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Theoretical and Empirical Essays on the Effects of Proposed and Existing Environmental Policies

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I am submitting herewith a dissertation written by Luke Robert Jones entitled "Theoretical and Empirical Essays on the Effects of Proposed and Existing Environmental Policies." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

Christian A. Vossler, Major Professor

We have read this dissertation and recommend its acceptance:

Michael Price, Mohammed Mohsin, Christopher Clark

Accepted for the Council:
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Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Theoretical and Empirical Essays on the Effects of Proposed and Existing Environmental Policies

A Dissertation Presented for the Doctor of Philosophy Degree
The University of Tennessee, Knoxville

Luke Robert Jones
December 2011

DEDICATION

To my father

Mark Jones

and my grandmother

Roberta Jones

ACKNOWLEDGEMENTS

First, I would like to express my deep thanks to my advisor, Christian Vossler. He has been extremely generous in supporting my development and guiding my dissertation. He has been patient, reliable, thorough, enthusiastic, and challenging. I am extremely thankful for the opportunities I have had to work with him and for him. His work ethic and professionalism and the pride he takes in his work are inspiring to me. I am immensely grateful to be his first PhD student and to have him as a mentor. To the other members of my committee, thanks to Michael Price for his input and for career-related advice and guidance over the last year, and to Christopher Clark and Mohammed Mohsin for their feedback and overall support. I would also like to thank Chris Cherry, to whom I am indebted for providing me opportunities that shaped both my dissertation and my graduate career, including two separate research trips to Asia. I would like to thank Jill Caviglia-Harris for being a long-standing mentor, from encouraging me to pursue economics in undergrad, to calling me the day before my defense to offer encouragement. I want to thank Todd Cherry, Stephen Cotten, Mary Evans, and Mike McKee, from whom I have received much advice and knowledge, and benefited greatly. I want to thank Mark Burton for providing me with a research assistantship at the Transportation Research Center and for connecting me with rewarding projects, and I want to thank Ken Baker for the knowledge I gained from him as his teaching assistant. I also wish to thank the Head of the Department of Economics, Robert Bohm, and the Graduate Directors during my tenure, Matthew Murray and Don Bruce. Thanks to Cristina Reiser and Stephen Ogden who were always up for lunch and coffee. Thanks to all the faculty, staff and fellow graduate students that made the economics department such a friendly place. Finally, for their unfailing love, support and encouragement, thank you to my father Mark, my grandmother Roberta, my sisters Kristin and Jamie, my aunt Deborah, and my great aunts Elizabeth and Willene.

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ABSTRACT

This dissertation consists of three chapters that explore environmental policy. Chapter 1 empirically investigates the potential for incentives to encourage the adoption of low-emission alternatives to gasoline motorcycles. Hanoi, Vietnam, like many Asian cities, is experiencing rapid growth in the ownership of personal gasoline-powered motorcycles and scooters, and along with this heightened air quality issues. Electric scooters have the potential to reduce air pollution as an alternative to gasoline-powered motorcycles; however, electric scooters have yet to penetrate the Vietnamese and other large Asian markets. This study uses a choice experiment survey to elicit the demand for electric scooters, with focus on the effects that economic incentives and technology improvements have on adoption.

Chapter 2 takes the first steps toward incorporating point sources into the theoretical discussion on nonpoint pollution ambient taxes. Previous investigations into the use of ambient taxes for nonpoint source pollution have not addressed the role of point sources, even though many watersheds have both source types. This paper examines the use of taxes for jointly regulating point and nonpoint sources. A model of point-nonpoint pollution is developed, and within this framework taxes are applied to achieve different regulatory objectives, including implementing optimal emissions reductions, as well as meeting exogenously specified environmental goals at least cost. Discussion centers on comparison of the point and nonpoint taxes in each scenario.

Chapter 3 is an experimental economics examination of the design of markets for water quality trading. Water quality trading is endorsed by policymakers as a tool for

reducing pollution in watersheds in a cost-effective manner, and many watersheds in the U.S. have established water quality trading programs. As a whole, these programs have not been successful. It is hypothesized that common features of these programs, such as the market institutions in place, may contribute to the limited success. As a first step in empirically investigating water quality trading markets, this study uses laboratory experiments to isolate how different institutions affect economic efficiency. In particular, we compare cap-and-trade, two forms of baseline-and-credit institution, and a tax/subsidy regulation, and examine the effect of introducing fixed technology costs with these four institutions.

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CHAPTER 1 : ESTIMATING THE EFFECT OF INCENTIVES ON THE ADOPTION OF ELECTRIC SCOOTERS: A STATED CHOICE EXPERIMENT IN VIETNAM

1.1 Introduction

A growing body of research examines the effectiveness of economic incentives for adopting cleaner and more energy efficient vehicles. The majority of this work almost exclusively focuses on the potential for alternatives to gasoline-powered cars, such as electric, alternative fuel, and hybrid vehicles. Consequently, findings from the literature are less applicable in areas where private motorized transportation is dominated by motorcycles. This is certainly the case in much of the developing world and especially in developing Asia.

Fueled by rising incomes, a greater demand for personal mobility, and congested roadways, Asia's motorcycle population is the largest in the world and growing rapidly. As a result many developing Asian cities are experiencing shifts from relatively low-emitting transportation modes such as walking, cycling, and public transportation to motorcycles. In seven Asian countries (including China and India), motorcycle ownership has grown by more than 10% annually from 1989-2002 (Meszler 2007).

In these highly motorizing countries, the relevant alternatives to examine are low-emitting motorized two-wheelers. Electric scooters (e-scooters) are two-wheeled motorized vehicles that are similar to gasoline-powered motorcycles, but have zero local tailpipe emissions, operate solely on battery power, and are recharged by plugging in at home or work rather than refilled at a gasoline station. They are a leading technology to emerge among low-emitting motorcycle alternatives in Asia. E-scooters offer potentially large benefits in the forms of urban air pollution reductions and energy efficiency gains. However, like demand for their car-counterparts, demand for e-scooters has been slow to develop.[1] We are aware of no other studies that examine the effect of incentives on the adoption of low-emitting motorcycle alternatives. In this study, we use a choice experiment survey of Hanoi, Vietnam residents to estimate e-scooter demand and explicitly estimate the effect of economic incentives and technological improvements on the demand for e-scooters.

Hanoi's motorcycle population is one of the fastest growing in the world and a major contributor to Hanoi's urban air quality impairment, making Hanoi a prime location for examining the potential for e-scooters. In 2005, Hanoi had 1.5 million registered motorcycles for a population of three million people, and the number of motorcycles has been growing at an average annual rate of about 15 percent (Meszler 2007; Tuan and Shimizu 2005). Motorcycles comprised about 65 percent of the city's vehicular trips in 2005 (World Bank 2006) and have the largest share of vehicle emissions at 43 percent of particulate matter and more than 54 percent of carbon monoxide and hydrocarbons (World Bank 2008).

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[1] China has been a remarkable exception. In the past decade in China, a massive transportation mode switch has seen the Chinese e-bicycle and e-scooter market grow from 40,000 produced in 1998 to over 20 million produced in 2009 (Jamerson and Benjamin 2005). It is estimated that there are 40-50 million electric two-wheelers in China now. This dramatic transition was driven by China's burgeoning demand for personal mobility, historic reliance on two-wheeled vehicles, and government restrictions on the use of competing gasoline-powered motorcycles (Weinert, Ma et al. 2007).

The impact that Hanoi's motorcycles have on its air quality is indicative of the threat motorcycles pose throughout developing Asia. According to the most recent estimates by the World Health Organization, developing Asian countries accounted for about half of approximately one million worldwide annual deaths attributable to urban air pollution in 2004 (World Health Organization 2009), and the growth in the Asian motorcycle population is expected to have a significant impact on worsening this problem. Unlike cars, many of the motorcycles being driven in Asian cities lack sophisticated exhaust treatments, so their emission rates of conventional local air pollutants such as particulate matter (PM), volatile organic compounds (VOC) and carbon monoxide (CO) are quite high.

While there are some e-scooters in Hanoi very few consumers are actually adopting this mode. Given the low adoption rates and our objective to identify the effects of economic incentive and technology improvements that are beyond the scope of existing data, we rely on using a stated preference survey. Stated-preference methods are frequently used in marketing for forecasting new product demand (Louviere and Hensher 1983), and are especially valuable when market data are limited or when evaluating proposed policies, both of which our true in our case. For these same reasons, stated preference surveys have been the primary means of investigating the demand for electric, hybrid and alternative fuel cars (Brownstone and Train 1999; Bunch et al. 1993; Calfee 1985; Dagsvik and et al. 2002; Ewing and Sarigollu 1998; Ewing and Sarigollu 2000; Hensher 1982; Potoglou and Kanaroglou 2007). To the best of our knowledge, the study by Chiu and Tzeng (1999) represents the only stated preference study that examines the demand for e-scooters. In particular, they conduct a survey in Taiwan to evaluate the choice between a large-engine motorcycle, a small-engine motorcycle, and an e-scooter based on a number of vehicle attributes; however, the effects of economic incentive instruments were not explicitly considered.

We use the data from our stated choice experiment to estimate the parameters of a mixed logit model. We find that sales tax incentives have a strong effect on mode choice. These results are consistent with studies on incentives for electric, hybrid and alternative fuel cars that show sales tax incentives to be one of the most powerful tools for stimulating adoption. Stated choice experiments by Ewing and Sarigollu (2000) and Potoglou and Kanaroglou (2007) find that sales tax incentives have a strong effect on vehicle purchase decisions relative to other incentives such as exemption from road access fees and parking fees and access to HOV lanes. Recent work that analyzes data on actual sales of hybrid cars reaches similar conclusions about the significant impact of sales tax incentives on vehicle purchasing decisions (Chandra et al. 2010; Gallagher and Muehlegger 2011). While our results complement these findings, they also expand on them by demonstrating the significance of sales tax incentives for the purchase decision of motorized two-wheelers.

We reject the hypothesis that the effect of a sales tax change on vehicle choice is equivalent to the effect of an equal change in the purchase price of a vehicle, finding that the effect of sales tax is significantly greater than that of purchase price. Related findings have been obtained from surveys that examine the influence of payment vehicle on the valuation of public goods.[2] A stated preference study by Morrison et al. (2000) finds that willingness to pay (WTP) for a project differs based on whether it is funded by increases in income taxes versus increases in water rates. A stated preference study by Bergstrom et al. (2004) and stated choice experiments by Swallow and McGonagle (2006) and Nunes and Travisi (2009) all find higher WTP under budget reallocation as opposed to the introduction of a new tax. While these studies regard the funding of public projects: a groundwater drainage pipe (Morrison et al. 2000); ground water quality protection (Bergstrom et al. 2004); costal land conservation (Swallow and McGonagle 2006); and a rail noise abatement program (Nunes and Travisi 2009), ours regards the purchase of a private good. In a paper more closely related to our own, Gallagher and Muehlegger (2011) analyze actual sales data and find that the effect of a sales tax waiver on hybrid car sales is ten times larger than the effect of an income tax credit of the same amount.

The summarized findings demonstrate that the way in which a good is paid for matters, either in peoples' stated values, their actual values, or in both, although it is perhaps more surprising to find the divergence between the effects of purchase price and sales tax than to find a difference between alternative payment vehicles, or in the case of Gallagher and Muehlegger (2011), alternative incentives. In our experiment, we essentially have a hybrid payment vehicle that consists of the purchase price and sales tax. What we observe is consumers responding disproportionately to the components of that hybrid payment vehicle even though those components enter the final price in an

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[2] In stated preference surveys the payment vehicle refers to the mechanism that will finance a public project. For example, conservation of an environmental resource might be funded by an increase in sales tax, income tax, rates, or entry fees, by a reallocation of budget, by voluntary contributions, etc.

identical way. The observation leads to natural questions about the reasons for this difference in the effects of purchase price and sales tax and the implications for researchers and policymakers, which we discuss in the conclusion.

The remainder of the paper is organized as follows. Section 1.2 describes the choice experiment; Section 1.3 describes the survey and data collection process; Section 1.4 specifies the mixed logit model; Section 1.5 presents model estimation; Section 1.6 presents marginal willingness to pay estimates; Section 1.7 examines the effect of various sales tax scenarios on the e-scooter market share; Section 1.8 calculates implicit discount rates for operating cost and maintenance cost savings; and Section 1.9 concludes.

1.2 The Choice Experiment

We designed the choice experiment in order to evaluate factors that affect the purchase choice of a two-wheeled motorized vehicle. We presented respondents with information on the levels of nine vehicle-related attributes for three choice alternatives: an e-scooter, a standard gasoline motorcycle, and a large gasoline motorcycle.[3] Characterizing these vehicles in terms of nine attributes meant that the experiment did not include all of the attributes hypothesized to be important to the purchase decision; however, limiting the number of attributes in a choice experiment is necessary in order to limit the cognitive burden placed on respondents. In an attempt to control for the

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[3] We define standard and large gasoline motorcycles as those with engine displacement around 100cc and 250cc, respectively.

omission of relevant variables, we instructed respondents to assume that all omitted attributes were identical across alternatives.

The choice experiment included the following attributes: purchase price; range; refuel/recharge time; operating cost; maintenance cost; acceleration; speed; license requirement; and sales tax. We based the selection of these attributes on discussions with Vietnamese riders and consultation with experts at Hanoi University of Transport and Communications, as well as a review of results from stated preference studies on the demand for motorcycles and e-scooters (Chiu and Tzeng 1999; Tuan and Shimizu 2005). The levels of the attributes reflect the existing technologies, costs and policies in Hanoi in 2008, as well as potential advancements in e-scooter technology and alternative economic and policy scenarios.

At the time of the survey the sales tax rate on gasoline motorcycles and e-scooters was 10% of the purchase price. Gasoline motorcycle riders required a driver's license, while e-scooter riders did not. We obtained vehicle performance information for gasoline and e-scooters from literature (Cherry and He 2010), pre-survey GPS-based vehicle performance (speed and acceleration) studies and advertised ranges of various vehicle types. We estimated operating costs based on advertised and measured fuel economy (Cherry et al. 2009; Meszler 2007) and fuel cost rates (VND 20,000/liter gasoline, VND 1,200/kWh electricity) at the time of the survey.[4] We estimated maintenance cost attributes through surveys of routine maintenance for motorcycles (i.e. oil changes and routine part replacement) and from the cost of replacement batteries for e-scooters (based

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[4] VND – Vietnamese dong. 16,500 VND/USD (July 2008).

on 2007 prices for lead acid and lithium ion batteries in-use on e-scooters in China) (Weinert, Burke et al. 2007). Table 1.1 shows the levels for each experimental attribute.

Given the information on the levels of the attributes for the three alternatives, respondents indicated the vehicle they would prefer to purchase.[5] Figure 1.1 presents an example of a choice question from the survey. Different choice questions reflect different combinations of attribute levels for the three alternatives. The full factorial

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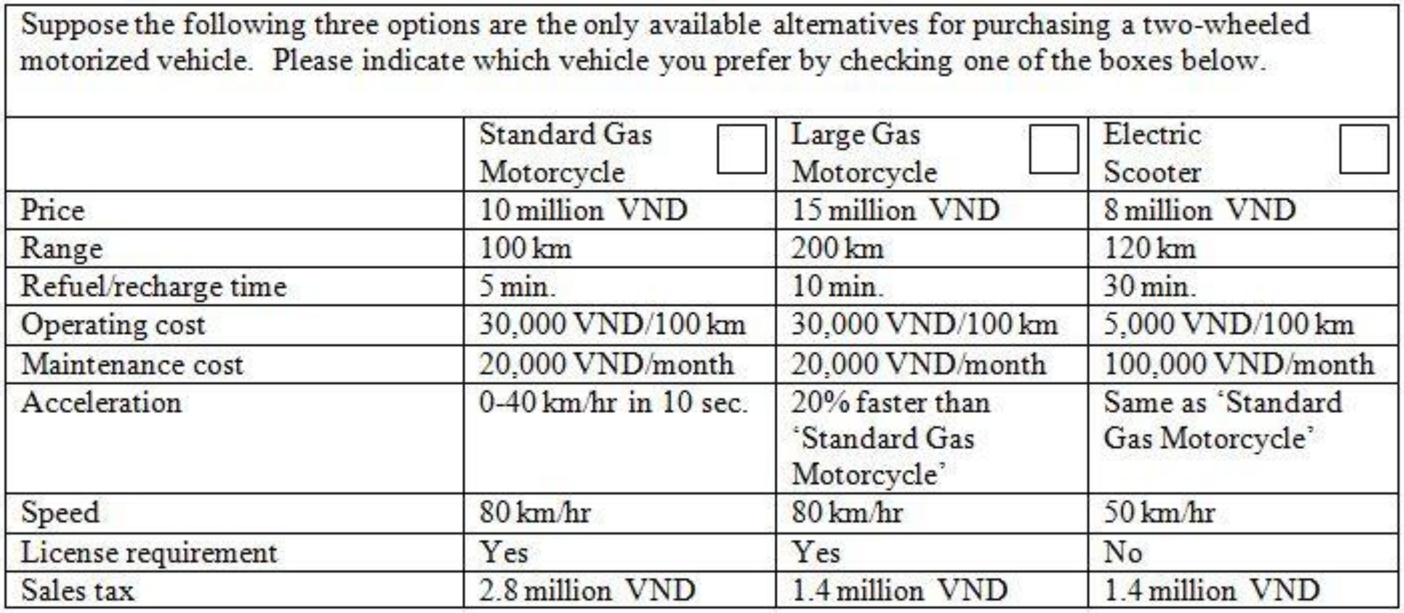
[5] A "no purchase" option was not included in the choice set. This decision was based on a filter question in the survey which indicated that a large proportion of the sample planned to purchase a two-wheeled motorized vehicle in the next 5 years, and was therefore considered to be in the market.

