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ESSAYS IN MARKET DESIGN FOR EMISSIONS TRADING SCHEMES

Phillia A. Restiani

Supervisors:

Dr. Regina Betz

Professor Robert Marks

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This dissertation explores the issues of market design for emissions trading schemes by focusing on penalty designs and initial allocation mechanisms. Penalty design is defined in terms of penalty types and levels and the allocation mechanism compare free allocation with auctioning. The first essay employs a theoretical model to examine compliance incentives and market efficiency under three penalty types: the fixed-penalty rate (FPR), the make-good provision (MGP), and the mixed penalty design. Using a simple two-period model of firm's profit maximisation, we analyse compliance decisions and the efficient penalty level under each penalty type. Our findings indicate that the penalty type does not affect compliance decisions provided that the efficient penalty level is applied. Market efficiency is retained regardless of penalty types. These findings are used as the hypotheses for the second essay.

The behavioural implications of penalty designs on market performance are investigated in the second essay using an experimental method. Three penalty types and two penalty levels are enforced in a laboratory permit market with auctioning wherein subjects make compliance decisions by undertaking irreversible abatement investment decisions or by buying permits. In contrast to theory, we find that penalty levels serve as a focal point that indicates compliance costs and affects compliance strategies. The MGP penalty provides stronger compliance incentives than the other penalty types. Most importantly, a trade-off between investment incentives and efficiency is observed.

Using a laboratory experiment, the third essay studies how the initial distribution of permits through free allocation or auctioning, may affect price discovery, allocative and static efficiency under the presence of three penalty designs. Price discovery is not influenced by the initial allocation mechanism. Permit prices remain above the efficient level due to the presence of irrational bidding and trading behaviour as well as risk aversion. Uncertainty regarding permit prices results in a modest allocative efficiency as over-investment prevails. Auctioning evidently generates higher static efficiency due to stronger price signals. This result supports the majority of literature which argues for auctioning. An appropriate auction design is crucial to avoid the risk of overbidding which will inflate the auction price and diminish efficiency.

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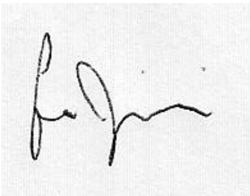
Signed ………  ……………………………

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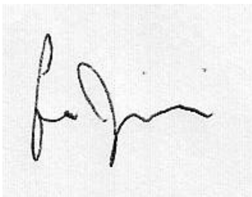
Signed …………  ……………………………………

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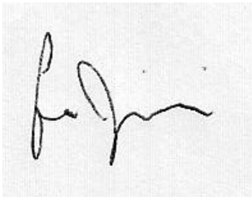
Signed …………  ……………………………………

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Abstract

This dissertation explores the issues of market design for emissions trading schemes by focusing on penalty designs and initial allocation mechanisms. Penalty design is defined in terms of penalty types and levels and the allocation mechanism compare free allocation with auctioning. The first essay employs a theoretical model to examine compliance incentives and market efficiency under three penalty types: the fixed-penalty rate (FPR), the make-good provision (MGP), and the mixed penalty design. Using a simple two-period model of firm's profit maximisation, we analyse compliance decisions and the efficient penalty level under each penalty type. Our findings indicate that the penalty type does not affect compliance decisions provided that the efficient penalty level is applied. Market efficiency is retained regardless of penalty types. These findings are used as the hypotheses for the second essay.

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Using a laboratory experiment, the third essay studies how the initial distribution of permits through free allocation or auctioning, may affect price discovery, allocative and static efficiency under the presence of three penalty designs. Price discovery is not influenced by the initial allocation mechanism. Permit prices remain above the efficient level due to the presence of irrational bidding and trading behaviour as well as risk aversion. Uncertainty regarding permit prices results in a modest allocative efficiency as over-investment prevails. Auctioning evidently generates higher static efficiency due to stronger price signals. This result supports the majority of literature which argues for auctioning. An appropriate auction design is crucial to avoid the risk of overbidding which will inflate the auction price and diminish efficiency.

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Chapter One

Introduction

In spite of the overwhelming scientific evidence on climate change, taking the required action to solve this problem is anything but simple. As mentioned by Garnaut (2008), climate change has been dubbed a diabolical policy problem that poses new challenges to policy making. It is characterised by uncertainties in its forms and its extent, is insidious in nature, and involves long-term horizons for both its impacts and its remedies to take effect. From an economic perspective, climate change is argued to be the greatest and widest-ranging market failure ever seen (Stern, 2007). Due to the central role of uncertainties, economic analysis on taking early action is a very challenging task. Nevertheless, with a more than 66% likelihood that climate change can lead to abrupt or irreversible impacts, such as the partial loss of ice sheets on polar land, which could imply metres of sea level rise, with a business-as-usual scenario (IPCC, 2007), there should be no delay in taking early actions implementing mitigation and adaptation measures.

A tradable permit system is one of the necessary economic instruments to mitigate climate change with the purpose of creating a price on carbon and a market that could facilitate a transformation to a low-carbon economy. It is a market-based instrument that has been widely used in practice to address environmental problems in a cost-effective way. In the context of greenhouse gases as uniformly mixed pollutants, an emissions trading scheme as a form of a tradable permit system offers the advantage of flexibility in terms of the spatial dimension in achieving low-cost abatement measures as well as the potentially large cost savings when marginal abatement costs vary widely across sources and over time. As long as the integrity of the emissions reduction target, or emissions cap, is maintained, the system has an in-built capacity to deal with a certain degree of uncertainties, as changes to the system are reflected in terms of the price of permits.

Undoubtedly, it is crucial that an emissions trading scheme be well designed to achieve its goals rather than merely introducing excessive costs and distorting existing markets. Existing large-scale emissions trading schemes, such as the US Acid Rain Program and the European Union Emissions Trading Scheme (EU ETS), have given us success stories as well as lessons to learn pertaining to the schemes' design features. Although the learning process over time might enhance the performance of the scheme, in the meantime, inefficient costs are incurred, and incorrect price signals have been transmitted. Therefore, every single design feature needs careful consideration, as an inappropriate design or even little compromises to an efficient design will diminish the benefits of the scheme. In this spirit, this dissertation offers to contribute to the literature of market design for emissions trading schemes.

This dissertation consists of three interrelated essays that focus on the assessment of penalty design and initial allocation mechanisms as two important design features in emissions trading schemes. Penalty design as reflected in terms of penalty types and penalty levels is essential in promoting the compliance of market participants so that the environmental goal is achieved. On the other hand, the initial allocation mechanism of permits to market participants has been considered the most contentious element of a trading scheme, one that might have serious consequences on efficiency as well as welfare distribution. The assessment employs a theoretical framework as well as a laboratory experiment as a method to address research questions. Following the results of the experiments, statistical tests and econometric techniques are used to analyse the data.

The first essay in chapter two examines compliance incentives related to each penalty design. We consider three penalty types that are normally observed in the existing emissions trading schemes: the fixed penalty rate, which uses a constant marginal financial penalty, the make-good provision, which applies a concept of 'quantity penalty', where each missing permit in the current period is to be offset with a ratio (restoration rate) in the following period, and, finally, a mixed penalty, which combines the two penalty types. A simple two-period theoretical model is formulated as a firm's profit maximisation problem under a permit market. Firm compliance strategies are modelled as an irreversible investment in abatement measures and permit buying in the market. Using the analytical framework and the illustrative simulation, we assess how each penalty design influences firm compliance decisions and market efficiency in terms of the optimal production level, abatement level, and permit holding.

Our findings from the first essay show that firms will find it profit-maximising to comply as long as the penalty level is set at the efficient level, which is a penalty rate higher than the permit price for the fixed penalty rate and a restoration rate that is higher than the ratio of the first-period permit price over the second-period permit price. For both penalty designs, the penalty type does not affect compliance incentives as long as this condition is met. In the mixed penalty design, the efficient level of the penalty rate in the second period is crucial to the inducement of a firm’s compliance. Although we do not find that the presence of double penalties in the mixed penalty design compromise market efficiency, this penalty design provides a stronger compliance incentive compared to other penalty designs. The findings from the first essay are used as the basis on which to formulate the hypotheses in the second essay, which also examines the issue of penalty design using a laboratory approach.

Following the results of chapter two, chapter three employs the use of a laboratory experiment to investigate the behavioural implications of penalty design on subjects’ compliance decision. It has been argued that risk aversion might induce over-investment (Baldursson and von der Fehr, 2004) and penalty levels, as non-binding price controls, might serve as a focal point of price (Isaac and Plott, 1981, Schaeffer and Sonnemans, 2000, Ivanova, 2007). Therefore, the experiment aims to assess whether different penalty designs in an auctioned permit market induce different compliance incentives and market performance under the presence of risk preferences. Subjects’ risk preferences are measured using Holt and Laury’s (2002) lottery-choice experiment. We have five treatments based on three penalty types and two penalty levels as treatment variables. The mixed penalty design is incorporated as a test-bed for the proposed design in the Australia Carbon Pollution Reduction in which the mixed penalty design includes a novel trait of tying the penalty rate to the auction price; hence the penalty rate does not serve as a focal point. This feature would ensure that the penalty rate always has the same distance to the permit price. As before, we have a two-period model in which compliance strategies are simplified to irreversible investment decisions and permit buying. To isolate the effect of penalty design, we abstract from introducing exogenous uncertainties; therefore, uncertainties regarding permit prices are endogenous and result from subjects’ decisions. The effect on market performance is measured in terms of price discovery in the permit market, the efficient investment level, the compliance rate, and static efficiency.

In contradiction to the theory, the results from the second essay reveal that under the presence of subjects’ risk preferences and some degree of uncertainty in permit prices, penalty levels serve as a focal point that indicates the total cost of compliance, which consequently affect compliance rates. In terms of the penalty types, the make-good provision apparently provides stronger compliance incentives compared to the fixed penalty rate. However, the theory holds with regard to permit price discovery, as we find no evidence of the effect of penalty design on auction price. Interestingly, risk preference does not directly affect subjects’ compliance decision, but it does influence price discovery, which evidently is a significant factor in subjects’ compliance decision as well as in the level of efficiency. Most importantly, we find a trade-off between investment levels and efficiency, which is attributed to penalty design. This result sheds light on the importance of penalty design on efficiency, which has not received sufficient attention from policy makers.

The third essay on another experimental study is presented in chapter four. Even though the theory suggests that the way in which permits are distributed does not matter, in practice, the presence of transaction costs, uncertainties, market power, and existing market distortions might have a substantial impact on market efficiency. This chapter seeks to answer how the initial allocation mechanism of permits, in terms of free allocation and auctioning, might affect market efficiency in terms of price discovery, compliance incentives, allocative efficiency and static efficiency. Furthermore, the cost-effective measure of static efficiency is further disaggregated into its cost elements: permit costs, investment costs, and penalty costs. In general, the same experimental design as in the second essay is employed. The contribution to the existing experimental literatures on the topic is made by the following experimental design features: the abstraction of exogenous uncertainty to isolate the effect of treatment variables, the incorporation of penalty design as an indication of price caps, the use of a two-period model to take into account the effect of irreversible investment as a compliance strategy, and, finally, the clock auction is used as a format in the auction treatment. We conduct six treatments based on a 2x3 balanced-design of the initial allocation mechanism and penalty design.

The results from the third essay indicate that the initial allocation does not affect permit price discovery, although auctions generate stronger price signals, which is reflected in a much smaller standard deviation of average permit prices. These price signals serve as an important factor in determining compliance incentives as well as market efficiency. As in the second essay, risk aversion is also found to be a significant factor in permit price discovery. The test of treatment effects show that auctioning provides better investment and compliance incentives. Nevertheless, when we control for other variables, it is the penalty design, rather than the initial allocation mechanism, that significantly affects investment decisions and the compliance rates of net buyers. Due to over-investment, we obtain a modest allocative efficiency in the experiment. On the other hand, regression estimates confirm that auction treatments produce much higher static efficiency compared to grandfathering. Our findings support the strand of literature that argues for the use of auctions as a way to distribute initial permits. Nevertheless, a well-designed auction format is necessary to preclude overbidding, which is found in our experiment and erodes the allocative efficiency of an auction market.

The last chapter summarises the main results as well as discusses the policy implications of these results. Possible further extensions of research ideas are explored to take into account some factors that might implicate the results.

Chapter Two

A Theoretical Model of Profit-Maximising Compliance Decisions under Different Penalty Designs in Emissions Trading Markets

2.1. Introduction

In the past few decades, emissions trading schemes have played an important role as a market-based instrument used to tackle the problem of controlling air pollution. The critical issue of climate change has put the issue of the design for emissions trading into the limelight as growing number of trading schemes are implemented or under development all over the world in an effort to put a price on carbon. It should be noted that emissions trading can achieve the targeted emissions reduction efficiently if it is designed properly, and penalty design is a crucial market feature needed to maintain the integrity of the environmental goal. A poorly designed scheme might not achieve its efficiency and, even worse, might distort the existing market without meeting its emissions reduction target.

Despite the large body of literature regarding the enforcement model in the context of emissions trading schemes, very few discuss the effect of the penalty type as an element of enforcement. This essay looks at how penalty designs in terms of penalty types and penalty levels might affect compliance incentives and how firm chooses its profit-maximising compliance decision. Three penalty types are considered: the fixed penalty rate, the make-good provision, and the mixed penalty, a combination of both penalty types. We use a simple analytical model at the firm level to assess different compliance incentives related to each penalty type and further analyse the implications of having a different penalty level from the efficient level. The efficient level of penalty is the minimum level required to induce compliance of the firm. Market efficiency in the model is evaluated in terms of optimal production level, abatement level, and permit holding under the conditions of firms' compliance and profit maximisation.

The rest of the chapter is organised as follows. Section two overviews the studies on enforcement in emissions trading scheme and clarifies the motivation of this essay. The next section describes each penalty design and its application in the existing trading schemes. Section four explains the basic assumptions used in each model. The following sections discuss the model for each penalty type. Section eight discusses the implications of the results, and the last section concludes the findings.

2.2. Enforcement in Emissions Trading Schemes

The use of tradable pollution permits as a market-based instrument has gained in popularity in recent decades due to its advantages over the command-and-control approach in achieving environmental goals at the least possible cost. It was Coase (1960) who first proposed the idea of transferable property rights as a response to Pigouvian taxes to address externalities such as pollution. These transferable property rights are argued to offer more flexibility than the command and control approach by allowing the market to distribute the rights to its highest value users. The concept of tradable permits was first applied in the context of water pollution (Dales, 1968) and air pollution (Crocker, 1966). A general theoretical framework by Montgomery (1972) proves that a tradable permit system can achieve efficiency for a given environmental target or emissions cap.

Although the actual implementation of an emissions trading scheme began in the mid-1970s with the US Environmental Protection Agency Emissions Trading (EPA ET) for stationary sources, a large-scale system was not created until the US Sulfur Dioxide (SO_2) permit trading or Acid Rain Program was initiated in 1995 (Ellerman et al., 2003). The programme, which tackles SO_2 as a local pollutant, is more successful than a standard approach not only in achieving its emissions target (addressing the effectiveness criterion) but also in cutting abatement costs (addressing the efficiency criterion) (Ellerman et al., 2000).

Recently, there have been more emissions trading schemes implemented to address global pollutants such as greenhouse gases wherein the concentration of pollutants in a particular area (hot spots) is not a problem. For example, the European Union introduced a trading scheme (EU ETS) in 2005 covering more than 30 countries today and the Regional Greenhouse Gas Initiatives (RGGI) scheme, which began in 2009, is the first large-scale mandatory cap-and-trade system for greenhouse gases in the US covering ten states. Australia developed its first trading scheme in 2003 with the implementation of New South Wales Greenhouse Gas Reduction Scheme (GGAS). Whereas the EU ETS and RGGI are cap-and-trade system, the GGAS requires participants, who are electricity retailers and other individual participants, to meet a benchmark level of emissions reductions by undertaking project-based emissions reduction activities. The scheme is basically a baseline-and-credit system in which a credit is awarded to a facility that reduces emissions beyond the pre-specified emissions baseline or benchmark. These credits must first be certified and can then be used for compliance or traded with another facility (New South Wales Greenhouse Gas Reduction Scheme, 2008). Although the scheme claims to have made significant reductions, from 8.65 ton CO_2/capita to 7.27 ton CO_2/capita (Independent Pricing and Regulatory Tribunal, 2009), it has been severely criticised for a number of design problems, such as the fungibility of its emissions reductions activities, imputed emissions, its methods of calculating the baseline, and its complicated baseline rules, which are believed to result in a price that is much lower than the true scarcity price of carbon (MacGill et al., 2006).

In spite of the potential that emissions trading markets offer, in practice, some issues can have adverse effects on the efficiency of the market. Stavins (1995) points out some examples of these issues, such as market power in the permit market, market power in the product market, non-profit-maximising behaviour, pre-existing regulatory environments, and the degree of monitoring and enforcement. It is argued that the presence of transaction costs will create higher marginal abatement costs for permit buyers (Stavins, 1995) and less trading participation (Gangadharan, 2000). Likewise, under the presence of market power, dominant firms might manipulate permit markets to their own advantage, making total pollution control costs more expensive than the efficient level (van Egteren and Weber, 1996, Hahn, 1984).

It is important to recognise that the environmental effectiveness and economic efficiency of a tradable permit system depends, among other things, on the enforcement mechanism used to encourage the compliance of market participants. An enforcement mechanism can include a number of elements: penalty design in terms of level and type, reporting procedures, the verification of reports, monitoring, and sanctioning. Furthermore, each of these elements entails some cost. Three different penalty designs can be distinguished: 1) a fixed financial penalty rate per missing permit, which can be thought of as a ‘price penalty’, 2) a make-good provision requiring firms to surrender missing permits at a given restoration rate or make-good factor, which can be thought of as a ‘quantity penalty’, or 3) a mixed approach combining the price and quantity penalty (henceforth referred to as a mixed penalty). In general, most existing trading schemes have shown compliance rates that are very high compared to those achieved under the regulatory emissions standard approaches. The chosen enforcement mechanism may not only have a direct impact on firms’ compliance decisions (whether a firm chooses to be compliant or non-compliant) but may also indirectly impact permit prices, which might in turn influence the ability of the programme to achieve potential cost savings and related economic benefits (Murphy and Stranlund, 2006). Other factors apart from the penalty design itself that might influence compliance decisions under emissions trading programs are the risk attitudes of market participants, the probability of an audit, flexibility in banking (saving permits for future use) or borrowing (using future permits in the current compliance period), initial allocation rules, trading rules such as auction rules, and any form of market failure, including market power, transaction costs and uncertainties.

The literature on compliance decision and enforcement builds from Becker's (1968)on the economics of crime and punishment. The first theoretical work on enforcement in the area of environmental policy was conducted by Downing and Watson (1974) and focused on standards and effluent fees. Further work on pollution permits was conducted by Malik (1990), who examines market efficiency in the presence of non-compliance and finds that compliance decisions will affect the demand for permits and can shift the equilibrium permit price upward or downward, resulting in lower market efficiency.

Following those early works, numerous studies on enforcement models in emissions trading markets have been conducted. Under the presence of market power, the initial allocation of permits to the dominant firm can be used as an enforcement tool in which the regulator can control policy parameters specifically for the price-setting firm rather than adjusting them for all firms (van Egteren and Weber, 1996). However, when marginal enforcement cost is increasing in the initial allocation of permits to the dominant firm, then the initial permits should be distributed such that the dominant firm becomes a net buyer (Chavez and Stranlund, 2003). Keeler (1991) studies compliance decisions under marginal penalty functions with different shapes. Baldursson and von der Fehr (2004) and Stranlund (2008) take into account the influence of risk aversion on compliance. The observed phenomenon of high compliance rates in spite of less frequent inspections or non-severe penalties for discovered violations has been explained using dynamic enforcement models by Greenberg (1984), Harrington (1988), Landsberger and Meilijson (1982), and Stranlund et al. (2005). Theoretical analyses of compliance rules in the context of the Kyoto Protocol and its effects on permit price are assessed by Nentjes and Klaasen (2004) and Godal and Klaasen (2006). Furthermore, Stranlund et al. (2005) study the effect of high penalties on reporting violations rather than permit violations under banking provision.

These existing studies have emphasised the effects of monitoring, different audit probabilities and penalty rates, targeted enforcement, self-reporting, and cheating as important factors in the enforcement of emissions trading schemes. However, we believe that even in cases where we have perfect monitoring and sanctioning mechanisms as well as costless sanctioning costs, it is interesting to see the behaviour of market participants with regard to different penalty types.

This essay aims to use a simple analytical model to assess how different penalty types, specifically the fixed penalty rate, make-good provision and mixed penalty design, can affect firm's profit-maximising compliance decision and the effectiveness of emissions trading markets. The effectiveness of emissions trading market, which is to realise emissions reduction targets, are only feasible when there is full compliance of firms in the market. On the firm level, the profit maximising compliance decision requires the firm to be compliant and at the same time to maximise its profit by maximising its total revenues and minimising its total costs. Consequently, the firm needs to decide on the optimal level of production and compliance strategies, i.e. abatement level and the number of permit holding. These are the firm's choice variables in our model. At the aggregate level, the optimal levels of those choice variables determine market efficiency, which is the capability of market in using resources in the least total costs possible. The market can only realise its optimal outcomes when both effectiveness and efficiency occur.

We seek to contribute to the existing literature by focusing on the following aspects:

1) The effects of penalty design on compliance incentives.

   To our knowledge, only a few of the existing studies focus on penalty design. Nentjes and Klaasen (2004) look at the compliance incentives associated with the Kyoto Protocol, which include both a make-good provision and a fixed penalty rate. However, they do not undertake a theoretical analysis and do not focus on emissions trading. Moreover, they ground their analysis in the cost of reputation protection for buyers and sellers. Likewise, Godal and Klaasen (2006) use a game theoretical approach under the scenario of market power and US participation and consider how they may affect committed parties on the road to final compliance under the Kyoto Protocol. Some studies discuss the use of an intertemporal trading ratio to discourage the borrowing of permits that has a similar function to the ratio in the make-good provision (Kling and Rubin, 1997, Stranlund et al., 2005). However Kling and Rubin (1997) do not focus their model on enforcement while Stranlund et al (2005) emphasize the use of tying the penalty to reporting violations. In contrast to those studies, we do not consider reporting violation and rather focus on the equilibrium in a perfectly competitive permit market under different penalty designs.

2) We abstract from enforcement and monitoring costs or audit probability

   As we want to isolate the effects of the chosen penalty type on compliance decisions, we assume that the violating firms will always be discovered and penalised. Meanwhile, numerous studies, such as those of Stranlund and Dhanda (1999), Sandmo (2002) and Arguedas (2008), consider audit probability as an important variable.

3) Our emphasis is on violation with regard to two main compliance strategies

   The compliance strategies are simplified to irreversible investment in emissions reduction measures and permit trading. We model an investment decision as an irreversible decision to highlight that once the decision is made, it cannot completely be undone because it has created a positive or zero sunk cost; e.g. the installed equipment cannot be removed simply, and its scrap value is insignificant or zero. Furthermore, we follow Kolstad's (1996) definition, in which irreversibility means that today's choices restrict tomorrow's choices. In this case, we consider a two-period model in which the investment decision needs to be made in the first period.

Our theoretical model is mainly built on the work of Malik (1990) and Baldursson and von der Fehr (2004). Malik examines compliance decisions shaped by a marginal penalty as a function of violation and permit price, whereas Baldursson and von der Fehr consider how the initial allocation impacts the level of investment in pollution reduction under the assumption of risk aversion. They also incorporate the effects of aggregate-level and firm-level risks on the choice of investment level. However, they do not allow for non-compliance in their model. Although they take into account the idea of irreversible investment, they also add the option of undertaking incremental abatement measures that force firms to be compliant. This reduces the irreversibility effect of investment. We combine the models to examine the effects of penalty design on profit-maximising compliance decision and optimal investment level of abatement measures under the assumption of risk neutrality.

2.3. Penalty Design

At present, different types of penalty designs have been adopted in emissions trading schemes (see Table 1). In general, three basic types of penalties can be distinguished: 1) a fixed financial penalty rate per missing permit (price penalty), 2) a make-good provision requiring firms to surrender missing permits at a given restoration rate or make-good factor (quantity penalty), and 3) a combination of the two penalty types, which we call a mixed penalty.

A fixed penalty rate, henceforth referred to as an FPR, can provide an incentive and a clear signal of the maximum cost of compliance for firms. With the FPR, firms face a constant marginal penalty for each unit of violation. The FPR acts as an indication of the maximum compliance costs for firms in choosing their compliance strategy: whether to invest in an abatement technology or to trade in the permit markets. Under some circumstances, a particular level of a fixed penalty rate may also act as a safety valve. The effective safety valve is triggered when the permit price rises above the chosen penalty level. In such a case, the emissions target is not achieved and firms pay the penalty, which is similar to a tax. In this light, we can view the safety valve as a hybrid instrument, a mix between a tradable permit and an emissions tax. This idea is presented by Jacoby and Ellerman (2004) and is similar to a concept proposed by Roberts and Spence (1976).

There are two ways of implementing a safety valve. First, firms can buy additional permits from the government or the market at a fixed price to meet their obligations and remain compliant. The limitation of this approach is that it does not guarantee that the targeted level of emissions reduction will be achieved because firms can buy as many permits as they want at this trigger price. Secondly, the companies can be temporarily exempted from their obligation (e.g. for a month) to surrender permits. This leeway will similarly compromise any progress made towards reaching the emissions target and undermine the cap-and-trade system. The two approaches have different implications with regards to the compliance status because the first approach does not automatically ensure that firms will be in compliance once the safety valve is triggered, whereas the second approach does. A critical issue with the design of safety valves is the price level, which can be used to maintain the emissions target. When the triggered price is set at a relatively low level, the permit price becomes an effective price cap (price limit) on the cost of polluting or a binding price ceiling for the permit price. Hence, it indicates the maximum compliance costs. If it is set at a relatively high level, the price acts as a fixed penalty rate that deters firms from polluting. The issue of penalty level is crucial to the FPR penalty design in practice because the regulator will not necessarily have the perfect knowledge with regard to damage costs, firms' marginal abatement costs, or even the current emissions levels, which are important in setting the theoretical equilibrium permit price and the penalty level based on that permit price.

The second type of penalty design is the make-good provision, henceforth referred to as the MGP, in which firms must compensate for their missing permits in one period at a particular make-good factor or restoration rate in the following period. In the Kyoto Protocol, there is also an additional rule that suspends the non-compliant firms in any particular year, keeping them from selling their permits in the following year (Betz et al., 2006). This MGP ensures that the environmental goal is achieved because it reduces the allowable aggregate emissions in the following year should it be exceeded in the previous year. Assuming that the number of permits allocated by the regulator remains the same every year, non-compliance under this penalty design will create either an increase in the demand for permits to make up for non-compliance during the previous year or a decrease in the number of permits sold in the market because the non-compliant firms are not allowed to sell any permits. Thus, non-compliance in the current year will exert an upward pressure on future permit prices. Furthermore, this type of penalty introduces additional uncertainties as the compliance costs are uncertain because they are linked to the future permit price, which is unknown. This is not the case for financial penalties in which the magnitude of the penalty rate is fixed and is publicly announced at the outset.

Most emissions trading schemes employ a mix of the FPR and MGP penalty design. For instance, the EU Emissions Trading Scheme, which is currently the largest trading programme in terms of coverage with over 12,000 installations. This mix of penalty mechanisms then acts as a double penalty for market participants. Some examples of penalty design in the existing trading schemes are listed in Table 1.

Table 1 Penalty Designs in the Existing Emissions Trading Schemes

Penalty type	Schemes	Pollutants	Sector coverage	Penalty level	Compliance Rate and Permit price
FPR	NSW GGAS	6 GHGs	Electricity generators 41 participants	A$12.50 incl. taxes	95% compliance rate, 0.01% carried forward shortfalls in 2008 Average $5.85 spot price[a]
	Chile	PM	680 sources emitting >$1000m^3$/h	Penalty fee	Low, then high[b]
	LA RECLAIM	NOx,SOx	292 facilities for NOx and 32 facilities for SOx (2009)	$500/violation/day, determined by court	95% for NOx, 97% for SOx (2009) $809-4780 for NOx, $653-1488 for SOx (2009)[c]
MGP	US NOx Budget Program	NOx	2568 units of power plants and large combustion sources in eastern US	Automatic quota reduction at 3:1	Nearly 100% (2008) $825(Jan) - $592 (Dec)[d]
Mixed penalty	US Acid Rain	SO_2	3456 electricity-generating units	Penalty $2000/ton + MGP 1:1	100% (2008) $509(Jan) - $179 (Dec)[e]
	EU ETS	CO_2	Over 10,000 installations	€100 (2008) + MGP 1:1.3	98% compliance rate, 3% failed to submit verified emissions[f]
	Australian CPRS*	6 major GHGs	Stationary energy, transport, fugitive emissions, industrial processes, waste and forestry sectors at the start	Predetermined value or max. 110% of benchmark average auction price increased by 5% in real terms annually and MGP 1:1[g]	-
	RGGI (10 participating states) 2009	CO_2	Fossil fuel electricity generators above a size threshold of 25 MW	MGP 3:1 + penalty set by each state 3 year control period	June 2010 reserve price $1.86[h]
	WCI (7 Western US States and 4 Canadian Provinces) *	6 major GHGs	electricity generation, commercial and industrial combustion, and industrial process emissions; gas and diesel for transportation; residential fuel uses	MGP 1:3 + penalty set by each state[i]	-
	UK Carbon Reduction Commitment *	CO_2	Large non-energy-intensive businesses and public sector entities that are not covered by the EU ETS	Safety valve, linked to EU ETS, first set at £40[j]	Allowance price set at £12 in introductory phase
	New Zealand ETS	6 major GHGs	Forestry first, then all sectors by 2013	Penalty NZ$30 + MGP 1:1 and can be raised to NZ$60 + MGP 1:2[k]	-

Note: * schemes are not implemented yet

Source: [a] Independent Pricing and Regulatory Tribunal (2009), [b] Montero et al. (2002), [c] Haimov (2010), [d] US EPA (2009c), [e] US EPA (2009b), [f] EU Directive 2003/87/EC (2010b), Community Independent Transaction Log (2010a), [g] The Parliament of the Commonwealth of Australia (2009), [h] Regional Greenhouse Gas Initiative(2009), [i]Western Climate Initiative (2010), [j] UK Department of Energy and Climate Change (2010), [k] New Zealand Government (2007)

Those different penalty designs create different compliance incentives and have different effects on market efficiency. Compliance rates are generally very high and have reached 100% in the US Acid Rain Program. The data show that higher penalty levels, through either an FPR or an MGP or a mix of both, will encourage higher compliance rates. Slightly lower compliance rates than under the US Acid Rain Program, as experienced in the Los Angeles Regional Clean Air Incentives Market (LA RECLAIM) and Chile's TSP-Emissions Trading Program, are due more to the monitoring and enforcement issues in those schemes. LA RECLAIM uses a complicated procedure and an ad-hoc court approach in deciding the final compliance status of a violating firm (EPA Clean Air Markets Division, 2006). This approach clearly reduces the influence of the very high fixed penalty rate on compliance and increases administration costs, although the compliance rate is still fairly high. In Chile, permit allocations are made using a proxy-based benchmark approach that has performed poorly with very limited historical emissions information. This problem was exacerbated by poor institutional capacity, which made enforcement more difficult for the programme (Montero et al., 2002). Typically, as markets develop over time and more firms reveal their emissions history, the authority's enforcement capacity is also enhanced.

As shown in Table 1, most of the existing emissions trading programmes use a combination of the FPR and the MGP. Most of the schemes will also publish the non-compliance statuses of the firms in question, providing an additional incentive for compliance due to the risk for firms of losing their reputation. Apart from high compliance rates in those existing schemes, very limited information is available on the actual efficiency of those markets compared to their potential efficiency. In the EU ETS given the generous allocation and mixed penalty design, the compliance rate is very high. The New South Wales Greenhouse Gas Abatement Scheme also shows a very high compliance rate, with only 0.01% of permit shortfalls being carried forward. It is important to note that as the New South Wales Greenhouse Gas Abatement Scheme is a baseline-and-credit system rather than a cap-and-trade system, which is the focus of our study, it may offer different compliance incentives because participating firms act as suppliers of credit, and the credit supply is not fixed.

Drawing from the available empirical data, it is difficult to determine how market efficiency is impacted by penalty design. Because information on actual firms' emissions levels and marginal abatement costs are not always known in practice, it is difficult to determine whether existing permit markets have achieved their full potential efficiency gains. Our theoretical analysis of an emissions trading scheme uses a stylised model that allows us to focus on a few choice variables related to compliance decisions under the assumed market setting. The simplicity of the model also provides insights that are generally applicable, provided the assumptions are met. The comparative statics of the model also provide us with straightforward implication of the effect of a particular variable on the variable of interest. Therefore the analysis of firm's profit-maximising compliance decision and market efficiency under different penalty design merits the use of a theoretical model.

2.4. Model Assumptions

Consider an emissions trading scheme that consists of *n* firms that are price takers in both the permit market and a downstream market, which is independent of the permit market. For a given quantity of outputs, the production activity of firm *i* generates emissions e_i and revenues in which the price of the commodity, τ, is exogenous.

Firms are required to have a permit for each unit of pollution that they produce, and these permits can be obtained through endowments (as in the case of free initial allocation or grandfathering) or purchase (as in the case of auctioning). There is a central authority that conducts spot checks of reported data to prevent cheating and enforcement, ensuring that firms that produce more emissions than is allowed by the number of permits that they hold are penalised.

The objective of the central authority is to induce full compliance in the market with the least total cost of abatement as any degree of non-compliance will reduce market effectiveness. Thus, the efficient level of penalty is critical to ensure firm's compliance. On the other hand, the firm's objective is to maximise its profit under compliance. Nevertheless, as we would like to look at the efficient penalty level for each penalty design and how the firm makes its profit-maximising compliance decision, our model allows for non-compliance as a constraint to the firm's objective function. Market efficiency is then observed through how the firm chooses its optimal level of production and compliance strategies, which comprises of the optimal level of investment in abatement measures and the optimal number of permit holding.

The central authority initially allocates free permits to firms or auctions those permits. Without loss of generality, we take the free initial allocation of permits (grandfathering) as a basic model, although the model also applies when permits are auctioned by holding the amount of free permits at zero. We define an initial stock of permits at time *t* in the market, S_t, which is fixed over time and is the sum of gratis permits given to each firm, $S_t = \overline{S} = \sum s_{it}$. The aggregate emissions level in the business-as-usual (BAU) scenario, E_t, is the sum of firms' BAU emissions levels $E_t = \sum e_{it}$. Since the authority seeks to reduce the aggregate emissions level, the emissions cap or the permit supply is kept lower than the BAU emissions level, $S_t < E_t$. The total number of permits in the market at the end of a compliance period t is denoted by L_t and should be the same as the initial amount of stock because we are considering a closed permit market that does not allow for linking with other permit systems.

$$L_t = \sum_{i=1}^{n} l_{it} = S_t = \sum_{i=1}^{n} s_{it} < E_t \; ; \; i \in \{1,2,...,n\}; t \in \{1,2\} \qquad \textbf{(1)}$$

where l_{it} is the number of permit holdings of firm i at the end of compliance period t.

The compliance strategies consist of:

1) Investing in an abatement technology.
2) Trading permits.

To inspect the effect of irreversible investment on enforcement in a permit market, we use a stylised two-period model. We model investment as an irreversible decision that will commit firms to undertaking abatement measures in the first period. Rather than including a lump sum investment cost in the model, the investment decision is indicated by a positive abatement level a_i that will operationalise the same abatement costs over time $c_{it}(a_{it}) = c_i(a_i)$. As investment decisions are irreversible and cannot be undone (and the associated costs cannot be recovered), we require that $a_i \geq 0$. Hence, once firm decides to make an investment in the abatement measures, those measures will be performed for both periods.

Firms are assumed to be price takers not only in output markets but also for permit markets and they differ in their abatement costs, $c_i(a_i)$, which are continuous, increasing, and convex. $c_i(0) = 0$, $c_a > 0$ and $c_{aa} > 0$. A firm's output level is a function of capital, k_{it}.

$$q_{it} = f(k_{it}), \; \partial q_{it} / \partial k_{it} > 0, \; \partial^2 q_{ti} / \partial k_{it}^2 < 0 \qquad \textbf{(2)}$$

Likewise the firm's initial emissions levels are a function of their output level and technology parameter θ_{it}. The technology parameter explains how the same level of resources may generate different emissions levels, as is the case in the real world. However, in our model we do not address further the affect of technology parameter on emissions level and put the emphasis on the capital use, k.

$$e_{it} = h(q_{ti}(k_{ti}), \theta_{it}) \qquad \textbf{(3)}$$

We assume that an increasing production level will increase the firm's emissions levels at a decreasing rate and that the same applies for the effect of better technology in decreasing emissions levels.

$$\partial e_{it} \big/ \partial q_{it} > 0, \quad \partial^2 e_{it} \big/ \partial q_{it}^{\,2} < 0, \quad \partial e_{it} \big/ \partial \theta_{it} < 0, \quad \partial^2 e_{it} \big/ \partial \theta_{it}^{\,2} < 0 \qquad \textbf{(4)}$$

The regulator chooses the type of penalty in the form of a fixed penalty rate, denoted by f , or a restoration rate, ρ .[1] When firm decides to invest in abatement measures, its emissions level will be $\hat{e}_i = e_i - a_i$.

With regard to information structure, firms receive common information regarding the penalty type that is set by the central authority, its level and the initial allocation mechanism. When initial allocation is done through grandfathering, the number of free initial permits allocated to each firm is denoted by $s_i \geq 0$. When the penalty design is FPR, the authority announces the fixed penalty rate f . If MGP is used as the penalty design, the restoration rate, ρ, is revealed. In the mixed penalty design, both f and ρ are announced. These parameters of penalty design are exogenous to firms.

Firms also acknowledge that the probability of their being caught in a violation and the probability of their being sanctioned are equal to one (under perfect monitoring and penalty enforcement). Furthermore, penalty enforcement is assumed to be costless because this is not our focus. This information is also available to all firms. Thus, if their emissions level after making irreversible investment decision in abatement measures, $\hat{e}_i$, exceeds the number of permits held l_i, the penalty will be automatically enforced.

Firms also know about the equilibrium permit price in each period so that firms can make their profit-maximising compliance decision based on that information. In our model, the equilibrium permit price p is the price that minimizes the total abatement costs in the market. This variable is exogenous to firms.

Apart from the common information, firms only know about their own abatement cost $c_i(a_i)$, product price τ and capital rent r , and not about that of other firms . Firms maximise their profits by setting the optimal production level q_i to generate the firm's total revenue; at the same time, production activity creates pollution and determines the firm's initial emissions level, e_i, before an abatement measure is adopted.

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[1] Many emissions trading schemes allow for banking and/or borrowing to provide more flexibility for firms dealing with price fluctuations due to external shocks. However, to keep the model simple and tractable, we do not allow for banking or borrowing in this paper or for trading in futures markets.

To assess firms' compliance, the central authority carries out compliance check and penalties are automatically imposed on non-compliant firms. In our model, the central authority aims to create full-compliance in the market to achieve the targeted emissions (the sum of firms' emissions level after investment decisions), $\hat{E}_t = \sum_{i=1}^{n} \hat{e}_{it}$, with the least total abatement costs: $\lfloor \hat{E}_t = S_t \rfloor$ conditional upon $\sum_{i=1}^{n} C_{it}^{\min}$.

The theoretical framework also builds on the assumption that the law of one price applies so that the auction price (in the primary market) is equal to the permit price in the spot markets (secondary markets). Given this assumption, the auctioned permit price should be the same as it is when free allocation occurs. In the following sections, we will analyse the efficient penalty level that corresponds to the three different forms of penalty design and how the firm makes its profit-maximising compliance decision by choosing the optimal production level, investment in abatement measures and permit holding.

2.5. Fixed Penalty Rate

With a fixed penalty rate, the two-period model can be simplified into a static model because basically there are no differences in market structure across the two periods and non-compliance will have the same effect by the end of each period, unlike with the MGP. Without loss of generality, we remove the time subscript *t* from our variables.

Let e_i be firm *i*'s initial emissions, s_i be firm *i*'s initial permits, a_i be firm *i*'s abatement level, l_i be firm *i's* number of permit holding, and $c_i(a_i)$ be firm *i*'s abatement investment costs. The firm's violation level is denoted by

$$v_i = e_i(q_i(k_i)) - a_i - l_i \geq 0 \qquad \textbf{(5)}$$

Equation (5) can also be expressed in terms of the emissions level after making irreversible investment decision, $v_i = \hat{e}_i - l_i \geq 0$.

The firm's total costs are expressed as

$$C_{(a_i, l_i \mid \bar{f}, \bar{s}\ , \bar{p})} = c_i(a_i) + pd_i + fv_i \qquad \textbf{(6)}$$

where $d_i = l_i - s_i$. d_i specifies the number of permits traded by firm *i* in the market.

When $d_i > 0$, the firm is a net buyer, which means that by the end of a compliance period, that firm buys more permits than it sells. Accordingly, if $d_i < 0$, the firm in question is a net seller. The firm's profit function prior to an investment decision and trading in permits is expressed as

$$B_i = \tau\, q_i(k_i) - r\, k_i \qquad \textbf{(7)}$$

where τ and r symbolise the price of the good and the capital rent. These parameters are exogenous to the firm and hence are not the firm's choice variables.

As we are interested in compliance decisions, the firm is allowed to choose a non-negative violation $v_i \geq 0$. Firm i's profit maximisation function is

$$\underset{a_i, l_i, k_i}{Max} \quad \Pi_i = \tau\, q_i(k_i) - r\, k_i - c_i(a_i) - p[l_i - s_i] - f\, v_i \qquad \textbf{(8)}$$

$$\text{subject to} \quad v_i \geq 0, e_i \geq 0, \; a_i \geq 0, l_i \geq 0, k_i \geq 0$$

The profit maximisation problem yields a Lagrangian equation:

$$L = \tau\, q_i(k_i) - r\, k_i - c_i(a_i) - p[l_i - s_i] - f\, v_i + \lambda\, v_i \qquad \textbf{(9)}$$

We derive the Kuhn-Tucker conditions as follows:

$$\frac{\partial L}{\partial k_i} = \tau \frac{\partial q}{\partial k} - r - [f - \lambda]\left(\frac{\partial e}{\partial q}\frac{\partial q}{\partial k}\right) \leq 0 \qquad \textbf{(10)}$$

$$\frac{\partial L}{\partial a_i} = -c_a + f - \lambda \leq 0 \qquad \textbf{(11)}$$

$$\frac{\partial L}{\partial l_i} = -p + f - \lambda \leq 0 \qquad \textbf{(12)}$$

$$\frac{\partial L}{\partial \lambda} = v_i = e_i(q_i(k_i)) - a_i - l_i \geq 0 \qquad \textbf{(13)}$$

$$k_i \geq 0\,,\; k_i \frac{\partial L}{\partial k_i} = 0\,; \qquad a_i \geq 0\,,\; a_i \frac{\partial L}{\partial a_i} = 0\,;$$

$$l_i \geq 0\,,\; l_i \frac{\partial L}{\partial l_i} = 0\,; \qquad \lambda \geq 0\,,\; \lambda \frac{\partial L}{\partial \lambda} = 0 \qquad \textbf{(14)}$$

Taking an internal solution, we need to hold (11) and (12) equal to zero to obtain

$$\lambda = f - c_{a_i} = f - p \qquad \textbf{(15)}$$

A rational firm will choose its optimal investment in abatement measures so that the efficient marginal abatement costs $c_{a_i}^{*}$ are equalised across firms and will be the same as the equilibrium permit price *p*. This is a common finding and highlights the advantage of a permit market.

$$c_{a_i}^{*} = p \qquad \textbf{(16)}$$

A profit-maximising compliance decision for the firm is obtained when (12) holds as equality when (13) equals zero. The Kuhn-Tucker conditions in (14) require that $\lambda \geq 0$ when $\frac{\partial L}{\partial \lambda} = 0$, which implies that compliance is optimal as long as the fixed penalty rate is equal to or higher than the equilibrium price.

$$f \geq p \qquad \textbf{(17)}$$

Proposition 1 *Firms will find it profit-maximising to comply as long as the fixed penalty rate is set greater than or equal to the equilibrium permit price..*

This is the usual condition for achieving perfect compliance. Using this logic, tying the fixed penalty rate to the equilibrium price with a factor of greater than one will ensure that the fixed penalty rate is higher than the equilibrium permit price and ensure perfect compliance in the market. When that factor is kept slightly above one, the fixed penalty rate will be above but remain very close to the equilibrium permit price. However, tying the penalty rate to the equilibrium permit price may in fact introduce an uncertainty into the firm's decision-making process because the marginal penalty will always change following the equilibrium permit price.

