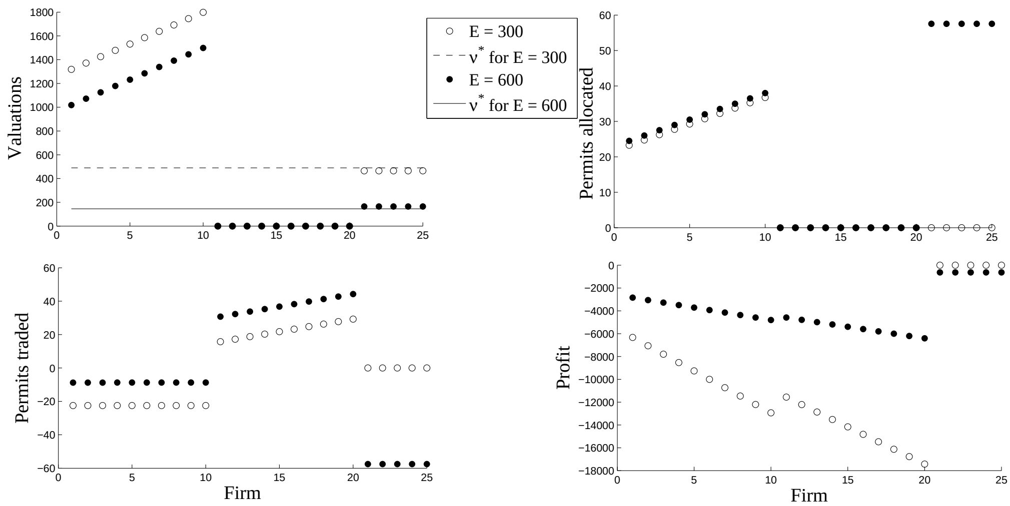


Figure 2.6: Equilibrium with heterogeneity in the expected BaU emissions
$\gamma_f = 1.5(f + 15)$, $\epsilon = -3.81$, $\sigma^2 = 4$,
$\theta_f = 10$, $\alpha_f = 0.4$, $\rho_f = 0.05$, $f = 1, \ldots, N$, $\rho_s = 0.001$, $s = 1, \ldots, M$

The expected BaU emissions matter for polluters' bidding behavior only through the use component in their valuations, in a linearly increasing manner (see equation (2.16) and the upper-left picture in the figure). Note from (2.A.4) that the bid-shading factors are independent of the expected BaU emissions. Therefore, differences in the initial permits endowments are only due to differences in the expected BaU emissions through the use component of the valuations (upper-right picture). Hence, the auction-participating polluters trade mostly on their speculative component, which, in this case is the same for all firms. Therefore, their

CEU eTD Collection

trading positions are similar, but for the high emitters the environmental compliance is more expensive, hence, the lower profits depicted in the lower-right picture. Note, however, that the model abstracts from the output market, which might, in fact, bring more revenue to the high emitters. Finally, when the environmental constraint is relaxed, going from $\overline{E} = 300$ to $\overline{E} = 600$ permits, all polluters are better off due to the lower permits price, but, from the same reason, the speculators are worse off.

2.4.4 The role of the speculators

In this section I discuss how the presence of the speculators and their risk aversion affect the equilibrium of the ETS game and the profits of the polluters. Thus, the empty circles in Figure 2.7 show the outcome for the case in which the speculators are absent from the permits markets ($M = 0$), while the filled circles show the case in which they are present ($M = 10$). Moreover, when the speculators are present in the game, I assume that they are significantly less risk averse than the polluters, which is the most realistic case to consider.

First, consistent with the theory of multi-unit uniform price auction, I find that when the number of bidders increases, in this case through the inclusion of the speculators, the auction clearing price increases towards its competitive value (upper-right picture of the figure). This is the well-known result that underpricing in multi-unit uniform price auctions decreases in the number of bidders (Keloharju et al. (2005)). This was also anticipated by Figure 2.3, which shows how the bid shading vanishes with the number of the speculators.

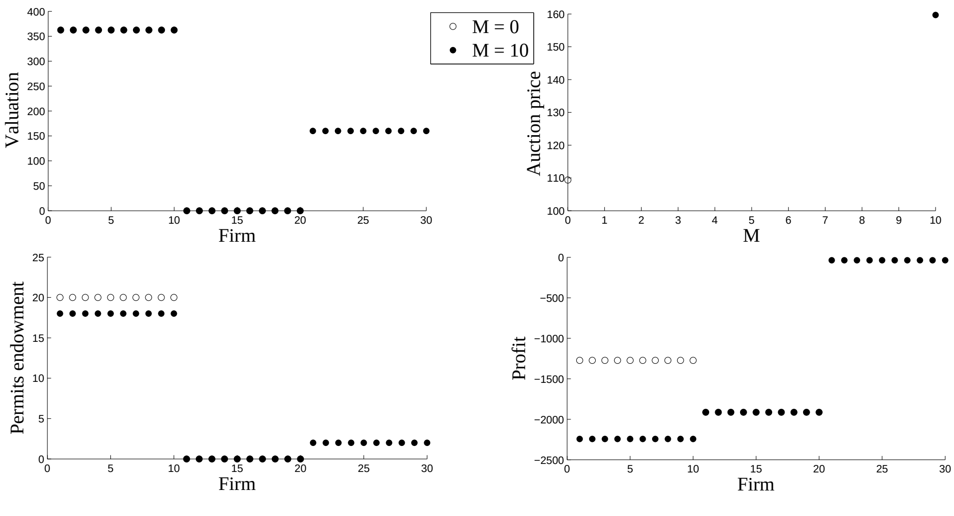


Figure 2.7: The effect of the speculators: $\overline{E} = 200$, $N = 20$, $N_a = 10, \sigma^2 = 4$, $\gamma_f = 18$, $\theta_f = 10$, $\alpha_f = 0.3$, $\rho_f = 0.05$, $f = 1, \ldots, N$; $\rho_s = 0.001$, $\forall s = 1, \ldots, M$

Figure 2.7 also shows that for the chosen parameters, allowing for speculators to participate

CEU eTD Collection

in the markets for permits has the effect of hurting the profits of the auction-participating polluters (the lower-right picture of the figure).[20] The reason is the following. Everything else constant, polluters' true valuations for permits are the same, regardless of the presence of the speculators. However, the introduction of the speculators increases the competition and changes polluters' bidding strategies (their bid-shading factors), which, in turn, affect the auction clearing price. Hence, some permits are allocated to the speculators, thus decreasing the polluters' initial allocations. The fact that the polluters are worse off when speculators enter the game results from the auction price increase outweighing the decrease in their initial endowments. Thus, firms pay more for the initial endowment in the auction and, they make less revenue on the secondary market, since they have lower permits inventories, or even losses if they need to buy the deficit of permits from the speculators.[21]

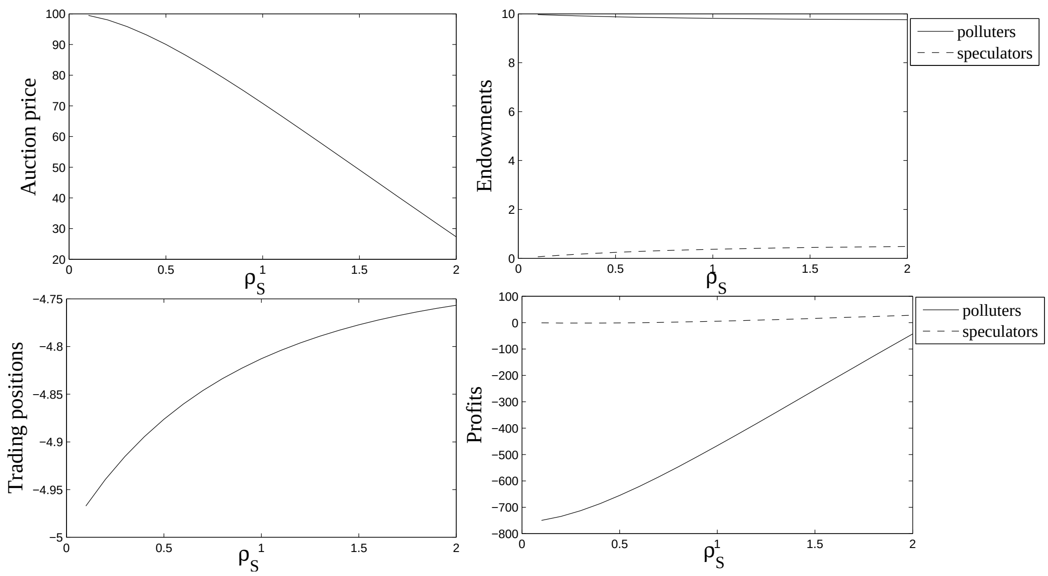


Figure 2.8: Speculators' risk aversion
$\overline{E} = 100$, $N = 20$, $N_a = 10$, $M = 5$, $\sigma^2 = 4$, $\epsilon = -3.81$,
$\gamma_f = 10$, $\theta_f = 10$, $\alpha_f = 0.2$, $\rho_f = 0.3$, $f = 1, \ldots, N$

CEU eTD Collection

Since risk aversion is a key characteristic determining speculators' participation in the permits markets, I also consider the effect of their risk aversion on the main equilibrium variables. Thus, Figure 2.8 shows how the auction clearing price (upper-left picture), the permits endowments of both polluters and speculators (upper-right picture), the trade positions of the polluters (lower-left picture) and the profits (lower-right picture) vary with speculators' coefficient of risk aversion. Although speculators' valuations for the first permit are independent of their risk aversion and equal to the expected secondary market price, as their risk aversion

[20]Note that I keep the realization of the shock constant such that the secondary market does not affect the differences in profits.

[21]Recall that the secondary market price is unaffected by the presence of the speculators. For the same reason, the profits of those polluters who do not bid in the auction remain unchanged.

increases, they shade their bids more. This depresses the auction clearing price, which has a direct effect on polluters' profits who benefit from cheaper permits at the auctioning stage. As the price decreases, the speculators also earn more permits, thus being able to make positive profits. This is because the difference between their valuations, which stay constant regardless of the risk aversion, and the auction clearing price becomes positive. Consequently, polluters' endowments decrease and she makes less revenue from re-sale in the secondary market. Nevertheless, their profits increase because the secondary market trade loss is outweighed by the lower price they pays for purchasing the permits from the regulator. Hence, this is a situation beneficial for the polluters. However, since in reality we expect that the speculators are rather risk neutral, such outcome is very unlikely.

2.5 Conclusions

This paper developed a static model that mimics an ETS in which the regulator allocates the permits via an auction of shares. The main result is that when polluters are not committed to abatement investment before they know their true emissions, the presence of the speculators has an adverse effect on polluters' profits. The reason for this is that speculators participation in the auction increases its clearing price, which is, however, beneficial for the revenue accrued to the regulator. Moreover, the speculators have no influence over the secondary market price, which only depends on the characteristics of the regulated firms. Consequently, firms' abatement decisions are unaffected by the presence of the speculators.

Contrary to the policy discourse around the optimal auction format for the distribution of emissions permits, which often ignores the existence of a secondary market, I find that, with risk averse firms and bid-shading, there will always be trade in the secondary market. Moreover, the relationship between the price of this market and the auction clearing price is ambiguous. The difference between these prices depends directly on polluters' characteristics and indirectly on the bid shading behavior of the speculators, which affects the auction clearing price. Therefore, I show that, with a competitive secondary market, the auction need not serve as a price signal but it is rather the expectation about the secondary market that affects bidders behavior and thus, the auction clearing price.

In addition, I derive polluters' endogenous marginal valuations for permits, which allows to understand how they form their bidding behavior. The valuations are decreasing function of permits holdings both for the polluters and for the speculators. Hence, it turns out that the polluters do not base their bids solely on the expectations about the secondary market price or only on their expected permits needs. Instead, a polluter's valuation for the first permit consists of a speculative component, which depends on the secondary market price, and a use component, which depends on her expected permits needs. Therefore, it is possible that a

CEU eTD Collection

polluter attaches a higher value to the first permit than its expected secondary market value. By contrast, a speculator will not bid for the first permit higher than its expected secondary market value. This difference in valuations, between a polluter and a speculator, implicitly shows how an emissions permit differs from other financial instruments.

The main conclusion of this modeling exercise is that, under reasonable assumptions, the speculators have an overall negative effect on polluters welfare. Therefore, in terms of policy recommendations, this model suggests that instead of allowing for the speculators to participate in the auction, the regulator could lessen polluters' access to the auction. An additional solution, which is already implemented by the EU ETS, is that the regulator organizes frequent auctions. This would encourage the participation of the small polluters which may be cash-constrained or unable to bear the risk of holding permits in their balance sheets for very long periods of time. The increased auction participation from among the polluters would also increase the auction revenue to the regulator.

Some extensions of the current model are worth considering for further research. First, a multi-period model in which firms are allowed to bank permits from one period to another is a more realistic set-up in line with the actual ETS regulations. Second, assuming incomplete information about abatement cost functions is another avenue of research which depicts more accurately the information structure in an ETS. Third, one could model long-run compliance decisions by having the polluters commit to abatement investment before the uncertainty in their permits demand is resolved. Finally, once could relax the assumption of exogenous number of speculators and, instead, model their auction entry decision.

CEU eTD Collection

2.A Appendix

2.A.1 Derivation of the bidding schedules

Each bidder $j \in \{f, s\}$ chooses her optimal bidding strategy maximizing the utility in (2.13), if she is a polluter or in (2.15), if she is a speculator, acting as a monopsonist on the residual supply of permits $\overline{E} - D_{-j}(\nu)$, where $D_{-j}(\nu) = \sum_i D_i(\nu)$, $i = 1, \ldots, j-1, j+1, \ldots, N_a + M$.

The equilibrium concept is the supply function equilibria (Klemperer & Meyer (1989)). A strategy for bidder j is a non-increasing schedule $D_j(\nu)$ which specifies the quantity demanded for every price ν. Precisely, focusing on linear strategies, the demand schedules have the form:

$$D_j(\nu) = x_j - y_j\nu, \quad \text{with } x_j,\, y_j \geq 0. \tag{2.A.1}$$

Thus, each bidder solves the following problem:

$$\max_{\nu} \widehat{U}_j(D_j(\nu), \nu) \ \text{ such that } \ D_j(\nu) = \overline{E} - D_{-j}(\nu),\ j = 1, \ldots, N_a, 1 \ldots, M. \tag{2.A.2}$$

The first order condition for this problem reads:

$$\frac{\partial \widehat{U}_j(D_j(\nu), \nu)}{D_j(\nu)} \left(- \frac{\partial D_{-j}(\nu)}{\partial \nu} \right) + \frac{\widehat{U}_j(D_j, \nu)}{\partial \nu} = 0,\ j = 1, \ldots, N_a, 1 \ldots, M \tag{2.A.3}$$

Substituting (2.A.1) in (2.A.3), grouping around ν and using the method of identifying coefficients, it yields:

$$\begin{aligned} y_f =& (1 - \kappa_f \Omega^2 y_f) y_{-f},\ y_{-f} = \sum_{i=1,\, i \neq f}^{Na+M} y_i,\ \forall f = 1, \ldots, N_a, \\ y_s =& (1 - \sigma^2 \rho_s \Omega^2 y_s) y_{-s},\ y_{-s} = \sum_{i=1,\, i \neq s}^{Na+M} y_i,\ \forall s = 1, \ldots, M. \end{aligned} \tag{2.A.4}$$

and

$$\begin{aligned} x_f =& \left(\bar{\lambda}^* - \kappa_f \Omega B_f \right) y_f,\ \ \forall f = 1, \ldots, N_a \\ x_s =& \bar{\lambda}^* y_s,\ \ \forall s = 1, \ldots, M. \end{aligned} \tag{2.A.5}$$

CEU eTD Collection

Chapter 3

Sunk-Cost Fallacy with Partial Reversibility: An Experimental Investigation

The research partially to this chapter was sponsored by Central European University Foundation, Budapest (CEUBPF). The theses explained herein are representing the own ideas of the author, but not necessarily reflect the opinion of CEUBPF.

3.1 Introduction

Normative economic theory indicates that only marginal costs and benefits should matter for decision making; therefore, costs incurred in the past are irrelevant for future marginal payoffs. Nevertheless, actual human behavior often violates this theory and people tend to account for historical costs. Thaler (1980) labeled people's failure to ignore sunk costs as the *sunk-cost effect*, also called *sunk-cost fallacy* or *Concorde fallacy* after the famous airplane development project of the British and French governments (Arkes & Ayton 1999).[1] In common language, the fallacy of sunk cost is the irrational behavior of "throwing good money after bad.", i.e. once found on a course of action to which they committed an investment (e.g. time, money, effort), people continue to stay on that course of action and invest even more resources despite it being unprofitable.

