2016

Three essays on environmental economics and intra-household decision making

Maria Jimena Gonzalez Ramirez
Iowa State University

Three essays on environmental economics and intra-household decision making

by

María Jimena González Ramírez

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Economics

Program of Study Committee:

Catherine L. Kling, Major Professor
J. Gordon Arbuckle, Jr.
Joseph Herriges
Brent Kreider
Peter Orazem

Iowa State University

Ames, Iowa

2016

DEDICATION

Para mi familia,

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

I would like to express my gratitude to those individuals who made this dissertation possible. First and foremost, I would like to thank my major professor, Dr. Cathy Kling, for her valuable feedback, unconditional assistance, guidance, and generous financial support. I would like to thank Dr. Kling for providing me with a wonderful research environment at CARD. I am very grateful for being part of the CARD community and for participating in the weekly donut meetings. I also appreciate the ample opportunities she gave me to improve my communication skills by presenting my research in front of the Environmental Policy group and at conferences. I am also grateful for her advice that extends beyond this dissertation. Dr. Kling's wisdom was extremely helpful throughout graduate school and for the job market.

My gratitude extends to my committee members: Dr. Peter Orazem, Dr. J. Arbuckle Jr., Dr. Brent Kreider, and Dr. Joseph Herriges for their time, valuable feedback, and suggestions. A special thank you goes to J. for providing the data for the second chapter, for sharing his knowledge about Iowa's agriculture, and for exposing me to a different social science.

I would like acknowledge Niccolo Meriggi, the co-author of my third chapter, for his contributions and help. I would like to express my gratitude for his data and for his valuable feedback, suggestions, and contributions to the chapter. I appreciate that he was part of the data collection process in Cameroon and that he has shared his experimental and development economics knowledge with me. I am very grateful for this collaboration.

I take the time to recognize Dr. Dave Keiser, Dr. Wendong Zhang, Dr. Ivan Rudik, and Dr. Gabe Lade for their feedback on my job market seminar and their valuable information on the job market. I extend my gratitude to those who attended my different research seminars for their time, comments, and suggestions. A special thank you goes to Deung Yong Heo and Yongjie Ji, who were always willing to discuss research ideas, and to Dr. Phil Gassman for sharing his knowledge about conservation practices. Moreover, I would like to extend my gratitude to Dr. Georgeanne Artz for being my mentor for a year. I enjoyed our weekly meetings, and I am very thankful for her time, guidance, and valuable advice.

I want to thank my family in Colombia for their love, support, and care. Despite the distance, my parents were always present throughout this journey. I would like to especially thank my husband for his unconditional support and love throughout graduate school. Since my first day at Iowa State, he has been by side encouraging me to follow my dreams and to not give up. Lastly, I am also grateful for my closest friends who also provided support throughout this process.

Finally, I would like to acknowledge that my research and research assistantship were supported by the following collaborative projects: *“Water Quality Benefits from Agricultural Conservation Actions and Programs: A Proposal to NRCS”* (Funded by USDA-NRCS - Award number 68-7482-10-516); *“Evaluating the Integrity of Agricultural GHG Offsets: The Costs and Consequences of Altering Baselines and Program Options”* (Funded by USDA-ERS - Award number 58-6000-0-0095); *“Nudging in the Face of Risk and Ambiguity Aversion: Adopting Cover Crops to Reduce Nutrient Pollution”* (USDA-ERS - Award number 58-6000-5-0028); *“Cropping Systems Coordinated Agricultural Project (CAP): Climate Change, Mitigation, and Adaptation in Corn-Based Cropping Systems”* (Funded by USDA-NIFA - Award number 2011-68002-30190); *“Collaborative Research: Northern Gulf of Mexico Hypoxia and Land Use in the Watershed: Feedback and Scale Interactions”* (Funded by NSF - Award number DEB-1010259); *“A Market Feasibility Assessment for a Reverse Auction in the Walnut Creek Watershed”* (Funded by EPA - Award Number WS-97704901); *“A Market Feasibility Assessment for a Reverse Auction in the Boone Watershed”* (Funded by EPA - Award Number WS-97704701); and *“A Market Feasibility Assessment for Water Quality Trading and Reverse Auctions in the Raccoon River Watershed”* (Funded by EPA - Award Number WS-97704801).

ABSTRACT

This dissertation is divided into two major topics. The first two chapters belong to the field of environmental economics and the third chapter belongs to development and behavioral economics. The work on environmental economics is divided into two parts: Chapter 1 studies the design of environmental markets when pollutants are complements and Chapter 2 studies the effectiveness of a subsidy program that promotes cover crops, a new pollution abatement technology in agriculture, in Iowa. Lastly, the work on development economics in Chapter 3 studies intra-household dynamics using a lab-in-the-field risk experiment in rural Cameroon.

As environmental concerns are gaining more attention, the need for more research on environmental markets seem pertinent. Among the topics that require more attention is the usage or prohibition of double-dipping or stacking, which occurs when a firm is allowed to obtain payments for two environmental services that come from the same action. Given the various implementations of payments for ecosystem/environmental services (PES), understanding the usage of payments for several environmental services becomes very relevant for policy makers. Motivated by the relevance of this subject, Chapter 1 includes a theoretical framework on the design of environmental programs for pollutants that are complements and Chapter 2 includes an empirical assessment of a payment program to increase the adoption of a new pollution abatement technology.

The interest in the design of environmental programs for pollutants that are complements is motivated by the current state of the literature. In particular, the literature lacks a consensus on whether program participants should be compensated for reductions of both pollutants, which is commonly referred to as double-dipping or stacking (Woodward 2011, Murray et al. 2012, Cooley & Olander 2012, Greenhalgh 2008, Moslener & Requate 2005). Several authors have attempted to understand the implications of double-dipping, but there are unresolved questions in need of additional study. Chapter 1's contribution to the literature is to further expand

the understanding of different environmental program designs (e.g. prices versus quantities (Ambec & Coria 2011, Weitzman 1974)). Chapter 1 includes a theoretical framework that expands Woodward's model to consider more policy designs. Chapter 1 compares quantities with prices. Under prices, a regulator can allow or prohibit double-dipping. Hence, three policy choices are essentially compared. The chapter starts with a regulator who has full information. Then, it moves to a second-best setting modeling two scenarios in which full information is absent for the regulator. The first scenario is based on two uncoordinated regulators who set either prices or quantities without taking into account the other regulator's environmental program. The second scenario is based on a regulator who designs two environmental programs ignoring complementarity. A contribution of Chapter 1 is to explicitly model the regulators' behavior. Under each scenario, there are market characteristics that favor one policy over the other. In particular, the curvature of the marginal benefit curves favors the usage of prices versus quantities, not ruling out prices with stacking. By understanding different environmental program designs, policy makers can design better programs that attain pollution abatement more efficiently.

The motivation for Chapter 2 is based on water quality problems that remain severe across much of the United States. Improvements are particularly challenging in agricultural regions where upwards of 90 percent of the pollution load comes from sources that fall outside regulatory control under the Clean Water Act. These nutrient sources are responsible for a large dead zone in the Gulf of Mexico, the closure of Toledo's drinking water facility, and ubiquitous damage to recreational amenities. In Iowa, several state and federal programs encourage the adoption a new agricultural pollution abatement technology, cover crops, through cost-share funding opportunities, in which farmers receive matching funds or incentive payments to cover a proportion of the conservation costs. The promotion of cover crops through cost-share funding combined with a longitudinal data set with large Iowa farm operators including information on farmers both before and after introduction of the subsidy program provides an identification strategy to evaluate the effectiveness of funding for this promising new abatement technology. Using propensity score matching and a Tobit estimator that takes into account non-adoption, Chapter 2 finds that cost-share funding significantly increases the proportion of cover crops planted and cover crops acres among both recipients of funds and among adopters. These results have critical implications for finding solutions to address persistent water quality problems with limited conservation budgets.

Lastly, Chapter 3 is motivated by the importance of intra-household dynamics and spouses' relative influence on household expenditure decisions for the success of development strategies. The study is based on the results from a lab-in-the-field risk experiment in rural Camerooon, in which husband and wife individually participated in isolation and then participated together as a couple. Using the experimental results, Chapter 3 focuses on risk preference differences between spouses, spouses' individual influence over the couple's joint decision, and the relation between this relative influence and different expenditure decisions. Chapter 3 answers the following research questions: (i) Are there differences in risk preference between husbands and wives within households?; (ii) are there differences in the relative influence of each spouse over joint decisions involving risk?; and (iii) how does this relative influence affect household educational and medical expenditure decisions?

Chapter 3 finds evidence of risk aversion among husbands, wives, and couples (i.e. husband and wife together) on average, in which husbands are more risk averse than wives and couples. The study identifies some factors influencing the heterogeneity in risk preferences between spouses including whether the wife chose her husband for marriage and whether the wife worked during the past year. For the relative influence of spouses over couple's decisions under risk, Chapter 3 finds variables that increase the likelihood that one spouse is closer to the couple. Moreover, using a proxy for female bargaining power based on the difference in choices between each spouse and the couple, the study finds that monogamous wives are more likely to be more empowered than polygamous wives. At the same time, monogamous wives married to Muslim husbands are more likely to be less empowered than monogamous wives married to non-Muslim husbands. Lastly, the proxy for female bargaining power is positively correlated with educational and medical expenditures. Chapter 3's results provide a deeper insight into intra-household dynamics in the studied area, but more research is required to continue informing policy and supporting the generation of more effective development strategies in the region.

CHAPTER 1. DOUBLE-DIPPING IN ENVIRONMENTAL MARKETS UNDER TWO SECOND BEST SCENARIOS

1.1 Abstract

As policy makers explore the creation or modification of environmental markets for pollutants that have complementarities, they must take into account the way these complementarities affect the design and results of their policies. Given the attainment of several environmental outcomes from a single conservation practice, landowners could potentially be compensated in multiple markets that pay for environmental improvements. This concept of allowing payments stemming from a single action that has several benefits is known as double-dipping or stacking in the literature.

The major contribution of this paper is to explicitly model the setup of prices and quantities under a second best setting and to subsequently compare a price policy allowing double-dipping to two policies: a quantities policy and a price policy prohibiting double-dipping. We aim at understanding when each of these policy designs is more efficient under two second-best scenarios. The first scenario we study is the case of two uncoordinated policy makers who do not take into account the other's environmental program. The second scenario we study is when complementarity is ignored in the policy design. The paper points to specific market characteristics that favor one policy over the others, which further expands our understanding about the implications of allowing double-dipping in environmental markets.

1.2 Introduction and Literature Review

As policy makers explore the creation or modification of environmental markets for pollutants that have complementarities, they must take into account the way these complementarities affect their policy design and subsequent results. This is especially true for environmental markets that are designed for farmers who do not face any mandatory regulation and whose single conservation practice can bring a variety of environmental benefits. For example, the adoption of cover crops on a farm land improves water quality and increases carbon sequestration. Given the attainment of several environmental benefits from a single action (e.g. cover crops), landowners could potentially be compensated in multiple markets (e.g. carbon and water quality markets) that pay for environmental improvements. This concept of allowing multiple credits or payments stemming from a single action that has several benefits is known as double-dipping or stacking in the literature. A major objective of this paper is to understand the implications of allowing or prohibiting double-dipping in environmental markets under two second best scenarios in which the regulator does not possess full information.

Regarding pollutants' complementarities, several papers point to the importance of taking production relations into account. For instance, Moslener and Requate (2005) solve a dynamic multi-pollutant problem focusing on pollutants that are either complements or substitutes. They conclude that environmental policy based on one pollutant can be inaccurate if there is any complementarity or substitutability between pollutants. Feng and Kling (2005) study the consequences of co-benefits from carbon sequestration programs. They view these co-benefits as externalities that arise from emission reduction credits that are traded in the carbon market. They emphasize the importance of taking these co-benefits into account as the free market allocation is not likely to attain the social optimum. Ambec and Coria (2011) perform a prices versus quantities analysis following Weitzman (1960) with multiple pollutants, which considers whether pollutants are substitutes or complements in the cost function. Their analysis does not address double-dipping and imposes some symmetry assumptions that are not used in this paper. In particular, they assume that all firms are identical and optimize using the same functional forms. Lastly, Woodward (2011) emphasizes the importance of pollutants' production relations and explicitly models double-dipping focusing on the complementarity of pollutants in the abatement cost function in a static model.

In the current literature, several papers point to the potential benefits and concerns that arise from allowing double-dipping. Focusing on the former, Cooley and Olander (2011) argue that multiple payments provide several sources of revenue that could spark landowners to manage their land focusing on more than one environmental service. Similarly, Moslener and Raquete (2005) state that by focusing on more environmental services, we can achieve a larger provision of ecosystem services. Greendhalg (2008) argues that the inclusion of several ecosystem services can stimulate the interest of potential participants in the program. On the other hand, most papers list additionality as a major concern that might prevent policy makers from allowing double-dipping in environmental markets (Woodward 2011, Cooley and Olander 2012, Moslener & Requate 2005, Murray et al. 2012). To prevent concerns about additionality, program participants should only be paid for abatement that is truly additional, discarding any practices that would have been adopted without the policy.

Double-dipping in environmental programs is modeled in a variety of ways. Horan et al. (2004) explore two policy designs: a coordinated policy in which both payments and trading programs are designed assuming farmers participate in both programs and an uncoordinated policy in which the trading program is designed taking the existing payment program as given. They conclude that efficiency gains emerge with coordination since both programs are able to jointly influence farmers' marginal decisions. Without coordination, double-dipping can increase or decrease efficiency depending on the way the agri-environmental policy is targeted (Horan et al. 2004). Their paper differs from this one as it does not focus on pollutants' complementarities, but focuses on the coordination of two environmental policies. From a different study, Montero (2001) states that pollution markets should be integrated using optimal pollutant exchange rates when the marginal abatement cost curves in the various environmental markets are steeper than the marginal-benefit curves. If those conditions are reversed, then environmental markets should be separated. Cooley and Olander (2012) argue that stacking credits is not a major concern when there are incentive payments and when credits are given for practices that are located in spatially distinct parts of the land. When credits are vertically stacked and when they come from a single management practice, they must be handled correctly to avoid any net loss of environmental services. They are primarily concerned about stacking offset or mitigation credits as they can become problematic due to double-counting and additionality. Their paper focuses on the difference between payments for ecosystem services (PES) and offsets, which is not a focus of this paper.

Lastly, Woodward (2011) explores double-dipping with a model motivated by firms that face caps on pollution imposed by a regulator(s) and who seek to satisfy these caps by purchasing offsets from uncapped sources. He concludes that whenever abatement caps are set optimally, double-dipping is the preferred policy choice. However, when abatement caps are set incorrectly, a policy eliminating double-dipping may provide larger net benefits for society. Given that caps are set incorrectly, he concludes that when there is significant pollutants' complementarity, relatively flat marginal benefit curves, and greater cost heterogeneity in abating firms, a policy prohibiting double-dipping is likely to increase net benefits for society. He states that double-dipping is preferred when the above conditions are reversed and when the marginal benefits curves per unit of abatement for pollutants are very different.

Rather than considering the specific market scenario of an uncapped firm that might participate in two PES systems stemming from a command and control policy given to capped firms, we consider the more general case where two PES systems are designed by a regulator(s), consisting of possible payments to a firm providing two different environmental goods without being tied to any capped sectors. We do this in order to differentiate the usage of quantities versus prices. Nonetheless, since quantities are also important, we also contrast these PES[1] with a command and control[2] policy. This provides a more broad based assessment of the conditions under which efficiency improves when double-dipping is allowed and abstracts from specific market contexts.

Following Woodward (2011), cases of first and second best solutions are considered. The policy choices we analyze are a command and control policy, a price scheme allowing double-dipping and a price scheme prohibiting double-dipping. The main focus of this paper is to find

[1] We refer to PES, prices and subsidies interchangeably

[2] We refer to command and control, quantities and standards interchangeably

out which policy is preferred given that the regulator sets quantities or prices in a second-best way due to the lack of full information. Knowing that this is more plausible in the real world, we want to know which is the best policy for the regulator. Woodward (2011) also studies the case in which caps are set incorrectly. However, he does not model the way these caps are set incorrectly. For instance, in his theoretical model, he assumes the regulator imposes the same cap for both pollutants and he does not model the ways these caps are set in a second best fashion. In reality, having the same caps for two different pollutants does not seem very realistic because the pollutants may have different units and there is no fundamental scientific or economic reason for setting them equal to each other. This paper explicitly models the set up of quantities or prices in two second best setting. However, we note that Woodward's (2011) model incorporates heterogeneity of firms and he performs some numerical analysis, which could potentially explain the assumptions behind his set up of the caps. In this paper, we do not incorporate heterogeneity of firms because we want to focus on the implications behind the set up of the caps in second best scenarios. We attempt to expand on Woodward's work to further understand the implications of allowing or prohibiting double-dipping.

Suppose a policy maker is interested in maximizing net benefits for society from the abatement of two pollutants. For concreteness, think about these pollutants as Carbon and Phosphorus. An abatement action such as no-till can reduce the amount of Carbon in the atmosphere and can also reduce the amount of Phosphorus in the water streams. Should policy makers pay farmers for abating both pollutants that come from the same abatement practice? or should they make the farmer choose one environmental market knowing that he or she can only get paid for one environmental output, even if the action taken results in positive abatement levels for both pollutants? or should the policy maker impose quantities instead of prices to achieve his environmental goals? In order to answer these questions, this paper begins with the full information case in which a single social planner knows the cost and benefit functions of both environmental outputs as well as the complementarity between pollutants in Section 1.3. For every scenario, we model prices versus quantities and under prices, we model whether double-dipping is allowed or prohibited, which is referred to as the single-market following Woodward (2011). We begin with the well known result that given the availability of full information for the regulator, there is no difference between quantities and prices as long as double-dipping is allowed. Furthermore, we show that double-dipping is preferred over a single-market even if the regulator takes the single market structure into account when designing the environmental program as long as there is full information.

Since it is unlikely that the regulator will posses full information, we secondly explore the case in which there are two uncoordinated policy makers each independently designing an environmental program without taking into account the other (Section 1.4). If each regulator knows the existence of complementarity but is not aware of the other program being designed, then the quantities and prices derived independently will be second best solutions. In order to understand which policy is better or what factors favor one policy over the others, we compare deadweight losses among each of the three policy designs we study and look at some comparative statics. First, the policy that performs better is the one that gets closer to the optimum. We focus on two cases in which the slopes of marginal benefit curves across two markets are very different. In one case, quantities dominates a price policy prohibiting double-dipping and we compare the performance of double-dipping versus quantities. In the other case, disallowing double-dipping is preferred over quantities and we compare both price policies. Furthermore, we find that making the steeper marginal benefit curve even steeper tends to favor a single market or quantities over double-dipping.

Alternatively, it could be the case a policy maker is not aware of the complementarity between pollutants (Section 1.5). Complementarity could be ignored either due to lack of knowledge or understanding about the production relationships, which results in a regulator choosing prices or quantities in a second best setting. We again compare deadweight losses under the different policies to assess the best policy choice for the regulator and look at some comparative statics. We focus on two cases that are determined by the slope of the marginal benefit curve in the market in which the firm is not compensated under the prohibition of double-dipping, which we denote the unchosen market. We focus on this market because its results are substantially affected by the lack of knowledge about the complementarity. The first case we study is one in which the marginal benefit curve is steeper in the unchosen market. In this case, we compare quantities with a single market because the latter outperforms double-dipping. Making the marginal benefit curve even steeper favors the usage of quantities over a single market. The second case we study is characterized by a relatively flatter marginal benefit curve in the unchosen market and a very low complementarity between pollutants. Having very low complementarity brings very similar results among the different policies in the chosen market. However, in the unchosen market, making the slope of the marginal benefit curve even flatter benefits double-dipping over quantities, but there are not substantial differences when the complementarity is very low. Furthermore, this flatness in the marginal benefit curve substantially affects the performance of the single market. Both double-dipping and quantities outperform the single market when the marginal benefit is relatively flatter in the unchosen market or when there is very low complementarity, making the single market very unlikely to be favored under these characteristics. This paper illustrates that allowing or prohibiting double-dipping depends on market characteristics under these two second best scenarios.

1.3 Full Information Case

Given that the policy maker knows the cost and benefit functions as well as the complementarity between pollutants, this section includes the social planner problem, the firm's problem under a quantities policy, the firm's problem under a price policy allowing for double-dipping, the firm's problem under a price policy prohibiting double-dipping, and the welfare analysis between the policy choices. Assume there is only one firm and there are two pollutants that are complements in the cost function. In particular, abating one pollutant decreases the marginal cost of abating the other pollutant. Following Woodward (2011), the cost function is given by:

$$g(a_1, a_2) = \frac{\alpha_1}{2}a_1^2 + \frac{\alpha_2}{2}a_2^2 - \gamma a_1 a_2 \tag{1.1}$$

where a_1 and a_2 are the abatement levels for pollutant 1 and pollutant 2 respectively, α_1 and α_2 are positive parameters, and γ is the interaction term between pollutants. Pollutants are complements as long as $\gamma \geq 0$ since $\frac{\partial}{\partial a_j}\frac{\partial g()}{\partial a_i} \leq 0$.This cost function is strictly convex as long as $\frac{\partial^2 g()}{\partial a_i^2} = \alpha_i > 0$ for $i = 1, 2$ and $\alpha_i\alpha_j - \gamma^2 > 0$. Following Woodward (2011), the benefit functions used in this model are:

$$B_1(a_1) \quad = \quad \Omega_1 a_1 - \frac{\theta_1}{2}a_1^2 \tag{1.2}$$

$$B_2(a_2) \quad = \quad \Omega_2 a_2 - \frac{\theta_2}{2} a_2^2 \tag{1.3}$$

where Ω_1, Ω_2, θ_1, and θ_2 are positive parameters. Each benefit function is strictly concave as long as $\frac{\partial B_i()}{\partial a_i} = \Omega_i - \theta_i a_i > 0$ for $i = 1, 2$ and $\frac{\partial^2 B_i()}{\partial a_i^2} = -\theta_i < 0$ for $i = 1, 2$.[3]

1.3.1 Social Planner Problem

Quantities

The social planner maximizes net benefits for society by solving

$$\max_{a_1, a_2} W(a_1, a_2) = \max_{a_1, a_2} B_1(a_1) + B_2(a_2) - g(a_1, a_2) \tag{1.4}$$

The first order conditions are:

$$\begin{aligned} a_1 \quad &: \quad \frac{\partial B_1(a_1)}{\partial a_1} = \frac{\partial g(a_1, a_2)}{\partial a_1} \\ a_2 \quad &: \quad \frac{\partial B_2(a_2)}{\partial a_2} = \frac{\partial g(a_1, a_2)}{\partial a_2} \end{aligned}$$

The solutions derived from these first order conditions are denoted by a_1^* and a_2^*. With the functional forms (1.1),(1.2), and (1.3), the problem becomes:

$$\max_{a_1, a_2} \Omega_1 a_1 - \frac{\theta_1}{2} a_1^2 + \Omega_2 a_2 - \frac{\theta_2}{2} a_2^2 - \frac{\alpha_1}{2} a_1^2 - \frac{\alpha_2}{2} a_2^2 + \gamma a_1 a_2$$

Solving for a_1^* and a_2^*, we obtain the first best solutions:

$$a_1^* \quad = \quad \frac{(\alpha_2 + \theta_2)\,\Omega_1 + \gamma \Omega_2}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \tag{1.5}$$

$$a_2^* \quad = \quad \frac{(\alpha_1 + \theta_1)\,\Omega_2 + \gamma \Omega_1}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \tag{1.6}$$

Prices

If the social planner opts for the usage of prices instead, he solves for the optimal prices. Denote τ_1 and τ_2 as prices received by the firm for abating pollutant 1 and 2 respectively. The social planner knows that the firm maximizes profits equating the price for each pollutant to

[3] There is no complementarity in the benefits function. While this assumption can be relaxed, this could make the analysis more complicated and less clear

its marginal cost of abatement:

$$\begin{aligned}\tau_1 &= \frac{\partial g(a_1,a_2)}{\partial a_1} = \alpha_1 a_1 - \gamma a_2 \\ \tau_2 &= \frac{\partial g(a_1,a_2)}{\partial a_2} = \alpha_2 a_2 - \gamma a_1\end{aligned}$$

Using these equations, the social planner obtains the firm's reaction functions:

$$\begin{aligned}a_1^R(\tau_1,\tau_2) &= \frac{\alpha_2\tau_1 + \gamma\tau_2}{\alpha_1\alpha_2 - \gamma^2} \\ a_2^R(\tau_1,\tau_2) &= \frac{\alpha_1\tau_2 + \gamma\tau_1}{\alpha_1\alpha_2 - \gamma^2}\end{aligned}$$

The social planner then maximizes net benefits with respect to prices:

$$\max_{\tau_1,\tau_2} B_1(a_1^R(\tau_1,\tau_2)) + B_2(a_2^R(\tau_1,\tau_2)) - g(a_1^R(\tau_1,\tau_2), a_2^R(\tau_1,\tau_2))$$

The first order conditions are

$$\begin{aligned}\tau_1 &: \frac{\partial B_1}{\partial a_1^R}\frac{\partial a_1^R}{\partial \tau_1} + \frac{\partial B_2}{\partial a_2^R}\frac{\partial a_2^R}{\partial \tau_1} - \frac{\partial g}{\partial a_1^R}\frac{\partial a_1^R}{\partial \tau_1} - \frac{\partial g}{\partial a_2^R}\frac{\partial a_2^R}{\partial \tau_1} = 0 \\ \tau_2 &: \frac{\partial B_1}{\partial a_1^R}\frac{\partial a_1^R}{\partial \tau_2} + \frac{\partial B_2}{\partial a_2^R}\frac{\partial a_2^R}{\partial \tau_2} - \frac{\partial g}{\partial a_1^R}\frac{\partial a_1^R}{\partial \tau_2} - \frac{\partial g}{\partial a_2^R}\frac{\partial a_2^R}{\partial \tau_2} = 0\end{aligned}$$

We can solve for the optimal price levels, which will be denoted by τ_1^* and τ_2^*. Notice that these price levels can also be derived by equating the price to the marginal benefit of abating the optimal quantity for each pollutant: $\tau_i^* = \Omega_i - \theta_i a_i^*$ for $i = 1,2$. In Section 1.7, Figures (1.1) and (1.2) contain graphical depictions of the social planner's solution under each market.

1.3.2 Firm's Problem

Quantities

Under a quantities policy, the regulator imposes a minimum level of reduction for each pollutant. The firm then has to abate at least the level of the imposed quantity. The firm's problem:

$$\max_{a_1,a_2} -g(a_1,a_2) \text{ s.t. } a_1 \geq a_1^* \text{and } a_2 \geq a_2^* \tag{1.7}$$

The Lagrangian for this problem:

$$\pounds = -g(a_1,a_2) + \lambda_1(a_1 - a_1^*) + \lambda_2(a_2 - a_2^*) \tag{1.8}$$

The first order conditions:

$$\begin{array}{llll}
a_1: & -\frac{\partial g(a_1,a_2)}{\partial a_1}+\lambda_1 \leq 0 & a_1^c\left[\frac{\partial \pounds}{a_1}\right]=0 & a_1^c \geq 0 \\
a_2: & -\frac{\partial g(a_1,a_2)}{\partial a_2}+\lambda_2 \leq 0 & a_2^c\left[\frac{\partial \pounds}{a_2}\right]=0 & a_2^c \geq 0 \\
\lambda_1: & a_1-a_1^* \geq 0 & \lambda_1^c\left[\frac{\partial \pounds}{\lambda_1}\right]=0 & \lambda_1^c \geq 0 \\
\lambda_2: & a_2-a_2^* \geq 0 & \lambda_2^c\left[\frac{\partial \pounds}{\lambda_2}\right]=0 & \lambda_2^c \geq 0
\end{array}$$

where the quantities solutions are denoted by a_1^c and a_2^c where c stands for command and control. Facing this problem, the firm chooses to reduce pollution at a level equal to each given quantity:

$$a_1^c = a_1^* = \frac{(\alpha_2+\theta_2)\,\Omega_1+\gamma\Omega_2}{(\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2} \tag{1.9}$$

$$a_2^c = a_2^* = \frac{(\alpha_1+\theta_1)\,\Omega_2+\gamma\Omega_1}{(\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2} \tag{1.10}$$

As long as $\lambda_1 = \frac{\partial B_1(a_1)}{\partial a_1}$ and $\lambda_2 = \frac{\partial B_2(a_2)}{\partial a_2}$, then $a_1^* = a_1^c$ and $a_2^* = a_2^c$. In other words, as long as the shadow price of pollution reductions equals their respective marginal benefits, then the policy achieves the optimum and the firm chooses pollution reductions equal to the quantities set by the regulator.

Prices - Double-dipping - Multiple Markets

Alternatively, suppose the regulator uses prices instead of quantities. The firm's problem becomes:

$$\max_{a_1,a_2} \tau_1^* a_1 + \tau_2^* a_2 - g(a_1,a_2) \tag{1.11}$$

Without the cost functional form, the first order conditions are

$$a_1 \; : \; \tau_1^* = \frac{\partial g(a_1,a_2)}{\partial a_1}$$

$$a_2 \; : \; \tau_2^* = \frac{\partial g(a_1,a_2)}{\partial a_2}$$

The solution to this multiple markets problem is denoted by a_1^{mmp} and a_2^{mmp} where mm stands for multiple markets and p stands for prices. Again, as long as $\tau_1^* = \frac{\partial B_1(a_1)}{\partial a_1}$ and $\tau_2^* = \frac{\partial B_2(a_2)}{\partial a_2}$, then $a_1^* = a_1^{mmp}$and $a_2^* = a_2^{mmp}$. With the specific cost functional form, we obtain

$$a_1^{mmp} = \frac{\alpha_2\tau_1^*+\gamma\tau_2^*}{(\alpha_1\alpha_2-\gamma^2)} \tag{1.12}$$

$$a_2^{mmp} = \frac{\alpha_1 \tau_2^* + \gamma \tau_1^*}{(\alpha_1 \alpha_2 - \gamma^2)} \tag{1.13}$$

Since, $\tau_1^* = \frac{\partial B_1(a_1^*)}{a_1}$ and $\tau_2^* = \frac{\partial B_2(a_2^*)}{a_2}$, we can conclude that there is no difference between using quantities or prices under a multiple markets structure as long as the regulator possesses full information (i.e. $a_i^* = a_i^c = a_i^{mmp}$ for $i = 1, 2$). The optimal levels are the same regardless of whether the regulator sets prices or quantities, since the regulator has full information. See Figures (1.3) and (1.4) in Section 1.7 for a graphical illustration. This result also appears in Woodward (2011) but recall that we are explicitly modeling the regulator's behavior in two second best settings.

Prices - Disallowing Double-dipping - Single Market

The prohibition of double-dipping is applicable under a payment framework. Suppose the firm is only allowed to receive payment from abating one pollutant. Even if the firm reduces the other pollutant, it would only be able to receive payment for one. Hence, the firm has to choose to participate in an environmental market that is most optimal. Under a quantities framework, there is not an analogous single market. If the regulator establishes standards, then the firm is bounded by those levels. It is unrealistic to think that the firm would only have to follow one standard level or that it would have a choice between following either one. Hence, we do not consider a single market structure for a quantities policy. Nevertheless, we compare the differences between setting prices while allowing double-dipping, setting prices while prohibiting double-dipping, and setting quantities for both pollutants. We are primarily concerned with the regulator's policy choice. The firm's problem under a price scenario in which double-dipping is prohibited is the following:

$$\max \left\{ \max_{a_1, a_2} \tau_1^* a_1 - g(a_1, a_2); \max_{a_1, a_2} \tau_2^* a_2 - g(a_1, a_2) \right\}$$

This problem can be viewed as a two stage process. First, the firm maximizes as if it was participating in each market separately. For instance, the first order conditions of the optimization problem given that the firm is being compensated for the reductions of pollutant i instead of j are:

$$a_i \quad : \quad \tau_i^* = \frac{\partial g(a_1, a_2)}{\partial a_i} = \alpha_i a_i - \gamma a_j$$

$$a_j \quad : \quad 0 = \frac{\partial g(a_1, a_2)}{\partial a_j} = \alpha_j a_j - \gamma a_i$$

Given the maximization results, the firm chooses the market that achieves the highest profit. Unless $\frac{\partial B(a_j)}{\partial a_j} = 0$, the single market solution will not equal the first best solution (See Figures 1.3 and 1.4). Only when $\frac{\partial B(a_j)}{\partial a_j} = 0$, the first best is achieved as illustrated by Figure (1.5). However, one cannot assume this special case holds. Hence, in general, the solution does not equal the first best. If it is more profitable for the firm to be compensated for the reductions of pollutant 1 instead of pollutant 2, the solutions for this problem are denoted by a_1^{sm1p} and a_2^{sm1p}, where sm stands for single market, 1 refers to the fact that the firm chooses market for pollutant 1, and p signifies that the regulator sets prices instead of quantities [4]:

$$a_1^{sm1p} = \frac{\alpha_2 \tau_1^*}{\alpha_1 \alpha_2 - \gamma^2} \tag{1.14}$$

$$a_2^{sm1p} = \frac{\gamma \tau_1^*}{\alpha_1 \alpha_2 - \gamma^2} \tag{1.15}$$

1.3.3 Welfare Analysis

Since both prices and quantities are set using full information, they both achieve the first best under a multiple market structure for prices. In order to compare the difference in welfare levels between setting prices imposing a single market as opposed to allowing for double-dipping, we first look at the difference between abatement levels under each policy:

$$\begin{aligned} a_1^* &= a_1^c = a_1^{mmp} = \frac{\alpha_2 \tau_1^* + \gamma \tau_2^*}{\alpha_1 \alpha_2 - \gamma^2} \geq \frac{\alpha_2 \tau_1^*}{\alpha_1 \alpha_2 - \gamma^2} = a_1^{sm1p} \\ a_2^* &= a_2^c = a_2^{mmp} = \frac{\alpha_1 \tau_2^* + \gamma \tau_1^*}{\alpha_1 \alpha_2 - \gamma^2} \geq \frac{\gamma \tau_1^*}{\alpha_1 \alpha_2 - \gamma^2} = a_2^{sm1p} \end{aligned}$$

See Figures (1.3) and (1.4) in Section 1.7 for a graphical illustration of these rankings. Notice that the equality only holds for the special case in which $\frac{\partial B(a_j)}{\partial a_2} = 0$ as depicted by (1.5). Without this special case, we conclude that price policy allowing for double-dipping reduces pollutants by a larger amount than a price policy imposing a single market restriction. Furthermore, we show the difference in deadweight losses between double-dipping and a single market keeping in mind $a_1^{mm} = a_1^*$. Define DWL_i^{sm1p} and DWL_i^{mmp} as the deadweight losses in the

[4] Throughout the paper, we assume that the firm chooses to participate in the market for pollutant 1 without any loss of generality. We refer to the market for pollutant 1 as the "chosen market" and the market for pollutant 2 as the "unchosen market" throughout the paper.

market for pollutant i for a single and multiple markets policy respectively. Further define the difference in deadweight losses as:

$$
\begin{aligned}
W_1^F &= DWL_1^{sm1p} - DWL_1^{mmp} \\
&= \frac{1}{2}(\alpha_1 + \theta_1)\left(a_1^{mmp} - a_1^{sm1p}\right)\left[2a_1^* - a_1^{mmp} - a_1^{sm1p}\right] \\
&= \frac{1}{2}(\alpha_1 + \theta_1)\left(a_1^{mmp} - a_1^{sm1p}\right)\left[\left(a_1^* - a_1^{sm1p}\right) - (a_1^{mmp} - a_1^*)\right] \\
&= \frac{1}{2}(\alpha_1 + \theta_1)\left(a_1^{mmp} - a_1^{sm1p}\right)\left[\left(a_1^* - a_1^{sm1p}\right)\right] \\
&= \frac{1}{2}(\alpha_1 + \theta_1)\left(a_1^{mmp} - a_1^{sm1p}\right)^2 \geq 0
\end{aligned}
$$

Since this difference is generally positive, except for the special case in which $\frac{\partial B(a_j)}{\partial a_2} = 0$, double-dipping is generally preferred over a single market policy given the availability of full information for the regulator. Even under the special case, double-dipping performs the same as the single market. Hence, double-dipping should always be preferred over the single market given full information. For a graphical illustration of these findings, refer to Section 1.7 (Figures 1.3 and 1.5). The graphs show the magnitude of the deadweight losses. When the regulator sets quantities using full information, he attains the first best. Similarly, when the regulator sets prices using full information and allowing for double-dipping, he also achieves the first. Moreover, the single market is not able to outperform double-dipping under full information when the regulator sets up prices. Under a price policy, for the market for pollutant 1, there is no deadweight loss if double-dipping is allowed. The deadweight loss under a price policy prohibiting double-dipping is depicted by the blue triangle from Figure (1.3) for the market for pollutant 1. Similarly, the deadweight loss is depicted by the green triangle from Figure (1.4) for the market for pollutant 2 in Section 1.7. We confirm that as long as the regulator sets standards or prices correctly using full information, double-dipping is preferred over a single market. Consequently, if a policy maker has to choose between quantities or a prices having full information, there is no difference in the results as long as double-dipping is permitted. If, however, the policy maker is to disallowed double-dipping under a price policy, then it is preferable to use quantities instead of prices.

1.3.4 Full Information - Alternative Market Design

Some might argue that the regulator could incorporate the prohibition of double-dipping when setting up prices. This section looks at this scenario and shows that even if the regulator takes into account the prohibition of double-dipping in his design, the best policy is still to allow double-dipping due to the availability of full information to the regulator. For this section, we only concentrate on the single market outcome for the firm facing prices that are designed taking into account the prohibition of double-dipping.

Regulator's Problem - Prices

Imagine a regulator who has full information but who decides to prohibit double-dipping possibly for political reasons or additionality concerns. In this case, the regulator takes into account different reaction functions knowing that the firm has to choose between receiving compensation from a single environmental program. If the regulator assumes that the firm will participate in the market for pollutant 1, its reaction functions are:

$$\begin{aligned} a_1^R(\tau_1) &= \frac{\alpha_2 \tau_1}{\alpha_1 \alpha_2 - \gamma^2} \\ a_2^R(\tau_2) &= \frac{\gamma \tau_1}{\alpha_1 \alpha_2 - \gamma^2} \end{aligned}$$

The regulator maximizes net benefits with respect to τ_1 taking into account the reaction functions functions:

$$\max_{\tau_1} B_1(a_1^R(\tau_1)) + B_2(a_2^R(\tau_1)) - g(a_1^R(\tau_1), a_2^R(\tau_1))$$

Solving for τ_1, we obtain the following optimal price:

$$\tau_1^{sm1*} = \frac{(\alpha_1 \alpha_2 - \gamma^2)(\alpha_2 \Omega_1 + \gamma \Omega_2)}{\alpha_2^2(\alpha_1 + \theta_1) - \gamma^2(\alpha_2 - \theta_2)} \neq \tau_1^* \tag{1.16}$$

For the market for pollutant 2, the process is analogous but the regulator maximizes with respect to τ_2 instead of τ_1. The optimal price under this policy is:

$$\tau_2^{sm2*} = \frac{(\alpha_1 \alpha_2 - \gamma^2)(\alpha_1 \Omega_2 + \gamma \Omega_1)}{\alpha_1^2(\alpha_2 + \theta_2) - \gamma^2(\alpha_1 - \theta_1)} \neq \tau_2^* \tag{1.17}$$

Firm's Problem - Single Market

The firm's problem: $\arg\max\left\{\max_{a_1,a_2}\tau_1^{sm1*}a_1 - g(a_1,a_2);\max_{a_1,a_2}\tau_2^{sm2*}a_2 - g(a_1,a_2)\right\}$. Suppose the firm chooses to participate in the market for pollutant 1, then firm's optimal abatement levels become:

$$a_1^{sm1*} = \frac{\alpha_2\left(\alpha_2\Omega_1+\gamma\Omega_2\right)}{\alpha_2^2(\alpha_1+\theta_1)-\gamma^2(\alpha_2-\theta_2)} \neq a_1^* \quad (1.18)$$

$$a_2^{sm1*} = \frac{\gamma\left(\alpha_2\Omega_1+\gamma\Omega_2\right)}{\alpha_2^2(\alpha_1+\theta_1)-\gamma^2(\alpha_2-\theta_2)} \neq a_2^* \quad (1.19)$$

If the firm chooses to participate in the market for pollutant 2, the optimal abatement levels are:

$$a_1^{sm2*} = \frac{\gamma\left(\alpha_1\Omega_2+\gamma\Omega_1\right)}{\alpha_1^2(\alpha_2+\theta_2)-\gamma^2(\alpha_1-\theta_1)} \neq a_1^* \quad (1.20)$$

$$a_2^{sm2*} = \frac{\alpha_1\left(\alpha_1\Omega_2+\gamma\Omega_1\right)}{\alpha_1^2(\alpha_2+\theta_2)-\gamma^2(\alpha_1-\theta_1)} \neq a_2^* \quad (1.21)$$

Even if the regulator takes into account the single market structure when designing the environmental policy, the solutions are different than the first best because the regulator does not consider that the marginal abatement benefits are positive for both pollutants if there is any complementarity between them. In other words, since the price for abating one of the pollutants is imposed to be zero, then the solution is never going to reach the first best unless the marginal benefit for one of the pollutants is indeed zero (Figure 1.5). Not surprisingly, given full information, the regulator should always opt for double-dipping over prohibiting it.

1.4 Uncoordinated Regulators

1.4.1 Uncoordinated Regulators' Problem:

A major contribution of this paper is to model policy choices when the regulator does not have full information. Instead of assuming that the regulator sets prices or quantities incorrectly, we model the way these latter are set up. The first scenario we study is the possibility of having uncoordinated regulators. Suppose there are two government agencies. Each one has the task of designing an environmental program targeting a specific pollutant. We first analyze quantities and then prices. We study these uncoordinated regulators because it could be the case in which a government agency knows about the complementarity between pollutants but it is not aware of the existence of the other program targeting the other pollutant. Also, there is no guarantee that both government programs are designed at the same time taking into account one another.

