# ESSAYS ON RESOURCE AND ENVIRONMENTAL ECONOMICS: EVIDENCE FROM A NATURAL EXPERIMENT, LABORATORY EXPERIMENT, AND SCENARIO FORECASTING

A Dissertation

by

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ABSTRACT

This dissertation examines impacts of product information and environmental events on individual behavior and the economy. This is done using a causal inference econometric approach, an eye-tracking laboratory experiment, and scenario forecasting.

The first essay evaluates the effects of unit-based pricing (UBP) of municipal solid waste and a mandatory recycling (MR) policy on waste reduction, recycling, and illegal waste dumping in Taiwan. The results suggest that the UBP policy curbed the quantity of unsorted waste and increased disposal of biodegradable waste but did not significantly increase the quantity of recycling. In contrast, the MR policy boosted biodegradable waste and recycling but did not necessarily decrease the amount of unsorted waste. The UBP policy also stimulated a temporary increase in illegal dumping.

The second essay applies an eye-tracking experiment to investigate how consumers react to honey product origin, adulteration, and review information. The experimental results suggest that the certified local honey seal and honey adulteration information independently raise WTP for local honey but do not interact to jointly raise WTP. The results also show that negative honey product reviews cause a much larger reduction in WTP than the increase produced by positive reviews.

The third essay reports on an investigation of how rice yield increases over time are influenced by climate, $CO_2$ fertilization, and research investment. To allow identification of $CO_2$ effects, the study integrates FAO reported yield data with data from the free air carbon dioxide enrichment (FACE) experiments. The result suggests that an increasing atmospheric CO2 concentration has made a significant contribution to rice yield increases, amounting to about 52% of the observed rice yield growth. The result also shows that increasing precipitation and temperature cause reductions in rice yields, implying that CO2 mitigation and climate change are yield growth depressing factors. On the other hand, the result indicates that research investments increase yields, and this finding raises a potential need for more investment in agricultural research and development if society is to offset CO2 mitigation and climate change effects.

DEDICATION

Dedicated to my dear family.

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## Contributors

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NOMENCLATURE

| | |
|---|---|
| AGRD | Agricultural research and development |
| ATE | Average treatment effect |
| CO2 | Carbon dioxide |
| FACE | Free air carbon dioxide enrichment |
| MR | Mandatory recycling |
| NTC | New Taipei City |
| TPC | Taipei City |
| UBP | Unit-based pricing |
| WTP | Willingness-to-pay |

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

Page

# CHAPTER I

# INTRODUCTION

The economy, market information, and the environment are interconnected and jointly affect each other. Costs associated with economic growth and product adulteration are often neglected. Failing to identify negative externalities and lower quality products could lead to unsustainable and inefficient growth plus food safety issues. Thus, identifying the effectiveness of environment and market information policies is needed to safeguard the environment and maintain a beneficial and safe economy.

Studying the economic effect of environmental policies/practices, market information and environmental characteristics helps address the above problem but can be a challenging task. Because of the nature of observational data and limits of statistical analyses of human behavior, empirical economic studies oftentimes contain potentially biased estimation results due to at least one confounding or endogenous variable that is correlated with unobserved factors. One way to address the confounding concern is to conduct controlled experiments, but these are usually expensive and not always feasible plus can be difficult to cover real word market situations. Alternatively, causal inference using econometric techniques with appropriate identification assumptions and scenario forecasting can also provide useful insights (Bessler and Palma 2018).

This dissertation reports on studies of the causal impacts of environmental and market developments through three independent essays. This is done by separately applying a causal inference econometric approach, a laboratory experiment, and a mixed observational and experimental data-based econometric estimation coupled with scenario forecasting. In particular,

- The first essay reports on an evaluation of the effects of municipal waste policies on residents' waste disposal behavior. Specifically, the chapter reports on an investigation of the effects of unit-based pricing (UBP) of municipal solid waste and mandatory recycling (MR) policies as they impact the volume of waste disposal, waste recycling, and illegal waste dumping in Taiwan.
- The second essay reports on an eye-tracking experiment that explored how consumers react to quality and point of origin information on honey products in terms of their willingness-to-pay.
- The third essay reports on an analysis done regarding the effects of climate, CO2 fertilization, and research investment on Asian rice yield productivity.

Figure I-1 demonstrates the dissertation framework on the applied economic research validity spectrum. The rest of this dissertation is structured as follows: the three essays are presented in chapters II, III, and IV, respectively. Finally, the conclusion section in chapter V summarizes the main findings and contributions from this work.

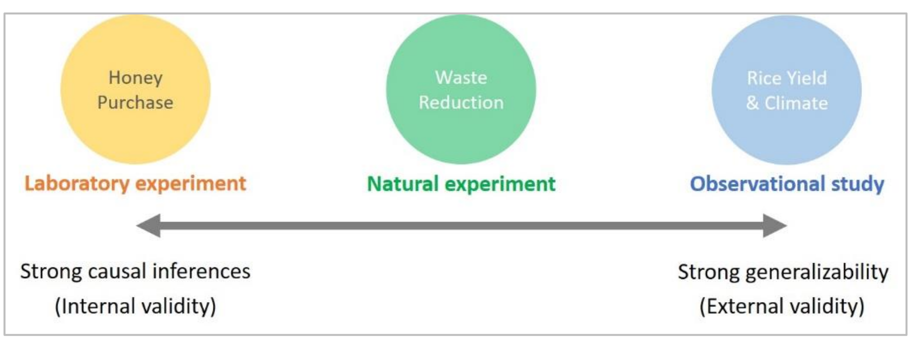


**Figure I-1 Dissertation framework**

CHAPTER II

WASTE REDUCTION AND WASTE SPILLOVERS: EVIDENCE FROM UNIT-BASED PRICING OF MUNICIPAL SOLID WASTE IN TAIWAN[1]

## II.1 Introduction

A poorly-designed waste management system can have negative impacts on the environment, human health, and biodiversity. Eighty percent of the world's projected population is anticipated to reside in cities and have sufficient disposable income to generate significant volumes of waste, necessitating advances in waste management (Wilson et al. 2015). Wilson et al. (2015) forecast a global population of 46% more than today by the end of the 21st century meaning the waste volume and associated disposal issue will certainly grow over time.

Policy needs to confront the growing waste disposal issue. Traditionally, waste management strategies have relied on command and control (C&C) approaches which set specific laws/standards on waste handling, recycling and disposal behavior. Examples of C&C policies are mandatory recycling (MR) or mandatory sorting practices.

Alternatively, policy makers have used unit-based pricing (UBP) policies (a.k.a pay-as-you-throw) which charges residents a per-unit waste disposal fee coupled with recycling incentives/possibilities, potentially providing incentives to both curb waste and

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[1] This is an accepted manuscript of an article published by Taylor & Francis in the *Journal of Environmental Economics and Policy* on December 17, 2020, available online: https://www.tandfonline.com/doi/full/10.1080/21606544.2020.1844064.

promote recycling. A UBP can be practically implemented by applying fees to use of waste bins, waste bags, or attached official tags/stickers. Units of waste can be measured by volume, weight, frequency, or some combination thereof. The pay-as-you-throw approach follows the 'polluter pays' principle, providing economic incentives to reduce waste. It has been shown to be a potentially efficient approach to reduce the quantity of collected waste (Callan and Thomas 1999; Dijkgraaf and Gradus 2009).

Waste management is a critical issue in Taiwan because of its limited land and high population density. Taiwan is one of the most densely populated countries[2] and has implemented a series of waste management policies to confront the disposal issue. Among those waste management policies, UBP policies and an MR policy have received considerable attention worldwide[3].

Taipei City (TPC), the capital of Taiwan, first implemented a UBP policy in July 2000. New Taipei City[4] (NTC), which surrounds Taipei City, introduced a pilot UBP program in July 2008, and a city-wide program in December 2010. Under that policy residents pay a waste-disposal fee based on the volume disposed. Residents must use

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[2] The territorial area of Taiwan is 36,193 $km^2$, and the total population is 23,519,518 in 2016. The population density is 649/ $km^2$, which is second highest among the countries with at least 10,000,000 people in the world.

[3] "Taiwan: The World's Geniuses of Garbage Disposal." The Wall Street Journal. May 17, 2016. Online. (Accessed December 12, 2017). "Taiwan's Recycling Boom: A Shining Example for Asia, the World." The Diplomat. December 3, 2013. Online. (Accessed December 12, 2017). "Short on Space, Taiwan Embraces a Boom in Recycling." The New York Times. November 29, 2013. Online. (Accessed December 12, 2017).

[4] Despite similar names, Taipei City and New Taipei City are distinct cities, each with its own municipal government and waste disposal policies.

authorized waste bags, which are sold in retail stores and priced by size. In New Taipei city, the price ranges from US $0.04 for the smallest bag to US $1.60 for the largest bag. Prices are almost identical in Taipei City and New Taipei City (see Panel A of Table II-1). There are also neighboring municipalities and other major cities that do not have municipality-wide UBP policy: these include Keelung City, Yilan County, Taoyuan City, Taichung City, Tainan City, and Kaohsiung City.

The presence of the UBP policy in Taipei City and New Taipei City coupled with nearby cities that do not have a UBP provides a natural experimental setting in which the effectiveness of UBP on waste related behavior can be studied relative to a behavior in a control group of municipalities without a UBP. The map in Figure II-1 shows the control group municipalities and their distances from the greater Taipei area. The spatial and intertemporal variation in UBP policies allows this study to estimate whether there are policy spillovers, where residents subject to UBP policies avoid fees either by shifting disposal to cities without such policies (i.e., a practice sometimes referred to as "waste tourism") or by illegal dumping. Kinnaman (2006, 2008) argues the overall effect of UBP is ambiguous if there are unintended side effects (e.g. waste tourism or illegal dumping), and this ambiguity will be addressed herein.

In addition to the UBP policy, Taiwan also implemented a nationwide MR policy in January of 2006. Under that policy, people who dispose of recyclable waste mixed with ordinary waste will be fined NT $1,200 – 6,000 (US $1 = NT $30), and waste-collection crews can refuse to collect mixed wastes. Details of the waste collection system in Taiwan are discussed in Section 2.2.