As Thaler (1980) points out, gathering field evidence to test the sunk-cost fallacy hypothesis is often hindered by problems of self-selection. Hence, evidence of the sunk-cost fallacy has been thus far limited to hypothetical scenarios and field experiments, while efforts for documenting

[1]Throughout, I will use these terms interchangeably.

CEU eTD Collection

it in laboratory are still surprisingly scarce and provide mixed evidence (Ashraf et al. 2010). On the one hand, hypothetical questions lack saliency and the subjects are always asked to *imagine* various scenarios based on which they *state* their decisions. On the other hand, field experiments are most of the time contextual and use real commodities (Harrison & List 2004). This interferes with subjects' unobserved Bayesian priors and experience in relation to the particular experimental context. At the same time, it is not unreasonable to conceive that (consumption) decisions in the field are rarely individual. Hence, rather than observing individual behavior, very often the experimenter observes a group behavior (e.g. family or couple), which is affected by the relative bargaining power in the group's decision making.

In this paper I design a lab experiment in which subjects fall into three different groups depending on the size of the cost they pay for entering an initial course of action, i.e. the sunk cost. This cost can be either zero or positive. If the cost is positive, then it can be either low or high. Once found on the initial course of action, the subjects are offered a possibility to *revert* from it, towards accomplishing a given experimental goal. Moreover, they are *explicitly* given the alternative course of action to the initial course of action, while the returns offered by each course of action are non-stochastic and known by the subjects. Therefore, the decision environment in this experiment is *void of ambiguity and uncertainty.*[2]

The experimental parameters set the full adoption of the alternative course of action and the total abandonment of the initial one as the rational choice. The results show a surprisingly small adoption of the alternative course of action even for those subjects who enter the initial course of action at no cost. This motivates the restriction of the analysis to subsamples which I conjecture to have a good comprehension of the experimental task. Under this restriction, indeed, I find that there is a significantly higher adoption of the alternative course of action in the group of subjects who entered the initial course of action free of charge relative to those who incurred a cost. In addition, cognitive ability appears to increase the treatment effect, i.e. higher cognitive ability subjects are more prone to the sunk-cost fallacy.

The motivation of this paper is twofold. On the one hand, as already discussed, the scarce and mixed evidence of the sunk-cost fallacy in lab experiments leaves room for more experimental work attempting to document the fallacy. On the other hand, the current study aims at shedding some light on the reasons behind its manifestation. The literature has identified several psychological channels for explaining the sunk-cost bias. First, *cognitive dissonance* makes it hard for people to admit they made wrong decisions in the past. Hence, in order to rationalize their past decisions they resort to *ex-post* self-justification by investing even more resources into an unprofitable course of action. Second, the literature on *ambiguity aversion* has pointed to the sunk-cost fallacy as being one of the anomalies generated by the

[2]For example, Tan & Yates (1995) find that the explicit specification of the expected future returns decreases the sunk-cost bias.

CEU eTD Collection

aversion to uncertainty (AlNajjar & Weinstein 2009). Third, Thaler (1980) used the prospect theory, specifically the *loss aversion*, to explanation why people fall pray to the sunk-cost fallacy. Instead, my experiment attempts to identify the sunk-cost fallacy in an environment void of these psychological drivers. Hence, the main contribution is that of showing that the previously acknowledged psychological channels for the manifestation of the sunk-cost fallacy are not necessary for the bias to make itself visible. Moreover, I suggest the *realization utility* (Barberis & Xiong 2012) as the most plausible mechanism behind its manifestation. The realization utility hypothesis suggests that people feel a burst of pain when a loss is realized and, therefore, avoid or delay the realization of this loss.

The experimental manipulation consists of three groups, which differ with respect to the sunk cost incurred: one control group and two treatments. Subjects in each group were asked to make decisions regarding two assets, the initial asset and the alternative asset. For the sake of exposition I shall label them as asset A and asset B, respectively. Each group was randomized between subjects, within each experimental session. The initial endowment of the control group consisted of 40 units of asset A and 900 Experimental Euros (EE). The treatment groups were endowed only with cash and, instead, were offered to buy the 40 units of asset A from the experimenter. Hence, they had to make a binary choice between buying the 40 units of asset A and not buying any unit of asset A. The two treatment groups represent two levels of sunk-cost, low and high sunk-cost, respectively. A subject in the low sunk-cost condition faced an ask price of 100 EE, while one in the high sunk-cost condition was asked 200 EE for each unit of asset A. However, before making their purchase decision the subjects were informed that they will be able to sell the 40 units back to the experimenter at the end of the session, for a price of 300 EE. This was meant to create a strong incentive for investment since it resulted in a sure profit of 200 and 100 EE, respectively by selling them back to the experimenter. The cash endowments for the treatment groups were chosen such that, if the subjects decided to buy the 40 units of asset A, after the purchase they were left with the same amount of cash as the initial cash endowment of the control group. Therefore, after the investment stage, the financial position of the subjects was the same across all groups: 40 units of asset A and 900 EE. This overcomes income effects in decisions.

The subjects who decided not to buy the initial asset kept their initial cash endowment and made no further decisions during the main sunk-cost experiment. Therefore, they were excluded from the sample of interest. Despite the strong incentive for buying the initial asset, there was still a small percent of subjects who preferred to keep the initial cash endowment. At this point, the reader might be concerned that this procedure introduces a self-selection problem. However, as I will argue, this is very unlikely to affect the results of the data analysis. First, it should be noted that at the time of the purchase decision the subjects did not know about the upcoming stages of the experiment. Therefore, their decision to buy the 40 units of the initial asset had no particular motivation, except that they could make a sure

CEU eTD Collection

profit. Second, the subjects who chose not to invest in the 40 units of asset A were asked to wait in the lab until the end of the session. Therefore, the opportunity cost of time is also excluded from the explanation of why some subjects chose not to invest. However, the only plausible explanation for choosing the status-quo is that they might have had a poor understanding of the experimental task or they preferred not to engage in further cognitive effort entailed by the continuation of the experiment.

After the endowment with the initial asset was completed, either free of charge or for a cost, subjects in all groups were informed that their task in the experiment was to collect exactly 50 units of asset A and/or B, in any combination. Moreover, they were told that assets A and B have the same redemption value. For achieving the 50 units of asset A and/or B, the subjects in all groups had one single opportunity to engage in trade with asset A. Thus, they could buy more units of asset A,[3] sell all or some of them up to the endowment of 40 units, or keep all 40 units. Following the subject's trading decision, any missing unit for achieving the 50 units was automatically filled with units of asset B. Each unit of asset B had a cost which was also known to the subjects. However, this cost was below the trading price of asset A, such that it made it optimal for the subjects in any treatment to sell all 40 units of asset A and buy the required 50 units of asset B. It should be pointed out that the trading price, which was given and known to the subjects before they made their trading decisions, was lower than either of the initial purchase prices, i.e. the sunk costs of the treatment groups. This allows for part of the initial investment to always remain sunk and to disentangle the rational motive for re-sale from the pure speculative one.

Hence, any extra unit bought from asset A is interpreted as escalation on the initial course of action, while any unit sold is a step towards deescalation. Therefore, the confirmation of the sunk-cost fallacy would have the two treatment groups re-sell more of the initial asset than the control group, while the low sunk-cost treatment would re-sell more than the high sunk-cost treatment. Thus, varying the cost of the initial asset across the two treatment groups allows to test whether the sunk-cost fallacy is related to the size of the investment or rather to the mere fact of making an investment.

The results show no sunk-cost effect on the sample as a whole. This is mainly due to the fact that a large number of subjects were status-quo biased in the control treatment. In fact, only 27% of the subjects in the control group recognized the optimal course of action, i.e. sold all 40 units of asset A. Moreover, the average units of asset B used by the control group was 22 units, which is significantly below the optimal number of 50. This raises the concern that many of the subjects had a poor understanding of the experimental task. Therefore, I perform post-hoc analysis on subsamples which I conjecture to have had a better comprehension of the experimental task. Indeed, this analysis reveals a clear sunk-cost effect. Precisely, there are

[3] Note that, given the target of 50 units, the maximum number of units of asset A one could buy was 10.

CEU eTD Collection

significant differences between the control group and each of the sunk-cost treatments, but the difference is not significant between the two sunk-cost treatments. This result suggests a sunk-cost effect which is independent of the size of the investment and it supports the finding of Ashraf et al. (2010) that paying something results in more use than paying nothing. In sum, conditional on understanding the experimental task, I find confirmation of the sunk-cost fallacy, even in the obvious and non-stochastic decision environment of this experiment, void of the previously acknowledged psychological roots of the bias.

Further, the suspicion that many subjects did not have a full grasp of the experimental task suggested a more detailed analysis of the effect of the cognitive ability, on the use of the alternative asset. The score of the cognitive ability test, which was administered as the second part of the experimental session, was used as a proxy for the comprehension of the experimental task. Indeed, regression analysis indicates that the cognitive ability score is a significant explanatory variable for the use of the alternative asset in the control group, i.e. predicts mistakes in decisions, which, under the design of this experiment it translated into status-quo bias rather than sunk-cost bias. Moreover, the analysis shows a statistically significant effect of the interaction between the treatment and the cognitive ability score. This points to the fact that high-cognitive ability subjects might be more prone to the sunk-cost bias. Note, however, that the manifestation of the bias is conditional on the understanding of the experimental task. Since the high-cognitive ability subjects were more likely to have understood the task, they were also more likely to exhibit the bias. Therefore, this last result should be regarded with caution and more treatments are needed to check its robustness.

Notwithstanding the fact that the results of this study might not be replicable, mainly due to subjects' poor understanding of the experimental task, they do open a discussion on the effect of the cognitive ability on the manifestation of the sunk-cost fallacy. To the best of my knowledge this explanation was not explored or accounted for in the previous experimental studies of the sunk-cost fallacy. This may also explain why the sunk-cost fallacy was not confirmed in other laboratory experiments or it was even found in reverse (e.g. Friedman et al. (2007)). The remainder of the paper is organized as follows. The next section presents the existing literature on the sunk-cost fallacy. In Section 3.3 I describe the experimental design and the procedure employed in the paper. Section 3.4 presents the data analysis and the results. In Section 3.5 I discuss some potential applications derived from the current design and Section 3.6 concludes.

CEU eTD Collection

3.2 Existing Literature

Arkes & Blumer (1985) is, perhaps, the most prominent paper documenting the sunk-cost fallacy. Their field experiment was able to capture differences in behavior among three groups of theater season tickets buyers, who were randomly chosen to pay different prices: full price and two levels of discounted prices. The experiment shows that those who paid the full price of the ticket visited the theater more often during the season than those who paid a discounted price. Further, using situational questionnaires, the paper ascertains that people with training in economics are not less prone to failing to ignore the sunk cost than those without economics training.

Considered to be the second field experiment investigating the sunk-cost fallacy, Ashraf et al. (2010) employ a randomized control trial in Zambia to test whether higher prices induce more product use. Their experimental design is able to isolate the sunk-cost effect from the self-selection effect, but they find no evidence of the sunk-cost effect, at least in the domain of health products used in their study. Their experimental manipulation is inspired by the unexpected random discount in the offer price manipulated by Arkes & Blumer (1985). However, unlike Arkes & Blumer (1985) and similar to my design, they also include a treatment with zero transaction price. Using this treatment they test the hypothesis of paying a positive price versus paying zero price and they find a sunk-cost effect, although not statistically significant. Interestingly, Ashraf et al. (2010) find evidence of the sunk-cost effect in households' answers to hypothetical questions, which is, however, inconsistent with households' actual behavior. This result seems to undermine the reliability of the findings from previous studies based on hypothetical questions, and reinforces the need for more laboratory experimental work in order to discriminate among the mixed evidence.

Further, Roodhooft & Warlop (1999) use hypothetical scenario questions in the field. They found that hospital managers significantly under-engage in outsourcing of catering services when they are told to imagine that prior to the decision of outsourcing, the hospital had an in-house production of meals. This effect is even stronger when they are told that in the event of outsourcing, they will have to make caterer specific investment. My design bears some similarities with their hypothetical Scenario 1 (the control) and Scenario 3 (the sunk-cost condition) in that it can also be applied to the decision to vertically disintegrate (e.g. holding the initial asset is equivalent to in-house production, while buying the alternative asset represents investment in switching to outsourcing). However, my design differs from their hypothetical scenario in two ways. First, outsourcing and in-house production can be used in combination, thus allowing to measure various degrees of the sunk-cost fallacy. Second, unlike in their scenario, my experiment allows for partially recouping the initial investment in the in-house production. The latter element should alleviate the sunk-cost fallacy.

It appears that most of the experimental literature investigating the sunk-cost fallacy makes use of contexts and situation, particularly in field studies where real goods are used. For this reason, the results obtained in such studies are rather confined to the context, the particular commodity used or the population treated. Along this line, Tan & Yates (1995) showed that

CEU eTD Collection

the decision to escalate on an initial course of action is sensitive to the context in which the problem is formulated. Again using hypothetical scenario questions, the authors show that students who had prior instructions in sunk-cost principles did ignore it when the context of the problem was similar to the textbook examples. However, they failed to do so when the decision reflected a real-life situation such as choosing between two resorts near Singapore. By contrast, my study attempts to examine the sunk-cost fallacy in a neutral environment, void of context, and thus void of *a priori* believes, preferences or learned norms.

I am aware of only three studies investigating the sunk-cost fallacy in laboratory. First, using lottery valuations as a measure of escalation of commitment, Phillips et al. (1991) show that when the sunk costs are made more transparent, they are more likely to be ignored. Nearly half of their subjects failed to ignore the sunk cost when this was not explicitly paid, but it was rather only a verbal commitment. However, only 19% of their subjects exhibited the bias when the sunk cost was made more salient through the physical act of paying the lottery ticket (the sunk cost in their experiment). In the same study they show that market forces can significantly alleviate the sunk-cost fallacy. Second, Friedman et al. (2007) devised a computer game to isolate factors which determine the sunk-cost fallacy. They asked subjects to use mouse clicks from a given budget of clicks in order to discover "treasures" on "islands" on which they arrived by paying a sunk cost, which can be either low or high. Their data fail to find a significant difference in the number of clicks on the "cheap" versus "expensive" islands. Most recently, Robalo & Sayagy (2013) document the manifestation of the sunk-cost fallacy on the use of information in decisions under risk. Their experiment shows that subjects over-weight costly information relative to free information and shift their beliefs towards extremes, which is not consistent with Bayesian updating. Finally, the authors argue that the loss aversion is a suitable explanation for the observed behavior of their subjects.

Apart from documenting the bias *per se*, the literature has also identified the main psychological drivers for the manifestation of the sunk-cost fallacy. These drivers are important if one intents to educate against the bias, since it is the cause rather than the symptom that one needs to treat. First, several studies argue that cognitive dissonance (or self-justification) is one root-cause for the manifestation of the fallacy. The reason is that people do not like to admit they made bad decisions in the past. Their need to appear rational to themselves and to others determines them to continue the initial course of action despite the slim chances of success, in order to justify their past decisions. Supporting this view, Staw (1976) finds that people are more committed to a previously chosen alternative if they are made responsible for that decision at an earlier point in time, especially if this prior decision had negative consequences. Similarly, Bazerman et al. (1984) find that being responsible for the existence of a sunk cost increases the amount of resources allocated for the continuation of the project, both at the individual and group level. Further, Arkes & Blumer (1985) found *ex post* rationalization of past decisions, i.e. the presence of the sunk cost generated inflated optimism. In

CEU eTD Collection

the same vein, Knox & Inkster (1968) find that horse-race betters are more optimistic about the chances of success of their favorite horse immediately after committing a bet on it than before they made the bet. However, my experiment is designed such that self-justification cannot be an explanation for the sunk cost fallacy. The main argument comes from the way the information is supplied to the subjects. Specifically, when they decide on incurring the sunk cost, the only information they have is that this investment produces a sure return at the end of the experiment. Moreover, this return is explicitly specified and known in advance by the subjects. Since there is no deceiving in the experiment, the decision to invest is not only *ex-ante* optimal, but also *ex-post*. Therefore, there is no reason for self-justification on the side of the subjects.