Quantities

For regulator focusing on pollutant i, the problem becomes

$$\max_{a_1,a_2} B_i(a_i) - g(a_1, a_2) \tag{1.22}$$

The first order conditions are:

$$\begin{aligned} a_i &: \frac{\partial B_i}{\partial a_i} = \frac{\partial g(a_1, a_2)}{\partial a_i} \\ a_j &: 0 = \frac{\partial g(a_1, a_2)}{\partial a_j} \end{aligned}$$

For the regulator focusing on Pollutant i, his quantity is denoted by a_i^u, where the u stands for uncoordinated regulators and the i for the pollutant. For the regulator focusing on pollutant 1, his quantity is:

$$a_1^u = \frac{\alpha_2 \Omega_1}{\alpha_1 \alpha_2 - \gamma^2 + \alpha_2 \theta_1} \neq a_1^* \tag{1.23}$$

For the regulator focusing on pollutant 2, his standard is:

$$a_2^u = \frac{\alpha_1 \Omega_2}{\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2} \neq a_2^* \tag{1.24}$$

Prices

Let τ_1^u and τ_2^u be the prices imposed by each agency independently from the other. Again, we use the idea of reaction functions. The regulator for pollutant i knows the firm will optimize according to the following first order conditions:

$$\begin{aligned} \tau_i^u &= \frac{\partial g(a_1, a_2)}{\partial a_i} = \alpha_i a_i - \gamma a_j \\ 0 &= \frac{\partial g(a_1, a_2)}{\partial a_2} = \alpha_j a_j - \gamma a_i \end{aligned}$$

The regulator for pollutant i has in mind the following reaction functions:

$$
\begin{aligned}
a_i^R(\tau_i^u) &= \frac{\alpha_j \tau_i^u}{\alpha_1\alpha_2 - \gamma^2} \\
a_j^R(\tau_i^u) &= \frac{\gamma \tau_i^u}{\alpha_1\alpha_2 - \gamma^2}
\end{aligned}
$$

The regulator focusing on pollutant i maximizes net benefits taking into account these reaction functions:

$$
\max_{\tau_i^u} B_i(a_i^R(\tau_i^u)) - g(a_1^R(\tau_i^u), a_2^R(\tau_i^u))
$$

The first order conditions are

$$
\tau_i^u : \frac{\partial B_i}{\partial a_i^R}\frac{\partial a_i^R}{\partial \tau_i^u} - \frac{\partial g}{\partial a_1^R}\frac{\partial a_1^R}{\partial \tau_i^u} - \frac{\partial g}{\partial a_2^R}\frac{\partial a_2^R}{\partial \tau_i^u} = 0
$$

The regulator for pollutant 1 sets the following price:

$$
\tau_1^u = \frac{(\alpha_1\alpha_2 - \gamma^2)\Omega_1}{\alpha_1\alpha_2 - \gamma^2 + \alpha_2\theta_1} \tag{1.25}
$$

The regulator for pollutant 2 sets the following price:

$$
\tau_2^u = \frac{(\alpha_1\alpha_2 - \gamma^2)\Omega_2}{\alpha_1\alpha_2 - \gamma^2 + \alpha_1\theta_2} \tag{1.26}
$$

1.4.2 Firm's Problem

Quantities

Denote a_i^{cu} as the optimal abatement level for pollutant i chosen by the firm when facing standards set by the two uncoordinated regulators. The firm solves:

$$
\max_{a_1,a_2} -g(a_1, a_2) \quad \text{s.t.} \quad a_1^u \leq a_1 \text{ and } a_2^u \leq a_2
$$

Once again, the firm chooses abatement levels equal to the quantities imposed by the regulators:

$$
a_1^u = a_1^{cu} \tag{1.27}
$$

$$
a_2^u = a_2^{cu} \tag{1.28}
$$

Prices - Double-dipping - Multiple Markets

A multiple markets policy in this context assumes neither regulator states any participation restriction in other environmental programs under his program specifications. The solutions for the firm's problem are denoted as a_1^{mmpu} and a_2^{mmpu} where mm stands for multiple markets, p stands for prices, and u stands for uncoordinated regulators. The firm's problem and solutions are:

$$\max_{a_1,a_2} \tau_1^u a_1 + \tau_2^u a_2 - g(a_1, a_2)$$

$$a_1^{mmpu} = \frac{\alpha_2 \tau_1^u + \gamma \tau_2^u}{\alpha_1 \alpha_2 - \gamma^2} \neq a_1^* \tag{1.29}$$

$$a_2^{mmpu} = \frac{\alpha_1 \tau_2^u + \gamma \tau_1^u}{\alpha_1 \alpha_2 - \gamma^2} \neq a_2^* \tag{1.30}$$

Prices - Disallowing Double-dipping - Single Market

The single market policy assumes the program specifically prohibits the participation in any other environmental program for the other pollutant due to additionality concerns. Recall that each regulator is aware of the complementarity between both pollutants, but the regulators do not coordinate between each other. Essentially, each designs a program ignoring the existence of the other program. The firm's problem is:

$$\arg\max \left\{ \max_{a_1,a_2} \tau_1^u a_1 - g(a_1, a_2), \max_{a_1,a_2} \tau_2^u a_2 - g(a_1, a_2) \right\}$$

If the firm chooses to be compensated for the pollutant i, the optimal abatement levels are denoted by a_i^{smipu} and a_j^{smipu} where sm stands for single market, i stands for the chosen market, p stands for prices, and u stands for uncoordinated. Given that the firm decides to participate in the market for pollutant 1, the chosen market, the solutions are:

$$a_1^{sm1pu} = \frac{\alpha_2 \tau_1^u}{\alpha_1 \alpha_2 - \gamma^2} \neq a_1^* \tag{1.31}$$

$$a_2^{sm1pu} = \frac{\gamma \tau_1^u}{\alpha_1 \alpha_2 - \gamma^2} \neq a_2^* \tag{1.32}$$

1.4.3 Welfare Analysis

For the welfare analysis, we will assume strict complementarity (i.e. $\gamma > 0$). We first draw attention to a general graphical analysis to obtain some intuition. Refer to Figures (1.6) and

(1.8) for the market focusing on pollutant 1 and Figures (1.7) and(1.9) the market focusing on pollutant 2. While the deadweight loss under double-dipping appears larger than the single market (blue versus purple areas in Figure 1.8), we also observe that this is reversed in the market for pollutant 2 (grey versus orange areas in Figure 1.9). In fact, since the firm chooses to participate in the market for a_1, the difference in deadweight losses becomes larger in the market for a_2 in which the single market policy yields the largest deadweight loss. Since the firm faces zero compensation for abating pollutant 2, the firm abates at a point that is further away from the optimum relative to the distance between the double-dipping solution and the first best.

To understand the differences in efficiency among the three policies being studied, we rank each pollutant's abatement levels under each policy. As stated before, we assume that the firm chooses to participate in the market for pollutant 1 when facing a single market policy, which we refer to as the chosen market. For pollutant 1, we have the following ranking:

$$a_1^{mmpu} > a_1^* > a_1^{sm1pu} = a_1^u \tag{1.33}$$

For pollutant 2, we have two possible rankings:

$$\begin{aligned} a_2^{mmpu} &> a_2^* > a_2^{sm1pu} > a_2^u \\ a_2^{mmpu} &> a_2^* > a_2^u > a_2^{sm1pu} \end{aligned}$$

These rankings are explained in Section 1.8. To develop a graphical understanding of these rankings, we further define new terms. Let $a_j^{u'}$ be defined as a function of a_i^u.

$$\begin{aligned} a_2^{u'}(a_1^u) &= \frac{\gamma}{\alpha_2}a_1^u = \frac{\gamma}{\alpha_2}\frac{\alpha_2\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} = \frac{\gamma\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} = a_2^{sm1pu} \\ a_1^{u'}(a_2^u) &= \frac{\gamma}{\alpha_1}a_2^u = \frac{\gamma}{\alpha_1}\frac{\alpha_1\Omega_2}{\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2} = \frac{\gamma\Omega_2}{\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2} \end{aligned}$$

Recall that each regulator sets quantities separately. They are aware of the complementarity among pollutants and they use this information to set a single standard. Notice that $a_2^u > a_2^{sm1pu}$ implies $a_1^{u'} > a_1^u$ since $a_1^{u'}(a_2^u) = \frac{\gamma}{\alpha_2}a_2^u$ and $a_1^u(a_2^{u'} = a_2^{sm1pu}) = \frac{\gamma}{\alpha_2}a_2^{sm1pu}$. We consider two possible cases from the combinations of these rankings.

Case A

Case A is characterized by these rankings:

$$\begin{aligned} a_1^{mmpu} &> a_1^* > a_1^{sm1pu} = a_1^u > a_1^{u'} \\ a_2^{mmpu} &> a_2^* > a_2^{sm1pu} = a_2^{u'} > a_2^u \end{aligned}$$

We discard a quantities policy as the single market solution for pollutant 2 is closer to the optimum and the solution for pollutant 1 is equal to the quantities solution. Hence, the single market outperforms the quantities policy in the market for a_2 and equally performs in the market for a_1. We focus on the differences in deadweight losses between a multiple markets and a single market policy. Define $W_i^{Au} = DWL_i^{sm1pu} - DWL_i^{mmpu}$ as the difference in deadweight losses between a single market and multiple market policy in the market for pollutant i.

Pollutant 1

$$\begin{aligned} W_1^{Au} &= DWL_1^{sm1pu} - DWL_1^{mmpu} \\ &= \frac{1}{2}(a_1^* - a_1^{sm1tu})\left(\frac{\partial B_1(a_1^{sm1pu})}{\partial a_1} - \frac{\partial(a_1^{sm1pu}, a_2^*)}{\partial a_1}\right) \\ &- \frac{1}{2}(a_1^{mmpu} - a_1^*)\left(\frac{\partial(a_1^{mmpu}, a_2^*)}{\partial a_1} - \frac{\partial B_1(a_1^{mmpu})}{\partial a_1}\right) \\ &= \frac{1}{2}\left(a_1^{mmpu} - a_1^{sm1pu}\right)\left[\Omega_1 + \gamma a_2^* - (\alpha_1 + \theta_1)\left(a_1^{mmpu} + a_1^{sm1pu} - a_1^*\right)\right] \\ &= \frac{1}{2}(\alpha_1 + \theta_1)\left(a_1^{mmpu} - a_1^{sm1pu}\right)\left[(a_1^* - a_1^{sm1pu}) - (a_1^{mmpu} - a_1^*)\right] \end{aligned}$$

Pollutant 2

$$\begin{aligned} W_2^{Au} &= DWL_2^{sm1pu} - DWL_2^{mmpu} \\ &= \frac{1}{2}(a_2^* - a_2^{sm1pu})\left(\frac{\partial B_2(a_2^{sm1pu})}{\partial a_2} - \frac{\partial(a_1^*, a_1^{sm1pu})}{\partial a_2}\right) \\ &- \frac{1}{2}(a_2^{mmpu} - a_2^*)\left(\frac{\partial(a_1^*, a_2^{mmpu})}{\partial a_2} - \frac{\partial B_2(a_2^{mmpu})}{\partial a_2}\right) \\ &= \frac{1}{2}\left(a_2^{mmpu} - a_2^{sm1pu}\right)\left[\Omega_2 + \gamma a_1^* - (\alpha_2 + \theta_2)\left(a_2^{mmpu} + a_2^{sm1pu} - a_2^*\right)\right] \\ &= \frac{1}{2}(\alpha_2 + \theta_2)\left(a_2^{mmpu} - a_2^{sm1pu}\right)\left[(a_2^* - a_2^{sm1pu}) - (a_2^{mmpu} - a_2^*)\right] \end{aligned}$$

Refer to Section 1.8 for more details. The complementarity term plays a key role in our results. For pollutant 1, notice that $a_1^* - a_1^{sm1pu} \to 0$ as $\gamma \to 0$. Similarly, $a_1^{mmpu} - a_1^* \to 0$

as $\gamma \to 0$. Hence, as $\gamma \to 0$, there is no difference between either policy in the market for pollutant 1. Conversely, for pollutant 2, as $\gamma \to 0$, $a_2^{mmpu} \to a_2^*$, but $a_2^{sm1pu} \to 0$. Hence, $W_2^{Au} \to \frac{1}{2}(\alpha_2 + \theta_2)(a_2^*)^2 > 0$. Consequently, given $\gamma \to 0$, double-dipping is preferred over a single market policy. This is intuitively as a regulator should not prevent double-dipping if there is no complementarity. The existence of the complementarity is what gives rise to the debate of whether or not to allow or prohibit double-dipping.

Notice that the first two terms of W_i^{Au} are positive and its sign depends on the third term. As long as the distance between the first best and the single market is smaller than the distance between double-dipping and the first best, $W_i^{Au} < 0$ and the regulator should opt for the single market over double-dipping. Intuitively, prohibiting double-dipping makes sense when the solution for the multiple markets is further from the first best compared to the single market solution. The regulator should choose the policy that yields a solution closest to the optimum. How far are these solutions from the first best depends on the parameters of the functions. Furthermore, due to the interconnection between both markets, we must add W_1^{Au} and W_2^{Au}.

Case B

Case B is characterized by the following rankings:

$$\begin{aligned} a_1^{mmpu} &> a_1^* > a_1^{u'} > a_1^{sm1pu} = a_1^u \\ a_2^{mmpu} &> a_2^* > a_2^u > a_2^{sm1pu} = a_2^{u'} \end{aligned}$$

In this case, since the quantities solution gets closer to the first best for pollutant 2 than the single market, we discard the single market policy and focus on a comparison between prices allowing double-dipping and quantities. We define the difference in deadweight losses for each market:

Pollutant 1

$$W_1^{Bu} = W_1^{Au}$$

Pollutant 2

$$W_2^{Bu} = DWL_2^{cu} - DWL_2^{mmpu}$$

$$= \frac{1}{2}(a_2^* - a_2^u)\left(\frac{\partial B_2(a_2^u)}{\partial a_2} - \frac{\partial(a_1^*, a_2^u)}{\partial a_2}\right) - \frac{1}{2}(a_2^{mmpu} - a_2^*)\left(\frac{\partial(a_1^*, a_2^{mmpu})}{\partial a_2} - \frac{\partial B_2(a_2^{mmpu})}{\partial a_2}\right)$$

$$= \frac{1}{2}(\alpha_2 + \theta_2)(a_2^{mmpu} - a_2^u)\left[(a_2^* - a_2^u) - (a_2^{mmpu} - a_2^*)\right]$$

When $\gamma \to 0$, $a_2^{mmpu} \to a_2^* \to a_2^u$, implying that $W_2^{Bu} \to 0$. From Case A, we know $W_1^{Au} \to 0$ as $\gamma \to 0$. Hence, there is no difference between a quantities and prices allowing for double-dipping. Moreover, the analogous interpretation of W_2^{Bu} refers again to the distance between the optimum and the solutions for the respective policy. Whichever policy minimizes this distance becomes the second best policy given the context of these two uncoordinated regulators. Again, to truly know which policy is better, we need to assess whether $W_1^{Bu} + W_2^{Bu}$ is positive or negative. If it is negative, the regulator should choose quantities.

Analysis and Comparative Statics

In order to evaluate these three policy choices for these uncoordinated regulators, we first need to identify situations that make one case more likely to occur than the other. We first look at the complementarity term which is a crucial component of our model. In particular, notice that as $\gamma \to 0$, $a_2^{sm1pu} \to 0$ and $a_2^u > a_2^{sm1pu}$, and we focus on Case B. Recall that there is no difference in the market for pollutant 1 when $\gamma \to 0$. However, there is a difference in the market for pollutant 2 that favors Case B.

Whether we face Case A or B solely depend on whether a_2^{sm1pu} is greater or less than a_2^u. Most of the parameters enter both abatement levels and it is not straight forward to understand the comparative statics. Nonetheless, we already observe the way γ affects this inequality and the way the lack of complementarity favors Case B. However, we are interested in cases where $\gamma > 0$ and will concentrate on the way the slopes of the marginal benefit curves favor each case, since they appear once in either of the abatement levels and we already notice their effects on our graphical analyses in both cases. We concentrate on the way the above abatement levels change with θ_1 and θ_2:

$$\frac{\partial a_2^{sm1pu}}{\partial \theta_1} = \frac{-\alpha_2 \gamma \Omega_1}{(\alpha_1\alpha_2 - \gamma^2 + \alpha_2\theta_1)^2} < 0$$

$$\frac{\partial a_2^u}{\partial \theta_1} = 0$$

$$\begin{aligned}\frac{\partial a_2^{sm1pu}}{\partial \theta_2} &= 0\\ \frac{\partial a_2^u}{\partial \theta_2} &= \frac{-\alpha_1^2\Omega_2}{\alpha_1\alpha_2 - \gamma^2 + \alpha_1\theta_2} < 0\end{aligned}$$

Suppose we start assuming that the difference between a_2^{sm1pu} and a_2^u is very small. If we focus on the slope of the marginal benefit curve for the market for pollutant 1, we know that an increase in θ_1 decreases a_2^{sm1pu} while a_2^u remains the same. Hence, a high (low) θ_1 favors Case B (Case A). Focusing on the slope of the marginal benefit curve for pollutant 2, we know that a steeper slope decreases a_2^u while keeping a_2^{sm1pu} the same. Hence a high (low) θ_2 favor Case A (Case B). Combining both, we know that Case A is favored by a low θ_1 and a high θ_2 while Case B is characterized by a high θ_1 and a low θ_2.

We first start with some graphical analysis to obtain some intuition. For Case A, refer to Figures (1.6) and(1.7) and for Case B, refer to Figures (1.8) and (1.9) that are drawn based on the slope relations noted above. Focusing on the chosen market first, Figure (1.6) depicts a flatter marginal benefit curve that corresponds to Case A. This flatness favors double-dipping in the chosen market (blue versus purple areas). For Case B, when the slope of the marginal benefit curve is steeper (Figure (1.8)), then either quantities or the single market are favored over double-dipping in the chosen market (purple versus blue areas). Switching to the unchosen market, we see that relatively steeper marginal benefit curve could favor a single market over double-dipping (See Figure (1.7) and compare gray versus orange areas). Conversely, a flatter curve clearly favors double-dipping over both quantities and the single market (See Figure (1.9) and compare orange versus yellow and gray areas). In order to choose the best second-best policy, we need to take into account both chosen and unchosen markets. Focusing on Case B (Figures (1.8) and (1.9)), it is clear that a single market is not preferred. Double-dipping is preferred over the single market. However, quantities outperformed both price policies. Switching to Case A, the single market seems to be preferred. While double-dipping outperforms a single market (blue versus purple area) in the chosen market, the single market dominates in the unchosen market (gray versus orange areas).

Beyond a graphical analysis, we can perform some comparative statics based on these slopes. Focusing on Case A and taking into account the parameter relations just noted, we know that the term that determines W_i^{Au}'s sign is $2a_i^* - a_i^{mmpu} - a_i^{sm1pu}$. If $2a_i^* - a_i^{mmpu} - a_i^{sm1pu} > 0$, then $W_i^{Au} > 0$ and if this happens for both $i = 1, 2$, then the regulator should use double-dipping over a single market. Given the parameters that favor Case A and assuming that either $a_1^* - a_1^{sm1pu}$ is similar to $a_1^{mmpu} - a_1^*$ or that $2a_1^* - a_1^{mmpu} - a_1^{sm1pu} > 0$, we know that $\frac{\partial W_1^{Au}}{\partial \theta_2} < 0$ (Refer to Section 1.8 for details)[5]. Hence, for the market focusing on pollutant 1, having even steeper marginal benefit curve for the unchosen market makes W_1^{Au} more likely to be negative, favoring the single market over double-dipping. This results exemplifies the interconnection between markets. The slope of the marginal benefit curve in the unchosen market affects the results in the chosen market.

Turning to the market for pollutant 2, we follow the same thought process. Taking into account the characteristics of Case A and as long as $a_2^* - a_2^{sm1pu}$ is similar to $a_2^{mmpu} - a_2^*$ or as long as $2a_2^* - a_2^{mmpu} - a_2^{sm1pu} > 0$, then $\frac{\partial W_2^{Au}}{\partial \theta_2} < 0$ (See Section 1.8). Increasing θ_2 makes W_2^{Au} more likely to be negative favoring a single market over double-dipping. If the marginal benefit curve in the unchosen market becomes flatter, this could favor double-dipping. Nonetheless, this case requires a steeper curve. To sum up, when markets are characterized by a flatter and steeper marginal benefits curves for the chosen and unchosen markets respectively, making the steeper marginal benefit curves even steeper favors a single market over double-dipping.

Switching to Case B, we know this case is favored by a steeper and flatter marginal benefit curves in the chosen and unchosen markets respectively (i.e. high θ_1 and low θ_2). For this case, the comparison is between prices allowing double-dipping and quantities, since quantities outperformed the single market. Hence, a single-market policy is not favored under this case. In other words, the question we answer for Case B is whether the regulator should employ prices or quantities. Again, W_i^{Bu}'s sign is determined by the sign of $2a_i^* - a_i^{mmpu} - a_i^u$. If $2a_i^* - a_i^{mmpu} - a_i^u > 0$, then $W_i^{Bu} > 0$ and if this happens for both $i = 1, 2$, then double-dipping is preferred. We focus on comparative statics with respect to θ_1 (the steeper slope) for Case B. Taking into account the relative sizes of the slopes of the marginal benefit curves, we conclude that $\frac{\partial W_1^{Bu}}{\partial \theta_1} < 0$ (See Section 1.8). Increasing θ_1 even more, makes W_1^{Bu} more likely

[5]The signs of the comparative statics with respect to θ_1 are not as straightforward and require more assumptions about the parameters.

to be negative favoring quantities over double-dipping. In other words, quantities are likely to dominate when the marginal benefit curve in the chosen market is even steeper.

Focusing on the unchosen market, we keep the same parameter assumptions. Furthermore, assuming that either $a_2^* - a_2^u$ is similar to $a_2^{mmpu} - a_2^*$ or as long as $2a_2^* - a_2^{mmpu} - a_2^{smu} > 0$, then $\frac{\partial W_2^{Bu}}{\partial \theta_1} < 0$ (See Section 1.8). As the slope of the marginal benefit curve for the market focusing on pollutant 1 increases, then W_2^{Bu} decreases and could eventually make the deadweight loss for the quantities policy smaller than the one under double-dipping. Hence, this change favors the usage of quantities.

To sum up, double-dipping performs better in markets characterized by flatter marginal benefit curves. However, we study two cases in which the marginal benefit curves differ substantially across markets. Hence, the performance of double-dipping is always affected by the steeper marginal benefit curve. In fact, we find that in these two cases, double-dipping is not likely be favored by making the steeper curve even steeper. When the latter occurs, either a single market or a quantities policy tends to be preferred.

1.5 Complementarity Ignored by the Regulator

After studying the policy choices for uncoordinated regulators, the next scenario we study is one in which the regulator does not know about the complementarity between pollutants. Having a regulator with full information about the cost function is very unlikely in reality. A more plausible case is one in which the regulator sets either prices or quantities in a second-best sense due to this lack of information about complementarity.

1.5.1 Regulator's Problem

Quantities

If the regulator decides to use quantities, he chooses them by solving the following problem:

$$\max_{a_1,a_2} W(a_1, a_2) = \max_{a_1,a_2} B_1(a_1) + B_2(a_2) - g(a_1, a_2|\gamma = 0) \tag{1.34}$$

Without using the functional forms described above, the first order conditions are:

$$\begin{aligned} a_1 &: \frac{\partial B_1(a_1)}{\partial a_1} = \frac{\partial g(a_1, a_2|\gamma = 0)}{\partial a_1} \\ a_2 &: \frac{\partial B_2(a_2)}{\partial a_2} = \frac{\partial g(a_1, a_2|\gamma = 0)}{\partial a_2} \end{aligned}$$

The solution derived from these first order conditions are denoted a_1^0 and a_2^0. The zero is meant to signify that the policy maker thinks $\gamma = 0$. With functional forms, the problem and solution become:

$$\max_{a_1,a_2} \Omega_1 a_1 - \frac{\theta_1}{2}a_1^2 + \ \Omega_2 a_2 - \frac{\theta_2}{2}a_2^2 - \frac{\alpha_1}{2}a_1^2 - \frac{\alpha_2}{2}a_2^2 \tag{1.35}$$

$$a_1^0 = \frac{\Omega_1}{\alpha_1 + \theta_1} \neq a_1^* \tag{1.36}$$

$$a_2^0 = \frac{\Omega_2}{\alpha_2 + \theta_2} \neq a_2^* \tag{1.37}$$

Prices

If the regulator chooses prices instead of quantities, he takes into account the reaction function of the firm to set prices. Similarly to the full information case, the regulator knows that the firm maximizes profits equating the price for each pollutant to its marginal cost of abatement. However, different than the full information case, the regulator thinks that $\gamma = 0$. (i.e. there is no complementarity):

$$\begin{aligned} \tau_1 &= \frac{\partial g(a_1, a_2|\gamma = 0)}{\partial a_1} = \alpha_1 a_1 \Rightarrow a_1^R(\tau_1) = \frac{\tau_1}{\alpha_1} \\ \tau_2 &= \frac{\partial g(a_1, a_2|\gamma = 0)}{\partial a_2} = \alpha_2 a_2 \Rightarrow a_2^R(\tau_2) = \frac{\tau_2}{\alpha_2} \end{aligned}$$

Taking these reactions functions, the regulator's problem becomes:

$$\max_{\tau_1,\tau_2} \Omega_1\left(\frac{\tau_1}{\alpha_1}\right) - \frac{\theta_1}{2}\left(\frac{\tau_1}{\alpha_1}\right)^2 + \Omega_2\left(\frac{\tau_2}{\alpha_2}\right) - \frac{\theta_2}{2}\left(\frac{\tau_2}{\alpha_2}\right)^2 - \frac{\alpha_1}{2}\left(\frac{\tau_1}{\alpha_1}\right)^2 - \frac{\alpha_2}{2}\left(\frac{\tau_2}{\alpha_2}\right)^2$$

The optimal prices are denoted by τ_1^0 and τ_2^0, where 0 symbolizes that the regulator is ignoring complementarities:

$$\tau_1^0 = \frac{\alpha_1 \Omega_1}{\alpha_1 + \theta_1} \neq \tau_1^* \tag{1.38}$$

$$\tau_2^0 = \frac{\alpha_2 \Omega_2}{\alpha_2 + \theta_2} \neq \tau_2^* \tag{1.39}$$

Once again, these prices can also be found by equating $\tau_i^0 = \frac{\partial B_i}{\partial a_i} = \Omega_i - \theta_i a_i^0$ for $i = 1, 2$.

1.5.2 Firm's Problem

This section illustrates the case in which the firm possesses more information than the regulator as it understands the cost complementarities between pollutants

Quantities

Given that the regulator policy choice is to set quantities for each pollutant, the firm's problem becomes:

$$\max_{a_1,a_2} -g(a_1,a_2) \text{ s.t.} a_1 \geq a_1^0 \text{ and } a_2 \geq a_2^0$$

The firm has to decrease pollutants at least to the level equal to the given quantities. The corresponding Lagrangian for this problem:

$$\pounds = -g(a_1,a_2) + \lambda_1^0(a_1 - a_1^0) + \lambda_2^0(a_2 - a_2^0)$$

The first order conditions for this optimization problem are:

$$\begin{array}{llll} a_1: & -\frac{\partial g(a_1,a_2)}{\partial a_1} + \lambda_1^0 \leq 0 & a_1^{c0}\left[\frac{\partial \pounds}{a_1}\right] = 0 & a_1^{c0} \geq 0 \\ a_2: & -\frac{\partial g(a_1,a_2)}{\partial a_2} + \lambda_2^0 \leq 0 & a_2^{c0}\left[\frac{\partial \pounds}{a_2}\right] = 0 & a_2^{c0} \geq 0 \\ \lambda_1: & a_1 - a_1^0 \geq 0 & \lambda_1^{c0}\left[\frac{\partial \pounds}{\lambda_1^0}\right] = 0 & \lambda_1^{c0} \geq 0 \\ \lambda_2: & a_2 - a_2^0 \geq 0 & \lambda_2^{c0}\left[\frac{\partial \pounds}{\lambda_2^0}\right] = 0 & \lambda_2^{c0} \geq 0 \end{array}$$

The firm chooses to reduce pollution by an amount equal to the given quantity:

$$a_1^{c0} = a_1^0 = \frac{\Omega_1}{\alpha_1 + \theta_1} \neq a_1^* \tag{1.40}$$

$$a_2^{c0} = a_2^0 = \frac{\Omega_2}{\alpha_2 + \theta_2} \neq a_2^* \tag{1.41}$$

Prices - Double-dipping - Multiple Markets

If double-dipping is allowed, then the firm's problem becomes:

$$\max_{a_1,a_2} \tau_1^0 a_1 + \tau_2^0 a_2 - g(a_1,a_2)$$

The first order conditions are:

$$a_1 : \tau_1^0 = \frac{\partial g(a_1,a_2)}{\partial a_1}$$

$$a_2 : \tau_2^0 = \frac{\partial g(a_1,a_2)}{\partial a_2}$$

Since $\tau_i^0 = \frac{\partial B_i(a_i^0)}{\partial a_i} \neq \frac{\partial B_i(a_i^*)}{\partial a_i}$ for $i = 1, 2$, we know we are not able to attain the first best. Using the specific cost functional form, the solution for the firm becomes:

$$a_1^{mmp0} = \frac{\alpha_2 \tau_1^0 + \gamma \tau_2^0}{\alpha_1 \alpha_2 - \gamma^2} = \frac{\alpha_2 \left(\left(\alpha_1 + \theta_1 \right) \gamma \Omega_2 + \alpha_1 \left(\alpha_2 + \theta_2 \right) \Omega_1 \right)}{\left(\alpha_1 + \theta_1 \right) \left(\alpha_2 + \theta_2 \right) \left(\alpha_1 \alpha_2 - \gamma^2 \right)} \neq a_1^* \tag{1.42}$$

$$a_2^{mmp0} = \frac{\alpha_1 \tau_2^0 + \gamma \tau_1^0}{\alpha_1 \alpha_2 - \gamma^2} = \frac{\alpha_1 \left(\alpha_2 \left(\alpha_1 + \theta_1 \right) \Omega_2 + \left(\alpha_2 + \theta_2 \right) \gamma \Omega_1 \right)}{\left(\alpha_1 + \theta_1 \right) \left(\alpha_2 + \theta_2 \right) \left(\alpha_1 \alpha_2 - \gamma^2 \right)} \neq a_2^* \tag{1.43}$$

Prices - Disallowing Double-dipping - Single Market

Suppose that due to additionality concerns or political reasons, the regulator decides to prohibit the firm from getting compensated for the reductions of both pollutants. The firm's problem becomes:

$$\max \left\{ \max_{a_1, a_2} \tau_1^0 a_1 - g(a_1, a_2); \max_{a_1, a_2} \tau_2^0 a_2 - g(a_1, a_2) \right\}$$

Since this is a two stage optimization problem, the first order conditions for the first stage in which the firm is getting compensated for the reductions of pollutant i instead of j are:

$$a_i \ : \ \tau_i^0 = \frac{\partial g(a_1, a_2)}{\partial a_i} = \alpha_i a_i - \gamma a_j$$

$$a_j \ : \ 0 = \frac{\partial g(a_1, a_2)}{\partial a_j} = \alpha_j a_j - \gamma a_i$$

If it is more optimal for the firm to participate in the policy for pollutant 1, the firm's optimal abatement levels are:

$$a_1^{sm1p0} = \frac{\alpha_2 \tau_1^0}{\alpha_1 \alpha_2 - \gamma^2} = \frac{\alpha_1 \alpha_2 \Omega_1}{\left(\alpha_1 + \theta_1 \right) \left(\alpha_1 \alpha_2 - \gamma^2 \right)} \neq a_1^* \tag{1.44}$$

$$a_2^{sm1p0} = \frac{\gamma \tau_1^0}{\alpha_1 \alpha_2 - \gamma^2} = \frac{\alpha_1 \gamma \Omega_1}{\left(\alpha_1 + \theta_1 \right) \left(\alpha_1 \alpha_2 - \gamma^2 \right)} \neq a_2^* \tag{1.45}$$

1.5.3 Welfare Analysis

We follow the same thought process as with uncoordinated regulators[6]. For simplicity, we assume again that the firm chooses to participate in the market for a_1 when facing a single market policy. The ranking of the abatement levels in each market is useful to identify the

[6] As in Section 1.4, we assume, without loss of generality, the firm decides to participate in the market for pollutant 1, the "chosen market" and that $\gamma > 0$

cases to consider for this welfare analysis. For pollutant 1, we have two possible rankings:

$$\begin{aligned}\text{Case I} &: a_1^{mmp0} > a_1^* > a_1^{sm1p0} > a_1^0 = a_1^{c0} \\ \text{Case II} &: a_1^{mmp0} > a_1^{sm1p0} > a_1^* > a_1^0 = a_1^{c0}\end{aligned}$$

For pollutant 2, there are three possible rankings:

$$\begin{aligned}\text{Case 1} &: a_2^{mmp0} > a_2^* > a_2^{sm1p0} > a_2^0 = a_2^{c0} \\ \text{Case 2} &: a_2^{mmp0} > a_2^{sm1p0} > a_2^* > a_2^0 = a_2^{c0} \\ \text{Case 3} &: a_2^{mmp0} > a_2^* > a_2^0 = a_2^{c0} > a_2^{sm1p0}\end{aligned}$$

The conditions that determine which cases are more likely to occur rely on the relation between a_1^* and a_1^{sm1p0}, the relation between a_2^{sm1p0} and a_2^0, and the relation between a_2^{sm1p0} and a_2^*. For the first relation, we know that Case I is characterized by $a_1^* \geq a_1^{sm1p0}$ which implies that $\frac{(\alpha_2+\theta_2)\Omega_1+\gamma\Omega_2}{(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2} > \frac{\alpha_1\alpha_2\Omega_1}{(\alpha_1+\theta_1)(\alpha_1\alpha_2-\gamma^2)}$. Notice that θ_2 only affects a_1^*:

$$\frac{\partial a_1^*}{\partial \theta_2} = -\gamma \frac{\gamma\Omega_1 + (\alpha_1+\theta_1)\Omega_2}{\left((\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right)^2} < 0 \tag{1.46}$$

$$\frac{\partial a_1^{sm1p0}}{\partial \theta_2} = 0 \tag{1.47}$$

Suppose a_1^* are close to each other a_1^{sm1p0}. If we increase θ_2, a_1^* decreases while a_1^{sm1p0} stays the same, favoring Case II. Similarly, a decrease in θ_2 favors Case I.

For the second market, we focus on the difference between a_2^{sm1p0} and a_2^0 first. Since we get a clear distinction between the Case I and II for a_1 from changes in θ_2, we continue our analysis based on this parameter only:

$$\frac{\partial a_2^{sm1p0}}{\partial \theta_2} = 0 \tag{1.48}$$

$$\frac{\partial a_2^0}{\partial \theta_2} = -\frac{\Omega_2}{(\alpha_2+\theta_2)^2} < 0 \tag{1.49}$$

An increase in θ_2, decreases a_2^0 while a_2^{sm1p0} stays the same. Hence, an increase in θ_2 makes Cases 1 and 2 more plausible. A decrease in θ_2 favors Case 3.

Focusing on the second relation between a_2^{sm1p0} and a_2^*, we perform a similar analysis and focus on the derivatives for a_2^*:

$$\frac{\partial a_2^*}{\partial \theta_2} = -\frac{(\alpha_1+\theta_1)\left((\alpha_1+\theta_1)\Omega_2+\gamma\Omega_1\right)}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2} < 0 \tag{1.50}$$

We already know that a_2^{sm1p0} does not change with θ_2 from Equation (1.48). If we start with a_2^* and a_2^{sm1p0} close to each other, an increase in θ_2 decreases a_2^* making Case 2 more likely. Decreasing θ_2 makes Cases 1 and 3 more likely.

Combining the results for both markets, we know that Case II and Case 2 are favored by a steeper marginal benefit curve in the unchosen market. Likewise, Case I for Case 3 are favored by a flatter marginal benefit curve for a_2. Furthermore, observe that a very low complementarity term favors Case 3 as $a_2^{sm1p0} \to 0$ and $a_2^* \to a_2^0$ while there is little difference regarding Case I and II ($a_1^{sm1p0} \to a_1^0 \to a_1^*$). Overall, we can combine cases for both markets base on the slopes of the marginal benefit curves and the complementarity term. To avoid confusion with the uncoordinated regulators' cases, we refer to these cases as C and D: Case C combines cases II and 2 which are favored by a high θ_2. Case D combines cases I and 3 which are favored by a low θ_2 and a low complementarity. The following subsections study each combination of cases.

Case C

$$\begin{aligned} \text{Case II} &: \quad a_1^{mmp0} \geq a_1^{sm1p0} \geq a_1^* \geq a_1^0 = a_1^{c0} \\ \text{Case 2} &: \quad a_2^{mmp0} \geq a_2^{sm1p0} \geq a_2^* \geq a_2^0 = a_2^{c0} \end{aligned}$$

Given these rankings, we discard double-dipping as the single market outperforms it in both markets. Our focus is to compare quantities to prices prohibiting double-dipping (i.e. a single market). We start with a graphical analysis to gather some intuition. This combination of cases is depicted in Figures (1.10), (1.11) and (1.12). The first two graphs concentrate on the chosen market, since we have not imposed any assumptions about the size of the slope of the marginal benefit curve in the chosen market. Both figures show the single market doing better than double-dipping (pink versus blue areas). Again, we focus on the comparison between quantities and the single market. Figure (1.10) has a flatter marginal benefit curve, which favors the single market over quantities (pink versus purple areas). Conversely, Figure (1.11) shows a steeper marginal benefit curve that favors quantities. Lastly, Figure (1.12) illustrates the market for pollutant 2 and shows quantities outperforming the single market (yellow versus grey areas). Hence, quantities are favored by steeper marginal benefit curves in both markets for this case. Beyond the graphical intuition, we define the difference in deadweight losses in each market:

Pollutant 1:

$$W_1^{C0} = DWL_1^{c0} - DWL_1^{sm1p0} = \frac{1}{2}(\alpha_1 + \theta_1)\left(a_1^{sm1p0} - a_1^0\right)\left[(a_1^* - a_1^0) - (a_1^{sm1p0} - a_1^*)\right]$$

Pollutant 2:

$$W_2^{C0} = DWL_2^{c0} - DWL_2^{sm1p0} = \frac{1}{2}(\alpha_2 + \theta_2)\left(a_2^{sm1p0} - a_2^0\right)\left[(a_2^* - a_2^0) - (a_2^{sm1p0} - a_2^*)\right]$$

As long as $W_i^{C0} < 0$ for $i = 1, 2$, quantities are preferred over the single market and in general over prices. This occurs whenever quantities solutions get closer to the first best compared to the single market solutions as illustrated by Figures (1.11) and (1.12).

Analysis and Comparative Statics

For the comparative statics analysis, recall that the term that determines W_i^{C0}'s sign is $2a_i^* - a_i^{sm1p0} - a_i^0$ and moreover, the sign determines which policy is preferred. If it is positive (negative), a single market (quantities) is preferred. Focusing on the chosen market, the sign of the derivative of W_1^{C0} with respect to θ_2 is determined by the sign of the derivative of $2a_1^* - a_1^{sm1p0} - a_1^0$ with respect to θ_2, which is negative (See Section 1.8 for more details). Since we know Case C is favored by high θ_2 , we study the way W_1^{C0} changes as θ_2 becomes even larger. We conclude that quantities tend to be favored over the single market as the slope of the marginal benefit curve becomes steeper in the unchosen market. Turning to the market for pollutant 2, assuming $a_2^* - a_2^0$ is similar to $a_2^{sm1p0} - a_2^*$ or $2a_2^* - a_2^{sm1p0} - a_2^0 < 0$, we can conclude that $\frac{\partial W_2^{C0}}{\partial \theta_2} < 0$. Hence, making the marginal benefit curve steeper in the unchosen market also tends to favor quantities over the single market. To sum up, we can determine the second best policy by looking at the sign of $2a_i^* - a_i^{sm1p0} - a_i^0$ in each market $i = 1, 2$. If the sign is positive in both markets, the single market policy is preferred over quantities. Conversely, when the sign is negative in both markets, quantities are preferred over the single market price policy. Furthermore, in this case characterized by much steeper marginal benefit curve for the unchosen market, quantities are favored over a single market as we make the marginal benefit curve even steeper. .

Case D

Case D is characterized by a flatter marginal benefit curve for the unchosen market and small complementarity between pollutants. The rankings for this case:

$$\begin{aligned} \text{Case I} \quad &: \quad a_1^{mmp0} > a_1^* > a_1^{sm1p0} > a_1^0 = a_1^{c0} \\ \text{Case 3} \quad &: \quad a_2^{mmp0} > a_2^* > a_2^0 = a_2^{c0} > a_2^{sm1p0} \end{aligned}$$

Giving these rankings, we cannot rule out any of the policies, which makes the analysis more challenging. For the market for pollutant 1, the quantities policy is dominated by the single market policy. However, for pollutant 2, the single market is dominated by the quantities policy. To gather some intuition, we refer to Figures (1.13), (1.14) and (1.15). The first provides an example of what the curves have to look like in the chosen market in order to satisfy the ranking for a_1. We observe that the pink curve must be very close to the purple curve in order to match the ranking for this case. This suggests that the complementarity needs to be low and that the abatement level por pollutant 2 under the single market must be low too. The remaining two figures focus on the unchosen market as both depict a flatter marginal benefit curve. The difference between both curves relies on the relative size of the complementarity. For very low complementarity (Figure 1.14), we observe little difference between quantities and double-dipping. As we increase the complementarity, we observe that double-dipping outperforms the other policies in Figure (1.15). In both Figures, we observe that the efficiency of the single market is substantially affected by the flatness of the marginal benefit curve for a_2 resulting in very large welfare losses in each figure (See gray areas in Figures 1.14 and 1.15). Beyond a graphical analysis and while we cannot discard any policy, we opt to compare the deadweight losses between double-dipping and a single market for the chosen market and between double-dipping quantities for the unchosen market:

$$W_1^{D0} = DWL_1^{sm1p0} - DWL_1^{mmp0} = \frac{1}{2}\left(\alpha_1 + \theta_1\right)\left(a_1^{mmp0} - a_1^{sm1p0}\right)\left[\left(a_1^* - a_1^{sm1p0}\right) - \left(a_1^{mmp0} - a_1^*\right)\right]$$

$$W_2^{D0} \quad = \quad DWL_2^0 - DWL_2^{mmp0} = \frac{1}{2}\left(\alpha_2 + \theta_2\right)\left(a_2^{mmp0} - a_2^0\right)\left[\left(a_2^* - a_2^0\right) - \left(a_2^{mm1p0} - a_2^*\right)\right]$$

Analysis and Comparative Statics

Notice that the sign of W_i^{D0} depends on the sign of $2a_i^* - a_i^{mmp0} - a_i^{sm1p0}$ for $i = 1, 2$. For instance, if $W_i^{D0} > 0$ for both $i = 1, 2$, then double-dipping dominates the single market policy. For Case D, we know that as for very low γ, there is little differences in the chosen market as the abatement levels are very similar. Thus, we decide to concentrate on the unchosen market for this analysis and we compare double-dipping to a quantities policy. We find that as long as γ is small, $\frac{\partial W_2^{D0}}{\partial \theta_2} < 0$. Given that this case is characterized by a small θ_2, making the marginal benefit curve even flatter in the unchosen market increases W_2^{D0} favoring double-dipping over quantities. This is intuitive from Figures (1.14) and (1.15). To sum up, decreasing θ_2 even more going along with the characteristics of Case D makes double-dipping more likely to be preferred over both quantities and a single market. For this case, the single market performs very poorly resulting in large welfare losses in the unchosen market. Nonetheless, this case is based on very low complementarity, which is not as relevant for the debate about double-dipping. In essence, this case is more about a prices versus quantities analysis. In fact, the poor performance of the single market is very intuitive as the firm is not allowed to get paid for reductions in one pollutant. Hence, the firm is going to tend to reduce very little in that market, making the deadweightloss very large under a single market policy.

1.6 Conclusions

The major contribution of this paper is to compare a price policy allowing double-dipping to two policies: a quantities policy and a price policy prohibiting double-dipping. Hence, we aim at understanding when each of these policy designs is more efficient. We look at the full information scenario as a baseline for assessing these other policies. Under full information, we show that there is no difference between quantities and prices as long as double-dipping is allowed. Even when the regulator takes into account the structure of the single market when setting up prices, double-dipping is still preferred over a single market under full information.

Since full information is rarely available to a regulator(s), we study two scenarios in which some important information is not present. A contribution of this paper is the modeling of the set up of second best prices and quantities. The first scenario we study is the case of two disconnected or uncoordinated policy makers lacking information about the other's environmental program. In this case, we concentrate on two possible cases that are characterized by very different marginal benefit curves across markets. We notice that double-dipping tends to perform better in markets that have a flatter marginal benefit curve. For instance, when the marginal benefit curve is relatively flatter in the unchosen market, double-dipping outperforms both quantities and the single market in that market. In fact, this flatness substantially increases the deadweight loss that arises from the single market policy. Focusing on the steeper curve, making the marginal benefit curve even steeper in the unchosen (chosen) market favors a single market (quantities) over double-dipping. Hence, making the steeper marginal benefits curve even steeper does not favor double-dipping.

Comparing double-dipping with a single market and not taking into account a quantities policy, we conclude that double-dipping is likely favored over a single market when the marginal benefit curve is relatively steeper in the chosen market and relatively flatter in the unchosen market. Even though the steeper curve in the chosen market does not favor double-dipping, the flatter slope in the unchosen market substantially harms the performance the single market. Analogously, a single market is more likely to outperform double-dipping as long as the steeper curve effect dominates the flatter curve effect. Since the unchosen market is the one with the steeper curve, it is more likely that its effect will matter most. Taking both together, double-dipping is more likely to be preferred over a single market when the steeper curve is in the chosen market. Conversely, in the case when the steeper curve is in the unchosen market, a single market is more likely to be preferred over double-dipping.

Another way the regulator can set prices or quantities in a second-best setting is when complementarity is ignored in the policy design. Our analysis focuses on differences on the slope of marginal benefit curve in the unchosen market. If the marginal benefit curve is relatively steeper in the unchosen market, double-dipping is outperformed by a single market and we compare quantities versus the single market. Making the marginal benefit curve even steeper favors quantities over a single market. The second case is characterized by a flatter marginal benefit curve in the unchosen market and very low complementarity. In this case, no single policy is outperformed in both markets. The flatter slope substantially affect the performance of the single market resulting in a large welfare loss in the unchosen market making double-dipping preferred over a single market. Given the poor performance of the single market, we compare double-dipping and quantities. For the chosen market, the policies do not delivery very different results. Focusing on the unchosen market, making the slope even flatter favors double-dipping over quantities. Hence, for either case, changing the slope of the marginal benefit curve in the direction that characterizes each case never favors a single market.