Given this setting, the objectives of the work reported in this essay are:

1) to quantify the effect of UBP policy on the levels of unsorted waste, biodegradable waste[5], and recyclable waste[6]. This is accomplished by using a difference-in-difference (DID) model between the cities with and without UBP policies. Besides that, this study also investigates whether illegal dumping and waste tourism are induced by the UBP policy; and

2) to study the influence of the nationwide MR policy. The essay examines the effects of implementing the MR policy in the level of waste, as well as its unintended side effects. This is done by investigating changes in the quantity of different waste sources. The resultant findings can inform local and global policymakers addressing waste management problems on policy effectiveness.

[5] Biodegradable waste includes waste food, nut or seafood shells, fruit peels, coffee grounds, waste plants, and other decomposable waste which can use for animal feed or composting.

[6] Recyclable waste also can be classified into ordinary recyclable waste and large recyclable waste. The former category includes paper, metal, plastic, glass, aluminum can, retort pouch, textile, appliance, battery, used light bulb, tire, electronics, and other recyclable items (e.g., umbrella, helmet, luggage). The latter category includes large durable goods (e.g., sofas, mattresses, air conditioners, and refrigerators).


**Figure II-1 Geographical illustration of Taiwan**

The remainder of the essay is structured as follows. Section 2 reviews the waste management literature and describes the waste management situation in Taiwan. Section 3 describes the data used. Section 4 introduces the empirical strategies for estimating the effect of UBP policy and spillover effects. Section 5 presents estimates of static and dynamic policy effects of UBP and MR policies and their side effects. Finally, conclusions and policy implications are presented.

## II.2 Waste Management Literature Review

### *II.2.1 Global Studies*

Several previous studies have investigated the effect of UBP policies. These studies were fundamentally based on two types of data: (i) household survey, and (ii) city-level aggregate data. Studies using household survey data are reviewed first. Fullerton and Kinnaman (1996) estimate household responses to a UBP policy in Charlottesville, Virginia, and find that the policy reduces waste disposal volume and increases recycling volume, but does not necessarily decrease the weight of household waste. Hong and Adams (1999) investigate the effects of a change in waste disposal service price on recycling in Portland, Oregon. They conclude that households respond to a price increase by increasing recycling to avoid extra charges for waste disposal. Hong (1999) investigates the effect of an increase in waste collection fees on recycling in South Korea and finds that households do not decrease waste collection volume after fees are increased, exhibiting relatively inelastic demand. Linderhof et al. (2001) find significant and sizeable price effects of weight-based pricing on compostable and non-recyclable waste for households in Oostzaan, the Netherlands. Jenkins et al. (2003) estimate the effect of curbside recycling, MR program, and unit pricing implemented using a survey results in 20 U.S. metropolitan areas. They find that a curbside recycling program increases household recycling more than a unit pricing program with the effect varying across different recyclable materials. They also suggest that MR programs have an insignificant effect on recycling.

Allers and Hoeben (2010) suggest that there are two disadvantages of using household-level survey data to evaluate UBP policies. First, such studies suffer from sample-selection bias because environmentally-conscious or well-educated people are more likely to respond, distorting results andmisleading policymakers. However, statistical corrections to such potential bias can overcome this criticism (Fullerton and Kinnaman 1996). Second, these survey studies typically focus on a short study period and may not capture the long-term policy impact. This also may be overcome, if time varying panels with repeated household observations are developed. It is also worth noting that relative to aggregate data developing one's own survey allows responses to waste related targeted questions to be integrated into the analysis.

Studies have also used city-level aggregate data in evaluating UBP policy. Kinnaman and Fullerton (2000) use community-level cross-sectional data in evaluating waste fees and curbside recycling programs. They find that the effect of local waste management programs may be underestimated by assuming the policy is exogenous. Dijkgraaf and Gradus (2009; 2004) examines effects of a UBP policy in the Netherlands, finding that it reduces the amount of unsorted waste, compostable waste, and increase recyclable waste. The authors also note that administrative costs are significantly lower for bag-based pricing. Usui and Takeuchi (2014) estimate a fixed effects model in Japan finding a long-lasting effect of UBP on recycling and a differing effect by income group. Specifically the higher income groups are more likely to engage in recycling activities without economic incentives. Carattini, Baranzini, and Lalive (2018) use both administrative data and survey data to estimate the effect of a UBP policy in Switzerland and find that people accept 70% higher waste taxes after pricing waste by the bag compared to before the policy came into effect.

Overall findings on the effectiveness of UBP policies are mixed, especially in terms of welfare impacts. Dijkgraaf and Gradus (2004) find a large welfare gain from the UBP policy that reduces waste in the Netherlands because of a higher marginal cost of waste collection and disposal. But Kinnaman (2006; 2008) asserts that the net benefits of introducing the UBP policy are small or even negative given the high administrative implementation cost and the increase in illegal waste dumping. To quantify the effects on illegal dumping caused by the UBP policy, Fullerton and Kinnaman (1996) estimate the effect of UBP on illegal dumping by using indirect survey questions. Carattini, Baranzini, and Lalive (2018) evaluate illegal dumping by using the number of illegal dumping citations. Kim, Chang, and Kelleher (2008) estimate that a 1% increase in the unit price of a waste bag led to a 3% increase in the number of reports of illegal dumping in South Korea. Usui and Takeuchi (2014) find a small increase in disposal spillover to adjacent municipalities was identified when municipalities introduced their pricing schemes in Japan. Miranda and Aldy (1998) find that UBP do not increase illegal disposal of residential solid waste in U.S. communities. Given that estimated policy impacts vary in individual countries, more carefully done studies of differences in the impacts of country-specific UBP policies are needed, to explore why they seem to work fairly well in some countries, but not others (e.g. the U.S.).

### *II.2.2 Taiwanese Studies*

Several waste management related studies have been conducted in Taiwan. Lu (2006) overviews the waste management measures in Taiwan and highlights the importance of MR policy among other waste management measures in Taiwan. Yang and Innes (2007) investigate the impact of the Taipei City UBP policy using a fixed-effects pooled model and a seemingly unrelated regression, but the study does not estimate the side effects of the policy or the long-term policy effects. Yang and Innes (2007) also study a regional MR program (only in Kaohsiung City not nationwide one).

In search of the literature, no previous study estimates the effects of the UBP policy in New Taipei City or that of the national MR policy in Taiwan. Nor do existing literature quantify the effects of illegal dumping in terms of actual weight caused by relevant policy interventions.

### *II.2.3 Background on Waste Management Systems in Taiwan*

The waste collected by municipalities in Taiwan contains four components: unsorted waste, biodegradable waste, recycled materials, and large recyclable waste. Large recyclable waste is primarily large-sized durable goods (e.g., sofas, mattresses, air conditioners, and refrigerators) that are not subject to the UBP policy. This study excludes large recyclable waste in this study.

Municipal solid waste in Taiwan is typically collected by waste trucks five days a week. These trucks broadcast music to notify inhabitants of their arrival at a designated location. Usually, two different types of trucks arrive: an open-bed recycling truck and a waste truck. The recycling truck arrives 10 minutes before the waste truck, which collects unsorted and biodegradable waste. The recycling truck departs to the next pick-up area once the waste truck arrives. The system makes it difficult for households to avoid paying the disposal fee. Because residents have to personally deposit their waste in a waste truck that is monitored by the collection crew, it is relatively easy to inspect whether residents use officially-authorized waste bags or not. This collection system also allows collection crews to inform residents of the policy details and recycling options.

In addition to the truck system, there are a few stationary waste collection locations in two cities. These are also managed and monitored by collection crews and video cameras. Some apartments also have a centrally managed waste space that is also monitored by video cameras and managed by an outsourced environmental service company. Finally, some residents sell their recyclable waste to private waste collection services. Although residents can earn money using these services, the private collector's visits are irregular and are considered an inconvenience by residents. Also, the payments are relatively low, so the services are not widely used to dispose of recycling waste.

The Taiwanese EPA also creates an incentive for residents to be involved in monitoring illegal dumping. Residents can upload video or photographic evidence to an online platform and earn up to half of the value of any fines collected. For instance, people disposing recyclable waste along with ordinary waste or not using government-issued waste bags will be fined NT $1,200 – 6,000 (US $1 = NT $30). Also, waste-collection crews can refuse to collect those wastes.

Though all municipalities in Taiwan charge waste fees, only Taipei City and New Taipei City charge a variable fee by government-authorized waste bags. The other municipalities in Taiwan assess residents a flat waste fee that is included with water bills. These flat fees do not cause residents to face marginal fee changes and thus do not internalize external marginal collection and disposal costs. Some other major cities in Taiwan have expressed interest or implemented in a variable rate waste management policy. For example, Shigang Town, in Taichung City also has had UBP fees since 2000. However, Taichung City did not implement as it faced considerable opposition because of political considerations  and concerns over illegal dumping (Kinnaman 2006;2008). Note that although there is the small town in Taichung City implementing the UBP policy, this study do use Taichung City as one of control municipalities. Shigang Town is quite small (0.82% of the total area in Taichung City, and 0.55% of the total population in 2016) (see

Panel B of Table II-1). Because town-level data are not available, this study uses different subsets of data to conduct a robustness check to address potential confounding.

**Table II-1 Information of the UBP policy, Taichung City, and summary statistics.**

| Panel A: Information of unit-based pricing in Taipei city and New Taipei City | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Bag size (liter)** | **Max. load / bag (kg)** | **Bags / pack** | **Taipei City** | | | **New Taipei City** | | |
| | | | US$/pack | US$/bag | US$/L | US$/pack | US$/bag | US$/L |
| 3 | 0.6 | 20 | 0.70 | 0.04 | 0.01 | 0.80 | 0.04 | 0.01 |
| 5 | 1 | 20 | 1.20 | 0.06 | 0.01 | 1.33 | 0.07 | 0.01 |
| 14 | 2.9 | 20 | 3.33 | 0.17 | 0.01 | 3.73 | 0.19 | 0.01 |
| 25 | 5.1 | 20 | 6.00 | 0.30 | 0.01 | 6.67 | 0.33 | 0.01 |
| 33 | 6.9 | 20 | 7.90 | 0.40 | 0.01 | 8.80 | 0.44 | 0.01 |
| 76 | 15.9 | 10 | 9.10 | 0.91 | 0.01 | 10.13 | 1.01 | 0.01 |
| 120 | 25.1 | 5 | 7.20 | 1.44 | 0.01 | 8.00 | 1.60 | 0.01 |

| Panel B: Comparison between Taichung City and Shigang Town | | | | | |
|---|---|---|---|---|---|
| | **Area ($km^2$)** | **Population** | | **Density (Pop./$km^2$)** | |
| | | **2001** | **2016** | **2001** | **2016** |
| Taichung City | 2,214.9 | 2,485,968 | 2,767,239 | 1,122.38 | 1,249.37 |
| Shigang Town | 18.2 | 15,290 | 15,174 | 839.63 | 833.26 |
| Share of Taichung City | 0.0082 | 0.0062 | 0.0055 | - | - |

| Panel C: Summary statistics | | | | | |
|---|---|---|---|---|---|
| **Statistic** | **N** | **Mean** | **St. Dev.** | **Min** | **Max** |
| Unsorted waste (kg per capita) | 1,536 | 16.56 | 5.73 | 6.38 | 70.04 |
| Biodegradable waste (kg per capita) | 1,152 | 2.62 | 1.23 | 0.02 | 5.98 |
| Recycling (kg per capita) | 1,632 | 9.07 | 4.2 | 0.74 | 18.23 |
| Illegal dumping incident (count/1,000 ppl) | 1,296 | 0.64 | 0.66 | 0.01 | 3.74 |
| Income (NTD 1,000) | 1,632 | 1,163.46 | 207.05 | 874.4 | 1,697.89 |
| Percentage of babies | 1,632 | 0.04 | 0.01 | 0.02 | 0.06 |
| Household size | 1,632 | 2.94 | 0.25 | 2.45 | 3.49 |