When the penalty level is set lower than the equilibrium permit price, it will be profit-maximising for firms to be non-compliant ($v_i > 0$), so that the aggregate emissions level will be higher than the number of permits in the market $\hat{E} = \sum_{i=1}^{n} \hat{e}_i > S$. Hence, the emissions target will not be achieved and market effectiveness as well efficiency will not be realised. However, when the penalty level is set higher than the permit price, firms will be profit-maximizing by being compliant.

For an effective and efficient permit market to occur, full compliance in the market should be realised, $\sum_{i=1}^{n} v_i = 0$. This requires the firm's emissions level at the optimum to be equal to the sum of its optimal compliance strategies $e_i^{*} = a_i^{*} + l_i^{*}$ so that the same can be said at the optimal emissions level in the market.

$$\sum_{i=1}^{n} v_i = 0 \Rightarrow E^* = \left[\sum_{i=1}^{n} a_i^* + \sum_{i=1}^{n} l_i^* \right] \qquad \textbf{(18)}$$

At the market level, the targeted emissions level (the aggregate emissions level after abatement) should be: $\hat{E}^* = \left[\sum_{i=1}^{n} e_i^* - \sum_{i=1}^{n} a_i^* \right]$. This optimal level of targeted emissions is reflected by an exogenous variable set by the central authority, the permit supply S: $\hat{E}^* = S = L = \sum_{i=1}^{n} l_i^*$

Thus, at the optimum, the efficient marginal abatement costs requires that the targeted emissions level is equal to the permit supply. This ensures that market efficiency and effectiveness are achieved through the least coast marginal abatement costs, which is equal to *p*, and full compliance in the market.

$$c_a^* = \frac{\sum_{i=1}^{n} c_{ai}\left(a_i^*\right)}{n} = p \Rightarrow \hat{E}^* = \left[\sum_{i=1}^{n} e_i^* - \sum_{i=1}^{n} a_i^* \right] = \sum_{i=1}^{n} l_i^* = S \qquad \textbf{(19)}$$

Corollary 1 *As the penalty rate increases, the amount of abatement will also increase until the optimal level is achieved. At the optimum, the firm's marginal net benefit after taking into account the cost of compliance is equal to the firm's marginal cost of production.*

Proof: With a FPR below the efficient level $f < p$ and using equation (12) and (14), we derive that $l_i = 0$ when $\frac{\partial L}{\partial l_i} < 0$ because $l_i \frac{\partial L}{\partial l_i} = 0$. Hence, permit holding will be zero with the inefficient level of FPR. A positive violation level implies that the firm's emissions level is higher than the optimal level of emissions: $e_i > e_i^*$ .When $f = 0$, firm's emissions level will be $e_i^{\max}$, which represents the maximum production level without the existence of a permit market. Violation level is the difference between firm's emissions levels and abatement level: $v_i = e_i - a_i > 0$. Using the implicit function theorem, we obtain the logical result that $\frac{\partial v_i}{\partial f} = -\frac{\partial L / f}{\partial L / \partial v_i} < 0$. Increasing f will decrease the violation level, which implies that the abatement level will increase since permit holding equals to zero.

When λ is substituted in (15) to (11), we obtain

$$\tau \frac{\partial q_i}{\partial k_i} = r + p \frac{de_i}{dq_i} \frac{\partial q_i}{\partial k_i} \qquad \textbf{(20)}$$

Under a perfectly competitive permit market, we achieve the usual profit-maximising condition in which the firm's marginal benefit from undertaking a production activity, as expressed by the marginal revenue on the left-hand side, is equal to the sum of its marginal costs of production (capital rent) and its marginal compliance costs in the permit market on the right-hand side. As seen in the equation, this marginal cost is increasing in production level as the emissions level increases accordingly. *Q.E.D.*

To further illustrate the implications of Corollary 1, we use a simulation of the comparative statics. Holding other variables constant, we can see that the violation level decreases and then drops to zero as the penalty rate increases when $f < p$ (Figure 1a). The simulation is based on these functions and parameters: $c = a^2,\ e = q^{0.9},\ \ q = k^{0.5},\ \tau = 0.05,\ r = 0.15,\ p = 0.02$. This model confirms that firms will find it optimal to comply when the cost of being compliant is lower than the benefit of being non-compliant.

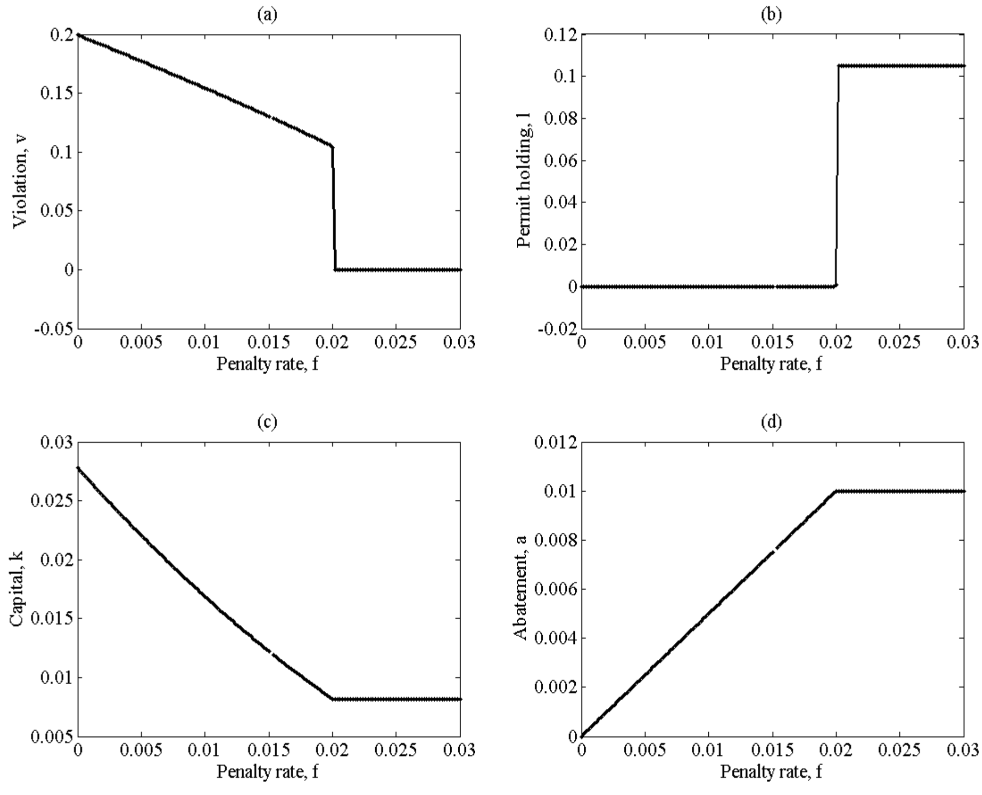


Figure 1 The Effects of Penalty Rates on Violation Levels, Compliance Strategies, and Production Levels under the FPR

Since the model simplifies compliance strategies to making investment decision in abatement measures and/or holding permit, the model can explain very well the effects of the levels of the penalty rate on both of these options (Figure 1b and 1c). When the penalty rate is less the equilibrium permit price, firms will not need to hold a single permit because it will be cheaper for them to either violate when their abatement cost is more expensive or to comply by investing in abatement measure when the abatement cost is cheaper than the permit price.

Considering that the model focuses on compliance decision and penalty design, the long-run incentive of making an early investment is not captured in the model. Rather, investment decision is merely a compliance strategy. Thus, any compliance strategies in this model, either abatement investment or permit holding, are expressed mainly as costs (permit selling is carried out more as a strategy to minimize compliance cost). In this sense, increasing the penalty rate renders higher compliance costs as firms need to hold permit in accordance with their output level. Consequently, firms reduce their output levels with increasing penalty rate up to the point where the penalty rate is equal to the equilibrium permit price, then firms achieve their optimal output level as expressed by the amount of capital use (Figure 1c).

It has been mentioned that market effectiveness requires full compliance of all firms while the market efficiency requires the least total costs of abatement in the market. This means that firms must choose their profit-maximising compliance decisions by choosing its optimal levels of compliance strategies..When the firm decides to make an investment decision and at the same time buys permits, it should choose an optimal mix of investment in abatement level and number of permit holding. However, if the firm should choose either one of the available compliance strategies based on the information on the equilibrium permit price, then its best compliance strategy should either be investing in an abatement measure or buying permit. In a permit market with a free allocation of permits (grandfathering), the choice of the firm's best compliance strategy will divide firms into two groups: net buyers and net sellers.

Proposition 2 *In a permit market with a fixed penalty rate in which the stock of permit is less than the aggregate emissions under business as usual and assuming that firms receive the same free allocation of permits, the firm's best compliance strategy is to be a net seller when its own marginal abatement cost is lower than the equilibrium permit price, or to be a net buyer when its own marginal abatement cost is higher than the equilibrium permit price. Hence, the efficient marginal abatement costs will be equalised across firms in the market.*

Proof: Let E and Q denote the *business as usual (*BAU) aggregate emissions level and the total production level, respectively.

Total emissions per period is

$$E = \sum_{i=1}^{n} e_i(q_i) \qquad \textbf{(21)}$$

Total output per period as denoted by

$$Q = \sum_{i=1}^{n} q_i \qquad \textbf{(22)}$$

When the total permit supply, which is equal to the total number of permit holding at the end of a compliance period, is lower than the BAU aggregate emissions level , some degree of abatement is required in the market.

$$S = L < E \qquad \textbf{(23)}$$

Then the optimal abatement level is required

$$A^* = E^* - L \qquad \textbf{(24)}$$

where

$$A^* = \sum_{i=1}^{n} a_i^* \qquad \textbf{(25)}$$

Given that $v_i = 0$ and $\mathrm{f} > p$, let $i = \{1,..., j, j+1,..., n\}$ and

$c_{a1} < c_{a2} < ... < c_{aj} < c_{aj+1} < ... < c_{an}$:

a) Firm $i \in \{1,..., j\}$ are net sellers of permits, with $c_{ai} \leq p$.

Then, making an investment decision in abatement measures and selling the freely allocated permits is the best compliance strategy for firm *i*, $\forall i \in \{1,..., j\}$.

For net sellers, denoted by *ns*, total emissions are:

$$E^{*ns} = \sum_{i=1}^{j} e_i^* = \sum_{i=1}^{j} a_i^{*ns}(p) \qquad \textbf{(26)}$$

b) Firm $i \in \{j+1,..., n\}$ are net buyers of permits, with $c_{ai} > p$.

Then, buying permits in the secondary market is the best compliance strategy for firm *i*, $\forall i \in \{j+1,..., n\}$ and firm *i* are net buyers in the permit market.

For net buyers (*nb*), total emissions are as follows:

$$E_i^{*nb} = \sum_{i=k}^{n} e_i^*(p) = \sum_{i=k}^{n} l_i^{*nb}(p) \qquad \textbf{(27)}$$

The optimal aggregate emissions level in the market is

$$E^*(p) = E^{*ns} + E^{*nb} = A^* + L = \sum_{i=1}^{j} a_i^{*ns} + \sum_{i=j+1}^{n} l_i^{*nb} \qquad \textbf{(28)}$$

where $a_i^* = 0 \ \forall \ i > j$ and $l_i^* = 0 \ \forall \ i < j+1$ *Q.E.D.*

Corollary 2 *Market efficiency is achieved when all firms choose their profit-maximising compliance strategy at the equilibrium permit price.*

Proof: Let the optimum aggregate profit in the market at the equilibrium permit price be

$$\Pi^*_{market} = \sum \Pi^*_i \left(a^*_i, l^*_i, k^*_i\right) = \Pi^*_1 + \Pi^*_2 + ... + \Pi^*_n \qquad \textbf{(29)}$$

Suppose we have one firm i =1 which does not choose its best compliance strategy such that $\Pi_1 < \Pi^*_1$; hence, $\Pi_{market} = \left[\Pi^*_1 + \Pi^*_2 + ... + \Pi^*_n\right] < \Pi^*_{marke\,t}$ *Q.E.D.*

2.6. Make-Good Provision

Under the make-good provision penalty design (MGP), a restoration rate ρ determines the ratio at which a firm should have to compensate for its missing permits. For instance, if a firm has 3 missed permits and $\rho=2$, then in the next period a firm should hold 6 more permits. Hence this penalty design allows a borrowing provision to the trading scheme. When $\rho=1$, the make-good provision allows for perfect borrowing from one period to another. However $\rho>1$ implies that there is an additional cost of borrowing. It can be said that the borrowing cost becomes more expensive with a higher restoration rate. In practice, the presence of a discount rate can encourage firms to shift emissions to today in order to push the costs further in the future (Kling and Rubin, 1997). Nevertheless, the absolute costliness of this borrowing provision in fact also depends on the permit price in the following period. As a result, to analyse the effects of a MGP, we need to develop a dynamic model.

Under a MGP, firms will not be penalized with a penalty fee when they have missed permits at a particular period *t*. For the sake of simplicity, let *t* = 1, 2 where period one is the first year and period two is the last year of a phase of an emissions trading scheme. Compliance is ensured only through a restoration rate which influences the initial allocation in period two. Thus the model is set such that the violation in the second period should be equal to zero. In practice, the regulator normally establishes a massive fine and/or serious legal consequences for violation at the end of a trading stage to ensure the firm's compliance in the market. In some countries, criminal charges or even incarceration are imposed in order to deter non-compliance in the market. Hence, firms need to keep their total violations equal to zero. However we do not take into account this legal implication as an additional compliance cost, rather we guarantee a condition of perfect compliance by setting the second period violation at zero. This assumption is a direct implication of the nature of MGP as a penalty design because firms can no longer compensate for its missing permits beyond the last year of a phase.

It is assumed that the total number of permits will be equal to the total number of initial permits given to each firm, which is constant in both periods.

$$S_1 = \sum s_{i1} = S_2 = \sum s_{i2} \qquad \textbf{(30)}$$

Furthermore, the total number of permits is lower than the total initial emissions of all firms to create an incentive to invest in abatement technology.

$$\sum_{i=1}^{n} e_{it} = E_t > S_t \qquad \textbf{(31)}$$

The key elements of permit market in this penalty design are basically the same to those in the FPR model. Firms have two compliance strategies: 1) investment of abatement measures, and 2) permit holding.

Firms can only make investment decisions in the first period to reflect the irreversible nature of investment. If firms choose to invest, the reduction in emissions levels will take place immediately, and the same abatement costs will also be incurred in the second period. If firms do not invest in the first period, they can only achieve compliance through permit trading.

$$\sum_t c_{it}(a_{it}) = 2c_i(a_i) \qquad \textbf{(32)}$$

The irreversible investment implies that while both compliance strategies are available in period one, permit holding is the only available compliance strategy in period two because in this period firms can no longer make their decisions with regard to abatement. The number of permit holdings is denoted by l_{i1} for period one and l_{i2} for period two.

Let firm *i*'s violation level in the first period be

$$\boldsymbol{v}_{i1} = \boldsymbol{e}_{i1}(\boldsymbol{q}_{i1}(\boldsymbol{k}_{i1})) - \boldsymbol{a}_{i1} - \boldsymbol{l}_{i1} \geq 0 \qquad \textbf{(33)}$$

The violation level in the second period is denoted by

$$\boldsymbol{v}_{i2} = \boldsymbol{e}_{i2}(\boldsymbol{q}_{i2}(\boldsymbol{k}_{i2})) - \boldsymbol{a}_{i2} - \boldsymbol{l}_{i2} = 0 \qquad \textbf{(34)}$$

Thus, firm *i*'s total violation level for both periods is

$$\sum_t v_{it} = \sum (e_{it} - a_{it}) - l_{i1} - l_{i2} \qquad \textbf{(35)}$$

When the firm violates in the first period, its initial permit allocation in the second period is reduced proportionately by a factor of ρ.

$$v_{i1} > 0 \rightarrow s_{i2} = (s_{i1} - \rho\, v_{i1}) < s_{i1} \qquad \textbf{(36)}$$

Firm *i*'s maximisation problem is

$$\underset{k_{i1},k_{i2},a_i,l_{i1},l_{i2}}{Max} \quad \Pi_i = \sum_t \tau\, q_{it}(k_{it}) - \sum_t r\, k_{it} - \sum_t c_{it}(a_{it}) - p_1[l_{i1} - s_{i1}] - p_2[l_{i2} - s_{i1} + \rho\, v_{i1}] \tag{37}$$

subject to $\quad \boldsymbol{v}_{i1} \geq 0, \;\; \boldsymbol{v}_{i2} = 0$

The Lagrangian equation for the profit maximisation problem is given by

$$L = \sum_t \tau\, q_{it}(k_{it}) - \sum_t r\, k_{it} - \sum_t c_{it}(a_{it}) - p_1[l_{i1} - s_{i1}] - p_2[l_{i2} - s_{i1} + \rho\, v_{i1}] + \lambda_1\, v_{i1} + \lambda_2\, v_{i2} \tag{38}$$

The Kuhn-Tucker conditions are

$$\frac{\partial L}{\partial k_1} = \tau \frac{\partial q_{i1}}{\partial k_{i1}} - r - [p_2\rho - \lambda_1]\left(\frac{de_{i1}}{dq_{i1}}\frac{\partial q_{i1}}{\partial k_{i1}}\right) \leq 0,$$

$$\frac{\partial L}{\partial k_2} = \tau \frac{\partial q_{i2}}{\partial k_{i2}} - r + \lambda_2\left(\frac{de_{i2}}{dq_{i2}}\frac{\partial q_{i2}}{\partial k_{i2}}\right) \leq 0 \tag{39}$$

$$\frac{\partial L}{\partial a_i} = -2c_{ai} + p_2\rho - \lambda_1 - \lambda_2 \leq 0 \tag{40}$$

$$\frac{\partial L}{\partial l_{i1}} = -p_1 + p_2\rho - \lambda_1 \leq 0 \tag{41}$$

$$\frac{\partial L}{\partial l_{i2}} = -p_2 - \lambda_2 \leq 0 \tag{42}$$

$$\frac{\partial L}{\partial \lambda_1} = e_{i1}(q_{i1}(k_{i1})) - a_i - l_{i1} \geq 0,$$

$$\frac{\partial L}{\partial \lambda_2} = e_{i2}(q_{i2}(k_{i2})) - a_i - l_{i2} = 0 \tag{43}$$

$$k_{i1} \geq 0,\; k_{i1}\frac{\partial L}{\partial k_{i1}} = 0; \qquad k_{i2} \geq 0,\; k_{i2}\frac{\partial L}{\partial k_{i2}} = 0;$$

$$a_i \geq 0,\; a_i\frac{\partial L}{\partial a_i} = 0; \quad l_{i1} \geq 0,\; l_{i1}\frac{\partial L}{\partial l_{i1}} = 0; \quad l_{i2} \geq 0,\; l_{i2}\frac{\partial L}{\partial l_{i2}} = 0;$$

$$\lambda_1 \geq 0,\; \lambda_1\frac{\partial L}{\partial \lambda_1} = 0; \quad \lambda_2 \geq 0,\; \lambda_2\frac{\partial L}{\partial \lambda_2} = 0 \tag{44}$$

Proposition 3 *The firm chooses its optimal level of investment in abatement measures by equalising its marginal abatement cost to the equilibrium permit prices in both periods. At the* *optimum, the firm's marginal net benefit after taking into account the cost of compliance is equal to the firm's marginal cost of production. This follows the result under a fixed penalty rate design.*

Proof: Assuming an interior solution, from (41) and (42), we obtain $\lambda_1 = p_2\rho - p_1$ and $\lambda_2 = -p_2$ These two equations are substituted back into equation (40) to obtain

$$-2c_{ai} + p_1 + p_2 = 0 \qquad \textbf{(45)}$$

Likewise, equations (41) and (42) are substituted into equation (39) to obtain

$$\tau \frac{\partial q_{i1}}{\partial k_{i1}} = r + p_1 \frac{de_{i1}}{dq_{i1}} \frac{\partial q_{i1}}{\partial k_{i1}}$$

$$\tau \frac{\partial q_{i2}}{\partial k_{i2}} = r + p_2 \frac{de_{i2}}{dq_{i2}} \frac{\partial q_{i2}}{\partial k_{i2}} \qquad \textbf{(46)}$$

Q.E.D.

This shows that the profit-maximising firm will increase its production level until the marginal revenue of production is equal to the sum of the marginal production cost and the marginal compliance cost under a permit market. In this sense, the degree of emissions increase that corresponds to a production increase is the key to the equation. Although we consider decreasing emissions levels as a result of abatement, we have not discussed the effect of the firm's technology θ_i on its emissions level. Accordingly, firms with cleaner technology have more of an advantage at a given level of capital.

Proposition 4 *Firms will find it profit-maximising to comply as long as the restoration rate is set at* $\rho \geq \frac{p_1}{p_2}$ *. This proposition holds when we consider a zero discount rate, which otherwise would have made different implications..*

Corollary 3 *When* $p_1 = p_2$*, increasing the restoration rate in the make-good provision will lower the firm's total violation level as the cost of borrowing increases until the restoration rate equals one, beyond which the firm will find it profit maximising to have a zero total violation level. The penalising effect of the borrowing cost will be higher when* $p_1 < p_2$*. Accordingly, when* $p_1 > p_2$*, the efficient restoration rate should be even higher than that when* $p_1 = p_2$*.*

Proof: Based on equations (41) and (43), we derive

$$\frac{\partial L}{\partial l_{i1}} = p_1 - p_2\rho + \lambda_1 \geq 0$$

$$\frac{\partial L}{\partial l_{i1}} = \frac{\partial L}{\partial \lambda_{i1}} \geq 0 \Rightarrow e_{i1}(q_{i1}(k_{i1})) - a_i - l_{i1} = v_{i1} = p_1 - p_2\rho + \lambda_1 \qquad \textbf{(47)}$$

Taking the first derivation of equation (47) with respect to ρ, we obtain the marginal effect of the restoration rate on first-period violations. Since $p_2 \geq 0$ and $v_{i2} = 0$, increasing the restoration rate will decrease the firm's total violation rate in the first period.

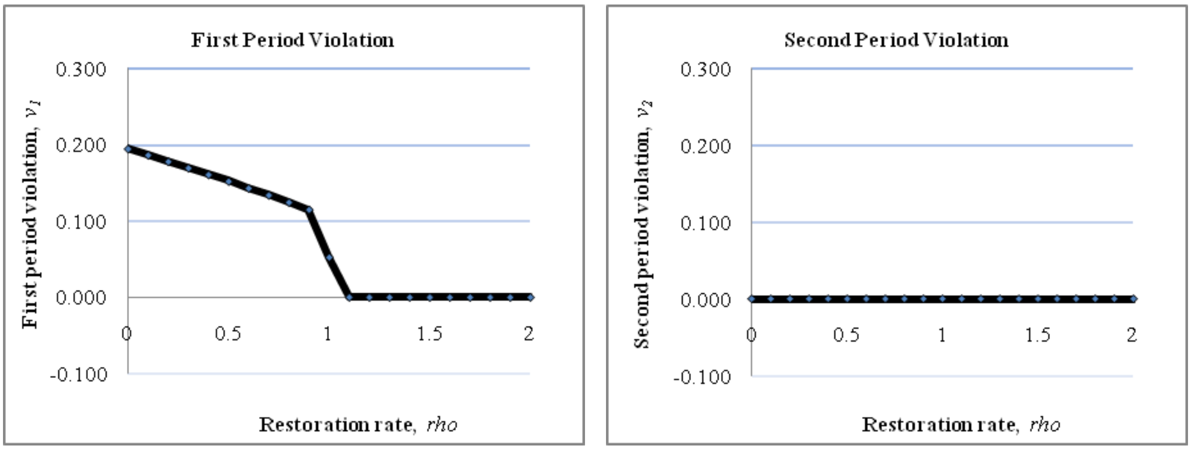
$$\frac{\partial v_{i1}}{\partial \rho} = -p_2 < 0 \qquad \textbf{(48)}$$

Profit-maximising compliance in the first period is achieved by setting equation (47) equal to zero. Since Kuhn Tucker's first order condition requires $\lambda_1 \geq 0$, we find that $\rho \geq \frac{p_1}{p_2}$. When we have non-zero discount rates, even higher levels of restoration rates are required as the discount rate will reduce the value of the second period permit price. *Q.E.D.*

In line with the case of FPR model, the firm starts with its maximum level of emissions by using its maximum capital use in the first period (k_1) when $p_2 \geq 0$. As the restoration rate increases the costs of being non-compliance becomes more expensive, hence the production level (capital use) decreases until it reaches the optimal level at $p_2 = 1$. This optimal level of capital use is maintained in the second period.

For illustrative purposes, we conduct a simulation that involves keeping the permit prices the same in both periods, $p_1 = p_2$. We use a comparative static analysis with the same parameters and functions as in the FPR design: $c = a^2$, $e = q^{0.9}$, $q = k^{0.5}$, $\tau = 0.05$, $r = 0.15$, $p_1 = p_2 = 0.02$.

The results indicate that when restoration rate is zero, which means that firms are not penalised for their missed permits in period one, the violation level reaches the maximum level, which is correlated with the maximum production level. As the restoration rate increases, the violation level decreases and then drops to zero when the restoration rate equals to one.



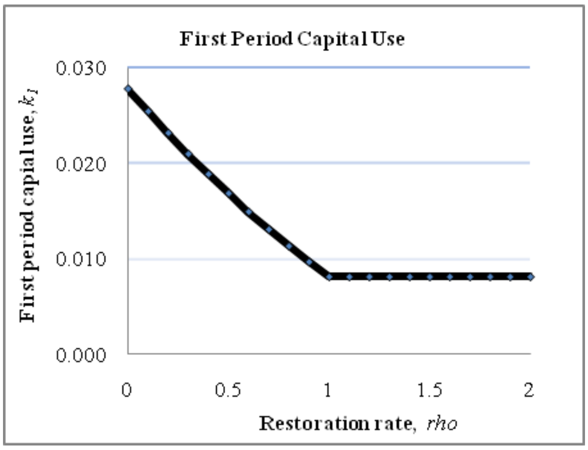
(a) The effect of restoration rates on the first period violation levels

(b) The effect of restoration rates on the second period violation levels

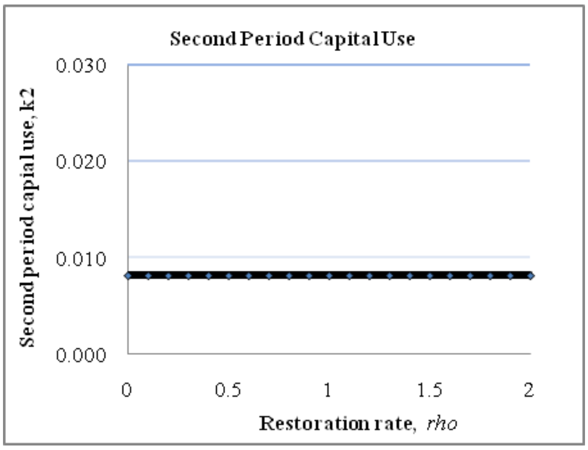
Figure 2 The Effect of Restoration Rates on Violation Levels under the MGP

This result confirms that when restoration rate equals to one, which implies a perfect borrowing across the two periods under zero interest rate, then firms are indifferent between violating in the first or second period. On the contrary, when the restoration rate is greater than one, the firm finds it more expensive to violate because there is a higher cost of borrowing and thus the firm keeps its violation rate to zero. As for the second period, the restoration rate has no effects in this model and the violation levels always equal to zero as required by the nature of MGP as a penalty design.

As shown in Figure 3, the restoration rate will affect the amount of capital use in the first period, but not in the second period. Increases in the restoration rate are matched by decreases in the firm’s first period capital because the restoration rate represents increasing compliance costs. This pattern continues until the restoration rate equals one, after which firms find it profit-maximising to have a zero first period violation by holding an optimal amount of capital under an emissions trading scheme. In the second period, firms use the same optimal amount of capital as in the first period regardless of the restoration rate.



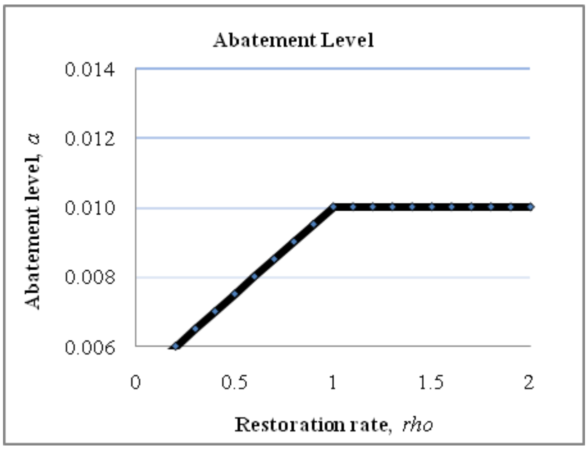
(a) The effect of restoration rates on the first period capital use (production levels)



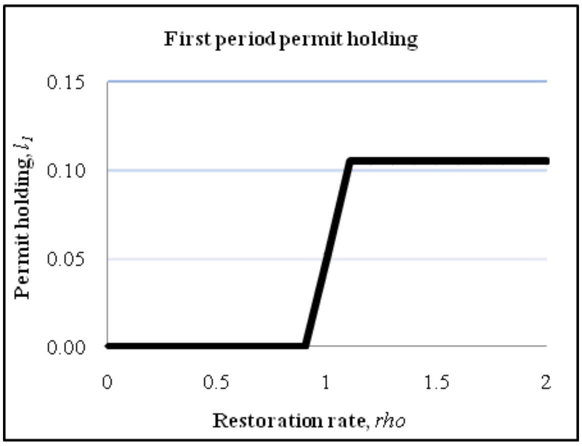
(b) The effect of restoration rates on the second period capital use (production levels)

Figure 3 The Effect of Restoration Rates on Production Levels under the MGP

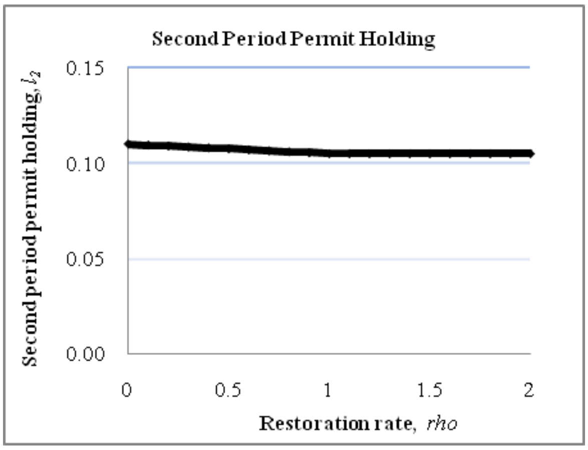
With regard to the choice of compliance strategies, the effect of restoration rate is as expected (Figure 4). Holding everything else constant, profit-maximising firms will increase their abatement levels with a higher restoration rate, and firms find the optimal abatement level when the restoration rate reaches one. Accordingly, in the first period, firms do not need to hold any permits when the restoration rate is still below one because it will be cheaper for them to violate. When the restoration rate exceeds one, then firms should hold the optimal number of permits. This result also explains why the violation level in the first period is positive when the restoration rate is less than one. Likewise, in the second period, firms hold the optimal number of permits regardless of the restoration rate after the restoration rate reaches one.



(a) The effect of restoration rates on abatement levels



(b) The effect of restoration rates on the first period permit holdings



(c) The effect of restoration rates on the second period permit holdings

Figure 4 The Effect of Restoration Rates on Compliance Strategies under the MGP

Proposition 5 *When the restoration rate is set at the efficient level, this restoration rate affects the firm's compliance strategies because it forces the firm to be compliant by either making an optimal investment in abatement measures or holding the optimal number of permits.*

Proof From equation (40) and (43) we derive the effect of the restoration rate on the amount of abatement.

$$\frac{\partial L}{\partial a_i} = 2c_{a_i} - p_2\rho + \lambda_1 + \lambda_2 \geq 0 \ , \ \frac{\partial L}{\partial \lambda_1} = e_{i1}\left(q_{i1}\left(k_{i1}\right)\right) - a_i - l_{i1} \geq 0 \ , \ \frac{\partial L}{\partial a_i} = \frac{\partial L}{\partial \lambda_1} \geq 0$$

By re-arranging the terms, we obtain a new function, $g(a)$, that is expressed in terms of abatement level.

$$g(a) = 2c_{a_i}^{-1}(a_i) + a_i = e_{i1} - l_{i1} + p_2\rho - \lambda_1 - \lambda_2 \quad \textbf{(49)}$$

Taking the first derivative of $g(a)$ with regard to the restoration rate yields

$$\frac{\partial g(a_i)}{\partial \rho} = p_2 \geq 0 \quad \textbf{(50)}$$

As $p_2 \geq 0$, the increasing restoration rate will increase the firm's abatement level until it reaches the optimal abatement level under the efficient restoration rate. When $\rho < \rho^*$, it will be profit-maximising for the firm to be non-compliant, and hence, it has a positive violation in the first period. With regard to permit holding, a non-compliant firm does not need to buy permits, as $v_{i1} > 0 \Rightarrow l_{i1} = 0$. However, when $\rho \geq \rho^*$, compliance becomes a profit-maximising strategy for the firm, and hence it will hold the optimal number of permits, $v_{i1} = 0 \Rightarrow l_{i1} > 0$. Permit holding in the second period remains at the optimal level to ensure firm's compliance in this period. This optimal level automatically follows the optimal level set in the first period given $\rho \geq \rho^*$. *Q.E.D.*

2.7. Mixed Penalty Design

Under the mixed penalty design (MIX), firms will be penalized with a restoration rate when they violate in the first period and at the same time they will be fined with a fixed rate, f, for their total violation level in both periods. The assumptions in this model follow from both the Fixed Penalty Rate (FPR) and Make-Good Provision (MGP) model. The important difference is that we allow for non-compliance in the second period, which is not the case in the MGP model. This is made possible due to the presence of FPR element that will penalise any violations. As before, it is assumed that we have a zero discount rate.

Firm *i*'s maximisation problem:

$$\underset{k_{i1},k_{i2},a_i,l_{i1},l_{i2}}{Max} \quad \Pi_i = \sum_t \tau\, q_{it}(k_{it}) - \sum_t r\, k_{it} - \sum_t c_i(a_{it}) - p_1[l_{i1} - s_{i1}] - p_2[l_{i2} - s_{i1} + \rho\, v_{i1}] - f[v_{i1} + v_{i2}] \quad \textbf{(51)}$$

subject to $\boldsymbol{v_{i1} \geq 0,\ \ v_{i2} \geq 0}$

The Lagrangian equation from the profit maximisation problem:

$$L = \sum_t \tau\, q_{it}(k_{it}) - \sum_t r\, k_{it} - \sum_t c_i(a_{it}) - p_1[l_{i1} - s_{i1}] \\ - p_2[l_{i2} - s_{i1} + \rho\, v_{i1}] - f[v_{i1} + v_{i2}] + \lambda_1 v_{i1} + \lambda_2 v_{i2} \tag{52}$$

The first-order conditions are obtained from the Kuhn-Tucker conditions:

$$\frac{\partial L}{\partial k_1} = \tau \frac{\partial q_{i1}}{\partial k_{i1}} - r - [p_2\rho + f - \lambda_1]\left(\frac{de_{i1}}{dq_{i1}}\frac{\partial q_{i1}}{\partial k_{i1}}\right) \le 0$$

$$\frac{\partial L}{\partial k_2} = \tau \frac{\partial q_{i2}}{\partial k_{i2}} - r - [f - \lambda_2]\left(\frac{de_{i2}}{dq_{i2}}\frac{\partial q_{i2}}{\partial k_{i2}}\right) \le 0 \tag{53}$$

$$\frac{\partial L}{\partial a_i} = -2c_a + p_2\rho + 2f - \lambda_1 - \lambda_2 \le 0 \tag{54}$$

$$\frac{\partial L}{\partial l_{i1}} = -p_1 + p_2\rho + f - \lambda_1 \le 0 \tag{55}$$

$$\frac{\partial L}{\partial l_{i2}} = -p_2 + f - \lambda_2 \le 0 \tag{56}$$

$$\frac{\partial L}{\partial \lambda_1} = e_{i1}(q_{i1}(k_{i1})) - a_i - l_{i1} \ge 0$$

$$\frac{\partial L}{\partial \lambda_2} = e_{i2}(q_{i2}(k_{i2})) - a_i - l_{i2} \ge 0 \tag{57}$$

$$k_{i1} \ge 0, \quad k_{i1}\frac{\partial L}{\partial k_{i1}} = 0; \qquad k_{i2} \ge 0, \qquad k_{i2}\frac{\partial L}{\partial k_{i2}} = 0;$$

$$a_i \ge 0, \; a_i\frac{\partial L}{\partial a_i} = 0; \qquad l_{i1} \ge 0, \; l_{i1}\frac{\partial L}{\partial l_{i1}} = 0; \qquad l_{i2} \ge 0, \; l_{i2}\frac{\partial L}{\partial l_{i2}} = 0;$$

$$\lambda_1 \ge 0, \; \lambda_1\frac{\partial L}{\partial \lambda_1} = 0; \qquad \lambda_2 \ge 0, \; \lambda_2\frac{\partial L}{\partial \lambda_2} = 0 \tag{58}$$

Proposition 6 *The optimal level of investment in abatement measures is attained by setting the firm's marginal abatement cost equal to the permit price in both periods.*

Corollary 4 *Under the mixed penalty design, the same results as in FPR and MGP models are derived in which the firm maximizes its profit by equalizing its marginal benefit after compliance cost to its marginal cost of production..*

Proof: Taking an interior solution, we derive $\lambda_1 = p_2\rho + f - p_1$ and $\lambda_2 = f - p_2$ from (55) and (56). We substitute these equations into equation (54) to obtain the optimal choice of abatement level:

$$-2c_a + p_1 + p_2 = 0 \quad \textbf{(59)}$$

In the same way, we substitute λ_1 and λ_2 into the Lagrange derivative of capital to obtain

$$\left(\tau - p_1 \frac{de_{i1}}{dq_{i1}}\right)\frac{\partial q_{i1}}{\partial k_{i1}} - r = 0$$

$$\left(\tau - p_2 \frac{de_{i2}}{dq_{i2}}\right)\frac{\partial q_{i2}}{\partial k_{i2}} - r = 0 \quad \textbf{(60)}$$

As with the MGP penalty, firms will be profit-maximising when the marginal revenue in each period is equal to the sum of capital rent and marginal compliance cost. *Q.E.D.*

Considering the efficient penalty level in the MIX penalty design, we need to look at each penalty element separately and then assess what happens when we vary their levels. Based on the first conditions (FOC), we see two differences between the MIX penalty and the MGP penalty. First, the fixed penalty rate now appears in both equations of partial derivative to permit holding in each period (55) and (56). Secondly, the sign of the partial derivative to the Lagrange multiplier with regard to the second period violation has changed. These changes lead to different implication in setting the efficient level of each penalty.

Proposition 7 *Under the mixed penalty design, the firm's compliance in the first period can be achieved only by setting either the fixed penalty rate or the restoration rate at an efficient level. Nevertheless, compliance in the second period is only attained by setting* $f \geq p_2$.

Corollary 5 *In the presence of a double penalty in the mixed penalty design, stronger compliance incentives are observed and the market efficiency is retained as in the other models.*

Proof: Focusing on compliance decisions in the first period, we make equations (55) and (57) equal to zero to attain

$$e_{i1}(q_{i1}(k_{i1})) - a_{i1} - l_{i1} = v_{i1} = p_1 - p_2\rho - f + \lambda_1 = 0 \quad \textbf{(61)}$$

Since $\lambda_1 \geq 0$, we can determine the efficient level of the fixed penalty rate.

$$f \geq p_1 - p_2\rho \quad \textbf{(62)}$$

Likewise, we solve for the efficient level of the restoration rate under the mixed penalty design.

$$\rho \geq \frac{p_1 - f}{p_2} \quad \textbf{(63)}$$

Both equations reveal that even if either $f = 0$ or $\rho = 0$, the other penalty type will still have a positive value and hold the firm's compliance at the optimal level. Nevertheless, the same cannot be said for the second period.

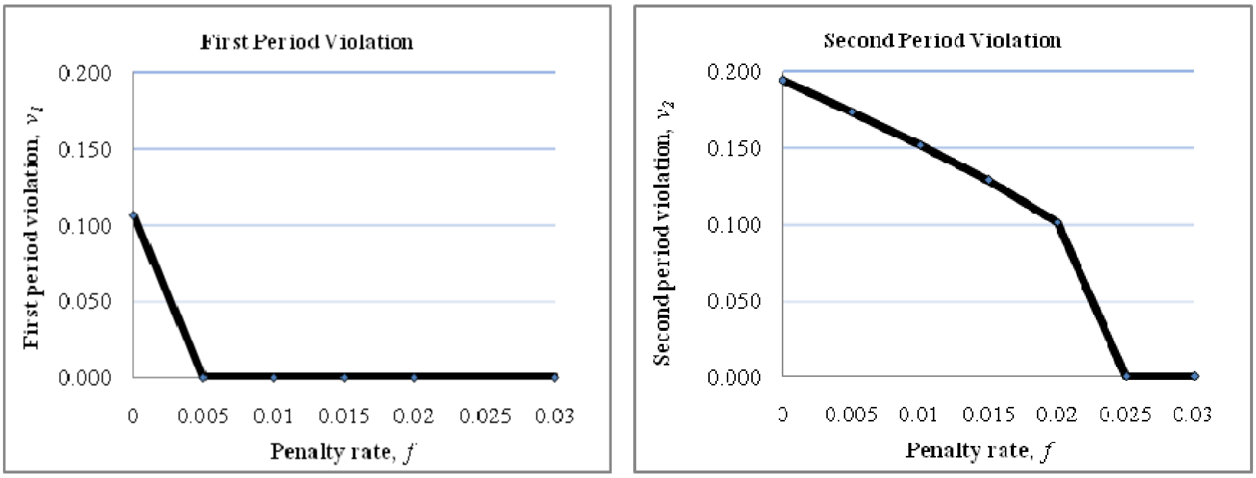
From (56) and (57), we obtain

$$e_{i2}(q_{i2}(k_{i2})) - a_{i2} - l_{i2} = v_{i2} = -p_2 + f - \lambda_2 = 0 \qquad \textbf{(64)}$$

Since $\lambda_2 \geq 0$, we derive the efficient fixed penalty rate for the second sub period

$$f \geq p_2 \qquad \textbf{(65)} \quad \textit{Q.E.D.}$$

As in the previous penalty designs, the same parameters and functions are used for the simulation; $c = a^2$, $e = q^{0.9}$, $q = k^{0.5}$, $\tau = 0.05$, $r = 0.15$, $p_1 = p_2 = 0.02$. Additionally, we set $\rho = 1$ to see the effect of an increasing penalty rate under the MIX. In general, the same effect as that in the FPR is obtained; a higher penalty rate decreases violation level until the efficient penalty rate is achieved. The difference is on the efficient level of penalty. As seen from Figure 5, the presence of restoration rate changes the efficient penalty level in the first period to a lower rate than it would be under the FPR alone. Obviously, the efficient level of penalty will change accordingly depending on the restoration rate as determined by equation (62). On the contrary, a much higher efficient level of penalty rate is required in the second period due to the presence of restoration rate. This effect illustrates the implication of the comparative static result in equation (65).

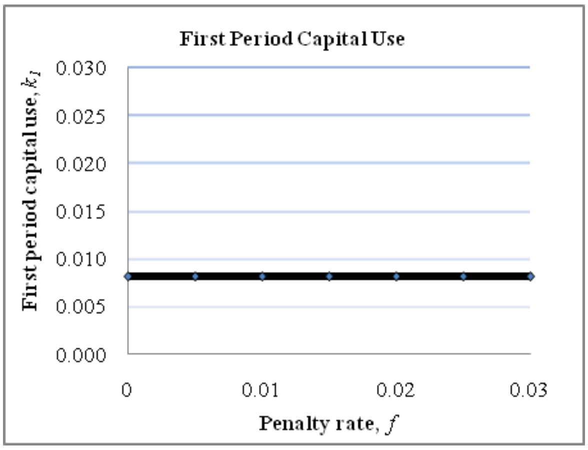


(a) The effect of penalty rates on the first period violation level under the MIX

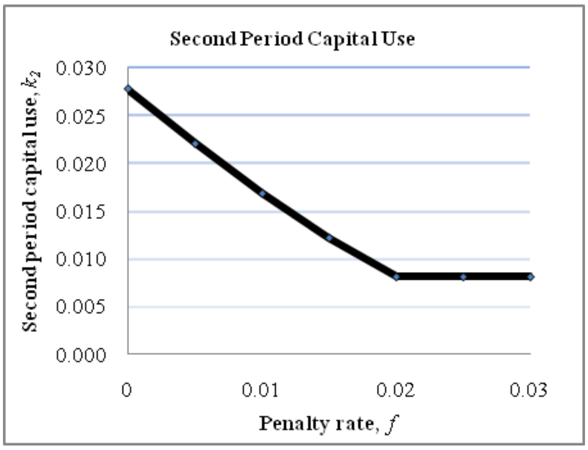
(b) The effect of penalty rates on the second period violation level under the MIX

Figure 5 The Effect of Penalty Rates on the Firm's Violation Levels under the MIX

The simulation results of the comparative statics on capital use show that the double penalty in the first period forces the firm to choose its optimal production level regardless of the penalty rate. When the effect of restoration rate is removed in the second period, the penalty rate has a similar effect as that of the FPR.