Second, in their theoretical study, AlNajjar & Weinstein (2009) argue that, in a dynamic setting, a decision maker with Ellsberg preferences fails to ignore sunk costs. This type of preferences is consistent with ambiguity aversion. The only experimental endeavor, of which I am aware, to explicitly investigate the role of the ambiguity aversion in leading people to honoring sunk costs is that of van Dijk & Zeelenberg (2003). However, they manipulate ambiguity with respect to the size of the sunk cost rather than with respect to the returns. They find that when the size of the sunk cost is ambiguous (no probabilities associated), the sunk-cost fallacy is lower compared to the case in which this size is specified. However, if ambiguity is manipulated with respect to the returns it is expected to increase people's tendency to account for sunk costs. Indeed, Tan & Yates (1995) find that the simple mentioning of the expected returns (the elimination of the ambiguity) reduces the sunk-cost bias. While the authors do not label this finding as being the effect of the ambiguity aversion, they discuss how the inclusion of information about the expected returns competes with the inclusion importance of the sunk cost such that it decreases its effect importance. Since everything is stated in deterministic terms, the design of my study is void of any ambiguity feature, both with respect to the sunk cost and the returns. Therefore, ambiguity aversion cannot account for the manifestation of the sunk cost fallacy in my experiment.

Finally, using prospect theory (Kahneman & Tversky 1979), Thaler (1980) explains how the psychic accounting system leads individuals to account for sunk costs. Because of the convexity of the utility function in the domain of losses, the decrease in utility from a loss is lower than the increase in utility from an equal-sized gain. Therefore, as Arkes & Blumer (1985) argue, once the decision-maker is found in the domain of losses, she will be willing to take further risks in the hope of an eventual gain, i.e. people are risk lovers in the domain of losses. The experimental design of the current paper does not put the subjects in the domain of losses, since after the initial investment their financial position is, in fact, higher than before the investment. Hence, my design also rules out the loss aversion as a root-cause of the sunk-cost fallacy.

CEU eTD Collection

3.3 Experimental Design

3.3.1 Treatments and parameters

Consider the situation in which a decision maker is pursuing a course of action towards achieving a given goal, at the time when she receives new information. At this point she learns that (i) for achieving the goal an alternative course of action is also available and (ii) she has the possibility of reverting from the initial course of action and partially recouping its investment. Given that according to the future costs and benefits it is optimal for the decision maker to abandon the initial course of action and adopt the alternative course of action, this experiment aims at investigating how much abandonment and how much adoption will occur. Failure to abandon the initial course of action is interpreted as sunk-cost fallacy, which, in this experiment, can occur in various degrees such that the sunk-cost fallacy can manifest itself in a continuous manner.

Formally, let us assume that there are two types of assets in the economy, asset A and asset B. The goal of the decision maker is to accumulate Q units of assets A and B in any combination. Furthermore, each asset has the same end unitary value p regardless of its type. Next, let us suppose that the decision maker has already invested in $A_0 < Q$ units of asset A for a unitary price p_0^A. Therefore, at the time of receiving new information the cost of purchasing the initial endowment of asset A, the amount $p_0^A A_0$, is sunk. When new information arrives, the decision maker learns that she can trade (sell or buy) units of asset A for a unit price p_1^A, and that she can buy units of asset B for the unit price p^B, such that she can collect the Q units. Let A_1 be the number of units of asset A she decides to sell ($A_1 < 0$) or buy ($A_1 > 0$), i.e. how much to revert from the initial investment and how much to escalate on the initial investment, respectively. Hence, the problem of the decision maker is to choose A_1 and B such that to maximize her payoff composed of the revenue from holding the Q units of asset minus the cost of buying units of asset B, minus the cost (plus the revenue) from trading the holdings of asset A and minus the sunk cost :

$$\begin{aligned} \max_{A_1,\, B} \Pi =& pQ - p_B B - p_1^A A_1 - p_0^A A_0 \\ & \text{such that} \\ Q =& A_0 + A_1 + B \\ A_1 \geq& - A_0 \text{ and } B \geq 0 \end{aligned} \tag{3.1}$$

It turns out that the problem has two corner solutions:

(i) if $p^B > p_1^A$, then $A_1 = Q - A_0$ and $B = 0$

(ii) if $p^B < p_1^A$, then $A_1 = -A_0$ and $B = Q$

CEU eTD Collection

Solution (i) says that it is optimal for the decision maker to keep the initial asset A and buy more units of this asset such that to complete the Q units. However, only solution (ii) predicts the abandonment of the initial investment, thus allowing to identify the sunk-cost bias. Therefore, the parameters of the experiment are chosen accordingly. Hence, the cost of the alternative course of action, p^B, was chosen to be lower than the re-sale price, p_1^A of the initial course of action. Moreover, in order for part of the initial investment to always remain sunk, this price must always be below the initial purchase price, i.e. $p_1^A < p_0^A$. The values of all experimental parameters are shown in Table 3.A.1 of Appendix 3.A.1.

The experiment consists of three manipulations regarding the unit price, p_0^A, of the initial investment in A, as shown in Table 3.A.1. While all treatments received the same number of units of asset A,[4] the price paid for each unit was different. Subjects in treatment groups T100 and T200 were given an initial cash endowment and were asked to invest part of this endowment in acquiring 40 units of asset A. They paid 100 and 200 Experimental Euros (EE), respectively, for each unit of asset A. Moreover, the initial investment was a sizable amount from the initial cash endowment, i.e. 80% and 90% for T100 and T200, respectively. These are the sunk-cost treatments. Subjects in the control treatment T0 received the endowment of 40 units of asset A free of charge. In order to avoid income effects, the initial cash endowments were such that, following the investment, subjects in all treatments had the same financial position: 40 units of asset A and 900 EE. Thus, apart from the free endowment of 40 units of asset A, subjects in treatment T0 also received a cash of 900 EE. This amount of cash was chosen such that to allow for the purchase of the extra 10 units of asset A to achieve the total of 50 units, in case the subject chose to fully escalate on the initial course of action.

Under the design of this experiment, the sunk-cost fallacy hypothesis can be formulated as follows:

Hypothesis 1 *Subjects in the control group* $T0$ *use more units of the alternative asset* B *than subjects in treatment group T100, who, in turn, use more units than those in the treatment group T200.*

Thus, the sunk-cost hypothesis is confirmed if the subjects in treatment T0 sell more units of the initial endowment than the subjects in treatment T100, who, in turn, will sell more than those in treatment T200.

[4] In order to avoid focal point effects or *a priori* preferences, assets' labels were randomized within treatments. Thus, in the same treatment, some subjects started with asset A and had B as the alternative asset, while other subjects started with asset B and had asset A as alternative. However, for the sake of exposition, I will continue using A for the initial asset and B for the alternative asset.

CEU eTD Collection

3.3.2 Procedure

Seven experimental sessions were conducted during December 2012 and April 2013 in the CESARE laboratory at LUISS Guido Carli in Rome. A total of 153 subjects participated in the experiment and they were recruited online through the ORSEE system (Greiner 2004), from the subjects pool of the laboratory composed of students at LUISS. The participants belonged to Economics, Business Administration, Political Science, Communication Science and Law majors, out of which 67% were Economics or Business students. No subject participated in more than one session, i.e. the analysis of the treatment effect is carried out in a between-subject design. There were between 18 to 26 subjects in each session, with an average of 22 subjects per session. Each experimental session lasted for approximately one and a half hour, including subjects' payment. The interface of the experiment was programmed in z-Tree (Fischbacher 2007). Snapshots of the experimental screens, containing the instructions, are presented in Appendix 3.A.2.

Upon arrival to the lab the subjects were randomly assigned to a working station. All subjects in the room saw the introductory screen in Figure 3.A.1. The instructions on this screen were read aloud by the experimenter. Subsequently the subjects followed the instructions on their respective screens and took their decisions individually. Every experimental session had three parts. The first part consisted of the main sunk-cost experiment. Subjects' payment for this part of the experiment was based on an exchange rate of 1500 EE for 1 euro. In the second part, all subjects (including those who chose not to invest in the main sunk cost experiment) answered the Holt & Laury (2002) (henceforth, HL) risk preference elicitation questions which were payment-incentivized (see Figure 3.A.8). One pair of lotteries was then randomly selected and the subjects were paid according to the lottery they chose in that pair. The exchange rate was 1000 EE for 1 euro. Finally, all subjects answered a cognitive quiz composed of five questions, with the value of 0.5 euro for each correct answer. The first three questions in the quiz consisted of the cognitive reflection test (CRT) (Frederick 2005) and the final two questions were selected from the math quiz in Benjamin et al. (2006). The complete quiz can be found in Appendix 3.A.3. Cumulative earnings from all three parts of the experiment ranged between 5.1 and 17.6 euro, with an average of 13.7 euro per subject. At the end of the experimental session the subjects answered demographic questions and they had the chance to give reasons for their trading decisions in the main sunk-cost experiment, in an open-answer question.

In the main sunk-cost experiment, the three treatments were randomized within sessions, with positive probability of each treatment, in each session. After the introductory screen, the subjects were presented with a screen in which they were informed about their initial endowments (see Figure 3.A.2). Thus, subjects in T0 were endowed with 40 units of asset A and 900 EE, while those in T100 and T200 were endowed *only* with cash in the amount of 4900

CEU eTD Collection

and 8900 EE, respectively (see Table 3.A.1). Unlike the subjects in T0, those in T100 and T200 had an additional screen in which they were offered to invest in exactly 40 units of asset A for a price of 100 and 200 EE respectively (see Figure 3.A.3). This was a take-it-or-leave it offer. If the subejcts chose to invest, they continued the experiment with further decisions. If they chose not to invest, they were asked to wait quietly in their seats until the end of the session. In order to make the investment salient, for those who invested the next screen in the experiment emphasized the change in their cash account and the holding of the 40 units of asset A (see Figure 3.A.4). In fact, during the whole experiment, the subjects could see their current financial position on the top-right corners of their screens.

Further, all subjects in T0 and those who invested in T100 and T200 faced the Trade decision (see Figures 3.A.5 and 3.A.6). At this stage they were told that they had to collect a total of 50 units of assets A and/or B, in any combination, and that they had the opportunity to trade (sell or buy) units of asset A, or keep the units they already posses. Trading was possible for a price which was randomly drawn from the uniform interval 50 to 90 EE, before they made their decision. The instructions emphasized that they had only one opportunity to trade and that asset B was automatically assigned given their trading decision such that in the end they would hold 50 units of assets A and/or B. Finally, the subjects were informed that each unit of asset B cost 30 EE and that the redemption value of each unit was 300 EE regardless of the type of asset, A or B. The experiment lasted for one period only.

3.4 Results

The data analysis is based on the sample composed of all subjects participating in the free treatment and those subjects in the sunk-cost treatments (T100 and T200) who decided to invest in the initial asset. I do not believe that this procedure poses any problem of self-selection for two reasons. First, the design creates a strong incentive for investment, since it was obvious that investing brings a sure profit. Second, at the time of the decision to invest the subjects were not aware of how and for what they could use the asset they bought. All they knew was that they could re-sell the asset for a higher price than the price paid for acquiring it. Nevertheless, out of the 105 subjects in the two sunk-cost treatments, 11 subjects (or 10%) still chose to keep the initial money endowment. The non-investors were significantly more in the T200, 8 out of 56, compared to 3 out of 49 in T100, reflecting the higher cash offered in this treatment but also the smaller profit from investing. One would expect risk aversion to be responsible for these subjects' decision of not investing, to the extent that they did not want to engage in a game of which they did not have enough information. However, this does not seem to be the case. Within the sample of non-investors, out of those who made consistent choices in the HL lotteries, only one subject exhibited risk aversion,

CEU eTD Collection

switching to the risky lottery only at the eighth pair. The majority of the subjects who did not invest were closer to risk neutrality, switching at the fourth or fifth pair. In fact, the sample of non-investors has on average a lower number of choices for the "safe" lottery than the sample who invested: 5.13 compared to 5.34. However, the only observable trait in which this sample seems to differ from that of those who invested, is the cognitive ability. Their average cognitive score was 2.27 correct answers as compared to 3.13 correct answers given by those who invested.[5] Hence, one possible explanation for the decision of not investing despite its obvious benefit, is the refusal to engage in the cognitive effort entailed by the continuation of the experiment. Thus, the decision to buy the asset is unrelated to the intention to use, and, therefore, this procedure should not impose concerns of self-selection.

Having established this, the final sample of analysis consists of 142 subjects distributed as 48, 46 and 48 subjects in T0, T100 and T200 respectively. The variable of interest for testing the hypothesis of this study is the number of units of asset B used by the subjects in their task of gathering 50 units of asset A and/or B. The possible values of this variable range from 0, indicating full escalation of commitment, to 50, meaning full abandonment of the initial course of action. Precisely, values from 0 to 10 indicate escalation of commitment (the subject's trading decision was to buy more units of the initial asset or passively keep them), while values from 11 to 50 indicate partial to full deescalation of commitment (the subject recognized the optimality of selling at least one unit of the initial asset). Hence, the set-up of this experiment allows for a continuous manifestation of the sunk-cost fallacy, in the sense that the subjects are not asked to fully abandon or fully escalate on the initial investment, but they can choose intermediate positions.

In the formal analysis I use the non-parametric Wilcoxon-Mann-Whitney (WMW) test and I report exact p-values. Corresponding to this test, the alternative hypothesis of my study is that the number of units used from the alternative asset by the T0 subjects is greater than that used by the T100 subjects, which, in turn, is greater than the number of units used by the subjects in the T200 condition. However, before proceeding to the main analysis, let us first notice whether there are any differences in subjects' individual characteristics across treatments. Descriptive statics by treatments are presented in Table 3.A.2 of Appendix 3.A.1. There are no significant differences among the three treatments with respect to the individual characteristics, except for the gender difference between T0 and T200 (WMW p-value$= 0.0371$).

Figure 3.A.9 in Appendix 3.A.4 shows the kernel density estimates of the distribution of the number of units of asset B used by each treatment. The first issue to note is that most of the subjects were unable to recognize the optimal decision. In fact, across all treatments, only 68% of the subjects used between 10 and 50 units of the alternative asset and only 18%

[5]Recall that the total number of questions in the cognitive quiz was 5.

CEU eTD Collection

recognized the optimal strategy of using 50 units. Next, it is readily visible that the subjects in T100 and T200 are more likely to have escalated on the initial commitment relative to those in the control treatment T0. Moving towards right, this order it reverted: the control treatment T0 has a higher likelihood of using units of the alternative asset closer to the optimal amount. However, only 27% of the subjects in the control treatment T0 chose to use the maximum possible number of units of the alternative asset and only 11% and 17%, respectively in treatments T100 and T200. At the same time, only 15% of the subjects in T0 escalated on the initial course of action by using 0 units of the alternative asset compared to 24% and 19% in treatments T100 and T200, respectively. These results show that there are slight treatment differences: those subjects who did not pay for their endowment of the initial asset were more prone to abandon the initial course of action and follow the alternative course of action compared to the sunk-cost treatments, T100 and T200.

Table 3.A.3 in Appendix 3.A.1 shows the averages of the units used from the alternative asset, as well as the averages of units sold (abandonment of the initial course of action) and bought (escalation on the initial course of action), by treatment.[6] While it appears that the subjects in the control treatment were more willing, on average, to disregard the sunk cost and embrace the alternative course of action (22.44 units in the control as compared to 15.7 and 19.46 units in the two treatment groups, respectively), non-parametric testing does not show statistically significant treatment differences. According to the 1-sided WMW test, there is a difference between T0 and T100 (p-value= 0.0277), but this does not carry over for T0 versus T200 (p-value= 0.2203). Moreover, when testing for the joint hypothesis that $T0 \geq T100 \geq T200$, the Jonckheere trend test fails to reject that the three samples come from the same population (1-sided p-value= 0.237). In sum, the hypothesis of the sunk-cost effect cannot be confirmed on the sample as a whole.

However, as in Ashraf et al. (2010), I conduct a test of whether there is an effect of a positive investment as opposed to zero investment, i.e. pooling T100 and T200 together and testing it against T0. Indeed, I find that, on average, the control treatment used the alternative asset more than the sunk-cost treatments together (22.44 units as opposed to 17.63 units) and this difference is statistically significant at 10% level (1-sided WMW test p-value= 0.061). This suggests that the sunk-cost fallacy might be a bias due to the mere fact of making an investment and not to the actual size of the investment. The effect seems to be somewhat stronger than the one found by Ashraf et al. (2010).