To summarize, this paper points to specific market characteristics that favor one policy over the others under two second-best scenarios, which further expands our understanding about the implications of allowing double-dipping in environmental markets. In fact, the interconnection between markets due to the complementarity augments the size of the deadweight loss associated with prices. Under both second best scenarios, incorrect prices are set above the first best, resulting in the over abatement of each pollutant. This over abatement appears in the other pollutants market through the vertical intercept, which is further from the true marginal cost and increases the deadweight loss associated with prices.

1.7 Figures

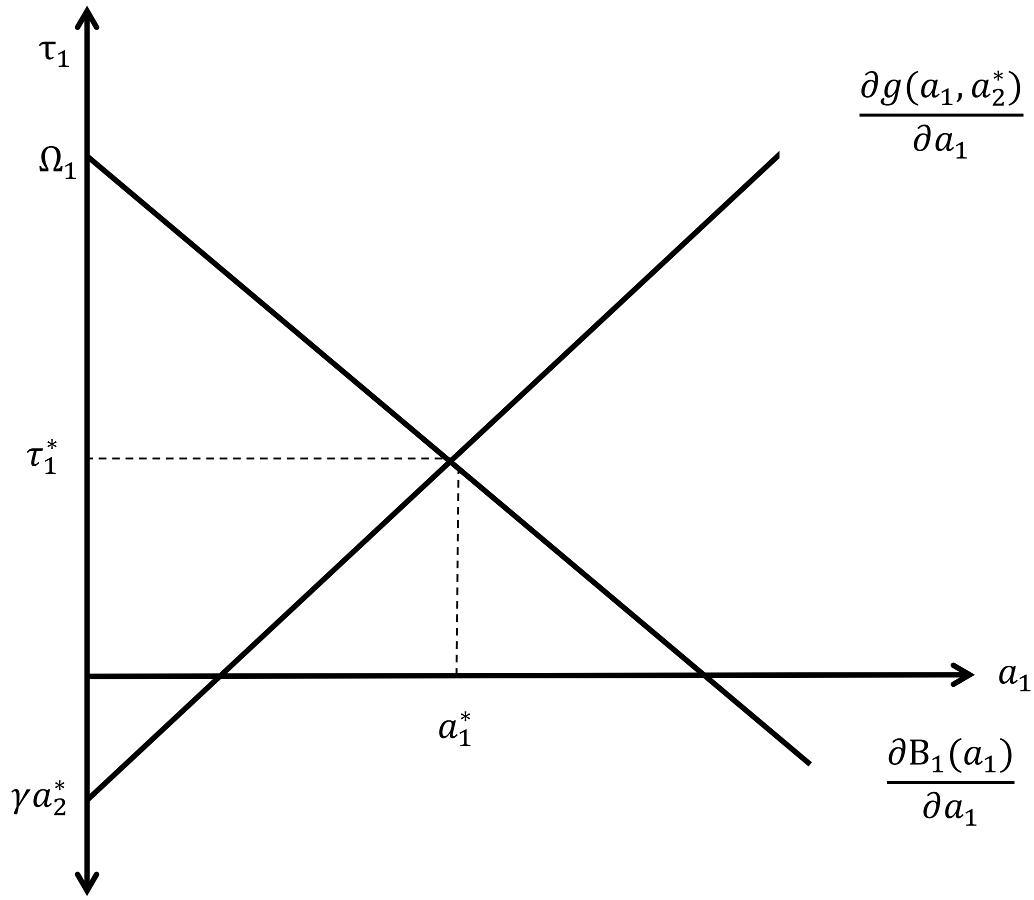

Figure 1.1 Full Information Social Planner- Pollutant 1

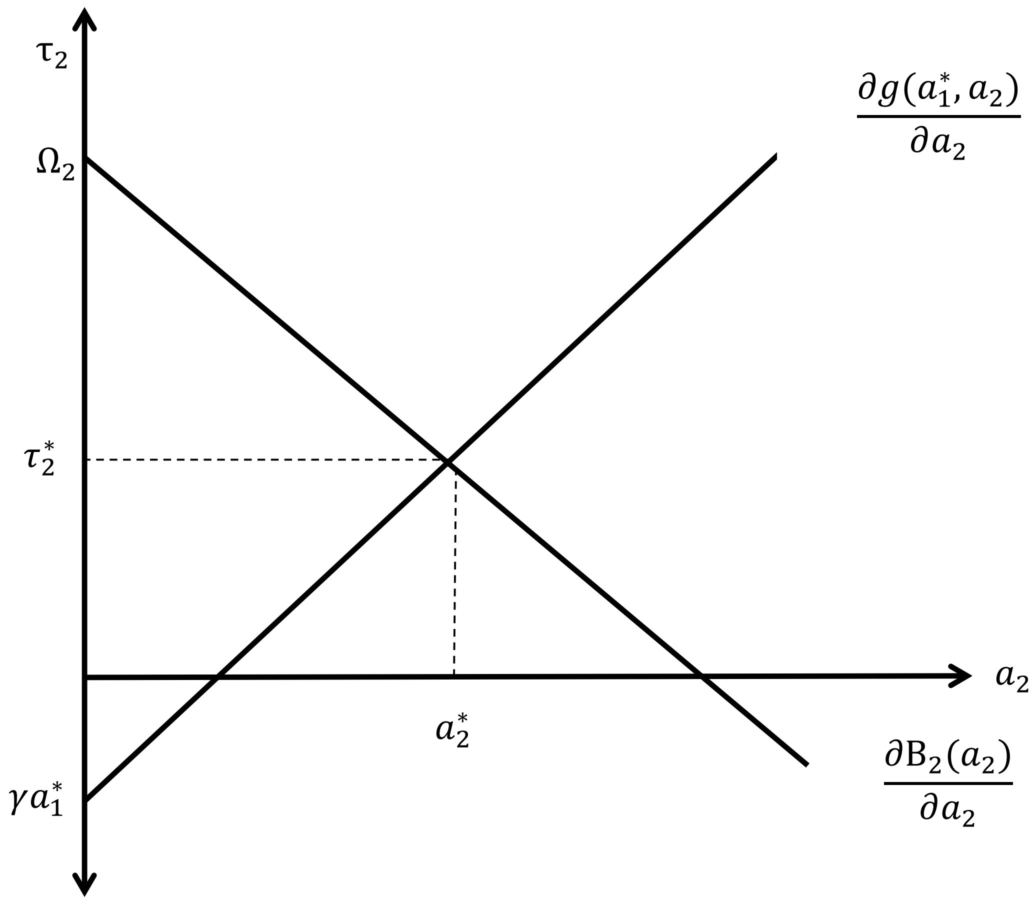

Figure 1.2 Full Information Social Planner- Pollutant 2

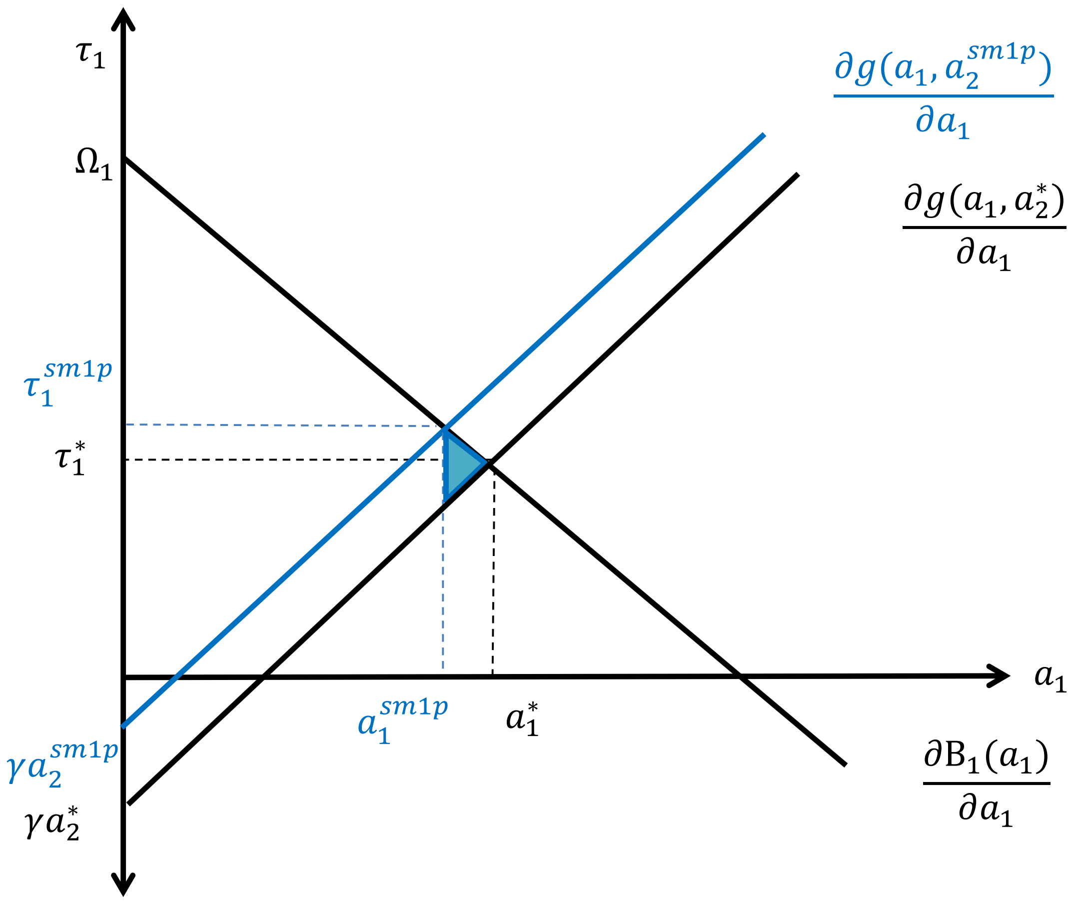

Figure 1.3 Full Information Single Market - Pollutant 1

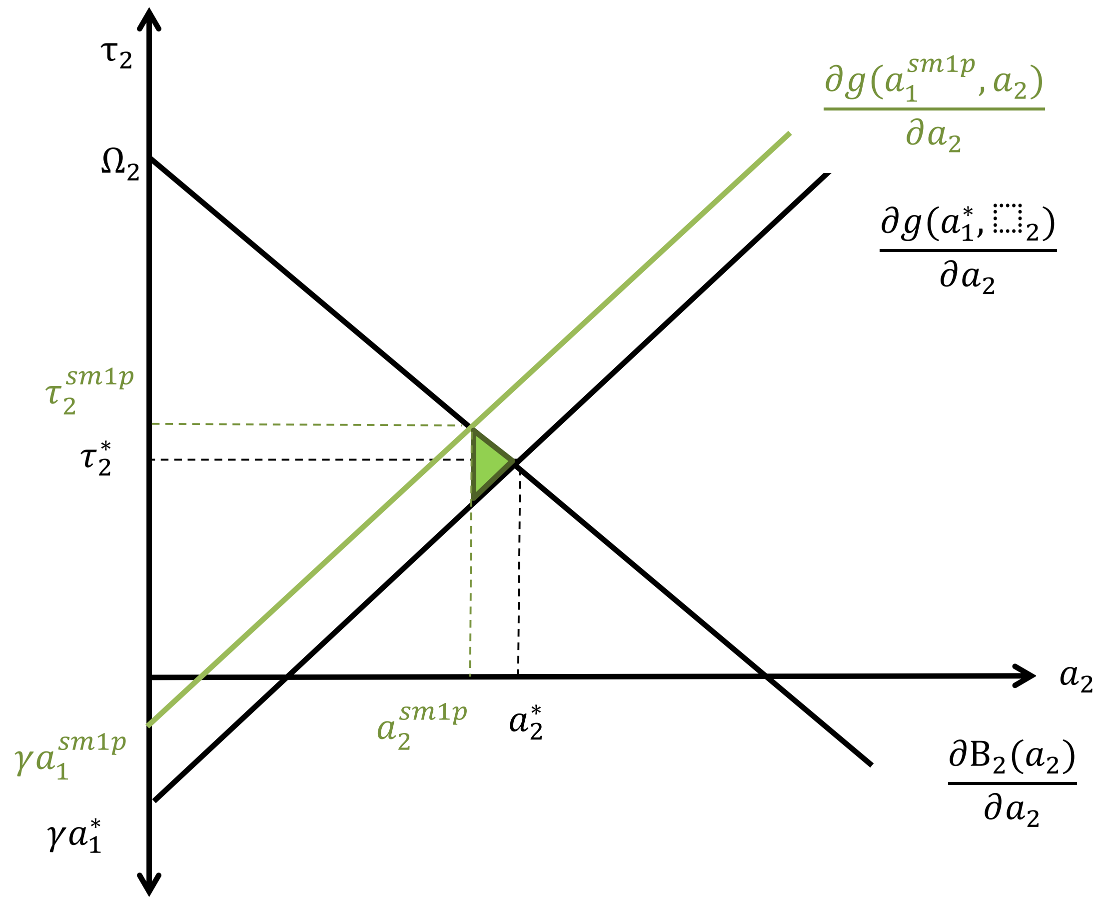

Figure 1.4 Full Information Single Market - Pollutant 2

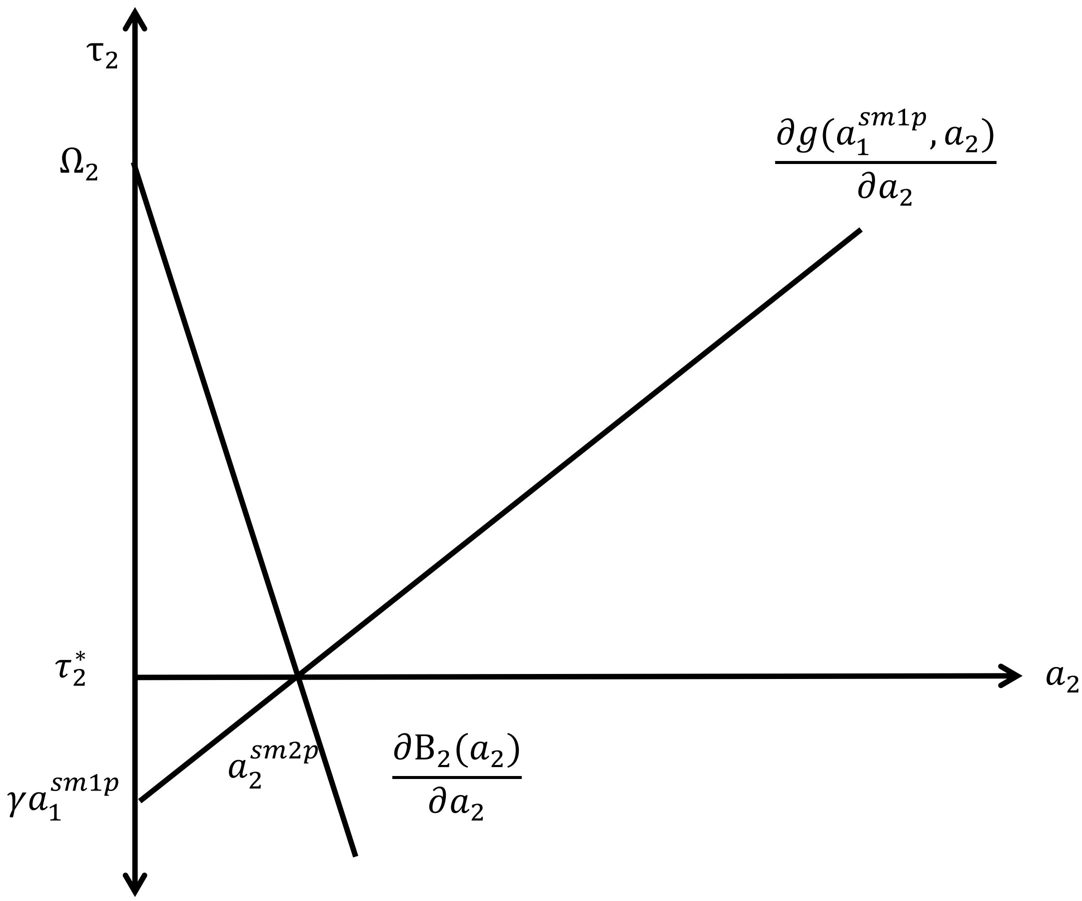

Figure 1.5 Full Information Single Market - Pollutant 2 - Special Case

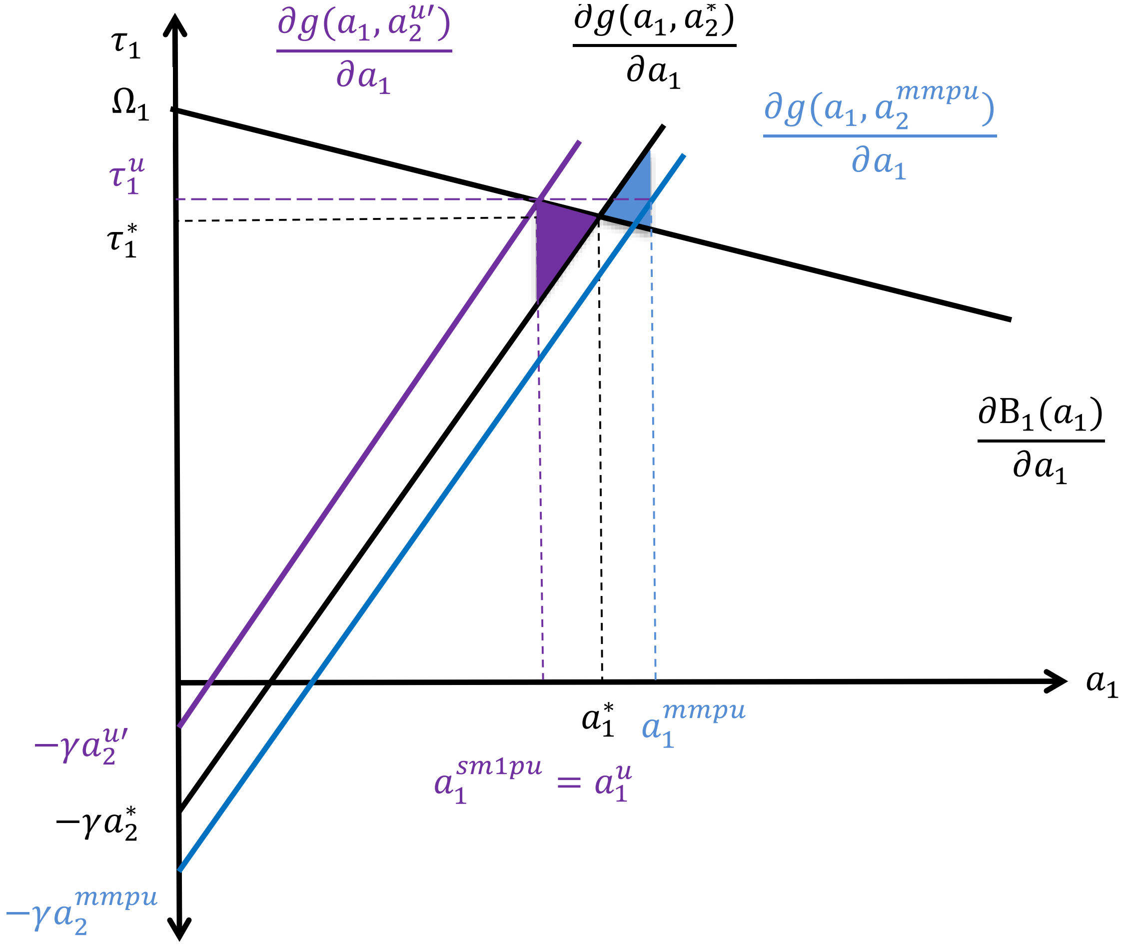

Figure 1.6 Uncoordinated Regulators - Pollutant 1-Case A

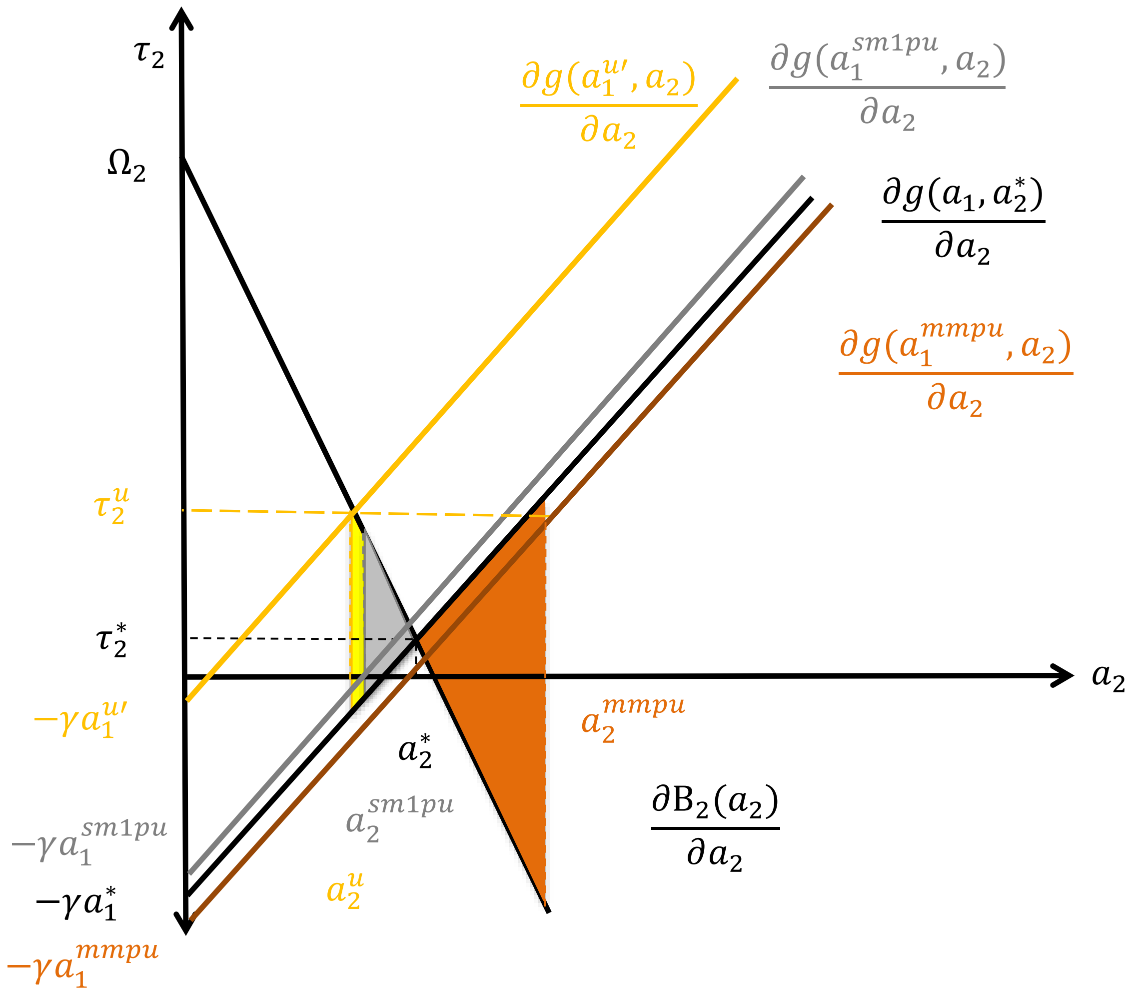

Figure 1.7 Uncoordinated Regulators - Pollutant 2 - Case A

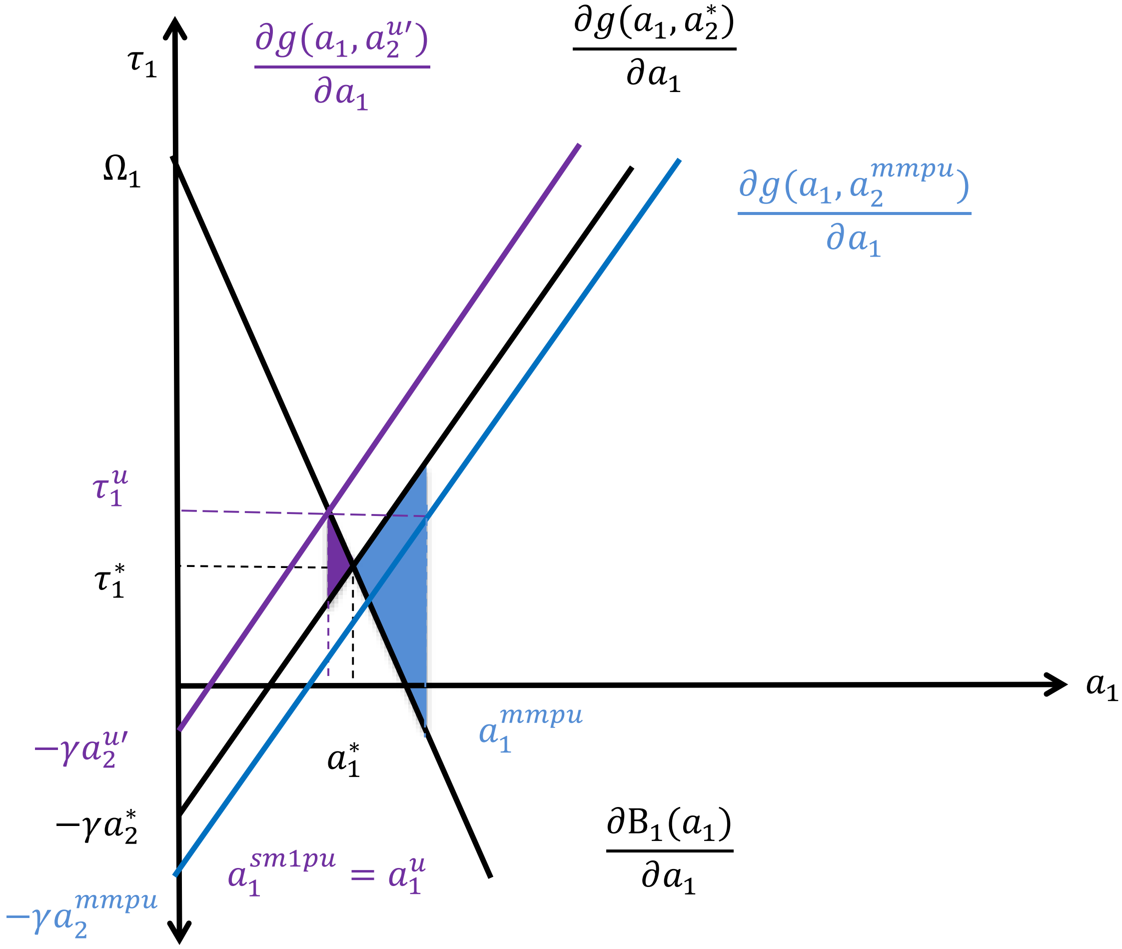

Figure 1.8 Uncoordinated Regulators - Pollutant 1- Case B

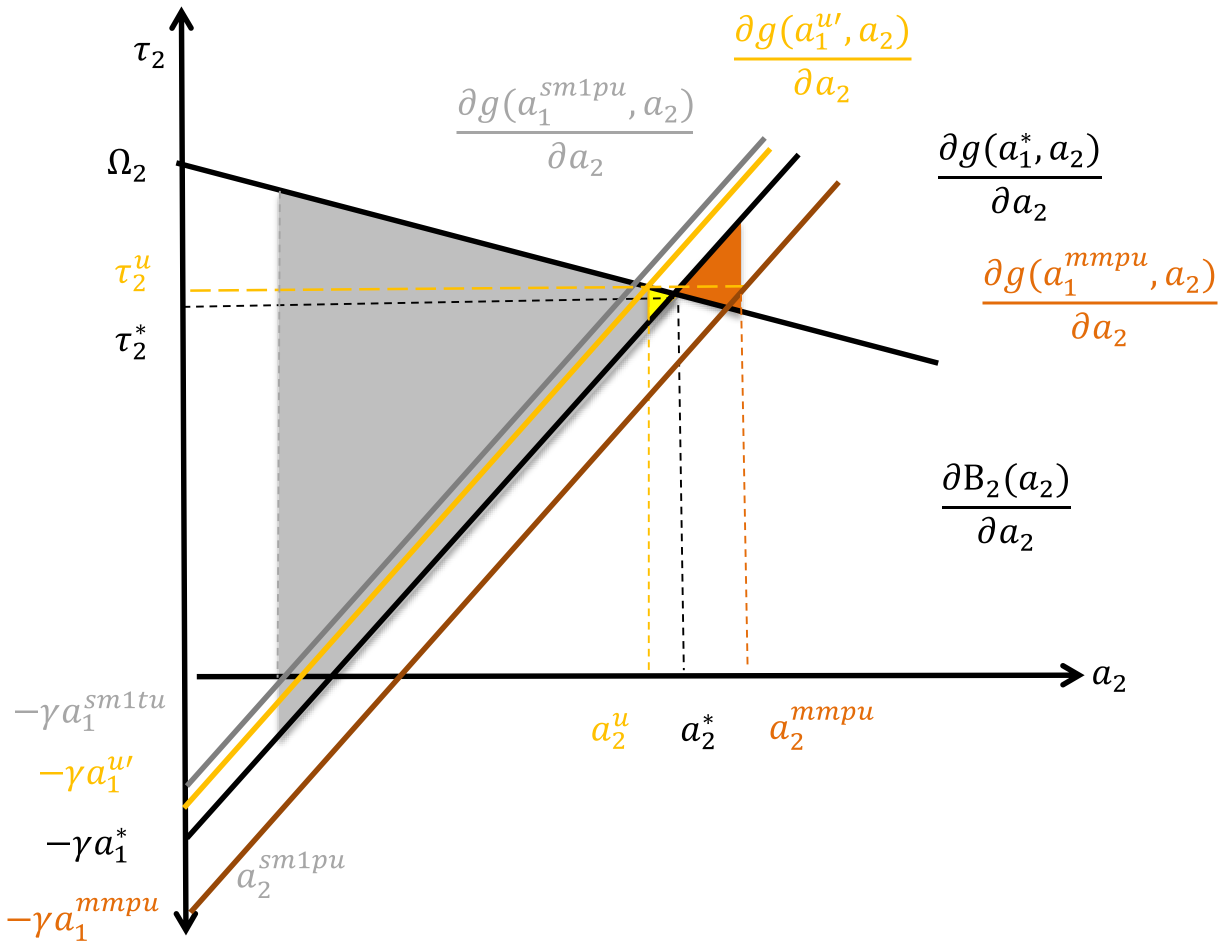

Figure 1.9 Uncoordinated Regulators - Pollutant 2 - Case B

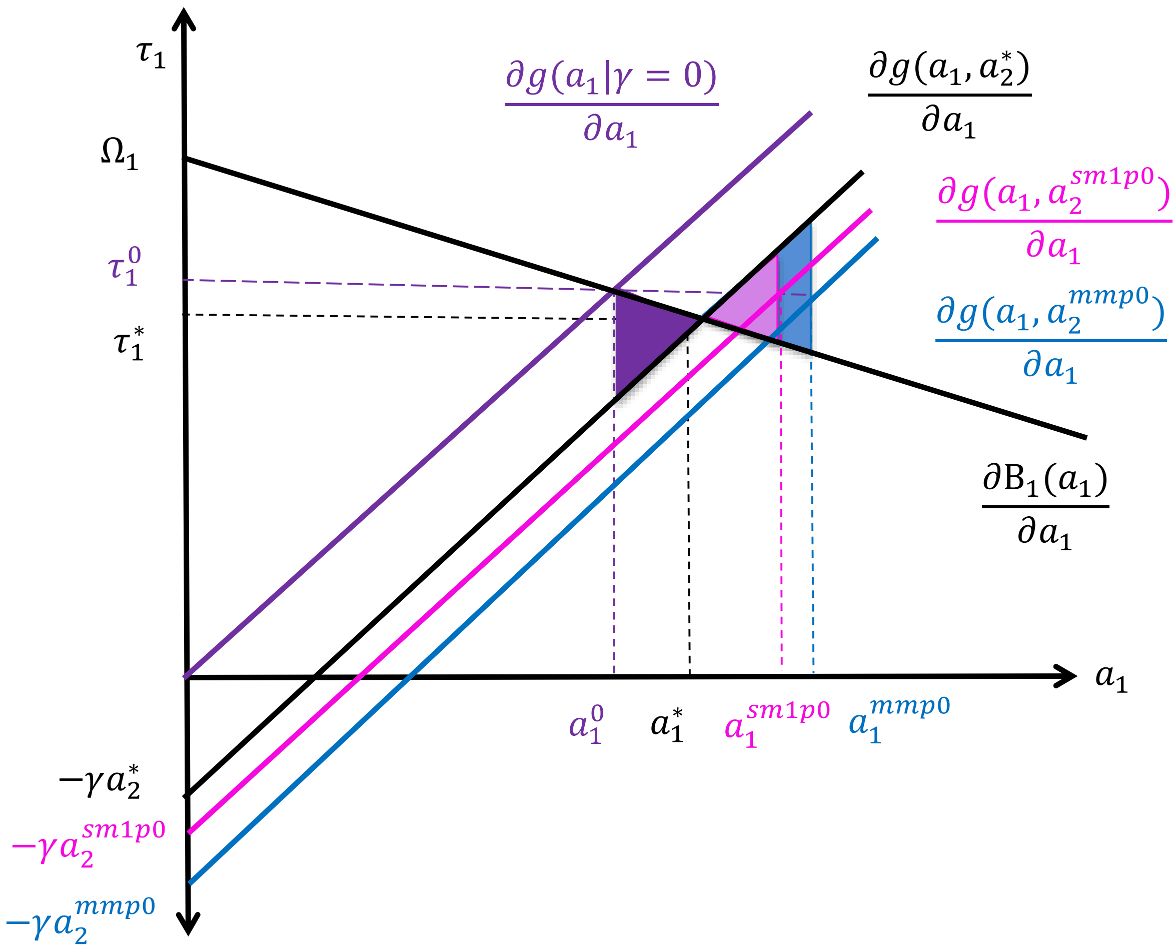

Figure 1.10 Complementarity Ignored by the Regulator - Pollutant 1- Case C

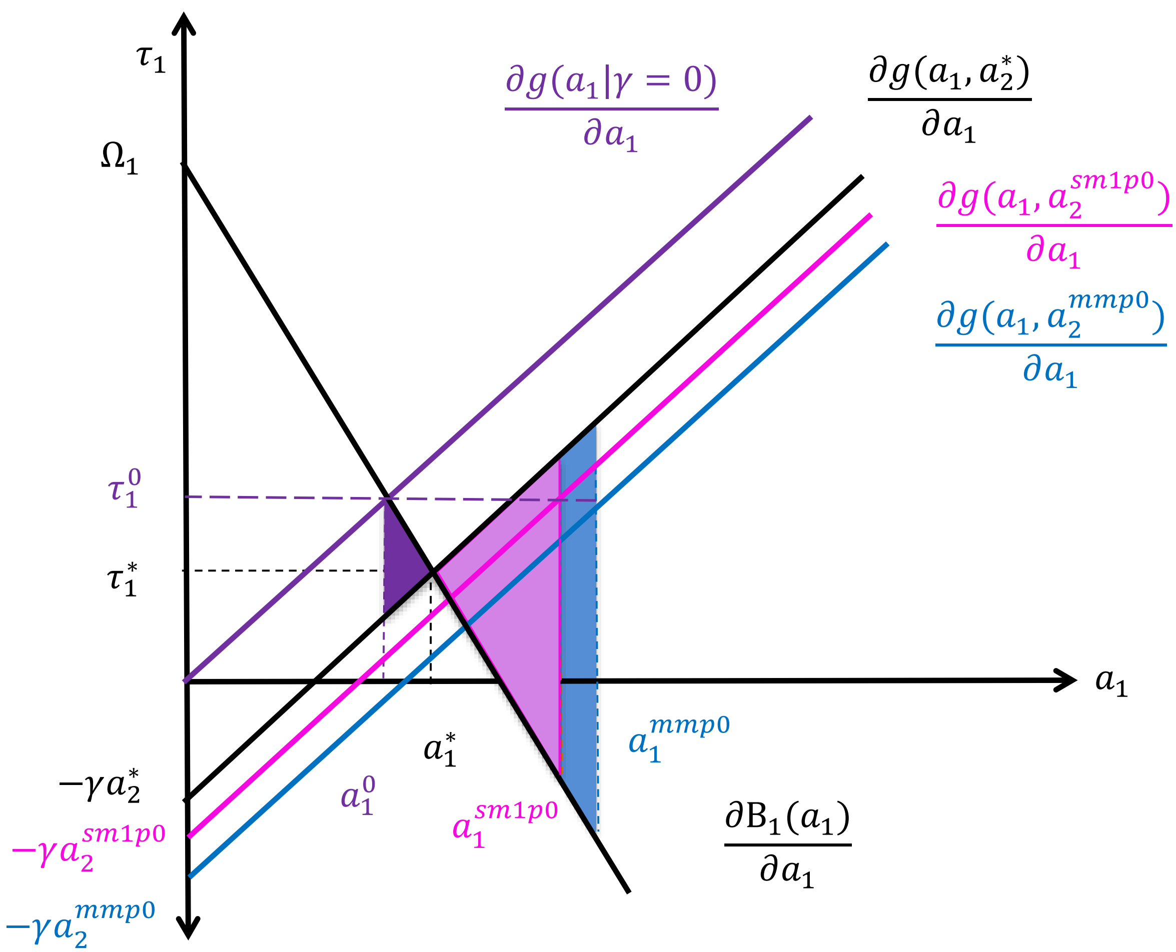

Figure 1.11 Complementarity Ignored by the Regulator - Pollutant 1- Case C

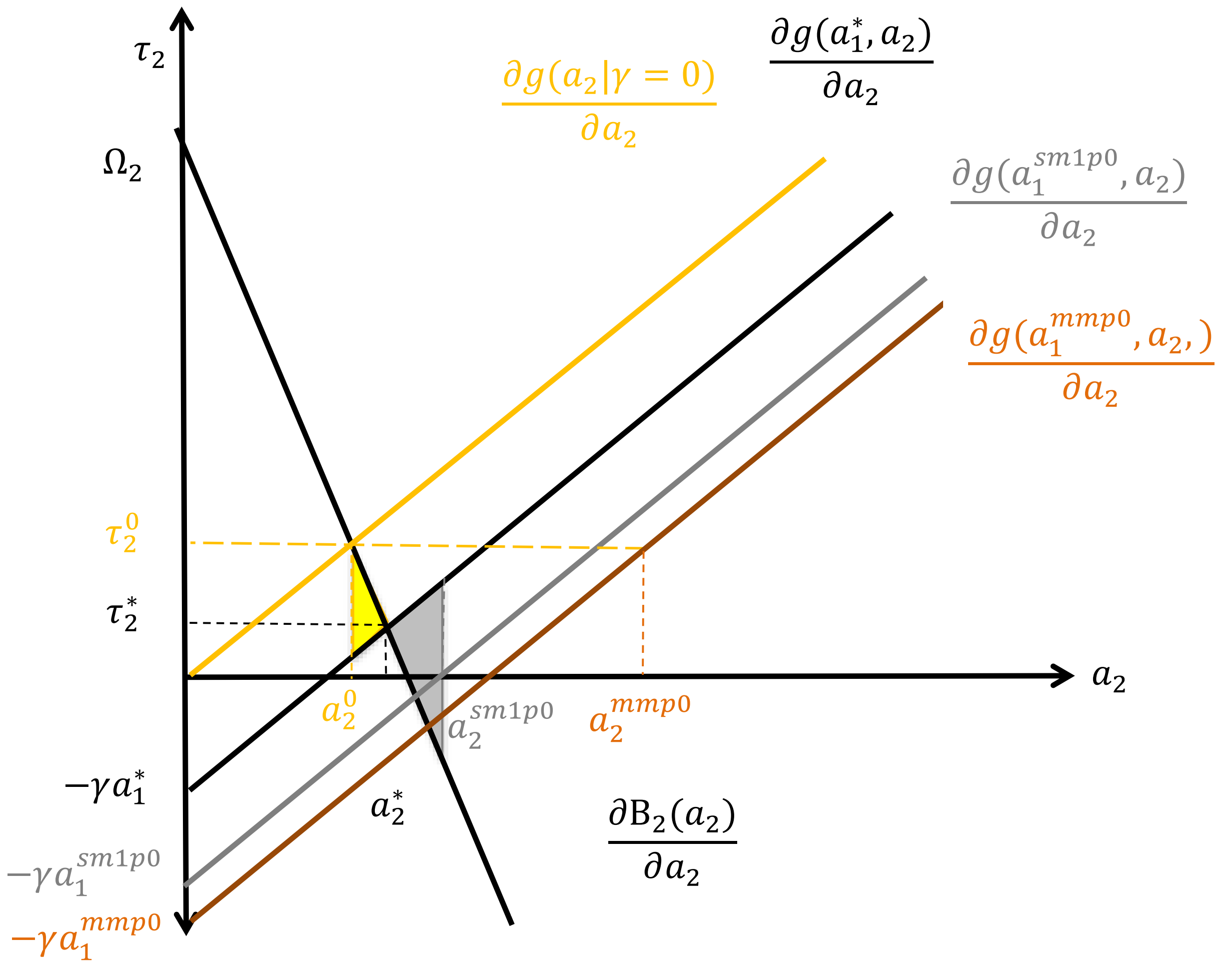

Figure 1.12 Complementarity Ignored by the Regulator - Pollutant 2- Case C

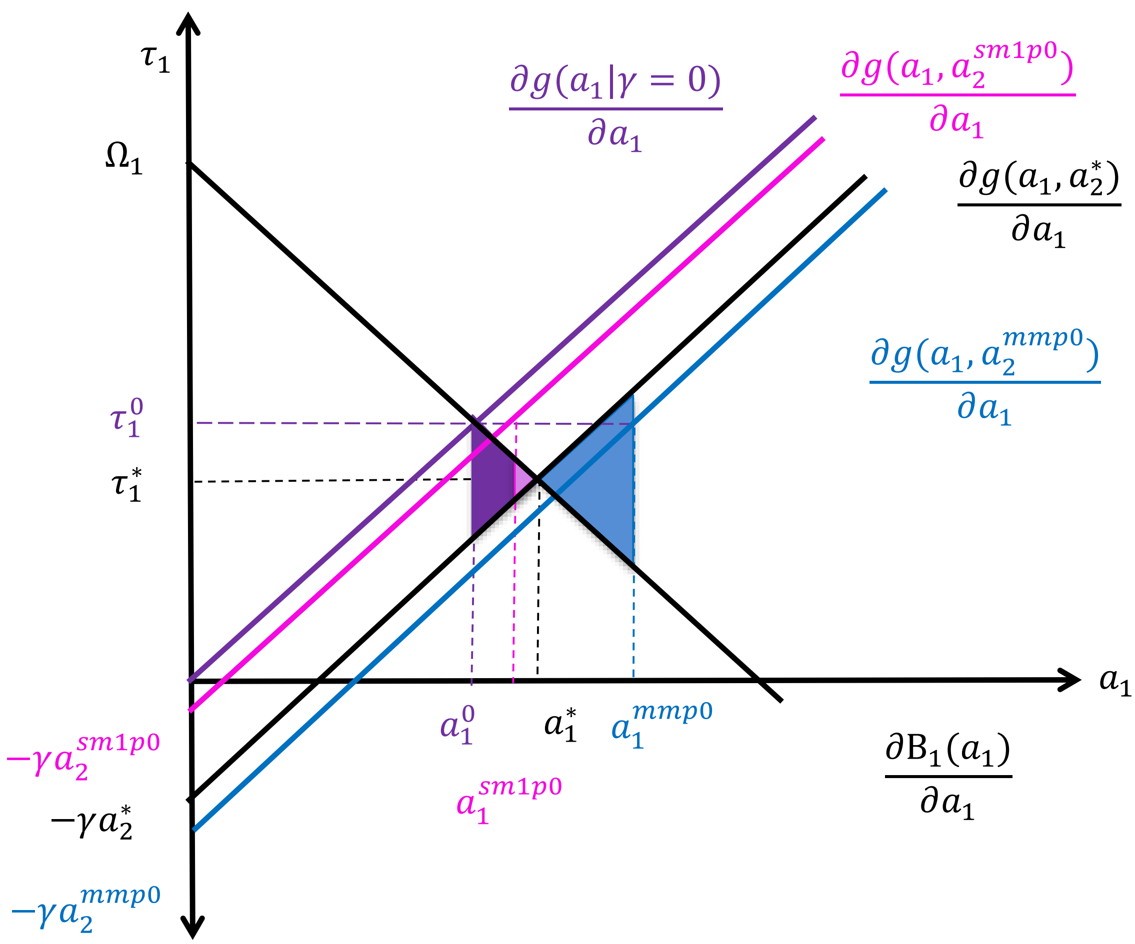

Figure 1.13 Complementarity Ignored by the Regulator - Pollutant 1 - Case D

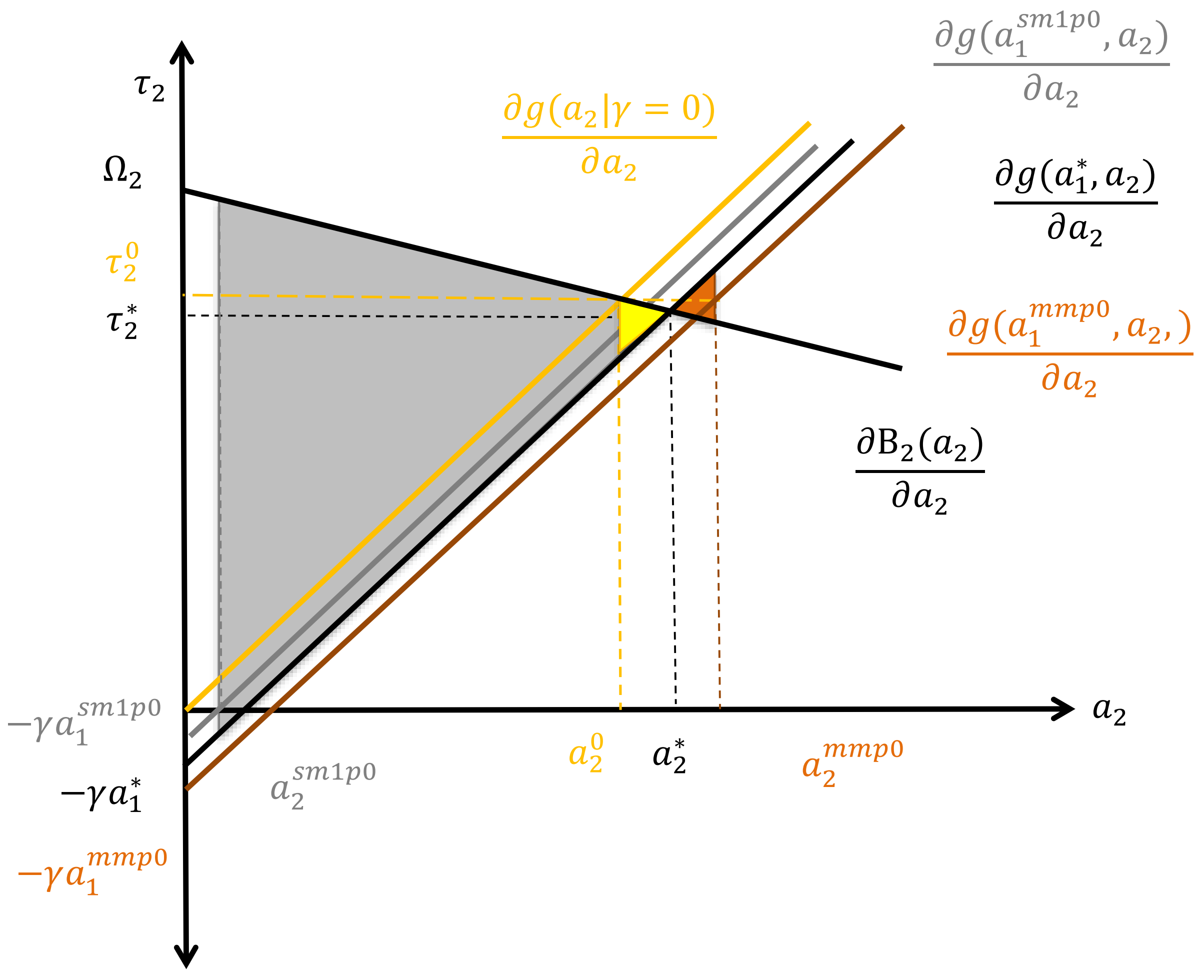

Figure 1.14 Complementarity Ignored by the Regulator - Pollutant 2 - Case D

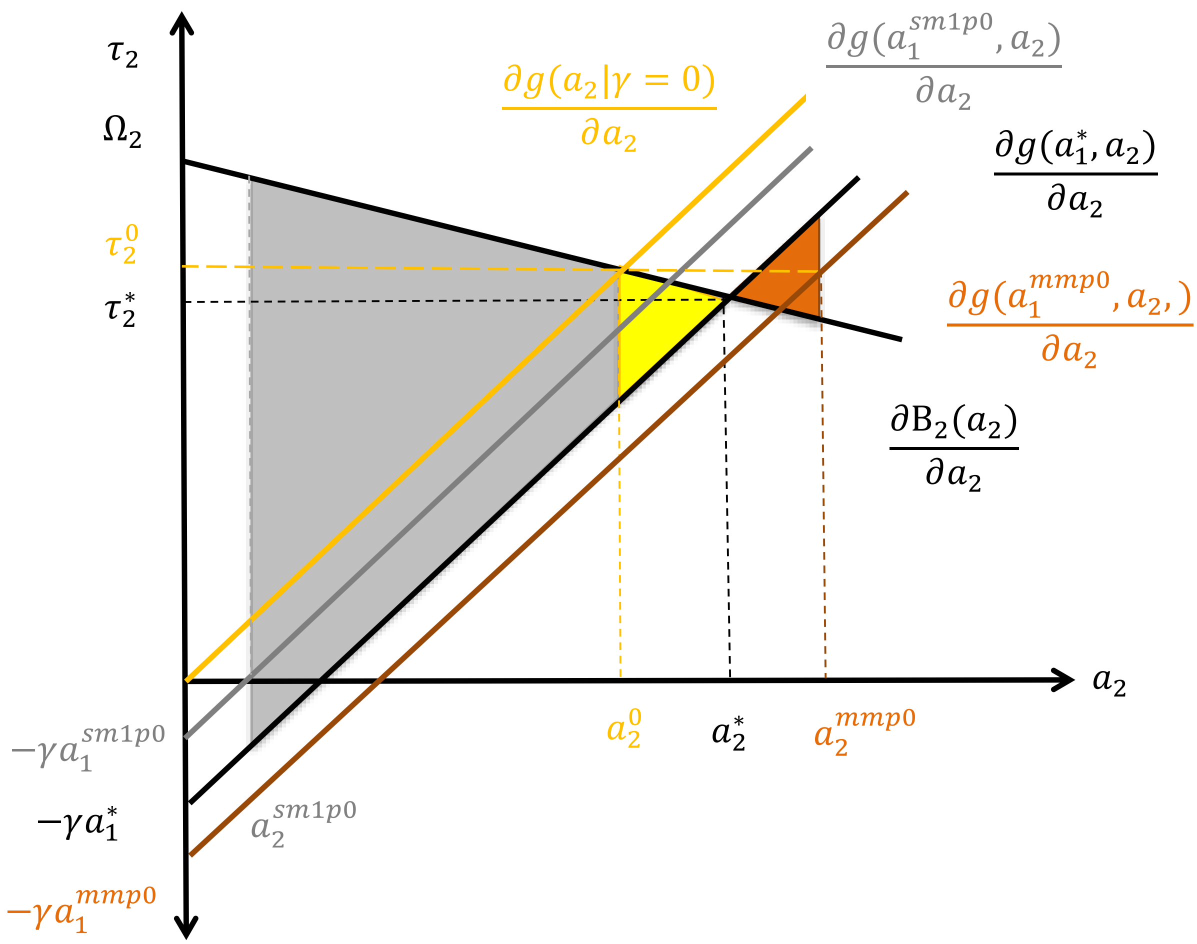

Figure 1.15 Complementarity Ignored by the Regulator - Pollutant 2 - Case D

1.8 Appendix A - Mathematical Derivations

Uncoordinated Regulators

The firm participates in the market for pollutant 1 as long as its profit denoted by π^{sm1pu} is larger than the profit obtained by the firm if it was participating in the market for pollutant 2, denote by π^{sm2pu}:

$$\begin{aligned}
\pi^{sm1pu} &= \tau_1^u(a_1^{sm1pu}) - \frac{\alpha_1}{2}(a_1^{sm1pu})^2 - \frac{\alpha_2}{2}(a_2^{sm1pu})^2 + \gamma a_1^{sm1pu} a_2^{sm1pu} \\
&= \tau_1^u\left(\frac{\alpha_2\tau_1^u}{\alpha_1\alpha_2-\gamma^2}\right) - \frac{\alpha_1}{2}\left(\frac{\alpha_2\tau_1^u}{\alpha_1\alpha_2-\gamma^2}\right)^2 - \frac{\alpha_2}{2}\left(\frac{\gamma\tau_1^u}{\alpha_1\alpha_2-\gamma^2}\right)^2 + \gamma\left(\frac{\alpha_2\tau_1^u}{\alpha_1\alpha_2-\gamma^2}\right)\left(\frac{\gamma\tau_1^u}{\alpha_1\alpha_2-\gamma^2}\right) \\
&= \frac{1}{2\left(\alpha_1\alpha_2-\gamma^2\right)^2}\left(2\alpha_2\left(\alpha_1\alpha_2-\gamma^2\right)\left(\tau_1^u\right)^2 - \alpha_1\alpha_2^2\left(\tau_1^u\right)^2 - \alpha_2\gamma^2\left(\tau_1^u\right)^2 + 2\alpha_2\gamma^2\left(\tau_1^u\right)^2\right) \\
&= \frac{\alpha_2\left(\tau_1^u\right)^2}{2\left(\alpha_1\alpha_2-\gamma^2\right)^2}\left(2\alpha_1\alpha_2 - 2\gamma^2 - \alpha_1\alpha_2 - \gamma^2 + 2\gamma^2\right) \\
&= \frac{\alpha_2\left(\tau_1^u\right)^2}{2\left(\alpha_1\alpha_2-\gamma^2\right)^2}\left(\alpha_1\alpha_2-\gamma^2\right) \\
&= \frac{\alpha_2\left(\tau_1^u\right)^2}{2\left(\alpha_1\alpha_2-\gamma^2\right)}
\end{aligned}$$

$$\begin{aligned}
\pi^{sm2pu} &= \tau_2^u(a_2^{sm2pu}) - \frac{\alpha_2}{2}(a_2^{sm2pu})^2 - \frac{\alpha_1}{2}(a_1^{sm2pu})^2 + \gamma a_1^{sm2pu} a_2^{sm2pu} \\
&= \tau_2^u\left(\frac{\alpha_1\tau_2^u}{\alpha_1\alpha_2-\gamma^2}\right) - \frac{\alpha_1}{2}\left(\frac{\gamma\tau_2^u}{\alpha_1\alpha_2-\gamma^2}\right)^2 - \frac{\alpha_2}{2}\left(\frac{\alpha_1\tau_2^u}{\alpha_1\alpha_2-\gamma^2}\right)^2 + \gamma\left(\frac{\gamma\tau_2^u}{\alpha_1\alpha_2-\gamma^2}\right)\left(\frac{\alpha_1\tau_2^u}{\alpha_1\alpha_2-\gamma^2}\right) \\
&= \frac{\alpha_1\left(\tau_2^u\right)^2}{2\left(\alpha_1\alpha_2-\gamma^2\right)^2}\left(2\alpha_1\alpha_2 - 2\gamma^2 - \alpha_1\alpha_2 - \gamma^2 + 2\gamma^2\right) \\
&= \frac{\alpha_1\left(\tau_2^u\right)^2}{2\left(\alpha_1\alpha_2-\gamma^2\right)}
\end{aligned}$$

In other words, as long as $\alpha_2\left(\tau_1^u\right)^2 \geq \alpha_1\left(\tau_2^u\right)^2$, the firm participates in the market for pollutant 1.

Rankings

To show $a_2^{mmpu} > a_2^*$, first simplify both abatement levels:

$$\begin{aligned}
a_2^{mmpu} &= \frac{\alpha_1\tau_2^u + \gamma\tau_1^u}{\alpha_1\alpha_2-\gamma^2} \\
&= \frac{\alpha_1}{(\alpha_1\alpha_2-\gamma^2)}\frac{(\alpha_1\alpha_2-\gamma^2)\Omega_2}{(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2)} + \frac{\gamma}{(\alpha_1\alpha_2-\gamma^2)}\frac{(\alpha_1\alpha_2-\gamma^2)\Omega_1}{(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1)}
\end{aligned}$$

$$= \frac{\alpha_1 \Omega_2}{(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2)} + \frac{\gamma \Omega_1}{(\alpha_1 \alpha_2 - \gamma^2 + \alpha_2 \theta_1)}$$

$$\begin{aligned} a_2^* &= \frac{(\alpha_1 + \theta_1)\,\Omega_2 + \gamma \Omega_1}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \\ &= \frac{(\alpha_1 + \theta_1)\,\Omega_2}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} + \frac{\gamma \Omega_1}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \end{aligned}$$

We now compare both parts of a_2^{mmpu} and a_2^* separately. Notice that $\frac{\gamma \Omega_1}{(\alpha_1 \alpha_2 - \gamma^2 + \alpha_2 \theta_1)} > \frac{\gamma \Omega_1}{(\alpha_1+\theta_1)(\alpha_2+\theta_2) - \gamma^2}$ since a_2^*'s denominator is larger. For the other part, to show $\frac{\alpha_1 \Omega_2}{(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2)} > \frac{(\alpha_1+\theta_1)\Omega_2}{(\alpha_1+\theta_1)(\alpha_2+\theta_2) - \gamma^2}$,

$$\begin{aligned} &\Rightarrow \frac{\alpha_1}{(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2)} > \frac{(\alpha_1 + \theta_1)}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \\ &\Rightarrow \alpha_1((\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2) > \alpha_1(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2) + \theta_1(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2) \\ &\Rightarrow \alpha_1((\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2 - \alpha_1 \alpha_2 + \gamma^2 - \alpha_1 \theta_2) > \theta_1(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2) \\ &\Rightarrow \alpha_1(\alpha_1 \alpha_2 + \alpha_1 \theta_2 + \alpha_2 \theta_1 + \theta_1 \theta_2 - \gamma^2 - \alpha_1 \alpha_2 + \gamma^2 - \alpha_1 \theta_2) > \theta_1(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2) \\ &\Rightarrow \alpha_1(\alpha_2 \theta_1 + \theta_1 \theta_2) > \theta_1(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2) \\ &\Rightarrow \alpha_1 \alpha_2 \theta_1 + \alpha_1 \theta_1 \theta_2 > \alpha_1 \alpha_2 \theta_1 - \theta_1 \gamma^2 + \alpha_1 \theta_1 \theta_2 \\ &\Rightarrow \theta_1 \gamma^2 > 0 \end{aligned}$$

Given the parameters of cost function, we can conclude that $a_2^{mmpu} > a_2^*$ given that each component of a_2^{mmpu} is larger than its respective component of a_2^*.

To show $a_1^{mmpu} > a_1^*$, we follow the same process as above and simplify each abatement level first:

$$\begin{aligned} a_1^{mmpu} &= \frac{\alpha_2 \tau_1^u + \gamma \tau_2^u}{\alpha_1 \alpha_2 - \gamma^2} \\ &= \frac{\alpha_2 \Omega_1}{(\alpha_1 \alpha_2 - \gamma^2 + \alpha_2 \theta_1)} + \frac{\gamma \Omega_2}{(\alpha_1 \alpha_2 - \gamma^2 + \alpha_1 \theta_2)} \end{aligned}$$

$$\begin{aligned} a_1^* &= \frac{(\alpha_2 + \theta_2)\,\Omega_1 + \gamma \Omega_2}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \\ &= \frac{(\alpha_2 + \theta_2)\,\Omega_1}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} + \frac{\gamma \Omega_2}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \end{aligned}$$

We now compare both parts of a_1^{mmpu} and a_1^* separately. Again, observe that $\frac{\gamma\Omega_2}{(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2)}$ $> \frac{\gamma\Omega_2}{(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2}$ since a_1^*'s denominator is larger. For the other part, to show $\frac{\alpha_2\Omega_1}{(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1)} >$ $\frac{(\alpha_2+\theta_2)\Omega_1}{(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2}$, we follow the same process as above:

$$\begin{aligned}
&\Rightarrow \quad \frac{\alpha_2}{(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1)} > \frac{(\alpha_2+\theta_2)}{(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2} \\
&\Rightarrow \quad \theta_2\gamma^2 > 0
\end{aligned}$$

Given the parameters of cost function, we can conclude that $a_1^{mmpu} > a_1^*$ given that each component of a_1^{mmpu} is larger than its respective component of a_1^*.

Thus far, we have the following rankings, $a_1^{mmpu} > a_1^*$ and $a_2^{mmpu} > a_2^*$. We can also add the following straightforward rankings:

$$\begin{aligned}
a_1^{mmpu} &= \frac{\alpha_2\tau_1^u+\gamma\tau_2^u}{\alpha_1\alpha_2-\gamma^2} > \frac{\alpha_2\tau_1^u}{\alpha_1\alpha_2-\gamma^2} = a_1^{sm1pu} \\
a_2^{mmpu} &= \frac{\alpha_1\tau_2^u+\gamma\tau_1^u}{\alpha_1\alpha_2-\gamma^2} > \frac{\gamma\tau_1^u}{\alpha_1\alpha_2-\gamma^2} = a_2^{sm1pu}
\end{aligned}$$

Also, notice $a_1^{sm1tu} = a_1^u$

$$a_1^{sm1pu} = \frac{\alpha_2\tau_1^u}{\alpha_1\alpha_2-\gamma^2} = \frac{\alpha_2}{(\alpha_1\alpha_2-\gamma^2)}\frac{(\alpha_1\alpha_2-\gamma^2)\Omega_1}{(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1)} = \frac{\alpha_2\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} = a_1^u$$

However,

$$a_2^{sm1pu} = \frac{\gamma\tau_1^u}{\alpha_1\alpha_2-\gamma^2} = \frac{\gamma\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} \neq \frac{\alpha_1\Omega_2}{\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2} = a_2^u$$

Furthermore, $a_1^{mmpu} > a_1^u$ and $a_2^{mmpu} > a_2^u$ since:

$$\begin{aligned}
a_1^{mmpu} &= \frac{\alpha_2\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} + \frac{\gamma\Omega_2}{\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2} > \frac{\alpha_2\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} = a_1^u \\
a_2^{mmpu} &= \frac{\alpha_1\Omega_2}{\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2} + \frac{\gamma\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} > \frac{\alpha_1\Omega_2}{\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2} = a_2^u
\end{aligned}$$

To show that $a_1^* > a_1^u$,

$$\begin{aligned}
&\Rightarrow \quad \frac{(\alpha_2+\theta_2)\Omega_1+\gamma\Omega_2}{(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2} > \frac{\alpha_2\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} \\
&\Rightarrow \quad \frac{(\alpha_2+\theta_2)\Omega_1+\gamma\Omega_2}{\alpha_2(\alpha_1+\theta_1)+\theta_2(\alpha_1+\theta_1)-\gamma^2} > \frac{\alpha_2\Omega_1}{\alpha_2(\alpha_1+\theta_1)-\gamma^2} \\
&\Rightarrow \quad \left[\alpha_2(\alpha_1+\theta_1)-\gamma^2\right]\gamma\Omega_2 > \theta_2\gamma^2\Omega_1 \\
&\Rightarrow \quad \frac{\Omega_2}{\Omega_1} > \frac{\theta_2\gamma}{[\alpha_2(\alpha_1+\theta_1)-\gamma^2]} \text{ true since } \tau_2^* > 0
\end{aligned}$$

To show $a_2^* > a_2^u$,

$$\Rightarrow \quad \frac{(\alpha_1+\theta_1)\,\Omega_2+\gamma\Omega_1}{(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2} > \frac{\alpha_1\Omega_2}{\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2}$$
$$\Rightarrow \quad \frac{\Omega_2}{\Omega_1} < \frac{\alpha_1\alpha_2+\alpha_1\theta_2-\gamma^2}{\theta_1\gamma} \text{ true since } \tau_1^* > 0$$

To show $a_2^* > a_2^{sm1pu}$,

$$\Rightarrow \quad \frac{\gamma\Omega_1}{\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1} < \frac{(\alpha_1+\theta_1)\,\Omega_2+\gamma\Omega_1}{(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2}$$
$$\Rightarrow \quad \frac{\gamma\Omega_1}{\alpha_2(\alpha_1+\theta_1)-\gamma^2} < \frac{(\alpha_1+\theta_1)\,\Omega_2+\gamma\Omega_1}{\alpha_2(\alpha_1+\theta_1)+\theta_2(\alpha_1+\theta_1)-\gamma^2}$$
$$\Rightarrow \quad \left(\alpha_2(\alpha_1+\theta_1)\gamma+\theta_2(\alpha_1+\theta_1)\gamma-\gamma^3\right)\Omega_1$$
$$< (\alpha_1+\theta_1)\left[\alpha_2(\alpha_1+\theta_1)-\gamma^2\right]\Omega_2+\left[\alpha_2(\alpha_1+\theta_1)\gamma-\gamma^3\right]\Omega_1$$
$$\Rightarrow \quad \left(\alpha_2(\alpha_1+\theta_1)\gamma+\theta_2(\alpha_1+\theta_1)\gamma-\gamma^3-\alpha_2(\alpha_1+\theta_1)\gamma+\gamma^3\right)\Omega_1 < (\alpha_1+\theta_1)\left[\alpha_2(\alpha_1+\theta_1)-\gamma^2\right]\Omega_2$$
$$\Rightarrow \quad \theta_2(\alpha_1+\theta_1)\gamma\Omega_1 < (\alpha_1+\theta_1)\left[\alpha_2(\alpha_1+\theta_1)-\gamma^2\right]\Omega_2$$
$$\Rightarrow \quad \frac{\theta_2\gamma}{[\alpha_2(\alpha_1+\theta_1)-\gamma^2]} < \frac{\Omega_2}{\Omega_1} \text{ true since } \tau_2^* > 0$$

Deadweight Losses

Deadweight loss for Case A:

$$
\begin{aligned}
& W_1^{Au} \\
= \; & DWL_1^{sm1pu} - DWL_1^{mmpu} \\
= \; & \frac{1}{2}(a_1^* - a_1^{sm1pu})\left(\frac{\partial B_1(a_1^{sm1pu})}{\partial a_1} - \frac{\partial g(a_1^{sm1pu}, a_2^*)}{\partial a_1}\right) - \frac{1}{2}(a_1^{mmpu} - a_1^*)\left(\frac{\partial g(a_1^{mmpu}, a_2^*)}{\partial a_1} - \frac{\partial B_1(a_1^{mmpu})}{\partial a_1}\right) \\
= \; & \frac{1}{2}(a_1^* - a_1^{sm1pu})\left(\Omega_1 - \theta_1 a_1^{sm1pu} - \alpha_1 a_1^{sm1pu} + \gamma a_2^*\right) \\
- \; & \frac{1}{2}(a_1^{mmpu} - a_1^*)\,(\alpha_1 a_1^{mmpu} - \gamma a_2^* - \Omega_1 + \theta_1 a_1^{mmpu}) \\
= \; & \frac{1}{2}(a_1^* - a_1^{sm1pu})\,(\Omega_1 + \gamma a_2^*) + \frac{1}{2}(a_1^{mmpu} - a_1^*)\,(\Omega_1 + \gamma a_2^*) \\
- \; & \frac{1}{2}(\alpha_1+\theta_1)(a_1^* - a_1^{sm1pu})a_1^{sm1pu} - \frac{1}{2}(\alpha_1+\theta_1)(a_1^{mmpu} - a_1^*)a_1^{mmpu} \\
= \; & \frac{1}{2}(\Omega_1 + \gamma a_2^*)\left(a_1^{mmpu} - a_1^{sm1pu}\right) - \frac{1}{2}(\alpha_1+\theta_1)\left((a_1^{mmpu})^2 - \left(a_1^{sm1pu}\right)^2 - a_1^*\left(a_1^{mmpu} - a_1^{sm1pu}\right)\right) \\
= \; & \frac{1}{2}\left(a_1^{mmpu} - a_1^{sm1pu}\right)\left[\Omega_1 + \gamma a_2^* + (\alpha_1+\theta_1)\left(a_1^{mmpu} + a_1^{sm1pu} - a_1^*\right)\right]
\end{aligned}
$$

$$
\begin{aligned}
&= \frac{1}{2}\left(a_1^{mmpu}-a_1^{sm1pu}\right)\left[\Omega_1+\gamma a_2^*-(\alpha_1+\theta_1)\,a_1^*-(\alpha_1+\theta_1)\left(a_1^{mmpu}+a_1^{sm1pu}\right)\right]\\
&= \frac{1}{2}\left(a_1^{mmpu}-a_1^{sm1pu}\right)\left[2\,(\alpha_1+\theta_1)\,a_1^*-(\alpha_1+\theta_1)\left(a_1^{mmpu}+a_1^{sm1pu}\right)\right]\\