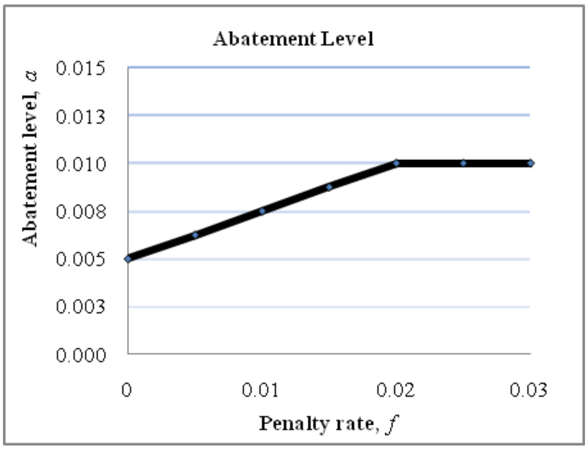


(a) The effect of penalty rates on the first period capital use (production levels) under the MIX

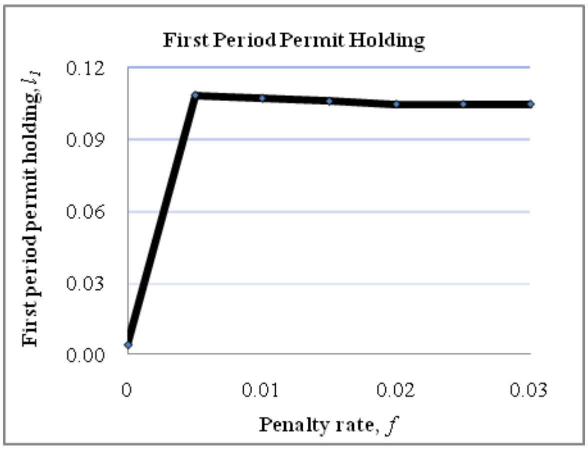


(b) The effect of penalty rate on the second period capital use (production levels) under the MIX

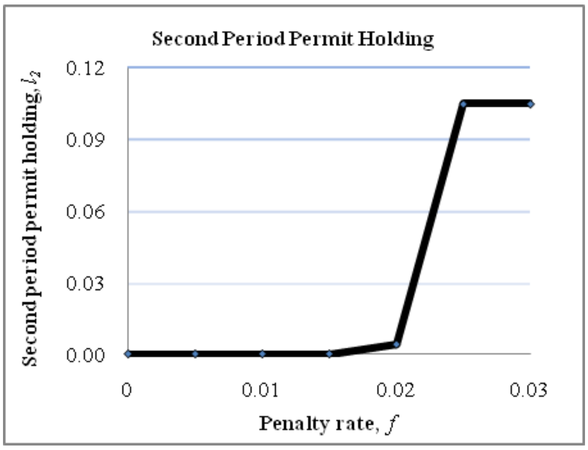
Figure 6 The Effects of Penalty Rates on Production Levels under the MIX



(a) The effect of penalty rates on abatement levels under the MIX



(b) The effect of penalty rates on the first period permit holding under the MIX

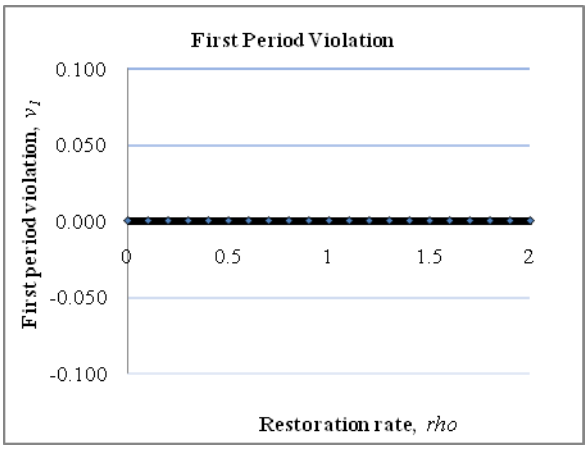


(c) The effect of penalty rates on the second period permit holding under the MIX

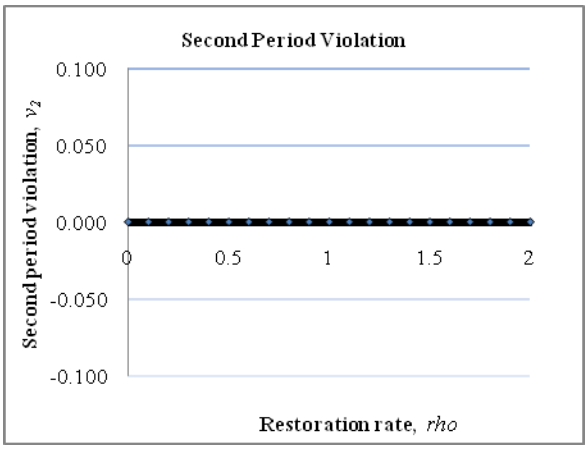
Figure 7 The Effect of Penalty Rates on compliance Strategies under the MIX

Compliance strategies under the mixed penalty design are affected by the penalty rate in fairly the same way as with the violation level and production level (capital use). Opposite to the effect on the second period capital use, increases in the penalty rate raise abatement levels until the optimal level is reached. The first period permit holding is increasing in the penalty rate until it reaches the optimal level. As in the case of violation level, a higher level of efficient penalty rate is required before permit holding in the second period achieves its equilibrium.

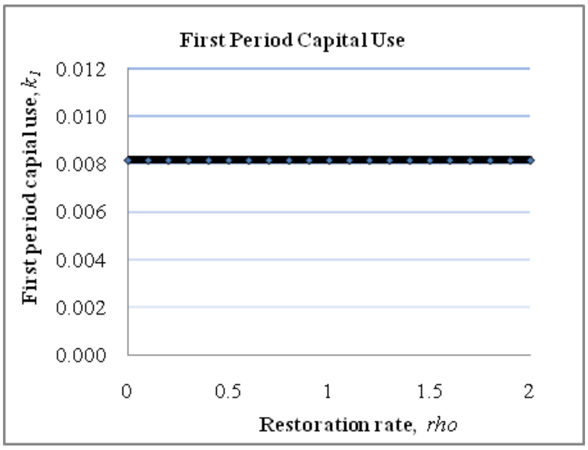
The restoration rate does not have as significant effect when an efficient level of penalty rate is enforced. A simulation of the comparative statics analysis is performed using the same parameters and functions as before with the penalty rate set at $f = 0.04$, which is twice the permit price.



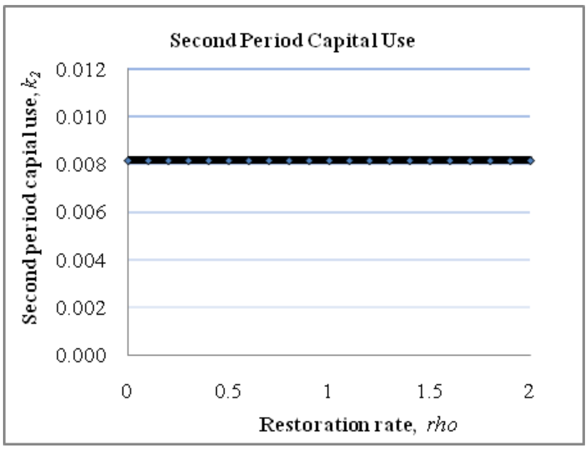
(a) The effect of restoration rates on the first period violations under the MIX



(b) The effect of restoration rates on the first period violations under the MIX



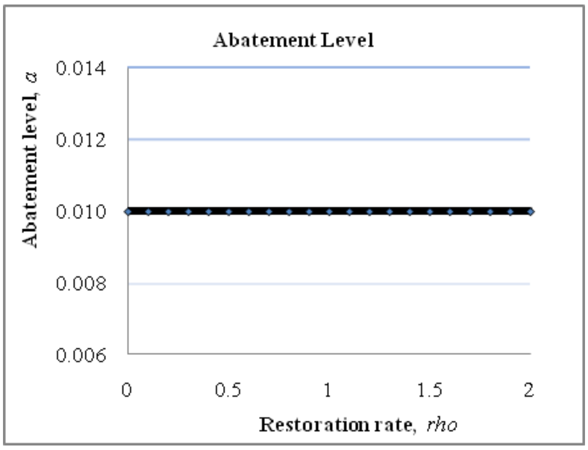
(c) The effect of restoration rates on the first period permit holding under the MIX



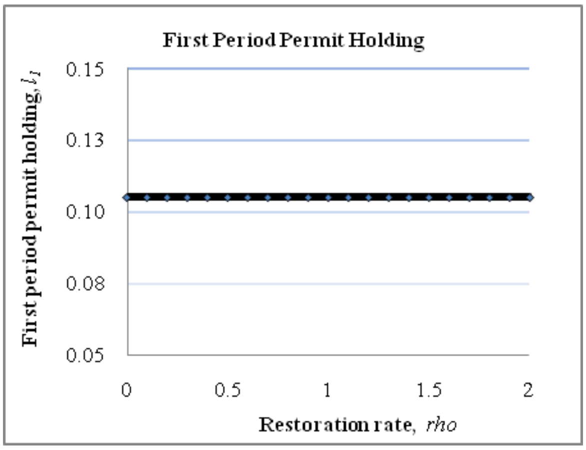
(d) The effect of restoration rates on the second period permit holding under the MIX

Figure 8 The Effect of Restoration Rates on Violation and Production Levels under the MIX

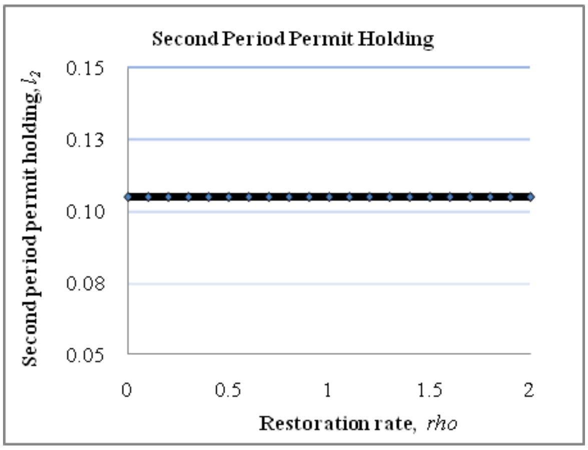
When we look at the violation level and production level, the simulation results indicate that the restoration rate does not play a role in determining the optimal level of those variables given that the penalty rate is established at the efficient level. Likewise, Figure 9 shows that all compliance strategy variables reach their optimal levels immediately at the beginning. It should be noted that those results are obtained when we set the penalty rate at the efficient level. Hence, the MIX model seems to guarantee that firms arrive at the optimal level of abatement level and permit holding immediately due to the presence of double penalties, which is different compared to the other models. Nevertheless, it is worth noting that the strong compliance incentive under the MIX does not compromise market efficiency as proven by equation (60).



(a) The effect of restoration rates on abatement level under the MIX



(b) The effect of restoration rates on the first period permit holding under the MIX



(c) The effect of restoration rates on the second period permit holding under the MIX

Figure 9 The Effect of Restoration Rates on Compliance Strategies under the MIX

2.8. Discussion

The assessment of the firm's profit-maximising compliance decision under three different penalty design show similar results. Those results are directly comparable as they are built on the same market structure. Each model allows for non-negative violation and look at the conditions that render it profit-maximising for firms to comply. Based on these conditions we can derive the efficient level of penalty as well as the optimal production level, abatement, and permit holding. In the MGP penalty design, the model forces firms to be compliant (to have zero violation level), which is different compared to the other penalty designs. Nevertheless, this difference is a direct implication of the nature of MGP as a penalty design, rather than a model assumption.

General findings from the three penalty design can be summarised as follows:

1. The firm finds its profit-maximising compliance decision through investing in the optimal level of abatement by equalising the efficient marginal abatement cost to the equilibrium permit price. This result is shown by equation (16) (FPR), Proposition 3 (MGP), and Proposition 6 (MIX), which is in line with the classic finding in earlier models of permit markets.
2. At the optimum, firm is compliant and profit maximising by equalising its marginal benefit after compliance costs to its marginal cost of production. Corollary 1 (FPR), Proposition 3 (MGP), and Corollary 4 (MGP) point out this finding.
3. The efficient penalty level for each penalty design:
    a. For FPR: $f \geq p$ as demonstrated by Proposition 1.
    b. For MGP: $\rho \geq \frac{p_1}{p_2}$ as shown by Propositions 4.
    c. For MIX: either $f \geq p_1 - p_2\rho$ or $\rho \geq \frac{p_1 - f}{p_2}$ in the first period and $f \geq p_2$ first period This is in line with the findings from the other penalty designs as indicated by Proposition 7.

The effect of increasing the penalty levels on violation level as well as the optimal production level, abatement and permit holding is simply demonstrated for FPR and MGP penalty design as shown by the proofs for Corollary 1 and Corollary 3. However, for MIX penalty design, there are more interconnected factors that determine the effect. Hence, the simulation of the comparative statics with an exemplary specific function can illustrate better the effect. The results of the simulation for MGP is also in line with the other penalty designs although the presence of second element of penalty in MIX, for instance the restoration rate element, puts some weight on the comparative statics of the effect of FPR in MIX.

As mentioned earlier, a theoretical model has the advantage of the simplicity of stylised facts. Nevertheless, some key issues related to the complexity of an emissions trading scheme need to be considered in order to gain an understanding of the implications that our results might have in practice.

One of the important functions of an emissions trading scheme is its role in the process of price discovery of the regulated pollutant. Typically, there is very little information of the permit price at the beginning of a trading scheme. At that point, the fixed penalty rate (f) is practically the first price signal received by firms apart from their own marginal abatement cost, as the maximum compliance cost. We can thus see the penalty rate as a focal point that serves as the first external reference point on which firms can base their compliance decisions. This signal will be adjusted as firms receive more price signals from the permit markets. On this ground, the initial allocation rule might actually influence the process of price discovery. This would contradict Montgomery's finding (1972) that the mechanism used to distribute initial permits to each firm should not affect the firm's behaviour in making an profit-maximising decision because it is assumed that each firm should be able to calculate the equilibrium permit price under the strong assumption of perfect competition and perfect information. In the case of grandfathering, price signals are generated by the secondary market. When permits are initially auctioned, firms will gain more signals at the earlier stage of a trading scheme about the expected permit price. Thus it is expected that there will be a faster convergence path to the Walrasian equilibrium when permits are auctioned off.

Another important issue to address in practice is the assumption of perfect information on the regulator's part. By and large, a regulating authority does not necessarily have all the required information on the firm's characteristics or emissions inventories, let alone its marginal abatement costs. Thus the authority makes its choice of fixed penalty rate under imperfect information (e.g. uncertainty about future emissions, perceptions about the risk of illiquidity in permit market). In such a situation, high penalty levels might lead to overinvestment in reduction measures because the cost of potentially being non-compliant for firms will be high compared to the cost of reducing emissions under the presence of uncertainties. This effect may increase when the number of permits is fixed, which means that the supply of permits will be inelastic in the short run. On the contrary, the penalty level may be set lower than the true equilibrium price, hence it acts as a price cap which provides lower investment incentives.

Under the absence of perfect information about the equilibrium permit price, there is no certainty that the penalty rate will always be above the equilibrium permit price, which is a very crucial issue especially if the penalty rate also functions as a price cap. Hence, the question about the level of the penalty rate becomes relevant. This concern has raised the idea of tying the penalty rate to an auction price to bring the penalty rate closer to the permit price and at the same time guarantees that the penalty rate will always be higher than the permit price given that the auction price is a good proxy of the permit price. The Australian federal government has put forward this concept in its proposal for the Australian trading scheme (the Carbon Pollution Reduction Scheme), in which the penalty rate is suggested to be capped at 110% of the benchmark average auction price. Nevertheless, it is important to note that in practice strategic bidding behaviour might drive down auction prices as firms understand that their bids will determine the maximum cost of compliance. Furthermore, this penalty design might create additional cost uncertainty which in turn will influence compliance decisions. In an extreme case, market players might collude to drive down the auction price to zero, creating a zero compliance cost. However, it is unlikely that the regulator would allow this to happen as the auction process should be designed to prevent such collusion from occurring and most auctions set a reserve price for that purpose. Most existing schemes, as shown by the rules applied by some Member States in the European Emissions Trading Scheme, also have additional penalties making violations a criminal offense and thus encourage further compliance by market players (Schleich et al., 2009). Firms are also exposed to additional reputation costs when they are non-compliant. In spite of this, it is worth to note the potential drawbacks of tying the penalty rate to the equilibrium permit price.

The use of a mixed penalty system should not affect the profit-maximising compliance strategies of firms, whether compliance is achieved through investment in abatement or through permit trading. Although this penalty design is perceived as a double penalty, under perfect knowledge about the equilibrium permit price and as long as the level of both the penalty rate and the restoration rate are set at the efficient level, in theory the optimal market condition is retained. However, this double penalty might have more deterrent effect for risk-averse market players and may encourage over-investment.

When a penalty rate and a restoration rate co-exist as a penalty design, firms arrive at the profit-maximising compliance strategies earlier than they do under the other penalty designs. Based on the comparative statics analysis, the fixed penalty rate seems to have a more prominent effect on compliance strategy than the restoration rate. Yet, the theoretical result rejects some concern that the MIX model will yield a lower efficiency level given the double penalty.

As shown in Table 1, the mixed penalty design seems to be favoured in practice, such as in the US Acid Rain Program, the EU ETS, the RGGI and the emerging schemes. This seems to be in line with the theoretical findings as stronger compliance incentives encourage faster convergence toward the profit-maximising compliance strategies.

2.9. Conclusion

Penalty design is an important element of permit markets which ensures that the market is capable of achieving both environmental effectiveness and economic efficiency. Our model shows that different penalty designs in the form of the fixed penalty rate (FPR) and the make-good provision (MGP) do not yield different results in terms of firms profit-maximising compliance strategy as long as the penalty level is set at the efficient level such that the penalty rate is greater than the permit price and the restoration rate is greater than ratio of the permit price in the first period to the permit price in the second period. For the mixed penalty design, perfect compliance in the first period can be achieved by setting either the penalty rate or the restoration rate at the efficient level. Nevertheless, the penalty rate element evidently plays a more important role to ensure compliance in the second period.

Efficiency in a permit market should be maintained regardless of the penalty design provided that each firm chooses its best compliance strategy and maximizes its profit by equalizing its marginal benefit to its marginal cost of production including compliance cost. Hence, if there is a firm in the market which does not choose its best compliance strategy, then market efficiency will be compromised.

Lastly, it is important to note that the final effects of different penalty designs on market efficiency are also influenced by the firm's risk attitude which is reflected in both investment level and the number of permit holding. On this ground, either the distance of the penalty level from the equilibrium permit price or the penalty type itself, which is not an issue in theory, might be a crucial design element for the regulator to consider.

Chapter Three

The Effects of Penalty Design on Market Performance: Experimental Evidence from an Emissions Trading Scheme with Auctioned Permits

3.1. Introduction

In order to achieve its environmental effectiveness, an emissions trading scheme requires a penalty which encourages compliance in the permit market. In spite of the wide recognition of its importance, the task of evaluating the efficacy of penalty design using empirical data is almost insurmountable due to differences in design features of the trading schemes as well as related market structures. Therefore, the use of a laboratory experiment offers an advantage in controlling for these design features and market parameters, which enables the isolation of the variables of interest.

This essay employs an experimental method to investigate the behavioural implications of penalty design on subjects' compliance decisions. In particular, we aim to assess how a specific penalty design in terms of penalty levels and penalty types in an auctioned permit market might induce different compliance incentives as well as market performance under the presence of subjects' risk preference. We consider the fixed penalty rate, the make-good provision, and the mixed penalty design as penalty types as well as low and high penalty levels for the first two penalty types. As a test-bed of a proposed policy design in the Australian Carbon Pollution Reduction Scheme, the third penalty type includes a novel trait of tying the penalty rate to the auction price. To isolate the effects of penalty design, we abstract from exogenous uncertainties, such as shocks in the emissions levels and changes in product prices, in the experiment. Furthermore, a two-period model is employed to highlight the effect of irreversible investment decisions as a compliance strategy other than permit buying. The evaluation of market performance is carried out by assessing price discovery in the permit market, the optimal investment level, compliance rates, and static efficiency.

The sections in this chapter are organised as follows. The next section outlines a literature review of penalty design in emissions trading schemes in practice, theory, and related experiments. This section also explains the motivation and the contribution of the study. Section three describes the experimental design, which is followed by the presentation of the experiment's hypotheses in section four. The following section displays results as shown by statistical summaries and the convergence path of some variables. Section six tests whether the results are statistically different from the equilibrium and further tests the hypotheses. Following results of the hypothesis testing, regression models are performed to control for other potentially influential variables. Section eight discusses the findings, and the last section concludes.

3.2. Literature Review

A penalty design that ensures the compliance of market participants is one of the key market design elements that enables an emissions trading scheme to deliver environmental effectiveness and economic efficiency. When a firm does not have the number of permits required for the levels of greenhouse gases it has reported, it will need to pay the penalty and/or 'make good' on its permit shortfall. From an economic perspective, it is often interesting to see how firms choose to comply with regulations in a particular setting to maximise their profits.

Generally, three types of penalties are widely used in existing emissions trading schemes. The first is the fixed penalty rate (FPR) system, which sets a constant fine for each missing permit. For example, the New South Wales Greenhouse Gas Abatement Scheme and the Los Angeles Regional Clean Air Incentives Market (LA Reclaim) for NOx and SOx pollutants use this type. The second penalty type is the make-good provision (MGP), which requires firms to make up for their permit shortfalls according to a particular ratio. Under this system, firms do not have a direct financial penalty to pay. Examples of this system include the US Ozone Transport Commission NOx Budget Trading Program, which imposes a 3:1 ratio. The last penalty type combines the two types (mixed penalty). This is the most widely used penalty design which serves as a double penalty to ensure that the relevant environmental goals are attained. This approach has been used in the European Union Emissions Trading Scheme (EU ETS) and some US emissions trading schemes. These practices are intended to prevent the continuous carrying-over of permit shortfalls, which in the end might undermine a scheme's reduction targets in the long term.

An important question with regard to penalty design is its effectiveness. A penalty is designed such that firms will choose to comply because the cost of being compliant is lower than the cost of not complying. Thus, a firm will prefer to buy enough permits to cover its emissions and avoid a penalty. Unfortunately, the equilibrium permit price, as a benchmark for penalty levels, is normally unknown to both the regulator and the firm. As the distance between the permit price and the penalty level decreases, the marginal benefit of being non-compliant increases. Thus, the question emerges of what the penalty level should be in the beginning, when the regulator does not have perfect information about the equilibrium permit price.

When compliance rates are used to measure the effectiveness of a penalty design, the existing schemes prove to have very high compliance rates. As permit prices can be quite volatile, the distance between penalty levels and permit prices varies accordingly. The Australian Carbon Pollution Reduction Scheme (CPRS) proposal links the penalty level to auction prices in an attempt to ensure that the penalty level would remain slightly above the expected permit price.

There have been many theoretical studies of enforcement in the context of pollution control. Among others, Malik (1990) employs a stylised enforcement model that focuses on audit probability and the magnitude of the penalty. By allowing for non-compliance rather than seeking a profit-maximising enforcement scheme, the model shows that non-compliance will alter the equilibrium permit price and market efficiency. Only a few studies discuss penalty types with regard to emissions trading schemes. Nentjes and Klaasen (2004) discuss the compliance incentives under the Kyoto Protocol but they look at the emissions trading scheme as an implicit compliance incentive rather than focusing on the penalty design within the trading scheme itself. It is argued that in cases in which a seller's reputation costs are lower than that of buyers and in which seller liability applies[2], the provision to trade will induce overselling on the seller's part, resulting in a lower compliance rate. Nevertheless, this conclusion is only valid when no further penalty is enforced in response to seller non-compliance. Furthermore, this condition is not fulfilled in the existing trading schemes because penalty costs are the same for all firms and reputational costs constitute an additional penalty. Additional penalty costs also exist due to different penalties for reporting violations in each Member State of the EU ETS. A study by CPB (2003) discusses the restoration rate or the make-good ratio as a means to induce early action rather than delaying in investment. A general equilibrium model is used to analyse the appropriate restoration rate under some particular scenarios and the degree of delay in six blocks of countries. The study suggests that the interpretation of the results is highly dependent on the particular setting of the model.

[2] The seller's liability rule states that a sanction will be imposed on permit sellers that have oversold their permits without making sufficient emissions reductions.

Trading schemes can have very different design elements, cover different industries, and operate in different market structures that are not directly comparable to one another. Thus, it is very difficult to assess the effectiveness of a particular penalty design empirically using field data. Experimental economics offers an approach in which subjects' decision-making can be observed while the parameters and environment in which a market operates are controlled within the laboratory. To our knowledge, there have been a limited number of experimental studies focusing on enforcement in the context of emissions trading schemes. Cason and Gangadharan (2006) use a dynamic enforcement model to assess the interactions among banking, uncertainty regarding emissions, and compliance. In the experiment, subjects were required to self-report their emissions level. The penalty design involves a higher audit probability and a fine for subjects found to falsely report their emissions levels. Their results show that a banking provision induces higher non-compliance. Murphy and Stranlund's study (2007) investigates the effects of targeted enforcement by differing marginal penalties, in terms of audit probabilities and penalty levels, for different characteristics of firms. They confirm the results of Stranlund and Dhanda's (1999) theoretical model that targeted enforcement does not increase the effectiveness of the enforcement scheme, although firms that are expected to be net buyers show a higher level of non-compliance than those that are expected to be net sellers.

There are a couple of experiments in tradable green certificates which also study the effects of penalty levels. Schaeffer and Sonnemans (2000) examine compliance incentives for mandatory and voluntary market participants under the provision of permit banking and/or borrowing, while Ivanova (2007) looks at the price effect of penalty levels in an oligopolistic market. Both studies conclude that penalty levels affect compliance rate and price levels. Nevertheless incomplete design of treatment variables, non-balanced sessions for each treatment, as well as the absence of control on voluntary and mandatory demand of permits in Schaeffer and Sonnemans (2000) might induce confounding effects on their findings. On the other hand, the oligopolistic setting in Ivanova (2007) does not suit our interest as we investigate a competitive permit market. Furthermore, the specific roles of buyers and sellers are not assigned to the subjects in our experiment as are the case in both experiments.

The existing literature seems to focus more on different audit probabilities and marginal penalties, targeted enforcement, and cheating as the main elements of enforcement in an emissions trading scheme. Employing a rather different perspective on the enforcement model, our study focuses on the types and levels of penalties given perfect monitoring. Hence, we do not consider the effect of audit probability. It is plausible that different penalty designs per se might have different effects on firms' behaviour especially under the presence of uncertainties regarding permit price as well as risk aversion. In particular, our study aims to contribute to the literature by investigating these aspects:

1) The effect of penalty levels

   Penalty levels provide information about the maximum compliance costs in the permit market and this information may serve as a focal point in the process of price discovery. To some degree, the penalty level can also be seen as an indication of a price cap. Some have argued that the presence of non-binding price controls, which are price ceilings (or floors) set above (or below) the equilibrium price, can be useful in lowering the costs of uncertainty and thus increasing the efficiency of emissions trading markets (Jacoby and Ellerman, 2004, Burtraw et al., 2010, Fell and Morgenstern, 2009, Szolgayova et al., 2008). An experiment by Isaac and Plott (1981) studying non-binding price controls indicates that price controls do not serve as a signalling price or a focal point. However, the study does not find conclusive evidence that price ceilings (or price floors) will bias prices below (or above) the competitive equilibrium. In contrast, Smith and Williams's (1981) experiment with a double auction market reveals that non-binding price controls affect price convergence. As mentioned previously, experiments in tradable green certificates find that a higher penalty level, combined with banking provision (Schaeffer and Sonnemans, 2000) or under the presence of market power (Ivanova, 2007), raises permit price. Thus, the level of the penalty may influence the price discovery process in the market because it may steer the direction of prices.

2) The effect of penalty types

   The penalty type itself may have different effects on a firm's behaviour. To our knowledge, no experiments have been done to test the effect of penalty type. Experiments focusing on emissions trading schemes that have used enforcement models have only employed fixed penalty rates. Given that the make-good provision (MGP) can be seen as a quantity penalty that allows non-compliant firms to 'borrow' from future permits, the cost of compliance under the MGP is reliant on future permit prices. Thus greater uncertainty about future permit prices will put more pressure on the cost of borrowing as well as uncertainty regarding fixed penalty rate. In contrast, a fixed penalty rate implies a fixed per unit cost of violation (fixed penalty rate). Hence, the different nature of the two penalty types might affect firms differently in choosing their compliance strategies.

3) We abstract from any uncertainties other than that which arises from subjects' decisions

   Our focus is on the effects of penalty design on the performance of an emissions trading market. To isolate the effects of the treatment variable, we do not introduce any form of uncertainties in the experiment. The only uncertainties that might arise are those that stem from subjects' decisions during the experiment. Hence, it allows us to isolate the effects of penalty types and levels on compliance rates and compliance strategies.

4) The use of two period model to highlight the effect of irreversible investment decision as one of the compliance strategies

   We simplify the spectrum of a firm's compliance strategies to two options: irreversible investment decisions and permit holdings. Investment decisions are modelled as irreversible in order to parallel with real-world conditions in which once the investment is made, e.g. installing a scrubber in a plant, the decision cannot be reversed and the scrap value of the installed abatement equipment is insignificant. In our model, each round of trading is comprised of two sub periods to reflect the two-period model. As a consequence, the investment decision can only be made in the first sub period and results in abatement measures to be undertaken in both sub periods.

5) The mixed penalty design in which the penalty rate is tied to the auction price

   The proposed Australian model uses a mixed penalty design in which the penalty level is set very close to the auction price, and the make-good factor is one. This design may encourage strategic bidding intended to drive down firms' compliance costs. Thus, we also consider this penalty design in our experiment.

To sum up, this experiment aims to investigate the effect of penalty design on compliance incentives and market performance. In order to evaluate the effects of penalty design on market performance, we look at permit prices and standard deviation of prices, the incentives of each penalty design on investment levels and compliance rates, and lastly how the penalty design affects efficiency. The details of the experimental design and the hypotheses upon which the evaluation is based are elaborated in the following sections.

3.3. Experimental Design

We consider five treatments with the level and the type of penalty as our treatment variables. For each penalty type, the fixed penalty rate (FPR) and the make-good provision (MGP), we consider a low and a high penalty level. Additionally we also study a mixed penalty that combines the FPR and MGP mechanism. For this mixed penalty, a low MGP ratio is used, and the penalty rate is linked to the auction price, as in the Australian model.

The experiment procedure consists of three sessions, each of which involves two groups of eight subjects. The groups remain the same for the whole session. Thus, we have six observation groups for each treatment. The subjects are randomly allocated to a group so that they do not know whether the people next to them belong to the same group. In each session, the subjects participate in the Holt and Laury's (2002) lottery-choice game before taking part in the emissions trading game[3]. However, the payoff from the Holt and Laury's experiment is only determined after the emissions trading game is concluded to avoid any endowment effects.

Table 2 Treatments for the Penalty Design Experiment

Penalty Design	Penalty levels	
	Low	High
Fixed penalty rate (FPR)	1.2 x equilibrium permit price[a] Treatment I (AFL)	3 x equilibrium permit price Treatment II (AFH)
Make-good provision (MGP)	1:1 ratio Treatment III (AML)	3:1 ratio Treatment IV (AMH)
Mixed penalty	MGP low level + FPR (1.2*auction price) Treatment V (AFM)	

[a] the equilibrium permit price equals to the Walrasian price

The subjects are undergraduate and postgraduate students at the University of New South Wales who were recruited through the ORSEE online recruitment system (Greiner, 2002). Each subject could only participate in one session as this experiment featured a between-subject design. Thus, a total of 240 students participated in the experiment. Each session lasted for 2.5-3 hours, and subjects earned an average of $24.48 for the emissions trading game and $34.20 for the whole session.

The emissions trading game was programmed using the University of Zurich's Z-Tree program (Fischbacher, 1999). Eight subjects in one group played six repeated rounds, and each round was comprised of 2 sub periods. Although we use terms related to the emissions trading scheme context in this essay, the subjects received instructions worded using neutral terminology. Emissions or other environmental terminology was not used at all in the instructions (Appendix).

[3] The Holt and Laury's (2002) experiment asked subjects to choose 10 paired lottery choices A and B for which the probability of a higher payoff from both choices was increased. A consistent risk preference attitude will require a change from the safer lottery A to lottery B somewhere within the 10 pairs. The combinations of safe and risky choices constitute an index from 1 to 9 in which a higher number represents greater risk aversion.

The subjects were told that they were firms that needed a license for each unit of good X that they produced. Firms' production levels before taking abatement measures represented their emissions levels. Permits expired at the end of each sub period. If a firm did not hold enough permits, it would incur a penalty. The regulator would determine the emissions cap, which was set at 50% of firms' initial emissions levels, and this cap remained the same for both sub periods. Firms had two compliance strategies from which they might choose: 1) making irreversible investment decision in abatement technology, and 2) holding enough permits to cover their emissions levels. Firms were allowed to undertake both measures although each firm's profit-maximising compliance strategy was only either one of them.

The key features of the emissions trading game are as follows:

1. Stages of the game

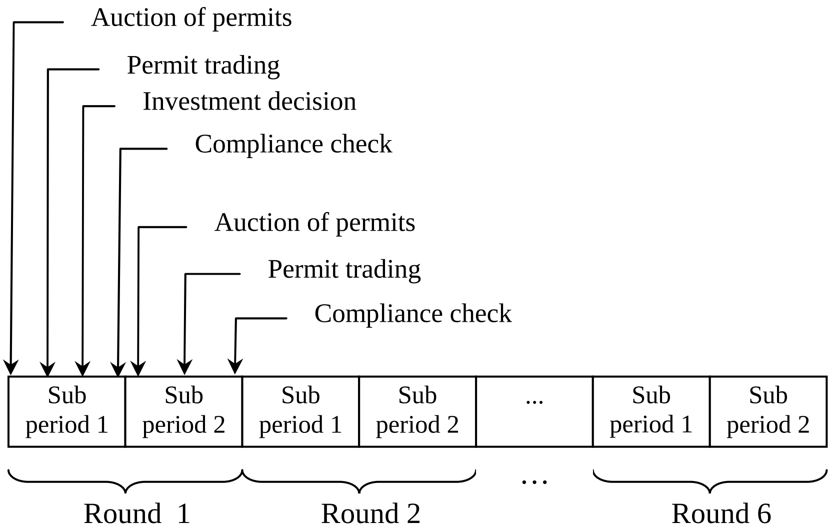


Figure 10 Stages in the Emissions Trading Game

There are four stages in the emissions trading game, as shown in Figure 1.

a) Stage 1: Auction of permits

The initial allocation of permits to firms is conducted through an auction using an ascending clock auction[4]. The auction supply is fixed at 80 permits in each sub period. At this stage, each firm needs to submit a non-negative bidding quantity during each bidding round. As the bidding rounds continue, firms are given the information about the gap between the aggregate demand and supply. This information may lead firms to collaborate to drive down the auction price (Klemperer, 2002). Nevertheless, this is

[4] In an ascending clock auction, the price is the clock, and the bidding price increases as long as the aggregate bidding quantity (aggregate demand) is higher than the total supply.

highly unlikely considering the number of subjects and the random matching of those subjects in each session.

The bidding price starts at Experimental Dollar (EX$) 18 and increases in EX$5 increments. We start with a bidding price lower than the lowest firm's marginal abatement cost to allow all firms to submit a positive bidding quantity. We choose these price parameters so that we will have enough bidding rounds to allow for a better price discovery process but still keep the auction stage from becoming too long and the experiment from taking too much time.

When the aggregate demand of permits equals the aggregate supply, then the last bidding price becomes the auction price and firms are allocated permits as many as their last bidding quantity. If the aggregate demand of permits is less than the supply in a bidding round, then the auction price is the price in the penultimate bidding round, and firms are allocated their last bidding quantity plus any remaining excess supply. The excess supply is allocated according to the order of the fastest bidders. In this fashion, we follow the Virginia NOx auction model, which gives bidders incentives to submit their bids promptly (Holt et al., 2007, Porter et al., 2009).

The clock auction format is used due to its simplicity and transparency. This dynamic auction type, which includes multiple bidding rounds, allow subjects to think carefully in submitting their bids as bidding price increases (Compte and Jehiel, 2007). An ascending auction is also likely to allocate the goods to bidders with the highest value because they can always rebid and top lower-value bidders who may have bid aggressively in earlier bidding rounds (Klemperer, 2002).

b) Stage 2: Permit trading

After receiving their permit allocation at the auction, firms trade permits using a posted-offer continuous double auction mechanism for one minute[5]. This mechanism allows firms to either buy or sell. Firms are free to accept any submitted (buy or sell) public offers at any time during the trading stage, although improved bidding rules are used to encourage faster convergence of offer prices[6]. Trade can only take place for each unit of license at a time. This double auction mechanism is a widely used trading institution in economic experiments and has proven to be highly efficient (Ledyard and Szakaly-

[5] We allow a relatively short trading period for the spot markets as the main permit allocation process should have taken place at the auction. Consequently, permit trading serves as a secondary trading institution used to 'clean up' the results of the auction if it does not yield the expected allocative efficiency.

[6] Improved bidding rules require that the buy offer be higher than the current highest-standing buy offer, whereas the sell offer should be less than the lowest-standing sell offer.

Moore, 1994). Following each trade, firms receive updated public information regarding standing offers and trading prices as well as private information about their money and permit holdings. At the end of the trading stage, the average trading price from that sub period is revealed to firms as a point estimate of the price signal.

c) Stage 3: Investment decision (only for sub period one)

The investment decision can be seen as a way to activate firm's abatement technology; hence, the investment cost is represented as the marginal abatement cost rather than as a lump sum capital cost. The decision to invest in abatement technology will ensure that the firm is compliant for both sub periods in a round. To reflect the irreversibility of investments in accordance with the theoretical analysis in chapter two, we only allow firms to make investment decisions in the first sub period; they cannot be changed or be undone in the second sub period. During this stage, firms also find out whether they have a short or long permit position before they make irreversible investment decisions. Partial investments are not allowed. This is meant to encourage firms to learn about their best compliance strategies. If firms are short only a few permits and decide to invest, they will be over-compliant because investment automatically guarantees compliance and firms can no longer sell their permits at that stage in a sub period.

d) Stage 4: Compliance check

The compliance check is the last stage in each sub period where subjects learn about their earnings for that sub period, their compliance status, and the penalties imposed on them if they are non-compliant.

2. Players' characteristics:

All firms produce a homogenous product and have the same production level of 20 units in each sub period throughout the experiment. Firms are only differentiated by their constant marginal abatement cost (MAC), which is one of these values: $c_i \in EX\$ \{20, 25, 30, 35, 40, 45, 50, 55\}$. The MAC is randomly allocated to each firm in each round and the set of MACs remains the same in all rounds. Based on the magnitude of a firm's marginal abatement costs, there are two types of firms: low-cost firms with MACs of EX\$ 20-35 and high-cost firms with MACs of EX\$ 40-55.

At the beginning of each sub period, firms receive the same total revenue of EX\$2800 from their production activity as the price of the good is exogenous and the same for everyone. Thus, the marginal revenue is constant at EX\$140, but firms have different marginal benefits of each unit of good.

3. Information structure

At the beginning of sub period one in a round, subjects receive common information about their initial emissions level, the emissions cap, and the penalty design. This common information is known to all firms and remains the same during all rounds. At this stage, the subjects also receive private information about their marginal abatement costs, available money, and required number of licenses. In sub period two, subjects are also reminded of their investment decisions and their compliance status in sub period one. The information structure basically enables participants to estimate profit-maximising decisions whether to invest in abatement technology or buy permits in the market. Subjects can even calculate where the equilibrium price should be under the assumption of risk neutrality. Nevertheless, different risk attitudes and different expectations regarding prices may create uncertainty in permit price.

4. Banking and borrowing are not allowed.

Because the focus of our experiment is on the penalty design, we simplify our two-period model to abstract from the effect of banking. By allowing neither banking nor borrowing, we attempt to keep the market structure the same for both sub periods; banking might create upward pressure on the expected permit price in the first sub period and will add more noise to the results. Hence the expected permit price should remain the same across the two sub periods in one round.

5. Penalty

The enforcement of the penalty design in the emissions trading game is conducted as follows:

a) In the FPR treatment, the penalty is imposed at the end of each sub period during the compliance check. If a firm is non-compliant, the penalty costs are deducted from that firm's earnings. The penalty rate is EX$ 45 for the low level FPR and EX$ 114 for the high level FPR.

b) In the MGP treatments, the penalty is enforced differently for the two sub periods.
   i) Non-compliance in sub period one has no financial penalty but the violating firms need to surrender the quantity of the missing permits by a ratio. For example, in the high level MGP treatment using a ratio of 3:1, if a firm is two permits short, then it must hold six additional permits in sub period two.

ii) As firms cannot further compensate ("make good") for non-compliance at the end of sub period two, we attempt to deter non-compliance by imposing an enormous financial penalty which is equivalent to the firm's total revenue (EX$ 2800).

6. Payoff

Firms can maximise their payoff by minimising their compliance costs or by maximising their profits from selling permits during the trading stage. The payoff function is the same for all firms.

Payoff =
+ total revenue
+ cash balance in sub period one of the same round
– number of licenses bought in auction * auction price
– investment costs
– trading price of licenses bought during trading stage
+ trading price of licenses sold during trading stage
– penalty costs

The payoff is accumulated for all rounds, and subjects' earnings are shown at the end of each round. Nevertheless, the amount of money that subjects receive in the beginning of each round (sub period one) is always equal to the total revenue. This helps us to avoid the issue of wealth effects for the subjects as the round goes on.

3.4. Hypotheses

In the competitive equilibrium, the permit price should lie between EX$35-40 under perfect compliance. Considering the design of the auction bidding price, the auction price should reach its equilibrium at a price of EX$38. At this equilibrium, the best compliance strategy for low-cost firms is an investment decision, while the high-cost firms should comply by buying permits. The equilibrium permit price is achieved when each firm chooses its best compliance strategy.

The findings from our theoretical models, as shown in the previous chapter, indicate that firms will find it profit-maximising to comply as long as the penalty rate is set higher than the equilibrium permit price (*Proposition 1*) or as long as the make-good ratio (restoration rate) is higher than or equal to one when permit prices remain the same in both sub periods (*Corollary 3*). The mixed penalty design, which uses both types of penalties, supports those findings, and the presence of the double penalty ensures that firm compliance is still achieved.

For this penalty regime, the comparative static analysis indicates that although the level of one penalty type is varied, compliance is still maintained due to the presence of the other penalty type (*Proposition 7*).

Based on those findings and the parameters of the experimental design, we derive the following hypotheses:

Hypothesis 1: The auction price should remain the same in all treatments because the supply and demand structure remains the same.

Based on the Law of One Price, it is expected that the auction price will be the same as the trading price.

Hypothesis 2: In the FPR treatments, investment levels and compliance rates should be the same at 100% regardless of the penalty levels because the penalty rate is set higher than the theoretical equilibrium permit price.

Hypothesis 3: The make-good ratio should not affect investment levels or compliance rates in the MGP treatments as long as it is set equal to or higher than one under the assumption that prices remain the same in the two sub periods.

Hypothesis 4: At the high penalty level, the compliance rates and investment levels in the FPR treatments should be the same as those in the MGP treatments. At the low penalty level, similar results are expected, although the penalty level is slightly higher in the low level FPR treatment (with a factor of 1.2), whereas the make-good ratio is 1.

Hypothesis 5: The mixed penalty treatment should yield the same compliance rates as the FPR and MGP treatments.