It should be noted that the weak result obtained on the sample as a whole might be due to several experimental implementation flaws and, therefore, it might not be robust to replications. First, the gender distribution on the three treatments is unbalanced, with the over-representation of males in the T200 treatment. Second, the English language proficiency of

[6] Column (1) is the mere consequence of columns (2) and (3), respectively.

CEU eTD Collection

the subjects is questionable.[7] Third, there is indication of low opportunity cost of subjects' time and low effort dedicated to the experimental task. Particularly, when asked to explain the reasoning behind their trading decision in the questionnaire administered at the end of the session, many subjects admitted that they had no specific motivation or that they made the decision randomly.[8] This together with the high percentage of status-quo subjects in the control treatment raise concerns regarding proper understanding of the experimental task by the subjects. Therefore, for the remaining of this section I conduct post-hoc tests on subsamples which I argue to be less affected by frivolous decisions and poor understanding of the experimental task.

3.4.1 Consistent HL lottery choices

One sensible way to account for frivolous decisions is to disregard from the analysis those subjects who made inconsistent choices[9] in the HL lottery menus for risk preference elicitation. Thus, in this subsection I use consistency in the HL lottery menus choices as a proxy for reliability of subjects' decisions in the main sunk-cost experimental. The rate of inconsistent choices in my sample is 27% (or 39 subjects out of 142), which is about twice as much as in the original HL study.[10] Charness & Viceisza (2011) find a very high percentage (about 75%) of inconsistency in the responses to the HL risk elicitation task among subjects in rural Senegal. The authors argue that this inconsistency is due to a low level of understanding of the task or frivolity in responses. Therefore, it seems reasonable to believe that those subjects who made consistent choices in the HL lottery menus, were also more likely to have made more conscious decisions in the main sunk-cost experiment. Those who made inconsistent choices, on the other hand, were more likely not to have taken the experimental task seriously due to a low opportunity cost of time or to have had a poor understanding of it.

The HL risk aversion questions were provided with real payment for one randomly selected pair of lotteries. Although this part of the experiment followed right after the main sunk-cost experiment, there is no evidence that the inconsistent answers were due to one treatment condition or another, i.e. no treatment driven "attrition". Indeed, the p-values of the WMW test of differences between T0 and T100, between T0 and T200, and between T100 and T200 regarding the inconsistent answers are 0.4964, 1 and 0.4964, respectively, indicating that

CEU eTD Collection

[7] Most of the subjects were Italian students and the ORSEE system for subjects recruitment did not give the experimenter the option to select students in English taught courses. However, the invitation to participate in the experiment was sent out in English and it explicitly stated that the understanding of the English language was a must.

[8] Among their answers I can quote: "I don't know", "It is a passion", "it was random", "curiosity", "for a new experience", "no reason".

[9] An inconsistent choice means switching from lottery A (the "safe" lottery) to B (the "risky" lottery) and back to A, or backwards choices switching from the "risky" to the "safe" lottery, or choosing lottery A in the last row of the menu. I classify those who chose only lottery B as consistent.

[10] Other studies show inconsistency between 10 and 15 percent (Charness & Viceisza 2011).

there are no distributional differences among the treatments with respect to the consistency of the lottery choices. Therefore, I can assume that the subjects with inconsistent HL choices are randomly distributed across the three experimental treatments and that the most likely explanation for their inconsistency is the low level of attention and/or effort exercised during the experiment.

Figure 3.A.10 in Appendix 3.A.4 shows the kernel distribution of the units used from the alternative asset, both for the subjects with consistent and those with inconsistent HL choices. While the inconsistent subjects do not exhibit a clear pattern, the subsample of consistent subjects shows treatment differences between the control and each of the treatment groups. Table 3.A.4 in Appendix 3.A.1 shows the treatment averages for the latter subsample as well as the number of subjects in each treatment. As it can be seen, the treatment groups are relatively balanced concerning the sample sizes and the treatment differences are sharper than on the sample as a whole. Precisely, the 1-sided WMW test shows that the number of units used of the alternative asset in the control group T0 is statistically larger, at conventional levels, than both those used by T100 and T200 groups (p-value=0.018 and p-value=0.056, respectively). The same test suggests no significant difference between T100 and T200 (p-value=0.481). This is in line with the findings based on hypothetical questions of van Dijk & Zeelenberg (2003), who found no statistical difference between their high and low sunk-cost groups. However, a test of the joint hypothesis that $T0 \geq T100 \geq T200$, rejects the null that the use of the alternative asset was the same across the three treatments (Jonckheere's trend test 1-sided p-value= 0.064).

Despite the fact that the size of the sunk cost does not appear to matter for the manifestation of the fallacy, the statistical difference between the control and the two treatment groups in the direction of the sunk-cost fallacy is surprising. One would expect that subjects who exhibit consistent preferences, in this case with respect to their risk attitudes, are also more likely to make rational decisions in other domains (Choi et al. 2011). Therefore, this post-hoc subsample selection should, in fact, invalidate the sunk-cost fallacy hypothesis of this study, which does not seem to be the case. Hence, taken together, these results indicate a sunk-cost effect which is independent of the size of the sunk cost, which leaves the hypothesis of this study only partially confirmed.

CEU eTD Collection

3.4.2 Cognitive ability

Similar to the previous subsection and making use of the cognitive score test administered in the third part of the experimental session, I conjecture that subjects with higher cognitive ability had a better understanding of the experimental task than those with low cognitive ability. Recall that the cognitive test involved real payment for each correct answer. It consists of five questions with the first three questions representing the cognitive reflection test (CRT) of Frederick (2005) while the final two are mathematical reasoning questions extracted from the cognitive quiz in Benjamin et al. (2006).[11] Hence, I split the sample in "low" and "high" cognitive ability according to the cognitive score of the 5-question cognitive quiz. I qualify the lowest 75th percentile (3 correct answers or less) as low-cognitive, and the highest 25th percentile (4 or 5 correct answers) as high-cognitive. Note that according to this manner of splitting the sample, a high-cognitive subject is one who answered correctly at least two questions of the CRT.

Figure 3.A.11 in Appendix 3.A.4 shows the kernel density functions of the units used from the alternative asset by treatment, separately for each of the two subsamples. Indeed, within the low-cognitive subsample there are no perceivable differences among the three treatments. Moreover, the average number of units used from the alternative asset is significantly below the optimal level in all treatments, including the control (see Table 3.A.5 in Appendix 3.A.1 for treatment averages and subjects' distribution across treatments). In fact, within the control group, there is a highly statistically significant difference between the low-cognitive and the high-cognitive group (WMW test p-value= 0.000). This reinforces the assumption that the low-cognitive group had a poor understanding of the experimental task. Therefore, this sub-sample does not appear suitable for the analysis of the treatment effect.

Focusing on the high-cognitive subsample it is easy to see that there are a few differences among the treatments. First, the distribution of the control group is shifted to the right, showing that, on average, this group made more use of the alternative asset than the two treated groups. Moreover, this distribution starts at 10 units, which indicates that subjects in this group recognized the optimality of switching to the alternative asset, even if they did not do it entirely. This does not hold for T100 and T200. Second, the share of the subjects who switched completely to the alternative asset is significantly higher in the control group than in any of the two treatments. These observations are confirmed by the WMW test. The p-values are provided in Table 3.A.6. They show a clear treatment effect of paying for the initial course of action as compared to the two treatment groups. However, as in the case of the analysis based on the sample of consistent HL answers, there is no statistical difference between the two sunk-cost treatments.

The results of this exercise also alleviate concerns of selection bias resulted from the existence of a group of subjects who chose not to invest. According to their cognitive score, these subjects would have fallen into the low-cognitive ability group had they invested. Therefore, they do not affect the results found for the high-cognitive subsample. Moreover, given their cognitive ability score, they are more likely to have had a poor understanding of the experimental task. Consequently, the extent to which the selection problem effects the overall results of the

[11] See Appendix 3.A.3 for the complete test.

CEU eTD Collection

experiment is that more subjects would have been status-quo biased and, thus, inconclusive for the analysis.

Summarizing, conditional on subjects' making conscious and non-frivolous decisions, the sunk-cost hypothesis of this study is partially confirmed. In particular, conditional on high cognitive level, there is a sunk-cost bias, which is, however, independent of the actual size of the initial investment. In Section 3.4.4 I investigate in more detail the role of the cognitive ability, using regression analysis.

3.4.3 Economists versus non-Economists

Because the literature has discussed the difference between the behavior of Economics versus non-Economics, or Accounting versus non-Accounting, students (Tan & Yates 1995, Arkes & Blumer 1985), I further split the sample according to the major of studies. In the "Econ" sample I include the subjects majoring in Economics or Business Administration and in the "non-Econ" sample I include all the other subjects. For each of these subsamples, Figure 3.A.12 in Appendix 3.A.4 shows the kernel distribution of the units used from the alternative asset. As this figure shows, for the subsample of Economists (N=92, distributed as 32, 26 and 34 on T0, T100 and T200, respectively) the treatment differences appear to be more consistent than on the sample as a whole. Indeed, the 1-sided WMW test shows significant statistical differences, suggesting that the subjects in the control condition T0 made use of the alternative asset more than both those in the T100 treatment (p-value= 0.045) and those in T200 treatment (p-value= 0.022), respectively. Consistent with the findings from the previous subsections, the test does not detect any difference between the two treatment groups, T100 and T200, reinforcing the idea that the sunk cost fallacy might be independent of the size of the sunk cost. Nevertheless, the multiple hypothesis testing using the Jonckheere trend test shows a significant trend in the use of the alternative asset across the treatments (1-sided p-value= 0.024).

Further, on the same subsample of Economists, I perform the test of paying nothing versus paying something, i.e. testing for the difference between the free condition (T0) and the sunk-cost condition (pooling T100 and T200 together), and I find a significant effect of a positive sunk cost (p-value= 0.015). This result suggests again, as in the case of the subsample of consistent HL choices, that the manifestation of the sunk-cost fallacy is independent of the size of the initial investment, at least on the subsample of Economists.

The subsample of non-Economists ($N = 50$), on the other hand, is distributed as 16, 20 and 14 subjects on the three treatments, T0, T100 and T200, respectively. Interestingly, this subsample shows a reverse sunk-cost effect. The T200 treatment has significantly higher values than the control (WMW p-value= 0.036) and the T100 treatment (WMW p-value= 0.004),

CEU eTD Collection

respectively, but the control and T100 treatment are not different from each other with respect to the number of units used from the alternative asset (2-sided WMW p-value= 0.3355). The surprising result among the subsample of non-Economists may be due to the unbalanced cognitive abilities across treatments within this subsample. The subjects in T200 seem to have significantly higher cognitive abilities than both those in T0 (WMW p-value= 0.025) and those in T100 (WMW p-value= 0.1095). No such differences exist on the subsample of Economists.

Finally, it should be noted that the "Econ" subsample has significantly higher cognitive abilities than the "non-Econ" subsample (WMW p-value= 0.013). Therefore, consistent with the conjecture from the previous subsection, it seems plausible to believe that the non-Economists might have been more confused by the experimental task, especially because it was formulated in the language of an economic problem, involving assets and prices. From this reason, the results obtained on the subsample of non-Economists should be regarded with caution and, instead, more confidence should be put on the results obtained on the subsample of Economists.

3.4.4 The role of cognitive ability

The previous non-parametric analysis pointed to the fact that cognitive ability may play a role in the manifestation of the sunk-cost fallacy. Therefore, in this subsection, I investigate this possibility, resorting to regression analysis. Cognitive ability has been found to be responsible for many behavioral biases such as the conjunction fallacy, anchoring, base rate fallacy, conservatism and overconfidence (Oechssler et al. 2009, Hoppe & Kusterer. 2011), but also for the risk aversion and impatience (Frederick 2005, Benjamin et al. 2006, Dohmen et al. 2010). However, to the best of my knowledge, there is no experimental evidence regarding the role of the cognitive ability on the manifestation of the sunk-cost bias.

Table 3.A.7 presents the regression results of the effect of the cognitive ability on the number of units used from the alternative asset. The specification in column (1) shows the conditional treatment effects after controlling for the cognitive ability, proxied by the normalized cognitive quiz score. As the non-parametric analysis from Subsection 3.4.2 showed, cognitive ability is responsible for mistakes in decisions. Since in this experiment mistakes can only induce less-than-optimal usage of the alternative asset, they can be confounded with the sunk-cost fallacy. Hence, after correcting for mistakes in decisions, the control group T0 appears to have used on average about 31 units of the alternative asset, which is still well below the optimal level of 50 units. Importantly, one standard deviation from the mean in the cognitive quiz score, reduces the mistake by 5 units and this is statistically significant.[12]. This suggests

[12]See the coefficient on "Cognitive" variable in Table 3.A.7

CEU eTD Collection

that people with higher cognitive ability are more likely to recognize the optimality of the alternative course of action, or more unlikely to make mistakes in decisions. The coefficients on T100 and T200 in column (1) show the treatment effects after controlling for cognitive ability. The negative signs of these coefficients show that there are, indeed, treatment effects in the expected direction. However, the coefficient is only marginally significant for T100 and insignificant for T200.

All these coefficients are robust to controlling also for the effort put in the experimental task, proxied by the time the subjects used to make their decisions in the "Trade" stage (see column (2)). This is a z-Tree recorded time and it includes the time used for reading the instructions in the "Trade" stage, cumulated with the time used for making their decisions at this stage. Although the effort variable turns out not to be statistically significant, it shows that putting more effort in making the decision leads to a greater use of the alternative asset, up to a turning point after which "over-thinking" leads to suboptimal decisions.

In column (3) I let the treatment effects vary with the cognitive ability. While the conditional treatment effects do not change significantly, the interaction terms of the treatment dummies with the cognitive quiz score show that the treatment effect increases in the cognitive ability. However, this result is driven by the fact that, as it was seen in the non-parametric analysis, the low-cognitive group did not exhibit any treatment differences, while being generally status-quo biased.

In equations (1) to (3) I considered the complete cognitive quiz, including both the CRT and the mathematics questions. In the specification from column (4) I consider only the CRT questions as a proxy for the cognitive ability. While most of the coefficients have the same significance and magnitude as in equation (3), the effect of the CRT score on the units used from the alternative asset is stronger than that of the complete cognitive quiz score.[13] This suggests that innate cognitive ability, which is better captured by the CRT test, is more important than learned cognitive ability which is quantified by the mathematics questions. Moreover, the coefficients of the interaction of the CRT score with the treatment dummies, are larger in magnitude than the corresponding coefficients in column (3). In addition, unlike in the specification including the score of the whole cognitive quiz, the effect of the cognitive ability on the sunk-cost bias of T200 turns out to be statistically significant, even if only marginally. Although the magnitude of the interaction coefficient with T100 is larger, a test of equality between the two coefficients fails to reject that the coefficients on the interaction terms of the treatment dummies with the CRT score are equal. The interaction terms show that, within the T100 treatment, one standard deviation above the mean in the CRT score is equivalent to the use of additional 1.2 units from the alternative asset. Similarly, within the

[13]Including both score of cognitive ability, the coefficient on the mathematics questions was not found significant.

CEU eTD Collection

T200 treatment, one standard deviation above the mean of the CRT score induces the use of additional 4.6 units of the alternative asset.

In sum, conditional on the cognitive ability, there is a treatment effect, which is higher in magnitude and significant for the T100 treatment than for the T200 treatment. Moreover, cognitive ability was found to be both economically and statistically significant for predicting mistakes in decisions. At the same time, higher cognitive ability subjects seem to be more prone to the sunk-cost effect. While this result seems to be the counterpart of the findings in the literature according to which infants and animals do not exhibit the sunk cost bias (Arkes & Ayton 1999), it must be regarded with caution. Due to the large number of subjects who seem to have had difficulties with understanding the experimental task, two competing explanations account for this result. First, it might, indeed, be the case that high-cognitive people misused the "don't waste" rule (Friedman et al. 2007). Second, exactly because they understood the experimental task better, the high cognitive ability subjects were more likely to exhibit the bias. The latter explanation is particularly appealing since, under the design of this experiment, mistakes due to the lack of understanding of the experimental task can only result in sub-optimal use of the alternative asset.