Table 1.1 Levels of experimental attributes

Attribute	Standard Gas Motorcycle	Large Gas Motorcycle	Electric Scooter
Price (millions of VND)	10	10, 15, 30	8, 12, 16
Range (km)	100	200	60, 120, 200
Refuel/recharge time (min.)	5	10	10, 15, 30, 360
Operating cost (VND/100 km)	30000	20000, 30000, 40000	2500, 5000, 7500
Maintenance cost (VND/month)	20000	20000	70000, 100000, 140000
Acceleration	0-40 km/hr in 10 sec.	– 20%, 0%, + 20%	– 20%, 0%, + 20%
Speed (km/hr)	80	60, 80, 100	40, 50, 60
License requirement	Yes	Yes	Yes, No
Sales tax (millions of VND)	0, 1.4, 2.8	0, 1.4, 2.8	0, 1.4, 2.8

(1) VND – Vietnamese dong. 16,500 VND/USD (July 2008).



Suppose the following three options are the only available alternatives for purchasing a two-wheeled motorized vehicle. Please indicate which vehicle you prefer by checking one of the boxes below.

	Standard Gas Motorcycle ☐	Large Gas Motorcycle ☐	Electric Scooter ☐
Price	10 million VND	15 million VND	8 million VND
Range	100 km	200 km	120 km
Refuel/recharge time	5 min.	10 min.	30 min.
Operating cost	30,000 VND/100 km	30,000 VND/100 km	5,000 VND/100 km
Maintenance cost	20,000 VND/month	20,000 VND/month	100,000 VND/month
Acceleration	0-40 km/hr in 10 sec.	20% faster than 'Standard Gas Motorcycle'	Same as 'Standard Gas Motorcycle'
Speed	80 km/hr	80 km/hr	50 km/hr
License requirement	Yes	Yes	No
Sales tax	2.8 million VND	1.4 million VND	1.4 million VND

Figure 1.1 Sample choice question

design including all combinations of attribute levels consists of $3^{13}*2*4$ unique choice questions. In order to obtain a manageable number of choice questions we used %mktex in SAS to generate an orthogonal (100% D-efficiency) main effects design consisting of seventy-two choice questions, which we then divided into twelve blocks of six using %mktblock. We presented each respondent with one block (i.e., each respondent faced six choice questions).

1.3 The Survey

We administered the survey to households in Hanoi City in July 2008. In order to obtain a sample we stratified the city by 14 districts and sampled randomly within each stratum.[6] We randomly distributed survey versions among a team of interviewers from Hanoi University of Transport and Communications who then administered the survey through in-person interviews conducted with a representative from each household. The interviewers presented each respondent with a small gift for participating in the survey, and fewer than five percent of visited households refused to participate. We surveyed a total of 400 households, yielding 2400 cases (i.e. 400 respondents*6 choice questions per respondent = 2400 cases).

The survey consists of three sections, which the interviewers administered sequentially as follows. In the first section, the interviewer provided the respondent, according to a script, an overview of the survey and description of an e-scooter,

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[6] The sampling scheme was based on Nguyen (2007).

instructions for the choice questions and an example of a choice question. In the second section respondents answered the six choice questions. The final section gathered information on socioeconomic and demographic characteristics, and on household motorcycle ownership, use, and purchase plans. Table 1.2 presents characteristics of the sampled households.

1.4 Model Specification

We estimated respondent preferences through mixed logit models, which accommodate preference heterogeneity by allowing some of the parameters for the observed attributes to be randomly distributed across individuals. Often cited advantages of the mixed logit model are that it allows for correlation and heteroskedasticity across alternatives, and relaxes the independence from irrelevant alternatives assumption of the standard conditional logit model (Brownstone and Train 1999; Hensher and Greene 2003; Revelt and Train 1998; Train 1998).

Let the utility for individual *i* associated with alternative *j* be written as:

$$U_{i,j} = \alpha_1 * escooter_j + \alpha_2 * lrg\ moto_j + \boldsymbol{\beta}'\boldsymbol{x}_{\boldsymbol{i,j}} + \boldsymbol{\delta}'\boldsymbol{z}_{\boldsymbol{i,j}} + \boldsymbol{\sigma}'\boldsymbol{\nu}_{\boldsymbol{i}}\boldsymbol{l}_{\boldsymbol{i,j}} + \varepsilon_{i,j} \tag{1.1}$$

The variables $escooter_j$ and $lrg\ moto_j$ are indicator variables for the e-scooter and large motorcycle, respectively, and α_1 and α_2 are associated alternative-specific constants (standard motorcycle is omitted); $\boldsymbol{x}_{\boldsymbol{i,j}}$ is a vector of the attributes in Table 1.1, and $\boldsymbol{z}_{\boldsymbol{i,j}}$ is a vector of interactions between individual-specific characteristics and the e-scooter indicator variable; $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are parameter vectors associated with $\boldsymbol{x}_{\boldsymbol{i,j}}$ and $\boldsymbol{z}_{\boldsymbol{i,j}}$,

Table 1.2 Characteristics of the sampled households

Variable	Mean or percent
Gender of respondent (n=395)	
Percent female	45.82
Age of respondent (years) (n=381)	41.33
Education of respondent (n=382)	
Percent high school or lower	61.26
Percent bachelor’s degree	34.82
Percent graduate degree	3.93
Household size (members) (n=397)	4.07
Household vehicles (number owned) (n=400)	
Total vehicles	2.70
Motorcycles	1.88
Bicycles	0.71
Cars	0.08
E-scooters	0.04
Trucks	0.01
Household income (millions VND/month) (n=399)	
Percent < 3	16.79
Percent 3-6	40.35
Percent 6-9	23.56
Percent 9-20	16.04
Percent > 20	3.26

(1) Total number of households interviewed = 400.

(2) n is the number of households responding to each item.

respectively; $\boldsymbol{\nu_i}$ is a vector of normal random variables for individual *i* with mean $\mathbf{0}$ and covariance matrix **I**; $\boldsymbol{l_{i,j}}$ is a subvector of $\boldsymbol{x_{i,j}}$ containing attributes whose parameters are specified as random; and $\boldsymbol{\sigma}$ is a vector of standard deviations of the random parameters; $\varepsilon_{i,j}$ is a mean zero random term distributed i.i.d. Type I extreme value.

Denote the deterministic component of (1.1) as:

$$V_{i,j} = \alpha_1 * escooter_j + \alpha_2 * lrg\ moto_j + \boldsymbol{\beta}'\boldsymbol{x_{i,j}} + \boldsymbol{\delta}'\boldsymbol{z_{i,j}} \tag{1.2}$$

Then following Greene's (2002) exposition, the probability that individual *i* chooses alternative *j* conditional on $\boldsymbol{\nu_i}$ is formulated as:

$$P(j|\boldsymbol{\nu_i}) = \frac{e^{V_{i,j}+\boldsymbol{\sigma}'\boldsymbol{\nu_i}\boldsymbol{l_{i,j}}}}{\sum_{m=1}^{3} e^{V_{i,m}+\boldsymbol{\sigma}'\boldsymbol{\nu_i}\boldsymbol{l_{i,m}}}} \tag{1.3}$$

The vector of normal random variables, $\boldsymbol{\nu_i}$, represents unobserved randomly distributed heterogeneity in preferences for the attributes in $\boldsymbol{l_{i,j}}$. Because $\boldsymbol{\nu_i}$ is unobservable, it must be integrated out in order to obtain the unconditional probability, which is:

$$P(j) = \int P(j|\boldsymbol{\nu_i}) f(\boldsymbol{\nu_i})\, d\boldsymbol{\nu_i} \tag{1.4}$$

where $f(\boldsymbol{\nu_i})$ denotes the density of $\boldsymbol{\nu_i}$. Since (1.4) does not have a closed form, this probability is simulated by calculating (1.3) for *R* draws of $\boldsymbol{\nu_i}$, where each draw of $\boldsymbol{\nu_i}$ is denoted $\boldsymbol{\nu_{i,r}}$, and then averaging these *R* conditional probabilities. Writing the simulated probability of each individual's observed choice as:

$$\hat{P}(j)_i = \frac{1}{R}\sum_{r=1}^{R} \frac{e^{V_{i,j}+\boldsymbol{\sigma}'\boldsymbol{\nu_{i,r}}\boldsymbol{l_{i,j}}}}{\sum_{m=1}^{3} e^{V_{i,m}+\boldsymbol{\sigma}'\boldsymbol{\nu_{i,r}}\boldsymbol{l_{i,m}}}} \tag{1.5}$$

the simulated log-likelihood is given by:

$$\log L_S = \sum_{i=1}^{N} \log \hat{P}(j)_i \tag{1.6}$$

The estimation of the model parameters is executed by maximizing (1.6) with respect to α_1, α_2, $\boldsymbol{\beta}$, $\boldsymbol{\delta}$, and $\boldsymbol{\sigma}$.

In order to specify the random parameters, we began by estimating a model in which we allowed all parameters to be random except for the parameter on price.[7] We then tested down from this model using Wald tests for joint significance of the estimated standard deviations. Based on this testing, we held constant the parameters on range, refuel/recharge time, maintenance cost, and faster acceleration (in addition to the parameter on price) in the final specification.[8]

Out of 2400 cases obtained by our household survey, 2236 cases did not have missing values for the specified model, and we used these cases in the estimation. Table 1.3 presents descriptions of the explanatory variables. We effects coded the attributes acceleration and license requirement, and treated all other attributes from Table 1.1 as continuous variables. Effects coding of acceleration resulted in two variables, one to indicate 20% faster acceleration than a standard motorcycle, and one to indicate 20% slower acceleration than a standard motorcycle. We scaled operating cost and maintenance cost to thousands of VND/100 km and tens of thousands of VND/month, respectively. We constructed sampling weights for each stratum and included these in the estimation. We accounted for correlation across the six choice scenarios faced by an

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[7] Assuming a fixed price coefficient has been a common practice in the estimation of random utility models, as allowing a random price coefficient can lead to identification issues and unrealistic marginal willingness to pay distributions (Scarpa et al. 2008).

[8] Estimating the model in which all parameters are random except for price, a Wald test of the hypothesis that the estimated standard deviations of the parameters on range, refuel/recharge time, maintenance cost, and faster acceleration are jointly equal to zero has $p = 0.272$.

Table 1.3 Description of explanatory variables

Variable	Description	Random Parameter
Price	Purchase price of the vehicle (millions of VND)	
Range	Distance that can be traveled on a full tank of gasoline or a full charge (km)	
Refuel/recharge time	Time required to refill an empty gasoline tank or to recharge a battery from zero charge (min.)	
Operating cost	Direct cost of fuel or electricity for operation of the vehicle (Thousands of VND/100 km)	X
Maintenance cost	Direct cost of routine maintenance (Tens of thousands of VND/month)	
Faster acceleration	20% faster than a standard motorcycle’s acceleration	
Slower acceleration	20% slower than a standard motorcycle’s acceleration	X
Speed	Top speed of the vehicle (km/hr)	X
License requirement	= 1 if a license if required to legally operate the vehicle, -1 otherwise	X
Sales tax	Sales tax paid in addition to purchase price (millions of VND)	X
Escooter	= 1 if the vehicle is an e-scooter, 0 otherwise	X
Lrg moto	= 1 if the vehicle is a large motorcycle, 0 otherwise	X
Income x Escooter	= household income in millions of VND/month if Escoot = 1, 0 otherwise	
College x Escooter	=1 if the respondent has a college degree and Escoot = 1, 0 otherwise	
Female x Escooter	=1 if the respondent is female and Escoot = 1, 0 otherwise	

(1) Acceleration of the standard motorcycle presented in the choice experiment was 0-40 km/hr in 10 sec. Faster acceleration and slower acceleration are interpreted relative to this omitted category.

(2) X indicates a random parameter was specified for the associated variable

individual by holding the vector of random draws the same across choice scenarios for a given respondent. Finally, we estimated the model using 1000 Halton draws, and computed heteroskedasticity-robust standard errors to account for noise introduced through the simulations.

1.5 Estimation

Table 1.4 presents results from estimation of the model. All of the coefficients for the attributes in Table 1.1 are of the expected signs. An increase in price, refueling/recharging time, operating cost, maintenance cost, or sales tax, having slower acceleration than a standard gas motorcycle, or having a license requirement, negatively affects the relative utility associated with a vehicle. An increase in range or speed, or having faster acceleration than a standard gas motorcycle has a positive effect. The effects of price, refueling/recharging time, operating cost, maintenance cost, faster acceleration, slower acceleration, speed, and sales tax, are all significant at the 1% level, while the effect of a license requirement is significant at the 10% level. Negative signs for the e-scooter and large motorcycle alternative-specific constants indicate that all else equal, these vehicles are associated with lower utility than a standard motorcycle; however, only the alternative-specific constant for the large motorcycle is significantly different from zero.

The estimated standard deviations of the random parameters for the e-scooter and large motorcycle alternative-specific constants, operating cost, and sales tax, are

Table 1.4 Mixed logit model

	Estimate	Std. err.	*p*-value
Variable			
Price	-0.165	0.016	0.000
Range	0.004	0.001	0.001
Refuel/recharge time	-0.002	0.000	0.000
Operating cost	-0.031	0.009	0.001
Maintenance cost	-0.062	0.020	0.002
Faster acceleration	0.228	0.068	0.001
Slower acceleration	-0.243	0.070	0.001
Speed	0.017	0.003	0.000
License requirement	-0.120	0.065	0.064
Sales tax	-0.271	0.039	0.000
Escooter	-0.357	0.352	0.311
Lrg moto	-0.467	0.199	0.019
Income x Escooter	-0.042	0.028	0.142
College x Escooter	0.497	0.249	0.046
Female x Escooter	0.250	0.207	0.228
Std. dev. Of random parameter			
Operating cost	0.028	0.010	0.004
Slower acceleration	0.245	0.147	0.096
Speed	0.012	0.008	0.130
License requirement	0.223	0.128	0.081
Sales tax	0.308	0.069	0.000
Escooter	0.863	0.262	0.001
Lrg moto	2.576	0.239	0.000
Model statistics			
N	2236		
Log-likelihood at start values	-2242.447		
Log-likelihood at convergence	-1964.631		
McFadden pseudo R^2	0.200		

significant at the 1% level, indicating significant heterogeneity in preferences for these attributes. The standard deviations of the random parameters for slower acceleration and license requirement are marginally significant, while the standard deviation of the speed coefficient is not significant. Overall, a Wald test rejects the hypothesis that the estimated standard deviations of the random parameters are jointly equal to zero at the 1% level ($p < 0.001$).

Turning to the preference heterogeneity modeled through interactions between individual-specific characteristics and the e-scooter alternative-specific constant, we find that the directions of the effects are as anticipated: an increase in household income is associated with a decrease in the relative utility derived from an e-scooter, although the effect is not statistically significant; the relative utility of e-scooter purchase is higher for those with a college degree compared with those without a college degree, statistically significant at the 5% level; and females associate higher relative utility with e-scooters than males, although this effect is not statistically significant. The effect of college is consistent with findings in other stated-choice experiments on electric vehicles Chiu and Tzeng (1999) found that a college degree had a significant positive effect on the purchase of an electric two-wheeler, and Brownstone and Train (1999) found that having some college had a significant positive effect on purchasing an electric car.

1.6 Marginal Willingness to Pay Estimates and Tax Effects

In order to provide meaningful interpretations of the estimated parameters, we calculated marginal willingness to pay (MWTP) estimates. Given an additively separable indirect utility function, the estimated parameters represent marginal utilities. The coefficient on price can thus be interpreted as the marginal utility of income. Multiplying another attribute's coefficient by the negative inverse of the price coefficient yields the marginal rate of substitution between that attribute and the price, i.e. the MWTP for that attribute (Holmes and Adamowicz 2003). Following this procedure and using the parameter estimates from the mixed logit model, we computed the MWTP and standard errors based on the delta method for selected attributes and present these in Table 1.5. The MWTP for the sales tax is -1.64 million VND, indicating a difference in the effects of price and sales tax on the purchase decision. The purchase price of a vehicle would have to be reduced by 1.64 million VND in order for a respondent to incur a one million VND increase in sales tax and have her utility remain unchanged; or a respondent would be willing to pay 1.64 million VND extra on the price of a vehicle, in order to avoid a one million VND increase in the sales tax. We performed a Wald test (Table 1.5) to examine whether this difference between the sales tax and price coefficients is significantly different from zero. We reject the hypothesis of equality between the price and sales tax coefficients at the 1% level, indicating that the sales tax has a significantly stronger effect on the purchase of a two-wheeler than does the price of the vehicle, a that result we discuss further in the conclusion.

In order to investigate the effect of sales tax on the e-scooter market share relative to other attributes, we extended the analysis by calculating marginal rates of substitution between the other attributes and the sales tax. For each attribute, we then used the marginal rate of substitution to equate a decrease in e-scooter sales tax with a change in the attribute in terms of the effect on the e-scooter market share. For the attributes that we

Table 1.5 Marginal willingness to pay estimates

	Estimate (millions VND)	Std. err.	*p*-value
Attribute			
Range	0.022	0.006	0.001
Refuel/recharge time	-0.009	0.003	0.001
Operating cost	-0.187	0.055	0.001
Maintenance cost	-0.375	0.121	0.002
Faster acceleration	1.376	0.422	0.001
Slower acceleration	-1.469	0.429	0.001
Speed	0.100	0.018	0.000
License requirement	-0.727	0.396	0.066
Sales tax	-1.640	0.255	0.000
Income x Escooter	-0.253	0.176	0.150
College x Escooter	3.004	1.505	0.046
Female x Escooter	1.510	1.245	0.225
Sales tax versus price			
$\beta_{\text{Sales Tax}} - \beta_{\text{Price}}$	-0.106	0.039	0.007

treated as continuous, we determined the change in each attribute that would yield an equivalent change in the e-scooter market share as would eliminating the e-scooter sales tax. Taking the price of the e-scooter as 12 million VND (the midpoint of the range of e-scooter prices used in the experiment) and using the 10% sales tax rate that prevailed in 2008, eliminating the e-scooter sales tax implies a reduction in sales tax of 1.2 million VND. Thus, for each continuous attribute we calculated the equivalent of a 1.2 million VND decrease in e-scooter sales tax.