3.5. Results

3.5.1. Subject Risk Preferences

The Holt & Laury (2002) lottery choice experiment shows that more than 75% of the subjects are risk neutral, slightly risk averse, or risk averse, as expected. We observe that some subjects made inconsistent risk preference choices by changing from one lottery to another more than once. However, only about 20% (or fewer) of the subjects in each treatment showed these inconsistencies (Figure 11). The data on subjects' risk preferences are later used in the estimation models because their risk attitude may be an important determinant of compliance strategy and auction prices.

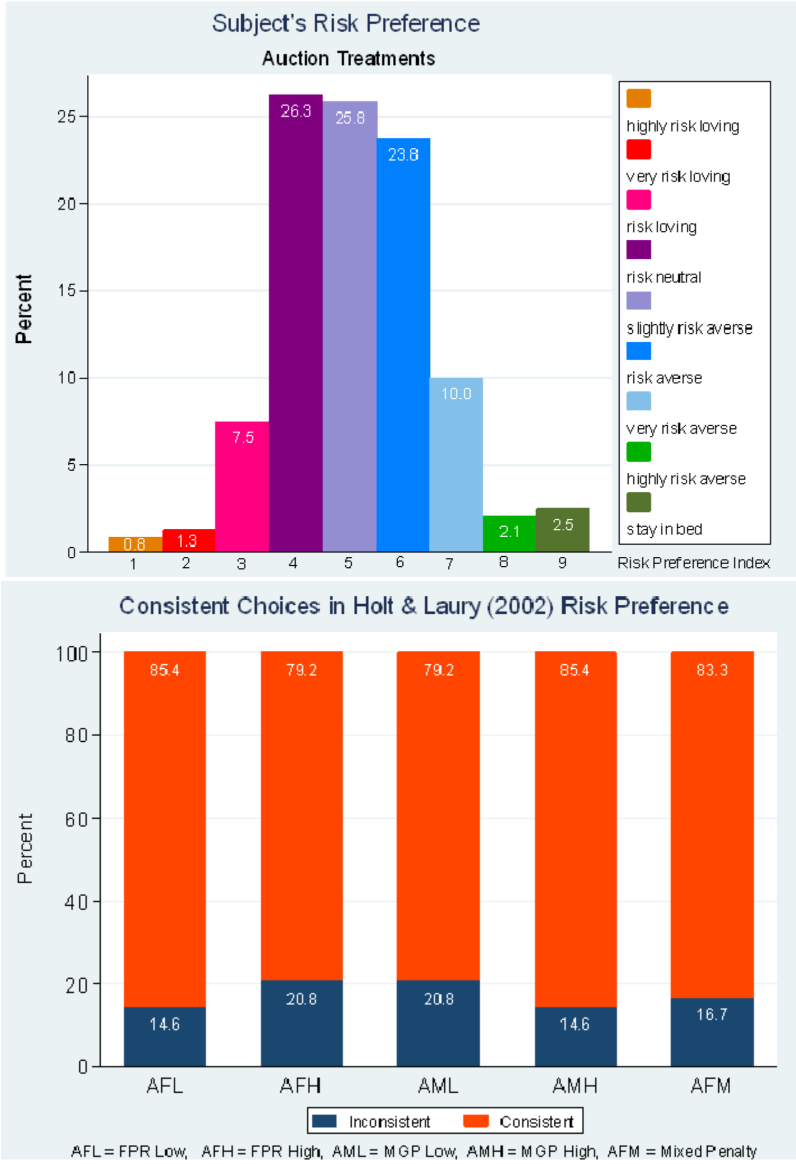


Figure 11 Results from the Lottery Choice Experiment

3.5.2. Convergence Path and Statistics Summary

This section discusses the statistics summary for the main variables of interest pertaining to prices, compliance strategies, and efficiency. Graphically presenting a particular variable over a period facilitates a closer inspection of the data at the group level and illustrates the existence of a discernible convergence path.

3.5.2.1. Price Variables

The results show that a high penalty level for each penalty type encourages a higher auction price (Figure 12). The figure shown for each treatment in Figure 12 is the mean value of 72 observations of each treatment. It is also clear that the auction has served as the primary market for distributing permits instead of the spot market (trading stage), with trade volume at less than 15% of the total number of permits in the market. Furthermore, the mean trading price is lower than the auction price in all treatments. Correspondingly, treatments with a high penalty level also have higher mean trading prices. The mixed penalty rate, which can be viewed as a double penalty regime, results in the highest mean trading prices, which are close to the auction price.

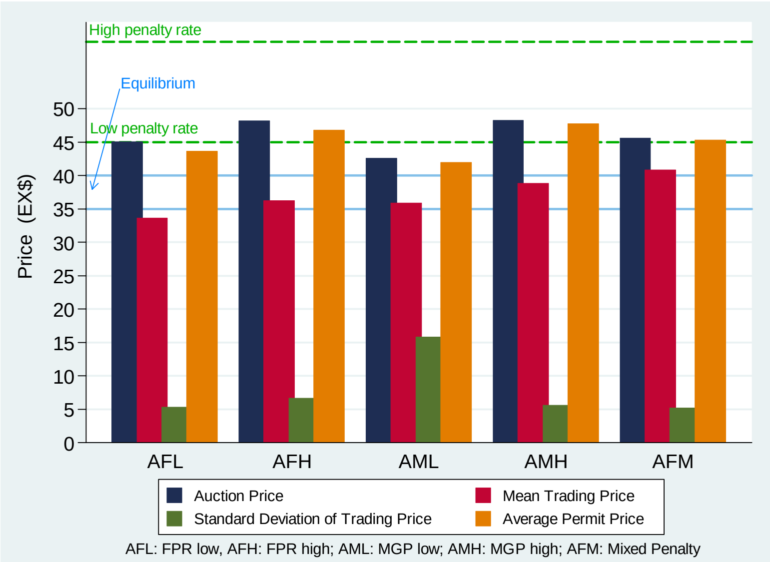


Figure 12 Price Variables by Treatment

When the standard deviation of prices is considered as a measure of strong price signals, the statistics in Table 3 reveal that there is a pattern across treatments, which is similar to that of auction prices. High penalty levels in the FPR penalty treatment are related to higher standard deviations for all three measures of prices. However, a more ambiguous link is found in the MGP treatments: the trading prices in the high MGP treatment have a lower standard deviation, but both auction price and average permit price have higher standard deviations. In this sense, the FPR provides a stronger price signal than does the MGP penalty, while the mixed penalty performs fairly well in this regard.

The difference between auction prices and mean trading prices may indicate that the spot market is used to dispose of any unwanted excess permits that a subject obtains. The resale value of the permit may be lower because subjects are keen to minimise the loss that they accrued by acquiring such excess permits at the auction. On the contrary, this can also highlight how the permit demand has been falsely increased at the auction, possibly due to strategic bidding behaviour rather than to a real need to acquire permits for compliance purpose. The data show that in 120 out of 360 observations, the auction price is equal to or higher than the mean trading price, which confirms that some buyers at the auction realise gains by trading in the spot markets. However, most of the time those buyers make losses as mean trading prices tend to be lower than the average auction price. A lower price at a resale market is not unusual as the opportunity of having a resale market induces a common-value character at the auction. Hence, subjects' bidding quantities are not only motivated by their private valuation of the permit but may be biased by the speculative wish to realise some gains at the resale market or the secondary market (Haile, 2003, Garratt and Tröger, 2006). As a result inefficiency occurs at the auction and this inefficiency is increasing in the uncertainty regarding the common-value or the resale value (Goeree and Offerman, 2003).

Table 3 Statistics Summary for Prices Variables (EX$)

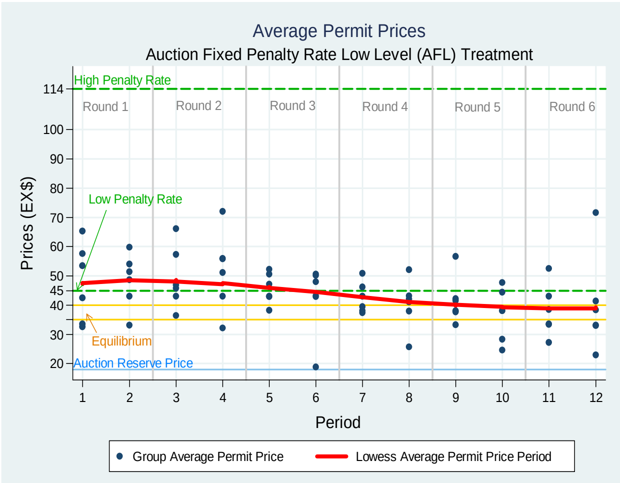
Treatment	Mean auction price	S.d.[a] auction price	Mean trading prices	Mean s.d. of trading prices in each sub period	Ave.[b] permit price	S.d. of ave. permit price	Trade volume (permits)
FPR Low (AFL)	45.01	11.59	33.63	5.36	43.66	10.72	11.75
FPR High (AFH)	48.21	11.79	36.25	6.70	46.80	11.19	10.25
MGP Low (AML)	42.58	21.73	35.91	15.82	41.94	20.82	6.35
MGP High (AMH)	48.28	27.67	38.85	5.63	47.77	27.00	8.22
Mixed Penalty (AFM)	45.57	14.09	40.85	5.23	45.30	13.97	6.81
Optimum	38	0	35-40	0	35-40	0	0

Notes: [a] s.d. = standard deviation, [b] ave. = average

The average permit price reflects the volume-weighted average based on the auction and trading price. Hence, it is not very different from the auction price. The average permit price in all treatments is constantly higher than the range of prices in the efficient equilibrium. The average prices lie around the low level FPR and remain well below the high level FPR.

Given the complexity of our experimental design, it is expected that a learning curve might affect subjects' decision making during the experiment. This learning effect is not directly observable from mean values but will be more discernable through a convergence path for permit prices over time. Based on the scatter plot and the fitted line of the average permit price using *lowess smoothing*[7] in Figure 13, we observe a general convergence path for permit price in all treatments, although this convergence pattern is stronger in the FPR and mixed penalty treatments than in the MGP treatments. Furthermore, an end-game effect[8] is evident in both of the MGP treatments as the price plummeted during the last round of the experiment.

[7] Lowess is a locally weighted regression of y (dependent variable) on x (independent variable). It is normally used for scatterplot smoothing and is desirable because it tends to follow the data.
[8] An end-game effect is a systematic change in behaviour that occurs as an experiment with repeated rounds reaches its conclusion.



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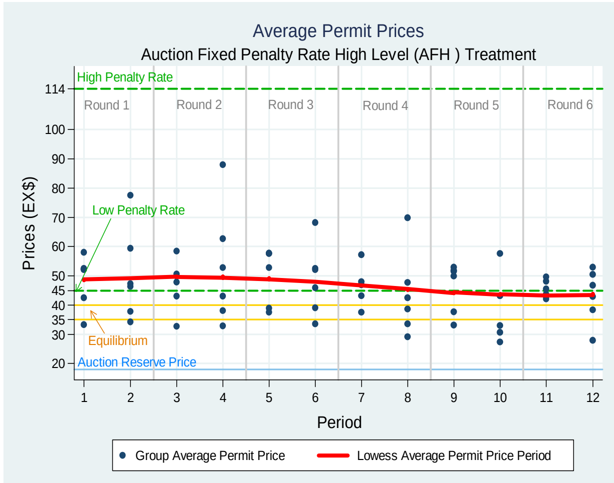

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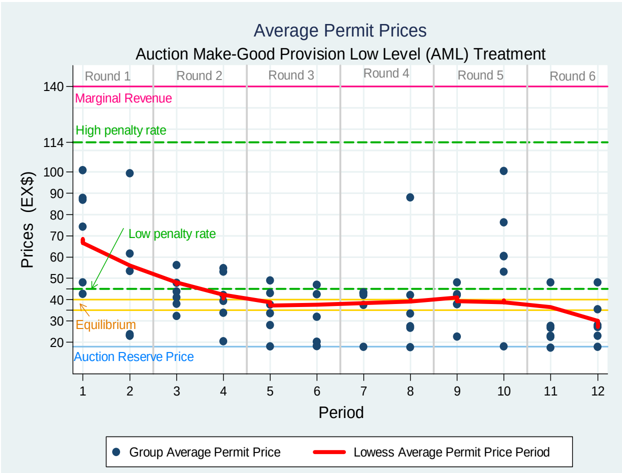

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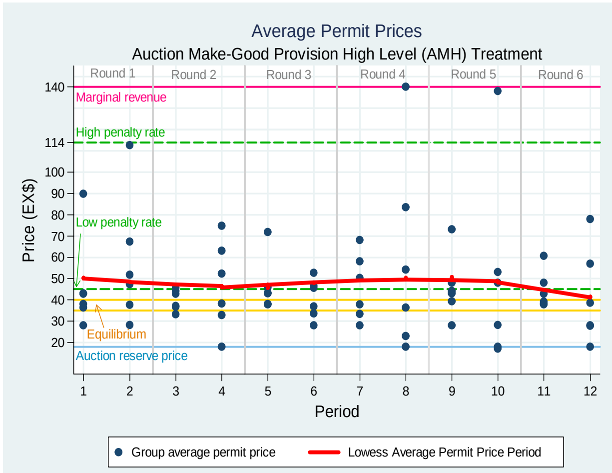

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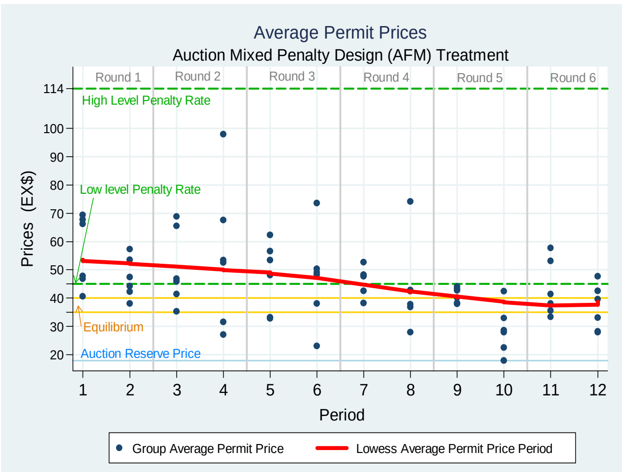


(e)

Note:
Each round consists of two sub periods.
Period with odd numbers represent sub period one of a round, while the even numbers represent sub period two of a round.

Figure 13 Convergence Path of Average Permit Price over Time

As shown in Figure 13(a), the permit price in the FPR low level treatment (AFL) begins above the low level penalty rate, (EX$45) in the first round and then rises slightly in the second round before starting to fall until round five, when it flattens out around the equilibrium price. A similar trend is also apparent in the FPR high level treatment (AFH). Nevertheless, the starting point of the permit price in the first round is slightly higher than in the AFL treatment. Moreover, in the two last rounds, the price stabilises above the equilibrium range and just slightly below the low penalty level of EX$45. The range of the scatter plot is also higher for AFH than for AFL.

In contrast, the convergence path for permit prices is markedly different for the low and high level MGP treatments (Figure 13 (c) and (d)). The price in the low level MGP treatment (AML) begins at a very high level at EX$70 in the first sub period of the first round. Then it starts to fall and continues to do so until the third round. Despite some fluctuation, the price then remains near the equilibrium until round five. Afterwards, there is an end-game effect in the last round. On the other hand, a more pronounced pattern of convergence of permit price over time is observed in the high level MGP treatment (AMH). The starting price in the first round is close to those of the FPR treatments at EX$50. Subsequently, the price remains adjacent to the low-level penalty rate at EX$45 for four rounds before the end-game effect takes place in the last round. The range of the scatter plot in the MGP treatment is much larger than that in the FPR treatments, and more outliers are observed with a maximum permit price of EX$193 in AMH. This is due to the penalty design in sub period two for the MGP treatments in which subjects will lose a total revenue of EX$2800, which is equal to a marginal penalty of EX$140 for 20 units of permits. If a subject is less than 20 units short on permits, the value of the marginal penalty will increase accordingly. Therefore, the permit price in sub period two of the MGP treatments can rise to a very high level.

The Mixed Penalty treatment (AFM) shows a convergence path that is more similar to that of the FPR treatments than to that of the MGP treatments. In the first round, the price starts slightly higher at around EX$55. After that, the price continuously falls until it stabilises right around the efficient equilibrium in the last round. Nevertheless, the range of permit prices in this treatment is obviously larger than those in FPR treatments, possibly due to the effect of having MGP element in the penalty design. Given that the penalty rate is linked to the auction price, we expect to see strategic bidding behaviour drive down the auction price and hence the compliance cost. Although relatively low prices are observed in period ten (sub period two of round five), these prices rise again in the next period. Hence, there is no clear evidence of that sort of collusion to drive down auction prices.

3.5.2.2. Compliance Strategy and Compliance Rate

We examine the main effects of penalty design on environmental effectiveness using two variables: investment level and compliance rate. The variables are expressed in terms of the number of firms and compared to the optimal level. At the equilibrium, there should be four investing firms – and thus the other four permit buying firms - and eight compliant firms, yielding the optimal scale of unity (Figure 14).

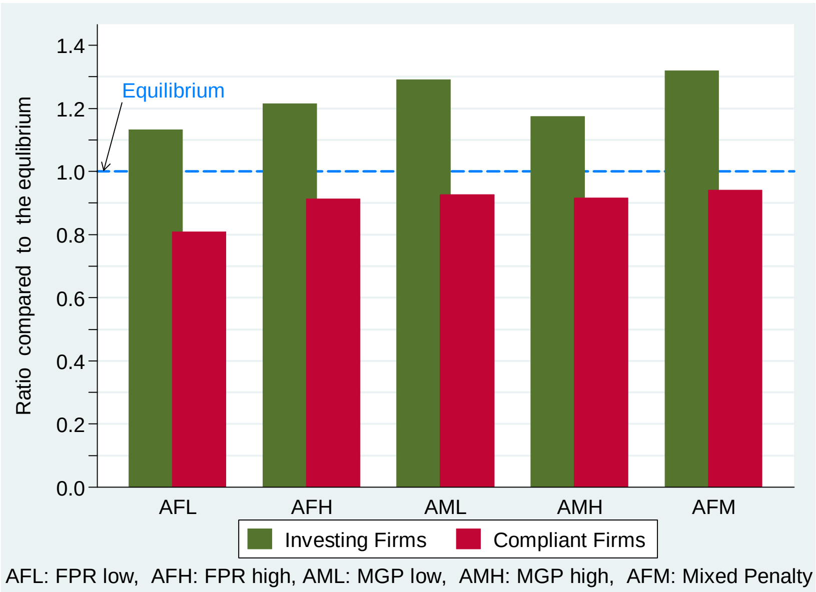


Figure 14 Investment and Compliance Levels by Treatment

As with the standard deviations of trading prices, the investment level is also higher with high level FPR treatments, but this is not the case with MGP treatments, which behave in the opposite manner. Over-investment is observed in all treatments as the mean investment level is higher than the optimal level. It seems plausible that a high penalty level will lead to a higher investment level because the mixed penalty design, which involves double penalties, exhibits the highest investment level. Nevertheless this inference will only be valid after a regression model is performed to control for influencing factors.

Interestingly, the observed over-investment is not translated into full compliance (where 100% of firms are compliant), although the trend in the investment level is also shown in the number of compliant firms. A high penalty level encourages a higher number of compliant firms in the FPR treatments, and the mixed penalty displays the highest compliance level.

Logically, if over-investment is prevalent, then there will be less of a demand for permits, which will consequently temper permit prices and renders cheaper compliance costs for permit-buying firms. Nevertheless, this is not observed in the experiment as prices remain high regardless of over-investment. This result highlights the inefficiency at the auction market as well as in the secondary market which fail to distribute permits to subjects who require them. The fact that full compliance is not realised in the market despite over-investment also means that some investing firms still hold excess permits at the end of a sub period and put buyers in a short position. Considering that the trade volume on the secondary market is pretty low, which imply that subjects had enough time to trade but only realised a few trades, this inefficiency is more likely to be attributed to the auction market. Nevertheless, it is plausible that permit buying firms at the auction were attempting to achieve gains from arbitrage trading, but mostly were unsuccessful. The competitive nature of clock auctions (Compte and Jehiel, 2007) can push prices to a fairly high level, which makes it more difficult for firms to make a profit in the spot market.

Comparing the processes that firms use to choose the best compliance strategy in the FPR and MGP treatments, we conjecture that the “quantity-penalty” nature of the MGP treatments creates much more price uncertainty for firms and more deterrent effects, resulting in more volatility in the market. Over time, this volatility makes it more difficult for firms to arrive at the best compliance strategies because price signals are more scattered. As shown in the standard deviation statistics (Table 4), although the low MGP treatment and the mixed penalty provide very strong compliance incentives, they also make it more difficult for firms to make investment decisions, as revealed by the high standard deviations of the investment level figures.

Table 4 Statistics Summary for Investment Levels and Compliance Rates

Treatment	**Mean investment level[a]**	**S.d.[b] investment level**	**Compliance rate[a]**	**S.d.[b] compliance rate**
FPR Low (AFL)	1.130	0.2481	0.810	0.1512
FPR High (AFH)	1.215	0.2232	0.913	0.1020
MGP Low (AML)	1.292	0.3168	0.927	0.0956
MGP High (AMH)	1.174	0.2125	0.917	0.1168
Mixed Penalty (AFM)	1.319	0.2560	0.941	0.0938
Optimum	1.000	0	1.000	0

Notes: [a] compared to the optimal level, [b] s.d. = standard deviation

In the theoretical equilibrium, firms with low marginal abatement costs (low MAC firms) should choose investment decisions as their sole compliance strategy, whereas those with high marginal abatement costs (high MAC firms) should not invest and should just buy permits, using this as their best compliance strategy. However, when the auction price is higher than the equilibrium, firm decisions about the best compliance strategies will not be as easy as expected, especially for the high MAC firms.

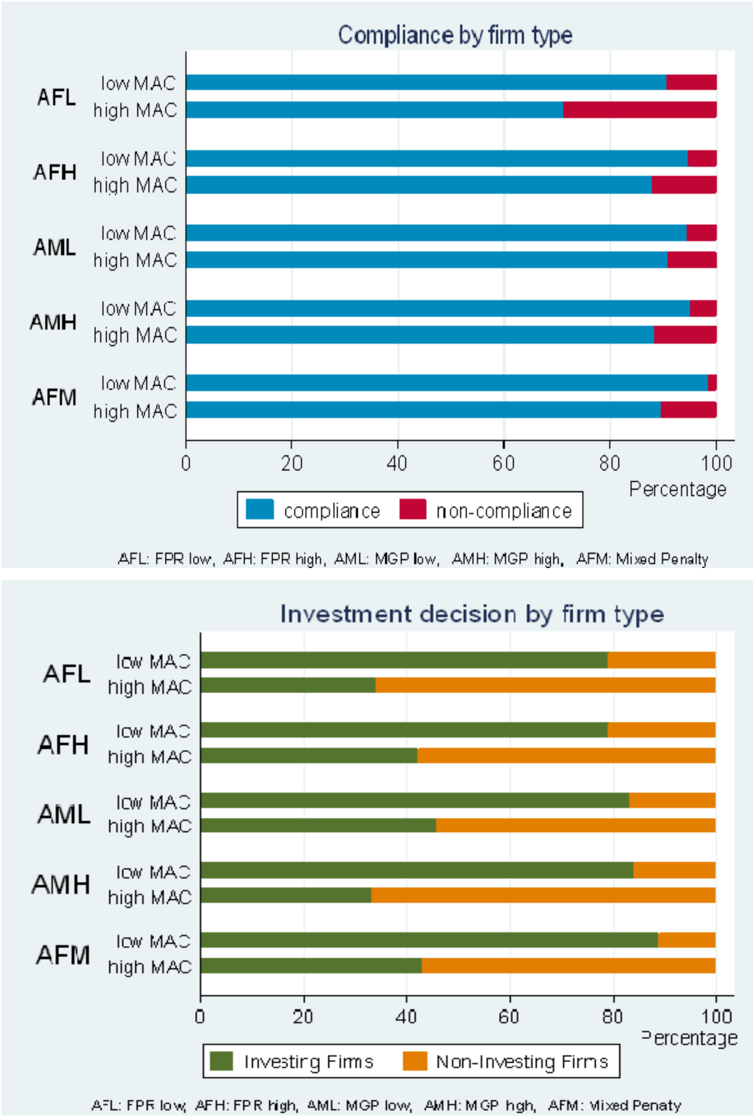
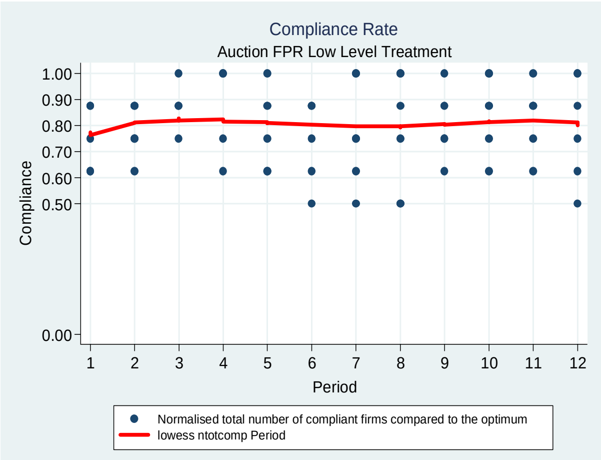


Figure 15 Compliance Rates and Investment Decisions by Firm Type

The data confirm that across treatments, firms with low MAC have higher compliance rates than do high MAC firms (Figure 15). Hence, buying permits are not always perceived as the best compliance strategy for high MAC firms because prices fluctuate at a higher level than the theoretical equilibrium permit price. Although the low MAC firms do not always choose investment as their best compliance strategy, the compliance rate for these firms is still higher than that of the high MAC firms. The non-parametric Kruskal Wallis test statistics verify that the differences in compliance rates and investment decisions by firm type are highly significant (p-value = 0.0001). For both firm types, the mixed penalty (AFM) provides the strongest compliance incentives. In terms of penalty type, MGP treatments also provide better compliance incentives than do FPR treatments, and yet it also induces stronger investment incentives for high MAC firms, which explain the incidence of over-investment in general.

When we consider the learning effect of compliance decisions, we note that the convergence path for compliance rates over time does not show a very strong effect compared to that of the average permit price (Figure 16). The *lowess* regression curves seem to have fairly stable patterns, although the compliance rates vary across treatments. We have six observations for each treatment in each period, and fewer scatter points imply that there are some repeated values for compliance rates.

The low FPR treatment exhibits a fairly low compliance rate of 75% before stabilising around the 80% level. Nevertheless, the scatter points are more dispersed in the low FPR, implying a higher standard deviation of compliance rates. Higher levels of compliance rates are clearly noticeable in both MGP treatments, in which they stay above the 90% level although more variance in the lower rates is also apparent in the high MGP treatment. A slightly different convergence path for compliance rates occurs with the mixed penalty treatment, where compliance rates begin very high at around 95% before decreasing to around 90% in the first half of the session and then stabilising back at the 95% level. The lowest standard deviation of compliance rates is achieved under the mixed penalty regime.



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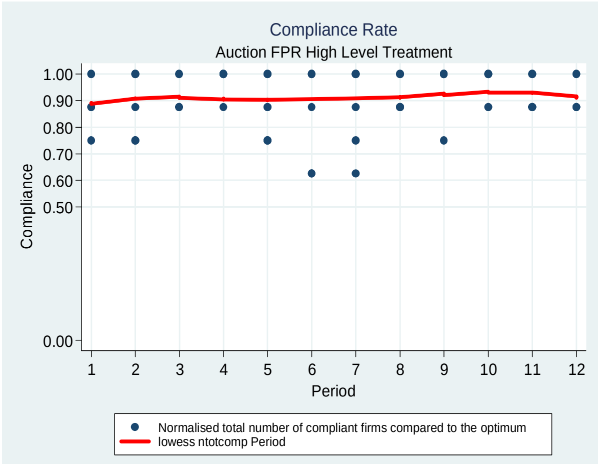

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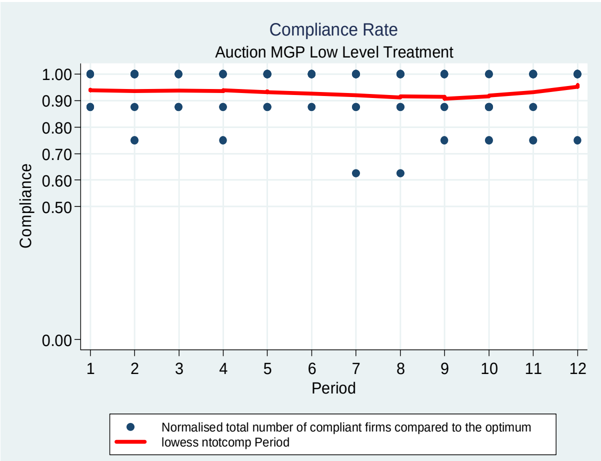

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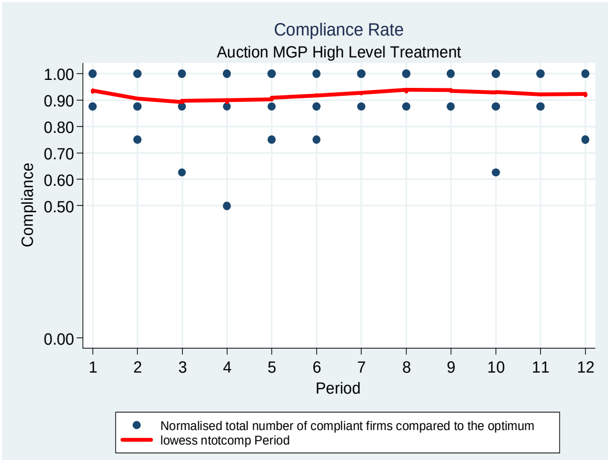

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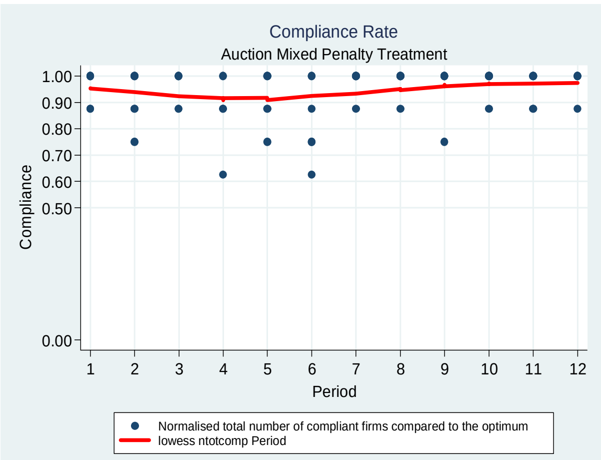

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Figure 16 Convergence Path of Compliance Rates over Time

3.5.2.3. Efficiency

At the end of each sub period, efficiency is the variable which sums up the measure of market performance. When high permit prices prevail in the market, the cost of compliance becomes more expensive and even unaffordable by some subjects. As a result, there exists some degree of non-compliance in the market. This non-compliance in turn compromises market efficiency. In this case, static efficiency is measured in terms of the actual group earnings compared to the theoretical optimum. Group earning is the sum of individual payoff in a sub period within the same group. This efficiency measure is chosen rather than the usual cost savings measure to obtain normalised values for efficiency since higher prices will yield some negative values for efficiency in terms of cost savings. The data show that a low penalty level results in greater efficiency and that the FPR treatment performs better than the MGP and the Mixed Penalty treatments in this regard (Figure 17). Nevertheless the difference is rather marginal and the result from this descriptive statistics needs to be corroborated through further statistical tests in the following section.

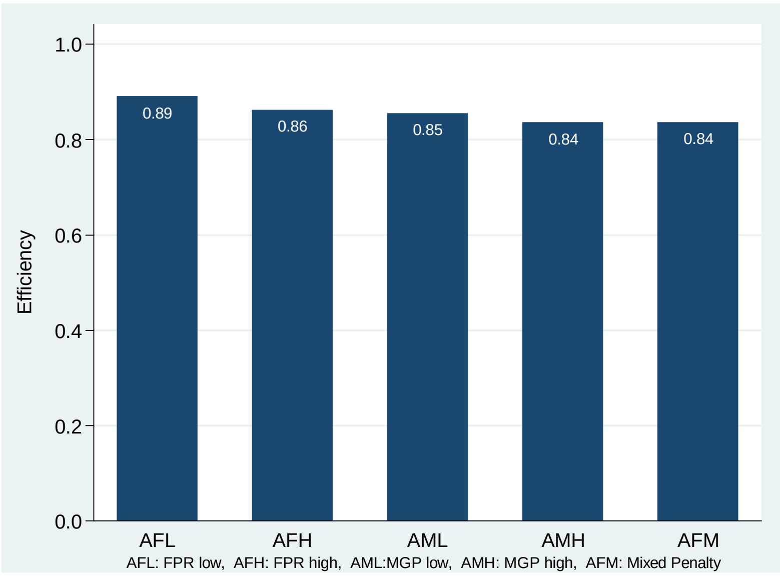

Figure 17 Efficiency by Treatment

3.6. Test of Treatment Effects

3.6.1. Test of Significant Difference to the Theoretical Equilibrium

The statistical summaries of prices and compliance strategies illustrate how the mean values generally deviate from the theoretical optimal values. In spite of the observable differences, further tests are required to confirm that these differences are statistically significant. Therefore this section looks at how the hypotheses are tested using the non-parametric Wilcoxon signed rank test. This test is performed to evaluate auction prices, investment levels, and compliance rates. It should be noted that the Wilcoxon signed rank test evaluates whether the medians (rather than the means) of those variables are significantly different from the hypothesised values.

Table 5 Test of Auction Price Equal to Theoretical Equilibrium

Treatment	**p-value from Wilcoxon Sign Rank test for H_0: Auction price= 38**		
	All periods	**Period 1-6 (Round 1-3)**	**Period 7-12 (Round 4-6)**
FPR Low (AFL)	0.0000***	0.0000***	0.1144
FPR High (AFH)	0.0000***	0.0000***	0.0003***
MGP Low (AML)	0.4452	0.1770	0.7582
MGP High (AMH)	0.0031***	0.0065**	0.1049
Mixed Penalty (AFM)	0.0000***	0.0000***	0.2722

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 72 for the whole session and 36 for half sessions.

The Wilcoxon test statistics reveal that the medians of the auction prices are significantly different from the optimal level at EX$38 for all treatments except the low level MGP treatment. The chosen optimal value is not only a mid-value within the optimal range (EX$ 35-40) but also the theoretical Walrasian auction price given by our experimental design.

In order to assess whether learning effect may affect the results, the data set is split into two half-sessions (round 1-3 and round 4-6). Similar results as for the whole data set are achieved for the first half of the session. In the second half of the session, the significant difference to the optimal equilibrium is only maintained for the high level FPR treatment. This result is in line with the convergence path for average permit price that illustrates how the prices start to enter the equilibrium range in round three or round four and remain there until an end-game effect takes place in the last round in the case of MGP treatments. Thus, there is a general indication of learning effect over rounds as subjects learn to arrive at the equilibrium auction price in the second half of the session.

The same test is also performed to assess whether the investment and compliance rates are significantly different from the optimal value of unity. Highly significant test statistics are obtained for all treatments.

Table 6 Test of Investment Level Equal to Theoretical Equilibrium

Treatment	p-value from Wilcoxon Sign Rank test for H_0: normalised investment level = 1		
	All periods	**Period 1-6 (Round 1-3)**	**Period 7-12 (Round 4-6)**
FPR Low (AFL)	0.0001***	0.0041**	0.0092**
FPR High (AFH)	0.0000***	0.0000***	0.0000***
MGP Low (AML)	0.0000***	0.0000***	0.0000***
MGP High (AMH)	0.0000***	0.0003**	0.0000***
Mixed Penalty (AFM)	0.0000***	0.0000***	0.0000***

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 72 for the whole session and 36 for half sessions.

Table 7 Test of Compliance Rate Equal to Theoretical Equilibrium

Treatment	p-value from Wilcoxon Sign Rank test for *Ho*: normalised compliance rate = 1		
	All periods	**Period 1-6 (Round 1-3)**	**Period 7-12 (Round 4-6)**
FPR Low (AFL)	0.0000***	0.0000***	0.0000***
FPR High (AFH)	0.0000***	0.0000***	0.0000***
MGP Low (AML)	0.0000***	0.0001***	0.0000***
MGP High (AMH)	0.0000***	0.0000***	0.0002***
Mixed Penalty (AFM)	0.0000***	0.0000***	0.0082**

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 72 for the whole session and 36 for half sessions.

One major difference between those two variables is the direction of the deviation from the optimal equilibrium. While the medians investment levels lie above the theoretical equilibrium, the median compliance rates mostly stay below the optimal perfect compliance rate.

3.6.2. Hypothesis Testing of Treatment Effects

3.6.2.1. The Effect of Penalty Design on Auction Price

Result 1: There are no differences in auction prices across treatments (consistent with Hypothesis 1) [9]*. Furthermore, auction prices remain above the optimal equilibrium level in earlier rounds but then converged to the equilibrium range in later periods.*

Support: The Kruskal-Wallis non-parametric test is used to test whether all five treatments have the same underlying distribution in terms of auction price. Each observation group is assumed to be independent, and no further assumptions are made with regard to the distribution of the data. Group-level data is collected for each round, and hence, the test is run over 360 observations. Since the test yields a p-value of 0.1537, we cannot reject the null hypothesis that auction prices come from the same underlying population distribution.

The Kruskal-Wallis test is the analog of the ANOVA test that is based on a normal distribution. These tests cannot determine whether only one or some of the samples exhibit a distribution that is significantly different from those of the rest of the samples. To answer that question, another test should be performed using a pairwise comparison. We employ the Wilcoxon rank sum test (Wilcoxon-Mann-Whitney test) and the Kolmogorov-Smirnov test to inspect the presence of treatment effects. Whereas the Wilcoxon-Mann-Whitney test evaluates whether the medians of two samples represent two populations with different median values, the Kolmogorov-Smirnov test looks at the differences between the underlying population distributions of the two samples (Sheskin, 2004).

In most cases, consistent results are obtained from the two tests (Table 8). Whereas the Kolmogorov-Smirnov test only confirms significant difference between median auction price in the low FPR and the low MGP treatment, more significant test results are obtained from the Wilcoxon-Mann-Whitney test. Significant test statistics at 5% level verifies lower medians of auction price in the MGP than the FPR treatment for both penalty levels, especially in earlier rounds. The median auction price is also lower in the low MGP compared to the Mixed Penalty treatment. However this lower median auction price in the MGP treatment is achieved through very volatile markets as the standard deviation of auction price is the highest in the MGP treatment.

[9] *Hypothesis 1* states that the auction price should remain the same in all treatments because the supply and demand structure remains the same.

Table 8 Test Statistics for Treatment Effects for Auction Price

Pairwise comparison	p-value All Periods		p-value by half-session			
			Period 1-6 (Round 1-3)		Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Penalty level in FPR (AFL & AFH)	0.1213	0.419	0.4841	0.965	0.0646	0.257
Penalty level in MGP (AML & AMH)	0.1706	0.213	0.5824	0.413	0.2045	0.615
Penalty type, low-level penalty (AFL & AML)	0.0413*	0.014**	0.0634	0.257	0.2468	0.083
Penalty type, high-level penalty (AFH & AMH)	0.0530*	0.062	0.0339*	0.083	0.4889	0.257
Mixed penalty and low FPR (AFM & AFL)	0.9085	0.992	0.8157	0.825	0.7795	1.000
Mixed penalty and low MGP (AFM & AML)	0.0483*	0.062	0.0376*	0.150	0.3816	0.257

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions.

Separate tests on the half session data unveils similar inferences as the whole session data that we cannot reject the null hypothesis of no differences in auction prices, except for the comparison of penalty type in the high level penalty and the comparison of the mixed penalty treatment to the low MGP treatment for the first half of the session.

3.6.2.2. The Effect of Penalty Level in the Fixed Penalty Rate Treatment

Result 2: There are differences between compliance rates but not between investment levels for the low and high level penalty in the FPR treatment. The compliance rate is statistically higher in the high level penalty treatments (which is inconsistent with Hypothesis 2) [10].

Support: A test of treatment effects is required only for two groups of independent samples. The Wilcoxon rank sum test and the Kolmogorov-Smirnov test are conducted to assess whether the statistics from the two samples are statistically different. The test statistics (Table 9) show that there is no significant difference between the investment levels at the low and the high level penalty and consistent results are obtained from both non-parametric tests. On the contrary, the test statistics for the compliance rates are highly significant for the whole session and the half-sessions.

[10] *Hypothesis 2* states that in the FPR treatments, investment levels and compliance rates should be the same at 100% regardless of the penalty levels because the penalty rate is set higher than the theoretical equilibrium permit price.

Table 9 Test Statistics for Treatment Effects of Penalty Levels in the FPR Treatment

Variable	p-value All Periods		p-value by half-session Period 1-6 (Round 1-3)		p-value by half-session Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Investment level	0.0658	0.419	0.3471	0.615	0.0899	0.615
Compliance rate	0.0000***	0.001***	0.0032**	0.043*	0.0017**	0.005**

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions.

3.6.2.3. The Effect of Penalty Level in the Make-Good Provision Treatment

Result 3: Penalty level does not significantly affect either investment levels or compliance rates in the MGP treatment (consistent with Hypothesis 3)[11].

Support: The Kolmogorov-Smirnov test shows that we cannot reject the null hypothesis that the two samples come from populations with the same underlying distribution. Nevertheless, the Wilcoxon test results show that the median investment level is just significantly different at 5% level. The results from the half session's data confirm that the difference is only significant for earlier rounds. Hence, the test statistics from the Kolmogorov-Smirnov show more conservative estimates than those from the Wilcoxon test and we conclude that the in general no significant differences are found in both investment levels and compliance rates.

Table 10 Test Statistics for the Effect of Penalty Levels in the MGP treatment

Variable	p-value All Periods		p-value by half-session Period 1-6 (Round 1-3)		p-value by half-session Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Investment level	0.0513*	0.419	0.0400*	0.083	0.3731	0.615
Compliance rate	0.7987	1.000	0.2051	0.965	0.3706	1.000

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions.

[11] *Hypothesis 3* states that the make-good ratio should not affect investment levels or compliance rates in the MGP treatments as long as it is set equal to or higher than one under the assumption that prices remain the same in the two sub periods.

3.6.2.4. The Effect of Penalty Type

Result 4: At the high penalty level, different penalty types do not provide different compliance incentives because there are no significant differences in terms of investment levels and compliance rates between the FPR and the MGP (which is consistent with Hypothesis 4) [12]*. On the other hand, different compliance rates are observed at the low penalty level in which the MGP treatments have higher compliance rates than the FPR treatments (which is inconsistent with Hypothesis 4). However, the same distinction does not exist between investment levels.*

Support: As shown by Table 11, we obtain consistent test statistics for the high level penalty treatments. We do not find enough evidence to reject the null hypothesis that the two samples are derived from the same population distribution. Meanwhile, the low level penalty treatment constantly demonstrates that compliance rates are significantly higher in the MGP penalty than in the FPR penalty for the whole session and the half-session data. Similar results are obtained for the median of investment levels, particularly in the first half-session as the subjects still learn to decide on their optimal compliance strategy.

Table 11 Test Statistics for Treatment Effects by Penalty Type

Variable	p-value All Periods		p-value by half session			
			Period 1-6 (Round 1-3)		Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Low-level penalty						
Investment level	0.0070**	0.213	0.0255*	0.022*	0.0739	0.615
Compliance rate	0.0000***	0.000***	0.0000***	0.002**	0.0041**	0.043*
High-level penalty						
Investment level	0.3116	1.000	0.4039	0.615	0.5217	0.615
Compliance rate	0.5571	1.000	0.9708	1.000	0.4004	0.965

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions.

[12] *Hypothesis 4* states that at the high penalty level, the compliance rates and investment levels in the FPR treatments should be the same as those in the MGP treatments. At the low penalty level, similar results are expected, although the penalty level is slightly higher in the low level FPR treatment (with a factor of 1.2), whereas the make-good ratio is 1.

3.6.2.5. The Effect of Double Penalty in the Mixed Penalty Design

Result 5: The mixed penalty design provides the same investment and compliance incentives as the low MGP treatment. However, the same conclusion cannot be drawn when the comparison is made to the low FPR treatment since significant differences are found with regard to investment levels and compliance rates (inconsistent with Hypothesis 5)[13].

Support: As the mixed penalty comprises of two penalty types with some modification, the evaluation of the effect of this penalty design is carried out using these elements. Hence, we assess the treatment effects by making a comparison with the low level MGP (AML) treatment and with the low level FPR (AFL) treatments. Unlike the AFL treatments, the mixed penalty design uses variable penalty rates over time because the penalty rate is linked to the auction price. As shown in Table 12, the test statistics are only significant when we draw a comparison with the AFL treatment. Once again, this result highlights the different compliance incentives provided by low level FPR and low level MGP.