## II.3 Data

This study uses both waste and municipal characteristics city wide data at a monthly frequency. The variables of interest are

- quantity (by weight) of unsorted waste, biodegradable waste, and recycling from the Taiwanese Environmental Protection Administration (2018) from January 2001 to December 2016.
    - Unsorted waste is collected five days a week and is either sent to incineration plants or sent to landfills after being collected.
    - Biodegradable waste data are available from January 2003 to December 2014.
    - Illegal dumping data, which provide the number of illegal dumping violations, are collected by the major municipalities (Taipei City, New Taipei City, Taoyuan City, Taichung City, Tainan City, and Kaohsiung City) and are available from January 1998 to December 2015. These data are based on the number of citations to illegal waste dumpers which are assessed by inspection crews in Environmental Protection Bureaus of local governments or, as are reported by residents.
- Municipal characteristic data include annual household income, monthly city population, percentage of babies (below 3-years-old), and the annual average household population. These data are available from January 1998 to December 2016.
    - Annual household income, available from the Statistical Bureau of Taiwan, consists of annual household salary, rents from other properties, and other transferred income.

- Monthly population data from the EPA records the monthly number of residents in each municipality.
- Household characteristic data, including the population distribution by age, are provided by the Ministry of the Interior database.

Summary statistics for the waste and municipal characteristic data are shown in Panel C of Table II-1.

## II.4 Estimation Strategies

This study first uses a difference-in-difference model to estimate the effect of the UBP policy, using monthly-municipal data. New Taipei City is viewed as a treatment Municipality. Taipei City is included as a treated control, and six other municipalities in Taiwan without UBP policies are included as controls. The empirical approach of a static DID model is presented in detail in section 4.1, and a dynamic DID model is introduced in section 4.2.

Spillover effects on neighboring municipalities without UBP policies are also investigated. In particular, this essay estimates whether municipalities adjacent to New Taipei City experienced an increase in waste disposal following the policy implementation using a regression discontinuity method. This spillover part of the empirical strategy is discussed in section 4.3.

### *II.4.1 Difference-in-Difference Analysis of UBP*

This research estimates the average treatment effect (ATE) of a unit pricing policy on waste disposal using the following specification:

$$Y_{itw} = \alpha \cdot X_{it} + \beta_{TT} \cdot TT_t + \beta_{TC} \cdot TC_i + \tau \cdot TT_t \cdot TC_i + \rho \cdot MR_t + \theta \cdot MR_t \cdot UBP_{it} + \gamma \cdot Trend_t + \mu_i + \lambda_t + u_{itw} \quad (1)$$

where

$Y_{itw}$ is the waste type *w* (i.e., quantity of unsorted waste, biodegradable waste, and recycling per person) in municipality *i* in period *t*.

$X_{it}$ is a set of controls for municipality *i* at time *t*, such as the percentage of babies, household size, and income. $\alpha$ is a vector of coefficient parameters for the set of controls for municipalities.

$TT_t$ is an indicator variable that equals 1 following the implementation of the UBP policy, and equals 0 before the policy.

$TC_i$ is an indicator variable that equals 1 if the observation belongs to a treated municipality and equals 0 otherwise. Note since the unit price of the UBP policy is almost identical in the treated cities (Taipei City and New Taipei City) (refer to Panel A of Table II-1), using the dummy variable to estimate the effect of the UBP policy in both cities is not problematic. The coefficient of the intersection term between $TT_t$ and $TC_i$, $\tau$, accounts for the ATE of the UBP policy.

$MR_t$ is an indicator variable that equals 1 if an observation is after January 2006, represents the presence of a nationwide mandatory waste recycling policy.

Note that there is no control group to conduct a DID analysis for the national MR policy because the MR policy was implemented in all municipalities. Thus, the simple dummy variable is employed to analyze the MR policy in Equation (1). Its coefficient, $\rho$, captures the MR policy effect.

$UBP_{it}$ is a dummy variable which is equal to 1 if the observation is in the period when the UBP policy is implemented in Taipei City or New Taipei City. The interaction term between $MR_t$ and $UBP_{it}$, $\theta$, captures differential effects of the MR policy on the non-UBP and UBP municipalities.

$Trend_t$ is a time trend which captures nationwide growth of environmental awareness and increasing familiarity with recycling behavior over the study period.

$\mu_i$ and $\lambda_t$ represent municipality-specific fixed effects and monthly fixed effects, which respectively control for unobserved geographical and seasonal factors.

$u_{itw}$ denotes an idiosyncratic error term.

### *II.4.2 Estimating Dynamic Effects of the UBP*

In addition to quantifying the intertemporal average effect of the UBP, the effect of the policy change over time is also relevant. To address this, this study constructs an alternative dynamic DID model (Equation 2):

$$Y_{itw} = \alpha \cdot X_{it} + \sum_{k=1}^{K} \beta_k \cdot LTT_k + \beta_{TC} \cdot TC_i + \sum_{k=1}^{K} \tau_k \cdot LTT_k \cdot TC_i + \delta \cdot Trend_t + \mu_i + \lambda_t + u_{itw} \quad (2)$$

where

$Y_{itw}$ is the waste type *w* (i.e., quantity of unsorted waste, biodegradable waste, and recycling per person).

$X_{it}$ denotes a matrix of characteristics of municipality *i* in time *t*, which is the same as defined in Equation (1).

$LTT_k$ denotes a set of indicator variables for $k$th lagged year after the implementation of the UBP policy. For instance, the UBP policy was first implemented in July 2008 in New Taipei City, so $LTT_1$ is 1 if an observation is in the first year lag (i.e. 2009) and is zero otherwise. Other year lag length indicator variables use the same notation except for the indicator variable 2008 which is equal to 1 if an observation is in the period from July to December of 2008 and is zero otherwise.

$\tau_k$ is a treatment effect of the UBP policy in $k$th lagged year.

$\mu_i$ represents municipality-specific fixed effects. Note that the model cannot include the MR policy dummy and yearly fixed effects simultaneously because of issues associated with multicollinearity. To estimate yearly dynamic treatment effects, the model needs to include yearly dummy variables instead of incorporating the MR policy dummy.

$\lambda_t$ is a set of month and year dummies, which control unobserved seasonal effects and nationwide impacts of the MR policy over time.

### *II.4.3 Potential Spatial Spillover Effects of UBP*

This section describes the identification strategy for spatial waste spillovers (or waste tourism) caused by the UBP policy. Given that waste disposal policies vary at the municipal level, it is possible for Taipei City and New Taipei City residents to avoid waste disposal fees by disposing of waste in nearby municipalities that do not have UBP. By moving waste from the treated to control municipalities, waste tourism would bias the estimated average treatment effect upward, making the policy appear effective even if the nationwide waste disposal levels were unchanged.

To examine the waste spatial spillovers, the following municipality-specific time-series model for municipality *i* is used:

$$Y_t = \alpha + \beta \cdot X_t + \gamma \cdot UBP_t + \rho \cdot MR_t + \delta \cdot Trend_t + \lambda_t + e_t \quad (3)$$

where

$Y_t$ denotes the quantity of unsorted waste per person in time *t*.

$X_t$ denotes a matrix of characteristics of neighboring municipality in time *t*, such as percentage of babies, household size, and income.

$\gamma$ is a coefficient on the policy spillover effects that is estimated using the policy dummy variables ($UBP_t$), which have a value of 1 if observation is after July 2008, and 0 otherwise.

$Trend_t$ is a linear time trend ($Trend_t$ that is used capture long-term time-variant unobservable trends, such as environmentally-conscious awareness and familiarity of recycling behavior, are controlled for using a in the model.

$\lambda_t$ is a set of month dummies, which control unobserved seasonal effects.

$e_t$ denotes the error term.

Results of Equations (3) are estimated using a generalized least squares approach to make the results robust to serial correlation.

## II.5 Empirical Results

### *II.5.1 Results on implementing UBP*

The quantities of unsorted waste, biodegradable waste, recycling, and illegal dumping are plotted over time for each city in the sample in Figure II-2, respectively. The first vertical dashed line in July 2000 marks the implementation of the UBP policy in Taipei City. The vertical dashed line in January 2006 and in July 2008 indicate the implementation of the nationwide MR policy and the beginning of the UBP pilot program in New Taipei City, respectively. The dashed line in December 2010 marks when the policy was expanded to cover the entire New Taipei City. Note that this study excludes observations for unsorted waste in September 2001 because there is an extremely high amount of unsorted waste in that period in Taipei City. This outlier was caused by Typhoon Nari which led to catastrophic flooding in Taipei City and caused huge damage in residential and commercial areas. In fact, the UBP policy was temporarily suspended during a one-month cleanup period.

Overall, Figure II-2 displays parallel trends for these variables of interest in the sample municipalities during the pre-treatment periods. Unsorted waste had a downward trend over the study period. Biodegradable and recyclable waste had an increasing trend (see Panel B and C of Figure II-2). The number of illegal dumping incidences in New Taipei City increased sharply right after the UBP policy extended to the entire city, but it fell a few years after implementation of the policy.