For categorical variables acceleration and license requirement, we calculated the sales tax change that would yield the same change in e-scooter market share as a discrete change in the attribute. In Hanoi in 2008, the status quo was that e-scooters had about 20% slower acceleration than standard gasoline motorcycles, so using this as our baseline we calculated the sales tax decrease that would have an equivalent effect on e-scooter demand as putting the e-scooter on par with the standard motorcycle in terms of acceleration. For license requirement, since e-scooters did not require a license, we examined the sales tax increase on e-scooters that would generate the same reduction in the e-scooter market share as implementing an e-scooter license requirement. These comparisons are reported in Table 1.6.

Examining these comparisons, we see that eliminating the e-scooter sales tax of 1.2 million VND would generate the same increase in e-scooter market share as would increasing the e-scooter range by about 90 km, reducing its recharge time by about 3.5 hours, reducing its operating cost by about 10500 VND/100 km, reducing its monthly maintenance cost by about 52500 VND, or increasing its speed by about 20 km/hr. Increasing the e-scooter acceleration from 20% slower than a standard motorcycle to the

Table 1.6 Equivalencies in terms of effect on e-scooter market share

Attribute	Change in e-scooter attribute	Equivalent change in e-scooter sales tax
Range (km)	+90.4	–1.2 million VND
Refuel/recharge time (min.)	–208.2	–1.2 million VND
Operating cost (VND/100 km)	–10534.1	–1.2 million VND
Maintenance cost (VND/month)	–52455.6	–1.2 million VND
Acceleration	20% slower than standard motorcycle to the same as standard motorcycle	–0.9 million VND
Speed (km/hr)	+19.7	–1.2 million VND
License requirement	no license required to license required	+0.4 million VND

same as a standard motorcycle would yield the same increase in e-scooter market share as would a sales tax decrease of about 0.9 million VND, while requiring an e-scooter license would cause a decrease in e-scooter market share equivalent to that caused by an approximate sales tax increase of 0.4 million VND.

While these comparisons demonstrate the individual tradeoffs between e-scooter sales tax and unilateral changes in the other e-scooter attributes in terms of effects on e-scooter market share, from a policy perspective they do not capture the entire picture. Eliminating the e-scooter sales tax is only part of a policy to encourage adoption of e-scooters, as in addition to eliminating the e-scooter sales tax, the sales tax rates on gasoline motorcycles could be increased. Furthermore, unilateral changes in the other e-scooter attributes are unlikely. For example, reductions in recharging time, increases in range, and improvements in speed and acceleration are likely to occur simultaneously as technology improves and are likely to be associated with increases in price, operating cost and maintenance cost. In the next section therefore, we present market shares for e-scooters and for standard and large gasoline motorcycles under several scenarios that involve different sales tax rates on the three vehicles, as well as different combinations of fuel prices and states of e-scooter technology.

1.7 Market Shares

We used the estimated mixed logit model to forecast market shares for motorized two-wheelers under different scenarios. We examined two different states of e-scooter technology: baseline and cutting-edge. We combined each state of e-scooter technology with both baseline and high gasoline prices, and combined each combination of e-scooter technology and gasoline price with six different sales tax scenarios, for a total of 36 scenarios. We calculated market shares for the e-scooter and for the standard and large gasoline motorcycles under each of these scenarios. The scenario considered to be the baseline reflects prices, costs, sales tax rates and technologies prevailing in Hanoi in 2008. Under baseline gasoline prices, the operating cost was set at 40,000 VND/100 km, based on a fuel price of 20,000 VND per liter (the approximate price of gasoline in Hanoi in late summer of 2008). Table 1.7 presents the attribute levels of the vehicles for the baseline scenario. In all of the scenarios, the interactions between the individual-specific characteristics and the e-scooter alternative-specific constant were evaluated at the means of the individual-specific characteristics obtained from the full sample.

The cutting-edge state of e-scooter technology involves significant enhancements in range, recharge time, acceleration and speed. Range increases from 60 km to 200 km, recharging time falls from 360 min to 10 min, acceleration increases from 20% slower than a standard motorcycle to the same as a standard motorcycle, and speed increases from 40 km/hr to 60 km/hr. These improvements are associated with an increase in the e-scooter purchase price from 12 million VND to 16 million VND, an increase in operating cost from 5000 VND/100 km to 7500 VND/100 km to account for higher energy requirements as well as higher capital costs of rapid charging devices, and an increase in maintenance cost from 100000 VND/month to 140000 VND/month to reflect the greater expense of an enhanced battery.

Table 1.7 Attribute levels in the baseline scenario

Attribute	Standard Motorcycle	Large Motorcycle	Electric Scooter
Price (millions of VND)	10	15	12
Range (km)	100	200	60
Refuel/recharge time (min.)	5	10	360
Operating cost (VND/100 km)	40000	40000	5000
Maintenance cost (VND/month)	20000	20000	100000
Acceleration	0-40 km/hr in 10 sec.	+ 20%	– 20%
Speed (km/hr)	80	80	40
License requirement	Yes	Yes	No

The high gasoline price scenario involves an increase in the operating cost of standard and large gasoline motorcycles from 40000 VND/100 km to 52000 VND/100 km, reflecting a 30% increase in the price of gasoline. For the sales tax scenarios we examine two different rates of e-scooter tax: 10% and 0%, and we combine these with three different scenarios of sales tax rates for the standard and large gasoline motorcycles: 10% on both standard and large motorcycles; 10% on the standard motorcycle and 20% on the large motorcycle; and 20% on both standard and large motorcycles. We present the estimated market shares and standard errors for baseline and high gasoline prices combined with the sales tax scenarios in Table 1.8 for baseline e-scooter technology and in Table 1.9 for cutting-edge e-scooter technology.

First, examining the case of baseline e-scooter technology in Table 1.8, the market shares for the baseline scenario are given in the first row of market shares. Under the baseline, e-scooters have a market share of about 13%, while standard and large motorcycles have shares of about 61% and 26%, respectively. Maintaining the 10% sales tax rates on all vehicles while increasing to the high gasoline price results in e-scooter market share of about 18%; alternatively, eliminating the e-scooter sales tax and maintaining the baseline gasoline price yields approximately the same e-scooter market share of 18%. Starting at the baseline gasoline price and baseline technology with 10% tax rates on all vehicles then, a 30% increase in the price of gasoline has approximately the same effect on the e-scooter market share as eliminating the e-scooter sales tax. However, increasing the sales tax rates on the standard and large motorcycles to 20% in addition to eliminating the e-scooter sales tax still under the baseline gasoline price

Table 1.8 Market shares under baseline e-scooter technology

Scenario		Market Shares		
Standard Gas Motorcycle Sales Tax	Large Gas Motorcycle Sales Tax	Standard Gas Motorcycle	Large Gas Motorcycle	Electric Scooter
Baseline Gasoline Price				
10% e-scooter sales tax				
10%	10%	0.610 (0.034)	0.257 (0.036)	0.133 (0.026)
10%	20%	0.668 (0.034)	0.187 (0.030)	0.145 (0.027)
20%	20%	0.605 (0.034)	0.222 (0.033)	0.173 (0.031)
No e-scooter sales tax				
10%	10%	0.580 (0.034)	0.244 (0.035)	0.175 (0.031)
10%	20%	0.632 (0.034)	0.177 (0.029)	0.191 (0.033)
20%	20%	0.567 (0.035)	0.208 (0.032)	0.225 (0.038)
High Gasoline Price				
10% e-scooter sales tax				
10%	10%	0.576 (0.038)	0.242 (0.036)	0.182 (0.043)
10%	20%	0.627 (0.042)	0.176 (0.030)	0.198 (0.045)
20%	20%	0.561 (0.041)	0.206 (0.033)	0.233 (0.050)
No e-scooter sales tax				
10%	10%	0.538 (0.041)	0.226 (0.036)	0.235 (0.051)
10%	20%	0.582 (0.044)	0.163 (0.029)	0.255 (0.053)
20%	20%	0.515 (0.045)	0.189 (0.033)	0.296 (0.059)

(1) Standard errors are in parentheses.

Table 1.9 Market shares under cutting-edge e-scooter technology

Scenario		Market Shares		
Standard Gas Motorcycle Sales Tax	Large Gas Motorcycle Sales Tax	Standard Gas Motorcycle	Large Gas Motorcycle	Electric Scooter
Baseline Gasoline Price				
10% e-scooter sales tax				
10%	10%	0.544 (0.034)	0.229 (0.033)	0.228 (0.035)
10%	20%	0.589 (0.036)	0.165 (0.027)	0.247 (0.036)
20%	20%	0.522 (0.035)	0.192 (0.030)	0.287 (0.040)
No e-scooter sales tax				
10%	10%	0.500 (0.035)	0.210 (0.032)	0.290 (0.041)
10%	20%	0.538 (0.036)	0.151 (0.026)	0.312 (0.042)
20%	20%	0.470 (0.037)	0.173 (0.029)	0.358 (0.047)
High Gasoline Price				
10% e-scooter sales tax				
10%	10%	0.493 (0.042)	0.208 (0.034)	0.299 (0.054)
10%	20%	0.530 (0.047)	0.148 (0.027)	0.322 (0.055)
20%	20%	0.462 (0.045)	0.170 (0.030)	0.368 (0.059)
No e-scooter sales tax				
10%	10%	0.442 (0.044)	0.186 (0.033)	0.372 (0.060)
10%	20%	0.472 (0.048)	0.132 (0.026)	0.396 (0.060)
20%	20%	0.405 (0.047)	0.149 (0.029)	0.446 (0.064)

(1) Standard errors are in parentheses.

increases the e-scooter market share to about 23%. This same set of tax rates under a high gasoline price increases the e-scooter market share to about 30%.

Now consider cutting edge e-scooter technology in Table 1.9. Under the baseline gasoline price and 10% sales tax on all vehicles, moving from baseline to cutting-edge technology increases e-scooter market share from about 13% to about 23%. Under the high gasoline price scenario with all tax rates still at 10%, moving to cutting-edge e-scooter technology increases e-scooter market share from about 18% to about 30%. Starting at baseline e-scooter technology with 10% tax rates on all vehicles then, improving to cutting-edge e-scooter technology would have about the same effect on the e-scooter market share as eliminating the e-scooter sales tax and increasing the sales tax rates on the standard and large motorcycles to 20%, under either gasoline price scenario.

Examining the market shares under the various scenarios it is clear that policies based on sales tax rates show the potential for a powerful effect on the market share of e-scooters, especially when the use of an e-scooter sales tax waiver is combined with increases in the sales tax rates on gasoline motorcycles. Moving from the baseline scenario to a scenario with high gasoline price, cutting-edge e-scooter technology, and with no e-scooter sales tax and 20% sales tax rates on standard and large motorcycles, the e-scooter market share increases from about 13% to about 45%. While this scenario has the highest forecasted market share for e-scooters, it is not evident that it offers the largest reductions in urban air pollution. For example, a policy that waived the e-scooter sales tax and increased the sales tax on large motorcycles to 20%, but instead left the sales tax rate on standard motorcycles at 10%, would forecast a lower e-scooter share, but would also have a lower share of large gasoline motorcycles. An analysis of environmental impacts is therefore required in order to better understand the effects of the various sales tax policies and resulting market shares on urban air pollution in Hanoi.

1.8 Implied Discount Rate for Maintenance and Fuel Savings

The cost structure of owning and operating an electric vehicle is different than a gasoline vehicle. One of the barriers of owning an electric vehicle is the relatively higher purchase and maintenance cost (mostly because of batteries), which is countered by lower operating cost over the life of the vehicle (because of lower fuel cost). Indeed, the total cost of ownership is lower for most electric vehicles, compared to their gasoline counterparts. The same is true of electric scooters compared to gasoline motorcycles. WTP for these cost differences varies. Vehicle purchasers have been shown to discount future benefits of lower operating costs (fuel economy) at a significantly higher rate than return on capital (14-42%) (Gallagher and Muehlegger 2011). Still, there is little consensus on how consumers value and pay for potential increases in fuel economy and associated savings in operating cost, potentially because of substantial uncertainty surrounding future fuel prices and savings (D. L. Greene 2010).

In this section, we investigate the potential discount rates of vehicle purchasers by analyzing their WTP for differential operating (fuel) costs and maintenance costs. To investigate the value of expected future savings, we apply the MWTP to the undiscounted savings, to derive the implied discount rate. The discount rate is sensitive to expected vehicle lifespan and use. We will address this in sensitivity analysis below. On average, we assume a vehicle lifespan of ten years and 5,500 vehicle-km/yr, consistent with travel behavior studies conducted in Hanoi (Schipper et al. 2008). We also assume static fuel and maintenance costs for both electric and gasoline vehicles. For expected fuel economy, we estimate undiscounted fuel costs of an e-scooter of over 2.75 million VND over the life of the vehicle, compared to 22 million VND for gasoline motorcycle, or 350 VND/km savings. Based on MWTP estimates presented in Table 1.5, we estimate that one is willing to spend, on average, 1/3 of the expected savings (6.5 million VND) in purchase cost. Assuming these benefits occur evenly over the life of the vehicle implies a discount rate of 40%. Similarly, we can estimate an implied discount rate based on a gasoline motorcycle maintenance cost of 20,000 VND/month and an e-scooter maintenance cost of 100,000 VND/month. Here we assume a ten-year lifespan and maintenance costs begin incurring immediately and costs are outlaid at the end of each year. In this case, the consumer is willing to substitute 3 million VND in the price of the gasoline motorcycle to save 9.6 million VND in lifetime maintenance cost, i.e., the consumer is willing to pay 31% of the future maintenance savings resulting in an implied discount rate of 45%. If we assume that the maintenance costs do not incur until the end of the first year (a reasonable assumption since <1-year old vehicles require little maintenance), then the implied discount rate drops to 29%.

Discount rate of fuel savings is very sensitive to our assumptions, particularly expected vehicle life and yearly travel. User expectations of vehicle life, vehicle use, fuel costs, and resale value contribute to willingness to pay for future savings. Unfortunately, there is little empirical evidence to model these expectations. To test the range of discount rates we might observe, we simulated vehicle life (years) and yearly use (km/year) [N(10, 1.7) and N(5500, 833), respectively] and estimated the sensitivity of the operating cost discount rate (range 6-75%) on fuel price and vehicle life. Figure 1.2 shows the distribution of discount rates based on the simulation. Discount rate increases as the combination of yearly mileage and vehicle lifespan increase.

Similarly, we estimate the discount rate, considering expected maintenance cost savings over a range of vehicle lifespans. The maintenance cost savings are not sensitive to vehicle use, since the variable is expressed in VND/month. Figure 1.3 shows the range of discount rates depending on vehicle lifespan and when maintenance begins. If maintenance costs occur in the first year, the discount rate ranges from 31-46%. If we assume there are no maintenance costs in the first year, the discount rate ranges from 10-31%.

The discount rate estimated by both of these methods is on the same order as other studies and is shown to undervalue future operation and maintenance cost savings. There are many possible explanations, including myopic consumers who do not consider future savings, uncertainty in future savings, and inability to recover expected savings in the future resale of the vehicle. Supporting these potential explanations is the high and unstable inflation rate experienced by Vietnam in recent years. In 2008 (the year of the survey), consumer prices increased by nearly 30%, followed by 2% (2009), and 9% (2010), implying high future price uncertainty among consumers.