Table 12 Test Statistics for Treatment Effects of the Mixed Penalty Design

Variable	p-value All Periods		p-value by half session Period 1-6 (Round 1-3)		p-value by half session Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	**Kolmogorov-Smirnov**	**Wilcoxon rank-sum**	**Kolmogorov-Smirnov**	**Wilcoxon rank-sum**	**Kolmogorov-Smirnov**
Mixed Penalty and low FPR						
Investment level	0.0001***	0.014**	0.0106**	0.083	0.0020**	0.083
Compliance rate	0.0000***	0.000***	0.0013***	0.022*	0.0000***	0.000***
Mixed Penalty and low MGP						
Investment level	0.3040	0.947	0.9439	0.615	0.1499	0.965
Compliance rate	0.2715	0.847	0.2956	0.965	0.0087**	0.083

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions.

3.7. Estimation models

The test of the treatment effects in the previous chapter cannot fully capture the relationship between our treatment variables and a particular variable of interest (the dependent variable) because the test procedure only takes into account the variation in one particular variable

[13] *Hypothesis 5* states that the mixed penalty treatment should yield the same compliance rates as the FPR and MGP treatments.

without holding other variables constant. Moreover, the subjects' characteristics might have some influence. In order to control for all of those factors and to isolate the treatment effects, we ran regression models to further examine the effects of our treatment variables on auction price, investment decisions, firm compliance through permit-buying, and efficiency.

Auction price is chosen as the first dependent variable because it is the first price signal that subjects receive before deciding on their compliance strategy through investment decisions and permit-buying in the spot market. Subsequently, investment decisions and firm compliance status of the non-investing firms (permit-buying firms) are also important dependent variables that represent the two available compliance strategies. Hence, regressions are performed on those dependent variables so that the treatment effects of penalty type and penalty level can be carefully verified. Finally, efficiency is a crucial measure of market performance as it is a major criterion of the economic success of an emissions trading scheme.

3.7.1. Auction Price

Considering that the auction is the first stage in each sub period in the emissions trading game, we can only include treatment variables and subjects' characteristics in each observation group as dependent variables. The estimation is performed using group-level data collected in each sub period with a total of 360 observations. The regression model for auction price is estimated using a robust panel data random-effects model.

Model 1 represents the basic model that contains the treatment variables for penalty design as the main regressors, i.e. a dummy for the FPR treatment, a dummy for the high-level FPR treatment, a dummy for the MGP treatment, and a dummy for the high-level MGP treatment. In the mixed penalty design, the dummy for high FPR is set at zero (the low level), although the penalty rate is actually varied. This measure is taken as the penalty rate is directly linked to the auction price; hence, it is not independent of the auction price. Including the penalty rate as a regressor will produce bias estimates toward higher significance. In view of the complexity of our experiment, round and sub period two are also included as regressors and used to examine subjects' learning curves over time.

In Model 2, the effects of risk-related variables are taken into account. The group risk preference index represents the aggregated value of each subject's Holt & Laury's (2002) risk preference index for each observation group. We also employ the same aggregation approach for the variable inconsistent risk preference choice.

Model 3 incorporates additional control variables related to subjects' income variables that include age, household income, number of household members, and individual income. Since most of the students are not financially independent, we control for the effects of these income variables on subjects' risk preferences. These demographic variables are measured in terms of the mean values of interval or ordinal variables.

An additional set of demographic variables pertaining to gender and education are added to Model 4. These variables are the number of females in a group, study degree (e.g. undergraduate, Master's, or PhD program), a dummy for majors related to economics, number of years in school, and full-time enrolment status. At the individual level, study program is a categorical variable that indicates whether a subject is undertaking an undergraduate, master's, or doctoral program. For group-level data, a mean value is used for each group. The same approach is used for the other demographic explanatory variables.

The estimate summary (Table 13) shows that the signs of the explanatory variables are intuitive and consistent across all models. The coefficients of the MGP treatment are always much smaller than those of the FPR treatment, although neither are significantly different than zero. On the contrary, the coefficients of the high level MGP are about 2 to 3 times larger than those of the high level FPR. The coefficients for penalty design are not statistically significant except in Model 3 for the high MGP treatment. Thus, we can conclude that the quantity-penalty nature of the high level MGP evidently raises the demand for permits vis a vis other penalty designs. Significant constant terms are also evident across models. The summary statistics also display the values of rho and theta to represent the influence of group-specific effects as an inherent term in a random-effects model.

The variable round has a negative sign, indicating that the learning curve has a negative effect on auction prices. This implies that at the beginning of the experiment, permits were in very high demand, possibly due to cautious behaviour (the subjects wanted to ensure that they would achieve compliance) or due to the required time for subjects to learn about the equilibrium permit price. The coefficient of round is also statistically and economically significant. Unsurprisingly, the auction price is slightly lower in sub period 2 because over-investment in sub period 1 effectively reduces permit demand. However, the coefficient is not statistically significant. In terms of the goodness of fit of the model, the overall correlation value is relatively small, and the model performs better in explaining the variation between observation groups than the variation within the same group.

Table 13 Estimates Summary for Auction Price Model

Regressors for auction price	Model 1 (basic)	Model 2 (Model 1 + Risk)	Model 3 (Model 2 + Income)	Model 4 (Model 3 + gender and study)
Dummy for FPR	2.9861	4.3953	5.0095	3.4850
	(2.6218)	(3.0792)	(3.2187)	(3.5141)
Dummy for high level FPR	3.1944	2.3382	2.8419	3.3898
	(3.7962)	(3.0537)	(3.6890)	(3.5971)
Dummy for MGP	0.5556	1.1085	0.6905	3.4868
	(3.5854)	(3.4998)	(3.5133)	(3.1911)
Dummy for high level MGP	5.6944	6.7694	8.1732*	5.2603
	(4.7587)	(4.2066)	(3.9863)	(3.9259)
Round	-2.4024***	-2.4024***	-2.4024***	-2.4024***
	(0.6777)	(0.6796)	(0.6835)	(0.6885)
Dummy for sub period two	-0.3611	-0.3611	-0.3611	-0.3611
	(1.7946)	(1.7997)	(1.8101)	(1.8232)
Group risk preference index		-0.3280	-0.5365*	-0.6538**
		(0.2126)	(0.2198)	(0.2501)
Number of subjects with		2.5873*	2.7198**	2.1594*
inconsistent risk choices		(1.1067)	(0.9997)	(0.9004)
Constant	50.6167***	59.2014***	72.1731***	115.0062*
	(4.5917)	(10.9804)	(15.9237)	(48.2215)
Observation	360	360	360	360
Within correlation	0.0580	0.0580	0.0580	0.0580
Between correlation	0.0897	0.2752	0.3570	0.4581
Overall correlation	0.0627	0.0904	0.1026	0.1177
Chi^2	15.4591	35.8100	47.9306	104.2794
Rho (% variance due to group-specific effect)	0.0926	0.0716	0.0816	0.1021
Theta[14]	0.3294	0.2792	0.3044	0.3496

Notes: The numbers in parentheses represent the standard errors of the estimates.
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

Based on the risk-related variables in Model 2, we see that subjects that make inconsistent choices during the Holt & Laury experiment may engage in irrational bidding behaviour that increases the demand for permits at the auction. The magnitude of the coefficient is also economically significant because the presence of only one irrational subject will increase the auction price by more than EX$2. The group risk preference index also shows the expected

[14] Theta =[0,1]. When theta equals zero, the regression can be performed directly using OLS estimators. If theta is one, then fixed-effect estimators are more appropriate.

relationship in which greater risk aversion is associated with more cautious bidding behaviour, which then results in a lower auction price albeit it is not statistically significant. According to the R^2 value, the goodness of fit is slightly greater than in Model 1, and the between correlation is triple enhanced.

Although the estimations in Model 3 seem to explain better compared to the other models, the constant term of the model also increases by 20%. In addition to the previously significant variables, the group risk preference index and the dummy for high level MGP also becomes significant. The coefficients of the latter variables have intensified as much as the constant term. Although none of the additional income variables have significant test statistics, the control of those risk-related variables noticeably improves the model. The signs of the income variables are also as expected. Higher group age and individual income are negatively correlated with auction price, indicating more sensible bidding behaviour that drives down auction price. In contrast, higher household income and more household members contribute to higher auction prices. Nevertheless, these relationships are statistically not different from zero. With regard to the goodness of fit as measured using the R^2 value, this model yields a slightly higher overall correlation than Model 2.

The inclusion of more demographic variables in Model 4 has slightly enhanced the overall correlation of the model at the expense of the escalated constant term, which is at about 60% of that in Model 3. As in the previous model, neither of the demographic variables is statistically significant. The significant independent variables remain the same except for the dummy for the high MGP treatment.

Overall, the regression models show that the penalty design does not significantly affect the price discovery process in the market with respect to auction price. The only exception is one model in which the high MGP treatment contributes significantly to a much higher auction price. These results are essentially in line with the test statistics for treatment effect for *Hypothesis 1*, in which the Wilcoxon rank sum test verifies the effect of the high MGP treatment, especially in the first half of the session. More importantly, the risk-related variables have the largest marginal effect on auction price. Higher risk aversion moderates speculative bidding behaviour and drives down auction price closer to the equilibrium. On the contrary, subjects with irrational risk choices can inflate auction price. The variable round confirms the presence of learning effects because it remains statistically significant across models.

3.7.2. Investment Decision

After participating at the auction, subjects can trade in the secondary market before deciding to make an investment in abatement technology in sub period one. At the investment decision stage, each subject is given information about his or her final permit holdings for that sub period and whether they are in a short or long permit position toward compliance. During this stage, if they are in a short position, then the only way to achieve compliance and avoid a penalty is by making an investment decision.

In view of the decision process, the penalty design treatment variables, the price variable, firm type and firm long permit position are used to regress individual investment decisions. Unlike in the estimation models for auction price, the penalty rate is used rather than a dummy variable for the high FPR because the penalty rate is now independent of the investment decision, which is not the case for the auction price estimation. The individual-level data from sub period one are used in the estimation. We employ panel data probit and logit estimation models because the investment decision is a binary choice. The regression summary is shown in Table 14.

The first four models are estimated using a probit model, and the results are consistent across all four. Model 1 is run using cluster-robust standard error OLS estimators. Models 2 to 4 are based on a robust random-effects probit model with bootstrapped estimates. A logit model similar to Model 4 is run in Model 5. Due to the nature of binary choice models, the interpretation of the estimation results is not straightforward in terms of magnitude. Nevertheless, the sign of the estimates indicates the effect of the regressors on the dependent variable.

The estimates reveal that different penalty types provide different incentives with regard to investment decisions. The FPR treatment has a negative but trivial effect on investment. In contrast, the MGP treatment has a significantly positive effect on investment. These findings are very reasonable because firms are allowed to have a lower marginal financial penalty in the FPR treatment than in the highly punitive MGP treatment. The effect of the penalty rate is almost negligible but positive as expected. On the contrary, a high MGP level has a negative effect on investment decisions even though it is not statistically significant. However, the regression models can better explain the effect of the MGP treatment because they control for other factors that might influence investment decisions.

According to the experimental design, high MAC firms should not invest and choose to comply by buying permits. The regression models confirm the theory as this variable has a negative sign and is highly significant. A similar effect is also produced by firm permit position. When firms learn that they have a long permit position (they have more permits than they need), they do not invest. In this sense, the firms show rational investment behaviour.

Table 14 Estimates Summary for Investment Decisions

Regressor for investment decisions	Model 1 Probit OLS cluster	Model 2 Probit RE bootstrap	Model 3 Probit RE bootstrap	Model 4 Probit RE bootstrap	Model 5 Logit RE bootstrap
Dummy for FPR	-0.045	-0.0746	-0.0713	-0.0515	-0.0534
	(0.2573)	(0.2573)	(0.2579)	(0.2767)	(0.5008)
Penalty rate	0.0023	0.0031	0.0032	0.003	0.0064
	(0.0026)	(0.0029)	(0.0029)	(0.0031)	(0.0056)
Dummy for MGP	0.5013*	0.5857**	0.5871**	0.5832**	1.0922**
	(0.197)	(0.2037)	(0.2033)	-0.1949	(0.3596)
Dummy for high-level MGP	-0.3369	-0.3787	-0.3755	-0.3455	-0.5245
	(0.1775)	(0.2152)	(0.2137)	(0.1765)	(0.34)
High MAC firm	-0.8266***	-0.9084***	-0.9067***	-0.8914***	-1.6401***
	(0.097)	(0.1296)	(0.1316)	(0.1347)	(0.2509)
Auction price	0.0121***	0.0142***	0.0132***	0.0138***	0.0247***
	(0.0034)	(0.0032)	(0.0033)	(0.0036)	(0.0063)
Mean trading price	0.0000	-0.0002	-0.0002	0.0000	0.0000
	(0.0014)	(0.0019)	(0.0019)	(0.0019)	(0.0036)
Permit long position	-0.1191***	-0.1393***	-0.1394***	-0.1406***	-0.2623***
	(0.008)	(0.0113)	(0.0114)	(0.0102)	(0.0194)
Round			-0.0179		
			(0.0396)		
Group risk preference index				0.0065	
				(0.0467)	
Subjects with inconsistent risk choices				0.3338	
				(0.1798)	
_cons	-1.0329***	-1.2810***	-1.1820***	-1.3977***	-2.5122***
	(0.3073)	(0.2813)	(0.3538)	(0.3478)	(0.5691)
No. obs.	1440	1440	1440	1440	1440
No. subjects	240	240	240	240	240
Log likelihood	-448.63	-431.01	-430.859	-429.065	-422.93
R^2	0.5433				
Wald chi^2	303.1957	227.3476	221.2588	285.8775	229.7005
% Correctly predicted	88.75				

Notes: The numbers in parentheses represent the standard errors of the estimates.
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

The auction price has a crucial effect on firm investment behaviour. Conversely, trading prices have essentially no effect on investment decisions. This proves that the main price signal for compliance strategy is determined at the auction as the primary market rather than in the secondary market.

We find that learning does not have an effect on investment decisions as indicated by the estimate for round. The additional risk-related variables in Model 4 and Model 5 are also not significant. Other demographic variables such as the subject's gender and age are also tested as regressors, but the results show that they are insignificant.

The statistics of the models show that the addition of more explanatory variables does not substantially increase the goodness of fit of the model. Overall, the models have considerably high predictive power (88.75%), as shown by the basic model (Model 1).

To sum up, the investment decision is influenced by price signals at the auction, firm type (high or low MAC firm), and permit holding position toward compliance. Furthermore, MGP as a penalty type provides significantly stronger investment incentives compared to other penalty designs.

3.7.3. Compliance Decisions through Permit-Buying

Since an investment decision automatically ensures firm compliance, this section discusses estimation models for compliance only through permit-buying. Therefore, only observations associated with those subjects who do not make investment decisions are used in the regression. Considering that compliance status is a binary variable, the regressions are performed using probit and logit estimators for random effect panel data.

With regard to penalty design, the summary of estimates in Table 15 shows results similar to those of the investment decision model. Subjects tend to be more non-compliant in the FPR treatment than in the MGP treatment. Nevertheless, unlike in the investment model, the penalty rate provides a highly significant compliance incentive for permit buyers. This finding is in line with *Result 2*, in which the compliance rate is higher when the penalty level is higher in the FPR treatment.

The MGP treatment generates the highest marginal effect on compliance, and this effect is also highly significant. A higher make-good ratio also increases the likelihood of subject's compliance although this effect is statistically not different to zero. The test statistics of the models validate *Result 3* in which the penalty level in the MGP treatment has no effect on compliance rates.

There is evidence of learning over time as the coefficient of round is statistically significant across models. The opposite effect is observed with the variable sub period two. In line with the experimental design, the estimates reveal that subjects find it more difficult to be compliant only through permit-buying, particularly in sub period two. This effect is undoubtedly true in MGP treatments in which even slight non-compliance by the end of sub period one can put very high pressure on permit demand in sub period two. Knowing that permit buyers will attempt to avoid penalties in the second sub period, permit sellers have the advantage of selling the permit at a much higher price than the theoretical equilibrium. Nevertheless, the effect is statistically not different than zero.

Table 15 Estimates Summary for Compliance Decisions

Regressors for compliance decisions	**Model 1 Probit OLS cluster robust**	**Model 2 Probit RE bootstrap**	**Model 3 Probit RE bootstrap**	**Model 4 Probit RE bootstrap**	**Model 5 Logit RE bootstrap**
Dummy for FPR	-0.0872	-0.1416	-0.1397	-0.142	-0.2593
	(0.1653)	(0.1911)	(0.2206)	(0.2189)	(0.3500)
Penalty rate	0.0087***	0.0089**	0.0088***	0.0089***	0.0152***
	(0.0021)	(0.0028)	(0.0024)	(0.0025)	(0.0046)
Dummy for MGP	0.9548***	0.9796***	0.9776***	1.0025***	1.6834***
	(0.2019)	(0.2354)	(0.2383)	(0.2298)	(0.4696)
Dummy for high level MGP	0.0779	0.1307	0.1306	0.1235	0.1954
	(0.1801)	(0.1870)	(0.1796)	(0.2176)	(0.3814)
Round	0.051	0.0749*	0.0750*	0.0727*	0.1263*
	(0.0291)	(0.0334)	(0.0331)	(0.034)	(0.0514)
Auction Price	-0.0088***	-0.0103***	-0.0102***	-0.0086**	-0.0175***
	(0.0025)	(0.0028)	(0.0026)	(0.0029)	(0.0043)
Dummy for sub period two			-0.0094		-0.0225
			(0.0762)		(0.1396)
Mean trading price				-0.0031	
				(0.0018)	
_cons	0.0802	0.1508	0.1559	0.1912	0.2811
	(0.2639)	(0.3028)	(0.2984)	(0.3093)	(0.5910)
N	1114	1114	1114		1114
Log likelihood	-592.4348	-572.8482	-572.8431	-570.8979	-572.347
R^2	0.0632	0.0461^	0.0461^	0.0493^	0.0456^
Chi2	41.7655	45.5528	62.4192	62.1237	60.0678
% correctly predicted	74.78				

Notes: The numbers in parentheses represent the standard errors of the estimates.
^ indicates estimated R^2 = (log likelihood – constant-only log likelihood) / constant-only log likelihood
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

It is not surprising that auction prices generate a negative effect on compliance incentive because higher permit prices increase compliance costs, causing the marginal benefit of being non-compliant to increase accordingly. This effect is highly significant, although it is much smaller in magnitude than the influence of the MGP treatment. The trading price also has a negative effect on compliance, but the magnitude of the effect is only half that of the auction price and is not statistically significant. It is important to point out that the coefficients on auction price and penalty rates counterbalance each other. Across models, we can see that their magnitudes are not very different. In all models except for Model 4, the marginal effect of the penalty rate is smaller than that of the auction price. In Model 4, the inclusion of the mean trading price moderates the marginal effect of the auction price.

The estimates are fairly consistent across models in terms of the sign of the coefficients. Statistically, the random effects binary choice models yield more consistent estimates than the OLS estimator. The OLS model shows that the model has fairly good predictive power with about 75% of the data correctly predicted. However, the value of R^2 is relatively small and slightly reduced in the random effect models.

Overall, the compliance decisions of net buyers are influenced by penalty designs (the level of penalty rate and the MGP penalty) and auction price. The adverse effect of high auction price on compliance decision surpasses the positive incentives given by penalty rates. The estimates explain the incidence of lower compliance rates in the FPR compared to the MGP and the mixed penalty treatment. Over time, subjects learn to make better compliance decision.

3.7.4. Efficiency

Regression models for efficiency are performed using Tobit estimators because the range of the possible values is truncated. As previously explained, efficiency is measured in terms of the actual group earnings compared to the theoretical optimum. Interestingly, we find some observations in which the efficiency level is higher than one due to the auction price below the optimal equilibrium. Those observations are mostly associated with the MGP treatment. There are some reasons why this might have happened. First, a low auction price might occur due to over investment, which would naturally lower permit demand. Furthermore, some subjects who have decided to make investment simply do not actively participate at the auction by submitting zero bidding quantity even at a low bidding price because they feel that they have chosen their best compliance strategy and hence are not interested in the outcome of the auction market. Low prices also emerge in sub period one of the MGP treatment, in which the financial penalty for non-compliance is zero. Thus, zero compliance cost does not provide an incentive for the subjects to actively participate in the auction. Therefore, we only use left censoring at zero in the estimation models. Group-level data is used to estimate the models because we would like to assess market-level efficiency instead of individual-level efficiency.

The estimation results are fairly similar across models (Table 16). The first model is performed with cluster-robust standard error estimators and with each observation group as the cluster identity. The penalty design treatment variable, price variables, and time variables are used as explanatory variables. Surprisingly, the dummy for the FPR treatment and the penalty rate have almost negligible effects on efficiency. As in the previous estimation models, the MGP treatment and auction price are highly significant in both economic and statistical terms.

Table 16 Estimates Summary for Efficiency

Regressor for efficiency	**Model 1**	**Model 2**	**Model 3**
	Tobit	**Panel data Tobit**	**Panel data Tobit**
Dummy for FPR	-0.0003 (0.0231)	-0.0024 (0.0297)	0.0094 (0.0117)
Penalty rate	0.0000 (0.0002)	0.0001 (0.0002)	-0.0004** (0.0001)
Dummy for MGP	-0.0437** (0.0156)	-0.0395* (0.0184)	-0.0786*** (0.0127)
Dummy for high-level MGP	0.0153 (0.0199)	0.0154 (0.0232)	-0.0058 (0.0111)
Auction Price	-0.0059*** (0.0004)	-0.0059*** (0.0004)	-0.0055*** (0.0002)
Mean trading price	-0.0003 (0.0002)	-0.0003 (0.0003)	-0.0001 (0.0001)
Round	0.0062** (0.0024)	0.0061* (0.0025)	0.0003 (0.0021)
Dummy for sub period two	-0.0697*** (0.0113)	-0.0690*** (0.0103)	-0.0678*** (0.0071)
Compliance rate			0.5168*** (0.0373)
Investment level			-0.2020*** (0.0166)
_cons	1.1733*** (-0.0324)	1.1709*** (0.0313)	0.9885*** (0.0324)
N	360	360	360
Log likelihood	383.5838	385.8185	470.3238
Chi2	180.0935	492.9965	1445.322

Notes: The numbers in parentheses represent the standard errors of the estimates.
^ indicates estimated R^2 = (log likelihood – constant-only log likelihood) / constant-only log likelihood
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level

The existence of a learning effect is also confirmed because the coefficient of round is highly significant. This indicates that overtime subjects learn to make better decisions in the game that contribute to higher efficiency in the market. The coefficient on sub period two has a negative sign, indicating that efficiency in this sub period tends to be lower than in sub period one. The high financial penalty in the second sub period for MGP treatment might be the underlying reason for this effect. Otherwise, it seems that investing firms attempt to make a profit selling in sub period two by buying more permits at the auction. Nevertheless, this attempt does not seem to be successful; the mean trading prices are lower than the auction price 70% of the time. Hence, efficiency is reduced for both buyers who cannot obtain the required permits and sellers who cannot achieve their preferred trading price.

Model 2 is very similar to Model 1 except for the fact that the regression is run with a panel data Tobit estimator. The estimation results are not very different, but the goodness of fit of the model is increased as shown by the value of the log likelihood.

The inclusion of the investment level and compliance rates variables in Model 3 changes the model estimates considerably. The sign of the FPR treatment is now positive, although it is not statistically significant. The penalty rate, on the other hand, becomes highly significant. This is reasonable as higher penalty rates are related to higher costs when non-compliance occurs. Similarly, the effect of the MGP treatment is almost doubled in this model, while the effect of high MGP levels is not significant. It can be inferred that the MGP penalty type and the level of the penalty rate are the main determinants of efficiency.

The important finding that we obtain from this model is that the investment levels and compliance rates have the opposite effect on efficiency. Higher compliance levels in the market contribute to greater efficiency. On the contrary, higher investment levels will reduce efficiency due to higher investment costs than necessary. As seen in Figure 15, it is also clear that some high MAC firms decide to make investment decisions that entail higher total investment costs than are optimal in the market. Furthermore, over-investment prevails in the market and exacerbates inefficiency.

3.8. Discussion

In line with the theory, our results show that different penalty designs do not necessarily indicate different permit prices. We find that auction prices do not significantly vary across treatments, as shown by *Result 1* and the regression models for auction price. The important determinants of auction price are the subject's risk attitude and rational thinking ability. This finding will have an important implication on the design of trading schemes in practice in which there is a tendency that auctions will increasingly be used as the initial allocation mechanism. Despite the advantages of having a system with auctioned permits, it is important to ensure that the extent of speculative or strategic bidding behaviour can be moderated with an appropriate auction design. Some studies have shown that reducing uncertainties regarding the expected permit price might be the key to address the problem.

Result 2 of this experiment has shown that contrary to the theory that predicts that there will be no difference in compliance rates as long as the penalty level is set above the equilibrium permit price, significantly higher compliance levels emerge with the high level FPR. This study reveals that subjects learn about different maximum compliance costs related to high penalty rates, which in turn affects their compliance strategy. However, high penalty rates do not provide a different incentive with regard to investment decision.

In contrast, *Result 3* confirms the theory that high penalty levels (make-good ratios) in the make-good provision penalty type do not produce different investment levels and compliance rates. It is believed that the feature of our experimental design ,which forces compliance by imposing huge financial penalty at the end of the second sub period, affect the result. This provision leaves little room for subjects to be more speculative unlike in the FPR penalty type.

Result 4 indicates that when a comparison is drawn across penalty types with similar penalty levels, difference compliance rates are only confirmed for low level penalty treatment. In this case, the MGP treatment provides a stronger compliance incentive than the FPR treatment even though the make-good ratio is slightly lower (a restoration rate of unity) than the penalty rate factor (1.2 of equilibrium price).

The statistics of the estimation models for compliance decision verify *Result 2* and *Result 4* as both the penalty rates and the MGP treatment are the significant penalty design variables.

With regard to the Mixed Penalty design, *Result 5* reveals that this double penalty encourages higher investment levels and compliance rates compared to the baseline low level FPR treatment. Nevertheless, the regression models prove that the MGP treatment is the only significant penalty design variable that affects investment decisions. The models also verify that subjects behave rationally in making their investment decisions.

A trade-off between efficiency and compliance is revealed as the regression models show that the MGP treatment has both statistically and economically significant effects on efficiency. Hence, the penalty design that encourages higher compliance levels might encourage lower efficiency levels when over-investment occurs in the market. As auction price plays a significant role in investment decisions, the presence of risk aversion might in practice indirectly contribute to this over-investment, leading to inefficiency in the market.

It is important to point out that our experimental design does not take into account banking, which is allowed in almost all existing trading schemes. The presence of banking might smooth out the uncertainties regarding the permit price and thus facilitates better price discovery and a convergence path of the permit price. Nevertheless, an experiment also shows that this provision might have an adverse effect on the compliance rate and emissions level due to the perceived benefit of underreporting under the condition of imperfect enforcement, in which the audit probability is less than one (Cason and Gangadharan, 2006).

Another feature that might change compliance incentives under different penalty designs is the presence of a discount rate and the use of longer sub periods to allow its effect to take place. The presence of a discount rate will reduce future costs, and when the costs and emissions cap in the trading scheme are stationary over time, firms might delay investment and shift their emissions towards the present, as pointed out by Kling and Rubin (1997). Therefore, it will be interesting to see the choice of firms' compliance strategies when the restoration rate is set equal to the discount rate to counterbalance the effect of decreasing costs due to the discount rate. Furthermore, longer compliance periods will also enhance the irreversible nature of investment in our model, in which risk preference might play a more important role in this case.

Finally, the use of a different auction design might reduce inefficiency due to overbidding. Sealed-bid auctions have been recommended as a format that might facilitate bidding behaviour closer to bidders' private valuations. The downside of this auction format is that inexperienced bidders do not have an opportunity to revise their bids and there is a potential of having a winner's curse problem. An alternative format that might enhance efficiency is the use of an Anglo-Dutch format as suggested by Klemperer (2002). In this format, an auction is first run with an ascending clock auction until two bidders, or a few subjects in this case, are left. The auction is then continued using a sealed-bid format.

It is important the note that findings from economic experiments have drawn some scepticism on the ground of external validity and thus the extent to which those findings can be generalised to the targeted population. This scepticism points out that subjects who participate in the laboratory, notably students, may have significant preferences, knowledge, and experience to the targeted population in the real world, and how the laboratory environment is too simplistic. Levitt and List (2007) further highlight the key differences between laboratory and the field. The use of field experiment is proposed as a bridge that combine the advantages of experiments and the real world (Harrison and List, 2004). However this will come at the expense of less control of the environment as well as higher costs. One needs to be aware that there will always be differences between the real world and the economic models, either theoretical models, econometrics model derived from natural data, and experimental models. Nevertheless, each methodology makes different contributions at providing economic insights of the problem of interest. Policy problems share some dimensions of parallelism with laboratory experiments (Plott, 2005). In this case, the experiment provides an opportunity to test a design question which otherwise will be difficult to test with natural data. Levitt and List (2007) also maintain that experimental findings are more readily generalizable in cases where morality and wealth are not competing objects, for example the public good experiments. Hence, we believe that external validity is not a significant issue for our experiment that uses neutral context with no moral attributes attached to the experimental design.

3.9. Conclusion

Although the importance of penalty design as an enforcement tool has been widely recognised in practice, the assessment of its efficacy on compliance rates in particular and market performance in general is difficult to make due to the unfeasibility of comparing existing trading schemes with different market structures and design features. A laboratory experiment offers the advantage of providing insight by isolating the effect of the penalty design in question as the market design features are held under control.

Our findings reveal that under the presence of subjects' risk preferences and some degree of permit price uncertainty, penalty levels provide an indication of total costs of compliance, which in turn affect firms' choice of compliance strategies as well as the compliance rate, although it does not influence the price discovery process. Surprisingly, risk preference does not have a direct role in influencing subjects' compliance decision. Nevertheless, it affects the permit price, which evidently is a significant determinant of compliance decisions and efficiency.

The make-good provision evidently induces higher investment and compliance levels than the fixed penalty rate does. It is important to point out that there is a trade-off between higher investment levels and efficiency because the penalty design that encourages higher investment levels for compliance purposes also corresponds to an adverse effect on efficiency. The inefficiency attributed to penalty design has not received sufficient attention, as the focus has been placed on compliance. These trade-offs should be considered before a policy is implemented; otherwise, the efficiency of a trading scheme will be compromised.

In practice the mixed penalty design is widely used in order to encourage higher compliance rates. The findings from our laboratory experiment support that view as the presence of a FPR element and a MGP element induce higher compliance rates. Nevertheless, only the MGP element in the mixed penalty provides higher investment incentives at the expense of lower efficiency levels.

The main findings from this experiment are summarised as follows.

Table 17 A Summary of the Main Findings of the Penalty Design Experiment

No.	Main Findings	Supports
1.	Penalty design does not affect permit price	Result 1 and regression models for auction price
2.	Higher compliance rates are found with higher penalty levels in the FPR penalty, but not in the MGP penalty	Result 2 and Result 3
3	MGP penalty type induces higher investment incentives than the FPR	Result 4 and regression models for investment decision
4	The mixed penalty design provides higher investment and compliance incentives relative to the low FPR penalty.	Result 5
5	There is a trade-off between investment incentives and efficiency levels as the MGP penalty corresponds to a lower efficiency level and a higher investment level.	Regression models for efficiency

The mixed penalty design in this study also shed some light on the effects of tying the penalty rate to the auction price as proposed by the Australian Carbon Pollution Reduction Scheme. We do not find the occurrence of bid shedding at the auction and both investment levels and compliance rates remain relatively higher compared to other penalty designs. It is only the MGP element of the double penalty, rather than the two penalty types (the FPR and the MGP element), that contributes to lower efficiency levels. With the presence of a reserve price at the auction, the proposed Australian model seems to serve its purpose of providing strong compliance incentives.

Overall, we believe that the experiment has provided valuable insights into how a specific penalty design can have an impact not only on compliance rates but also on market efficiency. Furthermore, a laboratory experiment can serve as a test-bed for policy makers to test how well the proposed design features of a trading scheme might work.

Chapter Four

The Initial Allocation Mechanism and Market Efficiency: A Laboratory Study on Emissions Trading Markets

4.1. Introduction

Some have argued that the initial allocation mechanism of permits is considered the most important yet contentious aspect of a market design for emissions trading markets. Although the manner in which permits are distributed should not matter in theory, in practice, the presence of transaction costs, uncertainties, market power and other kinds of market failures might make a significant difference. A large strand of literature has highlighted the advantages of auctioning permits, such as transparency, fairness, strong investment incentives, and the ability to address pre-existing distortions. Nevertheless, grandfathering is still the norm mainly due to political feasibility as well as other industries' concerns, such as the issue of carbon leakage and adverse industrial competitiveness.

This chapter seeks to answer how different initial allocation mechanisms might influence market efficiency, based on three criteria: price discovery, compliance incentives, and efficiency. We employ a laboratory experiment, which gives us the advantage of controlling market parameters and the environment in which the market operates. The contributions to the experimental study on the initial allocation mechanism are made through the following design features. First, to isolate the effect of the initial allocation mechanism we abstract from any exogenous uncertainties. Second, we incorporate a penalty design treatment to observe its interaction effect on the initial allocation mechanism to induce compliance as well as a loose indication of price caps. Third, we use a two-period model to take into account the effect of irreversible investment as a compliance strategy. Finally, the clock auction format is used in the auction treatment due to its simplicity and transparency.

This chapter is organised as follows. The second section outlines the literature review, which argues for each mechanism in theory and practice as well as existing experimental studies that specifically address the initial allocation mechanism in the context of emissions trading schemes. This second section concludes with an explanation of the motivation underlying this research. Subsequently, the experimental design and hypotheses are explained in section three. The fourth section analyses the results in detail and examines the presence of treatment effects in terms of the average permit price, compliance incentives, and efficiency. Results from estimation models are presented in the following section. The last section summarises our findings and the conclusions.

4.2. Literature Review

4.2.1. The Initial Allocation Mechanism in Theory and Practice

Emissions trading markets which are designed as a cap-and-trade system basically involve two main stages: first, the initial allocation of permits, and second, an organised permit trading[15]. The first stage can be thought of as the main mechanism for distributing permits from the authority to market participants, while the second stage is mainly conducted to enhance efficiency, due to uncertainties and external shocks that might occur between compliance periods, as well as to address any inefficiencies resulting from the initial distribution of permits. Two main mechanisms for distributing initial permits in a cap-and-trade system are free allocation (grandfathering[16]) and auctioning. In the free allocation mechanism, participating firms might receive some permits to cover a part of or the whole of their emissions levels. In this study the term grandfathering refers to the free allocation of permits in general; hence, it is used interchangeably with the term free allocation. When initial permits are auctioned, the auction market becomes the primary market of permits. Hence, permit trading in the second stage is called the secondary market, as it follows an auction and normally takes place in a spot market.

A number of approaches can be used as the basis for distribution of free initial permits, such as historical emissions records, expected output and technological benchmarks (benchmarking). Historical emission records have been widely chosen as the basis of grandfathering by most Member States in the European Union Emissions Trading Scheme (EU ETS) for the first two phases (2005-2012), although there was also much debate regarding the adoption of the benchmarking approach. Ellerman et al. (2010) point out that some underlying reasons for the

[15] Another emissions trading system is the baseline and credit system which does not have a stage of initial allocation of permits.

[16] Some view the term grandfathering as merely the free allocation of permits based on historic records, while some others use the term to refer to the free allocation of permits in general.

lack of support for benchmarking are: the pressing deadline to come to an agreed-upon benchmark; the heterogeneity of goods, processes and the conditions of production of similar goods; and the absence of any pre-existing standards with sufficient legal force. In the end, the benchmarking approach was applied for the allocation to new entrants (Ellerman et al., 2010). From 2013 onwards, the EU ETS will use benchmarking as a basis for transitional free allocation (EU Directive, 2009); hence, it provides greater incentives toward energy efficiency (Schleich et al., 2009).

The lack or absence of emissions inventory data, especially at the beginning of a trading system, is often mentioned as another reason to favour the historical emissions basis, as it gives incentives for firms to report their past emissions to receive free permits. Considering that there was a varying degree of compromise made by each EU Member State to secure the political acceptance of the trading scheme, in reality, similar installations in different Member States might receive different amounts of free permits. However this will change in the third phase (2013 onwards) when the allocation is harmonised (EU Directive, 2009).

A rather different approach is used in most US trading schemes that distribute free permits based on a combination of past records and some measure of technological benchmarks. For instance, the amount of freely allocated permits in the Los Angeles Regional Clean Air Incentives Market (LA RECLAIM) is the product of each facility's highest yearly production between 1989 and 1992 and the projected emission rates that would have applied to the sources under command and control between 1994 and 2003 (EPA Clean Air Markets Division, 2006). Likewise, the number of free permits in the US Acid Rain Program is based on an emission rate of heat input set by the EPA multiplied by each unit's baseline (Ellerman et al., 2003, US EPA, 2009a).

A gratis allocation of permits based on historical records or technological benchmarks is essentially a lump-sum transfer because it is determined upfront and does not change. Some researchers have advocated the use of a dynamic grandfathering. This would be based on an updating rule, for example installations with higher output levels as expected will receive additional permits. The proponents of this view believe that changes in market conditions due to e.g. external shocks need to be taken into account in the allocation of permits. Despite the discussion regarding the issue (Fischer, 2001, Böhringer and Lange, 2005, Burtraw, 1999), the formal adoption of this approach has been limited to the *ex post* adjustment provision in Germany's National Allocation Plan (NAP) during the first compliance period of EU ETS. The provision states that the excess allowances will be taken back when actual production is less than the projected level (Matthes and Schafhausen, 2007). However, a greater extent of indirect updating has actually occurred since many Member States have taken the 2005 emissions levels into account when allocating the allowances in 2008-2012 (Betz and Sato, 2006).

In practice, full auctioning of initial permits is such a rare case, and the only trading scheme that auctions nearly all of its allowances is the Regional Greenhouse Gas initiative's (RGGI) CO_2 Budget Trading Program (Regional Greenhouse Gas Initiative, 2009). Both the US Acid Rain Program and the EU ETS have auctioned only a small fraction of total permits due to the low political acceptance of auctioning. The heated debate regarding the initial allocation mechanism reflects not only the arguments in favour of each mechanism but also its proponents. While economists generally advocate the use of auctioning (Cramton and Kerr, 2002, Hepburn et al., 2006), the industries have always shown a strong resistance against it.

A theory by Montgomery (1972) maintains that the emissions level, the final portfolio of firm's permit holding, and the permit price at market equilibrium for a given supply of permits are independent of the initial distribution of permits. In the model, the freely allocated permits can be viewed as a lump-sum subsidy to the recipient firms, and they are independent of their actual or historic emissions levels. Hence, whatever the basis on which the regulator chooses to distribute initial permits, market efficiency is retained under the necessary conditions of perfect competition, perfect information, and no transaction costs; and only distributional differences occur. The theory is also supported by experience with six trading schemes in the US, which demonstrates that gratis allocation does not compromise the market's ability to realise their potential costs savings as well as reduction targets (Ellerman et al., 2003).

Since those necessary conditions in Montgomery's model are generally not met in practice, efficiency might be compromised. Due to the distributional consequences, the choice for initial allocation has become the most contentious aspect of the program, as the industries have always attempted to heavily lobby the regulator to receive free permits. This was clearly observed in the first and second compliance periods of the European Union Emissions Trading Scheme (EU ETS), for which the final decision on the allocation process was greatly based on political considerations to secure the acceptability of the program. Considering the large scale of carbon markets in EU ETS the lobbying costs involve large transaction costs, which diminish both the efficiency and harmonisation of the market.

Moreover the rents that firms receive from grandfathered permits have been highly criticised on the basis of equity and fairness (Ellerman et al., 2007, Raymond, 2003, Parry, 2003, Harrison, 1999). Although the pass-through of permit value to product price is economically justified, the gratis allocation also creates windfall profits to firms' shareholders that essentially imply a wealth transfer to a high-income group. It is important to point out that consumers will always pay for an increase in product price regardless of the initial allocation mechanism.

Other than the issues of political feasibility, arguments favouring the use of grandfathered allocation are lined to the possibility of carbon leakage and adverse industrial competitiveness effects. Carbon leakage occurs when the regulated industries relocate to places where carbon emissions are not constrained by emissions trading markets. However, some studies find that the extent of adverse effect on industrial competitiveness is not necessarily justifiable, e.g. relative to the sector value-added (Grubb and Neuhoff, 2006), and the leakage ratio is less than 10% (Demailly and Quirion, 2008). This effect is even less when producers are able to pass-through the increased costs, as is the case for the electricity sector (Hepburn et al., 2006, Burtraw et al., 2001). Two suggested measures to address the carbon leakage problem are a border tax adjustment (Reinaud, 2008, Kuik and Hofkes, 2010, Monjon and Quirion, 2010, Hourcade et al., 2008) and output-based free allocation (Fischer, 2001, Fischer and Fox, 2007). Yet, the latter solution (Fischer) might imply higher costs on other sectors (Fischer and Fox, 2007, Jensen and Rasmussen, 2000). Further distortions in price signals with grandfathering might occur when firms buy more permits to indicate an increased demand to the regulator ; and thus, by doing so, they inflate the permit price (Harstad and Eskeland, 2010).

In the presence of tax distortions, the cost of an environmental policy can be much higher than expected (Bovenberg and Goulder, 1996). One important argument in favour of auctioning is that it creates a 'double dividend,' which means that the policy instrument of emissions trading achieves the environmental effectiveness of emissions reductions; and at the same time, the revenues raised from auctioning can be used to correct any existing tax distortions (Parry, 1997, Parry and Bento, 2000, Parry et al., 1999). Thus, the efficiency gains from a trading scheme with auctioned permits are higher compared to when permits are gratis.

Despite the arguments for a greater use of auctioning as a preferred initial allocation mechanism, free allocation is still commonly practiced in most existing trading markets. Nevertheless, there is a tendency to gradually move toward full auctioning over a period of time. The EU ETS seeks to achieve full auctioning by 2013 for the electricity sector and by 2027 for the non-power sector (EU Directive, 2009). This shift recognises the complexities and problematic nature of justifying a fair basis for free allocation, on the one hand, and the transparency as well as other potential benefits arising from the auctioning of permits, on the other hand. Nonetheless, the realisation of efficiency gains in emissions trading markets and the resulting benefits also depend to a large extent on the auction design and its intricacies (Holt et al., 2007, Cramton and Kerr, 2002, Hepburn et al., 2006, Ledyard and Szakaly-Moore, 1994). Despite the large body of work to be found in auction theory, the complexities of auctioning in practice merit the test-bedding of its design in the laboratory to gain more insight into the mechanisms of its features.

4.2.2. Experiments on the Initial Allocation Mechanism

The question of efficiency in emissions trading markets has been greatly investigated through laboratory experiments. Among others, Muller and Mestelman (1998) outline a survey of early experiments in this area. In a laboratory setting, market parameters and the environment are held constant in an experiment; thus, experimental economics offers the advantage of isolating the effects of the question of interest. Although a vast number of experiments have been conducted to study various auction designs in the context of pollution permits trading, only a few have focused on the effect of the initial allocation mechanism. Previous studies investigate the design of the initial allocation mechanism, which resembles that of EU ETS design (Grimm et al., 2010, Benz and Ehrhart, 2007) and the extent of permit cost pass-through in product prices (Goeree et al., 2009, Wråke et al., 2008). Results from those experiments present mixed evidence regarding which initial allocation mechanism performs better. These differences also stem from different auction designs employed in the experiments as well as other market design features and parameters. Those studies indicate that the details in the auction design mechanism can greatly affect the success of an auction.

Benz and Ehrhart (2007) compare efficiency properties of a one-sided pure auctioning treatment (A), a pure grandfathering treatment (GF) and partial auctioning, in which one treatment uses a one-sided auction, wherein all firms are buyers (GF+A), and another one uses a double-auction mechanism, wherein firms can be both buyers and sellers (GF+DA). In all treatments, a secondary market follows the primary market. The primary market and secondary markets employs a Japanese auction[17] (English auction) as a trading institution. The results indicate that partial auctioning with a double auction (GF+DA) and pure auctioning performs better consecutively in terms of efficiency[18] and reliable price signals compared to grandfathering.