&= \frac{1}{2}\,(\alpha_1+\theta_1)\left(a_1^{mmpu}-a_1^{sm1pu}\right)\left[2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right]
\end{aligned}
$$

Comparative Statics

Case A - Market for Pollutant 1

We focus on the slope of the marginal benefit curve for the unchosen market (i.e. θ_2):

$$
\begin{aligned}
\frac{\partial W_1^{Au}}{\partial\theta_2} &= \frac{1}{2}(\alpha_1+\theta_1)\left(\frac{\partial a_1^{mmpu}}{\partial\theta_2}-\frac{\partial a_1^{sm1pu}}{\partial\theta_2}\right)\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)\\
&\quad+\frac{1}{2}(\alpha_1+\theta_1)(a_1^{mmpu}-a_1^{sm1pu})\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_2}\\
&= \frac{1}{2}(\alpha_1+\theta_1)\left(\frac{\partial a_1^{mmpu}}{\partial\theta_2}\right)\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)\\
&\quad+\frac{1}{2}(\alpha_1+\theta_1)(a_1^{mmpu}-a_1^{sm1pu})\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_2}
\end{aligned}
$$

Notice that: $\frac{\partial a_1^{sm1pu}}{\partial\theta_2}=0$. We first determine the sign of $\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_2}$ for Case A:

$$
\begin{aligned}
\frac{\partial\,(2a_1^*-a_1^{mmpu})}{\partial\theta_2} &= \frac{2\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2\right)\Omega_1-2\,(\alpha_1+\theta_1)\left[(\alpha_2+\theta_2)\,\Omega_1+\gamma\Omega_2\right]}{\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2\right)^2}\\
&\quad-\frac{-\alpha_1\gamma\Omega_2}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2}\\
&= \frac{2\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2-(\alpha_1+\theta_1)\,(\alpha_2+\theta_2)\right)\Omega_1-2\,(\alpha_1+\theta_1)\,\gamma\Omega_2}{\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2\right)^2}\\
&\quad-\frac{-\alpha_1\gamma\Omega_2}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2}\\
&= \frac{-2\gamma^2\Omega_1-2\,(\alpha_1+\theta_1)\,\gamma\Omega_2}{\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2\right)^2}+\frac{\alpha_1\gamma\Omega_2}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2}
\end{aligned}
$$

To show that $\frac{\partial\left(2a_1^*-a_1^{mmtu}\right)}{\partial\theta_2}<0$,

$$
\begin{aligned}
&\Rightarrow\ \frac{-2\gamma^2\Omega_1-2\,(\alpha_1+\theta_1)\,\gamma\Omega_2}{\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2\right)^2}+\frac{\alpha_1\gamma\Omega_2}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2}<0\\
&\Rightarrow\ \frac{\alpha_1\gamma\Omega_2}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2}<2\frac{\gamma^2\Omega_1+(\alpha_1+\theta_1)\,\gamma\Omega_2}{\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2\right)^2}\\
&\Rightarrow\ \alpha_1\gamma\Omega_2\left((\alpha_1+\theta_1)\,(\alpha_2+\theta_2)-\gamma^2\right)^2
\end{aligned}
$$

$$\begin{aligned}
&< \quad 2\gamma^2\Omega_1\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2+2\left(\alpha_1+\theta_1\right)\gamma\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2\Omega_2\\
&\Rightarrow \quad \alpha_1\Omega_2\left(\alpha_1\left(\alpha_2+\theta_2\right)+\theta_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2\\
&< \quad 2\gamma\Omega_1\left(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2\right)^2+2\left(\alpha_1+\theta_1\right)\left(\alpha_1(\alpha_2+\theta_2)-\gamma^2\right)^2\Omega_2
\end{aligned}$$

which holds for low θ_1 which matches Case A. Under Case A, $\frac{\partial\left(2a_1^*-a_1^{mmpu}\right)}{\partial\theta_2}<0$.
As long as $a_1^*-a_1^{sm1pu}$ is similar to $a_1^{mmpu}-a_1^*$ or as long as $2a_1^*-a_1^{mmpu}-a_1^{sm1pu}>0$ and given that $\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_2}<0$ under Case A, then $\frac{\partial W_1^{Au}}{\partial\theta_2}<0$.

Case A - Market for Pollutant 2

Concentrating on the slope of the marginal benefits curve for the unchosen market (i.e. θ_2):

$$\begin{aligned}
\frac{\partial W_2^{Au}}{\partial\theta_2} &= \frac{1}{2}(\alpha_2+\theta_2)\left(\frac{\partial a_2^{mmpu}}{\partial\theta_2}-\frac{\partial a_2^{sm1pu}}{\partial\theta_2}\right)\left(2a_2^*-a_2^{mmpu}-a_2^{sm1pu}\right)\\
&\quad+\frac{1}{2}(\alpha_2+\theta_2)(a_2^{mmpu}-a_2^{sm1pu})\frac{\partial\left(2a_2^*-a_2^{mmpu}-a_2^{sm1pu}\right)}{\partial\theta_2}
\end{aligned}$$

Note:

$$\frac{\partial a_2^{mmpu}}{\partial\theta_2}-\frac{\partial a_2^{sm1pu}}{\partial\theta_2}=\frac{-\alpha_1^2\Omega_2}{(\alpha_1\alpha_2-\gamma^2+\alpha_1\theta_2)^2}-0<0$$

We first determine the sign of $\frac{\partial\left(2a_2^*-a_2^{mmpu}-a_2^{sm1pu}\right)}{\partial\theta_2}$:

$$\begin{aligned}
\frac{\partial\left(2a_2^*-a_2^{mmpu}\right)}{\partial\theta_2} &= 2\left(\frac{-\left(\alpha_1+\theta_1\right)\left[\left(\alpha_1+\theta_1\right)\Omega_2+\gamma\Omega_1\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\right)-\frac{-\alpha_1^2\Omega_2}{\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}-0\\
&= -2\left(\frac{\left(\alpha_1+\theta_1\right)\left[\left(\alpha_1+\theta_1\right)\Omega_2+\gamma\Omega_1\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\right)+\frac{\alpha_1^2\Omega_2}{\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}-0
\end{aligned}$$

To show $\frac{\partial\left(2a_2^*-a_2^{mmpu}\right)}{\partial\theta_2}<0$:

$$\begin{aligned}
&= \quad -2\left(\frac{\left(\alpha_1+\theta_1\right)\left[\left(\alpha_1+\theta_1\right)\Omega_2+\gamma\Omega_1\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\right)+\frac{\alpha_1^2\Omega_2}{\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}<0\\
&\Rightarrow \quad \alpha_1^2\Omega_2\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2\\
&< \quad 2\left[\left(\alpha_1+\theta_1\right)^2\Omega_2+\left(\alpha_1+\theta_1\right)\gamma\Omega_1\right]\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2\\
&\Rightarrow \quad \Omega_2\left(\alpha_1\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_1\gamma^2\right)^2\\
&< \quad 2\left(\alpha_1+\theta_1\right)^2\Omega_2\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2+2\left(\alpha_1+\theta_1\right)\gamma\Omega_1\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2\\
&\Rightarrow \quad \Omega_2\left(\alpha_1\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_1\gamma^2\right)^2
\end{aligned}$$

$$
\begin{aligned}
&< \quad 2\Omega_2\left(\alpha_1\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\left(\alpha_1+\theta_1\right)\gamma^2\right)^2+2\left(\alpha_1+\theta_1\right)\gamma\Omega_1\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2 \\
&\Rightarrow \quad \Omega_2\left(\alpha_1\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_1\gamma^2\right)^2 \\
&< \quad 2\Omega_2\left(\alpha_1\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_1\gamma^2-\theta_1\gamma^2\right)^2+2\left(\alpha_1+\theta_1\right)\gamma\Omega_1\left(\alpha_1\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2
\end{aligned}
$$

Works for low θ_1 which characterizes Case A. Hence $\frac{\partial\left(2a_2^*-a_2^{mmtu}\right)}{\partial\theta_2}<0$

As long as $a_2^*-a_2^{sm1pu}$ is similar to $a_2^{mmpu}-a_2^*$ or as long as $2a_2^*-a_2^{mmpu}-a_2^{sm1pu}>0$ and given that $\frac{\partial\left(2a_2^*-a_2^{mmpu}-a_2^{sm1pu}\right)}{\partial\theta_2}<0$ under Case A, then $\frac{\partial W_2^{Au}}{\partial\theta_2}<0$.

Case B: Market for Pollutant 1

First, since $W_1^{Au}=W_1^{Bu}$ and $a_1^{sm1pu}=a_1^u$, we use W_1^{Au} as defined before. We focus on the slope of the marginal benefit curve of the chosen market (i.e. θ_1):

$$
\begin{aligned}
\frac{\partial W_1^{Au}}{\partial\theta_1} &= \frac{1}{2}(\alpha_1+\theta_1)\left(\frac{\partial a_1^{mmpu}}{\partial\theta_1}-\frac{\partial a_1^{sm1pu}}{\partial\theta_1}\right)\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right) \\
&\quad +\frac{1}{2}(\alpha_1+\theta_1)(a_1^{mmpu}-a_1^{sm1pu})\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_1}
\end{aligned}
$$

Note:

$$
\frac{\partial a_1^{mmpu}}{\partial\theta_1}-\frac{\partial a_1^{sm1pu}}{\partial\theta_1}=\frac{-\alpha_2^2\Omega_1}{(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1)^2}-\frac{-\alpha_2^2\Omega_1}{(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1)^2}=0
$$

Consequently, the sign of $\frac{\partial W_1^{Au}}{\partial\theta_1}$ is determined by the sign of $\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_1}$:

$$
\begin{aligned}
\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_1} &= 2\left(\frac{-\left(\alpha_2+\theta_2\right)\left[\left(\alpha_2+\theta_2\right)\Omega_1+\gamma\Omega_2\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\right) \\
&\quad -\frac{-\alpha_2^2\Omega_1}{\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2}-\frac{-\alpha_2^2\Omega_1}{\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2} \\
&= -2\left(\frac{\left(\alpha_2+\theta_2\right)\left[\left(\alpha_2+\theta_2\right)\Omega_1+\gamma\Omega_2\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\right)+\frac{2\alpha_2^2\Omega_1}{\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2}
\end{aligned}
$$

To show $\frac{\partial\left(2a_1^*-a_1^{mmpu}-a_1^{sm1pu}\right)}{\partial\theta_1}<0$,

$$
\begin{aligned}
&\Rightarrow \quad -2\left(\frac{\left(\alpha_2+\theta_2\right)\left[\left(\alpha_2+\theta_2\right)\Omega_1+\gamma\Omega_2\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\right)+\frac{2\alpha_2^2\Omega_1}{\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2}<0 \\
&\Rightarrow \quad \frac{2\alpha_2^2\Omega_1}{\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2}<2\left(\frac{\left(\alpha_2+\theta_2\right)\left[\left(\alpha_2+\theta_2\right)\Omega_1+\gamma\Omega_2\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\right) \\
&\Rightarrow \quad \frac{\alpha_2^2\Omega_1}{\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2}<\frac{\left(\alpha_2+\theta_2\right)\left[\left(\alpha_2+\theta_2\right)\Omega_1+\gamma\Omega_2\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}
\end{aligned}
$$

$$\Rightarrow \quad \alpha_2^2\Omega_1\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2 < \left(\alpha_2+\theta_2\right)\left[\left(\alpha_2+\theta_2\right)\Omega_1+\gamma\Omega_2\right]\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2$$

$$\Rightarrow \quad \alpha_2^2\Omega_1\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2 < \left[\left(\alpha_2+\theta_2\right)^2\Omega_1+\left(\alpha_2+\theta_2\right)\gamma\Omega_2\right]\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2$$

$$\begin{aligned}
\Rightarrow \quad & \Omega_1\left(\alpha_2\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_2\gamma^2\right)^2 \\
< \quad & \left(\alpha_2+\theta_2\right)^2\Omega_1\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2+\left(\alpha_2+\theta_2\right)\gamma\Omega_2\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2 \\
\Rightarrow \quad & \Omega_1\left(\alpha_2\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_2\gamma^2\right)^2 \\
< \quad & \Omega_1\left(\alpha_2\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\left(\alpha_2+\theta_2\right)\gamma^2\right)^2+\left(\alpha_2+\theta_2\right)\gamma\Omega_2\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2 \\
\Rightarrow \quad & \Omega_1\left(\alpha_2\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_2\gamma^2\right)^2 \\
< \quad & \Omega_1\left(\alpha_2\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_2\gamma^2-\theta_2\gamma^2\right)^2+\left(\alpha_2+\theta_2\right)\gamma\Omega_2\left(\alpha_2\left(\alpha_1+\theta_1\right)-\gamma^2\right)^2
\end{aligned}$$

This works for low θ_2 which matches the conditions for Case B. Consequently, $\frac{\partial W_1^{Bu}}{\partial\theta_1} < 0$.

Case B: Market for Pollutant 2

The market for pollutant 2 differs from Case A and we focus on a comparison between prices allowing double-dipping and quantities since the latter outperforms the single market. Focusing on θ_1 again:

$$\begin{aligned}
\frac{\partial W_2^{Bu}}{\partial\theta_1} &= \frac{1}{2}(\alpha_2+\theta_2)\left(\frac{\partial a_2^{mmpu}}{\partial\theta_1}-\frac{\partial a_2^u}{\partial\theta_1}\right)(2a_2^*-a_2^{mmpu}-a_2^u) \\
&\quad +\frac{1}{2}(\alpha_2+\theta_2)(a_2^{mmpu}-a_2^u)\frac{\partial\left(2a_2^*-a_2^{mmpu}-a_2^u\right)}{\partial\theta_1}
\end{aligned}$$

Note:

$$\frac{\partial a_2^{mmpu}}{\partial\theta_1}-\frac{\partial a_2^u}{\partial\theta_1}=\frac{-\alpha_2\gamma\Omega_2}{(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1)^2}-0<0$$

Focusing on the sign of $\frac{\partial\left(2a_2^*-a_2^{mmpu}\right)}{\partial\theta_1}$:

$$\begin{aligned}
\frac{\partial\left(2a_2^*-a_2^{mmpu}\right)}{\partial\theta_1} &= 2\frac{\Omega_2\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)-\left(\alpha_2+\theta_2\right)\left[\left(\alpha_1+\theta_1\right)\Omega_2+\gamma\Omega_1\right]}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2} \\
&\quad -\frac{-\alpha_2\gamma\Omega_1}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1\right)^2} \\
&= -2\gamma\frac{\gamma\Omega_2+\left(\alpha_2+\theta_2\right)\Omega_1}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}+\frac{\alpha_2\gamma\Omega_1}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1\right)^2}
\end{aligned}$$

To show that $\frac{\partial\left(2a_2^*-a_2^{mmpu}\right)}{\partial\theta_1}<0$

$$\begin{aligned}
&\Rightarrow \quad \frac{\alpha_2\gamma\Omega_1}{\left(\alpha_1\alpha_2-\gamma^2+\alpha_2\theta_1\right)^2}<2\gamma\frac{\gamma\Omega_2+\left(\alpha_2+\theta_2\right)\Omega_1}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\\
&\Rightarrow \quad \frac{\alpha_2\Omega_1}{\left(\alpha_2(\alpha_1+\theta_1)-\gamma^2\right)^2}>\frac{2\gamma\Omega_2+2\left(\alpha_2+\theta_2\right)\Omega_1}{\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2}\\
&\Rightarrow \quad \alpha_2\Omega_1\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2\\
&< \quad 2\gamma\left(\alpha_2(\alpha_1+\theta_1)-\gamma^2\right)^2\Omega_2+2\left(\alpha_2+\theta_2\right)\left(\alpha_2(\alpha_1+\theta_1)-\gamma^2\right)^2\Omega_1\\
&\Rightarrow \quad \alpha_2^2(\alpha_2+\theta_2)\Omega_1\left(\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\gamma^2\right)^2\\
&< \quad 2\alpha_2(\alpha_2+\theta_2)\gamma\left(\alpha_2(\alpha_1+\theta_1)-\gamma^2\right)^2\Omega_2+2\alpha_2\left(\alpha_2+\theta_2\right)^2\left(\alpha_2(\alpha_1+\theta_1)-\gamma^2\right)^2\Omega_1\\
&\Rightarrow \quad \left(\alpha_2+\theta_2\right)\left(\alpha_2\left(\alpha_1+\theta_1\right)\left(\alpha_2+\theta_2\right)-\alpha_2\gamma^2\right)^2\Omega_1\\
&< \quad 2\alpha_2(\alpha_2+\theta_2)\gamma\left(\alpha_2(\alpha_1+\theta_1)-\gamma^2\right)^2\Omega_2+2\alpha_2\left(\alpha_2(\alpha_1+\theta_1)\left(\alpha_2+\theta_2\right)-\alpha_2\gamma^2-\theta_2\gamma^2\right)^2\Omega_1
\end{aligned}$$

which works for a low θ_2, which matches Case B. Hence, $\frac{\partial\left(2a_2^*-a_2^{mmpu}\right)}{\partial\theta_1}<0$. As long as $a_2^*-a_2^u$ is similar to $a_2^{mmpu}-a_2^*$ or as long as $2a_2^*-a_2^{mmpu}-a_2^u>0$ and given that $\frac{\partial\left(2a_2^*-a_2^{mmpu}-a_2^u\right)}{\partial\theta_1}<0$ under Case B, then $\frac{\partial W_2^{Bu}}{\partial\theta_1}<0$.