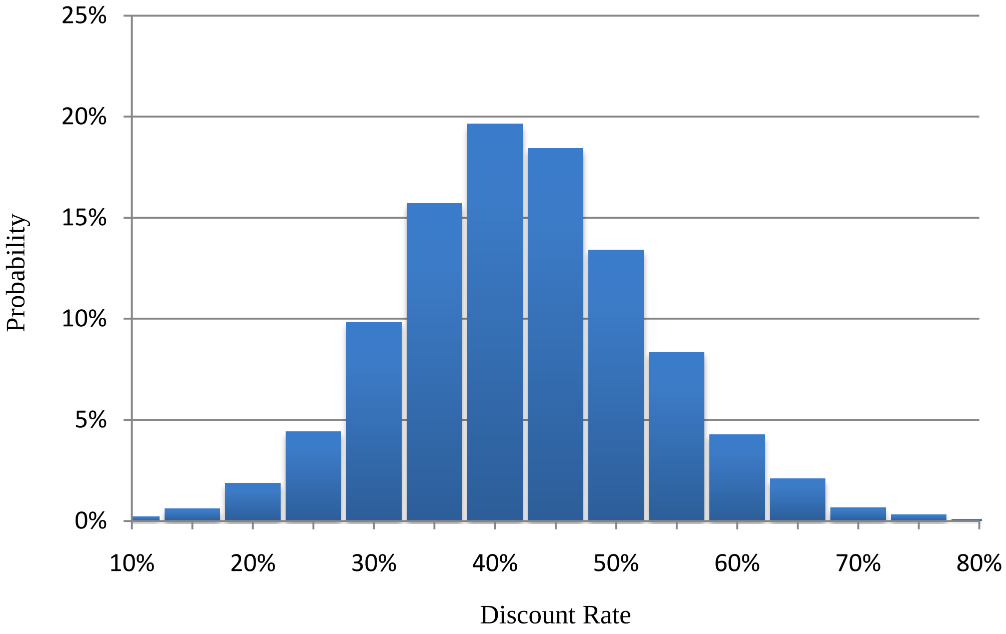

Figure 1.2 Distribution of implicit discount rates for operating cost

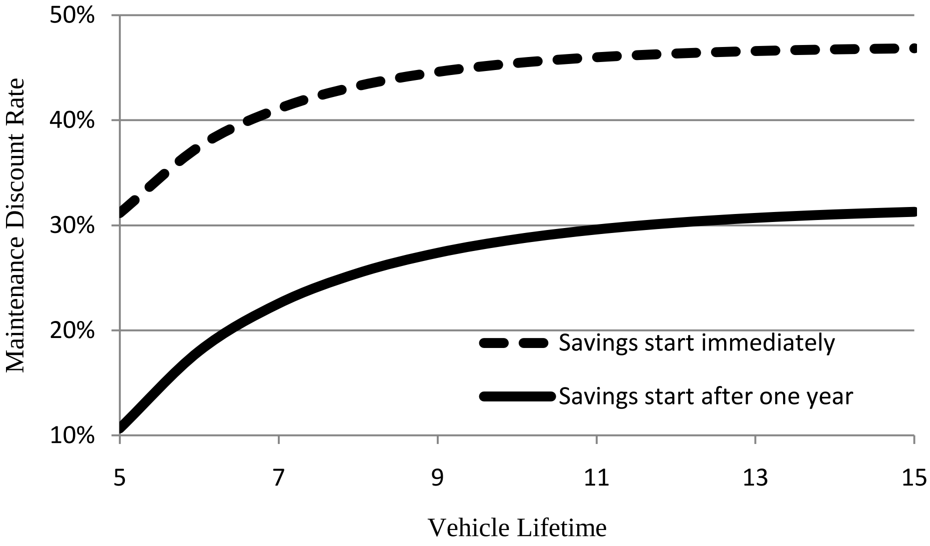

Figure 1.3 Implicit discount rates for maintenance cost

1.9 Conclusion

This paper uses a choice experiment to examine the potential for incentives to stimulate the adoption of e-scooters in Hanoi, Vietnam, and is the first investigation to explicitly estimate the effect of economic incentives for clean alternatives to motorcycles. The results of the mixed logit analysis indicate that a sales tax incentive has a powerful effect on the purchasing decision of a two-wheeled motorized vehicle, and that used as a tool to preferentially treat e-scooters, a tax shows significant promise for stimulating e-scooter demand. We find all other vehicle attributes in the experiment to be at least marginally significant determinants in the choice of a two-wheeled motorized vehicle, including price, range, refuel/recharge time, operating cost, maintenance cost, acceleration, speed, and license requirement. We also find that certain household and respondent characteristics affect the choice of an e-scooter. Having a college degree significantly increases an individual's willingness to pay for an e-scooter. Sales tax incentives, e-scooter technological improvements, and increases in gasoline price all demonstrate a substantial influence on e-scooter market share. We estimate that a policy combining the elimination of e-scooter sales tax with higher tax rates on gasoline motorcycles and enhancements in e-scooter technology will increase e-scooter market share substantially.

Although the results of this study indicate that incentives for e-scooters would increase e-scooter adoption in Hanoi, the conclusions regarding market and environmental outcomes are subject to limitations. There are many attributes important to the purchase of a motorized two-wheeler beyond those tested in the experiment, and many incentives for stimulating the adoption of e-scooters other than sales taxes. While our finding that the sales tax offers a powerful incentive is consistent with findings in the literature on incentives for alternative fuel cars and offers insight as to its relative potential, the actual market outcomes associated with implementing a sales tax policy depend on many factors outside the scope of our experiment. Furthermore, while e-scooters have lower tailpipe emissions than motorcycles, the typical battery used in an e-scooter is much larger than the battery used in a motorcycle and contains a large amount of lead. The extent to which a modal shift to e-scooters would be beneficial therefore depends on how well Hanoi's solid waste management system is able to accommodate an influx of used lead-acid batteries. Additionally, the benefits associated with the adoption of e-scooters are conditional on a substitution away from motorcycles. To the extent that e-scooter adoption comes at the expense of walking, riding bicycles and using public transportation, the benefits of stimulating e-scooter adoption could be diminished.

In the process of investigating the effect of a sales tax incentive on the adoption of e-scooters we find an interesting result: respondents exhibit a stronger response to sales tax than to the purchase price of a vehicle. One might expect individuals to be indifferent between a dollar in sales tax and a dollar in price, or if individuals believe that the sales tax collected contributes toward the provision of public goods, individuals might even prefer a dollar of sales tax to a dollar of purchase price. However, we observe the opposite.

The result could be context dependent, for example political corruption could make individuals wary of taxes. Or the result could be part of a more general phenomenon. The relationship between the price of a good and the value placed on the good is a topic addressed in several fields. In the marketing literature for example, there are studies that examine the notion that price may be used as an indicator of the quality of a product (Gardner 1971; Gerstner 1985; Lambert 1972; Monroe 1973). In neuroeconomics, a recent experiment involving wine tasting finds that higher prices for the same wine lead individuals to provide higher ratings of flavor and result in increased brain activity in an area thought to be associated with pleasure (Plassmann et al. 2008). In our study, if respondents do not treat all unspecified vehicle attributes as constant across alternatives, but instead use the price as an indicator of a vehicle's unobserved quality, then all else the same, we would expect respondents to be less deterred by increases in price than increases in sales tax. Unfortunately, we are unable to answer the question of why we see the divergence between the effects of sales tax and the price.

Still, the finding itself is of practical importance for researchers. A practice sometimes used in transportation demand studies is to use the effect of vehicle price as a proxy for the effect of a sales tax or vice versa. For example, Ewing and Sarigollu (2000), in their choice experiment study, use the effect of price to infer the effect of a sales tax on the demand for alternative fuel vehicles. Gallagher and Muehlegger (2011) using market data on hybrid vehicle sales, use the effect of sales tax to calculate the implicit discount rates on fuel cost savings. In either case, if consumers are more responsive to increases in sales tax than purchase price this could lead to distortions. Future research should further explore the effects of price and sales tax on vehicle purchase, aiming to understand whether differences between the effects are anomalous or pervasive and the sources of these differences when they do exist. An important issue related to the difference between the effects of price and sales tax is the determination of which of these effects, in a given study, provides the most accurate estimate of the marginal utility of money. At a minimum, researchers should be mindful of the potential for differences in the effects of different payment vehicles when undertaking transportation demand studies and interpreting results.

CHAPTER 2 : TAX MECHANISMS FOR THE JOINT REGULATION OF POINT AND NONPOINT SOURCE EMISSIONS

2.1 Introduction

Point source emissions, such as effluent emanating from the end of a factory pipe, are readily measured, and the actions that point sources take to reduce emissions (e.g. installing a filtration device) are effective with a relative degree of certainty. Nonpoint source emissions on the other hand, such as runoff from a farm, cannot be observed or readily measured without prohibitive cost. In addition, factors that help determine nonpoint emissions, such as soil type and rainfall, are subject to randomness and thus render emissions random. For these reasons, nonpoint source pollution is especially challenging for regulators.

In U.S. watersheds, nonpoint source pollution is a leading concern and for this reason has received a great deal of attention from both regulators and economists. Without being able to observe emissions, traditional economic mechanisms cannot be applied to regulate nonpoint sources. In part because of this, the approach has been to encourage Best Management Practices and to implement voluntary programs (e.g. Conservation Reserve Program), without pursuing direct regulation. In an attempt to encourage more pollution reductions from nonpoint sources and to benefit from their (perceived) lower costs of abatement, many watersheds have implemented water quality trading programs that allow for trading of emissions rights between point and nonpoint sources.

Indeed water quality trading is the current policy focus for addressing pollution in U.S. watersheds. Thus far, these water quality trading programs have had little practical success. Few trades have occurred relative to the number of programs that have been established, and nonpoint sources are reluctant to participate. Therefore, there is a clear need to explore alternative mechanisms.

Ambient taxes have demonstrated the ability to yield near efficient levels of emissions reductions in controlled laboratory experiments on nonpoint pollution regulation (Cochard et al. 2005; Suter et al. 2008; Vossler et al. 2006). Whereas water quality trading is subject to market frictions such as those that result from high transaction costs, abatement cost uncertainty, poorly constructed trading institutions and market power, taxes provide clear price signals to compare with emission reduction costs. Segerson (1988) first introduced the ambient tax, following Holmstrom's (1982) work on incentivizing individual effort based on observation of group output. In particular, Segerson's (1988) ambient tax charges *every* nonpoint source based on the *total* ambient level of pollution measured in some environmental medium, in lieu of observing and taxing individual emissions. In response to the ambient tax, the nonpoint sources theoretically have the incentive to equate, at the margin, the cost of reducing emissions with the expected decrease in the tax payment from reducing emissions. The appeal of the ambient mechanism is that nonpoint sources can be incentivized to abate at desired levels without the regulator observing their individual emissions or abatement.

Much of the work on nonpoint regulation following Segerson (1988) focuses on the performance of ambient taxes, and has led to important refinements. For example, Cabe and Herriges (1992) examine a setting where the regulator and polluters have asymmetric expectations over the randomness of nonpoint pollution. Horan, Shortle and Abler (2002) study ambient taxes in the presence of asymmetric expectations, multiple pollution controls, and risk aversion. Other papers examine the consequences of relaxing the distinction between point and nonpoint sources by making nonpoint source emissions observable, at least to some extent, but at a cost (Farzin and Kaplan 2004; Millock et al. 2002; Xepapadeas 1995). Motivated by the purported substantial regulatory costs of Segerson's (1988) mechanism, variants of the ambient tax have been proposed to reduce this burden through state-dependent taxes (Horan et al. 2002, 1998), damage-based taxes (Hansen 1998), and a variance-based tax (Hansen 2002). However, one important component of the regulatory setting that has yet to be addressed in the nonpoint tax literature is the role of point sources.

In reality, many water quality-impaired watersheds include both point and nonpoint pollution sources, and in such watersheds differences between polluter types have implications about the use of ambient taxes. In contrast to the literature on ambient taxes, several papers that focus on water quality trading mechanisms (e.g. cap-and-trade; baseline-and-credit) have explicitly modeled both polluter types. Findings in the literature on point-nonpoint trading demonstrate that, based on the uncertainty of nonpoint emissions, the optimal trading ratio between otherwise identical point and nonpoint sources will not in general be equal to one (Hennessy and Feng 2008; Horan and Shortle 2005). This suggests that there are inherently different values associated with emissions reductions from the two polluter types.

This paper is the first to explicitly examine the joint regulation of point and nonpoint sources using tax mechanisms. We begin with a simple model of point-nonpoint pollution, and use this framework to compare three tax regulations, and consider three regulatory objectives. The first mechanism taxes point sources on their observable emissions, and taxes nonpoint sources on ambient pollution using a simplified version of Segerson's (1988) ambient tax. The second instrument uses an ambient tax to regulate both point and nonpoint sources. The third is a version of Hansen's (1998) damage tax under which both source types are taxed based on total damages associated with measured ambient pollution. The first regulatory objective is (expected) social efficiency, which is practical when the social damages from pollution are known. The other two objectives are consistent with a cost-effectiveness framework, and include: meeting an ambient target "on average", and meeting an ambient target with a known probability.

2.2 A Point-Nonpoint Pollution Model

Consider a simple model of a watershed that includes m point sources (subscript k) and n nonpoint sources (subscript i). A primary metric of regulatory interest is the level of a key pollutant measured at a monitoring point in the watershed. Define the ambient pollution function as $x = \sum_{k=1}^{m} e_k + \sum_{i=1}^{n} e_i$, where: x is the ambient pollution level; $e_k = \beta_k l_k$ and $e_i = \beta_i(\theta_i) l_i$ denote point and nonpoint source ambient contributions, respectively; l_k and l_i denote each point and nonpoint source's emissions, measured in units of the pollutant; and coefficients β_k and $\beta_i(\theta_i)$, commonly referred to as "transfer coefficients", indicate the proportion of emissions that are discharged as ambient contributions. To be clear, the ambient pollution function maps "emissions" originating from the pollution sources, via the transfer coefficients, into a measurable level of ambient pollution at a monitoring point. Note that while the point source transfer coefficients are assumed to be site-specific constants, the nonpoint transfer coefficients depend on site-specific random variables, the θ_i.[9]

In addition to observing the ambient level of pollution, it is assumed that the regulator is able to observe each point source's emissions, but is unable to observe nonpoint emissions, and is unable to infer ambient contributions from the ambient level of pollution. Point and nonpoint sources can reduce their emissions at increasing cost, so that for k and *i* there are cost functions $c_k(l_k)$ and $c_i(l_i)$, respectively, that are decreasing and convex in emissions ($c' < 0$ and $c'' \geq 0$). Finally, it is assumed that social damages $D(x)$ from watershed pollution are an increasing and strictly convex function of the ambient level of pollution at the monitoring point ($D' > 0$ and $D'' > 0$).

2.3 Achieving Optimal Emissions with Point-Nonpoint Tax Mechanisms

Within this framework, we can define the social planner's problem as one of determining the emissions levels l_k^* and l_i^* that minimize the sum of firms' costs and expected social damages:

$$\min_{l_k, l_i} \sum_{k=1}^{m} c_k(l_k) + \sum_{i=1}^{n} c_i(l_i) + E\left[D\left(\sum_{k=1}^{m} \beta_k l_k + \sum_{i=1}^{n} \beta_i(\theta_i) l_i\right)\right] \tag{2.1}$$

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[9] The key feature of our model, which is present in other models on point-nonpoint trading (e.g. Horan and Shortle 2005), is that there is an *additional* source of uncertainty underlying nonpoint pollution. For a slightly richer model, we could assume randomness in the mapping of point source emissions to ambient concentrations, and two sources of randomness for nonpoint sources – in the mapping of emissions to ambient concentration, as well as in how firm actions translate into emissions. However, doing so adds additional complexity while leading to similar theoretical implications regarding relative tax rates.

Assuming an interior solution, the first-order necessary conditions are (2.2) and (2.3).

$$c'_k(l_k^*) + E[D^{'}(x^*)\beta_k] = 0 \qquad k = 1, \dots m \tag{2.2}$$

$$c'_i(l_i^*) + E[D^{'}(x^*)\beta_i(\theta_i)] = 0 \qquad i = 1, \dots n \tag{2.3}$$

These imply the familiar result that optimal emissions must, for each source, equate the marginal cost of emissions with the expected marginal benefit (i.e. negative of marginal damage) of emissions.

We now compare the optimal emissions across types. Rearranging, and dividing equation (2.3) by equation (2.2), allows us to examine the ratio of marginal costs between a particular nonpoint source and a point source:

$$\frac{c'_i(l_i^*)}{c'_k(l_k^*)} = \frac{Cov\left(D^{'}(x^*), \beta_i(\theta_i)\right)}{E[D^{'}(x^*)]\beta_k} + \frac{E[\beta_i(\theta_i)]}{\beta_k} \tag{2.4}$$

For purpose of comparison, we can place the two polluter types on equal footing by assuming they have identical cost functions as well as identical (expected) transfer coefficients. Then, a marginal cost ratio (MCR), $c'(l_i^*)/c'(l_k^*)$, given the curvature of the cost function, equals unity only when point and nonpoint emissions are equal. A ratio greater than (less than) unity implies that nonpoint emissions are less than (greater than) point emissions. $E[D^{'}(x^*)]$, β_k, and $E[\beta_i(\theta_i)]$ are strictly positive, such that deviation of the MCR from unity depends on the sign of $Cov\left(D^{'}(x^*), \beta_i(\theta_i)\right)$. *Ceteris paribus*, increasing the covariance between marginal damages and nonpoint transfer coefficients decreases the optimal nonpoint emissions relative to point source emissions, while decreasing the covariance term has the opposite effect. When the covariance term is zero, then the MCR equals unity.

In the model, $Cov\left(D'(x^*), \beta_i(\theta_i)\right)$ can take any sign, yet in practice this term is likely to be positive. In the special case where there is a single nonpoint source, there would – without assumption – be a positive covariance between marginal damages and the transfer coefficient of the nonpoint source. This is because a positive shock to the transfer coefficient translates into a positive shock to marginal damages. With multiple firms, the sign of the covariance term is not as clear, and depends on the joint distribution of the nonpoint transfer coefficients. If the transfer coefficients are independently distributed, i.e. shocks to the transfer coefficients of multiple firms are uncorrelated, then the covariance term is unambiguously positive. A negative covariance term might arise if a positive shock to a particular firm's transfer coefficient accompanied a negative (overall) shock to other firms. While this could be true for a particular firm, it seems likely that on average the shocks are positively correlated – e.g. rainfall causes more runoff from all farms. In practice, drawing from how trading ratios for water quality trading programs are typically established, tax rates would be based on data averaged across related firms – related in terms of location and/or purpose. As such, it is very likely that tax rates in this second-best setting would be universally higher for nonpoint sources (under the above equal-footing scenario).

In this section we consider three tax regulations that theoretically motivate firms to choose the optimal emission levels defined by the social planner's problem discussed above. The optimal point and nonpoint tax rates t_k^* and t_i^* and the optimal tax ratio (TR), t_i^*/t_k^*, are derived for three variants of ambient taxes, and the TRs are compared. It is implicitly assumed that regulation is needed, i.e. in the absence of regulation ambient pollution is higher than what is optimal from the perspective of the regulator.

Now consider each polluter's objective under a tax. Let T_k and T_i represent the tax payments for given point and nonpoint polluters. Each polluter's objective is to choose emissions in order minimize the sum of its costs and expected tax payments, as formulated in (2.5) and (2.6):

$$\min_{l_k} c_k(l_k) + E[T_k] \tag{2.5}$$

$$\min_{l_i} c_i(l_i) + E[T_i] \tag{2.6}$$

In order to induce socially optimal emissions, the regulator must impose a tax mechanism that provides incentives for firms to align with the social planner's problem; i.e. the tax mechanism must equate the necessary conditions of the social planner with those of the firms.