A similar experiment was conducted by Grimm et al. (2010) but with no partial auctioning. Instead, they add a treatment of frequent auctioning. Other differences lie in a sealed-bid auction[19] as the chosen auction type, an increasing marginal abatement cost, and a continuous

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[17] In the Japanese auction, the bidding price is continuously increased until demand meets supply. At each price, firms need to state their willingness to pay for the offered quantity or they can opt out and/or switch to become sellers by offering the quantity they would like to sell.

[18] Benz and Ehrhart (2007) measure efficiency as the actual cost savings compared to the theoretical optimum.

[19] With a sealed-bid auction, subjects can submit multiple bids at different prices in a single round. Alternatively they can also submit a demand schedule for a given price set by the auctioneer.

double auction as the trading institution for the secondary market. Contrary to Benz and Ehrhart's experiment, they find that there is no significant difference in static and allocative efficiency across treatments[20]. In line with the theory, compared to the free allocation, auctioning and more frequent auctioning provides greater incentive for abatement measures, at the expense of dynamic efficiency. These treatments exhibit a higher price volatility, which leads to a different distribution of abatement measures over time.

Since cost pass-though in the downstream market as a research question in Wråke et al (2008) and Goeree et al (2010) is not the focus of this study, we will not discuss their experimental designs. Their results confirm that firms do pass-through the value of the permit into the product price, even though they do not immediately recognise the opportunity cost of the permit value in early periods of the experiment. Furthermore, it is found that in a quantity choice setting of the product market, auctioning yields less cost pass-through, or a lower product price, and, hence, higher consumer welfare.

This study aims to contribute to the discussion by examining the efficiency properties related to each initial allocation mechanism. Specifically, our experiment seeks to answer how an initial allocation mechanism will affect:

1) reliable price discovery in an emissions trading market,
2) compliance incentives, measured by optimal investment level and compliance rate, and
3) efficiency, in terms of allocative and static efficiency.

As market efficiency is fully realised only when all firms choose their best compliance strategies by either reducing their emissions or buying permits, price signals provide important information for firms to arrive at those decisions. Auctioning will provide better incentives to make investments in cleaner technologies (Milliman and Prince, 1989, Jung et al., 1996), while grandfathering might give perverse incentives for incumbent dirty technologies to remain in industry, even when a closure or replacement is socially more efficient (Neuhoff et al., 2006). Because permit price is determined by the supply of and demand for permits in the market, accurate price signals will facilitate the optimal level of investment and yield permit prices that are equal to all firms' marginal abatement costs. Consequently, when the price signal is unreliable, over- or under-investment might occur and, hence, market efficiency is diminished.

[20] Grimm et al. (2010) use three criteria of efficiency. First, static efficiency as expressed by the permit price compared to the equilibrium. Second, dynamic efficiency is measured as the optimal amount of banked permits to reflect optimal abatement over time. Last, efficiency of permit allocation is measured by the percentage of permits owned by those who value them the most.

Weighing on the importance of firms' compliance to market efficiency, as shown in our previous chapters and the references therein, we investigate market performance of both initial allocation mechanisms under different penalty designs. Apart from encouraging full compliance in the market, the presence of a penalty design also conveys information on the maximum compliance cost in the market. This information is important, as firms learn that permit price should not go beyond the marginal cost of being compliant, and hence, it reduces the uncertainty regarding the possible range of permit prices. Uncertainties in permit prices might reduce firms' incentives to invest in abatement measures (Zhao, 2003).

To some extent, a fixed penalty can be seen as an indication of a price cap, although it does not possess a binding force like a price cap because it informs firms about the maximum compliance cost. To address industries' concerns about price volatility and the risk of having excessively high permit costs, a price cap is included in the proposed design of the Australian Carbon Pollution Reduction Scheme (CPRS) and will be implemented for the first few years of the scheme, should the scheme be approved by the legislature (The Parliament of the Commonwealth of Australia, 2009). Some studies argue that cost uncertainties will reduce firms' incentives to make irreversible investments in cleaner technology, as firms choose the wait-and-see strategy (Kolstad, 1996, Zhao, 2003).

The concept of price caps for dealing with unexpectedly high permit costs is basically a hybrid of a pure tax and permit system as proposed by Weitzman's (1974). The McKibbin-Wilcoxon proposal (2000) uses two kinds of emissions-related assets which aim to set a long term emissions target and limit the short run costs. The first one is a long term asset in which the supply is fixed and the price is flexible, hence reflecting the quantity approach. The second asset is a yearly permit with a fixed price. A rather different approach is taken by Roberts and Spence (1976), Pizer (2002) and Jacoby and Ellerman (2004) who propose a hybrid system with the use of a trigger price or a 'safety valve' that functions as a ceiling on permit prices. When the safety valve is triggered, the regulator needs to increase the supply of permits in the market. Although the use of the safety valve might reduce the costs related to uncertainties, this one-sided price control approach also runs the risk of increasing the emissions level. Furthermore, a price cap can become a disincentive to invest when it is set too low (Roques and Savva, 2009). Hence, a price floor is deemed to be important to maintain the incentives for investments in low-carbon technologies, especially when the emissions cap is inaccurately set, such as is the case at the initial stage of a trading scheme.

Two studies demonstrate that the use of both price caps and price floors, or a 'symmetric valve', can reduce the economic costs of uncertainty while maintaining the integrity of the emissions cap (Philibert, 2008, Burtraw et al., 2010). Because most auctions normally have a reserve price, Hepburn et al. (Hepburn et al., 2006) suggest to use this reserve price as a price floor. In our experiment, we will observe how the presence of a fixed penalty and a reserve price in the auction treatment might offer different compliance incentives compared to a grandfathering treatment, which only has a fixed penalty as a 'loose' price cap. A fixed penalty can be seen as a 'loose' price cap as it only serves as an indication of the maximum compliance costs and would not be binding as a price cap would because the permit price can still go beyond the fixed penalty rate.

In summary, this experiment attempts to shed more light on how different initial allocation mechanisms under the presence of different penalty designs might influence the price discovery process in the market, which guides firms' compliance decisions. These effects are measured through static and allocative efficiency[21].

4.3. Experimental Design and Predictions

4.3.1. Experimental Design

To answer our research questions, we focus on two treatment variables: the initial allocation mechanism and the penalty design. The three penalty designs that we employ are a low Fixed Penalty Rate (FPR), a high FPR, and a high Make-Good Provision (MGP). As explained in the previous chapter, the FPR is basically a monetary penalty, while the MGP serves as a quantity penalty in which the exact monetary penalty is determined by the permit price. For the low FPR, the penalty is EX$45 per missing permit, which is roughly 1.2 times the equilibrium permit price. Meanwhile, the penalty rate is increased in the high FPR to EX$114, that is, approximately three times the equilibrium permit price. With the high MGP treatment, three permits should be held in the second sub period for each missing permit in the first sub period. Overall, we have six treatments from a balanced 3 x 2 design (Table 18).

Table 18 Experimental Design for Initial Allocation Mechanism Experiment

Penalty design	Initial Allocation Mechanism	
	Auctioning	Grandfathering
Fixed Penalty Rate Low Level (penalty rate = 1.2 x equilibrium price)	Treatment 1: AFL	Treatment 4: GFL
Fixed Penalty Rate High Level (penalty rate = 1.3 equilibrium price)	Treatment 2: AFH	Treatment 5: GFH
Make-Good Provision High Level (make-good ratio = 3:1)	Treatment 3: AMH	Treatment 3: GMH

[21] We use the same definition of allocative efficiency as Grimm et al. (2010), but the static efficiency is based on the least total compliance costs, which will be explained in details in section 4.3.2.

The main differences of our experiment compared to previous experiments on the initial allocation mechanism are as follows:

1) We abstract from uncertainties other than the endogenous uncertainty, which are derived from subjects' decisions in the experiment.

   To highlight the effect of initial allocation on price discovery, we abstract from inducing additional uncertainties in the experiment other than those that arise from subjects' decisions and interaction in the market. On the other hand, in other relevant experiments, additional uncertainty is presented in product price (Goeree et al., 2009, Wråke et al., 2008) or external product demand (Grimm et al., 2010). To a lesser extent, the change in the permit market structure in Benz and Ehrhart (2007) adds further complexity, which requires more cognitive ability for subjects to arrive at the theoretical equilibrium. On the contrary, the market parameters remain the same throughout our experiment, and only subjects' decisions can cause the change in permit demand. This measure also allows us to observe whether or not learning takes place in the experiment.

2) Penalty design

   Penalty design is used not only to encourage firms' compliance but also as an indication of the maximum cost of compliance, which to some extent can be viewed as a loose price cap. At the same time, the existence of a reserve price in the auction treatment can be viewed as a price floor for auction price, which then determines the average permit price[22].

3) Irreversible investment decision

   The choice of reducing emissions is modelled as an irreversible investment decision, instead of incremental abatement measures, to highlight the risk in making such an investment, as would be the case in the real world. To take into account the effect of an irreversible investment as a compliance strategy as well as the effect of MGP as a penalty design, we use repeated rounds of a two-period model.

4) An ascending or English clock auction is used in the primary market

   Whereas Grimm et al. (2010) employ a sealed-bid auction, a Japanese auction format is used in Benz and Ehrhart's (2007) experiment. A one-sided Japanese auction format is basically the same as a clock auction. The clock auction format is preferred for our experiment, as it has been recommended as one of the suitable auction formats in the context of emissions trading schemes (Cramton and Kerr, 2002, Holt et al., 2007,

[22] The average permit price equals to the mean trading price in the grandfhering treatment, while for the auction treatment it is the volume-weighted mean of the auction price and the mean trading price.

Hepburn et al., 2006). Owing to its simplicity and transparency, this format is appropriate, particularly, for inexperienced bidders. Furthermore, the dynamic feature of the clock auction allows for updated information regarding bidders' valuations of the auctioned items to be transmitted in each bidding round. We apply a non-zero reserve price that is set slightly lower than the lowest marginal abatement cost in the market. Hence, the reserve price acts as a price floor at the auction. As the trading price is not constrained by the reserve price, this price floor at the auction market becomes merely a loose price floor for the average permit price. Nonetheless, if the trade volume in the secondary market is low, the presence of a reserve price as a price cap is fairly important in determining the average permit price, which is the volume-weighted mean of the auction and mean trading price for auction treatments.

The general setting of this experiment is similar to the penalty design experiment in the previous chapter. Each treatment consists of six observation groups with eight subjects per group. We employ a between-subject design, such that each subject only experiences one treatment. To control for personal bias, we do not frame the instructions in the context of an emissions trading scheme. Subjects are given a neutral context of a firm's production activity, for which licenses are required to produce goods. Otherwise, firms can choose to make investments that exempt them from the obligation of having those licenses. Furthermore, the failure to meet this requirement will incur a penalty. For the details of the instructions, please refer to the Appendix.

The subject pool was recruited from students of the University of New South Wales through the ORSEE online recruitment system (Greiner, 2002). In total, 288 subjects participated, and 45 % of them are female. The duration of the experiment was 2-2.5 hours for the grandfathering treatment, while the auction treatment lasted about a half an hour longer. Different exchange rates were used in both initial allocation treatments to take into account the different lengths of the experiments and the money to buy permits at the auction. Hence, the expected payoff for each subject was roughly the same in all treatments. The average earnings were A$33.24 for the grandfathering treatment and A$34.28 for the auction treatment.

To control for subjects' risk preferences, Holt and Laury's (2002) lottery choice game was conducted before the main experiment took place. During the experiment, subjects only interacted with each other through computer terminals, and no other interactions were allowed. The interface for the experiment was programmed with z-Tree experimental software (Fischbacher, 1999).

There are six repeated rounds of the emissions trading game in the experiment, in which each round consists of two sub periods. Hence, we have 12 periods of data from each group. The experiment stages remain the same as in the penalty design experiment, with the only differences being with respect to the initial allocation mechanism employed and the duration of the trading period. In the following, we outline the experimental stages as well as further important details.

1) Stage 1: initial allocation mechanism

   For the grandfathering treatment, each firm receives 10 permits, which account for half of their emissions level (20 units of emissions). In the experiment, the free permits are allocated when subjects receive information regarding their individual characteristics as well as common information on the permit market.

   For the auction treatment, an ascending clock auction is used to distribute a fixed permit supply of 80 units. The bidding price starts at Experimental Dollar (EX$) 18 and the price is increased by EX$5 increments when the aggregate demand is higher than the total supply. At each bidding round, firms submit non-negative bidding quantities and an improved bidding rule is applied[23]. The reserve price is set at EX$18.

   The auction price and the number of allocated permits are determined as follows:

   a) If the aggregate demand equals the aggregate supply, the auction price equals the last bidding price. The number of allocated permits is the same as each firm's last bidding quantity.
   b) If the aggregate demand is less than the aggregate supply, then the auction price is the price in the penultimate bidding round. In this case, firms receive permits as many as their last bidding quantity plus any remaining excess supply. Following the Virginia NOx auction model (Holt et al., 2007, Porter et al., 2009), the fastest bidders have the priority to be allocated the excess supply.

2) Stage 2: permit trading (secondary market)

   A continuous double auction is used as a trading institution in which subjects can both buy and sell permits, and all the posted offers as well as trading prices can be viewed publicly. An improved bidding rule is applied for all submitted offers. Nevertheless, subjects can freely choose the price at which they are willing to sell or buy.

   For the grandfathering treatment, the duration of the trading period is two minutes. A shorter trading period of one minute is conducted in the auction treatment, as it is assumed that the secondary market will only be used to reduce inefficiency at the auction as a primary market.

[23] The bidding rule requires that submitted bidding quantities should be non-increasing as the bidding round continues.

While the trading takes place, subjects receive updated information about their current permit holdings, money, the number of permits that they have bought or sold, and the required number of permits needed to be compliant. At the closure of a trading stage, subjects are informed about the average trading price for that sub period.

3) Stage 3: investment decision

The investment decision can only be made in the first sub period to reflect the irreversible nature of investments in reality. With this model, firms receive price signals from the secondary market (and from the auction in the case of auction treatment), before they decide to invest. In this light, there is no uncertainty about the current permit price at the time firms make investment decisions. Nevertheless, their investment decisions will determine permit demand in the second sub period, and thus, there is uncertainty concerning future permit costs.

Because no partial investment is allowed, the best compliance strategy will be to choose either just to invest or to buy permits. If firms choose to undertake both strategies to comply, then firms make an inefficient decision, as they incur more compliance costs than the efficient level. Thus, to arrive at the best compliance strategy and maximise profits, firms need to have a forward-looking perspective and not buy any permits at the auction, unless they can sell them at a profit in the secondary market. This is only possible when firms have a reliable expectation of the permit price.

4) Stage 4: compliance check

At the end of each sub period, subject's investment decisions and permit holdings are inspected. Subjects who do not make investment decisions and do not hold enough permits will be penalised. As in Grimm et al.'s (2010) experiment, we allow for non-compliance, while Benz & Ehrhart's model enforces full compliance by automatically imposing the required abatement levels to reconcile a permit shortage. Consequently, the extent of inefficiency is reduced by such measures, while allowing for non-compliance opens the possibility of greater inefficiency.

The key features of the emissions trading market are as follows.

a) Banking and borrowing are not allowed in order to control for the comparability of market structures between the two sub periods.
b) Firms' characteristics.

The set of a firm's marginal abatement costs remains the same for the whole session, $MAC \in EX\$ \{20, 25, 30, 35, 40, 45, 50, 55\}$, although these costs are allocated randomly to firms in each round. Other firm characteristics – the production level, initial emissions level, and total revenue from product sales – are fixed. Firm characteristics that will vary over periods as a result of subjects' decisions are money, investment decisions, permit holdings, and compliance status.

c) Payoff.

The payoff function is the same for all firms and is calculated as follows.

Payoff =

+ total revenue

+ cash balance in sub period one of the same round

– (number of licenses bought in auction * auction price) for auction treatment

– investment costs

– trading price of licenses bought during trading stage

+ trading price of licenses sold during trading stage

– penalty costs

4.3.2. Theoretical Equilibrium and Hypotheses

It is important to point out that although the permit market structure is kept the same for both sub periods throughout the experiment, the actual market structure might change as a result of subjects' investment decisions and non-compliance, especially in the MGP treatment. Naturally, over-investment might result in a demand reduction and lower permit price in sub period 2, and vice versa for the case of under-investment. In the same way, non-compliance in the MGP treatment will inflate permit demand in the second sub period. Nevertheless, a learning effect is expected to transpire, and over time, subjects learn to arrive at the theoretical equilibrium.

Since the setting of supply and demand for permits remains the same as in the previous design experiment, the same theoretical equilibrium still holds. The permit price should lie between EX$35-40, resulting in all low MAC firms to make investment decisions, while high MAC firms are compliant by buying permits in the market. Thus, full compliance should be observed.

The experimental design allows us to test the following hypotheses regarding the initial allocation mechanism.

Hypothesis 1: The average permit price should be the same in both the grandfathering and auction treatments.

While the average permit price is equal to the mean trading price for the grand fathering treatment, in the auction treatment the average permit price is determined by both the auction price and the mean trading price. Based on the basic model by Montgomery (1972), both initial allocation mechanisms should result in the same equilibrium permit price. Considering the two-period model that we have, the hypothesis requires that the market achieves an efficient permit price in both sub periods. Consequently, inefficiency in the first sub period might have important consequences on the following sub period. If this inefficiency stems from a non-optimal aggregate investment level in the first sub period, then permit price in the second sub period should change due to a change in permit demand. On the other hand, when inefficiency is brought about by the presence of non-compliance at the optimal aggregate investment level, this inefficiency is maintained under a make-good provision penalty design. Nonetheless, as a learning effect takes place, it is expected that during later rounds the permit price will reach the efficient equilibrium.

Another issue that might affect the permit price, especially in the auction treatment, is the possibility of bid-shading, or demand reduction, at the auction, which is a potential shortcoming of employing a uniform price auction for multi-unit items (Ausubel and Cramton, 1998). Bid-shading occurs when bidders deliberately bid below their true values in an attempt to influence the auction price. If bid-shading is prevalent, then the permit price at the auction might be lower compared to grandfathering. On the other hand, the transparency of the ascending clock auction might induce higher competition among bidders, as bidders learn in each bidding round that there are other bidders who value the item at least as much as they do (Holt et al., 2007). Furthermore, the opportunity for bidders to consider whether to remain or drop out of each bidding round facilitates a better learning experience, which can result in the auction price approaching the equilibrium price (Kagel and Levin, 2001).

Hypothesis 2: The auction treatment provides stronger or more convergent price signals compared to the grandfathering treatment.

Since subjects receive more price signals through primary and secondary markets in an auction treatment, it is expected that stronger price signals will be observed in the auction treatment. The convergence of price signals is measured by the standard deviation of the average permit price, where a smaller standard deviation implies stronger price signals.

An important criterion for assessing the market performance of a trading scheme is how the market design affects compliance incentives. For the purpose of constructing an experimental hypothesis, we observe how the initial allocation mechanism provides investment incentives and affects firms’ compliance rates.

Hypothesis 3: The auction treatment provides higher investment incentives.

If an investment decision is only determined by the permit price, then, in line with *Hypothesis 1*, investment incentives under the same penalty design should be the same regardless of the initial allocation mechanism. Nevertheless, some analytical models demonstrate that under the assumption of risk neutrality, auctioning induces a higher investment incentive at either the firm level (Milliman and Prince, 1989) or the industry level (Jung et al., 1996). When risk aversion is taken into account, a real-option study by Gagelmann (2008) and an analytical model by Baldursson and von der Fehr (2004) maintain that auctioning will induce over-investment, if there is a high uncertainty regarding the permit price, because all firms are basically buyers at the auction, and each firm is exposed to the risk of a high permit price. We expect that most subjects will be risk averse and hence auction treatment may induce higher investment incentives compared to grandfathering treatment.

Hypothesis 4 Compliance rate is higher in the auction treatment.

In contrast to the theory and referring to the results of the experiment in the previous chapter, the compliance rate is expected to be different across different penalty designs. When we control for the penalty design as a major determinant of the compliance rate, and in conformity with previous hypotheses, we expect that the auction treatment yields a higher compliance rate. This hypothesis is based on Grimm et al's (2010) experiment, which demonstrates that a higher average as well as a smaller standard deviation of compliance rates are observed in auction treatments compared to grandfathering treatments.

Specifically, we will also analyse whether or not the volatility in permit prices and the reliability of price signals might affect firms' compliance rates differently when they are permit buyers.

Hypothesis 5: Auctioning results in higher allocative efficiency compared to grandfathering.

Allocative efficiency requires that all permits be distributed to the firms who value them the most. The existing literature defines allocative efficiency in terms of the ratio of actual permit holdings by high MAC firms (firms whose marginal abatement cost is to the left of the permit equilibrium on the permit demand function) to the optimal permit holding by those firms (Holt et al., 2007, Cason and Gangadharan, 2003, Grimm et al., 2010). As the ascending clock auction has an advantage in allocating permits to bidders who value them the most and there are more trading opportunities with auctioning, allocative efficiency is expected to be higher in the auction treatment.

Hypothesis 6: Static efficiency is higher with auctioning.

Static efficiency is an essential criterion for measuring how well an emissions trading market achieves its emissions reduction target at the least cost possible. Normally, cost savings are used to express this criterion. Because we allow for non-compliance to occur in this experiment, the measure of static efficiency needs to take into account penalty costs as an element of total compliance costs in the market to highlight the effects of non-compliance to market performance. Thus, we measure static efficiency based on the least total compliance cost as a sum of the permit cost, investment cost, and penalty cost. This approach enables the assessment of efficiency by each cost element and also provides better information on which cost elements leads to higher inefficiency levels.

The benchmark of total compliance costs is measured at the market level, rather than at individual firm level. This benchmark is different in both treatments due to different permit costs. When permits are grandfathered, the optimal total permit cost in the market is zero, as permit costs for high MAC firms become permit revenues for low MAC firms. This is not the case in auction treatments, in which high MAC firms buy permits from the auctioneer or regulator, and permit costs, which are deducted from buyers' money, are not transferred to other firms in the market. The details about static efficiency measures and its elements are elaborated in the following table.

Table 19 Measurement of Static Efficiency

Variable	Auctioning	Grandfathering
Permit cost efficiency	(group total revenue - actual permit costs) / benchmark Efficient permit costs: EX$3040* Benchmark: EX$ 19360	(group total revenue - actual permit costs) / benchmark Efficient permit costs: 0 Benchmark: EX$ 22400
Investment efficiency	(group total revenue - actual investment costs) / benchmark Efficient inv. costs: EX$2200 Benchmark: EX$ 20200	(group total revenue - actual investment costs) / benchmark Efficient inv. costs: EX$2200 Benchmark: EX$ 20200
Penalty cost efficiency	(group total revenue - actual penalty costs) / benchmark Efficient penalty costs: 0 Benchmark: EX$ 22400	(group total revenue - actual penalty costs) / benchmark Efficient penalty costs: 0 Benchmark: EX$ 22400
Static efficiency	(group total revenue - actual total compliance costs) / benchmark Permit costs: EX$5240* Benchmark: EX$ 17160	(group total revenue - actual total compliance costs) / benchmark Permit costs: EX$2200 Benchmark: EX$ 20200

Notes: * based on average permit price EX$38

As static efficiency consists of three cost elements related to *Hypothesis 1*, *Hypothesis 3* and *Hypothesis 4*, we expect that static efficiency will be higher in the auction treatment.

4.4. Results

4.4.1. Subjects' risk attitudes

Most subjects' risk preferences range from risk-neutral to risk-averse. Compared to the penalty design experiment, there is a slightly higher percentage of subjects with a risk-neutral index and a lower percentage of risk-averse subjects in this experiment. A small percentage of subjects did not make consistent choices in the lottery game.

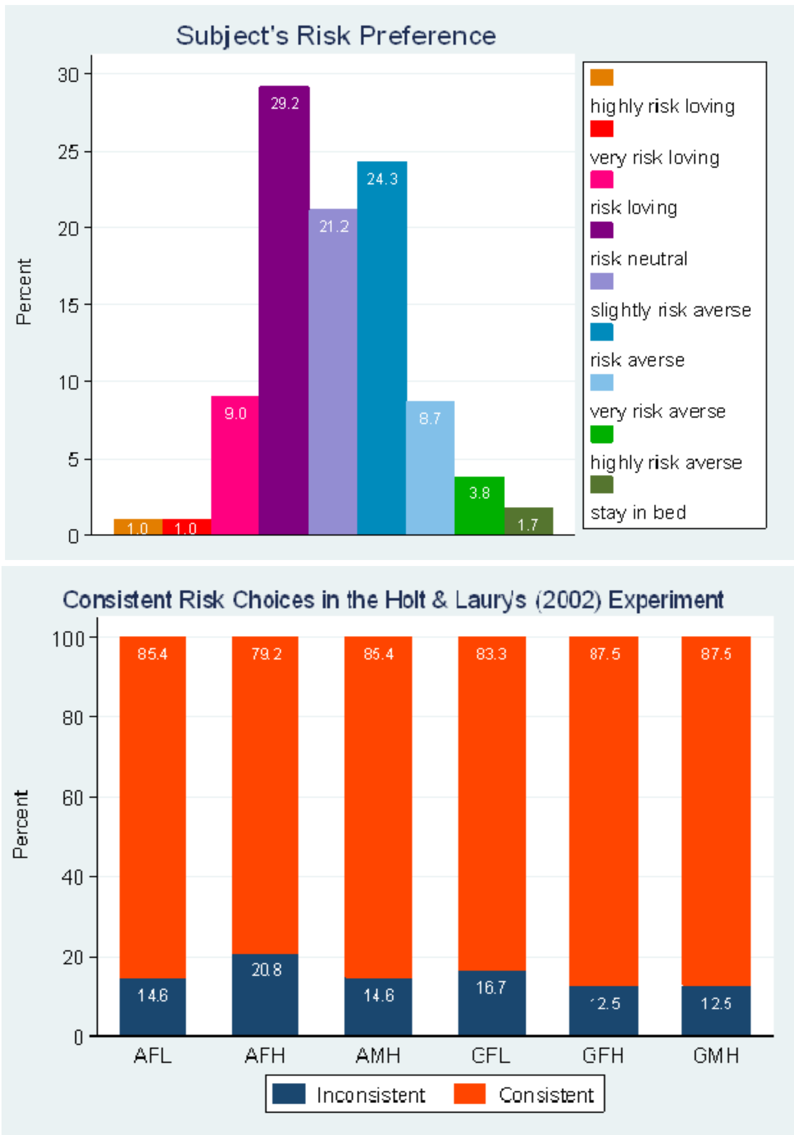

Figure 18 Subjects' Risk Preferences based on Holt and Laury's (2002) Experiment

4.4.2. Permit Price

4.4.2.1. Trading Price

As presented by the statistics summary in Table 20, the means of trading prices are closer to equilibrium in the auction treatments compared to the grandfathering treatments. However, the means of trading prices of the secondary market in the auction treatment are also lower than the auction price, which implies that the Law of One Price is not met in this case. The phenomenon of high auction prices when a secondary market exists has been explained in the literature (Haile, 2003, Garratt and Tröger, 2006), and it is also found in Grimm et al.'s (2010) experiment. It is argued that when an opportunity for a resale follows an auction, the resale market introduces a common-value element at the auction. Hence, bidders' valuations are endogenously determined, reflecting anticipated profits from buying or selling at the resale market.

Table 20 Statistics Summary for Permit Price Variables

Treatment	Auction Price	Trading Price	S.d. trading price	Total trades	Average Price	S.d. average price
Auction FPR Low (AFL)	45.01	33.63	5.36	11.75	43.66	10.72
Auction FPR High (AFH)	48.21	36.25	6.70	10.25	46.80	11.19
Auction MGP High (AMH)	48.28	38.85	5.63	8.22	47.77	27.00
Grandfathering FPR Low (GFL)	0	47.55	19.63	51.93	47.55	23.80
Grandfathering FPR High (GFH)	0	49.22	11.39	40.90	49.22	20.37
Grandfathering MGP High (GMH)	0	47.93	18.65	46.72	47.93	25.66
Optimum	38	35-40	0	40 (GF)	35-40	0

Likewise, the standard deviation of trading prices is also notably smaller in the auction treatment than the grandfathering treatment. Yet, this difference might be attributable to the low trade volume in the auction treatment, as the secondary market is used merely to reduce inefficient allocation at the auction or as an opportunity to gain profits. On the contrary, the minimal required trading volume for the grandfathering treatment is 40 trades.

To test whether or not the median trading price in each treatment is significantly different from the theoretical equilibrium price, the Wilcoxon rank sign test is run for the whole session data and the half sessions data (Round 1-3 and Round 4-6) as shown in Table 21. The test statistics confirm that the median trading price is not different from the hypothesised price of EX$38 only in the high penalty level of auction treatments (AFH and AMH). A closer look at the median and the standard deviation values reveals that trading prices in the low FPR auction treatment is within the range of equilibrium price (EXS35-40) but lower than the hypothesised value

(EX$38). For the high MGP grandfathering treatment, although the median value is within the competitive equilibrium, the standard deviation of trading prices is the second highest. Hence, the median trading price is statistically different from the theoretical equilibrium. Nevertheless, subjects learn to trade better over time, and by the second half of the session only the median trading price in the high FPR treatment is significantly higher than the equilibrium price.

Table 21 Test of Median Trading Price Equal to Theoretical Equilibrium

Treatment	Median trading price	p-value from Wilcoxon Sign Rank test for Ho: Median trading price= 38		
		All periods	Period 1-6 (Round 1-3)	Period 7-12 (Round 4-6)
Auction FPR Low (AFL)	36.18	0.0270*	0.1843	0.0897
Auction FPR High (AFH)	37.78	0.5538	0.6772	0.6771
Auction MGP High (AMH)	38.57	0.9173	0.5505	0.5042
Grandfathering FPR Low (GFL)	40.66	0.0125**	0.0553	0.1023
Grandfathering FPR High (GFH)	44.14	0.0001***	0.0007***	0.0326*
Grandfathering MGP High (GMH)	38.56	0.0482*	0.0339*	0.4603

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 72 for the whole session and 36 for half sessions.

Although starkly different values of mean trading prices are observed, further tests were conducted to inspect whether or not they are statistically different using the Wilcoxon rank sum test and the Kolmogorov-Smirnov test. The results in Table 22 confirm that the grandfathering treatment yields significantly higher trading prices than the auction treatment, except for the high MGP penalty design, in which the difference is only observed in early rounds.

Table 22 Test of Treatment Effect for Trading Price

Penalty design	p-value All Periods		p-value by half session			
			Period 1-6 (Round 1-3)		Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Low FPR	0.0006***	0.003**	0.0136**	0.043*	0.0236*	0.083
High FPR	0.0014***	0.024*	0.0051**	0.022*	0.0799	0.150
High MGP	0.1656	0.213	0.0450*	0.083	0.9641	0.413
Pooled data	0.0000***	0.001***	0.0000***	0.000***	0.0338*	0.075

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions, except for pooled data, which uses 432 observations for the whole session and 216 observations for half sessions.

4.4.2.2. Average Permit Price

In the grandfathering treatment, the average permit price is the same as the mean trading price in each sub period. Meanwhile, the average permit price in the auction treatment is the volume-weighted mean price, which takes into account both the auction price and the mean trading price in the secondary market. The figures in Table 20 illustrate that average prices are well above the competitive equilibrium price. Furthermore, higher prices occur in the grandfathering treatment in general as well as per penalty design. The estimates also demonstrate that the standard deviation of the average permit price is generally smaller in the auction treatment.

Nevertheless, the box plot of average permit prices (Figure 19) indicates that by penalty design the medians are closer to the equilibrium for the grandfathering treatment. The graph demonstrates that the presence of the reserve price at the auction might have some influence in precluding a price crash on the market, as the low adjacent values are generally close to or above the reserve price. In line with the results from the previous chapter, the medians also remain below the penalty level.

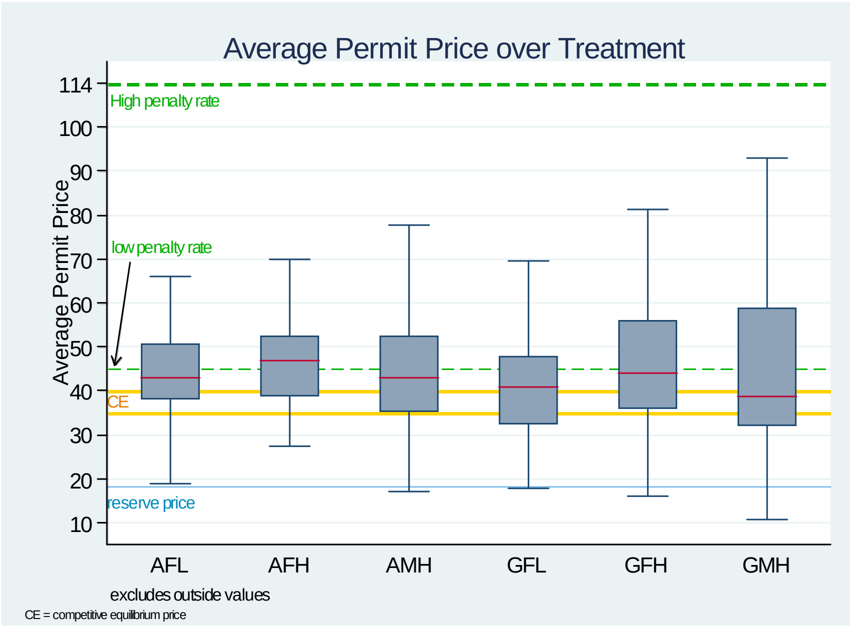

Figure 19 Box Plot for Average Permit Price

As subjects might not be able to immediately determine the expected equilibrium price and their best compliance strategy, it is important to note how the prices develop over time, as the learning curve occurs. Figure 20 illustrates the comparison of the scatter plot and locally weighted regression (*lowess smoothing*) over the period for each initial allocation.

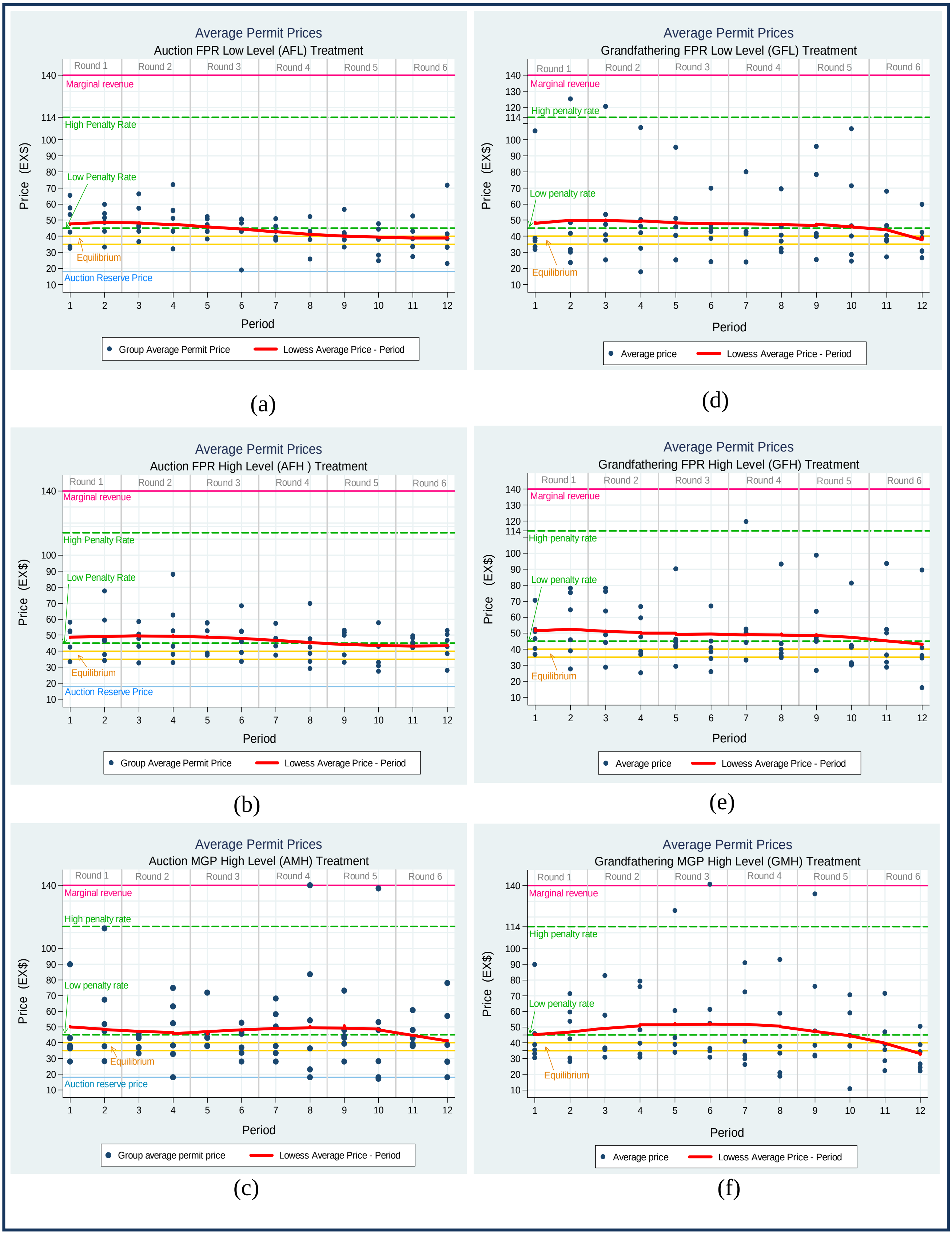

Figure 20 Convergence Path of Average Permit Price over Period

It is clear that the scatter plot is concentrated in the auction treatment, and over time prices converge into the range of the equilibrium price, except in the high MGP treatment (AMH), for which prices drop closer to the equilibrium due to an end-game effect[24]. On the other hand, the distribution of average prices is much wider in the grandfathering treatment, and the convergence of prices seems much weaker than in the auction treatment. Although a decreasing trend is observed, it might be the case that prices drop down to the equilibrium range due to an end-game effect. Furthermore, the grandfathering high MGP treatment indicates a trend of a price bubble to some extent.

To scrutinise the statistical significance of the difference in average prices and standard deviation of average prices, we conduct both non-parametric tests of the Wilcoxon rank sum test and the Kolmogorov-Smirnov test. Based on test statistics (Table 23), the initial allocation mechanism does not affect the average permit price, except for in early rounds of the low-FPR treatment. The Kolmogorov-Smirnov test, which is conducted on the pooled data set, also indicates that, in general, the permit price differs only in early rounds. Hence, this result confirms *Hypothesis 1*. Nevertheless, regression models are required to explain further which factors determine the permit price and if, by holding those factors constant, initial allocation might matter in price discovery.

Table 23 Test of Treatment Effect for Average Permit Price

Penalty design	**p-value All Periods**		**p-value by half session**			
			Period 1-6 (Round 1-3)		**Period 7-12 (Round 4-6)**	
	Wilcoxon rank-sum	**KS[a]**	**Wilcoxon rank-sum**	**KS[a]**	**Wilcoxon rank-sum**	**KS[a]**
Low FPR	0.3623	0.213	0.0527*	0.010**	0.5209	0.413
High FPR	0.4995	0.146	0.6362	0.413	0.6362	0.413
High MGP	0.6748	0.304	0.9730	0.413	0.5282	0.615
Pooled data	0.2858	0.024*	0.2621	0.024*	0.6553	0.202

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 24 for the whole session and 12 for half sessions, except for pooled data which uses 144 observations for the whole session and 216 observations for half sessions.

***Result 1**: In general, the initial allocation mechanism does not affect permit prices and only in early rounds are permit prices found to be lower and closer to the equilibrium with auctioning (consistent with Hypothesis 1).*

Using the same tests, we assess whether or not the initial allocation mechanism affects the strength of price signals, by looking at the standard deviation of the average price. This standard

[24] The end-game effect refers to a systematic change in subjects' behaviour near the conclusion of an experiment with repeated games.

deviation is measured by comparing average prices of the same treatment within the same period. The results, presented in Table 24, are extremely significant and verify that there are convergent price signals in the auction treatment.

Table 24 Test of Treatment Effect for Standard Deviation of Average Permit Price

Penalty design	p-value All Periods		p-value by half session			
			Period 1-6 (Round 1-3)		Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Low FPR	0.0000***	0.000***	0.0000***	0.000***	0.0000***	0.000***
High FPR	0.0000***	0.000***	0.0000***	0.000***	0.0000***	0.000***
High MGP	0.0096**	0.000***	0.0003***	0.000***	0.6841	0.022*
Pooled data	0.0000***	0.000***	0.0000***	0.000***	0.0000***	0.000***

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 24 for the whole session and 12 for half sessions, except for pooled data which uses 144 observations for the whole session and 216 observations for half sessions.

***Result 2**: The auction treatment provides much stronger price signals in emissions trading markets, and the convergence path of permit prices is much more discernible than that in the grandfathering treatment (consistent with Hypothesis 2).*

4.4.3. Compliance incentives

4.4.3.1. Investment

The statistics summary underscores that over-investment is prevalent in all treatments (Table 25), although it is more severe in grandfathering rather than in auction treatments. Moreover, it seems that subjects do not find it easy to determine whether it is best to invest or not, as demonstrated by the fairly large values of the standard deviation of the investment level. Nevertheless, over-investment is reasonably common in laboratory markets, especially in the context of an emissions trading scheme (Gangadharan et al., 2005, Grimm et al., 2010, Schleich et al., 2006).

Table 25 Statistics Summary for Investment Levels

Treatment	Total Investment[a]	S.d.[b] of Total Investment
Auction FPR Low (AFL)	1.132	0.248
Auction FPR High (AFH)	1.215	0.223
Auction MGP High (AMH)	1.174	0.212
Grandfathering FPR Low (GFL)	1.118	0.255
Grandfathering FPR High (GFH)	1.306	0.266
Grandfathering MGP High (GMH)	1.326	0.221
Optimum	1.000	0

Notes: [a] compared to the optimal level, [b] s.d. = standard deviation

In line with the theory, the presence of risk aversion, confirmed by nearly 60% of the subjects being at least slightly risk averse, might induce over-investment (Kolstad, 1996, Baldursson and von der Fehr, 2004, Gagelmann, 2008). This argument is even more valid considering that the experimental design forces subjects who are in permit short positions at the investment stage to either comply, by investing, or be non-compliant[25]. However, the results also contradict the theory that predicts that auctioning provides stronger investment incentives than grandfathering. Our conjecture is that the limited time for trading in the grandfathering treatment might induce a higher risk for buyers of being non-compliant and hence creates higher price volatility in the market. To reduce their exposure to market volatility, subjects with some degree of risk-aversion might over-invest. A real option study by Fuss et al. (2008) also maintains that uncertainty about the permit price leads to decisions that are different from the optimal strategies made under full information.

As shown in Table 26, the test statistics of the treatment effect from both non-parametric tests are not entirely consistent, and the effects are dependent on the penalty design. For the high MGP penalty, the investment level in the auction treatment is significantly lower and closer to the optimal level than the grandfathering treatment. For the low FPR penalty design, the initial allocation mechanism does not yield significantly different investment incentives. On the other hand, the auction treatment provides stronger investment incentives compared to the grandfathering treatment in the high FPR penalty, especially in earlier rounds. Using the whole data set, the Wilcoxon-Mann-Whitney test confirms that, the auction treatment generally yields a more optimal investment level than the grandfathering treatment. It is plausible that under the high penalty level (high FPR and high MGP penalty designs), stronger price signals in the auction treatment provide better information for making efficient investment decisions.

Table 26 Test of Treatment Effect for Investment Levels

Penalty design	p-value All Periods		p-value by half session: Period 1-6 (Round 1-3)		p-value by half session: Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Low FPR	0.7381	1.000	0.6394	0.615	0.8864	0.965
High FPR	0.0172*	0.097	0.0076**	0.022*	0.5507	0.965
High MGP	0.0001***	0.014**	0.0127**	0.083	0.0009***	0.083
Pooled data	0.0013***	0.071	0.0088	0.075	0.0578	0.271

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions, except for pooled data which uses 432 observations for the whole session and 216 observations for half sessions.

[25] Recall that permit trading occurs before the investment decision stage in the first sub period.

Result 3: *Stronger price signals in the auction treatment result in an investment level that is lower and closer to the equilibrium than in the grandfathering treatment (inconsistent with Hypothesis 3). Better investment incentives in auction treatments are noticeable, particularly with a high level penalty design.*

4.4.3.2. Compliance rate

The statistics summary in Table 28 indicates that, by and large, the total compliance rate is influenced by the penalty design, and slightly higher compliance rates are observed in the auction treatment. However, the non-parametric test results in Table 28 do not reveal any significant differences between auctioning and grandfathering.