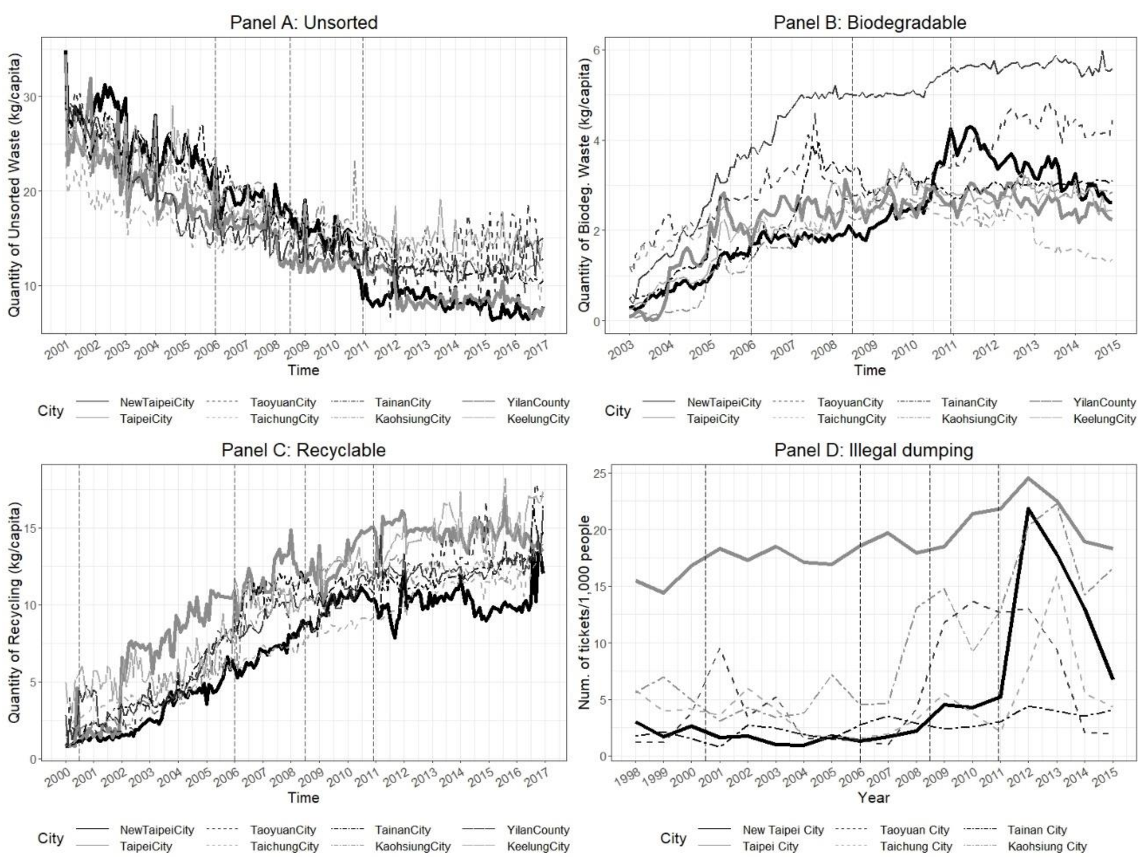


**Figure II-2 Trend for variables of interest**

Note: The vertical line in July of 2000 indicates the implementation of the UBP policy in TPC; the vertical line in January of 2006 indicates the implementation of the nationwide MR policy; the vertical line in July of 2008 indicates the implementation of the pilot UBP policy in NTC; the vertical line in December of 2010 indicates the implementation of the city-wide UBP policy in NTC.

Table II-2 presents the results of the basic DID model with and without including observations in Taichung City, using only observations on or after January 2006 after the MR policy was implemented nationwide. Although the UBP policy in Taiwan is volume-based, waste data are measured by weight, as opposed to volume. This is important for the following reasons. First, the volume of waste can vary based on household behavior because waste can be compacted, even if by hand. This potentially introduces endogeneity in volume. The weight of the waste does not depend on a change in volume. Second, the original units of the data are weights of the waste per month so that the data do not need to do any conversion. Third, most relevant studies also estimate policy effects by weight of the wastes, facilitating comparisons. Finally, the study can gauge possible illegal dumping by weight (refer to Section 6.2 for details) which is more precise compared to the number of illegal dumping citations.

This study estimates that the UBP policy in New Taipei City on average reduced the quantity of unsorted waste by 2.59 kg per capita per month, or a 14% decline. The combination of the UBP policy and MR policy caused a 3.48 kg per capita per month reduction in unsorted waste, or an 18% decline relative to New Taipei City's 2007 level. The MR policy alone had no statistically significant effect on reducing unsorted waste. Furthermore, the MR policy had a more significant effect on increasing biodegradable waste in New Taipei City compared to the UBP policy. Biodegradable waste disposal increased by 0.62 kg per capita per month (a 34% increase relative to New Taipei City's 2007 level) under the MR policy. The UBP policy boosted recycling in Taipei City by 2.6

kg per capita per month (a 59% increase relative to Taipei City's 2000 level), but the UBP policy alone in New Taipei City did not significantly increase recycling. The interaction term between the UBP and MR policy in the model, implying the combination effect of both policies, accounts for an additional increase of 0.99 kg per capita per month (a 14% increase relative to New Taipei City's 2007 level). The MR policy alone also helped to stimulate recycling by 1.6 kg per capita per month (a 31% increase relative to New Taipei City's 2005 level). The results also show that the UBP policy in New Taipei City increased illegal dumping by 0.27 violation incidences per 1,000 people relative to the control cities However, there is no statistical evidence showing that the MR policy increased illegal dumping.

There is a potential confounding issue caused by the pilot UBP program in Shigang Town of Taichung City, and to address this, the study estimates the policy effects on four variables of interest with all data and again by excluding data in Taichung City. Due to the small scale of the town in terms of sizes and populations compared to entire Taichung City, the town barely affected the level of waste in Taichung City. The estimation yields the similar result for all variables of interest with and without including data for Taichung City.

**Table II-2 Estimated effects of the UBP and MR policy on waste.**

| | Unsorted | | | Biodegradable | | |
|---|---|---|---|---|---|---|
| | All data | Exclude TCC | Post Jan-2006 | All data | Exclude TCC | Post Jan-2006 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Percentage of babies | 179.00** | 183.74 | -78.13 | -54.07** | -44.56** | -69.45** |
| | (90.80) | (132.89) | (102.56) | (22.14) | (20.79) | (31.29) |
| Household size | -5.48 | -8.27 | -5.72* | -8.5 | -7.94* | 0.23 |
| | (8.22) | (10.21) | (2.98) | (6.01) | (4.22) | (0.76) |
| Income (NTD 1,000) | 0.01 | 0.01 | 0.01** | 0.0003 | 0.002 | 0.001 |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| I(UBP in NTC) | -2.59*** | -2.81*** | -4.58*** | 0.18 | 0.38* | 0.88*** |
| | (0.31) | (0.23) | (0.59) | (0.34) | (0.22) | (0.11) |
| MR | -1.15 | -1.4 | | 0.62** | 0.79*** | |
| | (1.00) | (1.20) | | (0.27) | (0.25) | |
| I(UBP in NTC) × MR | -3.48** | -2.59** | | 0.69 | 0.3 | |
| | (1.36) | (1.15) | | (0.50) | (0.24) | |
| Time trend | -0.08** | -0.09** | -0.07*** | -0.02 | -0.01 | 0.01 |
| | (0.04) | (0.04) | (0.02) | (0.02) | (0.01) | (0.01) |
| Constant | 27.4 | 35.77 | 32.48*** | 27.28 | 23.30* | 2.49** |
| | (20.48) | (22.74) | (3.67) | (17.83) | (12.67) | (1.23) |
| Duration | Jan 2001 – Dec 2016 | Jan 2001 – Dec 2016 | Jan 2006 – Dec 2016 | Jan 2003 – Dec 2014 | Jan 1998 – Dec 2014 | Jan 2006 – Dec 2014 |
| Num. of municipalities | 8 | 7 | 8 | 8 | 7 | 8 |
| Observations | 1,536 | 1,344 | 1,056 | 1,152 | 1,008 | 864 |
| Municipal fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Monthly fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |

Note: *p<0.1; **p<0.05; ***p<0.01. The unit of income is NT$ thousands (US$ 1 = NT$ 30). The treatment effects of UBP and MR policies are in terms of kg per capita. All standard errors are clustered by cities. The results of municipal and monthly fixed effects are not shown in the table because of the limited space.

**Table II-2 Estimated effects of the UBP and MR policy on waste (cont.).**

| | Recycling | | | Illegal dumping incident | | |
|---|---|---|---|---|---|---|
| | All data | Exclude TCC | Post Jan-2006 | All data | Exclude TCC | Post Jan-2006 |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| Percentage of babies | -169.36*** | -214.09*** | -51.94 | 11.16 | 1.80 | -18.26*** |
| | (47.61) | (38.92) | (64.64) | (19.43) | (23.13) | (7.01) |
| Household size | 1.4 | 5.94 | -6.35*** | -1.87 | -0.6 | -1.48*** |
| | (5.64) | (4.43) | (1.66) | (2.87) | (3.79) | (0.11) |
| Income (NTD 1,000) | 0.002 | 0.002 | 0.001 | -0.0003 | -0.001 | -0.002 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| I(UBP in TPC) | 2.60*** | 2.33*** | | 0.35 | 0.27 | |
| | (0.39) | (0.39) | | (0.27) | (0.34) | |
| I(UBP in NTC) | -0.67* | -0.37 | 0.67* | 0.27* | 0.29 | 0.23 |
| | (0.37) | (0.29) | (0.36) | (0.14) | (0.20) | (0.17) |
| MR | 1.60*** | 1.79*** | | 0.02 | -0.001 | |
| | (0.54) | (0.53) | | (0.07) | (0.07) | |
| I(UBP in NTC) × I(UBP in TPC) × MR | 0.99* | 0.52 | | 0.002 | -0.1 | |
| | (0.52) | (0.40) | | (0.25) | (0.33) | |
| Time trend | 0.04** | 0.05*** | 0.01 | -0.004 | 0.0002 | 0.002 |
| | (0.02) | (0.02) | (0.01) | (0.01) | (0.01) | (0.00) |
| Constant | 5.69 | -6.2 | 27.63*** | 6.40 | 3.54 | 7.77*** |
| | (15.15) | (12.11) | (3.01) | 9.55 | (12.39) | (2.48) |
| Duration | Jan 2000 – Dec 2016 | Jan 2000 – Dec 2016 | Jan 2006 – Dec 2016 | Jan 1998 - Dec 2015 | Jan 1998 – Dec 2015 | Jan 2006 – Dec 2015 |
| Num. of municipalities | 8 | 7 | 8 | 6 | 5 | 6 |
| Observations | 1,632 | 1,428 | 1,056 | 1,296 | 1,080 | 720 |
| Municipal fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Monthly fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |

Note: *p<0.1; **p<0.05; ***p<0.01. The unit of income is NT$ thousands (US$ 1 = NT$ 30). The treatment effects of UBP and MR policies are in terms of kg per capita. All standard errors are clustered by cities. The results of municipal and monthly fixed effects are not shown in the table because of the limited space.