Emissions Tax on Point Sources and Ambient Tax on Nonpoint Sources. The first tax considered is an obvious one for regulating point and nonpoint sources. It regulates point sources with standard taxes on their observable emissions, and nonpoint sources, whose emissions are unobservable, are taxed based on ambient pollution. The form of the ambient tax used here and throughout the paper is a simplified version of Segerson's (1988) mechanism, under which the tax payment is equal to a tax rate multiplied by the ambient level of pollution. Thus, the point and nonpoint tax payments are $T_k = t_k l_k$ and $T_i = t_i x$. Expected marginal tax payments are, t_k and $t_i E\big(\beta_i(\theta_i)\big)$, i.e., the expected increases in tax payments per unit of point and nonpoint emissions, respectively. Setting these equal to the point and nonpoint expected marginal social damages at the optimum, $E[D^{'}(x^{*})\beta_k]$ and $E[D^{'}(x^{*})\beta_i(\theta_i)]$, respectively, and solving, gives the optimal point and nonpoint tax rates, (2.7) and (2.8). Dividing the nonpoint source rate by the point source rate gives the optimal TR (2.9).

$$t_k^{*}= E\left[D^{'}(x^{*})\right]\beta_k \tag{2.7}$$

$$t_i^{*} = \frac{Cov\left(D^{'}(x^{*}), \beta_i(\theta_i)\right)}{E[\beta_i(\theta_i)]} + \; E\left[D^{'}(x^{*})\right] \tag{2.8}$$

$$\frac{t_i^{*}}{t_k^{*}} = \frac{Cov\left(D^{'}(x^{*}), \beta_i(\theta_i)\right)}{E[\beta_i(\theta_i)]E[D^{'}(x^{*})]\beta_k} + \frac{1}{\beta_k} \tag{2.9}$$

Examining equations (2.7) and (2.8) reveals that in general the regulator requires individual-specific tax rates for all sources. Point source tax rates differ according to their transfer coefficients. Each nonpoint source is charged an individual-specific tax rate that varies between nonpoint sources according to $\frac{Cov\left(D^{'}(x^{*}),\beta_i(\theta_i)\right)}{E[\beta_i(\theta_i)]}$. Notice also that whether the TR departs from unity depends on the sign of $Cov\left(D^{'}(x^{*}), \beta_i(\theta_i)\right)$ and the magnitude of $\frac{Cov\left(D^{'}(x^{*}),\beta_i(\theta_i)\right)}{E[\beta_i(\theta_i)]E\left[D^{'}(x^{*})\right]\beta_k}$ relative to $1/\beta_k$. The TR contains no adjustment for the nonpoint expected transfer coefficient in the second term on the right hand side of (2.9), in contrast to the case of the MCR defined in equation (2.4). This is because nonpoint sources already take into account their expected transfer coefficient, given that they are being taxed on the ambient level.

Ambient Tax on Both Point and Nonpoint Sources. Now consider a mechanism under which both the point and nonpoint sources are taxed based on the ambient level, such that tax payments are given by $T_k = t_k x$ and $T_i = t_i x$. The nonpoint tax payment is the same as under the previous mechanism, but the point source is taxed on the ambient level pollution instead of its emissions. The optimal tax rates and optimal TR are given in equations (2.10) through (2.12):

$$t_k^* = E\left[D'(x^*)\right] \tag{2.10}$$

$$t_i^* = \frac{Cov\left(D'(x^*), \beta_i(\theta_i)\right)}{E[\beta_i(\theta_i)]} + E\left[D'(x^*)\right] \tag{2.11}$$

$$\frac{t_i^*}{t_k^*} = \frac{Cov\left(D'(x^*), \beta_i(\theta_i)\right)}{E[\beta_i(\theta_i)]E[D'(x^*)]} + 1 \tag{2.12}$$

Note that the tax rate on nonpoint sources remains the same as in equation (2.8), yet because the point sources are now taxed on the ambient level of pollution, they take into account their differential transfer coefficients, and therefore are taxed a common rate equal to the marginal damages at the optimum. It is no longer necessary to charge differential tax rates on point sources. Notice also that the optimal TR contains no adjustment for the relative magnitudes of point and nonpoint transfer coefficients in the second term on the right hand side in (2.12). Whether or not point or nonpoint sources receive a higher tax rate depends only on the sign of the covariance term.

From a regulatory standpoint, regulating both point and nonpoint sources through an ambient tax has two advantages over taxing point sources on observable emissions as in the previous case. First, the regulator is able to apply a uniform tax to point sources, which is perhaps more politically feasible than the differential rates required in the first case. Indeed, two identical firms could otherwise pay different tax rates simply because of their location on the watershed, which was presumably chosen prior to identification of the ambient monitoring point. Second, the regulator does not need to observe and monitor point source emissions in order to implement the tax. The only monitoring cost that the regulator incurs is the cost of monitoring the ambient level. Indeed, the reason why the mechanism was developed for nonpoint source pollution in the first place is because it does not require observation and monitoring of emissions (Segerson 1988).

Damage Tax. The final tax examined in this section is one that charges both point and nonpoint sources based on the total social damages from ambient pollution (Hansen 1998). The point and nonpoint tax payments are specified as $T_k = t_k D(x)$ and $T_i = t_i D(x)$. The expected marginal effects of emissions on these tax payments are $t_k E[D'(x)\beta_k]$ and $t_i E[D'(x)\beta_i(\theta_i)]$. Thus, the optimal TR equals 1. With damages as the tax base, nonpoint sources internalize the covariance between marginal damages and their transfer coefficient, so that the tax rates no longer need to adjust for this difference across sources. The damage tax is attractive because the regulator requires no firm-specific information in order to set the optimal tax rates, and because a common rate applied to all polluters may make the instrument more politically acceptable than the two tax mechanisms explored above.

Yet Hansen (1998, 2002) does note some potential issues with the mechanism. A major issue with the damage tax is that it shifts the information burden from the regulator to the regulated. Polluters now need to know the expected marginal effect of their emissions reductions on damages at the optimum. In order to know this information, polluters need to have some knowledge of the damage function and notions of how others will reduce emissions. Thus, it is evident that the damage tax also shifts the strategic environment. With ambient pollution specified as a linear combination of point and nonpoint emissions, the two ambient tax mechanisms implement the optimum in dominant strategies. The damage tax on the other hand implements the optimum in Nash strategies and may be unstable, and there may be incentives to collude on higher than optimal levels of emissions reductions.

2.4 Achieving an Ambient Target at Least Cost with a Joint Point-Nonpoint Tax Mechanism

In practice, the social damage function may be unknown. In general, uncertainties over the damage function make it difficult to determine the optimal level of ambient pollution. For this reason, the regulatory objectives in practice more often aim at meeting an environmental goal at least cost, instead of targeting optimal emissions reductions.

This section examines the use of ambient taxes to cost-effectively meet environmental goals. Two different environmental goals are considered: (1) meeting an ambient target "on average"; and (2) meeting an ambient target with a specified probability. Since it was demonstrated earlier that taxing point sources based on emissions as opposed to ambient pollution increases monitoring costs by requiring the regulator to observe point source emissions, the analysis is restricted to an ambient tax applied to both point and nonpoint sources.

Meeting an Ambient Pollution Target on Average. When the regulatory goal is to meet an ambient pollution target on average, the regulator's problem is formulated as one of minimizing the sum of emissions costs subject to the constraint that the expected value of ambient pollution is less than or equal to the target level, denoted by $\bar{x}$:

$$\min_{l_k, l_i} \sum_{k=1}^{m} c_k(l_k) + \sum_{i=1}^{n} c_i(l_i) + \lambda \left(E\left[\sum_{k=1}^{m} \beta_k l_k + \sum_{i=1}^{n} \beta_i(\theta_i) l_i \right] - \bar{x} \right) \tag{2.13}$$

The levels of emissions that satisfy (2.13) are, assuming an interior solution, characterized by (2.14), (2.15), and (2.16):

$$c'_k(l_k^*) + \lambda^* \beta_k = 0 \quad k = 1, \dots m \tag{2.14}$$

$$c'_i(l_i^*) + \lambda^* E[\beta_i(\theta_i)] = 0 \quad i = 1, \dots n \tag{2.15}$$

$$E\left[\sum_{k=1}^{m} \beta_k l_k^* + \sum_{i=1}^{n} \beta_i(\theta_i) l_i^* \right] - \bar{x} = 0 \tag{2.16}$$

Equations (2.14) and (2.15) can be combined to form the MCR:

$$\frac{c'_i(l_i^*)}{c'_k(l_k^*)} = \frac{E[\beta_i(\theta_i)]}{\beta_k} \tag{2.17}$$

Equation (2.17) requires that at the least-cost solution, the marginal rate of substitution between point and nonpoint marginal costs must equal the ratio of point to nonpoint (expected) transfer coefficients. Again for comparison, we assume identical point and nonpoint cost functions, as well as identical transfer coefficients. Then the MCR is equal to one, and the least cost level of emissions is the same for point and nonpoint sources. Because the goal is to meet the target on "average," there is no need for point and nonpoint emissions to differ based on the stochasticity of nonpoint emissions. Now consider using ambient taxes in order to satisfy (2.17). As earlier, the tax payments by point and nonpoint sources are $T_k = t_k x$ and $T_i = t_i x$. Setting the expected marginal tax payments equal to the expected marginal effects of emissions on the constraint gives $t_k^* = t_i^* = \lambda^*$ and $\frac{t_i^*}{t_k^*} = 1$, so the regulator is able to meet the environmental target at least cost by applying a uniform tax rate on the ambient level of pollution.

Meeting an Ambient Pollution Target with a Specified Probability. While meeting a target on average is one way to formulate an environmental goal when the damage function is unknown, the pollution control literature also recognizes the more general environmental goal of meeting a target with a specified probability (Beavis and Walker 1983; Ghosh and Shortle 2010; Horan 2001; Kampas and White 2004; Lichtenberg and Zilberman 1988; Qiu et al. 2001; Shortle 1990). This probabilistic formulation is consistent with a situation in which the regulator wishes to keep the probability that a threshold is exceeded below a given level, which might be the case for example if there are pollutant thresholds.

The regulator's problem is formulated as one of choosing the point and nonpoint emissions in order to cost-effectively meet the ambient pollution target$(\bar{x})$ with a specified probability. So the constraint can be stated as $\Pr(x \geq \bar{x}) \leq P$, where P is the exogenously specified probability with which the ambient level of pollution may exceed the target. Substituting for x gives $\Pr(\sum_{k=1}^{m} \beta_k l_k + \sum_{i=1}^{n} \beta_i(\theta_i) l_i \geq \bar{x}) \leq P$. Ghosh and Shortle (2010) point out that in watershed applications involving nonpoint sources, the information needed to express this constraint as a deterministic equivalent, namely, the joint distribution of ambient contributions, is often not known. The modeling of the probability statement therefore follows the method used by Gosh and Shortle (2010) of constructing an approximation of the probability constraint by applying Chebychev's inequality.

Following Gosh and Shortle (2010), Chebychev's inequality states that the following must be true:

$$\Pr\left(x \geq E(x) + \sqrt{\frac{Var(x)}{P}}\right) \leq P$$

Applying this inequality to the current problem gives

$$\Pr\left(x \geq \sum_{k=1}^{m} \beta_k l_k + \sum_{i=1}^{n} E[\beta_i(\theta_i)] l_i + \sqrt{\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} l_i l_j Cov\left(\beta_i(\theta_i), \beta_j(\theta_j)\right)}{P}}\right) \leq P \ ,$$

which implies that $\Pr(x \geq \bar{x}) \leq P$ will be satisfied by setting the ambient pollution target such that $\bar{x} \geq \sum_{k=1}^{m} \beta_k l_k + \sum_{i=1}^{n} E[\beta_i(\theta_i)] l_i + \sqrt{\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} l_i l_j Cov\left(\beta_i(\theta_i), \beta_j(\theta_j)\right)}{P}}$. Now the regulator's problem can be written as:

$$\min_{l_k, l_i} \sum_{k=1}^{m} c_k(l_k) + \sum_{i=1}^{n} c_i(l_i) + \lambda\left(\sum_{k=1}^{m} \beta_k l_k + \sum_{i=1}^{n} E[\beta_i(\theta_i)] l_i + \sqrt{\frac{Var(x)}{P}} - \bar{x}\right) \tag{2.18}$$

The necessary conditions for an interior solution to (2.18) are given by

$$c'_k(l_k^*) + \lambda^* \beta_k = 0 \quad k = 1, \ldots m \tag{2.19}$$

$$c'_i(l_i^*) + \lambda^*\left(E[\beta_i(\theta_i)] + \frac{2 l_i^* Var\left(\beta_i(\theta_i)\right) + \sum_{j \neq i}^{n-1} l_j^* Cov\left(\beta_i(\theta_i), \beta_j(\theta_j)\right)}{2\sqrt{Var(x^*)P}}\right) = 0 \tag{2.20}$$

$$i = 1, \ldots n$$

$$\left(\sum_{k=1}^{m} \beta_k l_k + \sum_{i=1}^{n} E[\beta_i(\theta_i)] l_i + \sqrt{\frac{Var(x)}{P}} - \bar{x}\right) = 0 \tag{2.21}$$

Dividing (2.20) by (2.19) and denoting $2l_i^*Var\big(\beta_i(\theta_i)\big) + \sum_{j\neq i}^{n-1} l_j^* Cov\left(\beta_i(\theta_i), \beta_j(\theta_j)\right)$ as $\partial Var(x^*)/\partial l_i^*$ allows comparison of the point and nonpoint source emissions through the MCR:

$$\frac{c'_i(l_i^*)}{c'_k(l_k^*)} = \frac{E[\beta_i(\theta_i)]}{\beta_k} + \frac{\frac{\partial Var(x^*)}{\partial l_i^*}}{\beta_k 2\sqrt{Var(x^*)P}} \tag{2.22}$$

As before, we assume identical point and nonpoint cost functions and expected transfer coefficients. The second right hand side term accounts for the stochasticity of the nonpoint transfer coefficient. If the marginal effect of *i*'s emissions on the variance of ambient pollution is negative, i.e., $\partial Var(x^*)/\partial l_i^* < 0$, then the second term on the right hand side is negative, and the level of nonpoint source emissions at the least cost solution is higher than the level of point source emissions. A positive relationship between emissions and the variance, i.e. $\partial Var(x^*)/\partial l_i^* > 0$, has the opposite effect.

Whether $\partial Var(x^*)/\partial l_i^*$ is positive or negative depends on the sign of the least cost emissions-weighted sum of covariance terms between *i*'s transfer coefficient and the transfer coefficients of the other nonpoint sources, $\sum_{j\neq i}^{n-1} l_j^* Cov\left(\beta_i(\theta_i), \beta_j(\theta_j)\right)$, and on this term's magnitude relative to the marginal effect of *i*'s emissions on the variance of its own emissions, $2l_i^*Var\big(\beta_i(\theta_i)\big)$. In either case, the decrease or increase in least cost nonpoint emissions relative to point source emissions is increasing in magnitude with $\left|\frac{\partial Var(x^*)}{\partial l_i^*}\right|$. Finally, the denominator in the second term on the right hand side of (2.22), $\beta_k 2\sqrt{Var(x^*)P}$, weights the contribution of $\partial Var(x^*)/\partial l_i^*$ to the satisfaction of the probabilistic constraint. As the effect of the nonpoint source's emissions on the variance of ambient pollution becomes smaller relative to the variance of ambient pollution, or as the probability with which the target may be exceeded increases, relatively less weight is placed on $\partial Var(x^*)/\partial l_i^*$ in determining the least-cost level of emissions for the nonpoint source.

The point and nonpoint marginal effects on the ambient tax payments are $t_k\beta_k$ and $t_iE\big(\beta_i(\theta_i)\big)$. Setting them equal to the point and nonpoint marginal effects on the constraint, $\lambda^*\beta_k$ and $\lambda^*\left(E[\beta_i(\theta_i)] + \frac{\frac{\partial Var(x^*)}{\partial l_i^*}}{2\sqrt{Var(x^*)P}}\right)$, and solving, gives the point and nonpoint tax rates that satisfy the constraint at least cost. Dividing them gives the least cost TR:

$$t_k^* = \lambda^* \tag{2.23}$$

$$t_i^* = \lambda^* + \lambda^* \frac{\frac{\partial Var(x^*)}{\partial l_i^*}}{E[\beta_i(\theta_i)]2\sqrt{Var(x^*)P}} \tag{2.24}$$

$$\frac{t_i^*}{t_k^*} = 1 + \frac{\frac{\partial Var(x^*)}{\partial l_i^*}}{E[\beta_i(\theta_i)]2\sqrt{Var(x^*)P}} \tag{2.25}$$

The tax rate on the point source is equal to the shadow value of the constraint at the least-cost solution. The nonpoint source tax rate has the added second term on the right hand side of (2.24) to account for the stochasticity of nonpoint emissions. Examining the least cost TR, the nonpoint source faces a tax rate that is greater than, equal to, or less than the point source tax rate as $\partial Var(x^*)/\partial l_i^*$ >,=,< 0. The regulator is able to implement the probabilistic standard at least cost with a common tax rate for all point sources, but must in general use an individual-specific tax rate for each nonpoint source.

2.5 Conclusion

This is the first paper to look at the use of taxes for joint regulation of point and nonpoint sources. When a regulator's goal is to achieve optimal emissions, we find that otherwise identical point and nonpoint sources may have different optimal tax rates based on the stochasticity of nonpoint emissions. While point and nonpoint tax rates are the same under a damage-based tax, under the other two mechanisms the tax rates for otherwise identical point and nonpoint sources will not in general be equal to one, a result that is analogous to the trading ratio of point to nonpoint emissions being generally different from one in the literature on water quality trading. When point sources are regulated with an ambient tax or with a damage-based tax, then they are all charged a uniform tax rate; however, nonpoint sources require individual-specific tax rates except in the case of a damage-based tax. The mechanism that taxes both point and nonpoint sources on ambient pollution has advantages over taxing point sources based on observable emissions, since it absolves the regulator of monitoring point source emissions and allows point sources to be taxed a common rate.