Table 27 Statistics Summary for Compliance Rates

Treatment	Total Compliance Rate	S.d.[a] of total compliance rate	Compliance Rate of Permit Buyer	S.d.[a] of compliance rate of Permit Buyer
Auction FPR Low (AFL)	0.809	0.151	0.780	0.155
Auction FPR High (AFH)	0.913	0.102	0.900	0.108
Auction MGP High (AMH)	0.917	0.117	0.899	0.127
Grandfathering FPR Low (GFL)	0.802	0.179	0.769	0.189
Grandfathering FPR High (GFH)	0.896	0.134	0.871	0.147
Grandfathering MGP High (GMH)	0.918	0.121	0.898	0.134
Optimum	1.000	0	1.000	0

Notes: [a] s.d. = standard deviation

Table 28 Test of Treatment Effect for Compliance Rates

Penalty design	p-value All Periods		p-value by half session: Period 1-6 (Round 1-3)		p-value by half session: Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Low FPR	0.9377	0.992	0.3601	0.825	0.3739	0.965
High FPR	0.7423	0.992	0.3690	1.000	0.1846	0.257
High MGP	0.7691	1.000	0.8355	1.000	0.4606	0.965
Pooled data	0.9278	0.998	0.9881	1.000	0.8584	0.994

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions, except for pooled data, which uses 432 observations for the whole session and 216 observations for half sessions.

The measure of compliance rate cannot indicate which compliance strategy is used to achieve compliance. Hence, further tests need to be conducted to assess the compliance rate only for permit-buying firms to see whether different initial allocation mechanisms induce different compliance incentives for net buyers. Although in theory the high MAC firms should be net buyers, it might not necessarily be the case in this experiment, as will subsequently be discussed in this section. Net buyers in this case are subjects who decide not to invest and choose permit-buying as their sole compliance strategy.

Table 29 Test of Treatment Effect for Compliance Rates of Net Buyers

Penalty design	p-value All Periods		p-value by half session			
			Period 1-6 (Round 1-3)		Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Low FPR	0.0186*	0.024*	0.4872	0.107	0.0002***	0.002***
High FPR	0.4878	0.433	0.0016*	0.069	0.0379*	0.001***
High MGP	0.0099**	0.022*	0.2164	0.953	0.0052**	0.009**
Pooled data	0.3037	0.279	0.2114	0.129	0.8233	0.226

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions, except for pooled data, which uses 432 observations for the whole session and 216 observations for half sessions.

After separating out the compliance rate that is attributable to the investment decision, the non-parametric tests verify that high compliance incentives in the auction treatment are evident when we control for the penalty design. The effects are particularly more significant in the later rounds. The statistics for the pooled data do not display any significant results, as the penalty design effect on the compliance rate is substantial.

These results underscore two main points. First, there is inefficiency within the secondary market, as it fails to distribute permits to buyers who need them for compliance purposes, despite over-investment, in which the effect of irreversible investment is supposed to reduce permit demand relative to the supply in the second sub period. An explanation might be that sellers have a high expectation of making gains, and thus, of the permit price at the trading stage. Hence, they prefer to keep holding their permits rather than selling them at a price lower than their preferred price. This might be worse in the grandfathering treatment when subjects do not recognise the opportunity cost of holding permits[26]. Experimental results reveal that some subjects need some time before they can recognise the concept of opportunity cost (Wråke et al., 2008).

Another reason might be attributed to the adoption of a non-optimal bidding or trading strategy. For the first sub period, a forward-looking perspective is required for subjects to arrive at their best compliance strategy, in which subjects who would make an investment decision, based on the expected permit price, should ensure that they are not holding any permits at the end of a

[26] This opportunity cost equals the income from selling the permit that firms receive for free with the grandfathering treatment.

trading stage. Nevertheless, uncertainties about permit costs and investment decisions might cause subjects to adopt non-optimal strategies at the auction or at the secondary market.

Lastly, trading inefficiency might also be due to the higher risk for the high MAC firms of being non-compliant, as compared to the low MAC firms, which forces them to settle on higher permit prices, especially when faced with a limited trading time. This argument is supported by the data, which indicates a lower compliance rate for the high MAC firms.

The second point of the test results is that the auction treatment provides better learning curves for the market to correct this inefficiency.

Result 4: *The auction treatment generates a higher compliance rate of net buyers and allows better learning curves to correct for inefficiency in trading markets (consistent with Hypothesis 4).*

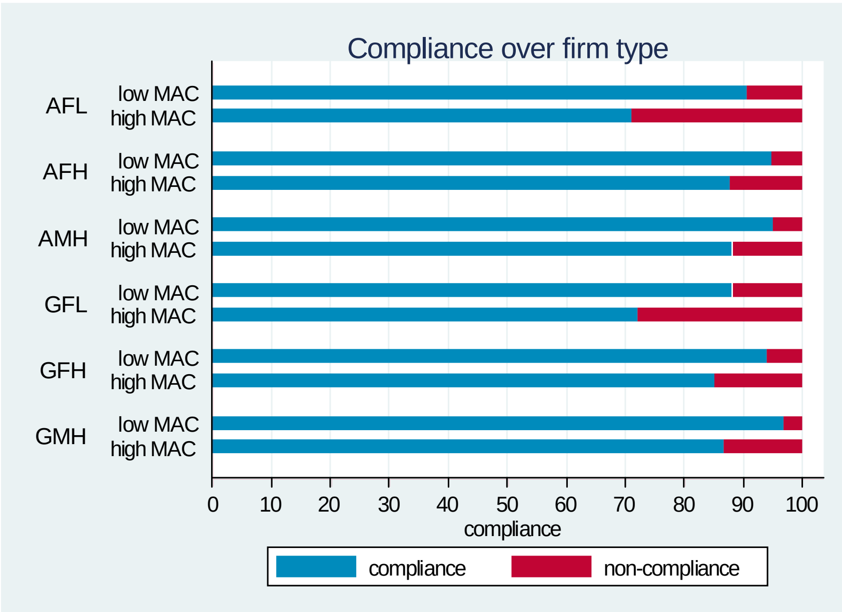

Figure 21 Compliance Rates by Firm Type

4.4.4. Efficiency

4.4.4.1. Allocative Efficiency

In evaluating allocative efficiency as a measure of how well the market distributes permits to firms who value them the most, we follow the approach of Grimm et al. (2010) by looking at pre-trade and post-trade allocative efficiency, where the trading stage is taken as a reference point. Hence, pre-trade efficiency refers to the allocative efficiency before the trading stage, while post-trade efficiency reflects the final allocative efficiency. This approach is used to measure the efficiency of the trading stage. By our experimental design, the pre-trade efficiency is exogenous for the grandfathering treatment. On the other hand, pre-trade efficiency in the auction treatment is endogenously determined by the auction market.

Table 30 Statistic Summary for Allocative Efficiency

Treatment	Pre-trade efficiency	s.d of pre-trade efficiency	Post-trade efficiency	s.d of post-trade efficiency
Auction FPR Low (AFL)	0.656	0.206	0.675	0.188
Auction FPR High (AFH)	0.640	0.222	0.660	0.208
Auction MGP High (AMH)	0.728	0.192	0.759	0.162
Grandfathering FPR Low (GFL)	0.500	0.000	0.649	0.143
Grandfathering FPR High (GFH)	0.500	0.000	0.682	0.156
Grandfathering MGP High (GMH)	0.500	0.000	0.689	0.205
Optimum	1.000	0.000	1.000	0.000

The result illustrates that the pre-trade allocative efficiency generated at the auction is fairly comparable to the post-trade efficiency of the grandfathering treatment. A slight increase of efficiency is gained after further trading on the secondary market, which confirms the view that secondary market is merely used to reduce inefficiency at the auction.

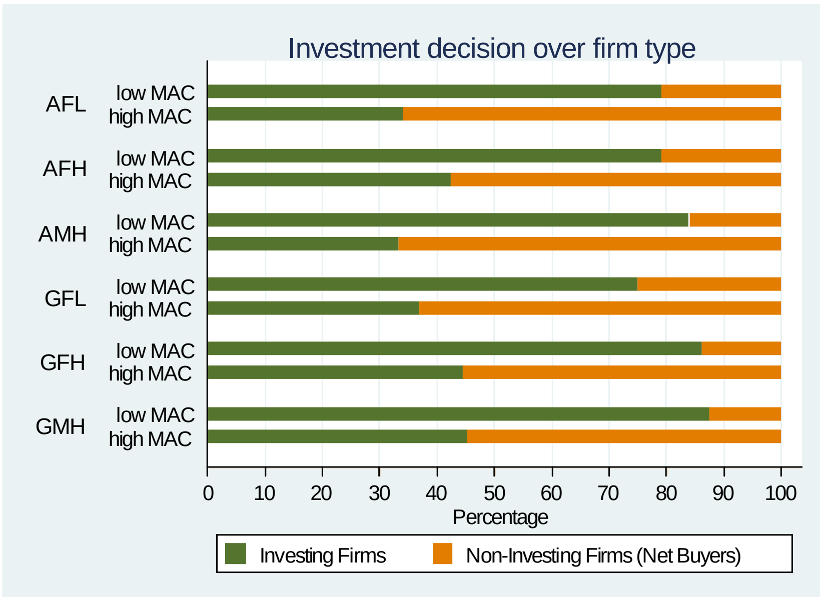

Figure 22 Investment Decision by Firm Type

Nevertheless, the post-trade allocative efficiency, in general, is not as high as would normally be the case for a continuous double auction, which is notorious for generating high efficiency in the laboratory. A plausible explanation for this is that the signals of high permit prices render more appeal for the high MAC firms to invest rather than to buy permits on the market. The data confirms our conjecture (Figure 22), as demonstrated by the significant percentage of high-

MAC firms who make investment decisions rather than be net buyers, as would be required by the theoretical equilibrium.

The presence of risk aversion and the high volatility of the permit price may encourage this shift of compliance strategy even further. Interestingly, the highly punitive penalty design, the high-MGP treatment, yields the highest post-trade allocative efficiency. It might be the case that a high compliance incentive pertaining to this penalty design encourages over-compliance of some firms, which for the high MAC firms might imply undertaking both compliance strategies. This means that high allocative efficiency in a high MGP treatment is obtained at the expense of static efficiency due to excessive compliance costs. The next section will discuss whether this is really the case.

The test results in Table 31 almost consistently reject the hypothesis of a significant effect of the initial allocation mechanism on allocative efficiency. Hence, we do not find evidence that a market with an auction yields a better distribution of permits.

Table 31 Test of Treatment Effect for Allocative Efficiency

Penalty design	p-value All Periods		p-value by half session			
			Period 1-6 (Round 1-3)		Period 7-12 (Round 4-6)	
	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]	Wilcoxon rank-sum	KS[a]
Low FPR	0.2537	0.014**	0.4401	0.257	0.3240	0.083
High FPR	0.3985	0.615	0.4400	0.615	0.6151	0.825
High MGP	0.0347	0.062	0.0436	0.257	0.4292	0.257
Pooled data	0.0954	0.054*	0.1953	0.271	0.2932	0.355

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions, except for pooled data which uses 432 observations for the whole session and 216 observations for half sessions.

Result 5: The *initial allocation mechanism does not affect allocative efficiency* (inconsistent with Hypothesis 5)

4.4.4.2. Static Efficiency

As mentioned earlier, the measure of static efficiency is decomposed into three components of cost-effectiveness, i.e., permit-cost efficiency, investment-cost efficiency, and penalty-cost efficiency. These measures complement previous measures which have been discussed earlier, i.e. average permit prices, investment level, and compliance rate, as they elaborate the costs related to those levels. In the end, static efficiency sums up the overall cost efficiency of the market.

In general, a relatively high degree of static efficiency is observed across treatments. Focusing on permit-cost efficiency, it seems that the effect of penalty design imposes different implications for different initial allocation mechanisms. As a high penalty level corresponds to higher permit prices, consequently, permit-cost efficiency is higher with a low penalty level in the auction treatment. On the contrary, the effect in the grandfathering treatment is ambiguous, which might be due to higher variance of permit prices in the grandfathering treatment, especially in the low FPR treatment.

Table 32 Statistics Summary for Static Efficiency

Treatment	Permit-cost efficiency	Investment-cost efficiency	Penalty-cost efficiency	Static efficiency	S.d. of static efficiency
Auction FPR Low (AFL)	0.950	0.962	0.975	0.867	0.087
Auction FPR High (AFH)	0.939	0.945	0.981	0.841	0.086
Auction MGP High (AMH)	0.939	0.959	0.948	0.815	0.222
Grandfathering FPR Low (GFL)	0.936	0.962	0.979	0.864	0.086
Grandfathering FPR High (GFH)	0.954	0.934	0.976	0.851	0.081
Grandfathering MGP High (GMH)	0.938	0.931	0.967	0.819	0.149
Optimum	1.000	1.000	1.000	1.000	0.000

In line with the results on the investment level, auctioning outperforms grandfathering in terms of investment-cost efficiency, except for the low FPR treatment, for which both treatments have the same score. Similar to permit-cost efficiency, most of the time, a lower penalty level delivers a higher efficiency level.

The initial allocation mechanism does not appear to fare differently in terms of penalty-cost efficiency, although the grandfathering treatment performs much better for the high MGP penalty. It is important to point out that non-compliance in a high MGP penalty, particularly in sub period two, results in a much higher inefficiency in penalty costs due to the enormous marginal penalty of missing even just one permit. As a result, lower efficiency is observed in the high MGP treatment.

When we look at the overall static efficiency, a rather ambiguous result is observed as it is not clear which initial allocation mechanism generates higher efficiency (Table 33). Non-parametric tests are conducted for each efficiency component as well as the overall static efficiency to test their statistical differences.

We find that although the auction treatment generates significantly higher investment-cost efficiency, overall static efficiency is relatively the same regardless of the initial allocation mechanism. These experimental results shed a different light than some of the literature, notably from Baldursson and von der Fehr (2004) and Gagelmann (2008), who argue that auctions might induce over-investment.

Table 33 Test of Treatment Effect for Static Efficiency

Penalty Design	Permit-cost efficiency		Investment-cost efficiency		Penalty-cost efficiency		Static efficiency	
	WRS	**KS[a]**	**WRS**	**KS[a]**	**WRS**	**KS[a]**	**WRS**	**KS[a]**
Low FPR	0.3457	0.557	0.7793	0.707	0.3098	0.304	0.9936	0.847
High FPR	0.0216*	0.001***	0.0992	0.039*	0.6622	0.947	0.2515	0.062
High MGP	0.7462	0.304	0.0002***	0.005**	0.1590	0.847	0.2354	0.097
Pooled data	0.5737	0.0614	0.0025**	0.002**	0.2491	0.632	0.8189	0.090

Notes: [a] KS = Kolmogorov-Smirnov test
* significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Number of observation is 144 for the whole session and 72 for half sessions, except for pooled data which uses 432 observations for the whole session and 216 observations for half sessions.

The non-parametric tests also show that there are not any significant differences with regard to permit-cost efficiency, except for the low FPR penalty, and penalty-cost efficiency.

Result 6: Static efficiency does not differ significantly with the initial allocation mechanism, although auctioning evidently yields higher investment cost efficiency (inconsistent with Hypothesis 6).

Nevertheless, we do not control for other factors that might affect static efficiency. Hence, the use of regression models is essential before we can make some general inferences.

4.5. Regression Models

As argued in the literature, firms' risk aversion plays an important role in determining how subjects will interact in the laboratory and make decisions in the market. Furthermore, the time constraint in a laboratory experiment requires subjects to be able to learn about the structure of the experiment and to determine in a relatively short time the equilibrium that will maximise their profits. Hence, subjects' cognitive abilities might play an important role in explaining the results of the experiment (Rydval and Ortmann, 2004). Furthermore, the variation in other variables might also have some effects on the variable of interest, and the non-parametric tests cannot control for these factors. Therefore, it is important to perform regression models to verify the results from our previous tests.

In the following sections, we carry out regression models for the average permit price, compliance rates, and efficiency to corroborate our results. The main treatment variables, i.e., the penalty design and the initial allocation mechanism, are used as the main regressors in each estimation model. We draw on the data from Holt and Laury's (2002) experiment to control for subjects' risk preferences. Furthermore, the data regarding subjects' inconsistent risk choices in that experiment is also included in the estimation models to control for subjects' cognitive abilities. Other relevant variables are also included in some models to see if they have considerable effects on the dependent variable.

4.5.1. Average Permit Price

The data used for the estimations is group-level data in which each observation represents parameters from a particular group in each sub period. The models give somewhat different results depending on the explanatory variables used in estimating the model. Random effects (RE) estimators with robust standard errors are used in regression Models 1 to 5, while Model 6 is performed with Hausman Taylor estimators to control for some potential endogenous explanatory variables, such subjects' ability in quantitative calculation and structural thinking, which will help them in making rational profit-maximising decisions. In terms of the key explanatory variables that control for treatment effects, some models include both the auction treatment and auction price, while other models use either one of them.

Model 1 employs dummy variables for both auction treatment and auction price. Hence, it has the advantage of having more control over variation in prices because the auction price heavily determines the average permit price in auction treatments. On the other hand, the auction price has no role in affecting the average permit price in the grandfathering treatment, which is basically the mean of all trading prices in each sub period.

Models 2 and 3 only control for the auction price without controlling for the dummy for auction treatment. In this case, the grandfathering treatments will have zero auction prices, while the minimum price for the auction treatment will be EX$18 as the reserve price.

Models 4 and 5 only control for the dummy for auction treatment to obtain a simple inference of the effect of an initial allocation mechanism. The models show that the auction treatment has a positive sign indicating that auction treatments have higher prices. However, the magnitude is very small and there is not a significant difference in the average price between auction and grandfathering treatments.

As expected, the dummy for the high FPR and the dummy for the MGP treatment have positive coefficients in Models 2 to 5, which denote that a higher penalty level induces a higher price for both treatments. Nevertheless, the effects are not statistically significant. Different effects of the penalty design are presented in Models 1 and 6.

Table 34 Estimates Summary for Average Permit Price

Variable	Estimation Model					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dummy for auction	-41.5843***			0.155	0.6172	-3.8977
	(5.7704)			(5.1575)	(5.1818)	(4.9821)
Auction price	0.8822***	0.6861***	0.7619***			
	(0.068)	(0.0525)	(0.1122)			
Dummy for high FPR	1.4002	2.4951	2.5015	2.2449	2.0351	-2.0211
	(4.2659)	(6.59)	(6.7002)	(4.0963)	(3.4268)	(4.9801)
Dummy for MGP	-0.5603	1.1736	1.0969	0.476	1.6543	-1.9963
	(4.0492)	(6.4788)	(6.4865)	(4.3003)	(3.4782)	(4.6533)
Round	-0.7938*	-0.9139*	-0.9739*	-1.6745***	-1.6925***	-1.6202***
	(0.3721)	(0.384)	(0.3994)	(0.494)	(0.4942)	(0.3598)
Total trades at the secondary market	-0.0376	0.0188	0.0981	-0.0718	-0.0536	-0.0897
	(0.0654)	(0.0526)	(0.0596)	(0.0893)	(0.0901)	(0.0856)
Min. trading price	0.1556**		0.1621**	0.3163***	0.3264***	0.2928***
	(0.0493)		(0.0521)	(0.0755)	(0.0765)	(0.0418)
Max. trading price	0.0673***		0.0674***	0.0745***	0.0756***	0.0693***
	(0.0041)		(0.0052)	(0.0063)	(0.0063)	(0.0057)
Dummy for Sub Period 2		-1.2089	-0.9268	0.0669	0.0901	0.0288
		(0.6865)	(0.6476)	(1.1054)	(1.0957)	(1.2328)
Range of trading prices		0.0568***				
		(0.0112)				
Number of posted offers		0.1352***	0.1278**	0.0404	0.0575	-0.0246
		(0.0379)	(0.0455)	(0.0844)	(0.0872)	(0.0558)
Min. offer price		0.2681***				
		(0.0408)				
Max. offer price		0.0096				
		(0.0101)				
Total risk index					0.1683	0.7472*
					(0.2747)	(0.3149)
Subjects w/ inconsistent risk choices					4.5278**	0
					(1.7121)	0
_cons	41.5239***	17.6778**	14.1920*	38.4348***	23.9955	0
	(6.871)	(6.679)	(7.2361)	(8.8242)	(14.1156)	0
Observation	432	432	432	432	432	432
Within correlation	0.8156	0.7999	0.7925	0.3653	0.3631	
Between correlation	0.6199	0.1695	0.1757	0.7186	0.7623	
Overall correlation	0.7007	0.4239	0.4158	0.4671	0.5154	
Chi2	1235.08	2984.33	1026.75	271.85	252.40	952.56
RMSE	6.9761	7.6326	7.9945	12.9301	13.0181	
Rho	0.5564	0.6290	0.5596	0.2521	0.1777	0.3748
Theta	0.7504	0.7835	0.7519	0.5548	0.4724	

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Standard errors in parentheses

When both the auction treatment and the auction price are included as regressors in Model 1, the regression results show that both variables are highly significant. The coefficient on auction treatment acts almost like a counter factor of the model's constant term, and the auction price becomes the main determinant of the average price. The learning effect is verified with a negative sign on the coefficient of round, and the effect is statistically highly significant. Furthermore, higher minimum and maximum trading prices also have the expected positive effects on the average permit price. On the other hand, higher trade volume reduces average permit price. Owing to the large standard errors of the estimates, the effect is statistically not different from zero. The goodness of fit of the regression model is fairly high, as measured by the R^2 value (0.7007) and the small root mean square of the error term (RMSE).

Instead of using the minimum and maximum trading prices, the regression in Model 2 is performed with the range of the trading price as an explanatory variable. Additionally, the minimum and maximum prices of submitted posted offers are also used as control variables. These are the main differences between Models 2 and 3. The results of the estimates are consistent for both models. Auction price and round have significant and similar effects as in Model 1, and likewise for the range of trading prices. Similarly, the minimum and maximum trading prices are both highly significant, but the economic effect of the minimum trading price is almost three times larger than that of the maximum trading price. It is likely that the buyers, who have more pressure to be compliant through permit-buying, are the ones who are more active in submitting the offers than the sellers. Thus, the first minimum offer price submitted by a potential buyer becomes the first price floor that is more significant in determining the trading price onwards. Although a higher number of posted offers raises the average permit price, the same conclusion cannot be drawn for the trade volume. The signs on trade volume are different for Models 2 and 3, although both estimates are not significant. Both models indicate that the R^2 value is much smaller than Model 1, at just over 40%.

As mentioned earlier, Models 4 and 5 provide a straightforward interpretation of how the initial allocation mechanism might affect permit price. Both models demonstrate that the coefficient on the dummy for auction treatment is not statistically different than zero, although the sign of the coefficient is positive. This means that the initial allocation mechanism does not significantly impact the average permit price. Learning effects are also confirmed in these two models, and the minimum and the maximum trading prices are also significant. For both models, the economic effect of the minimum trading price is four times more pronounced than that of the maximum trading price. Furthermore, Model 5 includes additional risk variables to assess whether or not risk factors might play an important role. Evidently, subjects who made inconsistent risk choices in Holt & Laury's (2002) experiment can significantly raise the average permit price, and this effect is also economically highly significant. The goodness of fit of Model 5 is fairly higher than Models 3 and 4, although it is still lower than Model 1, which controls for auction price.

The regression in Model 6 is estimated by the assumption that the explanatory variables other than the treatment variables and time variables might be endogenous. In this case, subjects who have made inconsistent risk choices generally might not really understand the concept of probability and risk. Hence, those choices are influenced by a quantitative cognitive ability, which is not controlled for in the regression model. The same factor might also have some bearing on the way subjects participate during a trading stage. This factor will generate a fixed effect for each observation group and cause the error terms to be correlated. The Hausman Taylor estimators have the advantage of allowing some explanatory variables to be correlated with group observation fixed-effects while at the same time keeping the time-invariant explanatory variables of interest, such as our treatment variables, included in the regression model. This approach is made possible by including more exogenous explanatory variables as instruments for those potentially endogenous variables. Hence, the total number of female subjects, an index indicating the subject’s background in economic studies, and an index indicating the subjects’ age are added as explanatory variables. However, we do not show the estimates of these regressors in the estimates summary.

The regression results of Model 6 present a rather contrasting view compared to the other models. All of the treatment variables – dummy for auction, dummy for high-FPR, and dummy for MGP treatment – have negative signs on their coefficients, which are counterintuitive to the expected effect, although they are not statistically different from zero. The number of submitted offers also has a negative effect on price. As in the other models, the variable round, the minimum trading price, and the maximum trading price are all highly significant. More importantly, the Hausman Taylor estimators generate a statistically significant effect on the subjects’ risk index and age index. The coefficient on the age index is also very significant economically and shows that a higher age index of an observation group induces a higher average permit price. In the same way, the presence of more risk-averse subjects in an observation group will increase the average permit price. It is reasonable that more risk-averse subjects are more likely to comply, at the expense of higher compliance costs, and hence push the permit demand higher.

As R^2 and RMSE estimates are not available for the Hausman Taylor estimators, the comparison with other models can only be carried out by looking at the *rho* value, which describes the fraction of the variance in the model that is due to the group fixed-effect (σ_{ui})

rather than the idiosyncratic error (σ_e), and the *theta* value, which expresses the appropriateness of the RE estimators for the data. Model 2 has the highest *rho* value, which indicates that the RE estimators are the most biased in this model. On the other hand, Model 5 has the lowest *theta* value, which provides support for the appropriateness of RE estimators.

In conclusion, Models 4 through 6, which provide more consistent estimates for average permit price, verify that there is no significant difference in the average permit price due to the initial allocation mechanism. It is the learning effect and factors related to individual characteristics in each group that are the determining factors of the average permit price. Overtime subjects learn to make better decision so that the permit price is declining and is closer to the theoretical equilibrium. Higher risk aversion and less irrational subjects drive up the permit price. These results also validate *Result 1* that the initial allocation mechanism does not affect the permit price.

4.5.2. Compliance

In this section, regression models are performed to observe how the initial allocation mechanism affects individual compliance decisions (compliance status). Hence, it is different than our previous non-parametric tests, which inspect the aggregate market data of the investment level and compliance rates. This difference is necessary to point out, as the focus on the individual-level data cannot completely capture the implications for the aggregate-level data. Nevertheless, more information can be gained by examining in-depth the determinants of these individual decisions.

We estimate compliance decisions using individual level data, which provides us with 3,456 observations. As a compliance decision is a binary choice, we estimate the models with robust (bootstrapped) probit and logit random effect estimators. The first two models employ the same set of regressors, and the results are very similar. In Model 3, additional demographic variables are included to control for individual characteristics that might affect compliance decisions. Furthermore, a dummy variable denoting firm type is added in Model 4. Lastly, two variables related to trading activity are incorporated into Model 5.

In general, consistent and intuitive estimates across models are obtained (Table 35). The highly significant independent variables are the average permit price, penalty design variables, and a dummy variable indicating sub period two. A higher average permit price has an adverse implication for subjects' compliance related to higher compliance costs. The coefficients on penalty design are also very significant economically, which underscores the importance of these variables in encouraging compliance, in particular for the MGP treatment.

Table 35 Estimates Summary for Compliance Decision

Regressors for compliance	Model 1 RE Probit	Model 2 RE Logit	Model 3 (Model 2 + demographic)	Model 4 (Model 3 + firm type)	Model 5 (Model 4 + trade var.)
Dummy for auction treatment	0.0375 (0.0977)	0.0711 (0.1568)	0.0345 (0.1459)	0.0387 (0.1867)	0.1935 (0.2830)
Average permit price	-0.0062*** (0.0018)	-0.0114*** (0.0034)	-0.0112*** (0.0031)	-0.0121*** (0.0035)	-0.0117** (0.0038)
Dummy for high FPR	0.4917*** (0.0993)	0.9173*** (0.1795)	0.9425*** (0.2109)	0.9872*** (0.1517)	1.0702*** (0.2181)
Dummy for high MGP	0.6286*** (0.1258)	1.1669*** (0.2266)	1.1550*** (0.2124)	1.2322*** (0.2239)	1.2267*** (0.2377)
Round	0.0305 (0.0214)	0.0522 (0.0461)	0.0523 (0.0427)	0.0567 (0.0411)	0.0590 (0.0448)
Dummy for Sub Period 2	0.1492*** (0.0442)	0.2764** (0.0877)	0.2766*** (0.0780)	0.2938*** (0.0854)	0.3065** (0.0997)
Risk index	0.0654 (0.0347)	0.1192 (0.0617)	0.1095 (0.0706)	0.1090 (0.0734)	0.1118 (0.0708)
Dummy for inconsistent risk choices	-0.0897 (0.0990)	-0.1437 (0.2209)	-0.1017 (0.1720)	-0.1243 (0.2102)	-0.1092 (0.2164)
Dummy for female			0.0141 (0.1444)	0.0182 (0.1791)	0.0083 (0.1727)
Dummy for economic study background			-0.0733 (0.1398)	-0.0584 (0.1694)	-0.0533 (0.1811)
Dummy for Master's program			-0.3364 (0.1718)	-0.3578* (0.1716)	-0.3769 (0.2490)
Dummy for PhD program			0.4075 (4.4689)	0.3310 (3.8113)	0.5468 (6.8962)
Year of study			-0.1071 (0.0706)	-0.0949 (0.0760)	-0.0804 (0.0677)
Dummy for high MAC firms				-1.3224*** (0.1772)	-1.3246*** (0.1761)
Group trade volume					0.0132 (0.0074)
Group no. of submitted offers					-0.0074 (0.0043)
_cons	0.7487** (0.2426)	1.2654** (0.4228)	1.6692** (0.5223)	2.4758*** (0.5977)	2.2538*** (0.6449)
N	3456	3456	3456	3456	3456
ll	-1.20e+03	-1.20e+03	-1.20e+03	-1.14e+03	-1.14e+03
ll_0	-1.24e+03	-1.24e+03	-1.24e+03	-1.24e+03	-1.24e+03
R^2	0.03226	0.03226	0.03226	0.08065	0.08065
Chi^2	61.1497	51.9760	82.2255	131.5218	170.9021

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Standard errors in parentheses

This result is also in accordance with our previous experiment on penalty design, which highlights the effectiveness of MGP as a penalty type for enforcement. The learning effect is not significant, as the marginal effect of variable round is statistically not different from zero. On the other hand, the dummy variable for sub period two is highly significant, indicating the effect of our experimental feature of irreversible investment on the subject's compliance decision.

Even though the initial allocation mechanism has a positive effect, this effect is statistically not different from zero. It should be noted that in this regression model we pool the observations rather than separate them into compliance by investment decision and by permit-buying strategy. Similar to the results in Table 28, the initial allocation mechanism does not affect the total compliance rate. Surprisingly, risk-related variables are not essential in influencing subjects' compliance.

In view of the additional variables, we find that firm type is highly significant in determining subjects' compliance. A high permit price renders it more difficult for high MAC firms to arrive at their best compliance strategy. Hence, it has an adverse effect on their compliance status. This finding confirms our conjecture that as high MAC firms are more exposed to the risk of price volatility, they might choose a less than optimal compliance strategy, which not only affects their compliance per se, but also deteriorates the allocative efficiency of the market.

Other demographic variables are not significant, aside from the estimate in Model 4 on the dummy for students undertaking a Master's program. It might be the case that these subjects tend to be more speculative and hence are less prone to being non-compliant. Nevertheless, this effect is not significant after controlling for total trades and total offers at the trading stage. Although both variables are not significant, to our surprise, they have opposite signs. Higher trade volumes seem to increase subjects' compliance, as the market works to distribute permits to those who need them. On the other hand, higher volume of posted offers has a negative effect. It is possible that non-competitive submitted offers lengthen the time required to close a transaction, and hence, fewer trades are realised within the given trading time.

As mentioned previously, those estimation models that pool compliance strategies into one measure of the subject's compliance status provide less information regarding the effect of the initial allocation mechanism on each compliance strategy. Hence, we run regression models with robust panel data probit estimators to investigate the effect separately. The estimation results for compliance through investment decision are shown in Table 36.

Table 36 Estimates Summary for Investment Decision

Regressors for investment decision	Model 1	Model 2	Model 3	Model 4
Dummy for auction Treatment	-0.1117	-0.1116	-0.1323	-0.1357
	(0.1135)	(0.1353)	(0.1124)	(0.1234)
Dummy for high FPR	0.3882*	0.3952*	0.3742*	0.3749**
	(0.1543)	(0.1799)	(0.1529)	(0.1368)
Dummy for high MGP	0.4023**	0.4050**	0.4024**	0.4089*
	(0.1349)	(0.1545)	(0.1542)	(0.1751)
Dummy for high MAC firms	-0.8685***	-0.8692***	-0.8658***	-0.8610***
	(0.1265)	(0.1291)	(0.1195)	(0.1277)
Average permit price	0.0053*	0.0051	0.0075*	0.0071
	(0.0022)	(0.0028)	(0.0032)	(0.0043)
Long permit position	-0.1551***	-0.1553***	-0.1551***	-0.1554***
	(0.0115)	(0.0117)	(0.0107)	(0.0130)
Round		-0.0333	-0.0299	-0.0300
		(0.0242)	(0.0278)	(0.0290)
Std. dev. trading price			-0.0029	-0.0028
			(0.0023)	(0.0028)
Subject's risk index				0.0105
				(0.0500)
Dummy for inconsistent risk choices				0.1375
				(0.1430)
_cons	-0.9570***	-0.8366***	-0.9129***	-0.9786**
	(0.1917)	(0.2541)	(0.2149)	(0.3547)
Number of observations	1728	1728	1728	1728
Log likelihood	-531.8768	-531.1428	-530.5895	-530.2070
Log likelihood constant only	-1.13e+03	-1.13e+03	-1.13e+03	-1.13e+03
R^2	0.52931	0.52996	0.53045	0.53079
Chi^2	212.2976	228.2560	260.9755	192.6198

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Standard errors in parentheses

To observe how an investment decision is made, we only use the data from the first sub period. The estimates summary in Table 36 verifies that the initial allocation mechanism does not significantly influence investment decisions. Nonetheless, subjects evidently make rational decisions regarding investments, as shown by the coefficient signs of the significant regressors. Apart from the strong influence of penalty design variables, firms with a short position of permits and low MAC firms are more likely to make investment decision. Contrary to the model for compliance decisions in Table 35, a higher average permit price encourages an investment decision, as it indicates higher costs of compliance through permit-buying. Hence, it is reasonable to reduce reliance on the market by investing.

Likewise, we regress compliance decisions of net buyers on some independent variables, using the data that excludes investing firms (Table 37).

Table 37 Estimates Summary for Compliance of Net Buyers

Regressors for compliance Decision of net buyers	Model 1	Model 2	Model 3
Dummy for auction	0.1900	0.3651	0.3665
	(0.1355)	(0.2852)	(0.2618)
Dummy for high FPR	0.6043***	0.6888***	0.6901***
	(0.1340)	(0.1620)	(0.1692)
Dummy for MGP	0.8208***	0.8327***	0.8443***
	(0.1510)	(0.1666)	(0.1871)
Dummy for high MAC firms	0.2402*	0.2650*	0.2641*
	(0.1165)	(0.1185)	(0.1093)
Average permit price	-0.0105***	-0.0095*	-0.0094**
	(0.0026)	(0.0037)	(0.0033)
Std. dev. trading price		-0.0009	-0.0009
		(0.0025)	(0.0025)
Total trades on secondary market		0.0142	0.0143*
		(0.0078)	(0.0060)
Number of posted offers		-0.0076*	-0.0077*
		(0.0034)	(0.0031)
Round		0.0934**	0.0932***
		(0.0291)	(0.0277)
Dummy for Sub Period 2		0.2713***	0.2707***
		(0.0788)	(0.0802)
Subject's risk index			0.0601
			(0.0596)
Dummy for inconsistent risk choices			-0.0313
			(0.1874)
_cons	0.3259	-0.3789	-0.6811
	(0.1669)	(0.4423)	(0.4394)
N	1362	1362	1362
ll	-760.3291	-744.4841	-743.5526
ll_0	-789.9493	-789.9493	-789.9493
R^2	0.03750	0.05755	0.05873
chi2	52.2459	118.0442	63.1739

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Standard errors in parentheses

The number of observations, 1,362, which is less than that of investment decision models, highlights the preference of subjects for investment over permit-buying as a compliance strategy. All regressions are carried out with robust panel data probit estimators. The estimates maintain that there is no evidence of the effects of the initial allocation mechanism on net buyers' compliance decisions. As before, we have convincing evidence that higher penalty levels lead to a higher compliance rate of net buyers. It is also logical that net buyers with higher MACs tend to comply more, as low MAC firms are worse off when they choose to buy permits.

The average permit price seems to have a stronger effect on net buyers' compliance rather than on investment decisions. Naturally, a higher permit price has a detrimental effect on net buyers' compliance. As in the general model of compliance decisions, total trades and the number of posted offers have opposite effects. Furthermore, we also find that the learning effect is significant, and a higher compliance rate is observed in the second sub period. These results are in accordance with those from the general compliance model.

To sum up, we have no evidence that the initial allocation mechanism affects compliance decisions either through investment or permit-buying. We need to emphasise that the regression models in this section observed individual choice of compliance strategy with the resulting compliance status, while our previous non-parametric test observed the optimal aggregate market level.

The penalty design variables, firm type, and permit holdings are found to be highly significant. Our experimental feature regarding irreversible investment also facilitates better compliance in the second sub period. Moreover, a high permit price provides stronger incentive for investment but brings about a detrimental effect on net buyers' compliance.

4.5.3. Static Efficiency

To evaluate the effect of the initial allocation mechanism on static efficiency, holding other factors constant, bootstrapped panel data tobit estimators are used, as the possible values of static efficiency are truncated. In theory, static efficiency should lie between zero and one. Nevertheless, we have 11 out of 432 observations for which static efficiency is marginally greater than one. This anomaly stems from a low auction price or a mean trading price below the optimal equilibrium. For our estimation models, we use a lower and upper censoring. Hence, the value of the dependent variable is constrained within the interval [0,1].

For the grandfathering treatment, a low trading price might be attributed to a lower expectation for the permit price or to a lack of comprehension of the opportunity cost associated with holding a permit. Another explanation relates to a myopic bidding strategy, in which subjects bid according to their MAC rather than the equilibrium price, which reflects the scarcity rent of permits. This bidding strategy will cause a demand reduction at the auction and result in a low auction price. Benz and Ehrhart (2007) find a similar result in their experiment.

Table 38 Estimates Summary for Static Efficiency

Regressors for static efficiency	Model 1	Model 2	Model 3	Model 4
Dummy for auction treatment	0.0859***	0.0827***	0.2010***	0.3209***
	(0.0172)	(0.01440)	(0.0258)	(0.02450
Dummy for high FPR	-0.0388***	-0.0384*	-0.0182	-0.0364***
	(0.0117)	(0.0161)	(0.0127)	(0.009)
Dummy for MGP	-0.0698***	-0.0677***	-0.0502**	-0.0634***
	(0.0145)	(0.0136)	(0.0186)	(0.0131)
Round	0.0002	0.0001	0.0005	0.0008
	(0.0017)	(0.0018)	(0.0015)	(0.0012)
Dummy for Sub Period 2	-0.0486***	-0.0486***	-0.0429***	-0.0446***
	(0.0107)	(0.0118)	(0.0121)	(0.0109)
Total investment level	-0.1793***	-0.1804***	-0.1757***	-0.1949***
	(0.0191)	(0.0193)	(0.0176)	(0.0157)
Compliance rate	0.3593***	0.3598***	0.3408***	0.3631***
	(0.0595)	(0.075)	(0.0743)	(0.0577)
Total risk index		0.0007		
		(0.0014)		
Subject w/ inconsistent risk choices		0.0037		
		(0.0047)		
Average permit price	-0.0042***	-0.0042***		
	(0.0005)	(0.0005)		
Trade volume	-0.0026***	-0.0026***		-0.0029***
	(0.0004)	(0.0003)		(0.0004)
Auction price			-0.0052***	-0.0051***
			(0.0005)	(0.0003)
Mean of trading price			-0.0023***	-0.0021***
			(0.0004)	(0.0003)
_cons	1.1409***	1.1077***	0.9192***	1.0601***
	(0.0426)	(0.0684)	(0.0487)	(0.0428)
N	432	432	432	432
ll	506.5921	507.0435	502.3966	544.2318
chi2	546.6174	657.252	413.7555	1282.813
rho	0.0494	0.0476	0.0753	0.0000

Notes: * significant at the 5% level, ** significant at the 1% level, *** significant at the 0.1% level
Standard errors in parentheses

Model 1 is the basic model with explanatory variables, including dummies for the initial allocation mechanism and the penalty design variables, time variables, trade volume, total investment level, and compliance rate. The average permit price is included as a price variable, which is expected to have a significant marginal effect on static efficiency. For the auction treatment, trade volume is calculated by accounting for auctioned permits rather than just total trades on the secondary market. Both the total investment level and compliance rates can be viewed as variables which represent compliance strategies, as the investment level ensures subjects' compliance. However over-investment, which causes excessive investment costs, undermines market efficiency. The measure of the compliance rate has a maximum value of one under perfect compliance.

Regression results for Model 1 verify that all treatment variables are statistically significant. Holding other explanatory variables constant, the auction treatment significantly has about 8.6% higher efficiency than the grandfathering treatment. The largest marginal effect is generated by market compliance rate for which perfect compliance increases market efficiency by 35.93%. Those positive effects are corrected for by other significant regressors, with the largest negative effect given by the variable total investment level. Similar to the compliance rate, the investment level is compared to the optimal level, and hence, over-investment in the market is denoted by a value larger than one. The variables that represent the penalty design treatment have the expected negative effect, as higher penalty levels correspond to higher penalty costs. In line with the estimation results for the compliance decision (Table 35 to Table 37), the make-good provision treatment has almost a twice larger marginal effect on efficiency than the fixed penalty rate treatment, at 6.98%.

Looking at price variables, the seemingly small negative marginal effect can actually surmount to that of the investment level, reaching 19.8% at the average value. Surprisingly, a larger trade volume has an adverse effect on efficiency due to inefficient trades. Higher or lower trade volumes, which result in market inefficiency, are common in laboratory markets, as pointed out by Camerer (1992). It is argued that subjects' optimism in their trading abilities might lead to an irrationally high volume of trades. Nonetheless, learning will reduce this inefficiency although not eliminate it entirely.

Unfortunately, there is no evidence of learning across the models. Static efficiency in the second sub period is slightly lower than that of the first sub period. As discussed previously, our experimental feature of a two-period model bears the risk of carried-over inefficiency across sub periods.

The addition of risk-related variables in Model 2 does not appear to considerably enhance the explanatory power of the model. Furthermore, the coefficients on these variables are not significant.

A rather different approach is employed in Model 3, in which the auction price and the mean trading price are used instead of the average permit price. By doing this, more variations in the auction price can be captured by the model. The approach boosts the effect of the initial allocation mechanism about 2.5 times while moderating the effects of penalty design variables.

Moreover, the economic effect of the auction price is slightly more than double that of the mean trading price. This result highlights the inefficiency brought about by a high auction price.

As a trade volume variable is included in Model 4, the explanatory power of the model is improved greatly. The coefficients of most of the significant variables are augmented, and the marginal effect of the auction treatment is further increased to 32%.

In summary, the estimation results for static efficiency allow us to draw two important inferences. First, the auction treatment induces a convincingly higher static efficiency, owing to a higher efficiency level in investment decisions and to higher compliance rates, which have proved to be significant economically and statistically. Nevertheless, the high auction price seriously undermines the advantage of auctioning over grandfathering. Second, a higher level of penalty imposes an adverse effect on static efficiency, in line with the results from the previous experiment on penalty design. These inefficiencies are exacerbated in the second sub period as a result of our two-period model.

4.5.4. Overbidding at the Auction

Following our previous discussion on the adverse effect of high auction prices on static efficiency, this section examines the issue of bidding behaviour at the auction, which might shed some light on the causes for a high auction price. Specifically, we will investigate the occurrence of overbidding and its determinants.

Taking into account the auction design that we use, some of the literature notes the risk of bid-shading in a multi-unit auction. However, we only find a small degree of bid-shading across treatments, which is declining in penalty levels (6.6% in AFL, 5.7% in AFH, and 4.1 % in AMH). On the other hand, the nature of the dynamic auction format, which involves multiple rounds of bidding, allows the updating of bidders' valuations of the object. It is plausible that the transparency of the bidding mechanism in the clock auction might induce a sense of competition, which in turn can intensify aggressive bidding. This aggressive bidding might be caused by bidders' overestimation of their trading abilities to make profit in the secondary market, or by auction fever. A possible explanation for auction fever is competitive arousal (Ehrhart et al., 2008). Surprisingly, this aggressive bidding behaviour in laboratory emissions trading markets is also observed with a sealed-bid auction (Grimm et al., 2010), which is lauded for facilitating a bidding strategy that is closest to bidders' true valuations.