The identification assumption of DID in this study is based on the fact that in the absence of the UBP policy, municipalities' waste level in the treated municipalities would have remained similar to the municipalities yet to be treated. This is known as a common trend assumption. To check the robustness of the estimated average treatment effect, a falsification or Placebo test, which evaluates the common trend identification assumption required in DID models, was conducted. The aim of these robustness checks is to demonstrate that the estimated treatment effect in Table II-2 is not simply the result of chance. Rather, the estimation is statistically different from counterfactual treatment effects which are estimated by creating artificial counterfactual policy interventions.

First, monthly counterfactual policy intervention dummies were created using data in the pre-treatment period. These policy dummies are equal to 1 from the time of counterfactual policy interventions through the end of the pre-treatment period and have zero values before the counterfactual policy interventions. Using the counterfactual policy dummies in Equation (1), rather than the actual policy dummy, the new model can be written as

$$Y_{it} = \alpha \cdot X_{it} + \beta_{CTT} \cdot ATU_t + \beta_{TC} \cdot TC_i + \tau_C \cdot ATU_t \cdot TC_i + \rho \cdot MR_t + \mu_i + \lambda_t + u_{it} \qquad (4)$$

where $ATU$ is the average treatment effect on the untreated, namely a counterfactual treatment time dummy indicating counterfactual policy interventions in each month during the pre-treatment period. The coefficient on the interaction term is the counterfactual treatment effect ($\tau_C$). The definitions of the rest of variables are identical to those used in Equation (1).

Iteratively replacing $ATU$ in Equation (4) with different counterfactual policy interventions yields different counterfactual treatment effects ($\tau_C$). The distribution of those counterfactual treatment effects using the same model specifications with Models (1), (4), (7), and (10) of Table II-2 is shown in Figure II-3, and its statistical summary is presented in Panel A of Table II-3. The result of the Placebo test shows that the true ATEs are significantly different with the counterfactual placebo treatment effects ($\tau_C$) for unsorted waste, biodegradable waste, and illegal dumping incidences, but the estimation in recycling appears to be less robust. In other words, except for the estimated effect in recycling, the treatment effect estimated by the DID model is larger than would be expected by chance, indicating that the estimated ATEs of Table II-2 capture the actual policy impact.

In addition to the Placebo test, this essay constructs a t-test to examine whether the quantity of unsorted waste, biodegradable waste, recycling, and illegal dumping have common trends for the treatment and control municipalities in the pre-treatment period. The growth rate is calculated by $(Y_{t+1} - Y_t)/Y_t$, where $Y_t$ is the quantity of unsorted, biodegradable waste, recycling, or illegal dumping in month $t$. The p-values of the t-tests are presented in Panel B of Table II-3. The null hypotheses, which assumes the average growth rates in the treated and control municipalities are identical in the pre-treatment period, cannot be rejected in a 90% confidence level. That is, the identifying assumption of parallel trends can be rejected using a difference-of-means test.

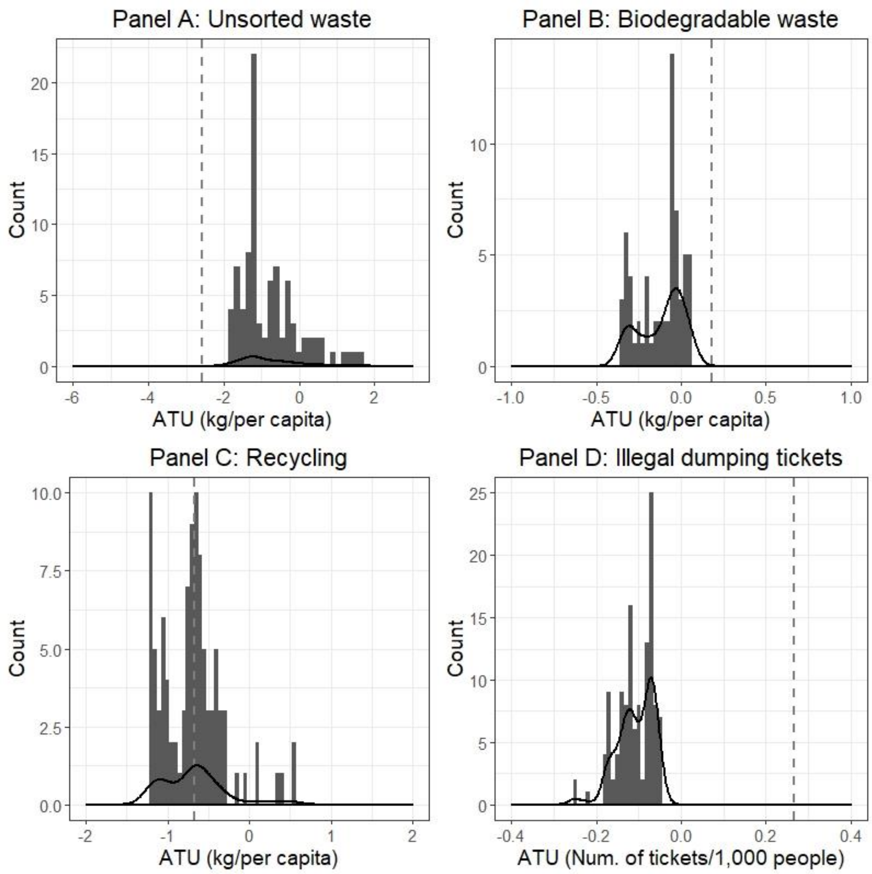


**Figure II-3 Placebo test for the difference-in-differences model.**

Note: The vertical dashed lines in the graphs indicate the average treatment effect on the untreated (ATU) estimated by using the same specification of Model (1), (4), (7), and (10) in Table II-2.

**Table II-3 Robustness check for the difference-in-differences model.**

| Panel A: Statistic summary of counterfactual treatment effect | | | | |
|---|---|---|---|---|
| | Unsorted waste | Biodegradable waste | Recycling | Illegal dumping |
| Mean | -0.783 | -0.118 | -0.689 | -0.1078 |
| 95% CI | (-0.9500, -0.6157) | (-0.15056, -0.0855) | (-0.7651, -0.6128) | (-0.1154, -0.1002) |
| P-value | 0.000 | 0.000 | 0.7075 | 0.000 |
| Actual ATE of UBP | -2.5900 | 0.1779 | -0.6745 | 0.2689 |

| Panel B: T-test for growth rate of variables of interest across municipalities | | | | |
|---|---|---|---|---|
| | Unsorted waste | Biodegradable waste | Recycling | Illegal dumping |
| NTC=TPC | 0.337 | 0.936 | 0.769 | 0.9878 |
| NTC=KLC | 0.425 | 0.666 | 0.398 | - |
| NTC=YLC | 0.536 | 0.623 | 0.695 | - |
| NTC=TYC | 0.572 | 0.125 | 0.731 | 0.8473 |
| NTC=TCC | 0.496 | 0.101 | 0.152 | 0.9244 |
| NTC=TNC | 0.516 | 0.525 | 0.602 | 0.9836 |
| NTC=KSC | 0.451 | 0.918 | 0.560 | 0.8977 |

Note: NTC represents as New Taipei City; KLC represents as Keelung City; YLC represents Yilan County; TYC represents Taoyuan City; TCC represents Taichung City; TNC represents Tainan City; KSC represents Kaohsiung City. Panel A shows the distribution of counterfactual treatment effects ($\tau_C$) using the same model specification with Model (1), (4), (7), and (10) of Table II-2. The values in Panel B are p-values obtained from t-test.

### *II.5.2 Dynamic Effects of UBP*

The dynamic treatment effects of the UBP policy in New Taipei City are reported in Figure II-4. The UBP policy effect on unsorted waste began with an insignificantly small reduction during the pilot program (i.e. 2008-2010, or lagging years 0-2), and the effect size increased and remained significant after the policy went into effect for all of New Taipei City (i.e. 2011-2016 or lagging years 3-8). On the other hand, the effect of UBP on biodegradable waste was not measurable during the pilot program, but a significantly positive effect is estimated at the beginning of the city-wide policy rollout (i.e. 2011-2012 or $3^{rd}$ - $4^{th}$ lagged year) and slightly diminishes as time passes. Unlike the significant results for unsorted and biodegradable waste, the UBP policy had an unclear effect on recycling in New Taipei City but had significant effects on increasing recycling in Taipei City. This result suggests that the growth in recycling in New Taipei City shown in Figure II-2 could be mainly explained by the MR policy, which is consistent with the estimated result for recycling in Table II-2.

Illegal dumping also changes over time. The dynamic DID model for illegal dumping shows that the incremental amount of illegal dumping in New Taipei City spiked after the UBP policy was introduced and diminished with the passage of time. Also note that the increase in illegal dumping was not evident during the pilot program (i.e. 2008-2010, or with years lagged at 0-2) and only became evident after the full implementation of the UBP policy (i.e. 2012 and 2014, or lagged years 4 and 6). However, the UBP policy in Taipei City did not increase illegal dumping.