Complementarity Ignored by the Regulator

The firm participates in the market for pollutant 1 as long as its profit denoted by π^{sm1p0} is larger than the profit obtained by the firm if it was participating in the market for pollutant 2, denote by π^{sm2p0}:

$$\begin{aligned}
\pi^{sm1p0} &= \tau_1^0(a_1^{sm1p0})-\frac{\alpha_1}{2}(a_1^{sm1p0})^2-\frac{\alpha_2}{2}(a_2^{sm1p0})^2+\gamma a_1^{sm1p0}a_2^{sm1p0}\\
&= \tau_1^0\left(\frac{\alpha_2\tau_1^0}{\alpha_1\alpha_2-\gamma^2}\right)-\frac{\alpha_1}{2}\left(\frac{\alpha_2\tau_1^0}{\alpha_1\alpha_2-\gamma^2}\right)^2-\frac{\alpha_2}{2}\left(\frac{\gamma\tau_1^0}{\alpha_1\alpha_2-\gamma^2}\right)^2+\gamma\left(\frac{\alpha_2\tau_1^0}{\alpha_1\alpha_2-\gamma^2}\right)\left(\frac{\gamma\tau_1^0}{\alpha_1\alpha_2-\gamma^2}\right)\\
&= \frac{1}{2\left(\alpha_1\alpha_2-\gamma^2\right)^2}\left(2\alpha_2\left(\alpha_1\alpha_2-\gamma^2\right)\left(\tau_1^0\right)^2-\alpha_1\alpha_2^2\left(\tau_1^0\right)^2-\alpha_2\gamma^2\left(\tau_1^0\right)^2+2\alpha_2\gamma^2\left(\tau_1^0\right)^2\right)\\
&= \frac{\alpha_2\left(\tau_1^0\right)^2}{2\left(\alpha_1\alpha_2-\gamma^2\right)^2}\left(2\alpha_1\alpha_2-2\gamma^2-\alpha_1\alpha_2-\gamma^2+2\gamma^2\right)\\
&= \frac{\alpha_2\left(\tau_1^0\right)^2}{2\left(\alpha_1\alpha_2-\gamma^2\right)}
\end{aligned}$$

$$\pi^{sm2p0} = \tau_2^0(a_2^{sm2p0})-\frac{\alpha_2}{2}(a_2^{sm2p0})^2-\frac{\alpha_1}{2}(a_1^{sm2p0})^2+\gamma a_1^{sm2p0}a_2^{sm2p0}$$

$$= \quad \frac{\alpha_1 \left(\tau_2^0\right)^2}{2\left(\alpha_1\alpha_2 - \gamma^2\right)}$$

Rankings

To show $a_i^* > a_i^0$,

$$\begin{aligned}
a_i^* &= \frac{(\alpha_j + \theta_j)\Omega_i + \gamma\Omega_j}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \\
&= \frac{(\alpha_j + \theta_j)\Omega_i}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} + \frac{\gamma\Omega_j}{(\alpha_1 + \theta_1)(\alpha_2 + \theta_2) - \gamma^2} \\
&> \frac{(\alpha_j + \theta_j)\Omega_i}{(\alpha_i + \theta_i)(\alpha_j + \theta_j) - \gamma^2} \\
&> \frac{(\alpha_j + \theta_j)\Omega_i}{(\alpha_i + \theta_i)(\alpha_j + \theta_j)} \\
&= \frac{\Omega_i}{(\alpha_i + \theta_i)} = a_i^0
\end{aligned}$$

To show $a_1^{sm1p0} > a_1^0$,

$$\begin{aligned}
&\Rightarrow \quad a_1^{sm1p0} = \frac{\alpha_1\alpha_2\Omega_1}{(\alpha_1 + \theta_1)(\alpha_1\alpha_2 - \gamma^2)} > \frac{\Omega_1}{(\alpha_1 + \theta_1)} = a_1^0 \\
&\Rightarrow \quad \frac{\alpha_1\alpha_2}{(\alpha_1\alpha_2 - \gamma^2)} > 1 \\
&\Rightarrow \quad \alpha_1\alpha_2 \geq \alpha_1\alpha_2 - \gamma^2 \\
&\Rightarrow \quad \gamma^2 > 0
\end{aligned}$$

To show $a_1^{mmp0} > a_1^{sm1p0}$,

$$\begin{aligned}
&\Rightarrow \quad a_1^{mmp0} = \frac{\alpha_2\tau_1^0 + \gamma\tau_2^0}{\alpha_1\alpha_2 - \gamma^2} > \frac{\alpha_2\tau_1^0}{\alpha_1\alpha_2 - \gamma^2} = a_1^{sm1p0} \\
&\Rightarrow \quad \gamma\tau_2^0 > 0
\end{aligned}$$

To show $a_2^{mmp0} > a_2^{sm1p0}$,

$$\begin{aligned}
&\Rightarrow \quad a_2^{mmp0} = \frac{\alpha_1\tau_2^0 + \gamma\tau_1^0}{\alpha_1\alpha_2 - \gamma^2} > \frac{\gamma\tau_1^0}{\alpha_1\alpha_2 - \gamma^2} = a_2^{sm1p0} \\
&\Rightarrow \quad \alpha_1\tau_2^0 > 0
\end{aligned}$$

To show $a_i^{mmp0} > a_i^*$,

$$a_i^{mmp0} = \frac{\alpha_j\tau_i^0 + \gamma\tau_j^0}{\alpha_1\alpha_2 - \gamma^2} > \frac{\alpha_j\tau_i^* + \gamma\tau_j^*}{\alpha_1\alpha_2 - \gamma^2} = a_i^*$$

we need to show that $\tau_i^0 > \tau_i^*$ for $i = 1, 2$:

$$\tau_i^0 > \tau_i^* \Rightarrow \frac{\alpha_i \Omega_i}{(\alpha_i + \theta_i)} > \frac{\alpha_i(\alpha_j + \theta_j)\Omega i - \gamma^2\Omega_i - \theta_i\gamma\Omega_j}{(\alpha_i + \theta_i)(\alpha_j + \theta_j) - \gamma^2}$$

We know that $d \equiv \frac{\alpha_i(\alpha_j+\theta_j)\Omega i - \gamma^2\Omega_i}{(\alpha_i+\theta_i)(\alpha_j+\theta_j)-\gamma^2} > \frac{\alpha_i(\alpha_j+\theta_j)\Omega i - \gamma^2\Omega_i - \theta_i\gamma\Omega_j}{(\alpha_i+\theta_i)(\alpha_j+\theta_j)-\gamma^2}$ Hence, it suffices to show $\tau_i^0 > d$ to prove that $a_i^{mmp0} > a_i^*$, since $\tau_i^0 > d$ and $d > \tau_i^*$ imply that τ_i^*. To show that $\tau_i^0 > d$,

$$\begin{aligned}
& \frac{\alpha_i \Omega_i}{(\alpha_i + \theta_i)} > \frac{\alpha_i(\alpha_j + \theta_j)\Omega i - \gamma^2\Omega_i}{(\alpha_i + \theta_i)(\alpha_j + \theta_j) - \gamma^2} \\
\Rightarrow \quad & \alpha_i(\alpha_i + \theta_i)(\alpha_j + \theta_j) - \alpha_i\gamma^2 > (\alpha_i + \theta_i)(\alpha_i(\alpha_j + \theta_j) - \gamma^2) \\
\Rightarrow \quad & \alpha_i(\alpha_i + \theta_i)(\alpha_j + \theta_j) - \alpha_i\gamma^2 > (\alpha_i(\alpha_i + \theta_i)(\alpha_j + \theta_j) - (\alpha_i + \theta_i)\gamma^2) \\
\Rightarrow \quad & \theta_i\gamma 2 > 0
\end{aligned}$$

Discarded Combinations of Cases

The following two combinations are discarded:

$$\begin{aligned}
\text{Case I} \quad &: \quad a_1^{mmp0} > a_1^* > a_1^{sm1p0} > a_1^0 = a_1^{c0} \\
\text{Case 2} \quad &: \quad a_2^{mmp0} > a_2^{sm1p0} > a_2^* > a_2^0 = a_2^{c0}
\end{aligned}$$

and

$$\begin{aligned}
\text{Case II} \quad &: \quad a_1^{mmp0} > a_1^{sm1p0} > a_1^* > a_1^0 = a_1^{c0} \\
\text{Case 1} \quad &: \quad a_2^{mmp0} > a_2^* > a_2^{sm1p0} > a_2^0 = a_2^{c0}
\end{aligned}$$

As long as $a_2^* < a_2^{sm1p0}$, we have $a_1^* < a_1^{sm1p0}$. The condition for $a_2^* < a_2^{sm1p0}$ is:

$$\begin{aligned}
\Rightarrow \quad & a_2^* = \frac{\alpha_1\tau_2^* + \gamma\tau_1^*}{\alpha_1\alpha_2 - \gamma^2} < \frac{\gamma\tau_1^0}{\alpha_1\alpha_2 - \gamma^2} = a_2^{sm1p0} \\
\Rightarrow \quad & \alpha_1\tau_2^* + \gamma\tau_1^* < \gamma\tau_1^0 \\
\Rightarrow \quad & \tau_2^* < \frac{\gamma}{\alpha_1}\left(\tau_1^0 - \tau_1^*\right)
\end{aligned}$$

Similarly, to show that $a_1^* < a_1^{sm1p0}$, we need:

$$\begin{aligned}
\Rightarrow \quad & a_1^* = \frac{\alpha_2\tau_1^* + \gamma\tau_2^*}{\alpha_1\alpha_2 - \gamma^2} < \frac{\alpha_2\tau_1^0}{\alpha_1\alpha_2 - \gamma^2} = a_2^{sm1p0} \\
\Rightarrow \quad & \alpha_2\tau_1^* + \gamma\tau_2^* < \alpha_2\tau_1^0 \\
\Rightarrow \quad & \tau_2^* < \frac{\alpha_2}{\gamma}\left(\tau_1^0 - \tau_1^*\right)
\end{aligned}$$

Of these two conditions, the first suffices for the latter. In particular as long as

$$\tau_2^* < \frac{\gamma}{\alpha_1}\left(\tau_1^0 - \tau_1^*\right) \Rightarrow \tau_2^* < \frac{\alpha_2}{\gamma}\left(\tau_1^0 - \tau_1^*\right)$$

since

$$\frac{\gamma}{\alpha_1}\left(\tau_1^0 - \tau_1^*\right) < \frac{\alpha_2}{\gamma}\left(\tau_1^0 - \tau_1^*\right) \Leftrightarrow \gamma^2 < \alpha_1\alpha_2$$

These combinations of cases are consequently ruled out.

Comparative Statics

Case C: Market for Pollutant 1

Focusing on θ_2, the comparative static for the difference in deadweight losses:

$$\begin{aligned}
\frac{\partial W_1^{C0}}{\partial \theta_2} &= \frac{1}{2}(\alpha_1+\theta_1)\left(\frac{\partial a_1^{sm1p0}}{\partial \theta_2} - \frac{\partial a_1^0}{\partial \theta_2}\right)\left(2a_1^* - a_1^{sm1p0} - a_1^0\right) \\
&\quad + \frac{1}{2}(\alpha_1+\theta_1)(a_1^{sm1p0} - a_1^0)\frac{\partial\left(2a_1^* - a_1^{sm1p0} - a_1^0\right)}{\partial \theta_2} \\
&= \frac{1}{2}(\alpha_1+\theta_1)(a_1^{sm1p0} - a_1^0)\frac{\partial\left(2a_1^* - a_1^{sm1p0} - a_1^0\right)}{\partial \theta_2}
\end{aligned}$$

Note:

$$\frac{\partial a_1^{sm1p0}}{\partial \theta_2} - \frac{\partial a_1^0}{\partial \theta_2} = 0 - 0 = 0$$

Hence, in this case the sign of $\frac{\partial W_1^{C0}}{\partial \theta_2}$ is determined by the sign of $\frac{\partial\left(2a_1^* - a_1^{sm1p0} - a_1^0\right)}{\partial \theta_2}$:

$$\begin{aligned}
&\frac{\partial\left(2a_1^* - a_1^{sm1p0} - a_1^0\right)}{\partial \theta_2} \\
&= 2\frac{\Omega_1\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2) - \gamma^2\right] - (\alpha_1+\theta_1)\left[(\alpha_2+\theta_2)\Omega_1 + \gamma\Omega_2\right]}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2) - \gamma^2\right]^2} \\
&= -2\gamma\frac{\left((\alpha_1+\theta_1)\Omega_2 + \gamma\Omega_1\right)}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2) - \gamma^2\right]^2} < 0
\end{aligned}$$

Hence, $\frac{\partial W_1^{C0}}{\partial \theta_2} > 0$.

Case C: Market for Pollutant 2

The comparative statics with respect to θ_2,

$$\frac{\partial W_2^{C0}}{\partial \theta_2} = \frac{1}{2}(a_2^{sm1p0} - a_2^0)(2a_2^* - a_2^{sm1p0} - a_2^0)$$

$$+\frac{1}{2}(\alpha_2+\theta_2)\left(\frac{\partial a_2^{sm1p0}}{\partial\theta_2}-\frac{\partial a_2^0}{\partial\theta_2}\right)\left(2a_2^*-a_2^{sm1p0}-a_2^0\right)$$
$$+\frac{1}{2}(\alpha_2+\theta_2)(a_2^{sm1p0}-a_2^0)\frac{\partial\left(2a_2^*-a_2^{sm1p0}-a_2^0\right)}{\partial\theta_2}$$

Note:

$$\frac{\partial a_2^{sm1p0}}{\partial\theta_2}-\frac{\partial a_2^0}{\partial\theta_2} = 0-\frac{-\Omega_2}{(\alpha_2+\theta_2)^2}>0$$

We first explore the sign of $\frac{\partial\left(2a_2^*-a_2^{sm1p0}-a_2^0\right)}{\partial\theta_2}$:

$$\frac{\partial\left(2a_2^*-a_2^{sm1p0}-a_2^0\right)}{\partial\theta_2} = -2\frac{(\alpha_1+\theta_1)\left((\alpha_1+\theta_1)\Omega_2+\gamma\Omega_1\right)}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2}-\frac{-\Omega_2}{(\alpha_2+\theta_2)^2}$$

To show that $\frac{\partial\left(2a_2^*-a_2^{sm1p0}-a_2^0\right)}{\partial\theta_2}<0$,

$$\Rightarrow\ -2\frac{(\alpha_1+\theta_1)\left((\alpha_1+\theta_1)\Omega_2+\gamma\Omega_1\right)}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2}+\frac{\Omega_2}{(\alpha_2+\theta_2)^2}<0$$
$$\Rightarrow\ \frac{\Omega_2}{(\alpha_2+\theta_2)^2}<\frac{\left(2(\alpha_1+\theta_1)^2\Omega_2+2(\alpha_1+\theta_1)\gamma\Omega_1\right)}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2}$$
$$\Rightarrow\ \Omega_2\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2<2(\alpha_1+\theta_1)^2(\alpha_2+\theta_2)^2\Omega_2+2(\alpha_1+\theta_1)(\alpha_2+\theta_2)^2\gamma\Omega_1$$

which is true since $\gamma^2>0$. Therefore, as long as $a_2^*-a_2^0$ is similar to $a_2^{sm1p0}-a_2^*$ or as long as $2a_2^*-a_2^{sm1p0}-a_2^0<0$, then $\frac{\partial W_2^{C0}}{\partial\theta_2}<0$.

Case D: Market for Pollutant 2

We concentrate on the slope of the marginal benefit curve in the unchosen market.

$$\frac{\partial W_2^{D0}}{\partial\theta_2} = \frac{1}{2}(\alpha_2+\theta_2)\left(\frac{\partial a_2^{mmp0}}{\partial\theta_2}-\frac{\partial a_2^0}{\partial\theta_2}\right)\left(2a_2^*-a_2^{mmp0}-a_2^0\right)$$
$$+\frac{1}{2}(\alpha_1+\theta_1)(a_2^{mmp0}-a_2^0)\frac{\partial\left(2a_2^*-a_2^{mmp0}-a_2^0\right)}{\partial\theta_2}$$

Note:

$$\frac{\partial a_2^{mmp0}}{\partial\theta_2}-\frac{\partial a_2^0}{\partial\theta_2}=\frac{-\alpha_2\gamma\Omega_2}{(\alpha_2+\theta_2)^2(\alpha_1\alpha_2-\gamma^2)}-\frac{-\Omega_2}{(\alpha_2+\theta_2)^2}$$

Furthermore, notice that $2a_2^* - a_2^{mmp0} - a_2^0$ tends to zero as γ is very small. Hence, the first term in the derivate tends to zero as γ is very small. We explore the sign of the second term by looking at the sign of $\frac{\partial\left(2a_2^* - a_2^{mmp0} - a_2^0\right)}{\partial\theta_2}$:

$$
\begin{aligned}
& \frac{\partial\left(2a_2^* - a_2^{mmp0} - a_2^0\right)}{\partial\theta_2} \\
= \quad & -2\frac{(\alpha_1+\theta_1)\left((\alpha_1+\theta_1)\Omega_2+\gamma\Omega_1\right)}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2} + \frac{\alpha_2\gamma\Omega_2}{(\alpha_2+\theta_2)^2(\alpha_1\alpha_2-\gamma^2)} + \frac{\Omega_2}{(\alpha_2+\theta_2)^2} < 0 \\
\Rightarrow \quad & \frac{\alpha_2\gamma\Omega_2}{(\alpha_2+\theta_2)^2(\alpha_1\alpha_2-\gamma^2)} + \frac{\Omega_2}{(\alpha_2+\theta_2)^2} < \frac{2(\alpha_1+\theta_1)^2\Omega_2 + 2(\alpha_1+\theta_1)\gamma\Omega_1}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2} \\
\Rightarrow \quad & \frac{\alpha_2\gamma\Omega_2 + (\alpha_1\alpha_2-\gamma^2)\Omega_2}{(\alpha_2+\theta_2)^2(\alpha_1\alpha_2-\gamma^2)} < \frac{2(\alpha_1+\theta_1)^2\Omega_2 + 2(\alpha_1+\theta_1)\gamma\Omega_1}{\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2} \\
\Rightarrow \quad & (\alpha_2\gamma + \alpha_1\alpha_2 - \gamma^2)\left[(\alpha_1+\theta_1)(\alpha_2+\theta_2)-\gamma^2\right]^2\Omega_2 \\
< \quad & 2(\alpha_1\alpha_2-\gamma^2)(\alpha_1+\theta_1)^2(\alpha_2+\theta_2)^2\Omega_2 + 2(\alpha_1+\theta_1)\gamma(\alpha_2+\theta_2)^2(\alpha_1\alpha_2-\gamma^2)\Omega_1
\end{aligned}
$$

which true for very small γ, which matches this case. Consequently, as long as γ is very low, $\frac{\partial W_2^{D0}}{\partial\theta_2} < 0$.

CHAPTER 2. COST-SHARE EFFECTIVENESS IN THE DIFFUSION OF A NEWLY PERCEIVED POLLUTION ABATEMENT TECHNOLOGY IN AGRICULTURE: THE CASE OF COVER CROPS IN IOWA

María Jimena González Ramírez and J. Gordon Arbuckle, Jr.

2.1 Abstract

Water quality problems remain severe across much of the United States. Improvements are particularly challenging in agricultural regions where upwards of 90 percent of the pollution load comes from sources that fall outside regulatory control under the Clean Water Act. These nutrient sources are responsible for a large dead zone in the Gulf of Mexico, the closure of Toledos drinking water facility, and ubiquitous damage to recreational amenities. The promotion of a newly perceived agricultural pollution abatement technology, cover crops, through cost-share funding opportunities combined with a longitudinal data set including information on adopters both before and after introduction of the subsidy program provides an identification strategy to evaluate the effectiveness of funding for this promising new abatement technology. Using propensity score matching and a Tobit estimator that takes into account non-adoption, we find that cost-share funding significantly increases the proportion of cover crops planted and cover crops acres among both recipients of funds and among adopters. These results have critical implications for finding solutions to address persistent water quality problems with limited conservation budgets.

2.2 Introduction

Water quality problems remain severe across much of the United States. According to the Environmental Protection Agency (EPA), nonpoint source (NPS) pollution is the Nation's largest source of water quality problems (EPA 2015). In the U.S., around 40 percent of surveyed rivers, lakes, and estuaries are so polluted that they are not clean enough for basic uses such as fishing or swimming (EPA 1996). Improvements in water quality are particularly challenging in agricultural regions where upwards of 90 percent of the pollution load comes from NPS that fall outside regulatory control under the Clean Water Act. These nutrient sources are responsible for a large dead zone in the Gulf of Mexico, the closure of Toledos drinking water facility, the Des Moines Water Works lawsuit against three drainage counties over water quality, and ubiquitous damage to recreational amenities. In fact, despite the creation of the Hypoxia Task Force in 1997 (EPA Task Force), substantial improvements in water quality are still necessary. For example, the 2014 Gulf Hypoxia zone of oxygen-depleted bottom-water was roughly 13,000 square kilometers, an area much higher than the Hypoxia Task Force goal of 5,000 square kilometers (EPA 2014). Nitrogen and phosphorus applications in agricultural production in the Upper Mississippi River have contributed to the formation of the Gulf Hypoxia (Rabotyagov et al. 2014). Current efforts to reduce agricultural runoff into water streams that are focused on the voluntary adoption of conservation practices have not been able to achieve substantial water quality improvements. It is now clear that to address this growing problem, it will be necessary to substantially change the way agriculture is practiced over much of the Upper Mississippi River Basin.

For example, Iowa developed a statewide Nutrient Reduction Strategy in 2013, which is a science and technology-based framework to assess and reduce nutrients to Iowa water and the Gulf of Mexico (Iowa NRS 2013). The strategy calls for a significant voluntary adoption of cover crops, crops that are planted between harvest and the planting of cash crops, which are able to reduce both nitrogen and phosphorus losses by approximately 30 percent (Iowa NRS 2013). While cover crops have been widely promoted as an effective conservation practice recently, there has been little adoption in Iowa. In 2009, Iowa had fewer than 10,000 cover crops acres.

In 2013, the number increased to 300,000 acres planted (Soil and Water Conservation Society 2015). In both years, the number of cover crops acres is very small relative to total corn and soybean crop land, which is around 24 million (USDA NASS 2014). These adoption statistics illustrate that cover crops are a newly perceived conservation practice in this region and that substantial efforts must be exerted to increase conservation acres. Carlson and Stockwell (2013) as well as Arbuckle and Roesch-McNally (2015) emphasize the lack of research on cover crop adoption in agriculture-intense regions and the importance of understanding it.

Several cost-share funding programs have promoted the adoption of cover crops. Based on the Iowa Nutrient Reduction Strategy, more cost-share funding became available to implement conservation practices in 2013, including cover crops. At the same time, state and federal programs also provided cost-share funding for new adoption of cover crops. Together, this cost-share funding can be viewed as an opportunity to study the come back of this practice in this very important agricultural region. Given the availability of cost-share and the importance of this practice for water quality, we study the effectiveness of cost-share funding in the planting of cover crops using a unique dataset with yearly farm level data on large farm operators. While the Iowa experience is relatively small, it provides an excellent source of information to draw on for other programs in areas in which cover crops are perceived as a new technology. We use matching methods combined with regression analysis to study the effectiveness of cost-share funding using the Iowa Farm and Rural Life Poll. Focusing on Iowa provides a unique opportunity to collect data on this new conservation practice in this region. Furthermore, Iowa's experience can inform the entire effort to solve the hypoxia zone problem.

Directly comparing cover crop decisions between farmers enrolled in cost-share programs and farmers who are not enrolled could result in estimates that suffer from selection bias and in incorrect policy advice concerning program expansion. To assess the effectiveness of cost-share funding, we need to know what the cover crop planting decision of farmers who received cost-share funding would have been in the absence of the funds. However, we can never observe the counterfactual (Imbens & Wooldridge 2008). Furthermore, since the participation in cost-share programs for cover crops is not random, we also face a selection problem that can come from both observable and unobservable factors. For instance, a farmer who has planted cover crops in the past might be more likely to plant cover crops today if his experience was positive. Similarly, a farmer who participates in a cover crop cost-share program may have invested in conservation practices in the past compared to a farmer who does not participate, since the former might have more experience managing conservation practices or may have lower adoption costs. We use matching methods to pair treated and untreated (control) farmers based on observable characteristics measured before treatment to overcome the selection problem and to have a valid counterfactual. Our unique dataset includes variables that have not been included in previous U.S. cost-share studies such as attitudinal and previous conservation and drainage expenditure information.

After matching and achieving covariate balance and satisfying the overlap assumption, we study two outcomes: the proportion of cover crops acres relative to total farm land and the amount of cover crops acres planted. We estimate two treatment effects: the average treatment effect on the treated and the average marginal treatment effect among adopters of cover crops. Previous studies have focused on the former, but we contribute to the literature by estimating the latter. Given the lack of adoption of cover crops in this region, it is important to take into account that most farmers are not using this practice. By differentiating between adopters and non-adopters, we are able to study the effectiveness of cost-share among farmers who are using cover crops. Our results indicate that, on average, farmers receiving cost-share increase the proportion of cover crop acres by about 20 percentage points relative to farmers who do not get the funds. For acres, we find that receiving cost-share funding induces farmers to plant more cover crops acres on average relative to non-recipients. However, the size of this effect varies between matching specifications.

In order to estimate the average marginal treatment effect among adopters, we follow a two step process. First, we use a Tobit regression on the matched data, since our outcome variables include corner solutions at zero due to the lack of adoption of this conservation practice. The Tobit estimator corrects the bias associated with these zeros (Green 2008). Secondly, we calculate the average marginal effect of receiving cost-share among adopters. We find that, on average, receiving cost-share increases the expected proportion of cover crops by around 18 percentage points among adopters only. For cover crops acres, we find that the average marginal effect of cost-share is about 104 acres among adopters. Taking all the estimation results, we conclude that cost-share funding is effective, as it increases the proportion and acres of cover crops among cost-share recipients and adopters.

2.3 Literature Review

Matching methods have been employed for program evaluations related to conservation. Liu and Lynch (2011) use matching methods to study the effect of land-use policies focused on the reduction of farmland loss. Ferraro et al. (2007) study the effectiveness of the U.S. Endangered Species Act on species recovery rates using matching methods. Adam et al. (2008) estimate the effectiveness of protected area networks on deforestation rates in Costa Rica. Cooper (2005) analyzes incentive payments for adopting a bundle of best management practices. Conservation Programs have also been studied using difference-in-difference matching. Chabé-Ferret & Subervie (2013) study European Union Agro-environmental schemes implementation in France. These schemes pay farmers to adopt greener practices. They study schemes that are meant to increase crop diversity, the planting of cover crops, the planting of buffer strips, and the conversion to organic farming. Using propensity score matching and difference-in-difference, they estimate the average treatment effect on the treated. They find that the Agro-environmental scheme increases the area planted with cover crops by around 10 ha (around 24 acres) on average (Chabé-Ferret & Subervie 2013). While we would like to use a difference-in-difference approach in this study, the Iowa Farm and Rural Life Poll does not ask the same questions every year. Nonetheless, we use matching techniques on pretreatment variables that are available in our dataset.

A few papers have studied cost-share in the state of Maryland, where cover crops are an established conservation practice. Lichtenberg and Smith-Ramirez (2003) take advantage of the large amount of Maryland farmers receiving cost-share funding for a variety of conservation practices to assess the impact of cost-sharing on overall conservation effort. They study three conservation measures: an aggregate indicator of cost-share funding award, the number of conservation practices adopted, and the acreage served by those conservation practices. They take into account transaction costs, factors influencing government agencies' cost-share funding allocation process, and possible economies of scale and scope. Using full information maximum likelihood, their estimation suggests that political influence and protection of crop productivity influence cost-sharing award decisions, while the proximity to water bodies does not. Furthermore, they find that farmers receiving cost-share use fewer practices and achieve no greater conservation coverage than farmers who do not receive cost-sharing (Lichtenberg & Smith-Ramirez 2003). More recently, Lichtenberg and Smith-Ramirez (2011) study whether cost-share induces farmers to expand cultivation on more vulnerable land for three of the most commonly used conservation practices in Maryland: contour farming, strip cropping, and cover crops. They find that farmers receiving cost-share funding allocate 8 percentage points more cropland to cover crops than in the absence of the funds. Furthermore, farmers who receive cost-share funding are roughly 36 percentage points more likely to use cover crops than farmers without the funds.

Fleming (2015) also studies the direct effect of cost-share funding on cover crops acres in Maryland, but he also studies the indirect effect of cost-share on conservation tillage and contour/strip cropping acres. He employs a two-stage simultaneous equation approach to correct for voluntary self-selection in the funding programs and which accounts for substitution effects among conservation practices. He finds that cost-share funding has a positive and significant effect on cover crops acres in Maryland (Fleming 2015). These studies in Maryland differ from ours as they use data from a state in which there is more adoption of cover crops, and in which indirect effects on other conservation practices are more likely as cover crops are a newly perceived in our region. Our paper focuses on an area in which cover crops are viewed as a new technology. Secondly, we differ in our methodologies based on the nature of the datasets employed in each analysis. While they utilize a cross section, we use the Iowa Farm and Rural Life Poll, which allows us to use information before cost-share funding is received by farmers. On the other hand, we take these Maryland studies as references in the selection of explanatory variables to control for transaction costs and the factors influencing award decision processes.

The previous research that is most relevant for this application is Mezzatesta et al. (2013), who also estimate the average treatment effect of cost-share programs and who address additionality concerns from conservation practices. They use matching techniques to estimate the average treatment effect on the treated of cost-share funding for several conservation practices, including cover crops, in Ohio using cross-sectional data. Their outcome variable is the proportion of acres under a particular conservation practice relative to total farm acres. Furthermore, they address additionality concerns by decomposing the average treatment effect on the treated according to relative contributions of adopters and non-adopters. They find that the average treatment effect on the treated of enrollment in cost-share programs is roughly 23 percentage points for cover crops. Our research utilizes a similar methodology, but we differ in the dataset employed for matching. While they use cross-sectional data, we use a unique dataset with yearly information on farmers that allows us to match treated and control units based on pretreatment characteristics, which is fundamental to obtain a valid counterfactual.

While previous research has studied cost-share funding in the United States, it has been focused on an area in which cover crops are more popular and in which there is substantial adoption of the practice. We contribute to the literature by studying the planting of cover crops in an area of the United States in which this conservation practice is newly perceived and in which cover crops are widely promoted to attain water quality goals at a local and regional level. Moreover, this area is extremely important as it is heavily farmed and as it contributes to both local water quality problems and the Gulf Hypoxia. While cover crops are recognized for their environmental benefits, limited peer-reviewed studies focused on the adoption of cover crops exist in the literature in this area (Arbuckle & Roesch-McNally 2015). Secondly, we contribute to the understanding of adoption decisions by using a unique dataset that allows us to observe characteristics prior to the allocation of cost-share funding, different than these previous U.S. studies that employ cross-sectional data. Hence, we address selection bias through matching techniques using information prior to receiving funding. Third, we also differ from these previous studies as we include attitudinal and past conservation and past drainage expenditure information in our matching process. Fourth, in addition to estimating the average treatment effect on the treated, we contribute to the literature by estimating the average marginal treatment effect among adopters. While some studies concentrate indirect effects (Lichtenberg & Smith-Ramirez 2011; Fleming 2015) of cover crops, we are able to focus on planting of cover crops on its own, given that this is a new conservation practice in this area. In essence, we are concerned about the effectiveness of cost-share funding in the sole planting of cover crops, given the little adoption in the area and the novelty of this practice in the region.

2.4 Background

Whereas the Iowa Nutrient Reduction Strategy is a relatively new effort that provides guidelines to improve water quality in Iowa and in the Gulf of Mexico, water quality has been promoted by both state and federal conservation programs in the past. These programs often provide cost-share incentives, in which matching funds or incentive payments are given to farmers to cover a proportion of the conservation costs. In Iowa, several cost-share program are available through USDA's Natural Resource Conservation Service (NRSC), including the Conservation Reserve Program (CRP), the Environmental Quality Incentives Programs (EQIP), the Conservation Reserve Enhancement Program (CREP), the Conservation Stewardship Program (CSP), among others. Some of these programs are focused on particular conservation practices such as land retirement in the case of CRP and wetlands in the case of CREP. Other programs promote a variety of conservation practices, including cover crops, such as EQIP or CSP. For instance, EQIP offers cost-share to first cover crop producers. Basic payment rates varied from roughly \$24 to \$35 per cover crop acre depending on the type of cover crop seed employed by the farmer (USDA NRCS 2013).

In August of 2013, \$2.8 million became available statewide to implement conservation practices based on the Iowa Nutrient Reduction Strategy through the Water Quality Initiative (Iowa NRS 2014). The funds were allocated for practices that could be implemented in a short time, with the goal of providing water quality benefits in 2013 and spring of 2014 (Iowa NRS 2014). One of practices that was promoted through this cost-share program was cover crops with a payment rate of \$25 per acre (Swoboda 2013). According to the Iowa NRS 2013-2014 Annual Progress Report, roughly 95,000 acres of cover crops were established through this state cost-share program. This number is very small relative to the total amount of corn and soybean crop land, which is around 24 million acres in Iowa (USDA NASS 2014). Overall, roughly 230,000 acres of cover crops were planted through both Federal and State cost-share program in 2013, capturing around 75 percent of total cover crop acres for that year. Given the availability of cost-share funding in 2013, we use a unique data set to assess the effectiveness of cost-share funding in the planting of cover crops.

2.5 Farmer's Model

A profit maximizer farmer chooses the amount of cover crops to be planted based on the following optimization:

$$\max_a \pi(a) = \max_a \tau a - g(a) \tag{2.1}$$

where a is acres of cover crops, τ is the cost-share funding payment per acre, and $g(a)$ is the cost function associated with planting cover crops.

Due to winter conditions and the lack of markets, cover crops do not have enough time to grow and are typically killed before planting the cash crop in the spring. Hence, the farmer does not receive any direct revenue associated with harvesting the cover crop. However, cover crops reduce soil erosion and nutrient loss and increase soil health (Arbuckle & Roesch-McNally 2015). These benefits can increase the cash crop yield. However, yield changes associated with cover crops are still a topic of debate, as more research is needed to understand the relation between cover crops and yields. For this reason, we include yield changes as part of the cost function. If cover crops decrease yield, the forgone revenue associated with the yield loss becomes a cost. Otherwise, the additional revenue becomes a negative cost[1]. The cost function also includes seed, labor, and any other costs associated with planting, managing, and killing the cover crop. A farmer plants cover crops (i.e. $a^* > 0$) as long as:

$$\tau = \frac{\partial g(a)}{a} \tag{2.2}$$

Essentially, a farmer plants cover crops as long as he or she receives cost-share funding per acre at the level where it equals the marginal cost. The above equation determines the amount of

[1] Since cover crops are newly perceived in this region, having data on the returns to cover crops is very hard. As limited adoption has taken place, information on yield changes is limited and researchers rely on experimental plots or integrated assessment models to understand these changes.

acres planted by the farmer. On the other hand, if the farmer is not offered enough cost-share funding compensation (i.e. if $\tau < \frac{\partial g(a)}{a}$), he or she will not plant cover crops, resulting in a corner solution at zero (i.e. $a^* = 0$). This simple model illustrates the behavior of a profit maximizer farmer. Beyond a farmer's cover crop planting decision, our paper is focused on the effectiveness of having cost-share funding (i.e. τ) on cover crop acres planted and the proportion of cover crops relative to total farm land.

2.6 Methodology

For the estimation of treatment effects, we would like to know the way the treatment participant would behave in the absence of the treatment as first formalized by Rubin (1974). The treatment effect for individual i is the comparison of i's outcome with treatment, denoted by $Y_{1,i}$, and i's outcome without treatment, denoted by $Y_{0,i}$. The fundamental problem when estimating treatment effects is that we only observe one of these potential outcomes for each individual (Holland, 1986). Basically, when estimating causal effects, we face a missing data problem, so we need to predict the unobserved potential outcomes (Rubin, 1976). In order to estimate treatment effects, $E(Y_1 - Y_0|X)$, we compare treated and control individuals that are very similar. Following Rosenbaum and Rubin (1983) and Heckman et al. (1998), two assumptions are made to estimate treatment effects: (1) strong ignorability assumption, in which the treatment assignment, denoted by T, is independent of potential outcomes (Y_0, Y_1) given the covariates X (i.e. $T \perp (Y_0, Y_1)|X$); and (2) overlap assumption, in which there is a positive probability, denoted by $P(T = 1)$ of receiving each treatment for all values of X (i.e. $0 < P(T = 1|X) < 1$ for all X). A weaker version of (1), in which $E(Y_0|X, T) = E(Y_0|X)$ and $E(Y_1|X, T) = E(Y_1|X)$, suffices for estimating the average treatment effect on the treated, defined as $ATT = E(Y_1 - Y_0|X, T = 1)$. For our research question, we focus two outcome variables: Y^1 which is the proportion of cover crops planted relative to total farm acreage and Y^2 which is the amount of acres of cover crops planted. The treatment indicator, T, is defined as follows:

$$T = \begin{cases} 1 & \text{if farmer is enrolled in cost-share program} \\ 0 & \text{if farmer is not enrolled in cost-share program} \end{cases} \tag{2.3}$$

In order to estimate treatment effects, the literature suggests a two-step process. To start, researchers use pretreatment information to select comparable treated and control units to analyze the treatment effect without using the outcome variable. Secondly, using the matched sample, researchers estimate treatment effects (Stuart & Rubin 2008). For the first step, matching techniques are employed to balance the distribution of covariates in the treated and control groups (Stuart 2010). In essence, by controlling for pretreatment differences between treatment and control, researchers are able to reduce bias by using a valid counterfactual. For the second step, researchers estimate treatment effects. We are interested in estimating two effects: the average treatment effect on the treated and the average marginal treatment effect among adopters. For the first, we estimate the ATT directly using a propensity score estimator:

$$\widehat{ATT} = \frac{1}{N_1}\left[\sum_{i \in I_1 \cap S_p}\left[Y_{1,i} - \hat{Y_{0,i}}\right]\right] \tag{2.4}$$

with

$$\hat{Y_{0,i}} = \sum_{j \in I_0} \hat{W}(i,j) Y_{0,j} \tag{2.5}$$

where Y is either Y^1 or Y^2, I_1 denotes the set of treatment observations, I_0 denotes the set of control observations, N_1 is the number of treated observations, S_p denotes the region of common support, and $\hat{W}(i,j)$ are the weights that depend upon the distance between the propensity scores for i and j and the number of matches per treatment observation. To assess the estimation results, researchers use Abadie and Imbens robust standard errors, which take into account that the propensity score is estimated.

To estimate the average marginal treatment effect among adopters, we use the matched data and regress the outcome variable on the treatment status and other relevant covariates. Matching methods and regression adjustment models can complement each other (Rubin & Thomas 2000, Glazerman, Levy & Myers 2003, Abadie & Imbens 2006). Intuitively, by selecting matched samples, the bias due to covariate differences is reduced and regression analysis for remaining small covariate differences increases the efficiency of treatment estimates (Stuart & Rubin 2008) and makes results less sensitive to model specifications (Ho et. al. 2007).

For the first step, propensity score matching is typically employed in non-experimental studies to attain balance and overcome the selection problem (Rosenbaum & Rubin 1983). First, a propensity score is calculated, which is each individual's probability of being included in the treatment, and it is calculated using observed covariates, X (Wooldridge 2010). Smith and Todd (2005) recommend the inclusion of covariates that influence both treatment status and outcome when estimating the propensity score. As emphasized by Ho et. al. (2007), the selection of covariates to be included in regressions can be based on previous research (i.e. Chabé-Ferret & Subervie 2013, Mezzatesta et al 2013, and Lichtenberg & Smith-Ramírez 2003, 2011) and scientific understanding. Furthermore, using covariates measured prior to treatment assignment is fundamental to avoid including variables that may have been affected by the treatment (Stuart & Rubin 2008).

Choosing appropriate covariates, nearest neighbor propensity score matching, and genetic matching are employed to obtain valid counterfactuals. Under nearest neighbor propensity score matching, best controls are found by minimizing a distance measure, the propensity score, for each treated unit one at a time (Ho et al. 2011). Genetic matching is a multivariate matching method that maximizes the balance of covariates across treatment and control (Diamond and Sekhon 2012). In essence, the method minimizes the discrepancy between distribution of potential cofounders in the treated and control groups, which allows for a maximized covariate balance (Sekhon 2011)[2].

We use *teffects psmatch* and *GenMatch* (Sekhon 2012) to estimate the ATT directly using nearest neighbor propensity score matching and genetic matching respectively and to estimate Abadie and Imbens (2012) robust standard errors. The latter take into account the usage of estimated treatment probabilities in the matching process. For nearest neighbor propensity score matching, we utilize several matching specifications, including both probit and logit propensity scores, caliper levels, and number of neighbors to be matched per treated observation. For genetic matching, we also try several specifications including number of neighbors, boots, and population size. To assess covariate balance, we compute standardized mean differences and variance ratios between treatment and control. To verify the overlap assumption, we plot kernel density plots of the propensity scores for both matched and raw datasets.

[2] We use *teffects psmatch* in Stata and *GenMatch* (Sekhon 2012) in R to match treatment and controls

After data is matched and covariate balance and overlap are attained, we employ a Tobit regression since our outcomes include a corner solution at zero for a substantial fraction of the observations (Wooldridge 2010). For corner solution responses, using conventional regression methods such as OLS yield biased results (Greene 2008). Under the standard Tobit model (Tobin 1985), the dependent variable is left censored[3] at zero.

$$Y_i^* = \beta_0 + \beta_T T_i + X_i^{'}\beta + \varepsilon_i \tag{2.6}$$

$$Y_i = \max\left(0, Y_i^*\right) \tag{2.7}$$

where i indicates the observation, Y_i^* is the latent variable, $X_i^{'}$ is a vector of explanatory variables, T_i is the treatment, β is a vector of unknown parameters, and ε_i is the error term. Both Y^1 and Y^2 have corner solutions at zero, since many farmers report zero cover crops acres. Likewise, no farms report planting cover cover crops on a 100 percent of their acreage, making $Y^1 < 1$ for all farmers. When estimating the treatment effect through these Tobit models, we apply the same set of covariates utilized in the matching process, X, to control for remaining covariate differences. To conclude the analysis, we focus on the average marginal effect of the treatment indicator among adopters of cover crops:

$$\frac{\partial E[Y|Y>0]}{\partial T} = \beta_T \left[1 - \lambda(\alpha)\left(\frac{X_i\beta}{\sigma} + \lambda(\alpha)\right)\right] \tag{2.8}$$

where $\lambda(\alpha) = \frac{\phi\frac{X_i\beta}{\sigma}}{\Phi\frac{X_i\beta}{\sigma}}$ is the Inverse Mills Ratio, σ is the Tobit scale, $\Phi()$ is the standard normal cdf and $\phi()$ is the standard normal pdf. This marginal effect indicates the treatment effect on on observations where $Y > 0$. However, since we are interested in the marginal effect of the treatment indicator, we compute the average discrete first-difference between treatment and control for the expected positive outcome using Stata's *margins*, which takes into account the matching weights and uses the Delta-method to calculate standard errors.

[3]Wooldridge (2010) prefers to avoid the word "censored" as it might suggest some data censoring. In this case, we work with a corner solution model, where the corner is at zero. This is similar to the charitable contribution example that is typically used to exemplified corner solution responses when the only corner is at zero (Wooldridge 2010).

2.7 Data

We use data from the Iowa Farm and Rural Life Poll (IFRLP) to estimate the effect of cost-share programs in the planting of cover crops in Iowa, which provides us with a unique opportunity to learn about this emerging conservation practice. The IFRLP is an annual longitudinal survey of Iowa farmers that started in 1982, which has a sample of roughly 2000 large operators that are repeatedly sampled. This survey is the longest-running survey of its kind in the United States (Arbuckle, Jr. et al. 2013). Iowa State University Extension in partnership with Iowa Agricultural Statistics and the Iowa Department of Agriculture and Land Stewardship are in charge of the survey. They mail the survey to the same group of farmers every spring. Nonetheless, as a response to attrition due to retirement and other factors, new samples are randomly drawn from the Census of Agriculture master list to refill the panel sample. As these new samples are drawn, smaller-scale farmers often decide not to participate. Arbuckle (2013) compares IFRLP (2008) and the Census of Agricultural statistics (2007) for Iowa and finds that the IFRLP sample has large-scale farmers. As in Arbuckle's (2013) study, this concentration of large farm operators is beneficial for our research purposes as large-scale farms operate a substantial amount of acreage relative to small-scale farms. Furthermore, we want to make sure our study captures large farmers, who ultimately have a larger impact on the environment.

The IFRLP focuses primarily on conservation-related policy, decision making, behavior, and attitudes among farmers. Questions from the annual survey are often developed in consultation with public agency stakeholders such as the Iowa Department of Natural Resources, the Iowa Department of Agriculture and Land Stewardship, and the USDA NRCS and are focused on a few particular subjects each year. The surveys are meant to facilitate the development and improvement of research and extension programs and to help local, state, and national leaders in their decision-making process (Arbuckle et al. 2011). For our analysis, we use data from the 2010 and 2011 polls, which provide pretreatment covariates.[4] In addition, the 2014 poll is used since it contains information for our outcome variables and identifies which farmers

[4] Each poll contains questions about the previous year

received cost-share funding to plant cover crops, which determines our treatment variable. We construct the proportion of cover crops using information on cover crops acres and the aggregate of responses on the amount of farmland acres devoted to several farming categories. Lastly, the 2014 poll also contains some pretreatment variables that do not change after harvest, when cover crop decisions are made and when cost-share is received. Using this data, we study the effect of cost-share funding on our two outcome variables.