It has been mentioned earlier that the efficiency in an auction with a resale market might suffer, as the opportunity to resell the good introduces a common-value element, which affects bidders' bidding strategies. Hence, bidders' bidding strategies are based on inter-dependent value rather than their private valuations. Bidders' valuations are uncertain, as they hinge on the expected profit in the resale market (Haile, 2003). Furthermore, the resale opportunity also creates a role of speculator that is a bidder who has no use value of the auctioned good (Garratt and Tröger, 2006). As a result, the presence of multi-dimensional information at the auction will preclude the efficient allocation of permits (Jehiel and Moldovanu, 2001).

An important experimental design issue that we need to point out is bidder information with respect to private valuation. Different from experiments in which the bidder's private value of each unit to be auctioned is given, or experiments where buyers and sellers roles are clearly defined, this experiment does not directly control for subjects' independent private values, as it depends on their ability to calculate the equilibrium price based on the information given to them. As described in the experimental design, the information basically enables them to calculate the equilibrium permit price. In that sense, the common-value element should be fairly dominant if each subject can calculate the equilibrium price and behave rationally. Nevertheless, since there is always uncertainty regarding the other subjects' decisions, each subject might have different beliefs and expectations regarding their valuation at the auction.

To investigate the occurrence of overbidding, regression models are performed to see which variables affect the degree of overbidding. For that purpose, we simply define overbidding as any positive bidding quantity when a bidder's MAC is lower than the bidding price, for any bidding price beyond the equilibrium price (EX$38). This definition is rather broad, as bidders might simply have to have a positive bidding quantity beyond their MAC or beyond the equilibrium price to be compliant, which in some cases might be profit-maximising rather than being non-compliant, especially in sub period two. In this regard, the MGP treatment might have a pronounced effect on bidders' bidding quantities in the second sub period since non-compliance in the first sub period requires higher permit holding in the second sub period. Hence, we control for this effect by including penalty design variables as well as a variable denoting the required number of permits that the subjects need to be compliant. On the contrary, overbidding might be more prevalent in sub period one as subjects might have more uncertainty regarding their best compliance strategy out of the two available compliance strategies in sub period one, while in the second sub period only one compliance strategy is available.

The regression models are performed with panel data tobit estimators because the possible values of overbidding are constrained to the interval [0,80]. Apart from the main penalty design and time variables, we take into account individual characteristics. The basic model (Model 1) incorporates risk-related variables and the required number of permit holdings. This variable is essential to point out the possible different bidding strategies in the two sub periods due to the possible compliance strategies, which include investment for sub period one. Models 2 and 3 add further demographic variables that describe sex, age, study program (undergraduate, Master's or PhD), and the year in school. We do not present all these variables due to limited space. The difference between the two models is the dummy for high MAC firms is used in Model 3 instead of the values of MAC as in Model 2.

We obtain consistent estimates across the model and their signs are also intuitive (Table 39).

Overbidding is more rampant in high FPR penalty treatment, wherein nearly six more permits are submitted. This result is not surprising considering higher compliance costs in this treatment incite more speculative bidding strategies. On the other hand, the MGP treatment is not a determinant of overbidding. It is likely that the highly punitive nature of a quantity penalty leaves less room for speculative bidding, as subjects are more likely to resort to investment decisions to avoid the enormous cost of being non-compliant. Nevertheless, an extremely high auction price is observed in the high-MGP treatment in the second sub period due to the pressure for non-investing subjects to be compliant by buying permits at the auction. This behaviour is rational, as the marginal penalty of missing one permit in that case is EX$2800, and this marginal penalty is decreasing in the number of missing permits.

Subjects' bidding strategies seem to be rational, as firms with higher MACs are less likely to overbid. The number of the required permits also affects overbidding, as it describes the basis for subjects' bidding quantities. There is no evidence of different degrees of overbidding between sub periods. However, the marginal effect of learning is highly significant, as subjects learn over time to submit more efficient bidding quantities.

In terms of subjects' individual traits, we find that risk-related variables significantly affect the extent of overbidding. More risk-averse subjects are less likely to overbid. On the other hand, the more irrational subjects, as indicated by their inconsistent risk choices, can bid 6-7 more permits than the efficient bidding quantity. This represents about a third of the required number of permits for each subject, and hence, it is very significant in economic terms.

The incidence of overbidding is also more likely when subjects do not have economic backgrounds and are undertaking a PhD degree. This result is in line with a belief that PhD students are not the best subjects for laboratory experiments, as they are more resistant to the induced values imposed upon them by the experimental design. Moreover, students aged 21-30 years old as well as those in years 2 and 4 of schooling are shown to have more speculative bidding behaviour in Model 2.

Table 39 Estimates Summary for Overbidding Quantity

Regressors for overbidding quantity	Model 1	Model 2	Model 3
Dummy for high FPR	5.3989***	4.5597**	5.7594***
	(1.4985)	(1.5341)	(1.5850)
Dummy for MGP	-1.3516	-0.9995	0.0428
	(1.5651)	(1.5804)	(1.3553)
Marginal abatement cost	-0.5482***	-0.5355***	
	(0.0609)	(0.0605)	
Dummy for high MAC firms			-9.7611***
			(1.1231)
Required number of permit	0.7113***	0.7104***	0.6857***
holding	(0.0637)	(0.0638)	(0.0539)
Round	-1.9289***	-1.9177***	-2.9959***
	(0.3670)	(0.3615)	(0.3046)
Dummy for Sub Period 2	-0.0399	-0.0150	-0.7184
	(1.2401)	(1.2213)	(1.0204)
Subject's risk index	-1.3452**	-1.3945**	-0.9392*
	(0.4335)	(0.4550)	(0.3682)
Dummy for inconsistent	8.8064***	6.3475***	5.5730***
	(1.5766)	(1.6558)	(1.3565)
Dummy for female		1.6874	0.7601
		(1.3305)	(1.0949)
Dummy for age 21-25 y.o.		7.2248***	0.1986
		(2.0523)	(1.5936)
Dummy for age 26-30 y.o.		8.1007**	-1.1483
		(3.0422)	(2.4521)
Dummy for age above 30 y.o.		13.1502	6.2075
		(7.4594)	(4.5383)
Dummy for economic		-4.3420**	-4.8473***
study background		(1.3250)	(1.1119)
Dummy for Master's program		-0.6373	3.3295
		(2.2146)	(1.7648)
Dummy for PhD		3.7693	8.7431*
program		(7.0571)	(4.1008)
_cons	-3.8530	-3.0984	-18.8071***
	(2.9283)	(3.1254)	(2.7472)
N	13336	13336	21496
Ll	-1.53e+04	-1.52e+04	-2.41e+04
chi2	225.8837	270.0441	340.7768
rho	0.4275	0.4150	0.4519

Notes: * significant at 5% level, ** significant at 1% level, *** significant at 0.1% level
Standard errors in parentheses

Overall, we find evidence of overbidding in a clock auction with a resale market, although these bids only account for 19% of all bids. Yet, it still has an impact on inefficient auction prices. The presence of overbidding in our experiment is influenced by the auction format that we use, and it is not an unusual phenomenon to be found in a laboratory market or in practice. Attention needs to be drawn to the high FPR penalty design, which is found to exacerbate the degree of overbidding, as emissions trading markets normally employ this penalty design. Furthermore, some individual traits might attribute further to the extent of the problem. Although a high auction price is good news for the auctioneer, in this case the regulator, it sends an incorrect signal of the scarcity value of the permit.

4.6. Discussion

To answer the question of how initial allocation mechanism might affect price discovery in the market, we need to look at how price signals are developed on the market and how the market works in each treatment. Bearing in mind that permit trading in the auction treatment is essentially a secondary market that serves to clean up any inefficiencies at the auction, rather than the main market mechanism for distributing permits; the comparison of the trading prices for both allocation mechanisms needs to take this difference into account. We find that the trading price and total trades at the secondary market are much lower in auction treatments, although the auction price is relatively high and comparable to the trading price in grandfathering treatments.

Average permit prices in general lie above the equilibrium price. The test statistics of treatment effects reveal that permit price discovery in auction treatments are closer to the equilibrium compared to the grandfathering treatment, particularly in earlier rounds. However, the regression models indicate that the way permits are initially distributed does not affect the price discovery process. We find that some trade variables have more effects on the average permit price. Interestingly, the minimum trading price, which is supposedly submitted by buyers, has more effect than the maximum trading price.

This result highlights that the implementation of a price floor might have important implications for submitted offers on the secondary market. As expected, risk aversion tends to cause an upward pressure on permit prices because risk-averse subjects are more willing to incur high permit costs to be compliant. Yet, this effect is much smaller than the effect of having irrational subjects on the market. Nevertheless, a learning effect is observed, and subjects learn to reduce this inefficiency over time, although prices are still higher than the efficient level. This finding is in line with the conclusions that Camerer (1992) draw from some laboratory experiments as well as the examples in some real markets. Considering how price signals are developed, one needs to examine the standard deviation of prices and the convergence path of prices over time. Auctioning noticeably generates stronger price signals, and over time, prices converge to the range of the equilibrium price.

With respect to our second research question regarding compliance incentives, the effect of the initial allocation mechanism is assessed in terms of investment incentives and compliance incentives for net buyers. In general, overinvestment is prevalent, but it is less severe with auction treatments than with grandfathering treatments, which contradicts some literature. This treatment effect is more noticeable in earlier rounds. Although the literature has attributed over-investment to risk aversion, we find that it is the penalty design that causes this over-investment, not risk aversion. Moreover, our regression results confirm that firms make rational investment decisions according to their firm type or due to their permit position.

Based on our tests of treatment effects, we find for each penalty design, that the compliance rate of net buyers is higher when permits are auctioned, especially in the later rounds. This finding highlights the inefficiency in a secondary market, particularly for grandfathering treatments. Furthermore, it also points to better learning with auctions to reduce trading inefficiency. After controlling for some relevant variables, we find that compliance of net buyers is substantially influenced by penalty design, and over time, subjects learn to have better trading strategies to be compliant.

Our last research question might be considered as the most important one, as it relates to the main effect of the initial allocation mechanism on the efficiency of emissions trading markets. We examine allocative and static efficiency to address how well the market works in distributing permits to those who have the highest value for them and in realising its potential cost-effectiveness. Our results show a rather poor allocative efficiency due to a shift of compliance strategy for the high MAC firms in the presence of market volatility and penalty design. This market volatility places more risks on the high MAC firms, which rely on the market for their compliance. We have no evidence of a significant difference in allocative efficiency when permits are auctioned or given for free.

We inspect static efficiency by reviewing three elements of costs: permit costs, investment costs, and penalty costs. In line with our finding regarding the average permit price, the initial allocation mechanism does not affect the efficiency of permit costs. Nevertheless, higher efficiency regarding investment costs is apparent with auction treatments, which is in accordance with our results regarding the investment level. Although a higher compliance rate is observed in the auction treatment, the difference in penalty cost efficiency is not significant.

When we control for relevant variables, we obtain convincing evidence that auctioning generates much higher efficiency than grandfathering. This empirical finding supports the literature.

Furthermore, we find that a high penalty level in the FPR penalty design also corresponds to overbidding at the auction. This overbidding, even to a small extent, might result in a significant rise in the auction price. Hence, it is important for policymakers to consider the appropriate mechanism design for auctioning permits to realise the full potentials of the emissions trading markets. Specifically, more attention needs to be drawn towards the design of an auction with a secondary market in which interdependent bidders' valuations are involved.

4.7. Conclusion

There have been a number of literatures that study how the way permits initially distributed may affect market performance. This study contributes to the existing literature by looking at how the initial allocation mechanism influences not only market efficiency but also the price discovery process and the choice of compliance strategy in terms of irreversible investment decision and permit buying. In order to answer our research questions, we incorporate the use of three penalty design as a means of enforcement. As each penalty design conveys information regarding the maximum cost of compliance, we expect to gain some insight regarding how a fixed penalty rate may function as a loose price cap.

Following the results from our penalty design experiment, there is a clear pattern of higher prices at high penalty levels in this experiment. Penalty design is viewed as a loose indication of a price cap, and it is found to be highly significant in almost each measure of market performance. In practice, the use of price controls will significantly influence firms' behaviours and impacts on market efficiency. Our findings confirm that penalty levels are used as focal points for firms, on which they base their expectations for the permit price. A very high penalty level, or even a binding price cap, will inflate the permit price upwards and diminish potential efficiency in the market. In terms of auctioning, a higher permit price implies higher auction revenues. Nevertheless, it sends an incorrect signal for optimal investment.

The results also point out to different markets at which inefficiencies occur in both treatments. When permits are initially auctioned off, the auction mechanism crucially determines market efficiency and the secondary market can only slightly increase pre-trade efficiency. Hence, the auction market is the main market at which the inefficiencies should be addressed. For the free allocation treatment, the trading institution and design at the secondary market have substantial bearing on market efficiency.

The main findings from this study are summarised as follows.

Table 40 A Summary of Main Findings for the Initial Allocation Mechanism Experiment

No.	Main Findings	Supports
1.	Initial allocation mechanism does not affect the price discovery process, but auction yields better price discovery in earlier rounds.	Result 1 and estimation models for the average permit price
2.	Stronger price signal and more discernible convergence of permit price is observed with auction treatments	Result 2
3	Penalty design and permit price, rather than the initial allocation mechanism, have positive effects on compliance through investment decision. However, auction provides better investment incentives for the high level penalty treatments.	Result 3 and estimation models for investment decision
4	The initial allocation mechanism does not influence compliance rates of net buyers, but auctioning provides better learning than grandfathering	Result 4 and estimation models for compliance decision through permit buying
5	Allocative efficiency is not influenced by the initial allocation mechanism	Result 5
6	Auctioning provides better investment-cost efficiency and yields much higher static efficiency	Result 6 and estimation models for static efficiency
7	Overbidding occurs at the auction and is worse in the high FPR treatment	Estimation models for overbidding quantity

We can conclude that the initial allocation mechanism does not affect price discovery in the market. Nevertheless, when permits are auctioned, stronger price signals are created in the market, and these price signals are crucial in providing efficient investment and compliance incentives. As a result, emissions trading with an auction market will generate higher efficiency than when permits are free. Our results support the strands of literature that mostly argue for the advantages of auctioning as the initial mechanism to allocate permits.

Chapter Five

Conclusions and Further Extensions

The aim of this dissertation is to assess different penalty designs and the initial allocation mechanism as a design feature in emissions trading schemes using both a theoretical framework and an experimental method. The results of the three essays reveal that there can be a considerable discrepancy between theoretical findings and laboratory results. This can be attributed to the fact that an experiment involves human subjects in the economic decision making while a theory mainly abstracts from behavioural aspects. We aim to balance the simplicity of our experimental market design with the real market environment in an emissions trading scheme in order to be able to assess the circumstances under which the theory still holds. Therefore we retained as many necessary structural assumptions of the emissions trading market as possible, but reduced the complexity where possible to ensure that subject's comprehension is not exceeded. If under this simple environment the theory does not hold, then in a more complicated system in the real world, there is less chance that the emissions trading market might function as predicted by the economic theory.

In theory, in which there is perfect knowledge regarding the permit price and marginal abatement costs, penalty design does not matter, as long as it is established at the efficient level. In practice policy makers do not possess the knowledge in order to determine the efficient penalty level. Therefore the mixed penalty design is widely used in the existing and the proposed schemes in view that the presence of double penalty would encourage higher compliance rates. Our theoretical findings support the practice since the mixed penalty design evidently provides stronger compliance incentives without compromising market efficiency, as previously concerned by some economists. Furthermore, the fixed penalty rate in the mixed penalty design plays a crucial role in encouraging perfect compliance in the market at the last compliance period as the make good provision could allow for the delay of compliance indefinitely if no other consequences are executed.

In contrast to our theoretical findings; the experimental results from the second essay indicate that the penalty design induces different compliance incentives under the presence of risk preferences and the uncertainties regarding the permit price. The penalty design undoubtedly serves as a focal point for permit price discovery. Therefore, when the design is solely focused on achieving the full compliance rate and providing investment incentives at the expense of higher permit prices, it might risk eroding market efficiency.

In practice, there are more uncertainties compared to our controlled experimental setting. Those include firms' initial emissions levels, damage costs, and abatement costs as well as the unknown or uncertain future economic environment. For a regulator, setting the efficient penalty level, which has some arbitrary nature due to the absence of perfect information, might be difficult. Based on our findings policy makers need to be aware that the price discovery process in the permit market may be influenced by the penalty design, as the level of penalty provides an indication of the maximum costs of compliance.

The main findings of the experiment on the penalty design also highlight the different incentives relating to each penalty design. The MGP penalty noticeably induces higher investment levels and compliance incentives compared to the FPR penalty. As expected, the mixed penalty design also encourages higher compliance rates due to the presence of an MGP element. This finding draws attention to the trade-off between investment incentives and efficiency levels imposed by the MGP penalty which again needs to be considered by policy makers.

A major finding of the last essay is that auctioning, instead of free allocation of permits, evidently generates higher efficiency and enables better learning curves in the face of uncertainty in the permit price, as auctioning provides a more coherent price signal. Likewise, the auction treatment also results in better investment-cost efficiency and more optimal investment levels, especially in the high penalty levels.

Nevertheless, the advantages of auctioning permits also place more weight on the importance of a particular auction design. Recognising that there is always a secondary market which normally follows any auctions, careful considerations in a mechanism design, which can suppress speculative bidding behaviour, is essential. Although a high auction price generates better revenues for the regulator, it undermines the efficiency of the scheme by sending incorrect price signals in the permit market. Therefore a carefully designed auction is also essential to achieve a high allocative efficiency.

There are several areas that can be explored to extend further research on design features related to the initial allocation mechanism and the penalty design. The first is the inclusion of banking and borrowing, which are fairly common in existing trading schemes. This provision is believed to provide more flexibility in smoothing the permit price and thus reduce price volatility. However, the provision of banking might reduce compliance incentives in some cases (Cason and Gangadharan, 2006) and promote over-investment (Gangadharan et al., 2005, Grimm et al., 2010, Ehrhart et al., 2003). Furthermore, there might be an interaction between banking and the restoration rate in the make-good provision. Naturally, the restoration rate acts like an interest rate for any banked or borrowed permits. To test the ability of the system to cope with uncertainties under the provision of banking or borrowing, additional uncertainties might be introduced to the market, such as emissions shocks, shocks in the downstream market that affects firms' revenues, the strategic reserve of permits held by the regulator, or allowing for new entrants.

A second extension might involve the use of a discount rate and a longer compliance period. In practice, this discount rate might reduce investment incentives under the presence of uncertainty, as firms delay their investment to have better information, which reduces this uncertainty. At the same time, it will be interesting to model the advantage of being a first-mover that undertakes risky investment in renewable technology with potential high returns. The restoration rate in a make-good provision will counterbalance the effect of a discount rate. It can also be seen how auctioning permits might have a different effect on the free allocation of permits.

Another extension that will provide valuable insights to policy making is the use of price collars or both price caps and price floors under a particular penalty design or an auctioned permit system. This concept has received considerable debate, and there are a growing number of studies using theoretical models and simulations to test its effects (Burtraw et al., 2010, Fell and Morgenstern, 2009, Philibert, 2008, Roques and Savva, 2009). It is argued that the use of both non-binding price controls - price cap and price floor - might enhance efficiency in the presence of uncertainty. The use of an experimental method could certainly contribute further to the debate. To our knowledge, there are only very few experiments on this topic using the context of asset markets (Isaac and Plott, 1981, Smith and Williams, 1981).

Finally, we propose to consider the adoption of the Australian Carbon Pollution Reduction Scheme (CPRS) approach, which ties the penalty rate to the auction price. The proposal also employs an MGP penalty to maintain the integrity of the emissions target. This mixed penalty design allows for the adjustment of the penalty level to a changing permit price which may occur from any kinds of uncertainties. We have included this penalty design in our second essay to test-bed the performance and the implications of this yet practically untested penalty design.

The results show that this penalty design encourages higher investment and compliance incentives with a compromise on efficiency level.

In line with the results of the experiment on the initial allocation mechanism, the auction design mechanism will substantially influence the efficiency of the Australian CPRS. Hence, the proposed auction design would benefit from further testing in the laboratory. Furthermore, the presence of a reserve price is fundamental to preclude any strategic bidding or collusions to drive down the permit cost that can reduce compliance incentives. This reserve price acts as a loose price floor which will maintain both investment and compliance incentives. More importantly, a number of studies have shown that this price floor would enhance market efficiency should a price cap be considered in order to reduce the costs of uncertainties.

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Appendix

Experiment Instructions

Introduction

Before the experiment started, subjects received written instructions at their desk. After subjects read the written instructions in private, the experimenter read instructions out loud so that each subject understood that everyone in that session received the same treatment. These instructions use neutral terminology as is normally the case in experimental economics.

In the lottery choice experiment, we used a modified version of Holt and Laury's (2002) instructions because balls in a bingo cage are used instead of ten-sided dies. This method is chosen to save the length of the experiment since our main experiment requires a fair amount of time. Furthermore, a modification to the original instructions are also necessary as the payoffs this experiment were given at the end of the session in order to avoid wealth effects of those payoffs on the main experiment.

The experiment instructions for each treatment in the penalty design experiment and the initial allocation mechanism experiment have the same basic structures. We provide an example of the instructions for the basic treatment of auction with a low-level fixed penalty rate (AFL). Under the make-good provision and the mixed penalty treatment, the section regarding the penalty is modified accordingly. Likewise, the instructions related to auction are removed when grandfathering treatment is involved.

Appendix 1 General Instructions

You are about to participate in a decision-making experiment. In this experiment you will be randomly assigned to 1 out of 2 groups and each group consists of 8 participants. You will remain in the same group throughout the experiment. The experiment will consist of two separate decision tasks. Your aim in the experiment is to maximise your earnings.

Task 1 will require you to make a choice between two options for a number of times. You need to fill in your choices in a record sheet. Once the record sheet is completed please raise your hand and an experimenter will collect your record sheet. The earnings from Task 1 will be determined after both tasks are completed.

Task 2 will require you to interact with other participants only through the computer where you are seated. Your earnings from Task 2 are based on the decisions that you and 7 other participants in your group make.

Every decision is confidential and anonymous.

Your total earnings will be the sum of your earnings in Task 1 and Task 2, and will be paid to you privately in cash at the end of the experiment. This money will be added to the amount of $5 for your participation in this experiment.

Your decision and earnings in Task 1 will not affect your earnings in Task 2.

Please remain silent throughout the experiment. If you have any questions, please raise your hand and an experimenter will come to you.

Appendix 2 Instructions for the Lottery Choice Experiment

Task 1 Instructions: Lottery Choice Decisions

Your decision sheet shows ten decisions listed on the left. Each decision is a paired choice between "Option A" and "Option B." You will make ten choices and record these in the final column, but only one of them will be used in the end to determine your earnings. Before you start making your ten choices, please let me explain how these choices will affect your earnings for this part of the experiment.

A cage which contains 10 balls will be used to determine payoffs; the balls are numbered from 1 to 10. After you have made all of your choices, we will pick a ball from the cage twice, once to select one of the ten decisions to be used, and a second time to determine what your payoff is 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 400 cents if the number of the ball is 1, and it pays 320 cents if the number is 2-10. Option B yields 770 cents if the number of the ball is 1, and it pays 20 cents if the 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 ball will not be needed since each option pays the highest payoff for sure, so your choice here is between 400 cents or 770 cents.

To summarize, you will make ten choices: for each decision row you will have to choose between Option A and Option B. You may choose A for some decision rows and B for other rows, and you may change your decisions and make them in any order.

After Task 1 and Task 2 are completed, a ball will be picked from a cage to select which of the ten Decisions will be used. The number on this ball will be announced and then this ball will be put back in the cage. Then we will pick a ball again to determine your money earnings for the Option you chose for that Decision. Earnings for this choice will be added to your previous earnings, and you will be paid all earnings in cash when we finish.

So now please look at the empty boxes on the right side of the record sheet. You will have to write a decision, A or B in each of these boxes, and then the ball pick will determine which one is going to count. We will look at the decision that you made for the choice that counts, and circle it, before picking a ball again to determine your earnings for this part. Then you will write your earnings in the blank at the bottom of the page.

Now you may begin making your choices. Please do not talk with anyone while we are doing this; raise your hand if you have a question.

Please raise your hand when you have finished with Task 1 and you are ready to proceed to Task 2. We will then collect the Task 1 paper.

Please proceed to Task 1.

RECORD SHEET

Decision Number	ion A	ion B	Your Choice
1	1/10 chance of A$ 4.00; 9/10 chance of A$ 3.20	chance of A$ 7.70; 9/10 chance of A$ 0.20	
2	2/10 chance of A$ 4.00; 8/10 chance of A$ 3.20	chance of A$ 7.70; 8/10 chance of A$ 0.20	
3	3/10 chance of A$ 4.00; 7/10 chance of A$ 3.20	chance of A$ 7.70; 7/10 chance of A$ 0.20	
4	4/10 chance of A$ 4.00; 6/10 chance of A$ 3.20	chance of A$ 7.70; 6/10 chance of A$ 0.20	
5	5/10 chance of A$ 4.00; 5/10 chance of A$ 3.20	chance of A$ 7.70; 5/10 chance of A$ 0.20	
6	6/10 chance of A$ 4.00; 4/10 chance of A$ 3.20	chance of A$ 7.70; 4/10 chance of A$ 0.20	
7	7/10 chance of A$ 4.00; 3/10 chance of A$ 3.20	chance of A$ 7.70; 3/10 chance of A$ 0.20	
8	8/10 chance of A$ 4.00; 2/10 chance of A$ 3.20	chance of A$ 7.70; 2/10 chance of A$ 0.20	
9	9/10 chance of A$ 4.00; 1/10 chance of A$ 3.20	chance of A$ 7.70; 1/10 chance of A$ 0.20	
10	10/10 chance of A$ 4.00; 0/10 chance of A$ 3.20	0 chance of A$ 7.70; 0/10 chance of A$ 0.20	

Session date : ____/____/______ **Sesssion time** : _________ **am/pm**

Desk number : ________________

Number of the decision : ________________

Your choice : ________________

Your earning : ________________

Appendix 3 Instructions for the Emissions Trading Experiment

Task 2 Instructions

This experiment consists of a number of repeated rounds, in which each participant represents 1 out of 8 firms in one group. In each round, you will be required to make decisions on behalf of your firm. All monetary value and earnings in the experiment are in Experimental Dollars (EX$) with a conversion of: **1 Australian Dollar = 900 Experimental Dollars.**

Structure of Task 2

There will be 6 rounds, in which each round has 2 sub periods. In each round, you will encounter exactly the same sequence of events as shown below.

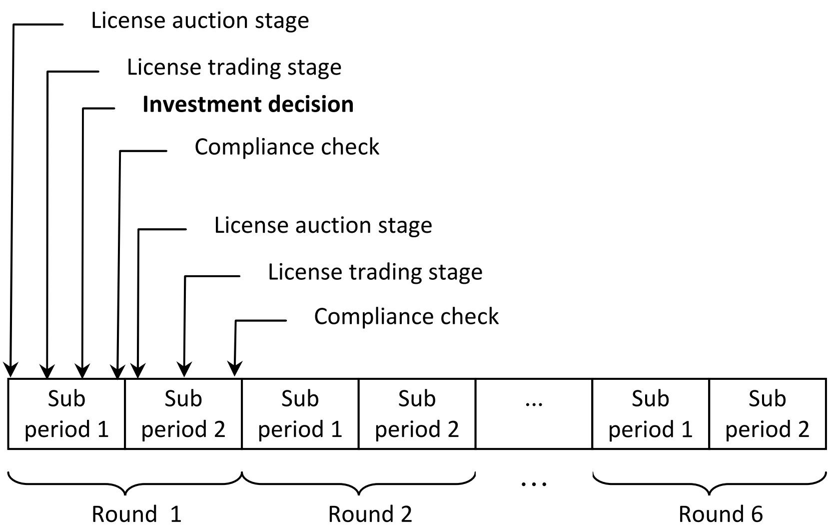

Figure 1. The sequence of Task 2

Sub periods of each round will consist of the following events in order:

1. Auction of licenses to firms.
2. Trading of licenses obtained in the auction.
3. Investment decision (**this will occur only in the first sub period of each round**).
4. Compliance check.

The only difference between the two sub periods is that an investment decision can be made in the first sub period. Remember, that **each ROUND is not linked to the other rounds**, although the two sub periods of a round are linked.

Rules of the Experiment

Each firm produces 20 units of a fictitious good *X* in each sub period*,* and this production level remains **fixed for the whole course of the experiment**. Thus, in total, 160 units of good *X* are produced by 8 firms in each sub period. From this production activity, each firm will receive “Total Revenue”.

Total Revenue = production level of good X x Revenue per unit of good X

= 20 units x EX$ 140 = EX$ 2800

You will need to undertake **one** of the two actions:

EITHER

1. **Purchase and hold a license for every unit of production.**

   You can get licenses by buying them during the auction stage or by buying them from other firms during the trading stage. ***Each license expires at the end of a sub period and cannot be carried over to the next sub period***. ***If you hold more licenses than you need at the end of a sub period, these licenses have a zero monetary value***.

OR

2. **Make an investment in technology during a round at a cost.**

   If you invest, the required number of licenses that you need to hold is zero. **Then you will incur investment costs in each sub period of that round** as follows:

   Investment Costs = 20 units x Per Unit Investment Cost

   You cannot do partial investment of less than 20 units.
   You can only make investment decision in the first sub period, and the effects will take place immediately for both sub periods. The **Per Unit Investment Cost** will be different for each participant and **ranges from EX$ 20 to 55 [20, 25, 30, 35, 40, 45, 50, 55].** This cost is randomly drawn and is assigned to each participant in each round. Thus, you will have *the same Per Unit Investment Cost in both sub periods of a round*; but this cost might change in the following rounds. Only you will know your Per Unit Investment Cost for your firm. The range of the Per Unit Investment Cost remains the same in all rounds.

Penalties

A compliance check is conducted at the end of each sub period to see whether you hold enough licenses OR whether you have made an investment.

1) If you do not invest in a new technology AND :
   a. You hold enough licenses as required, then you are COMPLIANT.
   b. You do not hold enough licenses as required, then you are NON-COMPLIANT.
2) If you invest in a new technology, then you are automatically COMPLIANT.

You will be penalised if you are NON-COMPLIANT.

The penalty for non-compliance is a fixed fine of EX$ 45 per license that you miss. For example, if you did not make an investment decision and you only hold 17 licenses, then you need to pay:

Penalty costs = (20-17) missing licenses x EX$ 45/missing license = EX$ 135.

License Auction

This is the first opportunity for firms to buy licenses. In the auction, each firm is a buyer. **The total quantity of licenses to be auctioned in each sub period, "Total Auction Supply", is 80**. The auction starts at a price of EX$ 18 and increases in EX$5 increments. At each price, you **bid the quantity** of licenses that you are willing to buy at that price on the bidding screen (Figure 2). You need to enter the quantity and **click the "Submit" button**. You have 20 seconds to submit your bidding quantity. In making your bid, you need to meet the following requirements:

1. Your bidding quantity must be less than or equal to your previous bidding quantity. The maximum bidding quantity that you can enter is equal to Total Auction Supply.
2. You must have a sufficient cash balance to purchase your bidding quantity at the current bidding price.
3. If you are not willing to buy any licenses at a particular bidding price, you should submit **a zero quantity**. Once you decide to do this, you can only submit a zero quantity in all subsequent bidding prices during the auction.

The sum of bidding quantity from all firms at the last bidding price is the “Total Auction Demand”.

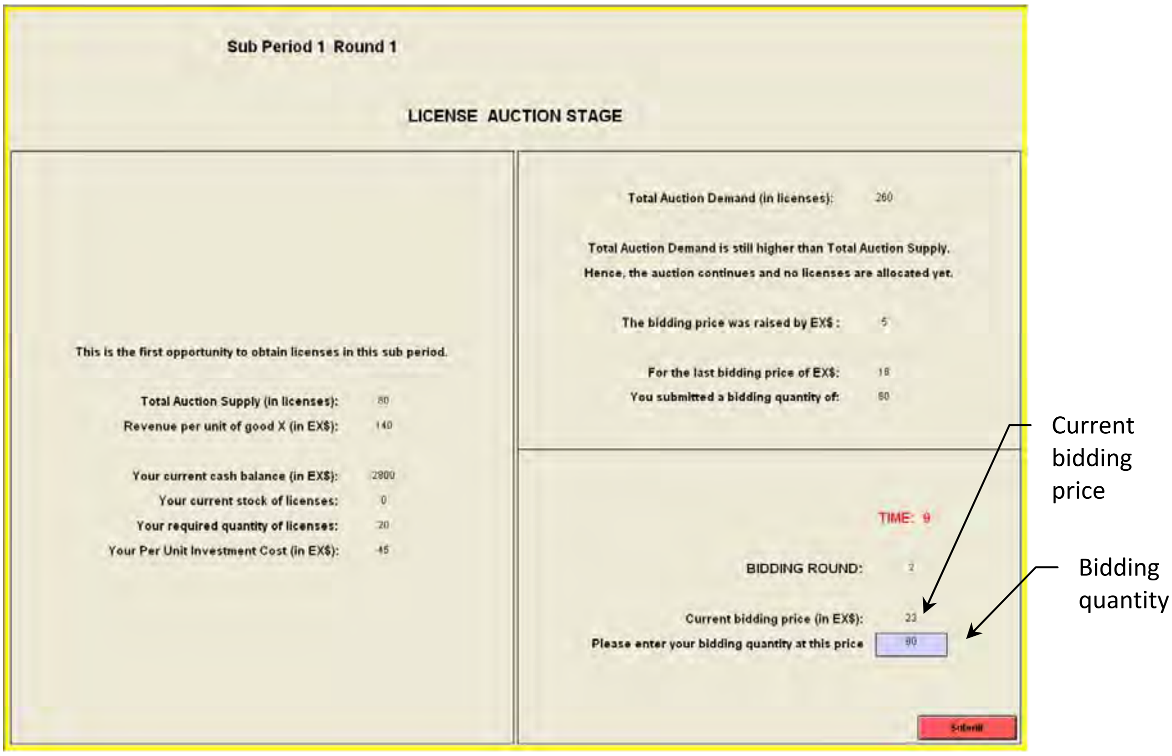

Figure 2. Screenshot for License Auction

When Total Auction Demand is higher than Total Auction Supply, the bidding price is increased and the auction continues. **The auction ends when Total Auction Demand is less than or equal to Total Auction Supply.** The auction price and the number of licenses allocated to each firm are calculated as follows:

1. **If Total Auction Demand equals Total Auction Supply**
   - The auction price is the last bidding price.
   - The number of licenses allocated to each firm is equal to its last bidding quantity.
2. **If Total Auction Demand is less than Total Auction Supply**
   - The auction price is the next-to-last bidding price.
   - Excess supply* will be allocated in the order of the fastest bidders at the next-to-last bidding price. So the faster you bid, the higher the chance that you receive some allocation of the excess supply. (*Excess supply = Total Auction Supply - Total Auction Demand)
   - The total number of licenses allocated to each firm is equal to its bidding quantity at the last bidding price PLUS any allocation from the excess supply.

Please note that **until the auction ends, no licenses are allocated to any firms.** The only way for firms to initially obtain licenses is by participating in the auction.

License Trading Stage

The trading stage will last for **1 minute** in each sub period. On the screen (Figure 3), there will be different boxes to enable you to **trade a single license at a time**.

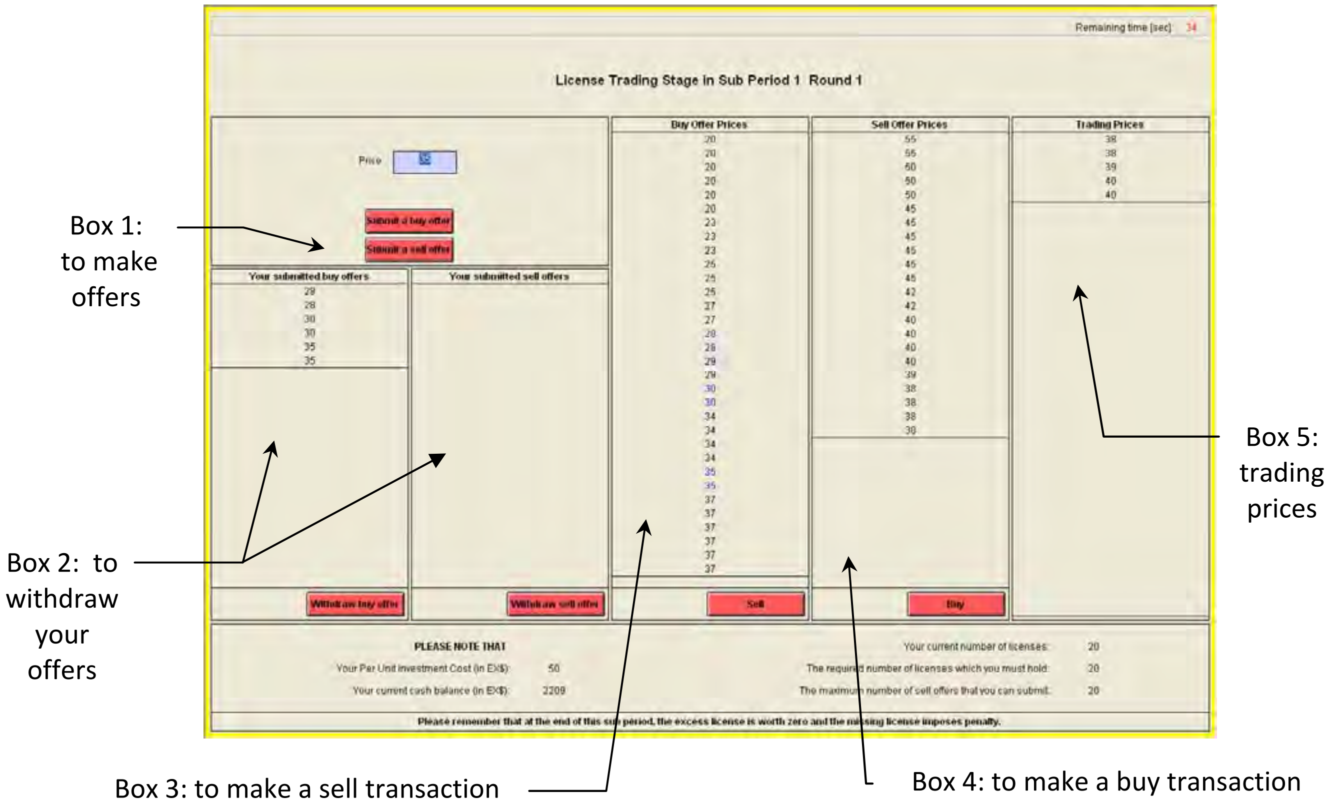

Figure 3. Screenshot for License Trading

1. **Box 1: to make a sell or a buy offer**
   A buy or a sell offer is a price signal that you give to other firms. Thus **no transaction is made yet when you submit an offer.**
   a. **To sell a license**
      Enter the price at which you are willing to sell and **click the "Submit a sell offer" button**. Your submitted offer is valid if:
      1) You actually hold a license. Y*ou can only submit one sell offer for each license*.
      2) The price you offer is less than or equal to the current lowest standing sell offer.
   b. **To buy a license**
      Enter the price at which you are willing to buy and **click the "Submit a buy offer" button**. Your submitted buy offer is valid if:
      1) You have a sufficient cash balance to purchase at the price you enter.
      2) The price you offer is greater than or equal to the current highest standing buy offer.

2. **Box 2: to withdraw your offers**
   This box **displays only those offers which are not yet traded** and allows you to withdraw those offers.

3. **Box 3 and Box 4: to trade (make a transaction)**.
   a. **Box 3: to make a sell transaction**
      From the **"Buy Offer Prices", select the price** at which you are willing to sell your license, and then **click the "Sell" button**. The Buy Offer Prices are sorted in an ascending order. Thus, higher and more recent prices are shown at the bottom of the list.
   b. **Box 4: to make a buy transaction**
      From the **"Sell Offer Prices**", **select the price** at which you are willing to buy, and then **click the "Buy" button**. The Sell Offer Prices are sorted in a descending order. Thus, lower and more recent prices are shown at the bottom of the list.

   In both boxes, your own offers are shown in blue font. You cannot accept your own offers.

4. **Box 5: to view trading prices**.
   The higher and more recent prices are shown at the bottom of the list.

Payment

Your cash balance will be automatically updated after each decision you make. Your cash balance at the end of Sub Period 1 will be added to your initial cash balance at the beginning of Sub Period 2. **At the end of Sub Period 2 of a round, your cash balance represents your "Earnings" of that round.** Your earnings are calculated as follows:

Earnings =
\+ Total Revenue
\+ cash balance of Sub Period 1 of the same round
– number of licenses bought in auction * auction price
– investment costs
– trading price of licenses bought during trading stage
\+ trading price of licenses sold during trading stage
– penalty costs

At the end of Task 2, you will be paid the value of your Cumulative Earnings.

Cumulative Earnings = Sum of "Earnings" from all rounds

Summary of Task 2

In each round you need to make decisions that will maximise your Earnings by <u>either</u>:
1. Making a technological investment, OR
2. Holding the required number of licenses

Please note that:
1. If you invest in a round, you will spend investment costs for both periods of that round. There are no additional benefits that you receive from investing.
2. If you hold more licenses than what is required, those licenses will worth zero by the end of a sub period.
3. If you have fewer licenses than what is required, you are penalised with a fee of EX$ 45/missing license.

Preliminary of Task 2

Before Task 2 starts, you will take a **short quiz** to assess your understanding of the task. You need to answer each question correctly in order to continue to the next question. You can enter answer more than once if necessary, until you arrive at the correct answer. After you complete the quiz, there will be **a Practice Round.** The earnings from this round will not be taken into account in your final payment. **The actual experiment will begin immediately following the Practice Round**.

Appendix 4 Demographic Survey

Session Date: ………/………/……… (dd/mm/yy)

Session Time: …………………… am / pm

Subject Number: …………………………

Please fill in your demographic details below. All information will be kept and treated with confidentiality.

(A) Birth: In what year were you born? ………………..

(B) Household Budget: Who in your household would you consider to be primarily in charge of expenses and budget decisions?

☐ self ☐ spouse ☐ parent ☐ other(specify) ☐ do not know

(C) Gender: What is your gender? ☐ male ☐ female

(D) Race: What is your ethnic background? ………………………………………………………………

(E) Marital Status: What is your marital status?

☐ single ☐ married ☐ divorced ☐ widowed ☐ other

(F) Employment: How would you best describe your current employment situation?

☐ student only ☐ work at university as a tutor/research assistant/casual employee

☐ full-time employment outside university

☐ part-time employment outside university ☐ other

(G) Household Income: Please indicate the category that best describes your household income from all sources before all taxes in 2008.

☐ 5,000 and under ☐ 5,001-15,000 ☐ 15,001-30,000 ☐ 30,001-45,000

☐ 45,001-60,000 ☐ 60,001-75,000, ☐ 75,001- 90,000 ☐90,001-100,000

☐ over 100,001.

(H) Number in Household: How many people are in your household? (Yourself and those who live with you and share your income and expenses) …………………...

(I) Own Income: Your own income from all sources before taxes in 2008. Do not include income from other household members.

☐ 5,000 and under ☐ 5,001-15,000 ☐ 15,001-30,000 ☐30,001-45,000

☐ 45,001-60,000 ☐ 60,001-75,000 ☐ 75,001- 90,000

☐ 90,001-100,000 ☐ over 100,001.

(J) Income Source: How do you receive your income?

☐ fixed source (salary) ☐ hourly rate ☐ loans/scholarships

☐parents ☐ other

(K) Student Status: What is your student status?

☐ full-time student ☐ part-time student

(L) Main field of study

What is your main field of study?

☐ Undergraduate programme ☐ Master's programme

☐ Other, specify: ……………………………………………………………….

In which area …………………………………………………………………

(M) Year in School: What year are you in the current semester?

☐ Year 1 ☐ Year 2 ☐ Year 3 ☐ Year 4 ☐ over year 4

(N) Tuition Source: Who is primarily responsible for your tuition and living expenses?

☐ self ☐ parent ☐ shared between self and parent

☐ scholarship/grant ☐ loans ☐ combination/other

(O) Vote Participation: Have you ever voted in an election? ☐ yes ☐ no

(P) Social Activity: What club or extracurricular activity that you are part of? (more than one answers is allowed)

☐ sports ☐ culture, music, art ☐ advocacy/political groups

☐ university/faculty/school student organisation ☐ environment ☐ other

(Q) Country background: Please state the country where you were raised.

……..…………………………………………………………