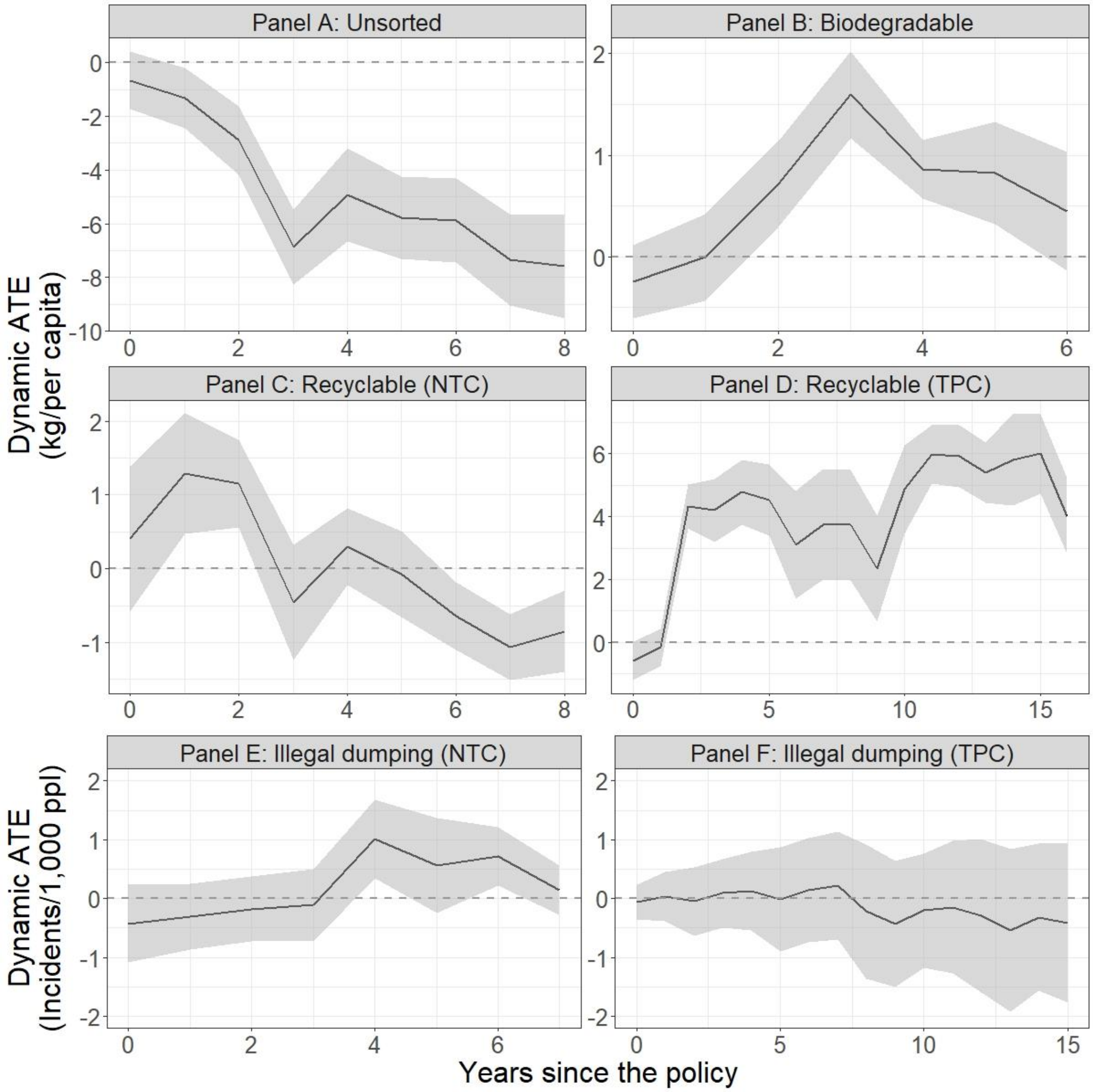


**Figure II-4 Dynamic average treatment effects (ATE)**

Note: *p<0.1; **p<0.05; ***p<0.01. Gray shades indicate a 95% confidence interval. All estimates control city and monthly fixed effects. All standard errors are clustered by cities.

### *II.5.3 Analysis of Spatial Spillover Effects of UBP*

The examination of potential spatial waste spillovers using the municipality-specific time-series model in Section 4.3 is presented in Table II-4. The insignificant coefficients of the UBP policy in New Taipei City suggest that there are no waste spillovers from New Taipei City to neighboring municipalities except for Yilan County. The marginally significant coefficient indicates that the UBP of New Taipei City may marginally increase unsorted waste in Yilan County, implying that there may be spatial waste spillover from New Taipei City to Yilan County. Besides that, the MR policy increased the amount of unsorted waste in Yilan County. Note that Yilan County is a rural area where the enforcement of inspecting non-recycling behaviors may not be as strict as urban areas are. The population density of Yilan county is much lower than in other urban municipalities, so it would be more difficult to observe neighbors' non-recycling behaviors.

Taken together, the results in Table II-4 suggests that the implementation of the UBP policy in New Taipei City did not induce waste tourism in its adjacent urban municipalities but likely in its neighbor rural municipality.

**Table II-4 Examination of spatial waste spillovers from New Taipei City to neighbor municipalities.**

| | Unsorted waste (kg per capita) | | | |
|---|---|---|---|---|
| | Taipei City | Taoyuan City | Keelung City | Yilan County |
| | (1) | (2) | (3) | (4) |
| Income (NTD 1,000) | 0.017 | 0.004 | 0.003 | -0.006** |
| | (0.011) | (0.005) | (0.004) | (0.003) |
| Percentage of babies | 51.470 | 781.951*** | 468.891*** | 966.927*** |
| | (83.636) | (118.284) | (157.717) | (176.111) |
| Household size | 42.210** | -43.733** | -38.316 | -0.848 |
| | (19.764) | (19.332) | (25.507) | (24.180) |
| I(UBP in NTC) | 0.647 | -0.625 | -2.107*** | 1.214* |
| | (0.838) | (0.815) | (0.753) | (0.682) |
| MR | -0.634 | -0.362 | -2.131** | 2.074** |
| | (0.941) | (0.755) | (0.968) | (0.815) |
| Time trend | -0.022 | -0.143*** | -0.092 | 0.007 |
| | (0.039) | (0.054) | (0.062) | (0.083) |
| Constant | -130.513** | 115.172** | 105.927* | -13.055 |
| | (59.828) | (57.766) | (61.402) | (70.265) |
| Observations | 190 | 190 | 190 | 190 |
| Monthly dummies | Yes | Yes | Yes | Yes |
| Log Likelihood | -343.210 | -346.390 | -350.374 | -289.835 |
| Akaike Inf. Crit. | 726.420 | 732.780 | 740.747 | 619.669 |
| Bayesian Inf. Crit. | 789.370 | 795.730 | 803.697 | 682.619 |

Note: *p<0.1; **p<0.05; ***p<0.01. The unit of income is NT$ thousands (US$ 1 = NT$ 30). The treatment effects of UBP and MR policies are in terms of kg per capita. All standard errors are with correction for autocorrelation of first order.

## II.6 Discussion

### *II.6.1 Comparison Between the UBP Policy and the MR Policy*

Which waste management instrument is more effective between the UBP and MR policy? To answer this question, this study first compare which policy instrument is more effective to achieve the basic policy goal of more greatly reducing unsorted waste, increasing biodegradable waste and recycling. The comparison is based on the estimates from the DID models presented in Section 5.

The results of the DID model in Table II-2 demonstrate that the UBP policy alone significantly reduced the quantity of unsorted waste in New Taipei City by 2.59 kg per capita/month, the combination of the UBP and MR policy decreased in unsorted waste by 3.48 kg per capita/month, and increased recycling by 0.99 kg per capita/month. Model 7 of Table II-2 shows that the UBP policy did not increase recycling in New Taipei City but did in Taipei City. A possible reason is that Taipei City implemented the UBP policy earlier than the MR policy and had a relatively lower benchmark level of recycling, so the UBP policy in Taipei City had much more room to stimulate recycling. The growth of recycling in New Taipei City was affected more by the MR policy than the UBP policy because the latter was implemented later in the period. On the other hand, the MR policy did not lead to reducing unsorted waste but inducing an increase in the quantity of biodegradable waste and recycling by 0.62 and 1.6 kg per capita/month, respectively. Importantly, the MR policy did not cause illegal dumping. However, the UBP policy in New Taipei City increased illegal dumping (Panel E of Figure II-4) but did not significantly increase illegal dumping (Panel F of Figure II-4) in Taipei City. Note that there is no waste tourism caused by both UBP and MR policy in neighbor urban municipalities but likely in adjacent rural municipalities (Table II-4).

Overall, according to the estimation results in Section 5, the UBP policy in New Taipei City was more effective than the MR policy in curbing unsorted waste but could also lead to increasing illegal dumping. On the other hand, the MR policy leads to increased biodegradable waste and recycling without causing illegal dumping. With these tradeoffs the optimal policy thus depends on policymaker's specific goals, as well as their available waste management resources. The cities need to have corresponding administrative resources ready to prevent the illegal dumping (Ichinose and Yamamoto 2011).

### *II.6.2 Quantifying Illegal Dumping*

Given the identification strategy and data, this study can assess the effect of the UBP policy on illegal dumping citations and a frequency range of weights based on the results of the DID model in Table II-2.

To estimate UBP effects on the approximate weight of illegal dumping caused by the UBP policy alone, this study uses the estimated results with the post-2006 model of Table II-2. The post-2006 model shows that the UBP policy significantly reduced the quantity of unsorted waste in New Taipei City by 4.58 kg per capita/month while it increased the quantity of biodegradable waste and recycling by 0.88 and 0.67 kg per capita/month. Part of the 4.58 kg reduction per capita/month of unsorted waste can be accounted for by an increase of 1.55 kg per capita/month in biodegradable and recyclable waste that would have otherwise been included in unsorted waste. After accounting for this, noting that there is no significant increase in waste tourism in municipalities nearby New Taipei City

(Table II-4), this leads to an estimated net unsorted waste reduction of 3.03 kg per person/month. This missing unsorted waste could be explained by illegal dumping, lifestyle changes, or other unobserved factors which can reduce residents' waste disposal and were not controlled for by time trend, time and municipal fixed effects. If all of the missing waste is considered to be illegal dumping, then the amount is 3.03 kg per capita/month or 143,160 tons per year (31% of average annual total collected waste from 2009 to 2016). One can scale this back by making assumptions on the proportion of missing waste that is illegal dumping. A detailed range analysis on illegal dumping is shown in the upper part of Table II-5.

## II.7 Summary and Concluding Remarks

The analysis reported on in this essay demonstrates that the UBP policy reduced the quantity of unsorted waste in all periods in the cities where it was applied. It also caused an increase in recycling in Taipei City as the policy was implemented in the period before the mandatory recycling was implemented, but not in New Taipei City as implementation did not occur until after the mandatory recycling policy was in place. The study also finds that there is no illegal out of city waste dumping caused by New Taipei City's UBP. We also found a mild increase in unsorted waste in an adjacent rural municipality after UBP implementation (Model 4 of Table II-4). Finally, the essay finds a short-term increase in illegal dumping that diminished in the long term. In contrast, the MR policy boosted biodegradable waste and recycling without detecting illegal dumping.