In practice, regulatory objectives may take the form of meeting a constraint at least cost, as opposed to implementing the optimal level of emissions. When the regulatory goal is to meet a level of ambient pollution on average, the regulator is able to meet this constraint at least cost with a uniform rate on the ambient level applied to both point and nonpoint sources. When the ambient tax is used to satisfy a probabilistic constraint, otherwise identical point and nonpoint sources face different tax rates based on the effect of the stochasticity of nonpoint emissions on the constraint. As in the case of implementing optimal emissions reductions with an ambient tax, point sources face a common tax rate while nonpoint sources require individual-specific tax rates.

There are more realistic ways of modeling the problem of point-nonpoint watershed pollution than the approach in this paper. The model developed is basic, in order to offer direct comparisons of point and nonpoint source tax rates and how they differ based on the uncertainty of nonpoint emissions. Thus, this work should be considered a first pass at incorporating point sources into the literature on nonpoint source pollution ambient taxes. Future research on ambient taxes, both theoretical and experimental, should consider frameworks that include both point and nonpoint sources, and give further consideration to the complexities of the point-nonpoint pollution problem.

CHAPTER 3 : EXPERIMENTAL TESTS OF WATER QUALITY TRADING MARKETS

3.1 Introduction

Surface water pollution is an issue of great concern for U.S. citizens and policy makers. Polluted waters pose human health risks, environmental risks, and economic risks associated with consequences such as water borne illnesses, consumption advisories, habitat degradation, drinking water closures, and reduced recreational opportunities (U.S. EPA 2002). According to the most recent available U.S. water quality assessments reported at the Environmental Protection Agency's (EPA) website, 50% of assessed river and stream miles, 66% of assessed lake, pond and reservoir acres, and 63% of assessed bay and estuarine square miles were not clean enough to support all of their designated uses (U.S. EPA 2011). In order to meet water quality goals, policymakers have increasingly endorsed adoption, on a watershed basis, of water quality trading (WQT) programs. This endorsement is at least in part because of the success of the U.S. sulfur dioxide (SO_2) emission market, and other high-profile air quality trading programs. A 2004 report identified more than 70 WQT programs in some phase of development throughout the U.S., about twice as many as there were in 1999 (Breetz et al. 2004; Environomics 1999).

After more than a decade of EPA support, the numerous WQT initiatives that have been established for watersheds in the U.S. are still realizing only a limited number of trades. Indeed, according to a recent EPA evaluation only 100 facilities had engaged in trade, with 80 percent coming from the Long Island Sound Trading Program (U.S. EPA 2008).[10] Several papers have highlighted unique characteristics of WQT programs, and have speculated that some of these features may explain the limited success (Boisvert et al. 2007; Farrow et al. 2005; Hoag and Hughes-Popp 1997; King 2005; King and Kuch 2003; Sado et al. 2010). At a very fundamental level, the institutions used in practice differ markedly from the textbook cap-and-trade institution that typifies programs such as the SO_2 emissions market. As a first step in empirically investigating WQT markets, this study uses laboratory experiments to isolate how the effects of market design affect economic efficiency. In particular, we compare cap-and-trade, two forms of baseline-and-credit institution, and a tax/subsidy regulation, and examine the effect of introducing fixed technology costs with these four institutions.

The majority of WQT programs involve baseline-and-credit trading institutions, under which polluters have an emissions baseline and tradable credits are linked to reductions beyond this baseline (Breetz et al. 2004; Environomics 1999).[11] That is to say, in contrast to cap-and-trade programs, there is no initial allocation of credits. There are two basic versions of baseline-and-credit institutions in practice. In the first, a polluter generates credits by establishing – and getting approved – an action plan that would lead to reductions below the baseline. This proposal is non-binding in the sense that reductions are not required in the event the proposer is unable to sell credits. Under the

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[10] As we discuss below, the “market” institution for this successful program differs substantially from the vast majority of permit trading markets.

[11] In the language of emissions trading, a tradable right to emit an amount of some pollutant is typically referred to as a permit or allowance when talking about cap-and-trade, and is referred to as a credit when discussing baseline-and-credit institutions. For sake of consistency this paper applies the term credit regardless of the institution being discussed.

second, a polluter only generates credits after it has been verified that emissions reductions below the baseline have occurred. The EPA (2007) strongly endorses the second version of baseline-and-credit in recent guidelines:

> The timing of trades is critical. A basic premise of water quality trading is that credits should not be used before the time frame in which they are generated. In general, a permitting authority should not allow for a pollutant reduction credit in a NPDES permit on the basis of the *proposed* treatment by another point source or an *unverified* commitment to install a BMP by a nonpoint source and their anticipated pollutant reduction (pg.34).

Both versions involve considerable transaction costs relative to cap-and-trade. Moreover, in the second version, there is additional market risk on the part of the abating firm given that costly actions take place prior to the realization of market prices and credit demand. Theoretical work on sunk investments has demonstrated that inefficiency can occur when investments and prices cannot be simultaneously determined (Mailath et al. 2004); the second version of baseline-and-credit presents this type of problem.

Although the two versions of baseline-and-credit seem to be the most prevalent institutions in practice, some programs are fashioned instead in the way of The Long Island Sound Trading Program (one of the lone WQT success stories), which does not involve credit trading in any conventional sense.[12] In trading jargon, polluters that exceed

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[12] As stated in U.S. EPA (2008), "[s]ome [WQT] program interviewees noted that their program lacks the defining features of trading (e.g., buyers and sellers, credits) and felt that EPA and others may apply the term too freely (pg.3-3)."

their baseline buy credits and those with emissions below their baseline sell credits. However, the “trading” is with the regulator who automatically charges/pays for credits at a pre-announced price at the end of a monitoring period. Further, there is no requirement that payments and receipts balance out. Thus, this mechanism is better described as a tax/subsidy regulation than a market trading institution. Because the tax/subsidy involves no market uncertainty, it serves as an interesting comparison with the baseline-and credit and cap-and-trade institutions, particularly when considering the effects of fixed technology costs.

It is typical for firms in WQT markets to have to incur fixed technology costs in order to adopt abatement technology and abate at the levels that realize efficiency gains. As discussed by Sado et al.(2010), Caplan (2008), Boisvert et al. (2007), and the EPA (1996), the abatement options available to sources of water pollution are often restricted to large investments associated with significant increases in abatement capabilities. Boisvert et al. (2007) and Sado et al. (2010) argue that fixed technology costs may impinge on trade in markets with few buyers and sellers, such as those often found in WQT. In order to abate at the efficient level, it might be necessary for a potential seller to adopt technology and take an upfront loss, in which case the seller would need to recover the technology costs in subsequent trades in order for the investment to be profitable. Where uncertainty exists over the number of trades and the prices at which they will occur there may be the potential for underinvestment and inefficiency. Thus as alluded to earlier, the tax/subsidy regulation may be more robust to fixed technology costs than the market trading institutions.

The ways in which the baseline-and-credit institutions, cap-and-trade, and the tax/subsidy relatively influence the performance of emissions trading, and the effect of fixed technology costs with these institutions, are open empirical issues that are investigated in this paper using economic laboratory experiments. Laboratory experiments have been fundamental and the primary tool in understanding the impact of institutional features related to cap-and-trade markets for air pollution. Although the experimental literature on emissions trading is vast (see Bohm (2003) and Muller and Mestelman (1998) for reviews), the majority of these experiments involve cap-and-trade, and few have focused on issues related to WQT markets.

Buckley et al. have several papers that constitute the only experimental work on baseline-and-credit versus cap-and-trade (2011, 2006, 2008). These papers however do not provide fundamental tests of the main distinguishing feature between baseline-and-credit and cap-and-trade of no initial credit allocation, nor do they provide a fundamental test of the second feature present in many baseline-and-credit markets, which is the need to pre-commit to abatement in order to generate credits.   Buckley et al. (2011) essentially test the joint effect of three institutional features, the two mentioned above along with one in which emissions ratios are enforced rather than aggregate emissions, of which two can and do differ in practice, and do so in a dynamic environment where learning is difficult and outcomes are history dependent.

The experiment reported in this paper systematically compares cap-and-trade, both versions of baseline-and-credit, and the tax/subsidy, both with and without fixed technology costs, in terms of their effects on the performance of emissions trading. The remainder of the paper is organized as follows. Section 3.2 describes the experiment design; Section 3.3 describes the experiment participants and procedures; Section 3.4 presents the results; and Section 3.5 concludes. In Sections 3.2, 3.3, and 3.4, the four institutions are referred to using the following labels: baseline-and-credit with non-binding proposal (BAC-1); baseline-and-credit with abatement pre-commitment (BAC-2); cap-and-trade (CAT); and tax/subsidy (TS). Furthermore, the terms Tech and No Tech are used to refer to treatments with and without fixed technology costs, respectively.

3.2 Experiment Design

The experiment design consists of the four institutions interacted with the fixed technology costs to yield eight treatments. There are four replications of each treatment, except for BAC-2 with Tech which for which there are six.[13] Each replication consisted of an eight-subject group participating in a common market over a sequence of 10 trading periods.[14] Although the number of periods was predetermined it was unknown to subjects. The basic features of the design in terms of subject types, abatement cost schedules, framing, and trading interface are loosely based on Cason and Gangadharan (2006). While the experiment itself was neutrally framed, for clarity of exposition we describe the experiment in the context of emissions trading.

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[13] Consistent with List et al. (2010) the additional sessions of BAC-2 were motivated by the higher variance we saw in this treatment.

[14] For convenience, we use market terminology when broadly characterizing the experiment, although we acknowledge that the TS treatments do not involve a market in a conventional sense.

In all treatments subjects faced a basic constraint in each period: their abatement ("production", in the instructions) had to be greater than or equal to a particular level. The required level of abatement was automatically enforced, so subjects did not face a compliance decision.[15] Subjects could alter their required levels of abatement by buying and selling credits ("coupons"); however, the specifics of how credits were obtained, bought and sold differed across institutions and are discussed in detail later. A subject's period earnings were equal to an endowment minus the costs of abatement and the costs of any credits purchased, plus earnings from any credits sold.

The particular level of abatement required by a subject at the start of each period (initial abatement requirement) was equal to 10 minus the subject's credit allocation in the TS and CAT treatments, and was equal to 10 minus the subject's baseline in the BAC-1 and BAC-2 treatments. While the credit allocation and the baseline both conferred equivalent rights to emit pollution in a status quo sense, the key difference between them was that a credit allocation allowed the sale of these emission rights, whereas a baseline did not. So for example, a subject with a credit endowment of four and a subject with a baseline of four would each have started the period required to abate six units to meet the constraint; however, the subject with a credit endowment would have started with four sellable credits, and the subject with the baseline would have started with zero credits to sell.

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[15] Although compliance in emissions trading programs is an important issue receiving increasing attention in economics experiments (Cason and Gangadharan 2006; Murphy and Stranlund 2007; Stranlund et al. 2011), excluding this element allowed us to focus on testing the underlying differences in the institutions at hand.

In each eight-person group there were four types which varied by endowments, credit allocations and baselines, abatement costs, and exchange rates. Types and groups were randomly assigned and remained the same for all 10 periods. In equilibrium, two of these types were buyers and two of these types were sellers, so that there were four buyers and four sellers in each group. However, subjects were not explicitly assigned buyer or seller roles; for the three trading institutions, subjects were allowed to both buy and sell credits. Baselines, credit endowments, and abatement costs for the four types are shown in Table 3.1. The column labeled MC in Table 3.1 indicates the marginal abatement cost associated with each unit of abatement, while the column labeled FC indicates the fixed technology cost. A subject's fixed technology cost was either 100 or 300 and was automatically determined by the number of units that the subject abated. Lower levels of abatement were associated with a fixed technology cost of 100, while higher levels of abatement were associated with a fixed technology cost of 300. The point along the abatement cost schedule at which the fixed technology costs switched was varied between buyers and sellers. Note that in the No Tech treatments, the fixed technology cost was zero for all levels of abatement, and there was no mention of technology in the instructions.

Given the parameters in Table 3.1, the equilibrium respectively has Type 1's and 2's each buying three and four credits, and Type 3's and 4's each selling four and three credits, for a total of 14 trades at an equilibrium price in the interval [220, 240] and potential gains from trade of 2400. Type-specific gains from trade at the competitive equilibrium are 300 for all types in the Tech treatments. In the No Tech treatments Type 1's and 4's have gains of 300, while Type 2's have gains of 100, and Type 3's have gains

Table 3.1 Abatement costs, credit allocations, and baselines by type

	Buyers				Sellers			
Abatement	Type 1		Type 2		Type 3		Type 4	
	MC	FC	MC	FC	MC	FC	MC	FC
1	100	100	155	100	17	100	25	100
2	150	100	170	100	18	100	27	100
3	200	100	185	100	19	100	30	100
4	260	100	200	100	20	100	35	100
5	330	100	215	100	50	300	40	300
6	400	100	240	100	130	300	50	300
7	475	100	250	100	220	300	60	300
8	550	300	260	300	310	300	130	300
9	625	300	270	300	450	300	200	300
10	700	300	425	300	575	300	300	300
Credit Allocation or Baseline	4		1		7		4	

(1) Note that MC gives the marginal abatement cost for the indicated unit of abatement, while FC gives the fixed technology cost associated with the indicated level of abatement.

(2) Note also that the numbers given in FC apply only to the treatments with technology. In treatments without technology FC=0 for all levels of abatement.

of 500. Importantly, our design is such that, under standard assumptions, the theoretical predictions are the same for all of the eight treatments; all four institutions are theoretically efficient both with and without fixed technology costs. However as we havealready conjectured, key differences between the institutions or/and the impacts of fixed technology costs may lead to inefficiencies empirically. The following descriptions indicate specifically the way in which TS, CAT, BAC-1, and BAC-2 were implemented in the experiment.

TS. With the TS institution, it was required that the sum of each subject's abatement and credits be equal to 10. Subjects were instructed to choose a level of abatement between one and 10 units. After subjects chose their abatement levels, credits were automatically bought or sold at a fixed price of 230 so that abatement and credits would sum to 10. So for example, if a subject had a credit endowment of four and chose seven units of abatement, she would automatically sell one credit at a price of 230. If she chose six units of abatement, she would neither buy nor sell. If she chose five units of abatement she would automatically purchase one credit at a price of 230.

CAT. As with the TS, CAT required each subject to satisfy the rule that abatement and credits sum to 10. However, in CAT subjects met this requirement by trading credits with one another in a computerized double auction. Each subject entered the market with her credit allocation, and then could buy or sell credits in order to adjust her credit holdings. After the market closed, each subject's abatement was automatically determined based on credit holdings. So for example, if a subject with a credit allocation of four was a net buyer of one credit in the emissions trading market, then she would automatically abate five units. If she did not alter her initial credit holding, then she would abate six units. If she was a net seller of one credit, then she would abate seven units.

BAC-1. In BAC-1, each period consisted of two stages. In the first stage, subjects were required to propose a level of abatement between one and 10. A subject could request credits to sell in the market by proposing a level of abatement that exceeded her initial abatement requirement. If a subject proposed a level of abatement higher than her initial abatement requirement, then the number of credits she received was equal to her proposed abatement minus her initial abatement requirement. If a subject proposed a level of abatement less than or equal to her initial abatement requirement, then she received zero credits for the emissions trading market. Proposing abatement in the first stage simply allowed the subject to request credits for the emissions trading market. Actual abatement was not determined until after the market in the second stage.

In the second stage, subjects traded credits with one another in a computerized double auction. Each subject began the trading period with the number of credits she requested in the first stage. At the end of the trading period, the subject's abatement was automatically determined so that the sum of the subject's baseline, abatement, and credit holdings minus requested credits would equal 10. So for example, if a subject had a baseline of four and proposed seven units of abatement, then she would receive one credit for the emissions trading market. If that subject was a net seller of one credit, then her abatement would be seven units. If she did not alter her credit holdings from the initial one credit, then her abatement would be six units. If she was a net buyer of one credit, then her abatement would be five units. From the description it is hopefully clear that the second stage of BAC-1 is essentially the same as CAT except for potentially different initial levels of credits.

BAC-2. As in BAC-1, each period in BAC-2 also consisted of two stages. The fundamental difference between BAC-1 and BAC-2 was that in BAC-2 subjects had to pre-commit to abatement decisions in the first stage in order to generate credits. In the first stage, subjects proposed a level of abatement between one and 10. If a subject proposed a level of abatement higher than her initial abatement requirement, then the number of credits she received was equal to her proposed abatement minus her initial abatement requirement. If a subject generated credits, then this was a binding abatement decision, and her abatement for the period was equal to her proposed abatement in the first stage regardless of what happened in the subsequent market. If a subject proposed a level of abatement less than or equal to her initial abatement requirement, then she generated zero credits, in which case her abatement was determined automatically at the end of the emissions trading market so that the sum of her baseline, abatement, and credit holdings would equal 10. So for example, if a subject had a baseline of four and proposed seven units of abatement, then she would enter the emissions trading market with one credit. Regardless of her market transactions, she would abate seven units for the period. If she instead had proposed six units of abatement, then she would enter the market with zero credits. If she were a net buyer of one credit, then she would automatically abate five units.