Based on the 2014 poll alone with over one thousand observations, roughly 14 percent of surveyed farmers stated that they planted cover crops in 2013. The mean among cover crops adopters was 98 acres (IFRLP 2014). The majority use cover crops on less than 100 acres of their land. After merging the polls from 2010, 2011 and 2014, we have 588 observations. While we lose observations by merging the responses from the three years, we proceed with the merging because we want to match based on pretreatment variables from the older surveys. Once we exclude observations with missing variables or inconsistent responses, our final sample is 530 observations. Table 2.1 summarizes adoption among these observations. With this subset of the polls, we observe that roughly 17 percent of respondents adopted cover crops in 2013. There are almost twice as many adopters without cost-share as with this funding.

Focusing on our outcome variables, Table 2.2 contains summary statistics among those who adopted cover crops from the merged surveys. For the proportion outcome, the mean is around 20 percent, and the median is roughly 12 percent for the whole dataset, showing that most farmers fall below the average proportion. Among cost-share recipients, the mean proportion is around 24 percent, which is about 5 percentage points higher than the mean among non-recipients. The range of the proportion is between 0.2 percent and 80 percent among all farmers, which is larger than the range among cost-share recipients. For acres, Table 2.2 shows that adopters planted around 109 acres in 2013. Among cost-share recipients only, an average of 119 acres were planted in 2013, which is about 15 acres higher than the mean among non-recipients. The range goes from 1 to 1700 acres among all farmers and among non-recipients. It is worth noting the large difference between maximum acres among recipients and non-recipients. First, we observe that the maximum of the whole dataset comes from a non-recipient of cost-share. Secondly, we observe that the maximum was 1700 and 500 among non-recipients and recipients respectively, illustrating a large difference between both groups. While non-recipients have a larger maximum, the average is higher among recipients. It is plausible that some of these summary statistics for non-recipients are substantially influenced by this maximum. In fact, half of the farmers without cost-share planted fewer than 35 acres. In contrast, the median among cost-share recipients was 75 acres. Despite having a much larger maximum acres among non-recipients, the remaining summary statistics are higher among cost-share recipients. From these tables, we observe that while there are more non-recipient adopters, their amount of acres planted are substantially lower relative to the acres planted among cost-share recipients.

To match treatment observations to valid counterfactuals, we use a list of covariates that affects both treatment and outcome variables. Following the literature, we use similar covariates as previous studies (Chabé-Ferret & Subservie 2013; Mezzatesta et al. 2013; and Lichtenberg & Smith-Ramírez 2003 & 2011) as well as additional variables available in the IFRLP. For instance, we include whether a farmer believes that Iowa farmers should do more to reduce nutrient and/or sediment runoff into waterways. We also include variables capturing whether the farmer had incurred in any costs associated with conservation practices and whether the farmer had any expenditure associated with agricultural drainage over the last 10 years in 2010. Our covariates occurred prior to receiving cost-share funding and prior to planting cover crops in 2013.

Table 2.3 describes each covariate used in the matching process and subsequent Tobit models, displaying a combination of demographic and farm characteristics as well as some conservation information that might affect the enrollment into the cost-share program and the subsequent cover crops planting decision. Pretreatment outcome variables are ideal explanatory variables to include in both matching and regression models. However, we do not have information about previous cover crops acres planted. As a proxy, we use an indicator variable that captures the farmers who adopted cover crops in the last five years prior to 2010. Farm and farming characteristics such as soil erosion problems, the presence of water running through or along the farm, farm size, proportion of farm acreage rented, the management of livestock, gross farm sales, and the proportion of farm acreage devoted to grain crops are included to help predict program enrollment as well as outcome variables. We emphasize the importance of soil erosion problems, as this indicator variable is influenced by soil erodibility, slope gradient and length, vegetation, conservation measures, and rainfall intensity and runoff. In particular, the higher the slope, the greater the amount of soil erosion by water. Moreover, cover crops help decrease soil erosion. We also include location information to capture some of the differences among geographic locations based on weather, soil characteristics, and other factors that are different among agricultural districts. Demographic and labor information such as age, experience, farm income, education level, and the number of days worked off farm are also included. Lastly, we include farmers' attitudes towards reducing nutrient or sediment runoff into waterways and previous conservation costs and drainage expenditures. The latter is included since land with little slope is more likely to require drainage systems.

Table 2.4 summarizes the explanatory variables prior to any matching process, showing some statistical significant difference in means between treated and control groups prior to matching. For instance, the sample mean of the dummy variable indicating water running on or along the farm is 0.90 for farmers receiving cost-share funding and 0.72 for farmers not receiving cost-share funding, a difference that is significantly different at a 1 percent level. The difference on the natural log of farm land is significantly different among treatment and control groups at the 5 percent level. Lastly, differences in age, age squared, and the indicator variable for prior use of cover crops are significantly different at a 10 percent level. This table illustrates the importance of matching before any treatment analysis, since the treatment and control groups exhibit explanatory variables that are significantly different.

2.8 Matching Results

For the first step of our analysis, we try different specifications of two matching algorithms: nearest neighbor propensity score matching and genetic matching. We use different caliper levels, discarding options, distance measures (i.e. Logit and Probit), and different number of control units to match to treated observations. As emphasized by Stuart (2010), we choose the best matched data set without using the outcome variable. For this section, we report results from the best matching method for our data. Robustness checks based on other matching methods are reported under the Robustness Checks Section.[5] We choose the best method based on the lowest standardized mean differences among all covariates and the verification of the overlap assumption. We obtain the best matching result using nearest neighbor propensity score matching with a probit propensity score, five nearest neighbors, no caliper, and allowing for replacement of controls.

We first report the probit propensity score results in Table 2.5. The probit estimation shows that having planted cover crops in the five years prior to 2010 has a positive effect in receiving treatment and its coefficient is statistically significant at a 1 percent level. Farm size and having water going through or along the farm also have a positive effect and their coefficients are statistically significance at a 5 percent level. The sign and significance of these coefficients are intuitive. In particular, farm size is a piece of information that is included in cost-share application processes and that is used by administrative bodies making cost-share award decisions. As explained by Lichtenberg and Smith-Ramírez (2003), we expect farm size to increase the likelihood of receiving cost-share, since larger farm operators are probably more knowledgeable about farm programs, more experienced dealing with government officials and application processes, and more influential politically. As far as the presence of water bodies, they explain that proximity to water bodies should be a decision criteria for awarding cost-share funds. They hypothesize that the coefficient on this water indicator should be positive and statistically significant, which is observed in our regression results. Looking at other explanatory variables, age affects treatment selection negatively, meaning that younger farmers are more likely to enroll in a cost-share program for cover crops. This negative relation has been observed in previous studies (Lichtenberg & Smith-Ramírez 2003 and Mezzatesta et al 2013), and it is explained by shorter time horizons and possibly resistance to change among older farmers. In contrast, farm experience increases the likelihood to enroll in the cost-share program. This positive relation is also observed by Lichtenberg and Smith-Ramírez (2003). More experienced farmers are likely to be more knowledgeable about conservation funding opportunities and application processes, decreasing their application transaction costs and increasing their likelihood of applying and subsequently receiving funding.

[5] Results from other matching methods are available upon request.

After matching using the specified method, we have 29 treated units matched to 117 control units for a total of 146 observations. Table 2.6 summarizes the standardized mean differences and variance ratios between treatment and control for all covariates. The former is the difference in sample means between treatment and control groups divided by the standard deviation of the average sample variance of both groups. The highest absolute standardized mean difference is 0.12. Only three covariates have absolute standardized mean differences above 0.10. Following Rosenbaum and Rubin (1985), absolute standardized mean differences below 0.20 are desirable. Moreover, according to Rubin (2001), each variance ratio should be between 0.5 and 2, since a ratio for a perfectly balance covariate is 1. Table 2.6 also summarizes the variance ratios of the matched sample showing that every ratio falls within the desired range. Figure 2.12 provides a graphical illustration of the improved balance of the variance ratios. After matching, we observe that variance ratios lie within the desired range of 0.5 and 2. Based on both standardized mean differences and variance ratios of covariates, we conclude that we attain a good balance.

To assess the common support of the matched sample, we use Figure 2.12, which depicts the overlap of the propensity scores between treatment and control groups before and after matching. Figure 2.12 displays the estimated propensity scores of treated, depicted in red, and control units, depicted in blue, for both raw and matched datasets, which illustrates the overall distribution of propensity scores in treated and control groups. From this figure, we observe that matched treated and control units have overlapping propensity scores, which is illustrated on the right panel. We also illustrate that the overlapping assumption is satisfied through two box plots of the estimated propensity scores before and after matching. Figure 2.12 shows the box plot of the estimated propensity scores from the raw treated and control groups on the left and the matched sample on the right. We can see that matched treated and control groups look very similar after matching.

2.9 Results

2.9.1 Estimation Results for the Proportion of Cover Crops Planted Relative to Total Farm Acreage

After finding the matching method that attains the best balance among treatment and control groups, we estimate two treatment effects. First, we directly estimate the average treatment effect on the treated. Secondly, we use a Tobit regression to estimate the average marginal treatment effect among adopters of cover crops. For the first method, we estimate the average treatment effect on the treated directly using equation (1), as explained in the methodology section. We take into account matching weights and compute Abadie and Imbens robust standard errors, which take into account that the propensity score is estimated. Estimation results are summarized in Table 2.7. We find that for cost-share funding recipients, getting the funding increases the proportion of cover crops planted by 20 percentage points on average relative to farmers who do not obtain any funds. This estimation result is statistically significant at the 1 percent level.

Since the proportion of cover crops planted has a corner solution at zero due to common non-adoption of cover crops, we utilize a Tobit model to secondly estimate the average marginal treatment effect of cost-share funding on the proportion of cover crops acres relative to total farm acreage (Y^1) among adopters, as explained in the methodology section. For the Tobit regression, we use the weights from the matching procedure and employ the same set of covariates used in the matching process (X) in addition to the treatment indicator (T). Table 2.9 summarizes the results from the Tobit regression on the proportion of cover crops acres. We observe that the treatment indicator (i.e. T = cost.share.I) affects the proportion positively, and its coefficient is statistically significant at a 1 percent level, confirming the effectiveness of cost-share funding in the planting of cover crops. Other covariates are statistically significant, correcting for residual covariate imbalance between the groups (Ho et. al. 2007).

In order to assess the magnitude of the effectiveness of cost-share funding among adopters, we compute the average marginal treatment effect on the expected proportion of cover crops acres planted. While estimating the marginal effect, we focus on adopters (i.e. farmers with positive outcome) and we take into account the weights from the matching procedure and the discrete nature of the treatment indicator. Table 2.10 summarizes the average marginal treatment effect and its standard error, which is calculated using the Delta-Method. The average marginal effect of receiving cost-share funding on the expected proportion of cover crops acres planted is around 18 percentage points among adopters, which is statistically significant at the 1 percent level. In other words, on average, we expect that farmers receiving cost-share increase the proportion of cover crops planted by 18 percentage points of their acreage relative to cover crop adopters who do not receive cost-share funding. Comparing both treatment estimations, we find that both are positive, statistically significant and similarly sized. We conclude that having cost-share funding increases the proportion of farm land devoted to cover crops among cost-share funding recipients and among adopters.

2.9.2 Estimation Results for Cover Crop Acres Planted

As with the proportion of cover crops, we follow the same estimation methods for assessing the effectiveness of cost-share funding in the amount of cover crops acres (Y^2), our second outcome variable. We first estimate the average treatment effect on the treated directly and find that receiving cost-share funding increases cover crops acres by roughly 81 acres. In other words, cost-share funding induces farmers to plant an additional 81 cover crop acres compared to non-recipient farmers on average. Using Abadie and Imbens robust standard errors, we find that this coefficient is statistically significant at the 5 percent level. Results from this estimation are summarized in Table 2.12.

Secondly, we use a Tobit regression to estimate the average marginal treatment effect on expected cover crops acres among adopters. Again, we use the weights from the matching procedure and regress the outcome variable on the same set of covariates using the matching process (X) as well as the treatment indicator (T). Table 2.14 summarizes the results from the Tobit regression and shows that the coefficient on the treatment indicator is positive and statistically significant at the 1 percent level, confirming cost-share effectiveness in the planting of cover crops. Lastly, to assess the magnitude of the effectiveness of cost-share funding among adopters, we find that the estimated average marginal treatment effect is around 104 acres, which is summarized in Table 2.15. On average, we expect that farmers receiving cost-share increase the planting of cover crops by 104 acres relative to cover crop adopters who do not receive cost-share funding. We use the Delta-Method to calculate standard errors and take into account the discrete nature of the treatment indicator. We find that the average marginal effect is statistically significant at the 1 percent level. Comparing the estimated ATT and the estimated average marginal treatment effect among adopters, we find that both are positive and statistically significant, but that they differ in size. We also find that the confidence interval for the estimated ATT is larger than the one for the estimated average marginal treatment effect. We conclude that having cost-share funding increases cover crops acres among adopters and cost-share funding recipients, but the magnitude of each effect is different among both subsets, with the effect among adopters having a smaller confidence interval.

2.10 Robustness Checks

As robustness checks, we repeat each estimation using different matched datasets from other matching specifications that attain a good balance during the first step of our research analysis. Nearest neighbor propensity score matching with a probit propensity score, four nearest neighbors, a 0.20 caliper, and allowing for replacement of controls also provides a decent balance. The lowest absolute standardized mean difference is 0.13.[6] Furthermore, nearest neighbor propensity score matching with a logit propensity score, five nearest neighbors, a 0.20 caliper, and allowing for replacements offers a decent match. The lowest standardized mean difference under this matching model is 0.19, which is higher than the other two matching models [7]. Lastly, we also include results from a genetic matching (Sekhon 2011) model with five neighbors and allowing for replacement.[8]. This matching method did not attain the best balance, with the highest absolute standardized mean difference being .33. However, we decide to include the best matching outcome under the genetic algorithm method. Tobit regressions are run for each outcome variable using each matched data set. For the six regressions, the coefficient on the treatment indicator is positive, and it is statistically significant at the 1

[6]Complete matching results are available upon request
[7]Complete matching results are available upon request
[8]Complete matching results are available upon request

percent level. Hence, we conclude that the sign and statistically significance of the treatment indicator does not vary across matching specifications.

For the proportion outcome variable, Table 2.8 summarizes estimated ATT coefficients under the three methods. We find that the second best matching method, displayed on the first row of the table, has the same estimated ATT coefficient, 0.20, as our main results in Table 2.7. With the other two matching methods, the estimated ATT is 2 percentage points higher than the estimated coefficient from the best matching model. Overall, all the coefficients are statistically significant at the 1 percent level and they are similar in size. We therefore conclude that receiving cost-share funding increases the proportion of cover crops acres by around 20 percentage points among funding recipients relative to not receiving the funds. Focusing on adopters only, Table 2.11 shows the estimated average marginal treatment effect on the expected outcome under each matching specification. We observe that the three estimated effects are very similar in size and are slightly higher than the marginal treatment effect estimated under the chosen matching model displayed in Table 2.10. It is worth noting that these marginal effects are similar to the estimated ATT under each method. We conclude that cost-share funding increases the proportion of cover crops planted by roughly 20 and 18 percentage points among funding recipients and adopters respectively relative to not receiving the funds.

For acres of cover crops planted, Table 2.13 summarizes estimated ATT coefficients under each matching specification. We observe that using the second best matched dataset, the estimated ATT is around 74 acres, which is statistically significant at the 1 percent level, and it is around 7 acres lower than the estimated ATT using the best matched dataset (See Table 2.12). For the other two matching specifications, the ATT coefficients are similar in size, but they are around 20 acres higher than the estimated ATT from Table 2.12. We conclude that having cost-share funding increases the amount of acres planted among recipients, but the magnitude of its effect differs between matching specifications. These differences might be explained by the large 95 percent confidence interval for the estimated ATT from Table 2.12. Focusing on adopters only, Table 2.16 summarizes the estimated average marginal treatment effect results from the three matching specifications. We observe that the estimated effects are similar in size and statistically significant at the 1 percent level. They are also very similar to the main results from Table 2.15, showing less variation compared to estimated ATTs. We also note that the 95 percent confidence interval is smaller in Table 2.15 compared to Table 2.12. We conclude that receiving cost-share funding increases the expected amount of acres planted by around 104 acres among adopters of cover crops relative to those who do not obtain cost-share funding.

2.11 Conclusions

Cover crops have been promoted to address agricultural water pollution at local and regional levels through Federal and State conservation programs. Based on the Iowa Nutrient Reduction Strategy, in August of 2013, additional cost-share funding became available to establish cover crops, among other conservation practices, with the goal of providing water quality benefits in 2013 and spring 2014 (Iowa NRS 2014). The availability of cost-share funding provides a unique opportunity to study its effectiveness in promoting this newly perceived technology in this agriculture-intense region. Specifically, we use matching methods combined with regression analysis to study the effectiveness of cost-share funding on the proportion of cover crops acres planted relative to total farm acreage and the amount of cover crops acres planted using a unique dataset that contains yearly information on large farm operators.

Following a two-step process, we first match treated and control units based on pretreatment information using a variety of matching specifications and two matching algorithms: nearest neighbor propensity score matching and genetic matching (Sekhon 2012). We choose the best matched data set based on standardized mean difference, variance ratios, and the overlap of propensity scores between treatment and control groups. For the second step, we estimate two treatment effects for both outcomes (i.e. proportion and acres): the average treatment effect on the treated and the average marginal treatment effect among adopters. For the former, we estimate the ATT directly and use Abadie and Imbens robust standard errors. For the latter and given that our outcomes include a corner solution at zero, we use a Tobit model in which we regress each outcome variable on the treatment indicator and other relevant covariates. We then estimate the average marginal treatment effect among adopters of cover crops.

We find that receiving cost-share funding has a positive effect on both cover crops acres and on the proportion of cover crops. In particular, receiving cost-share funding increases the proportion of cover crops acres by around 20 percentage points among recipients of the funds on average. The program also increases acres among recipients of the funds, but the estimated size effect varies by matching method. Focusing on adopters only, we use Tobit regressions and find that the treatment coefficients are statistically significant at the 1 percent level for each expected outcome variable, implying that receiving cost-share acres has a positive effect on expected cover crop acres and on the expected proportion of cover crops even when controlling for high non-adoption of cover crops. For the average marginal treatment effects, we find that, on average, we expect that farmers receiving cost-share increase the proportion of cover crops by around 18 percentage points relative to cover crop adopters who do not receive funds. For acres, the results show that, on average, we expect farmers receiving cost-share to plant an additional 104 cover crops acres relative to cover crop adopters without funding. In the end, cost-share funding is effective in increasing cover crops acres and the proportion of cover crops planted among both recipients of the funds and adopters of cover crops. Since cost-share is effective in increasing the planting of cover crops, policy makers concerned about water pollution from agriculture in this region, where cover crops are newly perceived, could allocate more cost-share funds to this practice. These results could assist policy makers in finding effective solutions to address persistent water quality problems with limited conservation budgets.

2.12 Tables and Figures

Table 2.1 Cover Crops Adoption

Number of Non-adopters	Number of Adopters with Cost-Share	Number of Adopters without Cost-Share	Number of Observations
442	29	59	530

Table 2.2 Summary Statistics for Cover Crops Outcome Variables among Adopters

Outcome Variable	Subset	Min	Median	Mean	Max
Y^1: Proportion	All	0.002	0.1237	0.196	0.80
Y^1: Proportion	Cost-Share=1	0.017	0.186	0.244	0.80
Y^1: Proportion	Cost-Share=0	0.002	0.068	0.172	0.80
Y^2: Acres	All	1	45	109.20	1700
Y^2: Acres	Cost-Share=1	8	75	119.17	500
Y^2: Acres	Cost-Share=0	1	35	104.27	1700

Note: This table focuses on the behavior of adopters only (i.e $Y^1 > 0$ and $Y^2 > 0$)

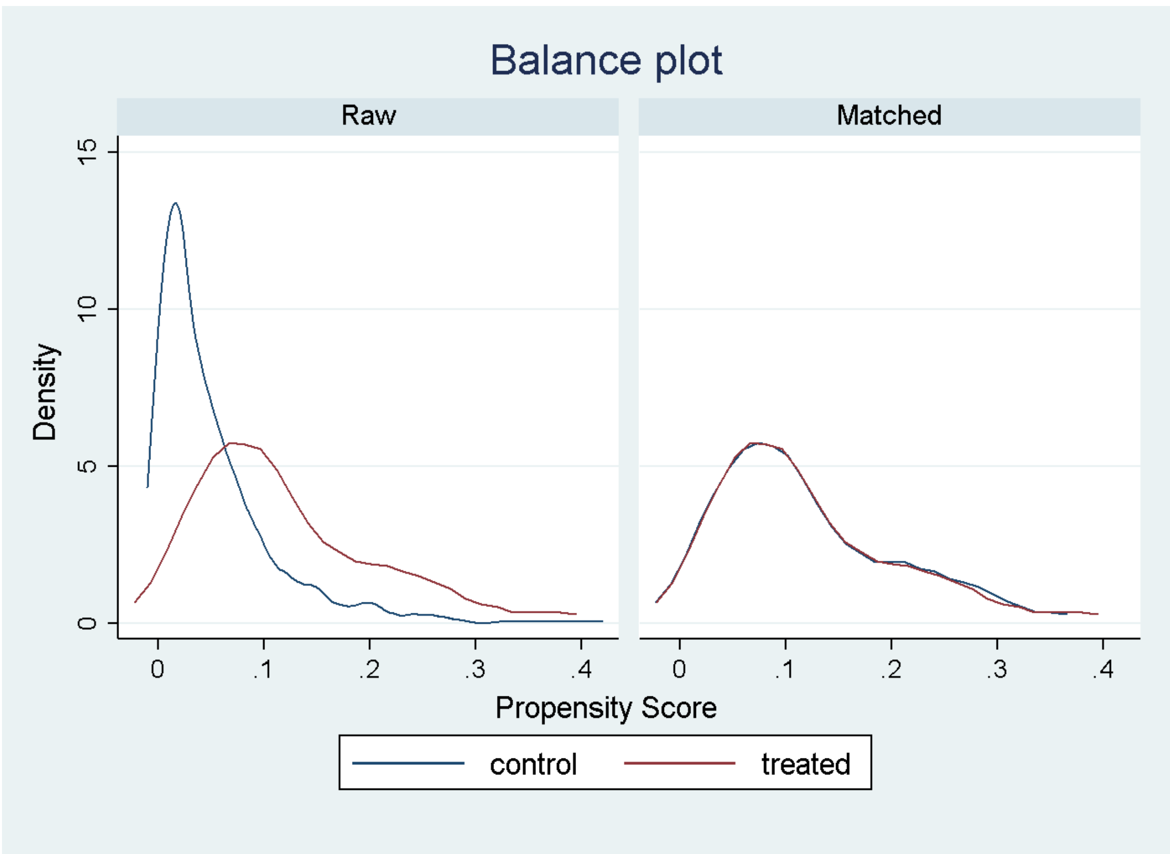

Figure 2.1 Balance Plot of Propensity Score

Table 2.3 Explanatory Variables Description

Covariate	Definition
cover.crops.2010.I	=1 if farmer planted cover crops in the last five years prior to 2010
water.on.or.along.farm	=1 if farmer indicated that creeks, streams, or rivers run through or along the farm
soil.erosion	=1 if farmer indicated to have had significant soil erosion on any of his or her land in the last five years in 2011
attitude.reduction	=1 if farmer believes that Iowa farmers should do more to reduce nutrient or sediment runoff into waterways
conservation.costs.I	=1 if farmer had incurred in any costs associated with conservation practices (excluding tile or similar drainage systems) over the past 10 years in 2010
drainage.expenditure.I	=1 if farmer had any expenditure associated with agricultural drainage systems over the past 10 years in 2010
log.ag.land	natural log of total farm acreage operated in 2013
rented	proportion of farm acreage rented in 2013
labor.off.farm	number of days worked off the farm in 2009
gross.farm.sales.I	=1 if farmer had gross farm sales above $250,000 in 2009
farm.income.I	=1 if percent of total net household income from the farm was above 51% in 2009
age	age of farmer
age.sq	age squared
college	=1 if the highest level of education completed was at least a Bachelor's degree in 2011
Central	=1 if farm is located in Central Agricultural District
East.Central	=1 if farm is located in East Central Agricultural District
West.Central	=1 if farm is located in West Central Agricultural District
North.Central	=1 if farm is located in North Central Agricultural District
North.East	=1 if farm is located in North East Agricultural District
North.West	=1 if farm is located in North West Agricultural District
South.Central	=1 if farm is located in South Central Agricultural District
South.West	=1 if farm is located in South West Agricultural District
livestock.I	=1 if farmer managed livestock in 2013
exp	number of years farming in the USA
exp.sq	experience squared
grains	proportion of farm acreage devoted to grain crops in 2013

Table 2.4 Summary Statistics of Explanatory Variables

	Treatment	Control	Difference in Means
cover.crops.2010.I	0.24	0.09	0.15 *
water.on.or.along.farm	0.90	0.72	0.18 ***
soil.erosion	0.31	0.28	0.03
attitude.reduction	0.83	0.83	0.00
conservation.costs.I	0.59	0.51	0.08
drainage.expenditure.I	0.59	0.54	0.05
log.ag.land	6.14	5.63	0.51 **
rented	0.37	0.32	0.05
labor.off.farm	90.48	78.94	11.54
gross.farm.sales.I	0.38	0.28	0.10
farm.income.I	0.52	0.51	0.01
age	62.66	66.18	-3.52 *
age.sq	4025.28	4463.62	-438.34 *
college	0.38	0.34	0.04
Central	0.17	0.14	0.03
East.Central	0.07	0.14	-0.07
West.Central	0.10	0.12	-0.02
North.Central	0.10	0.13	-0.03
North.East	0.17	0.12	0.05
North.West	0.14	0.14	0.00
South.Central	0.14	0.06	0.08
South.West	0.07	0.07	0.00
livestock.I	0.28	0.24	0.04
exp	39.79	41.40	-1.61
exp.sq	1671.17	1852.33	-181.16
grains	0.83	0.78	0.05

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level.
Statistical significance is based on Welch Two Sample t-tests.

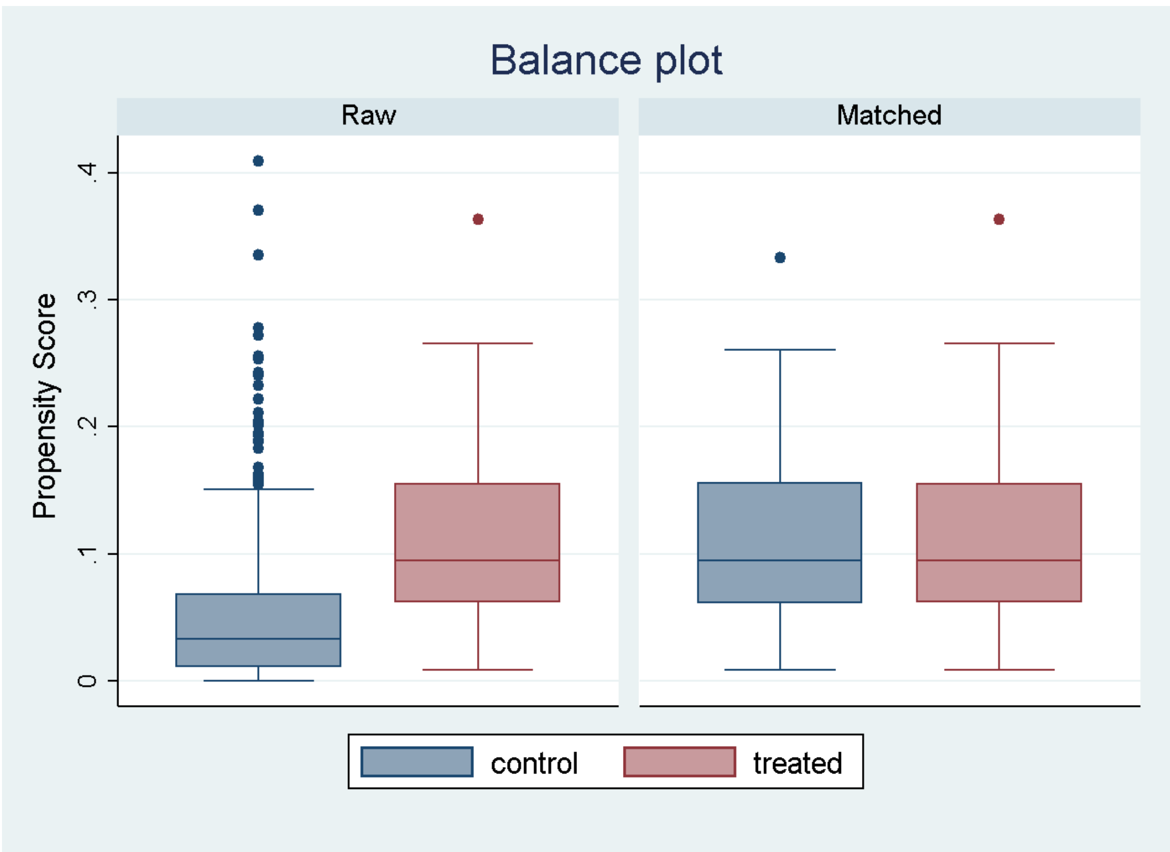

Figure 2.2 Box Plot of Propensity Score

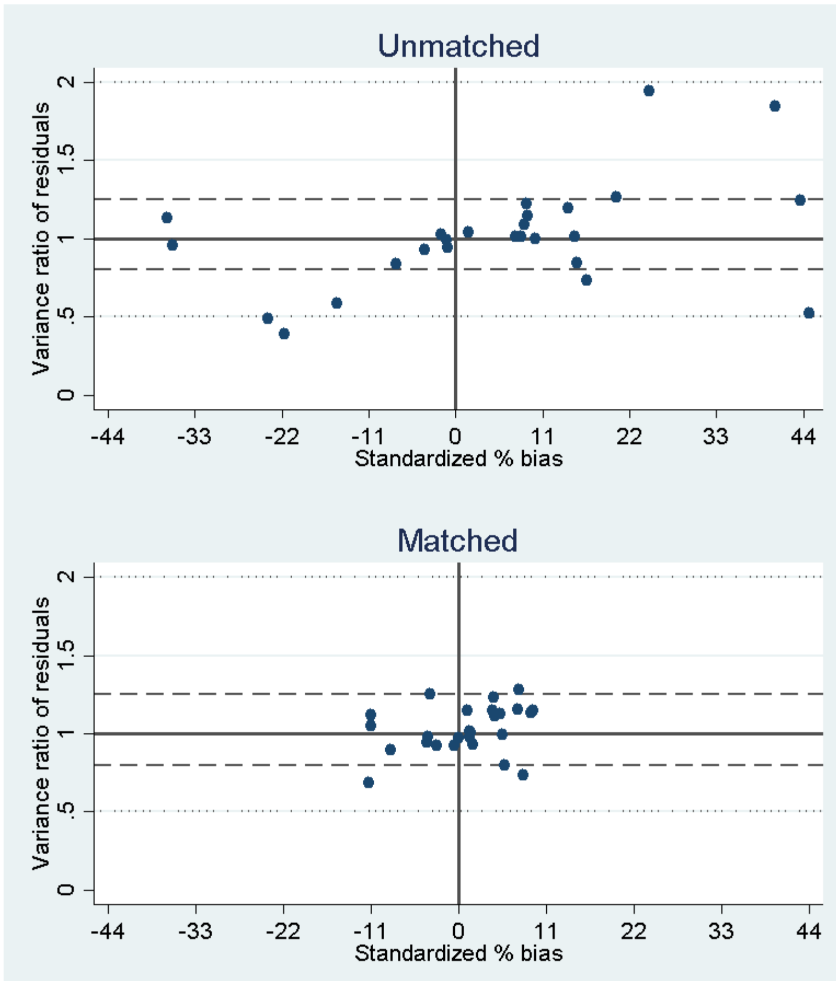

Figure 2.3 Variance Ratio of Residuals

Table 2.5 Probit Propensity Score Model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.5179	3.5331	0.15	0.8835
cover.crops.2010.I	0.7391	0.2732	2.71	0.0068 ***
water.on.or.along.farm	0.5947	0.3012	1.97	0.0483 **
soil.erosion	-0.0268	0.2306	-0.12	0.9073
attitude.reduction	-0.1646	0.2676	-0.62	0.5385
conservation.costs.I	-0.1535	0.2381	-0.64	0.5190
drainage.expenditure.I	-0.1136	0.2343	-0.48	0.6278
log.ag.land	0.3062	0.1530	2.00	0.0453 **
rented	-0.1975	0.3536	-0.56	0.5765
labor.off.farm	0.0006	0.0011	0.53	0.5946
gross.farm.sales.I	-0.1487	0.2857	-0.52	0.6028
farm.income.I	-0.1656	0.2605	-0.64	0.5249
age	-0.2086	0.1217	-1.71	0.0864 *
age.sq	0.0014	0.0010	1.51	0.1323
college	-0.0072	0.2252	-0.03	0.9745
Central	0.6780	0.5641	1.20	0.2294
East.Central	0.3855	0.6004	0.64	0.5209
West.Central	0.4840	0.5941	0.81	0.4153
North.Central	0.3949	0.5900	0.67	0.5033
North.East	0.7596	0.5711	1.33	0.1835
North.West	0.6671	0.5871	1.14	0.2559
South.Central	1.1256	0.6072	1.85	0.0638 *
South.West	0.5587	0.6335	0.88	0.3778
livestock.I	-0.0161	0.2489	-0.06	0.9484
exp	0.1300	0.0719	1.81	0.0706 *
exp.sq	-0.0015	0.0009	-1.71	0.0869 *
grains	0.1054	0.4948	0.21	0.8313

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level

Table 2.6 Matching Results

	Stand. Mean Difference	Variance Ratio
cover.crops.2010.I	0.06	1.09
water.on.or.along.farm	0.02	0.94
soil.erosion	0.01	1.01
attitude.reduction	-0.11	1.25
conservation.costs.I	-0.11	1.05
drainage.expenditure.I	0.01	1.00
log.ag.land	0.01	1.16
rented	0.08	0.84
labor.off.farm	0.09	1.19
gross.farm.sales.I	0.01	1.01
farm.income.I	0.05	1.00
age	0.04	1.14
age.sq	0.05	1.03
college	-0.08	0.97
Central	0.07	1.15
East.Central	-0.12	0.69
West.Central	0.00	1.00
North.Central	0.05	1.14
North.East	-0.04	0.94
North.West	-0.04	0.92
South.Central	0.04	1.09
South.West	-0.03	0.92
livestock.I	0.09	1.11
exp	-0.04	1.43
exp.sq	-0.01	0.97
grains	0.06	0.94

Table 2.7 Average Treatment Effect on the Treated for the Proportion of Crops Acres Relative to Total Farm Acreage (Y^1)

	Coefficient	AI Robust Std. Error	z	P> $|z|$	[95% Conf.	Interval]
ATT	0.20	0.04	4.73	0.000 ***	0.12	0.29

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level

Table 2.8 Average Treatment Effect on the Treated for the Proportion of Cover Crops (Y^1) using Other Matching Specifications

Method	ATT Coefficient	AI Robust Std. Error	P value
Nearest[2]	0.20	0.04	0.000 ***
Nearest[3]	0.22	0.04	0.000 ***
Genetic[4]	0.22	0.04	0.000 ***

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
[2] : probit propensity score matching with 4 neighbors and 0.20 caliper
[3] : logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement, 500 boots and 100 population size

Table 2.9 Tobit Model for Proportion of Cover Crops Planted Relative to Total Farm Acreage (Y^1)

	Estimate	Robust Std. Error	t value	Pr(>|t|)
(Intercept)	1.47	0.82	1.79	0.077
cost.share.I	0.40	0.05	8.65	0.000 ***
cover.crops.2010.I	0.13	0.06	2.09	0.039 **
water.on.or.along.farm	-0.03	0.06	-0.44	0.662
attitude.reduction	-0.01	0.09	-0.09	0.927
soil.erosion	-0.09	0.06	-1.49	0.140
conservation.costs.I	0.04	0.05	0.83	0.408
drainage.expenditure.I	0.03	0.06	0.59	0.558
log.ag.land	-0.10	0.04	-2.74	0.007 ***
rented	0.05	0.08	0.60	0.552
labor.off.farm	-0.00	0.00	-0.30	0.763
gross.farm.sales.I	0.11	0.06	1.88	0.062 *
farm.income.I	0.04	0.06	0.60	0.552
age	-0.03	0.03	-1.06	0.292
age.sq	0.00	0.00	0.99	0.324
college	-0.00	0.06	-0.07	0.948
Central	0.18	0.15	1.19	0.238
East.Central	0.12	0.15	0.76	0.446
West.Central	-0.00	0.13	-0.02	0.985
North.Central	-0.07	0.13	-0.55	0.586
North.East	0.08	0.15	0.51	0.611
North.West	0.10	0.16	0.61	0.541
South.Central	0.18	0.16	1.15	0.251
South.West	0.12	0.17	0.69	0.493
livestock.I	-0.04	0.06	-0.73	0.464
exp	-0.02	0.02	-0.73	0.466
exp.sq	0.00	0.00	1.02	0.310
grains	-0.02	0.12	-0.18	0.858

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Number of observations = 146
Number of corner solution outcomes at zero (i.e. non-adopters) = 97
Number of adopters of cover crops = 49

Table 2.10 Average Marginal Treatment Effect on the Expected Proportion of Cover Crops Acres Relative to Total Farm Acreage (Y^1) among Adopters

	Marginal Effect	Delta-Method Std. Error	z	P> $\|z\|$	[95% Conf.	Interval]
cost.share.I	0.18	0.02	8.65	0.000 ***	0.14	0.22

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level

Table 2.11 Average Marginal Treatment Effect on the Expected Proportion of Cover Crops Acres Relative to Total Farm Acreage (Y^1) among Adopters using Other Matching Specifications

Method	Marg. Effect	Delta-Method Std. Error	z	P> $\|x\|$	[95% Conf.	Interval]
Nearest[2]	0.20	0.04	4.51	0.000 ***	0.11	0.28
Nearest[3]	0.22	0.04	5.37	0.000 ***	0.14	0.30
Genetic[4]	0.21	0.02	8.82	0.000 ***	0.16	0.25

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
[2] : probit propensity score matching with 4 neighbors and 0.20 caliper
[3] : logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement, 500 boots and 100 population size

Table 2.12 Average Treatment Effect on the Treated for Cover Crops Acres (Y^2)

	Coefficient	AI Robust Std. Error	z	P> |z|	[95% Conf.	Interval]
ATT	81.37	32.37	2.51	0.012 **	17.92	144.82

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level

Table 2.13 Average Treatment Effect on the Treated for Cover Crops Acres (Y^2) using Other Matching Specifications

Method	ATT Coefficient	AI Robust Std. Error	P value
Nearest[2]	73.90	27.82	0.008 ***
Nearest[3]	102.70	9.39	0.000 ***
Genetic[4]	104	24.2	0.000 ***

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
[2] : probit propensity score matching with 4 neighbors and 0.20 caliper
[3] : logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement, 500 boots and 100 population size

Table 2.14 Tobit Model for Proportion of Cover Crops Acres Planted (Y^2)

	Estimate	Robust Std. Error	t value	Pr(>|t|)
(Intercept)	614.10	544.93	1.13	0.262
cost.share.I	280.85	59.75	4.70	0.000 ***
cover.crops.2010.I	136.81	85.35	1.60	0.112
water.on.or.along.farm	30.82	49.84	0.62	0.538
attitude.reduction	102.57	75.42	1.36	0.176
soil.erosion	-22.25	44.04	-0.51	0.614
conservation.costs.I	14.99	41.23	0.36	0.717
drainage.expenditure.I	124.18	66.13	1.88	0.063
log.ag.land	-6.24	32.73	-0.19	0.849
rented	51.50	79.29	0.65	0.517
labor.off.farm	-0.22	0.22	-1.00	0.321
gross.farm.sales.I	147.00	69.79	2.11	0.037 *
farm.income.I	2.40	45.20	0.05	0.958
age	-14.47	22.17	-0.65	0.515
age.sq	0.13	0.18	0.75	0.454
college	-35.51	44.58	-0.80	0.427
Central	328.88	177.49	1.85	0.066 .
East.Central	230.67	180.71	1.28	0.204
West.Central	201.40	159.85	1.26	0.210
North.Central	132.29	143.43	0.92	0.358
North.East	260.87	196.72	1.33	0.187
North.West	240.47	179.41	1.34	0.183
South.Central	221.84	172.12	1.29	0.200
South.West	186.70	167.15	1.12	0.266
livestock.I	-26.34	49.76	-0.53	0.598
exp	-49.44	27.01	-1.83	0.070 .
exp.sq	0.74	0.37	2.00	0.048 *
grains	-148.65	95.84	-1.55	0.124

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Number of observations = 146
Number of corner solution outcomes at zero (i.e. non-adopters) = 97
Number of adopters of cover crops = 49

Table 2.15 Average Marginal Treatment Effect on the Expected Cover Crops Acres Planted (Y^2) among Adopters

	Marginal Effect	Delta-Method Std. Error	z	P> |z|	[95% Conf.	Interval]
cost.share.I	103.78	17.66	5.88	0.000 ***	69.16	138.34

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level

Table 2.16 Average Marginal Treatment Effect on the Expected Cover Crops Acres Planted (Y^2) among Adopters using Other Matching Specifications

Method	Marg. Effect	Delta-Method Std. Error	z	P> |z|	[95% Conf.	Interval]
Nearest[2]	104.92	19.40	5.41	0.000 ***	66.90	142.93
Nearest[3]	103.65	14.12	7.34	0.000 ***	75.98	131.32
Genetic[4]	106.17	20.35	5.22	0.000 ***	66.29	146.05

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
[2] : probit propensity score matching with 4 neighbors and 0.20 caliper
[3] : logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement, 500 boots and 100 population size

CHAPTER 3. GENDER SPECIFIC RISK PREFERENCES, INTRA-HOUSEHOLD BARGAINING, AND INVESTMENT DECISIONS: EXPERIMENTAL EVIDENCE FROM RURAL CAMEROON

María Jimena González Ramírez and Niccolo Meriggi

3.1 Abstract

Motivated by the importance of intra-household dynamics both for the success of development policies and for the effectiveness of interventions intended to enhance social welfare, we study spouses' differences in risk preferences, the relative influence of spouses on household decisions under risk, and their implications on household educational and medical expenditure decisions in rural Cameroon. Our study is based on the results from a lab-in-the-field risk experiment in which husband and wife individually participated in isolation and then participated together as a couple. Using the experimental results, we focus on risk preference differences between spouses, spouses' individual influence over the couple's joint decision, and the relation between this relative influence and different expenditure decisions. Chapter 3 answers the following research questions: (i) Are there differences in risk preference between husbands and wives within households?; (ii) are there differences in the relative influence of each spouse over joint decisions involving risk?; and (iii) how does this relative influence affect educational and medical expenditure decisions within a household?

Our results provide evidence of risk aversion among husbands, wives, and couples (i.e. husband and wife together) on average, in which husbands are more risk averse than wives and couples. We identify some factors influencing the heterogeneity in risk preferences between

spouses including whether the wife chose her husband for marriage and whether the wife worked during the past year. For the relative influence of spouses over couple's decisions under risk, we find variables that increase the likelihood that one spouse is closer to the couple. Moreover, using a proxy for female bargaining power based on the difference in choices between each spouse and the couple, we find that monogamous wives are more likely to be more empowered than polygamous wives. At the same time, monogamous wives married to Muslim husbands are more likely to be less empowered than monogamous wives married to non-Muslim husbands. Lastly, we find that the proxy for female bargaining power is positively correlated with educational and medical expenditures. Our results provide a deeper insight into intra-household dynamics in the studied area, but more research is required to continue informing policy and supporting the generation of more effective development strategies in the region.

3.2 Introduction

Risk is intrinsic to everyone's daily life and many decisions revolve around risk considerations. Economic decisions made by households are no exception; yet, neo-classical economics has failed to adequately capture dynamics among household members (de Palma et al. 2011, Drichoutis & Koundouri 2012, Carlsson et al. 2013). Expected Utility models treat households as homogenous units with analogous preferences, allocating (scarce) resources to maximize joint welfare (Becker 1974, Chiappori and Meghir 2015). Under the unitary household model, consumption choices are modeled as a constrained utility maximization by a single decision-maker subject to a pooled resource constraint (Becker 1974). This assumption of a unitary household ignores the relative influence each household member has on the decision process and any differences in risk preferences among them. As a result, this unitary household model may not provide an accurate representation of household decisions ignoring, amongst other things, individual spouses' preferences and their relative influence on joint decisions (Carlsson et al. 2012, Sheremenko & Magnan 2015). Given the important influence of household heads and their spouse(s) over the allocation of households' resources, a lack of understanding of between-spouses/intra-household decision making processes may hinder the effectiveness of development policies targeting households' decisions.