The implications of the study results are as follows. First, the implementation of the UBP policy could increase illegal dumping. Still, the finding shows that the illegal dumping volume dropped over time. This result implies that the implementation of the UBP policy can cause unintentional environmental damage and additional administration costs to monitor illegal dumping and waste tourism that may diminish over time. Second, the UBP policy could reduce waste without inducing illegal dumping if there is a proper provision of waste management resources (Ichinose and Yamamoto 2011). This argument is supported by the estimation of the UBP policy in Taipei City, where the resulting finding shows that the UBP policy increases recycling volumes without increasing illegal dumping (see Table II-2, Panel D and F of Figure II-4). This result also supports work by Yang and Innes (2007), who found that illegal dumping is not a serious problem in Taipei City perhaps due to its larger level of funding for environmental affairs in the city budget. Third, the MR policy effectively increased the sorting out of biodegradable waste and the amount of recycling. Nevertheless, implementing the MR policy alone may not necessarily reduce unsorted waste since there is no monetary incentive for residents to do so. A combination of implementing the UBP and MR policy would be a favorable way to curb unsorted waste and to encourage sorting and recycling behaviors.

This study may shed some light on differences in estimated impacts of UBP programs in the literature. In this study, the UBP policy effects differed between Taipei and New Taipei cities and thus can be specific to the locale in case of Taiwan due to implementation timing and interaction with other waste policies (in this case the MR policy). This may help explain mixed conclusions in the literature about UBP policy effectiveness. Furthermore, many of the U.S. studies (Fullerton and Kinnaman 1995; 1996; Kinnaman and Fullerton 2000) find limited benefits of UBP due to leakage and illicit dumping. The studies conducted in European settings (Dijkgraaf and Gradus 2004; 2009; Allers and Hoeben 2010; Carattini, Baranzini, and Lalive 2018; Sterner and Bartelings 1999), provide a relatively optimistic aspect of UBP policies with lower illicit dumping conditional on enforcement. This study shows that there were some unintended effects of illegal dumping following by the implementation of the UBP policy in the short-run. However, the benefits of the UBP occurred in both short-run and long-run. Namely, this essay not only verifies the concern from U.S. studies but also finds appreciable benefits of the UBP policy as many European country studies find. This Taiwan based study suggests that the negative side effects appear to diminish as time passes, but the benefits brought by the UBP policy remain in the long-run. For Taiwan, a well-design mechanism and program to prevent an occurrence of side effects, the idea of 'polluter pays' is a plausible policy instrument to reflect the true social cost of managing waste.

The study has limitations and suggests some future research needs. First, policymakers may well be interested in learning how to design a UBP policy which can reduce the possibility of causing unintentional effects with a relatively low policy implementation cost. For instance, it would be useful to have research address how the UBP fee structure affects the magnitude of unintentional policy effects (e.g. illegal dumping and waste tourism). In addition, since an implementation of UBP can induce waste reduction, research could address the implications of UBP for needed solid waste combustion and incineration facilities as their costs and benefits.

# CHAPTER III

# CAN HONEY INFORMATION AFFECT CONSUMER BEHAVIOR IN AN EXPERIMENTAL SETTING? IMPLICATIONS OF ADULTERATION, ORIGIN, AND REVIEW INFORMATION

## III.1 Introduction

Honey is a product with labeling that contains ambiguous product related information. For example, the labels include terms such as "pure," "raw," or "natural" honey but there are no uniform standards on the honey product characteristics that merit such terms. In 1985, the U.S. Department of Agriculture (USDA) amended the voluntary Honey Grading System, classifying honey products into grades (A, B, and C) based on moisture content, absence of defects, flavor, aroma, clarity, and color (USDA 1985). However, with the grading System being voluntary, it is not enforced relative to labeling. Furthermore, not all consumers are informed on the grading system and what the grades mean to them.

Another challenge facing honey consumers is honey adulteration. The most common adulteration practice involves dilution with water or cheap sweeteners while still claiming that the product is pure, raw, or natural honey (Soares et al. 2017). Honey adulteration also increases food safety concerns, especially for adulterated honey from Asian countries (Olmsted 2016; The Economist 2018; Melnick 2011). In fact, honey has been reported as one of the most adulterated food products in terms of global value of adulterated products (Olmsted 2016; The Economist 2018). To avoid food safety issues associated with imported honey adulteration, some consumers seek out locally produced honey (Wu et al.

2015; Cosmina et al. 2016). Local honey is also desirable because of the environmental benefits of pollination services provided by local honey bee colonies (Wu et al. 2015). However, due to honeybee movement it is challenging to identify and accurately certify a honey product's geographic and botanical origin.

Nevertheless, informing consumers better on product quality and origin may provide consumers with desirable information and may induce consumers to be willing to pay a higher price. To address this possibility, research on product information and labeling was conducted in an experimental setting. Specifically, with assistance from a team of apiculture experts at Texas A&M University this research examined the possible introduction of a certified local Texas honey seal (hereafter abbreviated as the "Real Texas Honey seal"). The research was done as part of a project carried out with the Texas Department of Agriculture, the Texas Beekeepers Association.

Specifically, to explore willingness-to-pay (WTP) responses to sources of honey choice information, this essay aims to investigate how consumers react to various types of information when making choices. The study investigates consumer honey choice preferences based on the presence or absence of information on adulteration, and location of production information (certified Real Texas Honey seal), and customer responses to product reviews. The investigation was done in an experimental, eye-tracking laboratory setting utilizing information presented on a computer screen.

This research explores the following questions:

(1) Does honey adulteration information affect consumers' WTP for honey products?

(2) Do product reviews affect consumers' WTP for honey products? Are these effects symmetrical between positive and negative reviews?

(3) Does the presence of a Real Texas Honey seal increase consumers' WTP of certified Texas honey?

The rest of the paper is organized as follows: Section 2 presents an overview of past honey studies and relevant eye-tracking experimental studies. Section 3 describes the experimental design and data collection process. Section 4 explains the empirical methodology used to analyze the data collected from the experiment. Section 5 shows the experimental results. Lastly, the conclusions and the corresponding policy implications are presented in Section 6.

## III.2 Literature Review

### *III.2.1 Overview of Consumer Demand for Honey Products*

Numerous studies have investigated consumer preferences for honey products. Unnevehr and Gouzou (1998) use U.S. retail scanner data to examine the association between price premium for honey and characteristics showing the highest premiums are associated with unique monofloral sources with a distinctive flavor, such as acacia, alfalfa, and apple. Ghorbani and Khajehroshanaee (2009) apply a hedonic model to study price effects of honey characteristics using Iranian data from a cross-sectional honey purchasing database covering 360 consumers. They find that factors such as packing characteristics, dark color of honey, and scented honey have a positive effect on honey prices.

In addition, survey and questionnaire data has been used in honey preference studies. Murphy et al. (2000) in Ireland find that price and texture are the most critical honey attributes, followed by packaging, small-scale of production, and color. Gámbaro et al. (2007) study color effects across 30 honey sample finding that Uruguayan consumers dislike light-color honey. Yeow et al. (2014) find that health condition of respondents, product quality, brand reputation, and pricing influence purchasing intentions. Jensen and Mørkbak (2013) find that gastronomic attributes (terroir, freshness, appearance), externality attributes (local environment, creation of local jobs, reduced food miles i.e. the distance food is transported), price and availability are key factors in consumer decisions in Denmark. Bršćić, Šugar, and Poljuha (2017) find that designation of point of origin is desirable, and buying domestic honey origin is viewed as a way of contributing to domestic economy development.

Comparing to grading systems and local food labels, word of mouth seems to be a more appealing and accessible way to some consumers for making honey choices nowadays. An increasing number of consumers share their product experiences online, and more and more people rely on those online information to make their purchase decisions (Chevalier and Mayzlin 2006; Bolton, Greiner, and Ockenfels 2013; Fradkin, Grewal, and Holtz 2018). A specific example is that product reviews disclosing customer experiences have been shown to have an impact on purchasing decisions (Mudambi and Schuff 2010; Weathers, Swain, and Grover 2015).

Despite all the aforementioned findings, only a few studies have taken a direct experimental approach to test consumer preferences for honey products. Wu et al. (2015) conduct an auction experiment to evaluate consumer behavior related to the location of product origin and characteristic information, finding that consumer demand for honey varies significantly with these features. Cosmina et al. (2016) perform a choice experiment and find a higher WTP for honey produced from the respondents' country of origin and from organic beekeeping.

### *III.2.2 Eye-tracking and Consumer Behavior Studies*

Eye-tracking technology has been widely applied in consumer behavior and choice experiments (as reviewed in Van Loo, Grebitus, et al. 2018). Eye-tracking devices can provide visual metrics on areas of interest (AOI) including time to first fixation (ms), first fixation duration (ms), fixation time spent (ms or percentage of total time spent), fixations count, and revisits count. One challenge in using eye-tracking devices is how to link visual attention measurements with economic decision making. Using visual metrics captured by eye-tracking devices alone cannot provide meaningful economic implications. Consequently, to provide economic intuition to explain subjects' behavior, economically based eye-tracking studies endeavor to link their results with economic factors (Samant and Seo 2016; Van Loo et al. 2015). Adding interaction terms between product attributes including prices and visual metrics using an econometric model has been used to explain the relationship between visual attention and consumer choice outcomes (Van Loo et al. 2015; Rihn et al. 2016). This approach, however, raises potential endogeneity concerns because unobserved subjects' background factors are possibly correlated to those visual metrics (Takahashi, Todo, and Funaki 2018). Alternatively, grouping subjects by visual focus on distinct areas of interest then investigating choices in those groups allows researchers to investigate effects of visual characteristics on choice decisions (Behe et al. 2014; Balcombe, Fraser, and McSorley 2015; Van Loo, Grebitus, et al. 2018).

A few eye-tracking studies have been conducted with agricultural commodities. Behe et al. (2014) studied consumer preferences for commodity attributes and their association with visual searching behavior. Their results show that subjects, who were classified into cohorts based on their preferences on specific production methods, spent more time looking at labeling information that was related to production methods. Their results also suggested that retailers should carefully consider the impacts of retail signs on different groups of consumers. Van Loo et al.( 2015) utilize eye-tracking measures to identify the relationship between U.S. consumer visual attention and preferences for coffee products' sustainability attributes (carbon footprint, organic labeling, or belonging to the Rainforest Alliance). Their results show that consumers who pay more visual attention to sustainability attributes have a stronger preference and a higher WTP for coffee products with desirable sustainability attributes. Rihn et al. (2016) investigate the relation between purchasing likelihood (PL) and visual search behavior for ornamental plants, finding that organic production methods and domestic origin positively influenced PL.