3.4.5 Discussion

Despite the difficulty with subjects' understanding of the experimental task, the results of this experiment showed indication of the manifestation of the sunk-cost fallacy. Moreover, the bias made itself visible even under the experimental design sterile of the interference of its psychological drivers previously acknowledged by the literature. Hence, my study showed that ambiguity, cognitive dissonance and loss aversion are not necessary for the subjects to exhibit sunk-cost fallacy. Instead, the most likely explanation for the manifestation of the sunk-cost fallacy under the current experimental design can be adapted from the *realization utility* theory developed by Barberis & Xiong (2012). According to the authors, people feel a burst of pleasure when a gain is realized and a burst of pain when a loss is realized. In other words, people do not derive utility only from consumption of goods and services, as economic models often assume, but also from the mere act of selling an asset at a gain, right in the moment of executing the sale. This theory was confirmed in an experimental stock market by Frydman et al. (2012) who scanned subjects' brain activity at the moment of submitting their trading decisions.

Realization utility theory has been proven suitable for explaining the disposition effect in investors trading behavior, i.e. the greater propensity to sell a stock which increased in value relative to the purchase price and hold on to those which decreased in value relative to the purchase price. This is due to the fact that people do not think of their investment

CEU eTD Collection

history in terms of returns over the whole portfolio, but rather as separate investment episodes characterized by the name of the asset, the purchase price and the re-sale price (Barberis & Xiong 2012). This comes close to explaining why subjects in my experiment were reluctant to part with the initial asset when offered a price below their purchase price. Apparently, from the desire of avoiding the pain from the direct act of selling the initial asset for a loss (relative to the purchase price), the subjects were trapped into an unprofitable course of action, i.e. trapped into the sunk-cost fallacy. This theory is also in line with the results of an earlier experiment by Staw (1976), who found that people would invest more in a course of action with negative consequences (holding on an asset which decreased in value) than in one for which their prior decisions proved successful (parting with an asset which increased in value).

The partial reversibility nature of the investment is the element of the experimental design that makes realization utility the most pertinent explanation for the manifestation of the sunk-cost fallacy. While the experimental literature has not emphasized this element thus far, it is, nevertheless a realistic possibility. Below I discuss two such possibilities in which the investment in the initial course of action can be partially recouped and I illustrate the manifestation of the sunk cost fallacy in each situation.

3.5 Applications

The experimental design of the current study has several applications. First, the design applies straightforwardly to a practical problem related to carbon emissions trading schemes (ETS). In such schemes, the environmental agency distributes a number of permits to the regulated firms. Most commonly, the allocation can be free of charge for the emitters or through an auction. Hence, in the latter case the regulated firms have to pay for the emissions permits received. After the allocation is completed, firms can trade the permits among themselves in a secondary market. The experimental design of this paper captures the differences in trading behavior when carbon emissions permits are distributed for free as opposed to auctioning. Let us imagine that the polluter (the manager or trader of an energy company) invests in buying emissions permits when these are distributed in an auction. In terms of the design of this experiment this is equivalent to investing in the initial asset. Let us further suppose that a market for these permits opens and that also some emissions reductions technology becomes available. In the language of the experiment, this is to say that the initial asset can be sold and the alternative asset becomes available. Assuming the situation from the experiment, where the alternative asset (the emissions reduction technology) is cheaper than the re-sale price of the initial asset (the emissions permits), sunk-cost fallacy would result in sub-optimal adoption of the emissions reduction technology. By contrast, free allocation would provide a closer to optimum adoption of the emissions reduction technology.

CEU eTD Collection

Since different methods of initial allocation, particularly free allocation versus auctioning, can lead to different actual initial allocations, it turns out that even with frictionless markets, the distribution of property rights matters. Therefore, contrary to Montgomery (1972), the efficient equilibrium will not be achieved if managers are biased towards honoring previous investment in emissions allowances instead of recognizing the possibly cheaper emission reduction options or fuel switches. This will undermine the overall goal of an emissions trading scheme that is to spur green technologies. The results of this paper suggest that such concerns might not be undue.

Second, consider the situation of the decision to vertically integrate. The following case is close to the design of the experiment in this paper. Assume a vertically disintegrated company which has a contractual relationship with a supplier of an intermediate good. The supplier delivers the stock of the intermediate good at time t, according to the contract. At time $t+1$, the head of the R&D department informs the manager of the company that the intermediate good can now be produced in-house and that the company already has the necessary technology, i.e. no additional investment is needed. Moreover, the in-house production can be done at a lower unit cost than the contracted price.[14] However, the contractual relationship cannot be broken immediately, such that the supplier will continue to deliver the intermediate good until $t+2$. Hence, the price contracted for the delivery is the sunk cost. Nevertheless, a market for the intermediate good exists, such that the company could sell the current and future stocks of the intermediate good until $t+2$. Importantly, the market price is above the in-house production cost, but below the contracted price.[15] Hence, apart from the short-run needs until the in-house production is set-up, the optimal decision of the manager would be to sell the intermediate goods supplied through the contract rather than using it in the production. Instead, the final output could be produced using the intermediate good from the internal production. If, however, the manager fails to recognize this alternative and delays the in-house production until $t+2$, when the contractual relationship with the supplier can be broken, then she had fallen into the trap of the sunk-cost fallacy.

3.6 Conclusions

The experiment of this paper documented the sunk-cost fallacy in a laboratory setting. Despite the simplicity of the design, the results showed that subjects had difficulties in finding the optimal course of action. The control group, in which no sunk cost was incurred, used on average about 30 units of the alternative asset, which is well below the optimal level of 50

[14]This could also be regarded as a transfer price from a producer which is part of the same business group.

[15]This last assumption may seem unrealistic, but could be somewhat justified by the fact that the outsourcing contracts are signed for longer periods during which the market conditions could change, i.e. forward contracts which are common, for example, in the supply of electricity.

CEU eTD Collection

units.

While this study fails to confirm a sunk-cost bias on the entire sample of subjects, it does find evidence of the sunk-cost effect on subsamples which I argue to have a better comprehension of the experimental task, i.e. the subsample of subjects with consistent risk preferences, with high cognitive ability or Economics and Business majors. Thus, provided that the experimental task is well understood by the subjects, this experiment found manifestation of the sunk-cost fallacy, despite the obviousness of the alternative course of action, the deterministic decision-making environment and the partial reversibility of the initial investment, which characterize the design of this experiment. However, the sunk-cost fallacy was found to be independent of the size of the sunk cost. This confirms the findings of other studies that paying something results in more use that paying nothing. Finally, because the previously acknowledged psychological factors responsible for the sunk-cost bias are missing from the design of my experiment, it turns out that they are not needed for the sunk-cost fallacy to make itself visible. Instead, due the nature of the experimental design employed in this paper, in which the initial investment can be partially recouped, I put forth the realization utility as the most likely psychological phenomenon responsible for the bias.

Although the results of this study might not be robust to replications, particularly due to subjects' poor understanding of the experimental task, they open the question of the effect of the cognitive ability on the manifestation of the sunk-cost fallacy. The regression analysis conducted in this paper showed that after controlling for the cognitive ability and the effort put in the experimental task, cognitive ability continued to have the effect of increasing the sunk-cost bias. In other words, high cognitive ability subjects are more sunk-cost biased. While this result seems counter-intuitive, it appears to be the counterpart of the evidence that animals and infants are not prone to the sunk cost-fallacy. However, there is an alternative interpretation to this results. In particular, the high cognitive ability subjects are more likely to understand the experimental task and, for this reason, they are also more likely to exhibit the bias. While at this point the two interpretations cannot be disentangled, more research effort it worth putting into understanding the relationship between the sunk-cost bias and cognitive ability.

Hence, several extensions and refinements of the design merit consideration for further research. First, in order to avoid noisy decisions, the manifestation of the sunk cost could be made discontinuous. In this situation, subjects would be given the option to choose between buying 10 units of the initial asset or selling the 40 units of the initial asset. Second, in the sunk-cost treatments T100 and T200, after the investment stage is completed, the subjects could be asked the unit price for which they bough the asset. This would have the effect of both making the investment more salient and checking whether the subjects understood the instructions. For the same purpose, in a final questionnaire, the subjects would be asked to

CEU eTD Collection

remember the price for which they had bought the initial asset. This could allow the experimenter to verify whether the memory of the sunk cost is part of the information set of the subjects at the time of the trading decision. In the absence of this memory it would be hard to argue that decisions which appear to take into account the sunk cost are a consequence of a fallacy rather than a simple decision error. Finally, one should allow for learning. Allowing for multiple periods would give subjects the opportunity to learn disregarding the sunk cost in decision-making. This is in itself an important research question, since real-life problems give people the opportunity to learn the optimality of their decisions by repeatedly facing similar situations and observing the outcome of their decisions. Relatedly, in order to enhance the understanding of the experimental task, the experimenter could run a trial round in which all subjects are in the control condition.

CEU eTD Collection

3.A Appendix

3.A.1 Tables

Table 3.A.1: Experimental parameters

Treatment	T0	T100	T200
p_0^A (EE)	0	100	200
Initial cash (EE)	900	4900	8900
A_0 (units)	40	0	0
Q (units)	50	50	50
p_1^A (EE)	uniformly distributed between 50 and 90		
p^B (EE)	30	30	30
p (EE)	300	300	300

Table 3.A.2: Descriptive statistics for the sample who invested

Treatment	T0	T100	T200	Total
N	48	46	48	142
Economics or Business students	67%	57%	71%	65%
Males	48%	54%	71%	58%
Initial asset called "A"	52%	50%	58%	54%
Consistent answers to the HL questions	75%	68%	75%	73%
Risk aversion (average "safe" lotteries)	5.38	5.43	5.29	5.37
Average correct answers to the cognitive quiz	2.67	3.13	3.12	2.97

Table 3.A.3: Decision variables: all sample

	N	Use of alternative asset	Sales of the initial asset	Purchases of the initial asset
		(1)	(2)	(3)
T0	48	22.44 (2.74)	14.21 (2.48)	1.77 (.52)
T100	46	15.70 (2.43)	9.11 (2.03)	3.41 (.63)
T200	48	19.46 (2.54)	11.65 (2.24)	2.19 (.57)

Note: Standard errors in parentheses

CEU eTD Collection

Table 3.A.4: Averages for the subsample of consistent HL lottery choices

	N	Use of the alternative asset	Sales of the initial asset	Purchases of the initial asset
		(1)	(2)	(3)
T0	36	26.02 (3.17)	17.22 (2.93)	1.19 (0.53)
T100	31	16.90 (2.99)	10.06 (2.48)	3.16 (0.8)
T200	36	19.69 (3.03)	11.92 (2.69)	2.22 (0.67)

Note: Standard errors in parentheses

Table 3.A.5: Averages of units used from the alternative asset by cognitive level

	Lowest 75th percentile		Highest 25th percentile	
	N	Units of alternative asset	N	Units of alternative asset
T0	36	16.33 (2.68)	12	40.75 (4.30)
T100	25	14.32 (3.09)	21	17.33 (3.91)
T200	30	16.77 (2.70)	18	23.94 (5.00)

Note: Standard errors in parentheses

Table 3.A.6: Non-parametric test of treatment differences by cognitive level

Cognitive level	H0: T0=T100	H0: T0=T200	H0: T100=T200
High	0.0005	0.011	0.158
Low	0.269	0.362	0.171

Note: 1-sided p-values of the Wilcoxon-Mann-Whitney test are reported

CEU eTD Collection

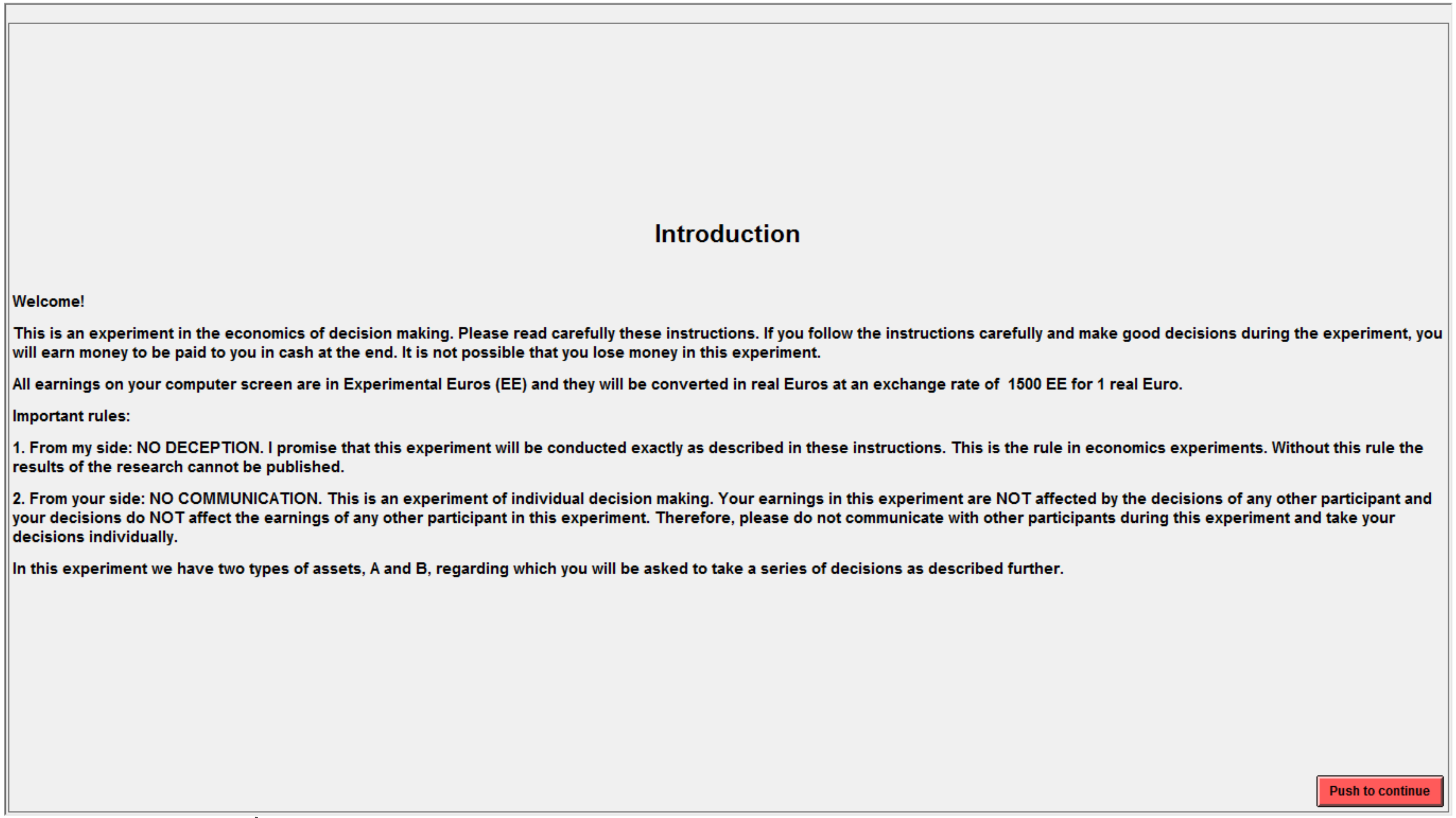
Table 3.A.7: The effect of the cognitive ability

Dependent variable:	Units of the alternative asset			
	(1)	(2)	(3)	(4)
Constant	31.38***	27.86***	30.56***	30.47***
	(4.651)	(6.434)	(6.581)	(6.221)
Cognitive	5.183***	5.083***	8.844***	
	(1.425)	(1.453)	(2.120)	
CRT				10.49***
				(2.160)
T100 X Cognitive			-7.367**	
			(2.919)	
T200 X Cognitive			-4.586	
			(3.772)	
T100 X CRT				-9.296***
				(3.091)
T200 X CRT				-5.889*
				(3.487)
T100	-8.239*	-8.330*	-8.734**	-8.511**
	(4.423)	(4.487)	(4.368)	(4.286)
T200	-1.949	-2.230	-2.930	-2.670
	(3.923)	(4.113)	(4.127)	(4.032)
Time		2.267	1.573	1.282
		(4.073)	(4.210)	(4.036)
Time sq.		-0.156	-0.0388	-0.00632
		(0.623)	(0.646)	(0.615)
Session dummies	Yes	Yes	Yes	Yes
Observations	142	142	142	142
R-squared	0.148	0.157	0.185	0.209

Note: Heteroskedastic robust standard errors in parentheses. The control group T0 is the omitted category. "Cognitive" and "CRT" are the standardized scores for the 5-question cognitive score and the cognitive reflection test score, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