In recent years, economists have acknowledged the complexity of intra-household dynamics, developed models taking into account the heterogeneity in preferences of different (key) household members, and therefore moved closer to an accurate representation and understanding of real world dynamics (Alderman et al. 1995; Bateman and Munro 2003, 2005, 2009; de Palma et al. 2011; Carlsson et al. 2012, 2013; de Brauw and Eozenou 2014; Butle et al. 2015; Castilla 2015; Sheremenko and Magnan 2015). While some of these models study heterogeneity in preferences within households, only some compare individual and joint decisions of spouses (Bateman and Munro 2005, 2009; de Palma et al. 2011; Carlsson et al. 2012, 2013; Butle et al. 2015). In reality, intra-household choices are affected by the bargaining power of each spouse (Sheremenko & Magnan 2015). Understanding female bargaining power is important as studies have observed stronger preferences for child schooling and health outcomes among females (Hoddinott and Haddad 1995, Duflo 2003). Also, women are less likely to allocate resources towards alcohol or tobacco (Hoddinott and Haddad 1995). Understanding these differences in preferences can facilitate the accumulation of human capital and ultimately result in better household outcomes. Taking into account spouses' influence on household decisions can therefore help researchers and policy makers design better development programs.

New advances in the literature have penetrated the policy sphere, and they are increasingly raising policy makers' awareness of the importance of intra-households dynamics and gender issues for development effectiveness (Doss 2013). This awareness has motivated increasing efforts to understand: i) the heterogeneity in risk preferences across spouses, which has been found to be gender specific in different contexts, ii) the relative influence of respective preferences on household joint decisions (i.e. bargaining power), and iii) their repercussions on the allocation of resources within a household. Motivated by the importance of intra-household dynamics both for the success of development policies and for the effectiveness of interventions intended to enhance social welfare, we study intra-household differences in risk preferences, the relative influence of spouses on household decisions, and their implications on household expenditure decisions in rural Cameroon. Our study is based on the results from a lab-in-the-field risk experiment in which husband and wife individually participated in isolation and then participated together as a couple. Using the experimental results, we focus on specific differences between spouses, spouses' individual influence over the couple's joint decision, and the relation between this relative influence and different household expenditure decisions. We answer the following questions: (i) Are there differences in risk preference between husbands and wives within households?; (ii) are there differences in the relative influence of each spouse over joint decisions involving risk?; and (iii) how does this relative influence affect household educational and medical expenditure decisions? By investigating these questions, we enhance the understanding of the dynamics underlying households' investment decisions in less developed countries.

Our results provide evidence of risk aversion among husbands, wives, and couples (i.e. husband and wife together) on average, in which husbands are more risk averse than wives and couples. We identify some factors influencing the heterogeneity in risk preferences between spouses including whether the wife chose her husband for marriage and whether the wife worked during the past year. For the relative influence of spouses over couple's decisions under risk, we find variables that increase the likelihood that one spouse is closer to the couple. Moreover, using a proxy for female bargaining power based on the difference in choices between each spouse and the couple, we find that monogamous wives are more likely to be more empowered than polygamous wives. Moreover, monogamous wives married to Muslim husbands are more likely to be less empowered than monogamous wives married to non-Muslim husbands. Lastly, we find that the proxy for female bargaining power is positively correlated with educational and medical expenditures. Our results provide a deeper insight into intra-household dynamics in the studied area, and can inform policy and support the generation of more effective development strategies in the region.

3.3 Literature Review

To better understand household's decisions, experiments have been employed to study intra-household dynamics and gender differences in preferences. While differences in risk preferences is a major component of our paper, it is worth mentioning studies that document other intra-household and gender-specific differences in preferences. For instance, Bateman and Munro (2009) use a choice experiment given to cohabiting couples to study differences between household and individual valuations of dietary health risks. They find significant differences between the values calculated from joint versus individual responses as well as between men and women. Carlsson et al. (2012) study differences in intertemporal choices among households. They analyze the relative influence of husband's and wife's own choices on their joint decisions and find that in the majority of the households, husbands have stronger influence over joint decisions relative to wives. Castilla (2015), using a trust game among married couples, finds that men return significantly more money than women. However, prior non-cooperation behavior among husbands is associated with less sharing by their wives. Lastly, de Brauw (2015) studies the way women's empowerment affect crop productivity and finds that the ability to make decisions in positively correlated with additional control over family income. These papers illustrate the expansion in the understanding of the heterogeneity in preferences within households that goes beyond differences in risk preferences.

Our study on intra-household dynamics and spouses' differences in risk preferences builds upon existing literature. Bateman and Munro (2005) is one of the first studies that looks at joint decisions among couples. Using experimental data from couples in Norwich, United Kingdom, they conclude that couples' joint choices are typically more risk averse than those made by individuals. Moreover, when studying whether couples' behavior follows the axioms from Expected Utility theory, they find that couples also exhibit the same anomalies observed among individuals. De Palma et al. (2011) use a series of binary choices with a sure amount as the safer choice to estimate both the spouses' and the couple's degrees of risk aversion in Germany. They focus on the dynamics of the decision-making process among couples and conclude that the balance of power is changeable. In most cases, the male partner has more decision-making power at the beginning. However, female partners gain more power over the course of the experiment. They find that the average couple tends to be less risk averse than its average members (de Palma et al. 2011).

Among the different experimental designs, two lab-in-the-field experiments appear to be the most popular methods to elicit risk preferences. Holt and Laury's (2002) multiple price lotteries experiment, in which the payoffs are fixed and the probabilities change in each choice task, has been widely employed to derive risk preferences in the literature (Drichoutis & Koundouri 2012, Carlsson et al. 2013, de Brauw & Eozenou 2014). On the other hand, Tanaka et al.

(2010) elicitation method is also commonly used (Tanaka et al. 2010, Sheremenko & Magnan 2015). Their method is different from Holt and Laury's (2002) as they employ three series of paired lotteries with a total of thirty-five choices that are used to derive three parameters from Prospect Theory (Kahneman & Tversky 1979). Besides the concavity of the utility function that has been used to characterize risk preferences, their method also derives parameters for nonlinear probability weighting and loss aversion. Differently from Holt and Laury (2002), they enforce monotonic switching, preventing subjects from switching more than once and enforcing the direction of the switch. Enforcing consistent choices (i.e. a single switching point) could bias the results, as individuals who would behave inconsistently are kept in the sample (Charness et al. 2013). In essence, if inconsistent choice data is treated as noise and is dropped from the analysis, researchers can be confident that the subjects in the remaining sample understood the instructions and are revealing their true preferences (Charness et al. 2013).

Tanaka et al. (2010) study risk preferences in Vietnamese villages and find that village mean income is correlated with risk and time preferences. However, they do not study intra-household dynamics or spouses' differences in preferences. Sheremenko and Magnan (2015) follow Tanaka et al.'s (2010) elicitation method and study the way experimentally derived risk parameters of individual spouses in farming households affect fertilizer use in Kenya. They also analyze the relation between female bargaining power, risk preferences, and household's agricultural choices and find that more empowered women who are more risk and loss averse apply less fertilizer than disempowered females in collective households.

Our paper utilizes data from a lab-in-the-field experiment that follows Holt and Laury's (2002) elicitation method. The study that is most related to ours is Carlsson et al. (2013), as they study the relation between couple's joint and individual spouses' choices using Holt and Laury's (2002) risk experiment in rural China. They observe that the joint decision is typically closer to the husband's decision and the couple is typically less risk averse than the husband. Moreover, they study factors that favor a stronger influence of the wife over the joint decision. For instance, female preferences tend to be better reflected in the joint decision in wealthier households. De Brauw and Eozenou (2014) also follow Holt and Laury (2002) and design a hypothetical experiment to elicit risk preferences focused on sweet potato production in Mozambique. They use their lab-in-the-field experiment to test different models of risk preferences, and they observe that rank dependent utility dominates expected utility theory. Furthermore, they reject the Constant Relative Risk Aversion (CRRA) hypothesis.

We contribute to the literature by expanding the understanding of intra-household dynamics using a unique dataset that contains information on 1689 households from rural Cameroon. The size of our sample is very large relative to other studies[1], and it includes results from a lab-in-the-field experiment for the head of the household, his wife, and the couple together. Using this large dataset, we study spouses' heterogeneity in risk preferences and the relative influence each spouse has on the decision process. We compare our results to previous studies. In addition, we construct a new proxy measurement of female bargaining power using individual spouses' and couple's experimental results. We contribute to the literature by analyzing factors that affect female empowerment and the relation between wife's bargaining power and household educational and medical expenditures.

3.4 The Experiment

3.4.1 Data Collection and Sample

Our study was conducted in 200 rural villages in the Adamawa region of Cameroon (See Figure 3.7 for map). The data collection was funded partly by the Dutch National Science Foundation[2] and carried out with the support of the Netherlands Development Organisation (SNV) and the Cameroonian Institute of Statistics (INS). These villages were randomly selected from a homogeneous sub-population (stratum) of all villages in the region (contained in 2005 census). Between May and July of 2013, 3600 households heads residing in the selected villages were administered a questionnaire capturing the living conditions of people in the region. The

[1] Bateman and Munro's (2005) sample has 76 couples; de Palma et al. (2011) have information on 22 couples who answered 3828 lotteries; Carlsson et al. (2012) has information on 101 couples; Carlsson et al. (2013) uses a sample of 117 households; de Brauw and Eozenou (2014) have information on 682 farmers from 439 households; Castilla (2015) has information on 188 married couples; and Sheremenko and Magnan (2015) has information on 304 individuals from 172 households.

[2] Nederlandse Organisatie voor Wetenschappelijk Onderzoek (NWO) grant number 453-10-001. The funding came through the "Biogas Research and Innovation Project." This project is linked to the Cameroonian National Biogas Programme, which was implemented in collaboration with the Cameroonian ministry of Water and Energy and the Cameroonian National Institute of Statistics.

same group of households were visited again between October and December of 2013 to take part of a sequence of lab-in-the-field experiments measuring individuals' risk preferences and social preferences (i.e. altruism, trust, trustworthiness and distributional preferences). The Cameroonian National Institute of Statistics (INS) helped with the data collection. The coordination and supervision of the project were led in collaboration with five senior INS members, two[3] Ph.D. and two MSc students from Wageningen University. The project hired and trained[4] 150 enumerators for the data collection, who were either current or formers students from the University of Ngaoundere or former INS workers who were very proficient. Having local enumerators was extremely important to overcome language and cultural barriers. Every four to six enumerators were assigned to a team that was coordinated by a team leader. At the same time, team leaders were supervised by the five senior INS members and the PhD and MSc students.

From the 3600 households in the initial sample, 3195 participated in the lab-in-the-field experiments. Given our research questions, we focus on households in which we observe responses for the lab-in-the-field risk preference experiment for the male head of the household, his wife or female partner, and the joint decision. In polygamous households, the wife was selected by the husband. Given this criteria, our sample includes married couples as well as couples living under common law, and it excludes single individuals, widows, widowers, and divorcees. This subset of couples has 1689 households.

Table 3.1 includes the average of several demographic characteristics. We observe that husbands[5] are over 10 years older than wives[6] on average. Most of our sample contains husbands and wives who are Muslim, and their religions are highly correlated. Around half of our sample

[3]Including Niccolo Meriggi, who provided the sampling, design, questionnaires, and training manual, and who also administered all the training.

[4]For each round of data collection, manuals and survey instruments were tested with a group of 10 enumerators first. Each pre-test lasted for about 12 days, and it consisted of lectures and simulations for the first week. The training continued by testing all instruments for 2 to 3 days at pre-test villages, five villages that were not part of the study sample. Improvements derived from this pre-test and training session were incorporated in the main training session for 170 enumerators. This main training lasted between 14 and 18 days, and it followed a similar format as the pre-test training. After the 10th day, enumerators were divided into smaller groups and went through some simulations supervised by previously trained enumerators. Enumerators were assessed throughout the training, and only the best performing enumerators were retained for the experiment.

[5]For now on, husbands refer to male heads of households, which include married men and men from common law partnerships.

[6]Wives refer to the female partner of the head of the household, and it includes both married women and women living under common law unions.

lives in a monogamous household. Amongst polygamous households, the first wife is more likely to be chosen as "game partner" by the male household head. The average number of children is around 5, but there is a higher number of sons than daughters on average. The majority of couples belong to the same ethnic group, and the majority of husbands paid a dowry for their wives. Only a third of wives were able to choose their husbands when they got married, as opposed to having a family member choosing for them. Around 70 percent of wives and 96 percent of husbands worked during the past year. Based on the question about their level of welfare relative to other households in the village, the average response is below the same level category.[7] In other words, the average household reports a slightly lower welfare level than other households in the village. A larger percentage of husbands have attended school relative to wives, but we observe that the majority has not attended any school. Adamawa is one of the least educated regions in Cameroon. Educational participation is low as there is a perceived association of formal schooling with Christianity or Westernization (Usman 2006).

3.4.2 Experimental Design and Procedure

Risk preferences were measured for the head of the household and (one of)[8] their spouses individually in each household, following the procedure described in Holt and Laury (2002). The experiment was administered by two enumerators, one male and one female. The male and female enumerators individually interviewed the husband and the wife respectively. At first, respondents (husband and wife) were presented with a sequence of ten paired lotteries individually in isolated locations within their household and were asked to decide their favored option in each lottery over hypothetical gains (see Table 3.2). Then, participants were brought to the same location and worked through the same lottery choices together. Both male and female enumerators were present, but only one[9] enumerator administered the questions. All

[7]Based on the following question: In your opinion, how is your household level of welfare relative to others in the village? =1 if much worse, =2 if worse/lower, =3 if the same, =4 if better, and = 5 if much better.

[8]For polygamous households, the husband chose a wife to participate in the experiment. Among polygamous households that participated in the lab-in-the-field experiment, we compare wives who were selected by their husband to participate in the risk game with wives who were not selected. The only major difference we find is age. It appears as if husbands selected older wives on average. However, for the other demographic characteristics, we find no statistically significant differences.

[9]The male enumerator more often administered the questions for the joint couple's portion of the experiment.

choices were made with the understanding that one of the choices would be randomly selected as a payoff at the end of the experiment.

From the lottery decisions in Table 3.2, Option A is considered safer than Option B, as the difference in payoffs for each probability is smaller. For both options, payoffs are constant, and probabilities change for each decision. Looking at the expected payoff from each option, a risk neutral individual switches from Option A to Option B after the fourth decision. Individuals who switch to Option B after the fifth decision are considered risk averse and individuals who choose Option B before the fourth decision are considered risk lovers. The later the individual switches to Option B, the more risk averse he or she is. Moreover, for the tenth decision, Option B should be selected, as it clearly has a higher payoff with certainty. Individuals who choose Option A at the tenth decision may not have understood the experiment.

3.4.3 Inconsistent Responses

Before we study intra-household and gender differences in risk preferences, we analyze the quality of the responses from the lab-in-the-field experiment by computing the number of inconsistent responses and by looking at a measurement of the understanding of the experiment. For the former, we compute the number of households with inconsistent responses that arise from two reasons: either the subject chose Option A at the tenth lottery or the subject had multiple switching points. Table 3.3 summarizes the number of inconsistent responses per group based on both criteria.

More husbands choose Option A at the tenth decision relative to wives. Once husband and wife make decisions jointly, we find that the percentage of inconsistent responses is the lowest. For multiple switching points, there are now more inconsistent wives relative to husbands. Again, couples have the least number of inconsistent choices. Considering both inconsistencies together, we observe a very similar percentage of inconsistent responses for husbands and wives, and a lower percentage for couples. This persistent decrease in inconsistent responses for couples suggests that each spouse is learning from the other.

The percentage of inconsistent responses at the tenth decision for each individual group is comparable to results found in other experiments that range from 6 to 23 percent (de Brauw

& Eozenou 2014, Carlsson et al. 2013, de Palma et al. 2011, Bateman & Munro 2005, Holt & Laury 2002). However, once we also remove inconsistent responses based on multiple switching points, we find that the percentage of inconsistent responses is higher relative to other studies. Nonetheless, as we remove households with inconsistent responses for either husband, wife, or couple, we expect to have a higher percentage removed. In fact, Carlsson et al. (2013) observe around 10 percent of inconsistent responses for husbands, wives, and couples separately. However, once they remove inconsistent households, the percentage of inconsistent responses almost doubles to 19 percent. We also observe that once we remove inconsistent responses at the household level, the percentage removed goes from around 30 percent for individual spouses and 21 percent for couples to 54 percent at the household level. Besides looking at the number of inconsistent responses, we also explore participants' understanding by looking at an assessment by the enumerators. After the last decision, each enumerator was asked to assess the understanding of each subject. The evaluation ranged from 1 to 10, with 10 being perfect understanding. For husbands, wives, and couples, the average evaluations are 9.36, 9.27, and 9.43 respectively. These high scores support the usage of the entire sample without removing inconsistent households.

3.5 Methodology and Results

Using the experiment and the survey, we study the difference in risk preferences between husbands and wives, the relative influence of each spouse on joint decisions, and the way this relative influence affects educational and medical household expenditures. Our research strategy consists of studying differences in risk choices at the aggregate level and at the household level. At the aggregate level, we study the proportion of individuals choosing the safe choice and the similarity in responses among different comparison groups at each decision. At the household level, we study factors that affect the similarity of the couple's joint decisions to each spouse's decision separately. We also study characteristics that affect the likelihood that a couple's decision is closer to the husband's decision, the wife's decision, or equally distant from both. Using a proxy for measuring wife's empowerment based on individual and joint experimental results, we further study factors that may increase or decrease the wife's relative influence over the joint decision. We conclude our study by analyzing whether this measurement of female bargaining power is correlated with educational and medical household expenditure decisions.

3.5.1 Intra-household Differences in Risk Preferences using Aggregate Data

Since a risk neutral individual is expected to choose four safe choices, the number of safe choices indicates the degree of risk aversion for each subject, where having more (fewer) than four safe choices implies risk aversion (loving). To study intra-household differences in risk preferences, we illustrate the experimental results with two graphs based on the raw data. Figure 3.7 depicts the number of safe choices per decision for three groups: husbands, wives, and couples. Husbands, wives, and couples do not respond as risk neutral decision-makers. As reference, the black dashed line represents the expected behavior of a risk neutral individual, who is expected to choose the safe choice (Option A) for the first four decisions, and then switch to the risky choice (Option B) from the fifth to the tenth decision. Around 10 percent of husbands, wives, and couples behaved a risk neutral decision makers. We observe some risk loving individuals to the left of the fourth decision choosing the riskier option.[10] At the first decision, we observe around 73, 75, and 78 percent of husbands, wives, and couples choosing the safe choice. At the fourth choice, we observe around 64, 65, and 67 percent of husbands, wives, and couples choosing the safe choice. Compared to Holt and Laury (2002) and de Brauw and Eozenou (2014), the decreasing proportion of safe choices per decision is also observed. However, these studies do not focus on gender and intra-household differences.

Concentrating on the different groups, we observe that couples (purple line with diamonds) tend to be closer to risk neutral relative to husbands (blue line with dots) and wives (red line with triangles). In particular, we observe a higher proportion of safe choices among couples during the first four decision and a lower proportion of safe choices after the sixth decision. For the fifth decision, we observe a higher proportion for couples, but the three groups are very close to each other. Moreover, we observe that the three groups tend to be closer to each other between the fourth and sixth decision. We notice a larger proportion of highly risk loving

[10] While other studies have also found risk loving individuals, Holt and Laury (2002) and de Brauw and Eozenou (2014) find a higher proportion of safe choices at decisions 1 through 4 ranging from 80 to 90 percent.

husbands at the first decision and highly risk averse husbands at the ninth and tenth decisions. The line for the proportion of safe choices among wives is between the couples' and husbands' lines.[11]

For the second visual illustration, we compare the percentage of identical choices among three comparison groups: i) husbands and wives ii) husbands and couples, iii) wives and couples, and iv) husbands, wives, and couples in Figure 3.7. As de Brauw and Eozenou (2014) explain, similar responses are expected around the tails of the experiment. We observe more similar choices at the end tail of the experiment relative to the beginning of the experiment.[12] As in their experiment, we observe more divergence in choices at the sixth decision for most comparison groups. In particular, we observe around 54, 60, and 70 percent of same responses among husband and wife[13], wife and couple, and husband and couple respectively. Furthermore, we observe around 42 percent of households with same responses for the husband, wife, and couple at the sixth choice. There are more response matches between husband and couple than for the other comparison groups at each decision. Focusing on the sixth choice, we observe that the husband and couple's choices within a household match 70 percent of the time relative to 60 percent between wife and couple's choices. This difference in percentages suggests that the husband's choice tends to be closer to the couple's choice within a household. There are more matches for the comparison groups between the couple and each spouse than for the husband and his wife (green and blue line are above purple line). Moreover, choices diverge the most when we compare the three subjects (i.e the husband, wife, and couple) within each household.[14]

Besides the visual representation of the experimental results, we also analyze the average number of safe choices per group summarized in Table 3.4. For inconsistent husbands, wives, or couples, we assign the median[15] between the first and last switch points from Option A

[11] We generated a similar figure using the subset of the data that excludes households with inconsistent responses (N=784). We observe a similar pattern in which each group does not follow risk neutral expectation, and in which we observe more highly risk loving husbands relative to wives and couples.

[12] De Brauw & Eozenou (2014) do not see major difference across tails.

[13] De Brauw & Eozenou (2014) find that husband and wife's choices only match 57 percent of the time at the sixth decision.

[14] We generated a similar figure using a subset of the data that excludes households with inconsistent responses (N=784). In general, we observe a similar pattern among the four comparison group lines.

[15] In cases where the median is not a whole number, we round up.

to Option B as the switching point for inconsistent subjects, as suggested by Carlsson et al. (2013). The number of safe choices is calculated as the assigned switch point minus one for subjects with inconsistent responses. The average number of safe choices is higher for husbands (5.02) relative to wives (4.84) and to couples (4.90), as was observed by Carlsson et al. (2013).[16] The average number of safe choices for the joint decision lies between the husbands' and wives' averages, which is also observed by Carlsson et al. (2013).[17] However, the difference in means seems smaller relative to their study.[18] These averages illustrate the existence of risk aversion in the aggregate data. Kolmogorov-Smirnov two-sided test finds statistically significant difference between the distribution of safe choices between husbands and wives with a p-value below 0.001.

Since the number of safe choices can be used as a proxy for risk aversion, we also analyze the proportion of subjects with a particular number of safe choices. From Table 3.5, we observe a large proportion of highly risk loving husbands, wives, and couples, who never chose the safe choice in any of the decisions.[19] Overall, a large proportion of husbands, wives, and couples have between four and six safe choices, which has also been observed in previous studies (Holt & Laury 2002, and Carlsson et al. 2013). Lastly, we also observe highly risk averse individuals who chose the safe choice nine to ten times.[20]

From this section, we start exploring our first and second research questions using aggregate data. Results from the lab-in-the-field experiment provide evidence of risk aversion among husbands, wives, and couples on average. While the majority of subjects do not behave as risk-neutral individuals, we find intra-household differences in risk preferences, in which there are

[16] Differently, Bateman and Munro (2005) find that couple's joint choices are typically more risk averse than those made by individuals based on their study in Norwich, United Kingdom.

[17] Differently, de Palma et al. (2011) find that the average couple tends to be less risk averse than its average members.

[18] Carlsson et al. (2013) study's average number of safe choices are 5.82, 5.39, and 5.65 for Chinese husbands, wives, and couples respectively among consistent choices only. We find that Chinese husbands, wives, and couples appear to be more risk averse relative to our study's results in Cameroon.

[19] Other studies find lower proportions of highly risk loving individuals: Holt and Laury (2002) find between 1 and 3 percent of individuals who chose zero to one safe choices. Carlsson et al. (2013) find 2, 9 and 6 percent of husbands, wives, and couples who chose zero to one safe choices. Lastly, de Brauw and Eozenou (2014) find 3 percent of individuals who chose zero safe choices.

[20] Carlsson et al. (2013) observe 25, 17 and 14 percent of husbands, wives, and couples respectively with 9 safe choices. Differently, Holt and Laury (2002) observe between 1 and 6 percent of individuals choosing between 9 and 10 safe choices depending on the payoff. Lastly, de Brauw and Eozenou (2014) observe 10 percent of individuals with 10 safe choices.

more risk averse husbands relative to wives and couples. For the second question, we observe more matches between husband's and couple's choices at each decision than between wife's and couple's choices, which suggests that husbands tend to be closer to the couple's choice within a household. While this aggregate data analysis offers a first glance at intra-household differences in risk preferences, we continue with a household level analysis that provides more insight in the remaining of the paper.

3.5.2 Differences in Risk Preferences among Spouses within a Household

Focusing on household level data, we continue addressing our first research question and studying whether there are differences in risk preferences among spouses within a household employing two strategies. Following Carlsson et al. (2013), we study the similarity of spouses' individual decisions using a negative binomial model and focusing on the absolute difference in risk preferences (i.e. safe choices). Secondly, we estimate the likelihood that a wife is more, equally, or less risk averse than her husband using an ordered probit model, incorporating the sign of the difference in safe choices.

For the first strategy, we estimate a negative binomial model with the absolute difference in safe choices by husband and wife as the dependent variable. For every model, we employ the assigned number of safe choices, calculated based on the median between first and last switch points, for inconsistent subjects. Table 3.6 summarizes the marginal effects, calculated as the average partial effect among all observations, of different factors that might influence the similarity, in absolute value, in risk choices between spouses. Couples with older wives are more likely to have a larger absolute difference in safe choices than couples with younger wives on average. However, the size of this marginal effect is very small. Wives who reported that they chose their husbands for marriage, as opposed to having any family member choosing for them, are more likely to have similar choices to their husbands. The absolute difference in safe choices decreases by about half a point for wives who chose their husbands on average. The decision power in the marriage process could favor the match of more similar spouses, which could explain the sign and significance of this marginal effect.

For the second strategy, we assign each couple to three categories based on their difference in risk preferences[21]: (1) wife is less risk averse than her husband[22], (2) wife is equally risk averse as her husband[23], and (3) wife is more risk averse than her husband[24]. Each category is assigned based on the difference in number of safe choices, where having a higher number of safe choices implies more risk aversion. We observe 753, 241, and 685 in each category respectively, showing again that we have more risk averse husbands relative to wives. We estimate an ordered probit model with the constructed categories as the dependent variable. We find that the predicted probability of a wife being less, equally, and more risk averse than her husband are around 45, 14, and 41 percent respectively. Hence, we observe heterogeneity in risk preferences among husbands and wives, as the majority of wives are predicted to be either more or less, but not equally risk averse to their husbands.

Table 3.7 reports the marginal effects for the ordered probit regression[25]. For dummy variables, the marginal effect is computed as the discrete change of the variable from 0 to 1. There are three variables that influence the likelihood of having heterogeneous preferences among spouses (i.e. of being in the first and last category). Whether the wife worked during the last year increases the heterogeneity in risk preferences among spouses in a statistically significant way. If a wife has worked in the past year, the probability of the wife being more risk averse than her husband decreases by around 7 percent and goes from 41 to 34 percent. Analogously, a wife who worked in the past year is more likely to have a more risk averse husband than a wife who did not participate. Labor force participation for the wife appears to contribute to some heterogeneity in risk preferences between spouses. Work might increase a wife's exposure to different experiences and perspectives, which could influence her and might increase the heterogeneity of preferences within a household. Taking into account that the majority of our sample of husbands and wives did not receive any formal schooling, whether the husband attended school also appears to contribute to differences in risk preferences between spouses. A husband with any schooling is more likely to be with a wife with different risk preferences. For example, an educated husband appears more likely to be with a less risk

[21] Without loss of generality, we employ comparisons with the wife as a reference.
[22] Wife has fewer number of safe choices than husband.
[23] Wife and husband have the same number of safe choices.
[24] Wife has more number of safe choices than husband.
[25] An ordered logit model yields similar results

averse wife. Nonetheless, once we additionally control for the husband's religion, we find that a Muslim husband with schooling seems less likely to be with a less risk averse wife than a non-Muslim husband with schooling.

From the two strategies in this section, we finish addressing our first research question and find different factors correlated with heterogeneity in risk preferences among spouses. From the first model, we find that whether a wife was able to choose her husband increases similarity of risk preferences among spouses in absolute value. For the second model, wife's labor force participation and husband's education status affect whether one spouse is more or less risk averse than the other, incorporating a direction in the difference in risk preferences compared to the first model. For our first research question, we find heterogeneity in risk preferences among spouses and a few factors that are correlated with this heterogeneity. Our results provide more evidence that supports the need for a better representation of individual spouses' preferences within household models. More research is required to understand heterogeneity in risk preferences among spouses, which can subsequently be incorporated in the design of more effective development policies targeting household outcomes.

3.5.3 Similarity of Individual and Joint Risk Preference Decisions

Given our unique dataset containing individual and joint responses, we study the similarity of each spouse's individual decisions to the joint couple's decision and continue addressing our second research question. We start by comparing the number of safe choices, as a proxy for the degree of risk preferences, chosen by the couple to the number of safe choices chosen by the husband and by the wife in two ways. First, we compute the absolute difference in safe choices among the following comparison groups: husband versus couple and wife versus couple. If this difference is very small between husband (wife) and couple, we interpret it as the husband (wife) having more similar risk preferences as the couple. We study these absolute differences, summarized in Table 3.8, to analyze possible characteristics that might make the husband's (wife's) and the couple's decisions more similar. From Table 3.8, the average absolute difference in safe choices is smaller between husband and couple than between wife and couple or between husband and wife. While we concentrate on the first two comparisons, we report the average absolute difference in safe choices between husband and wife to contrast the heterogeneity in risk preferences between spouses to the heterogeneity between individual and joint choices. Table 3.8 provides more evidence suggesting that the husband tends to have more influence over the couple on average relative to his wife.

Following Carlsson et al. (2013)[26], we estimate a negative binomial model with the absolute difference in safe choices as a dependent variable. Tables 3.9 and 3.10 report marginal effects from the negative binomial regression that are calculated as the average partial effects for all observations. For dummy variables, the marginal effect is computed as the discrete change of the variable from 0 to 1. From Table 3.9, among polygamous households, the order of marriage seems to influence the similarity in safe choices between husband and couple. The survey asked polygamous wives whether they are the first, second, third, or so on wife. Husbands who participated in the experiment with their first wives tend to have a lower absolute difference in safe choices with the couple. In other words, husbands tend to have more influence over the joint decision when playing with their first wives than with their second, third, fourth, or fifth wives. At the same time, husbands with more wives tend be more similar to the couple, suggesting more influence over the couple's choice. Being from the same ethnic group also increases the similarity in safe choices between husband and couple. While monogamous status does not have a marginal effect that is statistically significant, a monogamous Muslim husband tends to have more similar responses to the couple than a monogamous non-Muslim husband. From Table 3.10, we find no statistically significant marginal effects that make the wife's choice closer to the couple's choice. With these negative binomial regressions, we identify variables that make a husband's risk preferences closer to the couple's preferences, suggesting more influence by the husband over the couple. We continue addressing our second research question in the next subsection, in which we study the relative influence of each spouse on the couple's choices.

[26] Carlsson et al. (2013) use a negative binomial regressions on the absolute difference in safe choices between husbands and wives as they study heterogeneity in preferences between husband and wife. For this section, we focus on the similarity of decisions between each spouse and the couple.

3.5.4 The Relative Influence of Each Spouse on the Couple's Joint Decision

Besides analyzing the similarity between the husband's (wife's) and the couple's decisions, we now study the way each spouse influences the joint decision in an attempt to understand which spouse's risk preferences are better captured in the couple's joint decision. Following Carlsson et al. (2013), we categorize each household based on the similarity in the number of safe choices: (1) couple is closer to husband, (2) couple is equally distant from husband and wife, and (3) couple is closer to wife. We estimate an ordered probit model to study factors that influence the likelihood to fall into one of these three categories. Table 3.11 summarizes the predicted probabilities for each category. We observe that a couple's joint decision is more likely to be influenced by the husband (43 percent) than by the wife (36 percent). Furthermore, having equal influence on the joint decision is even less likely (20 percent).

The marginal effects of the ordered probit[27] regression are presented in Table 3.12. Two variables influence the likelihood that the couple is closer to the husband. On one hand, monogamous husbands are less likely to be closer to the couple relative to polygamous husbands, in which the predicted probability of being in this category decreases from 43 to about 30 percent. However, once we consider some interactions, we find that Muslim monogamous husbands are 13 percent more likely to be closer to the couple than non-Muslim monogamous husbands. Moreover, these same factors influence the likelihood that the couple's joint decision is closer to the wife's, but in the opposite direction. For instance, monogamous wives are around 12 percent more likely to be closer to the couple than polygamous wives. However, monogamous wives married to Muslim husbands are 12 percent less likely to be closer to the couple relative to monogamous wives married to non-Muslim husbands. This first model finds two variables, monogamous status and its interaction with Muslim husband, which influence the likelihood that one spouse has more influence over the joint decision. Policy makers designing household development strategies in regions in which polygamy is still prevalent should consider the way monogamous or polygamous statuses affect intra-household dynamics and the effectiveness of their strategies.

While these three categories from the first model inform us on who has more influence, we

[27] An ordered logit regression was also estimated obtaining very similar results.

expand the understanding of the relative influence of each spouse on the joint couple's decision by using a new proxy for bargaining power. We construct this proxy using the following formula:

$$female\ barg = \left(\frac{|S_{husband} - S_{couple}|}{10} - \frac{|S_{wife} - S_{couple}|}{10}\right) \tag{3.1}$$

where S equals number of safe choices by husband, wife, or couple. We look at the absolute difference in safe choices for each comparison group, and we divide by the maximum number of safe choices possible. Notice that *female barg* takes the value of 1 if the husband is as different from the couple and there is no difference in safe choices between wife and couple (i.e. wife has the most influence over the couple relative to her husband). Furthermore, *female barg* is 0 when both spouses have the same influence over the couple's decision and their differences in safe choices are equal. Lastly, *female barg* takes the value of -1 if the husband has identical choices as the couple, and the wife is as different to the couple as possible (i.e. wife has the least influence over the couple relative to her husband). With this definition, a positive *female barg* implies that the wife has more influence over the couple's choice, and a negative *female barg* implies that the husband is more influential. We then normalize this measurement such that if falls between 0 and 1. After this normalization, we observe that the average *female barg* is 0.49 and the median is 0.5, the point where both have equal influence over the joint profile.

With this female bargaining power measure constructed, we assign ordered categories depending on the wife's empowerment level or relative influence over the joint couple's decision as summarized in Table 3.13. There are more households below the equal influence category, in which 728 households have wives with less influence than their husbands. We observe 117 fewer households that have wives with more influence than their husbands, with a total of 611 households. Lastly, we find 340 households in which both husband and wife have same influence over joint decisions. We estimate an ordered probit with these categories as the dependent variable. The predicted probabilities are summarized in Table 3.13, which suggest that it is more likely for wives to have less influence over the joint decision than to have more influence.

Table 3.14 summarizes the marginal effects from the model. Monogamous status influences the likelihood of falling into each category. Wives from monogamous households are more likely to be more empowered than wives from polygamous households. The probability of falling into the categories with less influence (i.e. categories 1, 2, and 3) decreases for monogamous wives. At the same time, the probability of falling into the categories with more influence (i.e.5, 6, and 7) increases for monogamous wives, which is consistent with the findings from Table 3.12. However, the marginal effects vary in size per category, with larger effects, around 10 percentage points, for categories three and five. These two categories fall next to the category of equal influence from both spouses, which has a very small, but positive marginal effect. In particular, monogamous wives are more likely to have the same influence over the couple's decision relative to polygamous wives, and the predicted probability of falling within this equally influence category increases from 20 to around 21 percent. Once we consider monogamous status and religion together, we find that that wives are more likely to be less empowered within monogamous households with Muslim husbands relative to wives within monogamous households with non-Muslim husbands. Again, we observe larger marginal effects around the equally influence category, which has a small marginal effect that is not statistically significant. Seeing the different sizes of the marginal effects for each category confirms the importance of using these different categories. With this model, we confirm that monogamous status and its interaction with Muslim husband increase the likely that one spouse has more influence over joint decisions under risk. Moreover, we are able capture different marginal effects sizes for each wife's empowerment category that go beyond simply identifying which spouse is closer to the couple's joint decision.

From these two models in this subsection, we expand our understanding of intra-household dynamics and finish addressing our second research question. Our results suggest that husbands are predicted to have more influence over couples' joint decisions relative to their wives. Having husband and wife with equal influence over the couple is the least predicted category. Based on the first model, monogamous status and its interaction with Muslim husband increase the likelihood that one spouse is going to have more influence over the couple. For instance, monogamous wives are more likely to be closer to the couple than polygamous wives. At the same time, monogamous wives married to Muslim husbands are less likely to have more influence over the couple relative to monogamous wives married to non-Muslim husbands. For the second model, we construct a proxy for female bargaining power and assign each wife into seven empowerment level categories. Monogamous status and its interaction with Muslim husband also increase the likelihood that a wife falls within a particular empowerment level. In particular, monogamous wives are more likely to be more empowered than polygamous wives. At the same time, monogamous wives married to Muslim husbands are more likely to be less empowered than polygamous wives married to non-Muslim husbands. Lastly, we capture different marginal effect sizes with our second model, finding larger effects around the equal influence category. Our results support the need for more research and a better understanding of intra-household dynamics for the design of more effective development strategies targeting household outcomes.

3.5.5 The Relation between Female Bargaining Power and Household Expenditure Decisions

Our last research question is focused on understanding the way female bargaining power or wife's empowerment level, measured as the wife's relative influence over the joint decision, affects annual expenditures on education and on medical related goods. For polygamous households, we take the chosen wife's bargaining power as representative of other wives' empowerment levels. Focusing on educational expenditure, the survey includes questions about annual expenditures on tuition, school registration, books, newspapers, notebooks, or other expenses related to education. We use answers to these questions and construct an annual education expenditure variable. The average annual educational expenditure is 25870 XAF. We estimate a linear regression with the latter as the dependent variable, and we include *female barg* as an explanatory variable, among others.

Table 3.15 summarizes results from the regression. The proxy for wife's empowerment is positively correlated with educational expenditure, suggesting that households with more empowered wives tend to spend more on education on average. For instance, a 0.01 increase in female bargaining power, which ranges from 0 to 1, is associated with a 270 XAF increase in educational expenditure. This result confirms the importance of understanding the relative influence each wife has on the intra-household decision-making process. Development strategies that promote female empowerment could also potentially attain a higher educational investment.

We control for key household members risk preferences by including both husbands and wifes number of safe choices as proxies for their risk preferences. Households with older husbands appear to invest more on education on average, but the size of the coefficient is small. We control for the size of the household by including number of wives, sons, daughters, grandmothers, grandfathers, other male relatives, and other female relatives who live in the household. While the number of wives is negatively correlated with annual educational expenditure, the number of sons and daughters are positively correlated. The signs of these correlations are intuitive as having more wives could result in more expenditure on them, decreasing educational expenditure. Households with more sons and with more daughters tend to invest more on education than households with fewer sons and fewer daughters respectively on average. The size of the coefficient for number of sons is more than double the coefficient for the number of daughters, suggesting that households tend to allocate more money towards their sons' education. The number of other male relatives who live in the household is also positively correlated with educational expenditure. Having more male household members could result in additional household income, which can be allocated towards education.

With regards to adult education, households with educated[28] spouses tend to spend more on education relative to household with uneducated spouses. Households in which only one spouse is educated or in which both are educated tend to spend more on education relative to households with uneducated parents. We observe a larger coefficient for households in which only the husband received formal schooling. The coefficient for households in which only the wife attended school and in which both spouses attended school are similar in size. Lastly, we control for other variables such as wife's age, spouses' work information, religion, monogamous status, and average health[29], but their coefficients are not statistically significant.

[28] In this context, an educated person is one who attended school. Given the low level of education in the region, the majority do not obtain any formal schooling.

[29] To control for health status within the household, we utilize a question from the survey that asks respondents to assess their current health status by selecting one of the following: good, relatively good, fair, or bad. Each of these responses was assigned 3, 2, 1 and 0 respectively. The average health variable is computed as the

While we control for several variables, we understand that our data could be missing important information. Hence, we know we are finding correlations that call for more research to confirm any causation. Nonetheless, our findings suggests a positive relation between female bargaining power and educational expenditure that could be very useful for the effectiveness of development strategies.

For annual medical expenditures, the field survey includes questions about semi-annual expenditures on medicines, drugs, hygiene articles, and body-care products and about annual expenditures on examination, care, and hospital fees. We construct an annual medical expenditure variable with the answers to the former questions. The average annual educational expenditure is 69760 XAF, more than twice the average annual educational expenditure. We estimate a linear regression model that is summarized in Table 3.16. As with education, our proxy for wife's empowerment is positively correlated with annual medical expenditures. For example, a 0.01 increase in female bargaining power is associated with a 512 XAF increase in medical expenditure on average. The more influence a wife has on the couple's decision, the more medical expenditure her household has on average after controlling for other factors such as number of households members and average health. Finding this positive relation between female bargaining power and medical expenditure is important for development policies that are designed to attain better health outcomes. Nonetheless, more research is required to identify any causation.

Both number or sons and daughters are also positively correlated with medical expenditure, and the estimated coefficient are very similar. The more children within a household, the more medical expenditures are incurred. As with education, the number of other male relatives is also positively correlated with medical expenditure, which can also be explained by having more males who can work and contribute their income. Households in which only the husband received any formal schooling tend to spend more on medical expenditure relative to household with uneducated spouses.

We control for current health status of household members and recent diseases in a couple of

average of this numeric health assessment for every household member (i.e. head of household, wives, children, grandparents, and other relatives who live in the household).

ways. First, we construct an average health variable based on the subjective assessment of the health status of each household member. The coefficient for this average is negative, meaning that households with a higher average subjective health status (i.e. healthier households) tend to spend less on medical related products. However, this coefficient is not statistically significant. The survey also asked responded to state whether they had suffered four specific diseases in the last two weeks. The survey focused on malaria, diarrhea, respiratory diseases, and eye infections. We construct four variables that count the number of household members who had each disease in the last two weeks. Among the four diseases, the only statistically significant coefficient is for the number of households with respiratory diseases. Having more members with respiratory diseases in the last two weeks increases medical expenditures on average.

From this subsection, we conclude that female bargaining power has a positive and statistically significant relation with educational and medical expenditures after controlling for several variables. From both models, increasing wife's empowerment is associated with increases in educational and expenditure expenditures. While our analysis finds a positive relation, more research is needed to fully comprehend the way intra-household dynamics and female bargaining power influence household's decisions and to better design development strategies focused on education and health outcomes.

3.6 Conclusions

Given the importance of intra-household dynamics for the success of development policies, we study heterogeneity in risk preferences between husband and wife within a household, the relative influence of each spouse on joint decisions involving risk, and the way this relative influence affects annual educational and medical expenditures within a household using a lab-in-the-field risk experiment. Focusing on the aggregate data, we observe risk aversion in husbands, wives, and couples, in which husbands are observed to be more risk averse than wives and couples on average. Focusing on the percentage of same choices at each decision in the experiment, we find more matches between husband and couple than between wife and couple, suggesting more influence of husbands over couples' decisions. At the household level, we find heterogeneity in risk preferences between husband and wife. A wife who chose her husband for marriage tends to have more similar risk preferences, in absolute terms and on average, as her husband relative to a wife who did not chose. Moreover, we find characteristics that affect whether one spouse is more, equally, or less risk averse than the other, incorporating a direction in the difference in risk preferences. A working wife is less likely to be more risk averse than her husband relative to a non-working wife on average.

To study the relative influence of each spouse on joint decisions involving risk, we use individual and joint decisions from the lab-in-the-field to find which spouse is closer to the couple. We find that monogamous husbands are less likely to be closer to the couple relative to polygamous husbands, and that monogamous wives are more likely to be closer to the couple than polygamous wives on average. Besides considering which spouse is closer to the couple, we also study the relative influence of each spouse on joint decisions using a proxy for female bargaining power based on the difference in individual and joint decisions. Using this measure, we find that wives from monogamous households are more likely be more empowered relative to polygamous wives. At the same time, monogamous wives married to Muslim husbands are more likely to be less empowered than monogamous wives married to non-Muslim husbands.