In the CAT, BAC-1, and BAC-2 institutions, subjects traded credits with one another in a computerized double auction. Each trade was for one credit, and all subjects could submit offers to sell and bids to buy as well as accept standing offers and bids. Only the most favorable offer and bid were displayed on the auction screen, so that in order to have an offer displayed a subject had to submit a lower price than the standing offer, and in order to have a bid displayed a subject had to submit a higher price than the standing bid. When a subject accepted an offer or a bid, a transaction occurred immediately, and the current offer and bid were cleared from the trading screen. While there was no explicit restriction on the number of transactions a subject could make, subjects were not allowed to reduce their abatement below one unit, and automation was in place that prevented a subject from buying a credit if doing so would violate this rule. Information displayed on the trading screen other than standing bids and offers included a history of transaction prices and buyer and seller IDs, the subject's current period earnings, current earnings in the market, current level of required abatement, and current credit holdings, all of which were updated accordingly as transactions occurred. Also displayed onscreen was the time remaining in the market. The market lasted for three minutes in the first two periods of each session and then was reduced to two minutes and 30 seconds for the remaining periods.

3.3 Experiment Participants and Procedures

We conducted 17 sessions between April and June of 2011, with either one or two groups (i.e. markets) in each session (depending on how many subjects showed up for the experiment).[16] All treatments were implemented in terms of a between-subjects design, except for TS treatments. We ran two sessions for the TS treatments, each session having two groups and lasting 20 periods.[17] In one of these sessions, subjects faced No Tech in the first 10 periods, and then faced Tech in the second 10 periods. In the other session this order was reversed. In these TS sessions, subject types were randomly reassigned and the groups randomly rematched after the first 10 periods.

A total of 240 subjects participated in the experiments, all of whom were recruited from the student population at the University of Tennessee. The experiments were conducted in the University of Tennessee Experimental Economics Laboratory and run on client computers from a designated lab server using z-Tree (Fischbacher 2007). Subjects were assigned to individual computer stations separated by dividers, and prior to the subjects entering the lab each station was provided a pencil, a calculator, a blank sheet of paper, and a copy of the instructions for the experiment.

In each session, subjects participated in a standard risk preference elicitation lottery (Holt and Laury 2002) before participating in the emissions trading experiment.[18] Instructions for the lottery were read aloud by an experiment moderator while subjects followed along with the instructions at their computer stations. After the lottery, instructions for the emissions trading experiment were administered in the same manner, and questions were answered. During the instructions, two short multi-part quizzes were conducted in order to solidify the subjects' understanding of the experiment. In order to

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[16] Specifically, there were 13 two-group sessions, and four one-group sessions.

[17] It made sense to run two treatments in each TS session given that subjects progressed through the TS periods much faster than under the other institutions.

[18] Explorations of the effects of risk aversion are planned for future work.

encourage subjects to consider the quizzes carefully, they were incentivized with US$1 paid per quiz if all questions were answered correctly. Prior to the paid periods of the experiment, subjects participated in one unpaid practice period in order to gain familiarity with the software and decision environment, and after the practice period subjects were given a final opportunity to ask questions before beginning the actual experiment. At the conclusion of the experiment, payoffs from the lottery were displayed onscreen in US$ and subjects completed a short questionnaire.

Upon completion of the questionnaire, experimental dollars from the emissions trading experiment were converted to US$ at rates of 150:1 for Type 1's and 4's, 50:1 for Type 2's, and 250:1 for Type 3's in the No Tech treatments. In the Tech treatments the exchange rate was 150:1 for all types.[19] These exchange rates along with the endowments were chosen so that, for all types under all treatments, if a player did not trade she would make $.40 and with efficient trading she would make $2.40. Thus, there were large financial gains from trade. Earnings from the emissions trading experiment were added to the earnings from the lottery and quiz questions, and subjects were paid in cash. Sessions lasted between 90 and 105 minutes, and subjects earned an average of about $25 (not including earnings from the quiz questions), with a range of $10 to $82.

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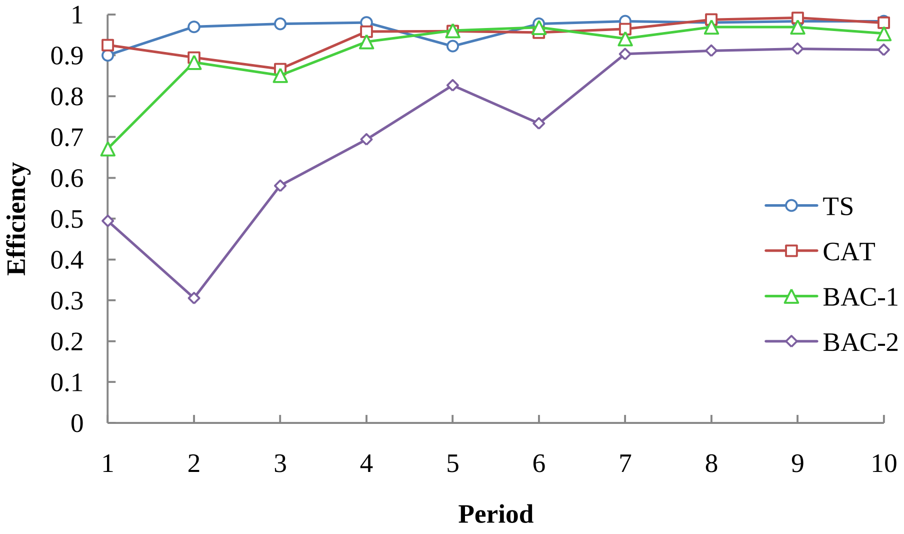
[19] In the TS treatments these exchange rates were doubled (i.e., half as many US$ per experimental dollar), since the sessions in the TS had twice as many periods as in the other treatments.

3.4 Results

Analysis of Efficiency. The analysis of the data is primarily organized around efficiency across the eight treatments. We define efficiency as the percentage of the potential gains from trade that are actually captured by a group in a given period. If no trades were to occur, group earnings would be 508 in the Tech treatments, and 488 in the No Tech treatments, for a given period. Therefore, observed gains from trade are calculated as observed group earnings minus 508 for the Tech treatments, and minus 488 for the No Tech treatments. We calculated the efficiency performance measure for each group in each period by dividing the observed gains from trade by the potential gains of 2400 and multiplying by 100. Note that it is possible for the efficiency measure to be negative if the observed group earnings are lower than they would have been in the absence of trading.

Figure 3.1 graphs the mean group efficiency in each period for each institution by Tech and No Tech. Examining this figure, BAC-2 clearly appears less efficient than the other institutions both without and with fixed technology costs, while CAT and BAC-1 appear to track each other closely. TS appears to have similar efficiency as CAT and BAC-1 without fixed technology costs, at least in the later periods; however, with technology TS appears to have higher efficiency than all three market trading institutions. Overall, levels of efficiency for all institutions appear higher under No Tech than under Tech, indicating the presence of a technology effect. Further evidence of such a technology effect is observed in Figure 3.2, which plots mean group efficiency for each period by Tech and No Tech within each institution. Fixed technology costs appear to

No Technology



Technology

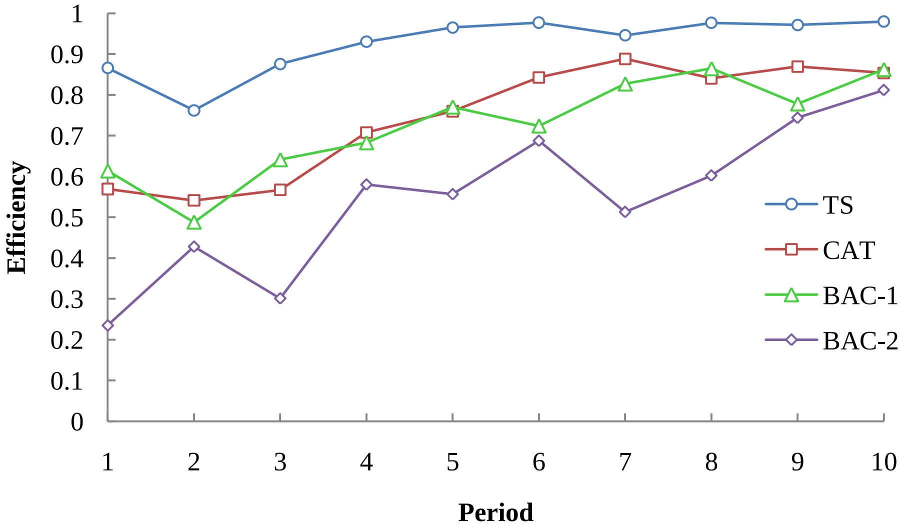


Figure 3.1 Mean efficiency by institution by technology

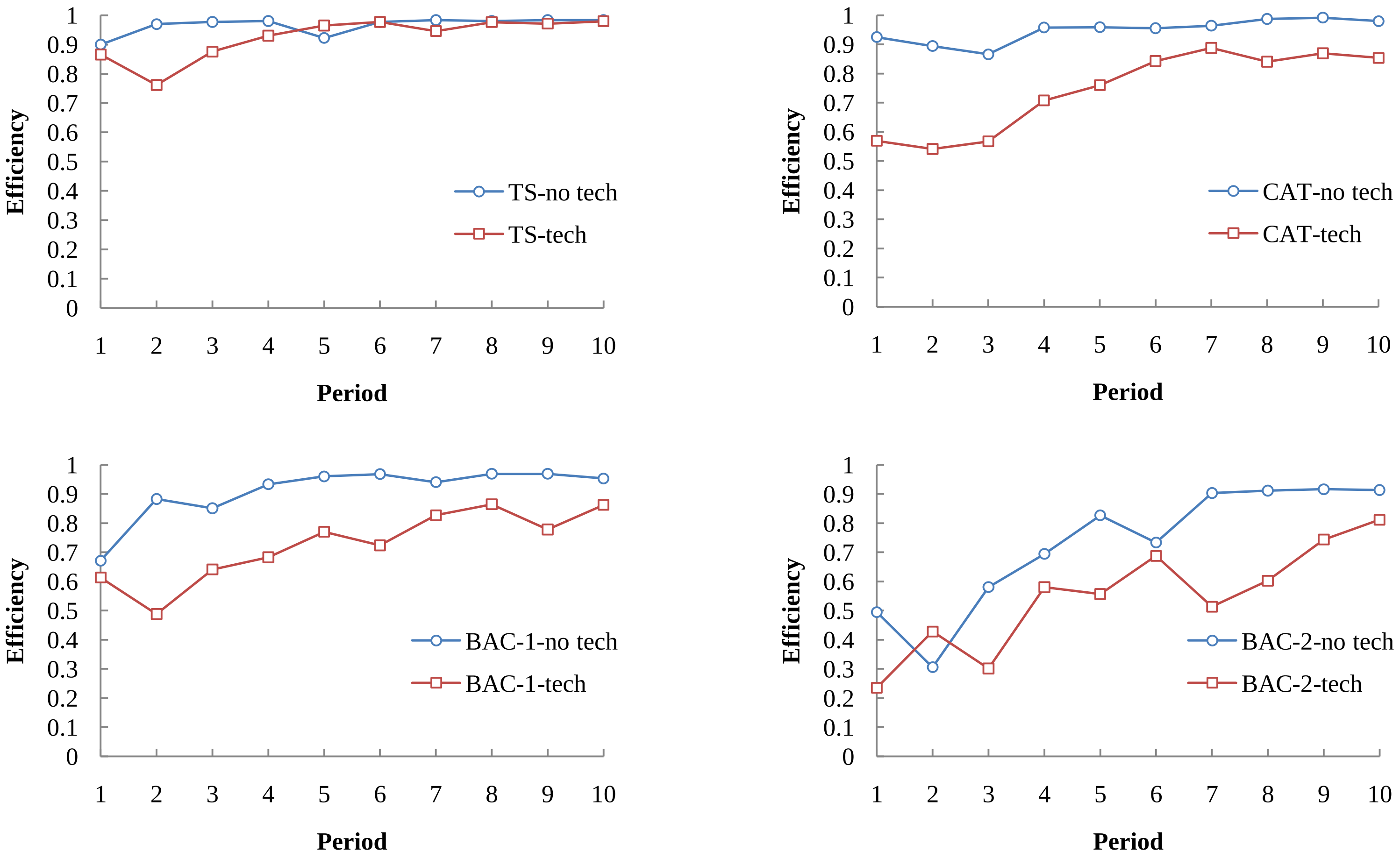


Figure 3.2 Mean efficiency within-institution by technology

lower efficiency in all institutions; however, consistent with Figure 3.1 the effect seems to be the strongest in CAT, BAC-1, and BAC-2.

In order to systematically investigate efficiency across treatments we ran OLS regressions of efficiency on indicators for the eight treatments interacted with an indicator variable for the first and last five periods. We observe efficiency for each group in each period, for a total of 340 observations. The estimated model is specified as:

$$
\begin{aligned}
Efficiency_{it} = \sum_{j=1}^{2} \{ & \beta_1 (TS \times No\ Tech)_{it} + \beta_2 (CAT \times No\ Tech)_{it} \\
& + \beta_3 (BAC1 \times No\ Tech)_{it} + \beta_4 (BAC2 \times No\ Tech)_{it} + \beta_5 (TS \times Tech)_{it} \\
& + \beta_6 (CAT \times Tech)_{it} + \beta_7 (BAC1 \times Tech)_{it} + \beta_8 (BAC2 \times Tech)_{it} \} \delta_{it}^{j} \\
& + \varepsilon_{it}
\end{aligned}
$$

where $Efficiency_{it}$ is the efficiency observed for group i in period t, and δ_{it}^{j} is an indicator variable for whether the observation of group i in period t is part of the first or last five periods. The results are presented in Table 3.2. Across all ten periods, the efficiencies with No Tech are 96.57% with TS, 94.81% with CAT, 90.99% with BAC-1, and 72.80% with BAC-2. With Tech, efficiencies were 92.49% with TS, 74.39% with CAT, 72.52% with BAC-1, and 54.60% with BAC-2. These estimates are consistent with the observations made regarding Figures 3.1 and 3.2.

Table 3.3 presents pairwise tests of equal efficiencies across the institutions by technology. First examining the No Tech treatments for all periods, the tests indicate that efficiency under the TS is indeed not statistically different from efficiency under CAT;

Table 3.2 Efficiency

Treatment	All Periods	1st 5 Periods	2nd 5 Periods
No Technology			
TS	96.57^{***}	94.99^{***}	98.15^{***}
	(1.32)	(1.78)	(0.89)
CAT	94.81^{***}	92.04^{***}	97.57^{***}
	(2.03)	(3.71)	(0.57)
BAC-1	90.99^{***}	85.98^{***}	96.01^{***}
	(2.25)	(4.45)	(0.62)
BAC-2	72.80^{***}	58.04^{***}	87.55^{***}
	(5.26)	(10.00)	(2.57)
Technology			
TS	92.49^{***}	87.97^{***}	97.01^{***}
	(0.49)	(2.05)	(1.23)
CAT	74.39^{***}	62.90^{***}	85.89^{***}
	(5.52)	(7.26)	(6.72)
BAC-1	72.52^{***}	63.92^{***}	81.13^{***}
	(5.49)	(5.56)	(5.96)
BAC-2	54.60^{***}	42.03^{***}	67.17^{***}
	(8.32)	(8.93)	(9.28)
N	340		
F	14717.20^{***}		
R^2	0.95		

(1) The dependent variable is the efficiency observed in each eight-subject market in each period, where efficiency is defined as the observed gains from trade as a percentage of the maximum possible gains from trade.

(2) Clustered robust standard errors are in parentheses. $^{***}p < 0.01$.

Table 3.3 Efficiency: tests of institution effect by technology

Hypothesis	All Periods	1st 5 Periods	2nd 5 Periods
No Technology			
H_O: TS = CAT	1.76	2.95	0.57
	(2.42)	(4.12)	(1.06)
H_O: TS = BAC-1	5.57^{**}	9.01^{*}	2.14^{*}
	(2.61)	(4.79)	(1.09)
H_O: TS = BAC-2	23.77^{***}	36.95^{***}	10.59^{***}
	(5.43)	(10.16)	(2.72)
H_O: CAT = BAC-1	3.81	6.06	1.56^{*}
	(3.03)	(5.80)	(0.84)
H_O: CAT = BAC-2	22.01^{***}	34.00^{***}	10.02^{***}
	(5.64)	(10.67)	(2.64)
H_O: BAC-1 = BAC-2	18.20^{***}	27.94^{**}	8.46^{***}
	(5.72)	(10.95)	(2.65)
Technology			
H_O: TS = CAT	18.10^{***}	25.07^{***}	11.13
	(5.54)	(7.54)	(6.83)
H_O: TS = BAC-1	19.97^{***}	24.06^{***}	15.89^{**}
	(5.52)	(5.92)	(6.08)
H_O: TS = BAC-2	37.89^{***}	45.94^{***}	29.84^{***}
	(8.33)	(9.16)	(9.36)
H_O: CAT = BAC-1	1.87	-1.01	4.76
	(7.79)	(9.14)	(8.98)
H_O: CAT = BAC-2	19.79^{*}	20.88^{*}	18.71
	(9.98)	(11.51)	(11.46)
H_O: BAC-1 = BAC-2	17.92^{*}	21.89^{**}	13.95
	(9.97)	(10.52)	(11.03)

(1) Results are the differences between the coefficients in Table 3.2.
(2) Standard errors are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

however, the TS efficiency is significantly higher than BAC-1 efficiency by 5.57 percentage points. We also confirm that CAT and BAC-1 are not significantly different from each other, and that TS, CAT, and BAC-1 are all significantly more efficient than BAC-2, by amounts of 23.77, 22.01, and 18.20 percentage points, respectively. With Tech, the TS does produce significantly higher efficiency than the market trading institutions, 18.10 percentage points higher than CAT, 19.97 points higher than BAC-1, and 37.89 points higher than BAC-2. CAT and BAC-1 are not significantly different from each other, and both have higher efficiency than BAC-2 at margins of 19.79 percentage points and 17.92 points, respectively, although these differences are only marginally significant. Looking at the first and last five periods in Tables 3.2 and 3.3, efficiencies appear to be increasing over time, but for the most part the rankings of efficiencies under the treatments do not change from those across all 10 periods.