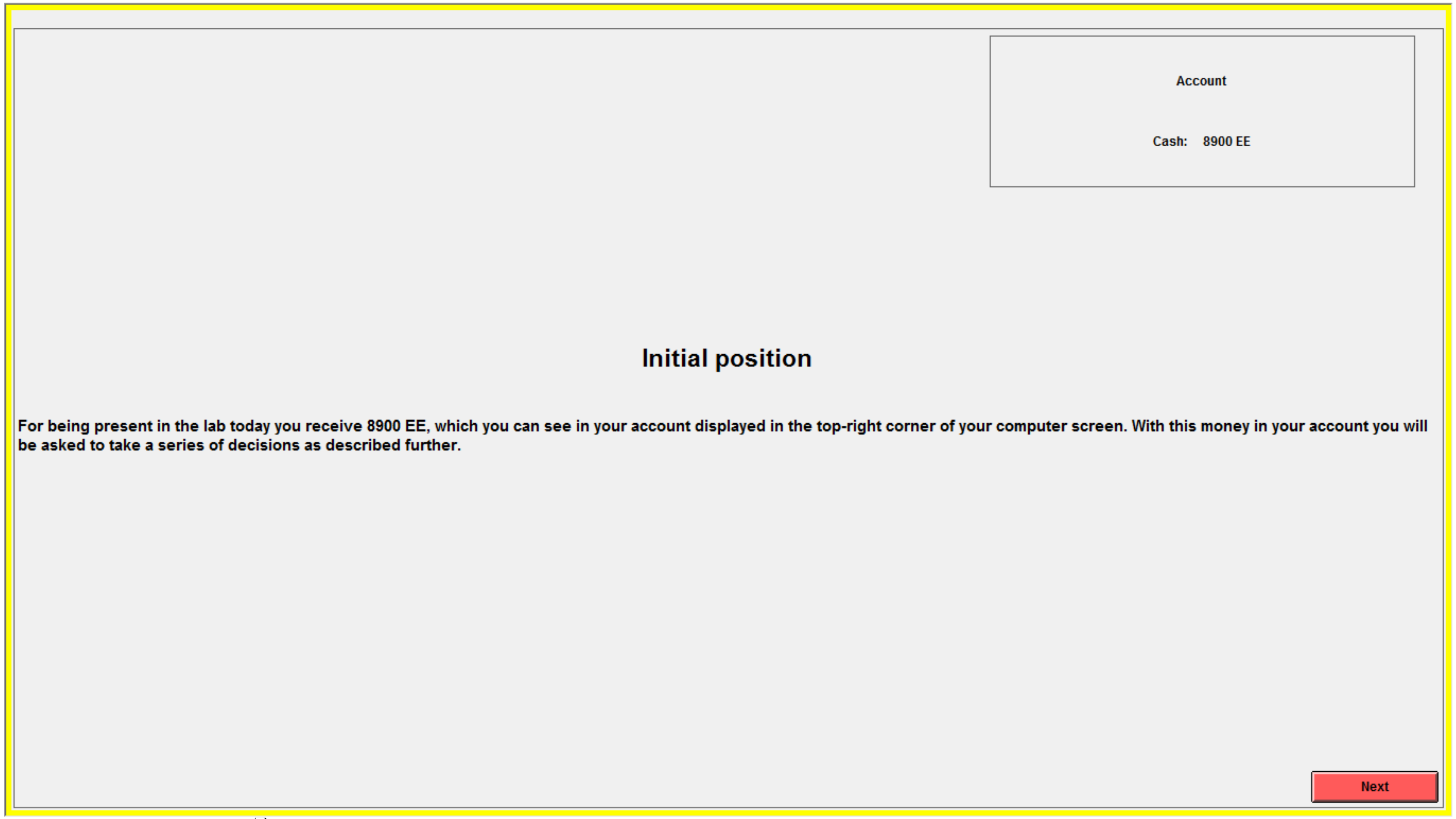
CEU eTD Collection

3.A.2 Instructions Screens



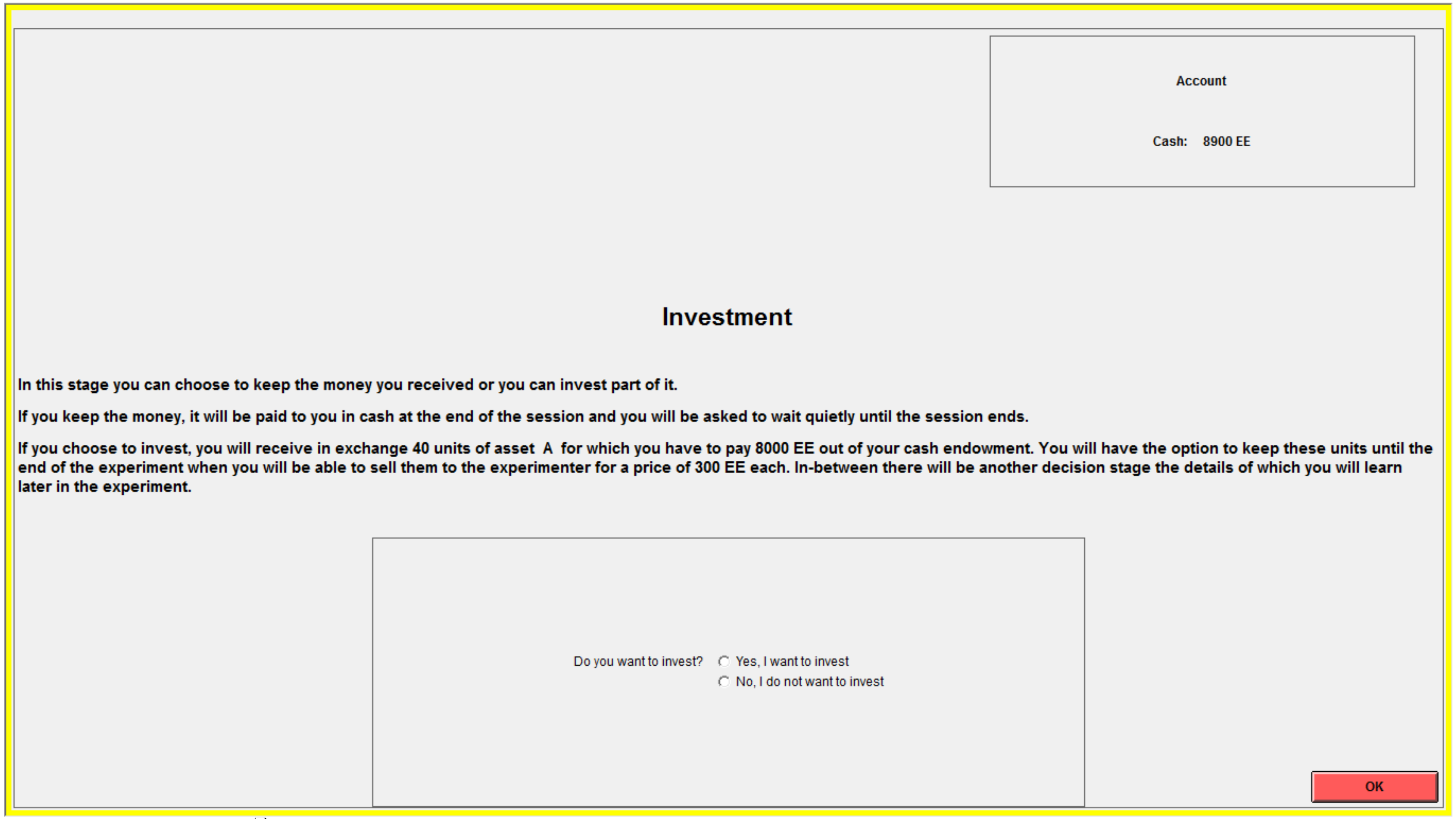
CEU e

Figure 3.A.1: Introduction Screen



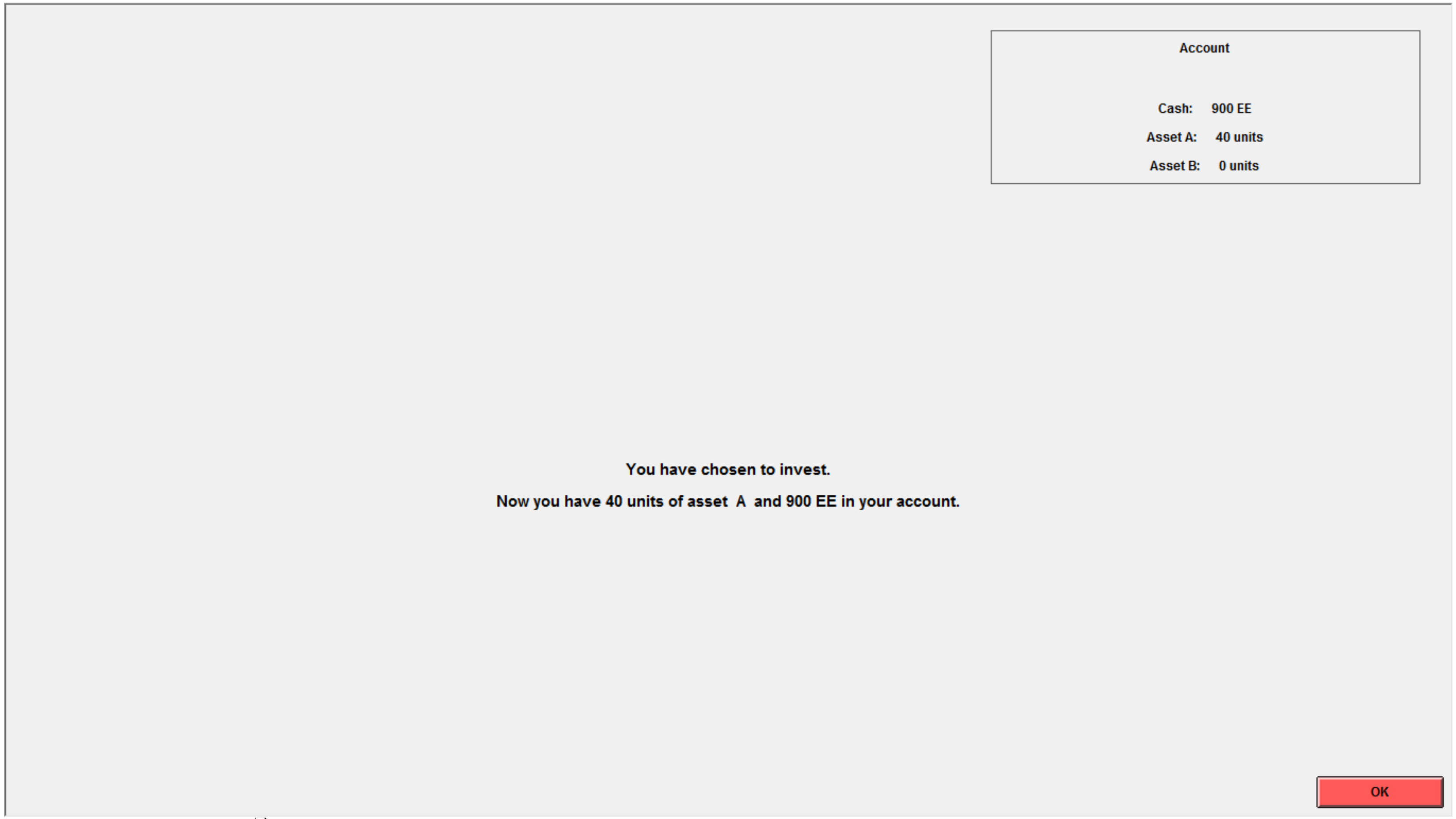
CEU

Figure 3.A.2: Initial position Screen



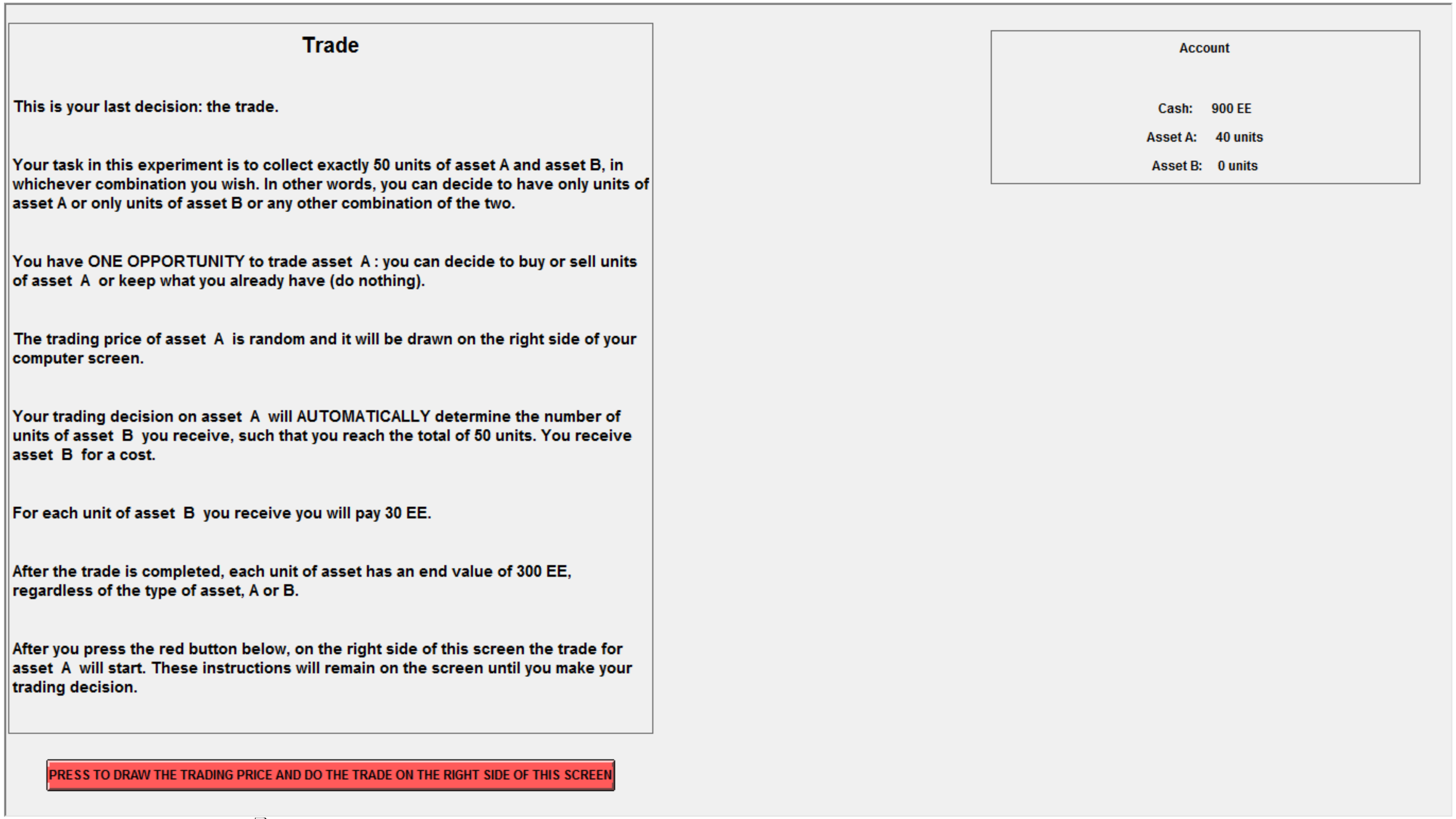
CEU

Figure 3.A.3: Investment Screen



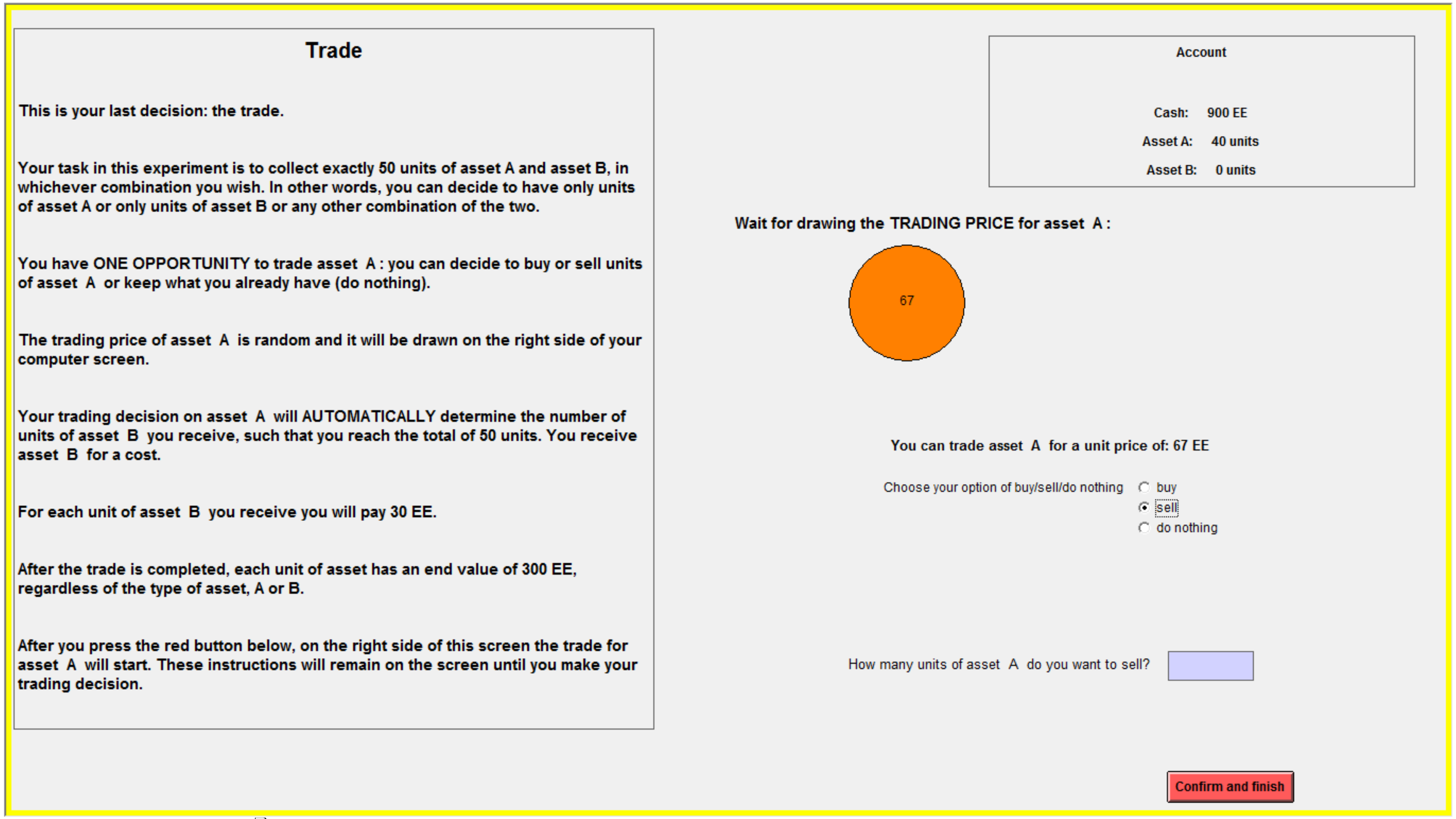
CEU

Figure 3.A.4: Financial position after investment Screen



CEU

Figure 3.A.5: Trade 1 Screen



CEU

Figure 3.A.6: Trade 2 Screen

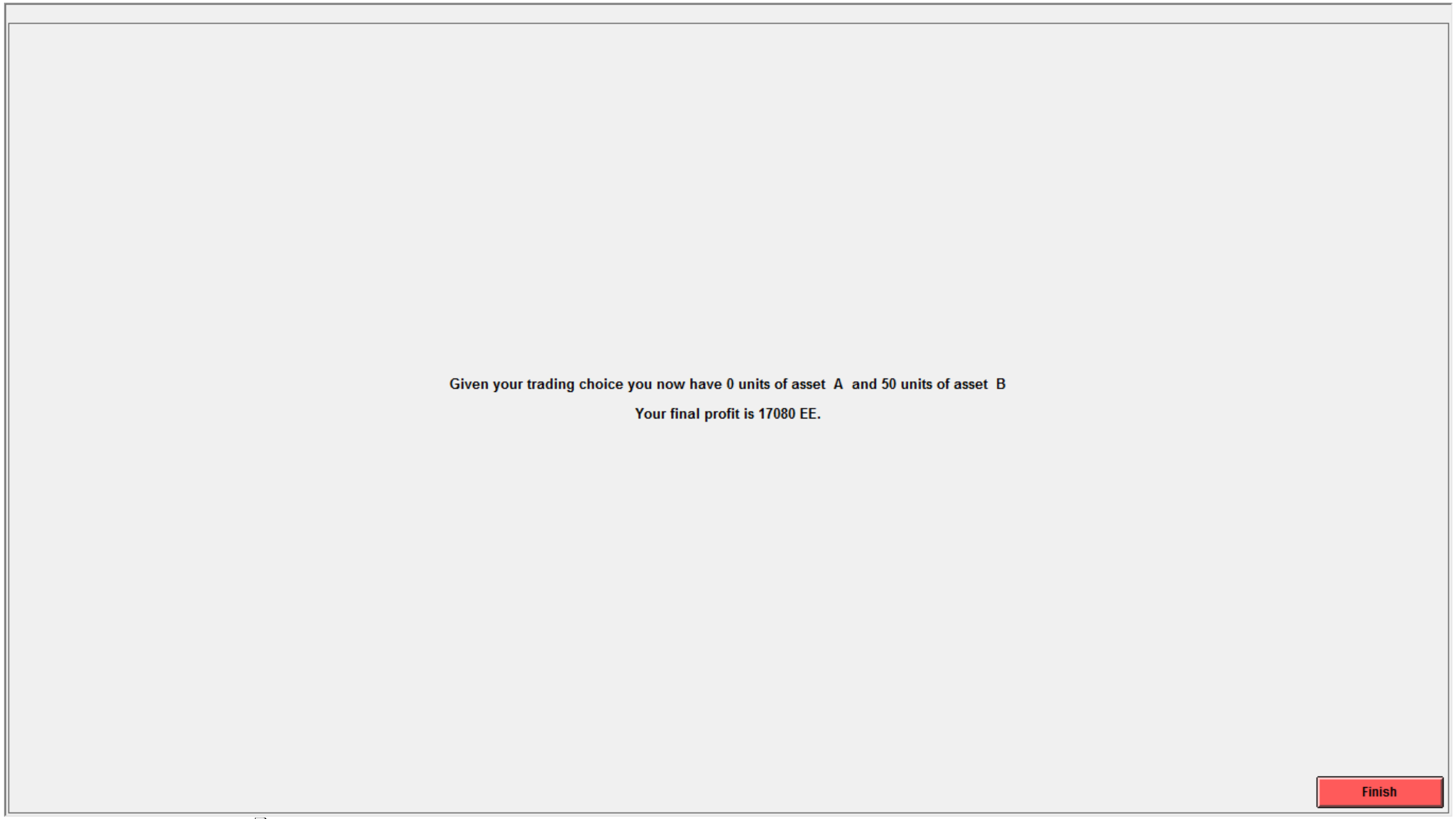
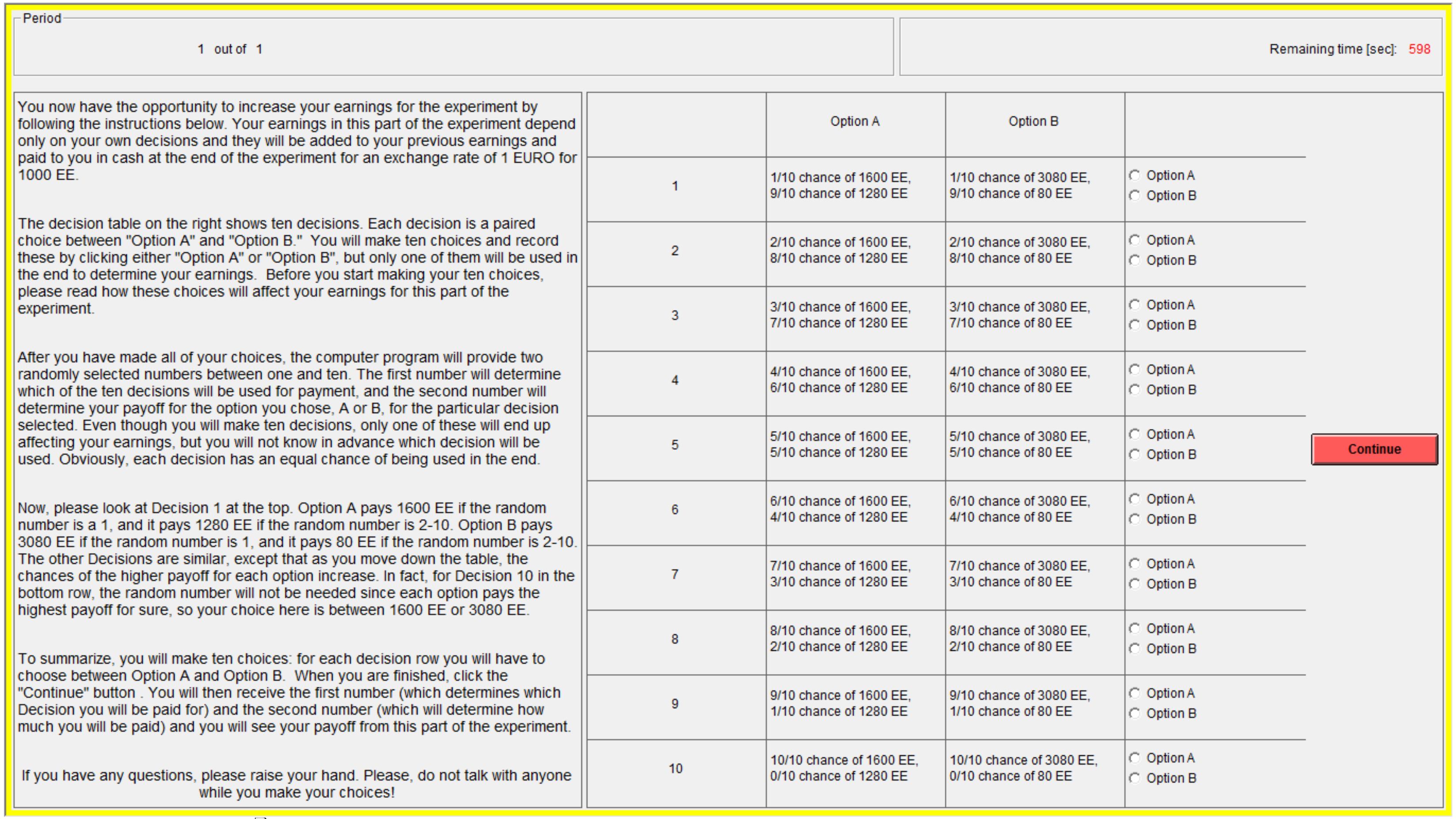


Figure 3.A.7: Profit Screen

CEU



Period

1 out of 1

Remaining time [sec]: 598

You now have the opportunity to increase your earnings for the experiment by following the instructions below. Your earnings in this part of the experiment depend only on your own decisions and they will be added to your previous earnings and paid to you in cash at the end of the experiment for an exchange rate of 1 EURO for 1000 EE.

The decision table on the right shows ten decisions. Each decision is a paired choice between "Option A" and "Option B." You will make ten choices and record these by clicking either "Option A" or "Option B", but only one of them will be used in the end to determine your earnings. Before you start making your ten choices, please read how these choices will affect your earnings for this part of the experiment.

After you have made all of your choices, the computer program will provide two randomly selected numbers between one and ten. The first number will determine which of the ten decisions will be used for payment, and the second number will determine your payoff for the option you chose, A or B, for the particular decision selected. Even though you will make ten decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used. Obviously, each decision has an equal chance of being used in the end.

Now, please look at Decision 1 at the top. Option A pays 1600 EE if the random number is a 1, and it pays 1280 EE if the random number is 2-10. Option B pays 3080 EE if the random number is 1, and it pays 80 EE if the random number is 2-10. The other Decisions are similar, except that as you move down the table, the chances of the higher payoff for each option increase. In fact, for Decision 10 in the bottom row, the random number will not be needed since each option pays the highest payoff for sure, so your choice here is between 1600 EE or 3080 EE.