Lastly, we explore the way this proxy for female bargaining power affects annual educational and medical expenditures. We find that households with more empowered wives tend to invest more on education than households with less empowered wives. At the same time, the more influence a wife has on the couple's decision, the more medical expenditure her household has on average, controlling for number of household members and subjective average health status. Our findings reaffirm the importance of understanding spouses' heterogeneity of risk preferences and the relative influence of each spouse on joint decisions. Considering spouses' differences in preferences and intra-household dynamics can result in more effective development strategies that target household outcomes. Furthermore, our results find that female bargaining power is positively correlated with educational and medical expenditures, which are often associated with development goals. We conclude by emphasizing the need and importance of more research in this area that can assist policy makers in designing more effective development strategies.

3.7 Tables and Figures

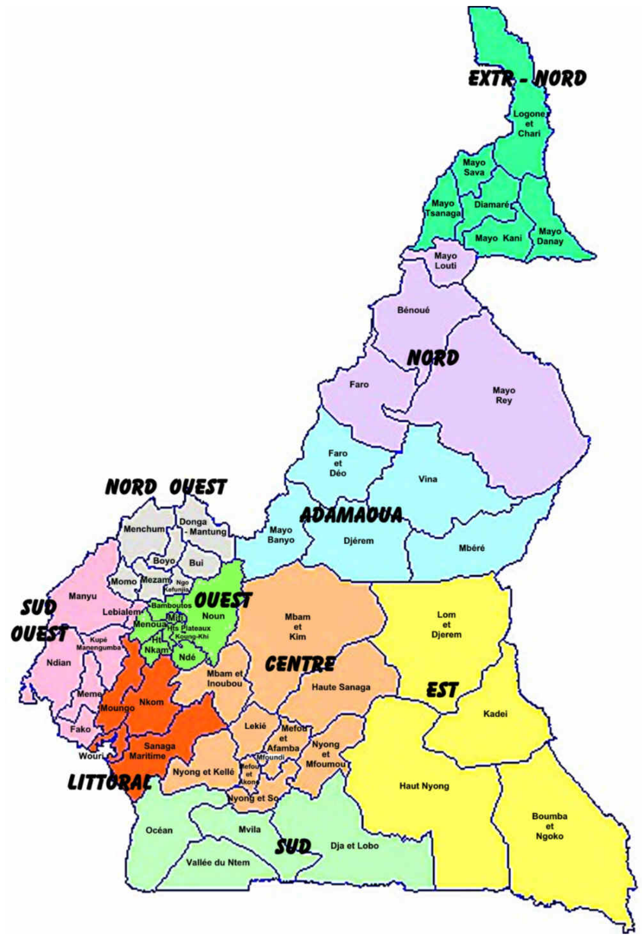

Figure 3.1 Cameroon Map

http://static.cameroonweb.com/GHP/img/pics.org/Regional-Map.jpg
Accessed on: 6/10/2016

Table 3.1 Summary Statistics

Variable	**Mean**
Wife's age	32.62
Husband's age	45.89
Older wife (=1)	0.01
Wife is Muslim (=1)	0.83
Husband is Muslim (=1)	0.84
Monogamous household (=1)	0.52
1^{st} wife in polygamous household (=1)	0.33
Number of wives	1.69
Number of children	5.19
Number of sons	2.72
Number of daughters	2.47
Same ethnicity among spouses (=1)	0.87
Dowry was paid by husband (=1)	0.97
Wife chose husband (=1)	0.32
Wife worked during the year (=1)	0.68
Husband worked during the year (=1)	0.96
Relative welfare[1]	2.85
Wife went to school (=1)	0.28
Husband went to school (=1)	0.40
Husband's expenditure on wife(s)	16.04
Number of observations	1689

[1]Based on the following question: In your opinion, how is your household level of welfare relative to others in the village? =1 if much worse, =2 if worse/lower, =3 if the same, =4 if better, and = 5 if much better

Table 3.2 Risk Experiment Lotteries

Decision	**Option A**	**Option B**	**Expected Payoff (A-B)**
1	$\frac{1}{10}$ of 2000 XAF , $\frac{9}{10}$ of 1600 XAF	$\frac{1}{10}$ of 3850 XAF , $\frac{9}{10}$ of 100 XFA	1165 XFA
2	$\frac{2}{10}$ of 2000 XAF , $\frac{8}{10}$ of 1600 XAF	$\frac{2}{10}$ of 3850 XAF , $\frac{8}{10}$ of 100 XFA	830 XFA
3	$\frac{3}{10}$ of 2000 XAF , $\frac{7}{10}$ of 1600 XAF	$\frac{3}{10}$ of 3850 XAF , $\frac{7}{10}$ of 100 XFA	495 XFA
4	$\frac{4}{10}$ of 2000 XAF , $\frac{6}{10}$ of 1600 XAF	$\frac{4}{10}$ of 3850 XAF , $\frac{6}{10}$ of 100 XFA	160 XFA
5	$\frac{5}{10}$ of 2000 XAF , $\frac{5}{10}$ of 1600 XAF	$\frac{5}{10}$ of 3850 XAF , $\frac{5}{10}$ of 100 XFA	-175 XFA
6	$\frac{6}{10}$ of 2000 XAF , $\frac{4}{10}$ of 1600 XAF	$\frac{6}{10}$ of 3850 XAF , $\frac{4}{10}$ of 100 XFA	-510 XFA
7	$\frac{7}{10}$ of 2000 XAF , $\frac{3}{10}$ of 1600 XAF	$\frac{7}{10}$ of 3850 XAF , $\frac{3}{10}$ of 100 XFA	-845 XFA
8	$\frac{8}{10}$ of 2000 XAF , $\frac{2}{10}$ of 1600 XAF	$\frac{8}{10}$ of 3850 XAF , $\frac{2}{10}$ of 100 XFA	-1180 XFA
9	$\frac{9}{10}$ of 2000 XAF , $\frac{1}{10}$ of 1600 XAF	$\frac{9}{10}$ of 3850 XAF , $\frac{1}{10}$ of 100 XFA	-1515 XFA
10	$\frac{10}{10}$ of 2000 XAF , $\frac{0}{10}$ of 1600 XAF	$\frac{10}{10}$ of 3850 XAF , $\frac{0}{10}$ of 100 XFA	-1850 XFA

Holt & Laury's (2002) payoffs were converted to the local currency in Cameroon.
XAF stands for CFA franc, the currency used in Cameroon.

Table 3.3 Summary of Inconsistent Responses

Group	Number choosing Option A on 10^{th} lottery	%	Number with multiple switching on points	%	Number with both inconsistencies	%
Husbands	248	15.68%	295	17.47%	513	30.37%
Wives	147	8.7%	419	24.81%	526	31.14%
Couples	134	7.93%	242	14.33%	362	21.43%
Households*	385	22.79%	685	40.56%	905	53.58%

*either husband, wife, or couple has inconsistent responses

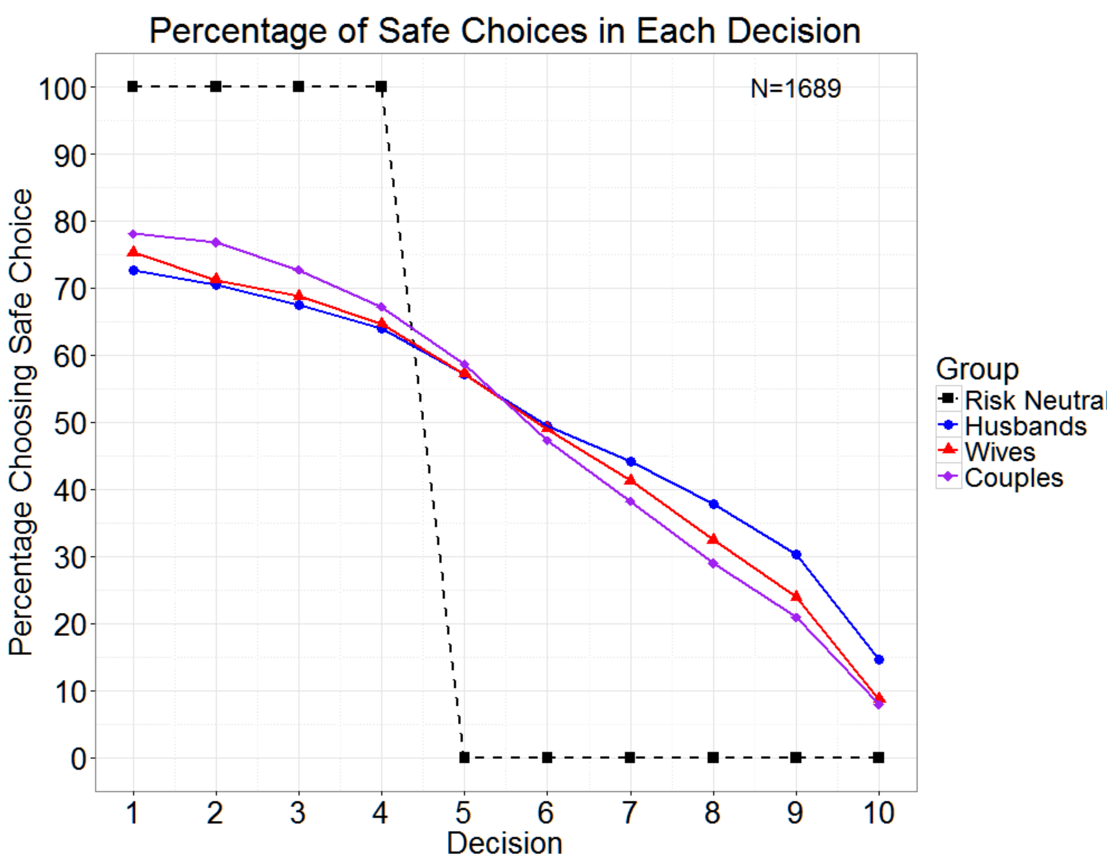

Figure 3.2 Percentage of Safe Choices in Each Decision

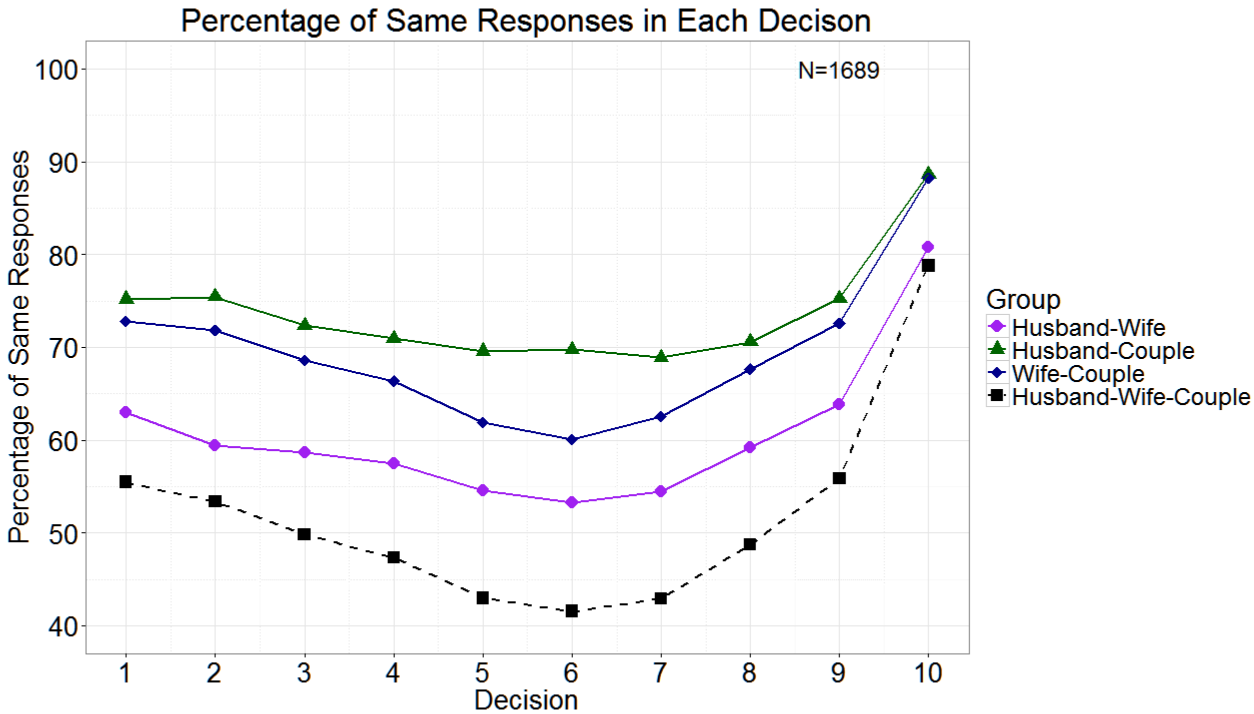

Figure 3.3 Percentage of Same Responses in Each Decision

Table 3.4 Average Number of Safe Choices by Group

Group	**Average Number of Safe Choices**
Husbands	5.02
Wives	4.84
Couples	4.90
Number of Households	1679

Table 3.5 Risk Aversion Classification Based on Lottery Choices

Number of Safe Choices	**Proportion of Husbands**	**Proportion of Wives**	**Proportion of Couples**
0	0.21	0.16	0.16
1	0.03	0.04	0.02
2	0.04	0.05	0.05
3	0.06	0.07	0.07
4	0.10	0.12	0.13
5	0.11	0.16	0.14
6	0.07	0.10	0.11
7	0.05	0.08	0.09
8	0.06	0.06	0.06
9	0.13	0.11	0.10
10	0.13	0.06	0.07

N=1679

Table 3.6 Marginal Effects of Negative Binomial Model for Absolute Difference in Safe Choices between Husband and Wife

Variable	**Marginal Effect**	**Robust Std. Error**	**P-value**
Wife's age	0.015	0.009	0.0995*
Husband's age	-0.003	0.008	0.7198
Older wife (=1)	-0.310	0.640	0.6279
Husband is Muslim (=1)	0.596	0.516	0.2481
Monogamous household (=1)	0.386	0.469	0.4113
1^{st} wife in polygamous household (=1)	-0.243	0.220	0.2686
Number of wives	-0.142	0.156	0.3626
Number of children	-0.005	0.021	0.7983
Same ethnicity among spouses (=1)	-0.151	0.212	0.4749
Wife chose husband (=1)	-0.443	0.150	0.0032***
Wife worked during the year (=1)	-0.057	0.153	0.7081
Relative welfare	-0.016	0.084	0.8469
Husband's expenditure on wife[1]	0.001	0.001	0.7166
Wife went to school (=1)	0.060	0.194	0.7587
Husband went to school (=1)	0.511	0.509	0.3155
Muslim Husband * Husband with any schooling	-0.699	0.462	0.1301
Muslim Husband * Monogamous	-0.595	0.424	0.1600

[1] For polygamous households, this expenditure is calculated as the average per wife
** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Robust standard errors are estimated.
Number of Observations = 1679

Table 3.7 Marginal Effects of Ordered Probit Regression on Spouses' Risk Preference Differences

	Marginal Effects		
Variable	**Wife less risk averse than husband**	**Wife equally risk averse as husband**	**Wife more risk averse than husband**
Wife's age	-0.0006	0.0000	0.0006
Husband's age	-0.0008	0.0000	0.0008
Older wife (=1)	-0.0188	0.0002	0.0187
Husband is Muslim (=1)	0.1395	0.0036	-0.1431
Monogamous household (=1)	0.0429	-0.0008	-0.0422
Number of wives	0.0257	-0.0005	-0.0252
Number of children	-0.0040	0.0001	0.0040
Same ethnicity among spouses (=1)	-0.0297	0.0009	0.0289
Wife chose husband (=1)	-0.0064	0.0001	0.0063
Wife worked during the year (=1)	0.0723***	-0.0005	-0.0718***
Husband worked during the year (=1)	-0.0083	0.0002	0.0081
Relative welfare	0.0035	-0.0001	-0.0035
Wife went to school (=1)	-0.0129	0.0002	0.0127
Husband went to school (=1)	0.1770**	-0.0060	-0.1711**
Husband's expenditure on wife	0.0001	0.0000	-0.0001
Muslim Husband * Husband with any schooling	-0.1670**	-0.0030	0.1700**
Muslim Husband * Monogamous	-0.0195	0.0003	0.0192

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Number of Observations = 1679

Table 3.8 Absolute Difference in Safe Choices

Absolute Difference in Safe Choices Between:	**Min**	**Mean**	**Max**	**Standard Deviation**
Husband and Couple	0	2.37	10	2.51
Wife and Couple	0	2.64	10	2.44
Husband and Wife	0	3.49	10	2.83

Table 3.9 Marginal Effects of Negative Binomial Model for Absolute Difference in Safe Choices between Husband and Couple

Variable	**Marginal Effect**	**Robust Std. Error**	**P-value**
Wife's age	0.012	0.008	0.1559
Husband's age	-0.004	0.007	0.5801
Older wife (=1)	0.850	0.663	0.1994
Husband is Muslim (=1)	0.574	0.403	0.1540
Monogamous household (=1)	0.120	0.441	0.7853
1^{st} wife in polygamous household (=1)	-0.535	0.180	0.0029***
Number of wives	-0.308	0.141	0.0288**
Number of children	0.015	0.018	0.4043
Same ethnicity among spouses (=1)	-0.343	0.204	0.0918*
Wife chose husband (=1)	-0.161	0.134	0.2299
Wife worked during the year (=1)	0.056	0.135	0.6805
Relative welfare	-0.074	0.073	0.3065
Husband's expenditure on wife	0.000	0.001	0.9872
Wife went to school (=1)	0.048	0.162	0.7671
Husband went to school (=1)	-0.110	0.381	0.7724
Muslim Husband * Husband with any schooling	-0.165	0.388	0.6713
Muslim Husband * Monogamous	-0.748	0.409	0.0675*

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Robust standard errors are estimated.
Number of Observations = 1679

Table 3.10 Marginal Effects of Negative Binomial Model for Absolute Difference in Safe Choices between Wife and Couple

Variable	**Marginal Effect**	**Robust Std. Error**	**P-value**
Wife's age	0.008	0.008	0.3272
Husband's age	0.001	0.007	0.9160
Older wife (=1)	-0.200	0.568	0.7240
Husband is Muslim (=1)	0.117	0.452	0.7965
Monogamous household (=1)	-0.624	0.421	0.1384
1^{st} wife in polygamous household (=1)	0.098	0.192	0.6106
Number of wives	-0.153	0.131	0.2405
Number of children	-0.022	0.017	0.2044
Same ethnicity among spouses (=1)	-0.046	0.191	0.8091
Wife chose husband (=1)	0.002	0.130	0.9903
Wife worked during the year (=1)	0.097	0.129	0.4536
Relative welfare	0.066	0.073	0.3625
Husband's expenditure on wife	0.001	0.001	0.2583
Wife went to school (=1)	0.019	0.170	0.9099
Husband went to school (=1)	0.366	0.426	0.3897
Muslim Husband * Husband with any schooling	-0.591	0.387	0.1262
Muslim Husband * Monogamous	0.640	0.419	0.1268

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Robust standard errors are estimated.
Number of Observations = 1679

Table 3.11 Predicted Probabilities of Joint Influence

Category	**Average Predicted Probability**
Couple closer to husband	0.43
Equal Distance	0.20
Couple closer to wife	0.36

Table 3.12 Marginal Effects of Ordered Probit Regression on Spouses' Influence on Joint Decision

	Marginal Effects		
Variable	**Couple closer to husband**	**Equal distance**	**Couple closer to wife**
Wife's age	0.000	0.000	0.000
Husband's age	0.000	0.000	0.000
Older wife (=1)	-0.040	0.001	0.039
Husband is Muslim (=1)	-0.040	0.003	0.038
Monogamous household (=1)	-0.129*	0.006	0.123*
Number of wives	-0.004	0.000	0.004
Number of children	-0.003	0.000	0.003
Same ethnicity among spouses (=1)	0.023	-0.001	-0.022
Wife chose husband (=1)	0.035	-0.002	-0.033
Wife worked during the year (=1)	0.016	-0.001	-0.015
Relative welfare	0.018	-0.001	-0.018
Wife went to school (=1)	0.032	-0.002	-0.030
Husband went to school (=1)	-0.024	0.001	0.023
Husband's expenditure on wife	0.000	0.000	0.000
Muslim Husband * Husband with any schooling	-0.012	0.001	0.011
Muslim Husband * Monogamous	0.126*	-0.008	-0.118*

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Number of Observations = 1679

Table 3.13 Female Bargaining Power Levels

Category	***female barg*'s range**	**Wife's empowerment level**	**Observations**	**Predicted probability**
1	=0	least influence over couple's decision	21	0.01
2	(0,0.25]	less influence than husband	147	0.09
3	(0.25,0.50)	less influence than husband	560	0.33
4	0.50	same influence as husband	340	0.20
5	(0.50,0.75]	more influence than husband	535	0.32
6	(0.75,1)	more influence than husband	66	0.04
7	=1	most influence over couple's decision	10	0.01

Table 3.14 Marginal Effects of Ordered Probit Regression on Spouses' Influence on Joint Decision

			Marginal Effects				
Categories →	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Variable							
Wife's age	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Husband's age	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Older wife	-0.004	-0.026	-0.061	-0.002	0.073	0.017	0.003
Husband is Muslim	-0.001	-0.004	-0.009	0.001	0.011	0.002	0.000
Monogamous household	-0.007*	-0.045*	-0.089**	0.008*	0.108**	0.021*	0.003*
Number of wives	0.000	0.000	0.001	0.000	-0.001	0.000	0.000
Number of children	0.000	-0.001	-0.003	0.000	0.003	0.001	0.000
Same ethnicity among spouses	0.001	0.007	0.015	-0.001	-0.018	-0.004	-0.001
Wife chose husband	0.001	0.009	0.018	-0.002	-0.022	-0.004	-0.001
Wife worked during the year	0.001	0.004	0.007	-0.001	-0.009	-0.002	0.000
Relative welfare	0.001	0.005	0.011	-0.001	-0.013	-0.003	0.000
Wife went to school	0.001	0.007	0.014	-0.001	-0.017	-0.003	-0.001
Husband went to school	0.002	0.012	0.024	-0.002	-0.029	-0.006	-0.001
Husband's expenditure on wife	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Muslim Husband * Husband with any schooling	-0.003	-0.018	-0.039	0.002	0.046	0.010	0.002
Muslim Husband * Monogamous	0.008*	0.047*	0.088**	-0.012	-0.108**	-0.021**	-0.003*

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Number of Observations = 1679

Table 3.15 Annual Educational Expenditure Regression

Variable	**Coefficient**	**Robust Std. Error**	**P-value**
Intercept	-21674	27434	0.4300
female barg	27033	15976	0.0920*
Husband's Number of Safe Choices	-258	848	0.7610
Wife's Number of Safe Choices	670	518	0.1970
Wife's age	69	154	0.6560
Husband's age	371	216	0.0870*
Husband is Muslim (=1)	-25045	15524	0.1080
Monogamous household (=1)	-7972	11265	0.4800
Number of wives	-6318	3485	0.0710*
Number of sons	5468	1458	0.0000***
Number of daughters	2495	1139	0.0300**
Number of grandfathers	-5324	10301	0.6060
Number of grandmothers	-10028	6253	0.1100
Number of other male household members	9295	5351	0.0840*
Number of other female household members	5996	3767	0.1130
Wife worked during the year (=1)	-2133	3979	0.5920
Husband worked during the year (=1)	-986	6812	0.8850
Only husband went to school (=1)	30485	11971	0.0120**
Only wife went to school (=1)	17727	6156	0.0040***
Both spouses went to school (=1)	19432	7097	0.0070***
Average health of household members	5939	4574	0.1960

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Number of Observations = 1678
Clustered standard errors at village level
R-squared=0.06

Table 3.16 Annual Medical Expenditure Regression

Variable	**Coefficient**	**Robust Std. Error**	**P-value**
Intercept	17408	47313	0.7130
female barg	51216	25313	0.0440**
Husband's Number of Safe Choices	642	1230	0.6030
Wife's Number of Safe Choices	-624	1170	0.5950
Wife's age	-573	457	0.2110
Husband's age	246	412	0.5510
Husband is Muslim (=1)	7768	17042	0.6490
Monogamous household (=1)	-7395	18932	0.6970
Number of wives	3114	11105	0.7790
Number of sons	5593	2410	0.0210**
Number of daughters	5650	3041	0.0650*
Number of grandfathers	-14633	26969	0.5880
Number of grandmothers	11266	22394	0.6150
Number of other male household members	11984	6631	0.0720*
Number of other female household members	-7068	4495	0.1180
Wife worked during the year (=1)	9943	9280	0.2850
Husband worked during the year (=1)	1669	18425	0.9280
Only husband went to school (=1)	30902	17379	0.0770*
Only wife went to school (=1)	2369	16162	0.8840
Both spouses went to school (=1)	1283	11911	0.9140
Average health of household members	-8895	8446	0.2940
Number with malaria in the last 2 weeks	2285	4060	0.5740
Number with diarrhea in the last 2 weeks	-7776	11165	0.4870
Number with respiratory diseases in the last 2 weeks	21948	10940	0.0460**
Number with eye infections in the last 2 weeks	20341	22230	0.3610

*** Significant at 1% level, ** Significant at 5% level, * Significant at the 10% level
Number of Observations = 1678
Clustered standard errors at village level
R-squared=0.04

BIBLIOGRAPHY

Chapter 1

[1] Ambec, S., & J. Coria (2013). Prices vs Quantities with Multiple Pollutants. *Journal of Environmental Economics and Management*, *66*(1), 123-140.

[2] Asquith, N.M., Vargas, M.T., & Wunder S. (2008). Selling two environmental services: In-king payments for bird habitat and watershed protection in Los Negros, Bolivia. *Ecological Economics*, *65*, 675–684.

[3] Caplan, A.J., & Silva, E.C. (2005). An efficient mechanism to control correlated externalities: redistributive transfers and the coexistence of regional and global pollution permit markets. *Journal of Environmental Economics and Management*, *49*, 68–82.

[4] Claassen, R., Cattaneo, A., & Johansson, R. (2008).Cost-effective design of agri-environmental payment programs: U.S. experience in theory and practice *Ecological Economics*, *65*, 737–752.

[5] Cooley, D., & Olander, L. (2012).Stacking Ecosystem Services Payments: Risks and Solutions *Environmental Law Reporter*,

[6] Dobbs, T.L., & Pretty, L. (2008). Case Study of agri-environmental payments: The United Kingdom. *Ecological Economics*, *65*, 765–775.

[7] Engel, S. P., Pagiola, S., & Wunder, S. (2008). Designing payments for environmental services in theory and practice: An overview of the issues. *Ecological Economics*, *65*, 663–674.

[8] Feng, H., & Kling, C.L. (2005). The Consequences of Cobenefits for the Efficient Design of Carbon Sequestration Programs *Canadian Journal of Agricultural Economics*, *53*(4), 461-476.

[9] Ferraro, P. J. (2008). Asymmetric information and contract design for payment for environmental services. *Ecological Economics*, *65*, 810–821.

[10] Greenhalgh, S. (2008).Bundled Ecosystem Markets - Are They The Future? *American Agricultural Economics Association Annual Meeting.* Orlando.

[11] Horan, R. D., Shortle, J. S., & Abler, D. G. (2004). The Coordination and Design of Point-Nonpoint Trading Programs and Agri-Environmental Policies. *Agricultural and Resource Economics Review*, 61–78.

[12] Kieser & Associates. (2004). *Ecosystem multiple markets: executive summary - Draft.* Kalamazoo: The Environmental Trading Network.

[13] Montero, J.-P. (2001). Multipollutant Markets. *The RAND Journal of Economics*, 762-774.

[14] Moslener, U., & Requate, T. (2005, April). Optimal Abatement in Dynamic Multi-Pollutant Problems When Pollutants can be Complements or Substitutes. *ZEW Discussion Papers*, Discussion Paper No. 05-27.

[15] Muñoz-Piña, C., Guevara, A., Torres, J. M., & Braña, J. (2008). Paying for hydrological services of Mexico's forests: Analysis, negotiations and results. *Ecological Economics*, *65*, 725-736.

[16] Murray, B. C., Jenkins, W. A., Busch, J. M., & Woodward, R. T. (2012). Designing Cap and Trade to Correct for "Imperfect" Offsets. *Duke Environmental Economics Working Papers Series.*

[17] Pagiola, S., Ramírez, E., Gobbi, J., de Haan, C., Ibrahim, M., Murgueito, E., & Ruíz, P. (2007). Paying for the environmental services of silvopastoral practices in Nicaragua. *Ecological Economics*, *64*, 374-385.

[18] Pagiola, S. (2008). Payments for environmental services in Costa Rica. *Ecological Economics*, *65*, 712-724.

[19] Pagiola, S., Ríos, A. R., & Arcenas, A. (2010). Poor Household Participation in Payments for Environmental Services: Lessons from the Silvopastoral Project in Quindo, Colombia. *Environmental Resource Economics*, *47*, 371-394.

[20] Taschini, L. (2010). Environmental Economics and Modeling Marketable Permits. *Asia-Pacific Financial Markets*, *17*, 325-343.

[21] Turpie, J., Marais, C., & Blignaut, J. (2008). The working for water programme: Evolution of a payments for ecosystem services mechanism that addresses both poverty and ecosystem service delivery in South Africa. *Ecological Economics*, *65*, 788-798.

[22] Wang, L. F., & Wang, J. (2009). Environmental taxes in a differentiated mixed duopoly. *Economic Systems*, 389-396.

[23] Weitzman, M.L. (1974). Prices vs. Quantities. *Review of Economic Studies*, *64*(4), 477-491.

[24] Woodward, R. T. (2011). Double-dipping in environmental markets. *Journal of Environmental Economics and Management*, *61*, 153-169.

[25] World Resource Institute. (2009, November). Stacking Payments for Ecosystem Services. *WRI Fact Sheet*.

[26] Wunder, S. (2005). Payments for Environmental Services: Some Nuts and Bolts. *CIFOR* CIFOR occasional paper No. 42.

[27] Wunder, S., & Albán, M. (2008). Decentralized payments for environmental services: The Cases of Pimampiro and PROFAFOR in Ecuador. *Ecological Economics*, *65*, 685-698.

Chapter 2

[28] Abadie, A. & Imbens, G. W. (2006). Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica*, *74*, 235-267.

[29] Abadie, A. & Imbens, G. W. (2012). Matching on the estimated propensity score *Harvard University and National Bureau of Economic Research*

[30] Andam, K. S., Ferraro, P.J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J.A. (2008). Measuring the Effectiveness of Protected Area Networks in Reducing Deforestation. *Proceedings of the National Academy of Sciences*, *105*(42), 16089-16094.

[31] Arbuckle Jr., J.G. & Roesch-McNally G. (2015). Cover crop adoption in Iowa: The role of perceived practice characteristics. *Journal of Soil and Water Conservation*, *70*(6), 418-429.

[32] Arbuckle Jr., J.G., (2013). Farmer support for extending Conservation Compliance beyond soil erosion: Evidence from Iowa. *Journal of Soil and Water Conservation*, *68*(2), 99-109.

[33] Arbuckle, J.G., & Lasley, P. (2013). *The Iowa Farm and Rural Life Poll 2013 Summary Report.* Ames: Iowa State University Extension.

[34] Arbuckle Jr., J.G., Morton, L.W., & Hobbs, J. (2013). Farmers beliefs and concerns about climate change and attitudes toward adaptation and mitigation: Evidence from Iowa. *Climate Change*, *118*, 551-563.

[35] Arbuckle Jr., J.G., Morton, L.W., & Hobbs, J. (2013). Understanding Farmer Perspectives on Climate Change Adaptation and Mitigation: The Roles of Trust in Sources of Climate Information, Climate Change Beliefs, and Perceived Risk. *Environment and Behavior*, 1-30.

[36] Arbuckle, J.G., Lasley, P., & Ferrell, J. (2011). *The Iowa Farm and Rural Life Poll 2011 Summary Report.* Ames: Iowa State University Extension.

[37] Arbuckle, J.G., Lasley, P., Korsching, P., & Kast, C. (2010). *The Iowa Farm and Rural Life Poll 2010 Summary Report.* Ames: Iowa State University Extension.

[38] Carlson, S., & Stockwell, R. (2013). Research priorities for advancing adoption of cover crops in agriculture-intensive regions. *Journal of Agriculture, Food Systems, and Community Development*, *3*(4), 125-129.

[39] Chabé-Ferret, S., & Subervie, J. (2013). How much green for the buck? Estimating additional and windfall effects of French agro-environmental schemes by DID-matching. *Journal of Environmental Economics and Management*, *62*, 12-27.

[40] Claassen, R., Duquette, E. & Horowitz, J. (2013). Additionality in agricultural conservation payment programs. *Soil and Water Conservation Society*, *68*(3), 74A-78A.

[41] Cocharn, W. G., & Rubin, D. B. (2013). Controlling Bias in Observational Studies: A Review. *Sankhya: The Indian Journal of Statistics, Series A (1961-2002)*, *35*(4), 417-466.

[42] Cooper, J.C. (2003). A Joint Framework for Analysis of Agri-Environmental Payment Programs. *American Journal of Agricutural Economics*, *85*(4), 976-987.

[43] Diamond, A., & Sekhon, J.S. (2012). Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies. *Review of Economics and Statistics (forthcoming)*, *2012*, 1-41.

[44] EPA (1996). *Nonpoint Source Pollution: The Nation's Largest Water Quality Problem.* EPA841-F-96-004A: http://www.epa.gov/polluted-runoff-nonpoint-source-pollution/nonpoint-source-fact-sheets Accessed on: 10/2015

[45] EPA (2014). *Northern Gulf of Mexico Hypoxic Zone.* Obtained from Mississippi River Gulf of Mexico Watershed Nutrient Task Force: http://water.epa.gov/type/watersheds/named/msbasin/zone.cfm Accessed on: 10/2015

[46] EPA (2015). *What is Nonpoint Source?* http://www.epa.gov/polluted-runoff-nonpoint-source-pollution/what-nonpoint-source Accessed on: 09/2015

[47] Ferraro, P. J., McIntosh, C., & Ospina, M. (2007). The Effectiveness of the US Endangered Species Act: An Econometric Analysis using Matching Methods. *Journal of Environmental Economics and Management*, *54*(3), 245-261.

[48] Flemming (2015). Agricultural Cost Sharing and Water Quality in the Chesapeake Bay: Estimating Substitution Effects among Conservation Practices. *Working Paper*,

[49] Glazerman, S., Levy, D. M. & Myers, D. (2003). Nonexperimental versus Experimental Estimates of Earnings Impacts. *Annals of the American Academy of Political Science*, *589*, 63-93.

[50] Greene, W. H. (2008). *Econometric Analysis* 6th edition. Prentice Hall.

[51] Heckman, J.J. (1998). Characterizing Selection Bias Using Experimental Data. *Econometrica*, *66*, 1017-1098.

[52] Hansen, B.B. (2004). Full Matching in an Observational Study of Coaching for the SAT. *Journal of the American Statistical Association*, *99*(467), 609-618.

[53] Ho, D. E., Imai, K., King, G., Stuart, E. A. (2011). MatchIt: Nonparametric Preprocessing for Parametric Causal Inference. *Journal of Statistical Software*, *42*(8), 1-28.

[54] Ho, D. E., Imai, K., King, G., Stuart, E. A. (2007). Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. *Political Analysis*, *15*, 199-236.

[55] Holland, P.W. (1986). Statistics and Causal Inference. *Journal of the American Statistical Association*, *81*, 945-960.

[56] Imbens, G.M., & Wooldridge, J.M. (2008). Recent Developments in the Econometrics of Program Evaluations. *NBER Working Papers Series*, Working Paper 14251.

[57] Iowa NRS (2013) Iowa Department of Agriculture and Land Stewardship; Iowa Department of Natural Resources. Iowa State University College of Agriculture and Life Sciences. *Iowa Nutrient Reduction Strategy*. Ames, Iowa.

[58] Iowa NRS (2014). *Iowa Nutrient Reduction Strategy 2013-2014 Annual Progress Report*. Ames: Iowa State University.

[59] Lichtenberg, E., & Smith-Ramiírez, R. (2011). Slippage in Conservation Cost Sharing. *American Journal of Agricultural Economics* , *93*(1), 113-129.

[60] Lichtenberg, E., & Smith-Ramiírez, R. (2003). Cost Sharing, Transaction Costs, and Conservation. *Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting*, Montreal, Canada, July 27-30, 2003.

[61] Liu, X., & Lynch, L. (2011). Do Agricultural Land Preservation Programs Reduce Farmland Loss? Evidence from Propensity Score Matching Estimator. *Land Economics*, *87*(2), 183-201.

[62] Mezzatesta, M., Newburn, D.A., & Woodward, R.T. (2013). Additionality and the Adoption of Farm Conservation Practices. *Land Economics*, *89*(4), 722-742.

[63] Rabotyagov, S.S., Kling, C.L., Gassman, P.W., Rabalais, N.N., & Turner, R.E. (2014). The Economics of Dead Zones: Causes, Impacts, Policy Challenges, and a Model of the Gulf of Mexico Hypoxic Zone. *Review of Environmental Economics and Policy*, *0*(0), 1-22.

[64] Rosenbaum, P. & Rubin, D.B. (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporates the Propensity Score. *The American Statistician*, *39*(1), 33-38.

[65] Rosenbaum, P. & Rubin, D.B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, *40*, 688-701.

[66] Rubin, D.B. (2001). Using Propensity Scores to Help Design Observational Studies: An Application to the Tobacco Litigation. *Health Services & Outcomes Research Methodology*, *2*, 169-188.

[67] Rubin, D.B. (1976). Inference and Missing Data (with discussion). *Biometrika*, *63*, 581-592.

[68] Rubin, D.B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, *66*, 688-701.

[69] Sekhon, J.S. (2011, May). Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching Package for R. *Journal of Statistical Software*, *42*(7), 1-52.

[70] Smith,J.A., & Todd, P.E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of Econometrics*, *125*, 305-353.

[71] Soil and Water Conservation Society (2015). *Iowa Cover Crops Conference to be held in West Des Moines* Obtained from Soil and Water Conservation Society News: www.swcs.org/index.cfm/70074/34066/iowa_cover_crops_conference_to_be_held_in_west_des_moines Published on: 1/14/2015. Accessed on: 09/2015

[72] Stuart, E. A. (2010). Matching Methods for Causal Inference: A Review and a Look Forward. *Statistical Science*, *25*, 1-21.

[73] Stuart, E. A., & Rubin, D.B. (2008). 11 Best Practices in Quasi-Experimental Designs: Matching Methods for Causal Inference. In J. Osborne, *Best Practices in Quantitative Methods*, Chapter 11. SAGE Publications, Inc.

[74] Swobdoba, R. (2013). *Iowa Cover Crop Cost-Share Funding Is In Big Demand*, Farm Progress Magazine http://farmprogress.com/story-iowa-cover-crop-cost-share-funding-big-demand-9-101856. Published on: 8/29/2013. Accessed on: 9/2015

[75] Tobin, J. (1958). Estimation of relationships for limited dependent variables *Econometrica*, *26*, 24-36.

[76] USDA NASS (2014). *Iowa Ag News Crop Production.* www.nass.usda.gov/Statistics_by_State/Iowa/Publications/Crop_Report/2014/IA_CropProd_08_14.pdf. Published on: 08/12/2014. Accessed on: 8/2015.

[77] USDA NRCS (2013). *Cover Crop Funding Opportunities* http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1082778.pdf Accessed on: 9/2015.

[78] Wooldridge, J.M. (2010) . *Econometric Analysis of Cross Section and Panel Data*. Cambridge: The MIT Press.

Chapter 3

[79] Alderman, H., Chiappori, P. A., Haddad, L., Hoddinott, J., & Kanbur, R. (1995). Unitary versus collective models of the household - is it time to shift the burden of proof? *The World Bank Research Observer*, *10*(1), 1-19.

[80] Bateman, I. J., & Munro, A. (2003). Testing economic models of the household: an experiment. *CSERGE working paper, University of East Anglia, Norwich.*

[81] Bateman, I., & Munro, A. (2005, March). An Experiment on Risk Choice Amongst Households. *The Economic Journal*, C176-C189.

[82] Bateman, I. J., & Munro, A. (2009). Household Versus Individual Valuation: What's the Difference? *Environmental Resource Economics*, *43*, 119-135.

[83] Becker, G. S. (1974). A theory of social interactions. *Journal of Political Economy*, *82*(6), 1063-1093.

[84] Bergstrom, T., Blume, L., & Varian, H. (1986). On the Private Provision of Public Goods. *Journal of Public Economics*, *29*(1), 25-49.

[85] Butle, E., Tu, Q., & List, J. (2015). Battle of the Sexes: How Sex Ratios Affect Female Bargaining Power. *Economic Development and Cultural Change*, *64*(1), 2-22.

[86] Cardenas, J. C. (2009). Experiments in Environment and Development. *Annual Review of Resource Economics*, *1*, 157-182.

[87] Carlsson, F., He, H., Martinsson, P., Qin, P., & Sutter, M. (2012). Household decision making in rural China: Using experiments to estimate the influence of spouses. *Journal of Economic Behavior & Organization*, *84*, 525-536.

[88] Carlsson, F., Martinsson, P., Qin, P., & Sutter, M. (2013). The Influence of Spouses on Household Decision Making under Risk: an Experiment in Rural China. *Experimental Economics*, 383-401.

[89] Castilla, C. (2015). Trust and Reciprocity between Spouses in India. *American Economic Review: Papers & Proceedings*, *105*(5), 621-624.

[90] Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: eliciting risk preferences. *Journal of Economic Behavior & Organization*, *87*, 43-51.

[91] Chiappori, P., & Meghir, C. (2015). Chapter 16 - Intrahousehold Inequality. In A. B. Atkinson, & F. Bourguignon (Eds.), *Handbook of Income Distribution* (Vol 2., pp. 1369-1418)

[92] de Brauw, A. (2015). Gender, control, and crop choice in northern Mozambique. *Agricultural Economics*, *46*, 435-448.

[93] deBrauw, A., & Eozenou, P. (2014). Measuring Risk Attitudes among Mozambican Farmers. *Journal of Development Economics*, *11*, 61-74.

[94] Doss, C. (2013, February). Intrahousehold Bargaining and Resource Allocation in Developing Countries. *World Bank Research Observer*, *28*(1), 52-78.

[95] Drichoutis, A. C., & Koundouri, P. (2012). Estimating Risk Attitudes in Conventional and Artefactual Lab Experiments: The importance of the underlying assumptions. *Economics: The Open-Access, Open Assessment E-Journal*, 1-15. Retrieved from http://dx.doi.org/10.5018/economics-ejournal.ja.2012-38 Accessed on: 02/2016.

[96] Duflo, E. (2003). Grandmothers and granddaughters: old age pension and intra-household allocation in South Africa. *World Bank Economic Review*, *17*, 1-25.

[97] Harrison, G., Humphrey, S., & Verschoor, A. (2010, March). Choice under Uncertainty: Evidence from Ethiopia, India, and Uganda. *The Economic Journal*, *120*, 80-104.

[98] Hoddinott, J., & Haddad, L. (1995). Does female income share influence household expenditures? Evidence from Cote d'Ivoire. *Oxford Bulletin of Economics and Statistics*, *57*, 77-96.

[99] Holt, C. A., & Laury, S. K. (2002, December). Risk Aversion and Incentive Effects. *American Economic Review*, *92*(5), 1644-1655.

[100] Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision Under Risk. *Econometrica*, *47*(2), 263-291.

[101] Liu, E. M. (2013). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cottom Farmers in China. *The Review of Economics and Statistics*, *95*(4), 1386-1403.

[102] Sheremenko, G., & Magnan, N. (2015). Gender-specific Risk Preferences and Fertilizer Use in Kenyan Farming Households. *AAEA and WAEA Annual Meeting.* San Francisco.

[103] Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data From Vietnam. *American Economics Review*, *100*(1), 557-571.

[104] Usman, L. (2006). Rural nomadic Fulbe boys' primary schooling: assessing repertoires of practice in Nigeria. *McGill Journal of Education*, *41*(2), 155-162.

[105] World Bank. (2011). *World Development Report 2012: Gender Equality and Development.* Washington, DC, USA: Work Bank.