For further evidence on the impact of fixed technology costs we present tests of equal efficiencies across the two treatments associated with each institution in Table 3.4. From these we see that technology significantly lowers efficiency in all institutions, but the magnitude of the technology effect appears much smaller under the TS than under the other institutions. While fixed technology costs lower efficiency in the TS by 4.08 percentage points, efficiencies under CAT, BAC-1, and BAC-2 are respectively 20.41, 18.47, and 18.20 points lower. Furthermore, the last five periods in Table 3.4 show that the technology effect eventually dissipates to insignificance under the TS, but remains statistically significant in CAT, BAC-1, and BAC-2, lowering efficiencies by 11.69, 14.89, and 20.38 percentage points, respectively, relative to the case of no fixed technology costs.

Table 3.4 Efficiency: tests of technology effect by institution

Hypothesis	All Periods	1st 5 Periods	2nd 5 Periods
TS			
H_O: No Tech = Tech	4.08***	7.02**	1.14
	(1.41)	(2.71)	(1.52)
CAT			
H_O: No Tech = Tech	20.41***	29.14***	11.69*
	(5.88)	(8.15)	(6.74)
BAC-1			
H_O: No Tech = Tech	18.47***	22.06***	14.89**
	(5.94)	(7.12)	(5.99)
BAC-2			
H_O: No Tech = Tech	18.20*	16.01	20.38**
	(9.84)	(13.41)	(9.63)

(1) Results are the differences between the coefficients in Table 3.2.
(2) Standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

The results are largely consistent with our expectations. BAC-2 is the only institution that requires subjects wishing to obtain credits to sell to make a binding abatement pre-commit, and we see that this institution is significantly less efficient than the other institutions both without and with fixed technology costs. While BAC-1 is similar to BAC-2 in that subjects initially have no credits to sell, the fact that the proposal of abatement is non-binding makes the institution functionally similar to CAT in that subjects are able to determine actual abatement in the market. Thus we expected that BAC-1 and CAT would be similarly efficient, as they indeed were. With regard to fixed technology costs, we were surprised to find that Tech lowered efficiency even under the TS, given that this mechanism is not subject to market uncertainty. However, for the same reason we were not surprised that in the presence of Tech the TS had higher efficiency than CAT, BAC-1, BAC-2.

Analysis of Efficiency Variance. As a further investigation of the efficiency implications of these institutions and the effects of fixed technology cost, we also analyzed the variance of efficiency. We calculated the variance of efficiency, using a formula similar to the one stated in Gilpatric et al. (2011), as the squared difference between a group's period efficiency and the period mean efficiency for a particular treatment. Specifically, the variance of efficiency for a particular treatment is specified as $(Efficiency_{it} - \overline{Efficiency_t})^2$, where $Efficiency_{it}$ is the observed efficiency for group i in period t, and $\overline{Efficiency_t}$ is the mean efficiency for that treatment in period t. We ran OLS regressions on the same set of regressors as those specified for the efficiency outcome regressions, and we present the results in Table 3.5. Tables 3.6 and 3.7 present tests of

Table 3.5 Variance of efficiency

Treatment	All Periods	1^{st} 5 Periods	2^{nd} 5 Periods
No Technology			
TS	0.17^{**}	0.31^{**}	0.03^{*}
	(0.08)	(0.14)	(0.02)
CAT	0.43^{*}	0.83^{*}	0.02^{***}
	(0.22)	(0.44)	(0.01)
BAC-1	1.20^{**}	2.35^{*}	0.06^{***}
	(0.58)	(1.15)	(0.02)
BAC-2	2.98^{***}	5.44^{***}	0.53^{***}
	(0.23)	(0.48)	(0.04)
Technology			
TS	0.34^{***}	0.58^{***}	0.09^{**}
	(0.08)	(0.13)	(0.04)
CAT	3.13^{***}	4.44^{***}	1.82^{*}
	(0.79)	(1.29)	(0.97)
BAC-1	1.68^{***}	1.52^{**}	1.84^{***}
	(0.55)	(0.65)	(0.47)
BAC-2	7.66^{**}	7.01^{**}	8.30
	(3.37)	(2.87)	(5.37)
N	340		
F	35.45^{***}		
R^2	0.17		

(1) The dependent variable is the variance of efficiency, calculated as the squared difference between a group's period efficiency and the period mean efficiency for that treatment.
(2) Clustered robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 3.6 Variance of efficiency: tests of institution effect by technology

Hypothesis	All Periods	1st 5 Periods	2nd 5 Periods
No Technology			
H_O: TS = CAT	-0.26	-0.52	0.01
	(0.23)	(0.46)	(0.02)
H_O: TS = BAC-1	-1.03^{*}	-2.03^{*}	-0.03
	(0.59)	(1.16)	(0.02)
H_O: TS = BAC-2	-2.81^{***}	-5.13^{***}	-0.49^{***}
	(0.25)	(0.50)	(0.05)
H_O: CAT = BAC-1	-0.77	-1.51	-0.03
	(0.62)	(1.23)	(0.02)
H_O: CAT = BAC-2	-2.55^{***}	-4.61^{***}	-0.50^{***}
	(0.32)	(0.65)	(0.05)
H_O: BAC-1 = BAC-2	-1.78^{***}	-3.09^{**}	-0.47^{***}
	(0.63)	(1.25)	(0.05)
Technology			
H_O: TS = CAT	-2.79^{***}	-3.85^{***}	-1.73^{*}
	(0.80)	(1.29)	(0.97)
H_O: TS = BAC-1	-1.34^{**}	-0.94	-1.75^{***}
	(0.56)	(0.67)	(0.47)
H_O: TS = BAC-2	-7.32^{**}	-6.43^{**}	-8.21
	(3.37)	(2.87)	(5.37)
H_O: CAT = BAC-1	1.45	2.91^{*}	-0.02
	(0.97)	(1.44)	(1.08)
H_O: CAT = BAC-2	-4.53	-2.57	-6.48
	(3.46)	(3.14)	(5.46)
H_O: BAC-1 = BAC-2	-5.98^{*}	-5.49^{*}	-6.46
	(3.41)	(2.94)	(5.39)

(1) Results are the differences between the coefficients in Table 3.5.

(2) Standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 3.7 Variance of efficiency: tests of technology effect by institution

Hypothesis	All Periods	1st 5 Periods	2nd 5 Periods
TS			
H_O: No Tech = Tech	-0.17	-0.27	-0.06
	(0.11)	(0.20)	(0.04)
CAT			
H_O: No Tech = Tech	-2.70^{***}	-3.60^{**}	-1.80^{*}
	(0.82)	(1.36)	(0.97)
BAC-1			
H_O: No Tech = Tech	-0.48	0.82	-1.78^{***}
	(0.80)	(1.32)	(0.47)
BAC-2			
H_O: No Tech = Tech	-4.67	-1.57	-7.78
	(3.38)	(2.91)	(5.37)

(1) Results are the differences between the coefficients in Table 3.5.
(2) Standard errors are in parentheses. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the regression coefficients to identify the effects of institution by technology and the effects of technology within institution, respectively.

When all ten periods are considered, there are three interesting observations. First, in the No Tech treatments, the variance of efficiency under BAC-2 (2.98 percentage points) is significantly higher than the variance of efficiency under the other three institutions (2.81 percentage points higher than in the TS, 2.55 points higher than in CAT, and 1.78 points higher than in BAC-1). In the Tech treatments, the variance under BAC-2 (7.66 percentage points) is significantly higher than under the TS (by 7.32 percentage points) and marginally significantly higher than under BAC-1 (by 5.98 percentage points). Second, in the Tech treatments the TS has significantly lower variance of efficiency than the other three institutions: 0.34 percentage points compared with 3.13, 1.68, and 7.66 points respectively in CAT, BAC-1, and BAC-2. Third, the CAT is the only institution in which fixed technology costs exhibit a significant effect on the variance of efficiency, increasing the variance by 2.70 percentage points relative to No Tech.

The first two observations reinforce the rankings of the institutions from the analysis of mean efficiencies. The first observation indicates that not only does BAC-2 exhibit significantly lower mean efficiency than the other institutions under both Tech and No Tech, it also exhibits significantly higher variance than under all other cases except for CAT with Tech. The second observation demonstrates that in the presence of fixed technology costs, the TS is more robust than the other institutions not only in terms of higher mean efficiency, but also in terms of lower variance of efficiency. While we do not have a ready explanation for the third observation, it is clearly the reason why the variance of efficiency under BAC-2 is not statistically different from the variance of efficiency under CAT in the Tech treatments.

Analysis of Individual Decisions. In addition to the analysis of group efficiency we also conducted an examination of individual-level abatement. In particular we investigated the deviations of individual abatement from the efficient levels of abatement by type. At the competitive equilibrium Type 1's abate three units, Type 2's abate five units, Type 3's abate seven units, and Type 4's abate nine units. We calculate deviations from expected by subtracting these competitive equilibrium levels from the levels actually observed in the experiment. We regressed these deviations on a full set of interactions between treatment indicators and type indicators. Regression results are presented in Table 3.8.

Type 1's and 2's are buyers at the competitive equilibrium, while Type 3's and 4's are sellers. What we see in Table 3.8 is that mean deviations from expected abatement are all positive for the buyers and are all negative for the sellers, which means that on average the buyers are overabating in all treatments, while the sellers are underabating. The extent to which the buyer types are deviating relative to each other and the extent to which the seller types are deviating relative to each other are addressed in Tables 3.9 and 3.10, respectively. Cases in which we might expect to see type-specific differences in deviations from abatement between seller types are in the Tech treatments. Given their respective credit allocations/baselines and their efficient levels of abatement, Type 3's would have had to switch from low to high fixed technology costs in order to abate at the efficient level, where as Type 4's would have started at high fixed technology costs and

Table 3.8 Deviations from expected abatement by type

Treatment	Type 1	Type 2	Type 3	Type 4
No Technology				
TS	0.06	0.50	0.00	-0.21*
	(0.13)	(0.44)	(0.02)	(0.11)
CAT	0.10***	0.33*	-0.31*	-0.11***
	(0.03)	(0.17)	(0.17)	(0.03)
BAC-1	0.09	0.84***	-0.60***	-0.33***
	(0.09)	(0.26)	(0.18)	(0.08)
BAC-2	0.68**	1.84***	-1.09***	-1.24***
	(0.32)	(0.28)	(0.20)	(0.15)
Technology				
TS	0.06***	0.06	-1.18***	-0.31
	(0.02)	(0.08)	(0.30)	(0.21)
CAT	0.88***	1.44***	-1.36***	-0.95***
	(0.16)	(0.33)	(0.42)	(0.21)
BAC-1	0.66**	2.31***	-2.16***	-0.81***
	(0.29)	(0.32)	(0.44)	(0.08)
BAC-2	1.29***	2.06***	-1.58***	-1.52***
	(0.31)	(0.37)	(0.28)	(0.33)
N	2720			

(1) The dependent variable is the difference between observed individual abatement and individual abatement at the competitive equilibrium.
(2) Clustered robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 3.9 Comparison of buyer types: Type1 deviation – Type2 deviation

Institution	No Technology	Technology
TS	-0.44	0.00
	(0.33)	(0.10)
CAT	-0.23	-0.56
	(0.19)	(0.35)
BAC-1	-0.75^{**}	-1.65^{***}
	(0.34)	(0.33)
BAC-2	-1.16^{**}	-0.77^{**}
	(0.50)	(0.36)

(1) Clustered robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 3.10 Comparison of seller types: Type3 deviation – Type4 deviation

Institution	No Technology	Technology
TS	0.21^{**}	-0.86^{*}
	(0.10)	(0.49)
CAT	-0.20	-0.41
	(0.19)	(0.54)
BAC-1	-0.28	-1.35^{***}
	(0.21)	(0.37)
BAC-2	0.15	-0.06
	(0.11)	(0.22)

(1) Clustered robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

therefore would not have had to cross this threshold. If the necessity to cross the threshold made Type 3's reluctant to invest we may have seen them underabating more than the Type 4's.

First examining the differences in deviations between Type 1's and 2's in Table 3.9, the tests indicate that Type 2's are overabating significantly more than Type 1's under BAC-1 and BAC-2 under both No Tech and Tech. The tests in Table 3.10 show that Type 3's are underabating significantly more than Type 4's under the TS and BAC-1 with Tech, while the Type 4's are underabating significantly more than Type 3's under the TS with No Tech. Therefore we do see weak evidence for the pattern of underabatement by Type3's relative to Type 4's described above: with fixed technology costs, Type 3's underabated more than Type 4's under all institutions, but the differences were only significant under the TS and BAC-1.

As a final step in analyzing individual abatement we grouped the types into (expected) buyers and sellers, and regressed deviations in expected abatement on a full set of interactions between treatment indicators and indicators for buyer and seller. Examining the results in Table 3.11 provides a look at the overabatement by buyers and the underabatement by sellers under each treatment. In CAT and BAC-1 the mean overabatement by buyers is exactly equal to the mean underabatement by sellers. Because abatement was determined solely on the basis of established market trades under these institutions it was necessarily the case that the aggregate abatement target was exactly met. This was not the case however under the TS or BAC-2. With the TS the aggregate abatement target could either be exceeded or could fail to be met, since the TS does not constrain the number of credits bought to equal the number sold. The TS

Table 3.11 Deviations from expected abatement by buyers and sellers

Treatment	Buyer	Seller
No Technology		
TS	0.28	-0.11*
	(0.27)	(0.06)
CAT	0.21***	-0.21***
	(0.07)	(0.07)
BAC-1	0.46***	-0.46***
	(0.09)	(0.09)
BAC-2	1.26***	-1.16***
	(0.16)	(0.17)
Technology		
TS	0.06	-0.74***
	(0.04)	(0.08)
CAT	1.16***	-1.16***
	(0.19)	(0.19)
BAC-1	1.49***	-1.49***
	(0.26)	(0.26)
BAC-2	1.68***	-1.55***
	(0.29)	(0.28)
N	2720	

(1) The dependent variable is the difference between observed individual abatement and individual abatement at the competitive equilibrium.

(2) Clustered robust standard errors are in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

resulted in aggregate overabatement without technology, and aggregate underabatement with technology, as buyers overabated more than sellers underabated in the first case, and vice versa in the second. In BAC-2, because subjects had to pre-commit to abatement in order to generate credits to sell, it was possible to have aggregate overabatement, and that is what was observed. Aggregate underabatement was not possible in BAC-2.

3.5 Conclusion

In contrast to the markets for air quality whose successes have contributed to the EPA's endorsement and support of WQT initiatives for more than decade, there are few success stories among the many U.S. watersheds that have attempted to establish WQT. Yet there are fundamental differences between the markets for air quality and those for water quality, and we have a much better understanding of air quality markets than we do of water quality markets. The latter fact is largely thanks to a sizable literature of economic experiments that has systematically evaluated the effects of institutional features related to the U.S. SO_2 Trading Program. In comparison, there is little empirical evidence on WQT institutions.

The experiment reported in this paper provides empirical evidence that enhances the understanding of WQT markets. The experiment evaluates the relative performance of three common WQT institutions and the standard cap-and-trade institution used in air quality markets. In addition it studies the effect of fixed technology costs within in each of these institutions. Overall there are four main findings. First, relative to the other institutions examined, a baseline-and-credit institution that requires abatement pre-commitment results in significantly lower efficiency both in the presence and absence of fixed technology costs, and in most cases results in higher variance of efficiency as well. Second, a baseline-and-credit institution without abatement pre-commitment exhibits similar efficiency as standard cap-and-trade. The first and second findings together suggest that it is pre-commitment to abatement that drives inefficiency, as opposed to the other characteristic of baseline-and-credit which is no initial credit allocation. Third, the presence of fixed technology costs significantly reduces efficiency in all of the institutions examined. This result provides a contribution to the experimental literature on air quality markets as well as the literature on WQT, as to the authors' knowledge the effects of fixed technology costs on cap-and-trade have not been previously studied. Fourth, in the presence of fixed technology costs, efficiency under a tax/subsidy is significantly higher and has significantly lower variance than under the other institutions examined, which we attribute to the fact that the tax/subsidy does not face market uncertainty.

These findings provide some evidence that the baseline-and-credit institutions requiring abatement pre-commitment, or/and fixed costs associated with abatement technology, could contribute to the impediment of functioning WQT markets. From a policy perspective, consideration should be given to determining the appropriateness of requiring abatement pre-commitment in order to generate credits in a WQT program. Furthermore, where high fixed technology costs are concerned, tax/subsidy may be more efficient than a baseline-and-credit or cap-and-trade, as the absence of market uncertainty appears to make the tax/subsidy more robust in such circumstances. However, the caveat in using tax/subsidy regulation is that the regulator's uncertainty over the optimal tax/subsidy rate (i.e. credit price) has the ability to invoke efficiency losses and distort the short and long-run incentives for investment in abatement technology. Indeed, the Long Island Sound Trading Program has required the state to deal with large imbalances between the number credits purchased and sold, implying that the program has more than met its water quality goals in some years, and has failed to meet them in others. For example, in the first four years of the program, which launched in 2002, the state purchased excess credits of $1.4 million, $312,000, and $873,081 in 2003, 2004, and 2005, respectively, and then in 2006 *sold* an excess of $1,152,365 (Connecticut State Treasury 2003, 2004, 2005, 2006).

While this experiment investigates several fundamental issues related to WQT markets, there are numerous explanations that have been postulated for the lack of success of WQT programs. Thus, there are many studies to be conducted in order to amass the same empirical knowledge of these institutions that has been gathered on air quality markets. Given the ability of experiments to parse the effects of particular institutional features and the lack of sufficient real world data on WQT markets, experiments should have a central role in identifying the factors that are causing WQT markets to fail and in generating insights on how to establish them for success.

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