To summarize, you will make ten choices: for each decision row you will have to choose between Option A and Option B. When you are finished, click the "Continue" button . You will then receive the first number (which determines which Decision you will be paid for) and the second number (which will determine how much you will be paid) and you will see your payoff from this part of the experiment.

If you have any questions, please raise your hand. Please, do not talk with anyone while you make your choices!

	Option A	Option B	
1	1/10 chance of 1600 EE, 9/10 chance of 1280 EE	1/10 chance of 3080 EE, 9/10 chance of 80 EE	Option A Option B
2	2/10 chance of 1600 EE, 8/10 chance of 1280 EE	2/10 chance of 3080 EE, 8/10 chance of 80 EE	Option A Option B
3	3/10 chance of 1600 EE, 7/10 chance of 1280 EE	3/10 chance of 3080 EE, 7/10 chance of 80 EE	Option A Option B
4	4/10 chance of 1600 EE, 6/10 chance of 1280 EE	4/10 chance of 3080 EE, 6/10 chance of 80 EE	Option A Option B
5	5/10 chance of 1600 EE, 5/10 chance of 1280 EE	5/10 chance of 3080 EE, 5/10 chance of 80 EE	Option A Option B
6	6/10 chance of 1600 EE, 4/10 chance of 1280 EE	6/10 chance of 3080 EE, 4/10 chance of 80 EE	Option A Option B
7	7/10 chance of 1600 EE, 3/10 chance of 1280 EE	7/10 chance of 3080 EE, 3/10 chance of 80 EE	Option A Option B
8	8/10 chance of 1600 EE, 2/10 chance of 1280 EE	8/10 chance of 3080 EE, 2/10 chance of 80 EE	Option A Option B
9	9/10 chance of 1600 EE, 1/10 chance of 1280 EE	9/10 chance of 3080 EE, 1/10 chance of 80 EE	Option A Option B
10	10/10 chance of 1600 EE, 0/10 chance of 1280 EE	10/10 chance of 3080 EE, 0/10 chance of 80 EE	Option A Option B

Continue

Figure 3.A.8: Holt and Laury risk aversion questions

CEU

3.A.3 The Cognitive Quiz

The CRT questions:

Question 1: An apple and an orange cost \$1.10 in total. The apple costs \$1.00 more than the orange. How much does the orange cost (in \$)?

Question 2: If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets (in minutes)?

Question 3: In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake (in days)?

The math questions

Question 4: Half of $-[-a + (b - a)]$ equals:

(A) $a - b/2$
(B) $a + b$
(C) $2a - b$
(D) $2a + 2b$
(E) $-a - b$

Question 5: If $x = y - 2$ and $xy = 48$, which of the following CANNOT equal either x or y?

(A) 6
(B) 8
(C) 12
(D) -6
(E) -8

CEU eTD Collection

3.A.4 Figures

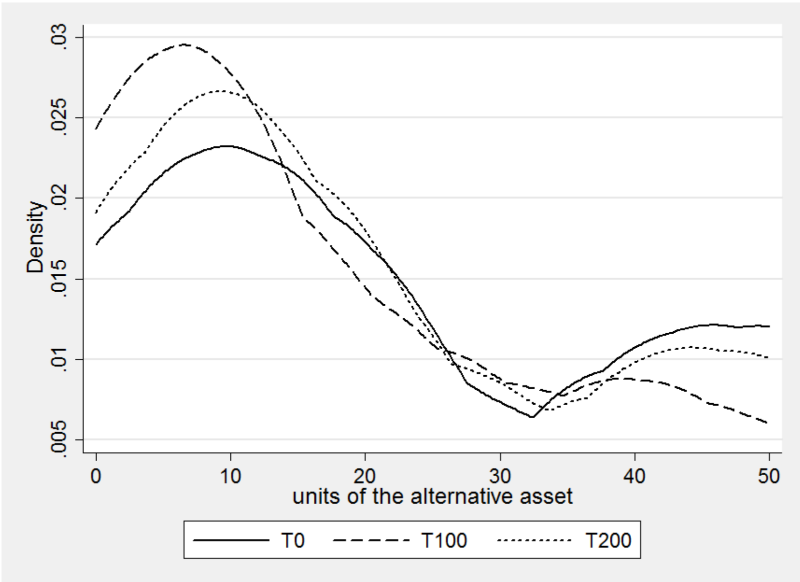


Figure 3.A.9: Distribution of units used from the alternative asset: All sample

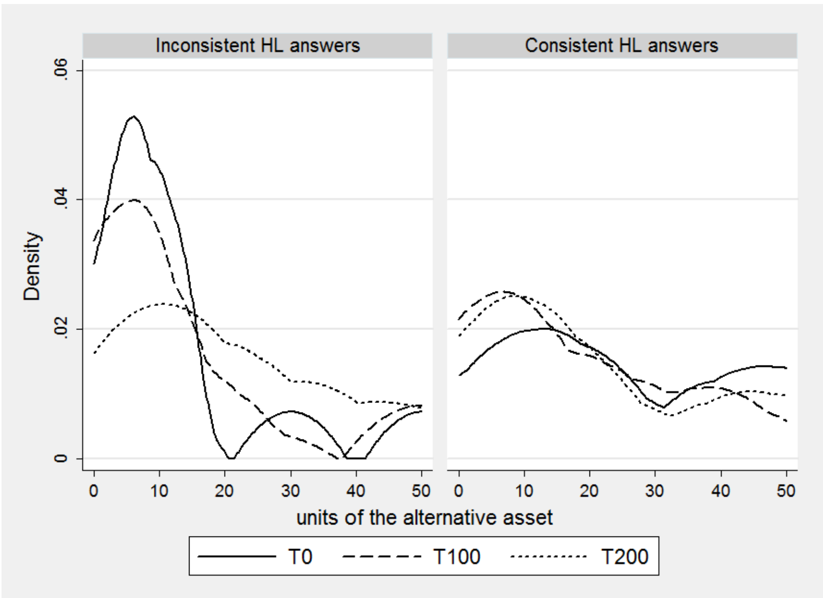


Figure 3.A.10: Distribution of the units used from the alternative asset by consistency of the answers to HL lotteries

CEU eTD Collection

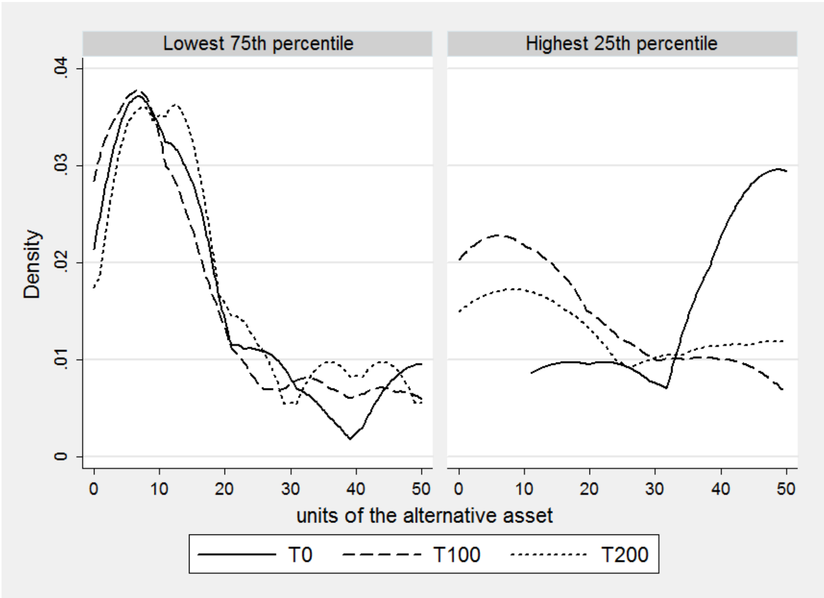


Figure 3.A.11: Distribution of the units used from the alternative asset by cognitive score

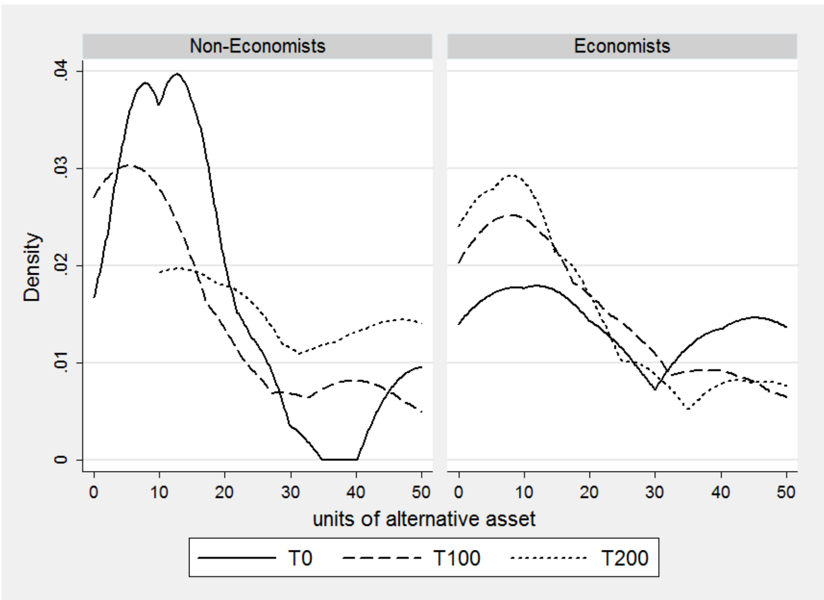


Figure 3.A.12: Distribution of the units used from the alternative asset by field of studies

CEU eTD Collection

Bibliography

Aatola, P., Ollikainen, M. & Toppinen, A. (2013), 'Price determination in the eu ets market: Theory and econometric analysis with market fundamentals', *Energy Economics* **36**(1), 380–395.

AlNajjar, N. I. & Weinstein, J. (2009), 'The ambiguity aversion literature: A critical assesment', *Economics and Philosophy* **25**(Special Issue 03), 249–284.

Arkes, H. R. & Ayton, P. (1999), 'The Sunk Cost and Concorde Effects: Are Humans Less Rational Than Lower Animals?', *Psychological Bulletin* **125**(5), 591–600.

Arkes, H. R. & Blumer, C. (1985), 'The psychology of sunk cost', *Organizational Behavior and Human Decision Processes* **35**(1), 124–140.

Ashraf, N., Berry, J. & Shapiro, J. M. (2010), 'Can higher prices stimulate product use? Evidence from a field experiment in Zambia', *American Economic Review* **100**, 2383–2413.

Ausubel, L. M., Cramton, P., Pycia, M., Rostek, M. & Weretka, M. (2013), 'Demand reduction, inefficiency and revenues in multi-unit auctions', *University of California mimeo* .

Baldick, R., Grant, R. & Kahn, E. (2000), 'Linear supply function equilibrium: Generalizations, application, and limitations', *POWER Working Papers Series PWP-078* .

Baldursson, F. M. & von der Fehr, N.-H. M. (2004), 'Price volatility and risk exposure: on market-based environmental policy instruments', *Journal of Environmental Economics and Management* **48**(1), 682–704.

Barberis, N. & Xiong, W. (2012), 'Realization utility', *Journal of Financial Economics* **104**, 251–271.

Bazerman, M. H., Giuliano, T. & Appelman, A. (1984), 'Escalation of commitment in individual and group decision making', *Organizational Behavior and Human Performance* **33**(2), 141–152.

CEU eTD Collection

Benjamin, D. J., Brown, S. A. & Shapiro, J. M. (2006), 'Who is 'Behavioral'? Cognitive ability and anomalous preferences', *Working paper, Harvard University* .

Benz, E., Loschel, A. & Sturm, B. (2008), 'Auctioning of co2 emission allowances in Phase 3 of the EU Emissions Trading Scheme', *ZEW Discussion Paper No. 08-081* .

Charness, G. & Viceisza, A. (2011), 'Comprehension and Risk Elicitation in the Field: Evidence from Rural Senegal', *IFPRI Discussion Paper 01135, International Food Policy Research Institute (IFPRI)* .

Chevallier, J., Ielpo, F. & Mercier, L. (2009), 'Risk aversion and institutional information disclosure on the european carbon market: A case-study of the 2006 compliance event', *Energy Policy* **37**(1), 15–28.

Choi, S., Kariv, S., Müller, W. & Silverman, D. (2011), 'WHO IS (MORE) RATIONAL?', *Working Paper 16791, NBER WORKING PAPER SERIES* .

Colla, P., Germain, M. & van Steenberghe, V. (2005), 'Environmental policy and speculation on markets for emission permits', *CORE Discussion Paper* .

Cramton, P. & Kerr, S. (2002), 'Tradeable carbon permit auctions. how and why to auction not grandfather', *Energy Policy* **30**(4), 333–345.

Demailly, D. & Quirion, P. (2006), 'CO2 abatement, competitiveness and leakage in the European cement industry under the EU ETS: Grandfathering vs. output-based allocation', *Climate Policy* **6**(1), 93–113.

Dohmen, T., Falk, A., Huffman, D. & Sunde, U. (2010), 'Are Risk Aversion and Impatience Related to Cognitive Ability?', *American Economic Review* **100**, 1238–1260.

Ellerman, A. D., Convery, F. J. & de Perthuis, C. (2010), 'Pricing carbon, The European Union Emissions Trading Scheme', *Cambridge University Press, New York* .

European Commission, E. C. (2003), 'DIRECTIVE 2003/87/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL'.

Fischbacher, U. (2007), 'z-Tree: Zurich Toolbox for Ready-made Economic Experiments', *Experimental Economics* **10**(2), 171–178.

Frederick, S. (2005), 'Cognitive Reflection and Decision Making', *Journal of Economic Perspectives* **19**(4), 25–42.

Friedman, D., Pommerenke, K., Lukose, R., Milam, G. & Huberman, B. A. (2007), 'Searching for the sunk cost fallacy', *Experimental Economics* **10**(1), 79–104.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P. & Rangel, A. (2012), 'Using neural

CEU eTD Collection

data to test a theory of investor behavior: An application to realization utility', *Yale ICF Working Paper No. 12-30* .

Green, R. (1999), 'The electricity contract market in England and Wales', *The Journal of Industrial Economics* **47**(1), 107–124.

Greiner, B. (2004), 'The Online Recruitment System ORSEE 2.0 - A Guide for the Organization of Experiments in Economics', *Working Paper Series in Economics 10, University of Cologne, Department of Economics* .

Hahn, R. W. (1984), 'Market Power and Transferable Property Rights', *The Quarterly Journal of Economics* **99**(4), 753–765.

Harrison, G. W. & List, J. A. (2004), 'Field Experiments', *Journal of Economic Literature* **XLII**, 1009–1055.

Hendricks, K. & McAfee, P. R. (2010), 'A theory of bilateral oligopoly', *Economic Inquiry* **48**(2), 391–414.

Hepburn, C., Grubb, M., Neuhoff, K., Matthes, F. & Tse, M. (2006), 'Auctioning of EU ETS phase ii allowances: how and why?', *Climate Policy* **6**(1), 137–160.

Hofmann, Y. (2006), 'Auctioning of CO2 emissions allowances in the EU ETS: Report under the project "Review of EU Emissions Trading Scheme"', *European Commission* .

Holt, C. A. & Laury, S. K. (2002), 'Risk Aversion and Incentive Effects', *The American Economic Review* **92**(5), 1644–1655.

Holt, C., Shobe, W., Burtraw, D., Palmer, K. & Goeree, J. (2007), 'Auction design for selling CO2 emission allowances under the Regional Greenhouse Gas Initiative'.

Hoppe, E. I. & Kusterer., D. J. (2011), 'Behavioral biases and cognitive reflection', *Economic Letters* **110**(2), 97–100.

Kahneman, D. & Tversky, A. (1979), 'Prospect theory: An analysis of decisions under risk', *Econometrica* **47**(2), 263–291.

Keloharju, M., Nyborg, K. G. & Rydqvist, K. (2005), 'Strategic behavior and underpricing in uniform price auctions: Evidence from Finnish treasury auctions', *The Journal of Finance* **60**(4), 1865–1902.

Klemperer, P. D. & Meyer, M. A. (1989), 'Supply function equilibria in oligopoly under uncertainty', *Econometrica* **57**(6), 1243–1277.

Knox, R. E. & Inkster, J. A. (1968), 'Posdecision dissonance at post time', *Journal of Personality and Social Psychology* **8**(4), 319–323.

CEU eTD Collection

Kyle, A. (1989), 'Informed speculation with imperfect competition', *The Review of Economic Studies* **56**(3), 317–355.

Lange, A. (2012), 'On the Endogeneity of Market Power in Emissions Markets', *Environmental Resource Economics* **52**(4), 573–583.

Leland, E. H. (1972), 'Theory of the firm facing uncertain demand', *The American Economic Review* **62**(3), 278–291.

Maeda, A. (2003), 'The Emergence of Market Power in Emission Rights Markets: The Role of Initial Permit Distribution', *Journal of Regulatory Economics* **24**(3), 293–314.

Malueg, D. A. & Yates, A. J. (2009), 'Bilateral oligopoly, private information, and pollution permit markets', *Environmental and Resource Economics* **43**(4), 553–572.

Marin, J. M. & Rahi, R. (1999), 'Speculative securities', *Economic Theory* **14**(3), 653–668.

Matthes, F. & Neuhoff, K. (2007), 'Auctions in the European Union Emissions Trading Scheme', *Report commissioned by WWF* .

Milgrom, P. (2004), 'Putting auction theory to work', *Cambridge University Press* pp. 255–264.

Montero, J.-P. (2009), 'Market Power in Pollution Permit Markets', *The Energy Journal* **30**.

Montgomery, D. W. (1972), 'Markets in licenses and efficient pollution control programs', *Journal of Economic Theory* **5**(3), 395–418.

Neuhoff, K. (2007), 'Auctions for CO2 allowances: a straw man proposal', *Climate Strategies* .

Oechssler, J., Roider, A. & Schmitz, P. W. (2009), 'Cognitive abilities and behavioral biases', *Journal of Economic Behavior and Organization* **72**, 147–152.

Phillips, Q. R., Battalio, R. C. & Kogut, C. A. (1991), 'Sunk and opportunity costs in valuation and bidding', *Southern Economic Journal* **58**(1), 112–128.

Robalo, P. & Sayagy, R. (2013), 'Paying is Believing: The Effect of Costly Information on Bayesian Updating'.

Roodhooft, F. & Warlop, L. (1999), 'On the role of sunk costs and asset specificity in outsourcing decisions: a research note', *Accounting, Organizations and Society* **24**(4), 363–369.

Rudkevich, A. (1999), 'Supply function equilibrium in Poolco type power markets: Learning all the way', *Technical Report Number 0699-1701, Tabors Caramanis and Associates* .

Rudkevich, A. (2005), 'On the supply function equilibrium and its applications in the electricity markets', *Decision Support Systems* **40**, 409–425.

CEU eTD Collection

Sandmo, A. (1971), 'On the theory of competitive firm under price uncertainty', *The American Econimic Review* **61**(1), 65–73.

Schleicher, S. P. (2012), 'Tcost of non EU ETS', *CEPS Carbon Market Forum, Berlin* .

Smith, S. & Swierzbinski, J. (2007), 'Assessing the performance of the UK Emissions Trading Scheme', *Environmental and Resource Economics* **37**(1), 131–158.

Staw, B. M. (1976), 'Knee-deep in the big muddy: A study of escalating commitment to a chosen course of action', *Organizational Behavior and Human Performance* **16**, 27–44.

Subramanian, R., Gupta, S. & Talbot, B. (2008), 'Compliance strategies under permits for emissions', *Production and Operations Management* .

Tan, H.-T. & Yates, J. F. (1995), 'Sunk cost effects: The influences of instructions and future return estimates', *Organizational Behavior and Human Decision Processes* **63**(3), 311–319.

Thaler, R. (1980), 'Toward a positive theory of consumer choice', *Journal of Economic Behavior and Organization* **1**, 39–60.

van Dijk, E. & Zeelenberg, M. (2003), 'The Discounting of Ambiguous Information in Economic Decision Making', *Journal of Behavioral Decision Making* **16**, 341–352.

Vargas, J. S. (2003), 'Bidder behavior in uniform price auction: Evidence from Argentina'.

Wang, J. J. D. & Zender, J. F. (2002), 'Auctioning divisible goods', *Economic Theory* **19**, 673–705.

Weretka, M. (2011), 'Endogenous market power', *Journal of Economic Theory* **146**(6), 2281 – 2306.

Westskog, H. (1996), 'Market Power in a System of Tradeable CO2 Quotas', *The Energy Journal* **17**(3), 85–103.

Wilson, R. (1979), 'Auctions of shares', *The Quarterly Journal of Economics* **93**(4), 675–689.

Wirl, F. (2009), 'Oligopoly meets oligopsony:the case of permits', *Journal of Environmental Economics and Management* **58**, 329–337.

CEU eTD Collection