Thus far, no studies have applied eye-tracking devices to investigate honey product choices with adulteration characteristic and product review information. Here this study uses eye-tracking technology to provide insights into how consumers respond to complex information in grocery decision-making processes.

## III.3 Experimental Design and Data Collection

### *III.3.1 Experiment Procedure*

This study employs an eye-tracking choice experiment and a post-experiment survey. The experimental procedure is as follows. Upon arrival, subjects signed a consent form and were randomly assigned to a control or a treatment group. At the beginning of the experiments, subjects in the treatment group were asked to read an article about honey adulteration fact that arose from the Netflix documentary: “Rotten” (Figure III-1). In contrast, those in the control group did not read the article. After this, subjects were directed to the eye-tracking stations and were led through eye-tracking device calibration using a Tobii Pro Spectrum (300 Hz, accuracy $0.3^{\circ}$, precision $0.06^{\circ}$ RMS) device.

## The truth about honey

Beehives produce about 160 million pounds of honey per year in the U.S., however, people in the U.S. consume 450 million pounds. The U.S. imports honey from other countries twice as much as it makes. The number of beehives (where pure and natural honey comes from) worldwide is growing, but honey exports (where part of honey products in the marketplace come from) are rising about eight times faster than beehives. In some way, there seems to be a surplus of honey. This indicates the fact that lots of the honey flowing around the world isn’t pure and natural honey. Dilution of honey with other cheap syrups is the main and more massive way to adulterate honey. It is the reason for this apparent surplus of honey all over the world.

**Figure III-1 Treatment article**

After calibration, subjects began an eye-tracking choice experiment, which was a hypothetical choice experiment covering twelve choice tasks. Each choice task involved two alternatives plus one no-purchase option (Figure III-1). Subjects were asked to choose the most preferable option among those three options. The attributes presented were selected based on previous interviews with local honey producers. They were price, origin, whether the honey was “organic,” “natural,” or “pure,” product reviews, and container types. The price attribute was defined in three levels: $6, $9, and $12 per honey product (reflecting the price range of most honey products in reference Nielsen data). The origin attribute included information on whether the honey in origin was imported, U.S., or Texas honey. The organic, natural, and pure attribute claims were displayed as either "yes" or "no" options. The product review attribute was either "positive" review, "negative" review, or case where no review was available. The positive and negative reviews used were real honey product reviews taken and revised from Amazon (refer to Table A1 of the Appendix for more details). The container type was either a bottle in the shape of a bear, a standard glass jar, or a plastic jar.

To investigate the effect of the Real Texas Honey seal on the subjects' WTP, whenever an alternative included a Texas origin, the Real Texas Honey seal was displayed next to the container. Additionally, there is no certified organic honey produced in Texas. Thus, this study added a restriction to the design. If an alternative was that the honey had a Texas origin, it could not be organic honey. All product attributes and their corresponding levels are shown in Table III-1 and Figure III-2. The experimental design of twelve choice sets was generated in Ngene using D-optimal design matrices, and the resulting D-error was 1.95.

After the eye-tracking choice experiment was completed, subjects' choice decisions were recorded and were directed to complete a post-experiment survey that asked subjects' socio-economic backgrounds, knowledge about honey, and attitudes toward the environment (refer to Table A2 of the Appendix for details). Upon completion of the survey, subjects collected their payment and ended the experiment.

**Table III-1 Attributes in the choice experiment**

| Attributes | Levels | | | |
|---|---|---|---|---|
| **Price** | $6 | $9 | $12 | (3 levels) |
| **Origin** | Imported (base) | Texas | U.S. | (3 levels) |
| **Organic** | No | Yes | | (2 levels) |
| **Natural** | No | Yes | | (2 levels) |
| **Pure** | No | Yes | | (2 levels) |
| **Review** | No review (base) | Positive review | Negative review | (3 levels) |
| **Container** | Plastic (base) | Glass | Bear shape | (3 levels) |

**Figure III-2 Illustration of the choice experiment and the Real Texas Honey seal**

| | **Option A** | **Option B** | **Option C** |
|---|---|---|---|
| **Price** | $12 | $9 | **No purchase** |
| **Origin** | U.S. | Texas | |
| **Organic** | No | No | |
| **Natural** | No | No | |
| **Pure** | No | Yes | |
| **Review** | Its taste is odd and seems more like corn syrupy. This honey is like a diluted honey, runny and watery. It even has a sour smell. Not a pleasant experience... | This honey has a great taste and rich flavor with a mild honey aroma. It's quite thick and takes time to move from one side of the container to the other. Love this honey! | |
| **Container** | Bear shape  | Glass jar  | |

### *III.3.2 Recruitment Process*

The recruitment process used local newspaper ads and a bulk email associated with an existing grocery shopper database in Bryan and College Station, Texas, which include both the general population and student subjects. To minimize possible inaccuracy of eye-tracking devices, the recruitment information indicated that participants must not have had eye corrective surgery and cannot wear glasses (contact lenses were acceptable). Participants were informed that they would receive a compensation fee of $30 for participation once they finish all the required tasks.

A total of 177 subjects participated in July and August 2018. Eye-tracking calibration failed for four subjects. Thus, valid responses of 173 subjects were compiled: 87 in the control group and 86 in the treatment group. The sample characteristics and the balance test are shown in Table III-2. Most of the variables passed the balance test between the number of subjects in the control and treatment groups, except for the subjects' weight variable, which was controlled as a covariate in the models.

**Table III-2 Sample characteristics**

| Variable | Control (n = 87) | Treatment (n = 86) | P-value |
|---|---|---|---|
| Gender (male is 1; female is 0) | 0.4 (0.5) | 0.4 (0.5) | 0.83 |
| Age | 30.9 (13.7) | 33.5 (15.7) | 0.247 |
| Income (1,000 USD) | 83.4 (60.8) | 75.6 (59.4) | 0.394 |
| Education | 0.6 (0.5) | 0.7 (0.5) | 0.359 |
| Weight (lbs) | 157.0 (35.4) | 169.8 (47.5) | 0.046 |
| Height (cm) | 168.7 (9.5) | 170.4 (9.4) | 0.251 |
| Household | 2.6 (1.4) | 2.5 (1.5) | 0.658 |
| Children | 1.4 (0.8) | 1.4 (1.0) | 0.64 |
| Race: White (%) | 0.6 (0.5) | 0.6 (0.5) | 0.711 |
| Race: African (%) | 0.1 (0.2) | 0.1 (0.2) | 0.985 |
| Race: Hispanic (%) | 0.1 (0.3) | 0.1 (0.3) | 0.839 |
| Race: Asian_Pacific (%) | 0.2 (0.4) | 0.2 (0.4) | 0.671 |
| Race: Other (%) | 0.0 (0.2) | 0.0 (0.2) | 0.69 |
| Employment: Full_time (%) | 0.3 (0.5) | 0.3 (0.4) | 0.348 |
| Employment: Part_time (%) | 0.1 (0.3) | 0.1 (0.3) | 0.603 |
| Employment: Student (%) | 0.5 (0.5) | 0.5 (0.5) | 0.822 |
| Employment: Retired (%) | 0.0 (0.2) | 0.0 (0.2) | 0.987 |
| Employment: Unemployed (%) | 0.0 (0.1) | 0.0 (0.2) | 0.556 |

*Note: Means, standard deviations (in parentheses), and p-values of bivariate t-test are reported.*

## III.4 Estimation Methodology

This research applies a logit-mixed logit model (LMLM) that used flexible mixing parameter distributions in the WTP space to estimate WTPs over the results from the eye-tracking supported choice experiments. This study use the LMLM as opposed to a mixed logit model to avoid less robust estimation issues in terms of WTPs estimated in preference space (Train and Weeks 2005; Balcombe, Chalak, and Fraser 2009; Thiene and Scarpa 2009; Bazzani, Palma, and Nayga 2018). Specifically, following Train (2016), the utility of the logit-mixed logit model for individual $n$ choosing alternative $j$ in choice situation $t$. $U_{njt}$ can be expressed as:

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} = -\sigma_n\left(p_{njt} + wtp_n' x_{njt}\right) + \varepsilon_{njt} \quad (1)$$

where

$\beta_n$ is a corresponding vector of utility coefficients varying randomly over people.

$x_{njt}$ is a set of product attributes including origin (i.e., Texas, U.S., or imported), whether the honey was organic, natural, or pure, the container type (i.e., bear shape, glass jar, or plastic jar), and product reviews (i.e., positive, negative, or no review).

$\varepsilon_{njt}$ is an error term capturing the unobserved component of utility.

$\sigma_n$is a random scalar, $\sigma_n = \frac{\pi_n}{k_n}$, where $\pi_n$ is the price coefficient in a preference space, and $k_n$ is the scale parameter of individual $n$.

$p_{njt}$ is the price variable.

In turn the vector of WTP's for each non-price attribute of individual $n$ is $wtp_n = \frac{\gamma_n}{\sigma_n}$, where $\gamma_n$ is the vector of non-price coefficients in a preference space. Following Train (2016), the resultant probability of choosing alternative $i$ in choice situation $t$ by individual $n$ conditional on $\beta_n$ can be expressed as:

$$Q_{nit}(\beta_n) = \frac{e^{\beta_n' x_{njt}}}{\sum_{j\in J} e^{\beta_n' x_{njt}}} = \frac{e^{-\sigma_n (p_{nit} + wtp_n' x_{nit})}}{\sum_{j\in J} e^{-\sigma_n \left(p_{njt} + wtp_n' x_{njt}\right)}} \quad (2)$$

The unconditional choice probability is:

$$Prob(n\ chooses\ i) = \sum_{r\epsilon S} W(\beta_r|\alpha) \cdot Q_{ni}(\beta_r) = \sum_{r\epsilon S} \left[\frac{e^{\alpha' \cdot z(\beta_\gamma)}}{\sum_{s\in S} e^{\alpha' \cdot z(\beta_S)}}\right] \cdot \left[\frac{e^{\beta_r' x_{ni}}}{\sum_{j\in J} e^{\beta_r' x_{nj}}}\right] \quad (3)$$

where $W(\beta_r|\alpha) = \frac{e^{\alpha' \cdot z(\beta_\gamma)}}{\sum_{s\in S} e^{\alpha' \cdot z(\beta_S)}}$ is the probability mass of $\beta_r$, which is in a finite support set $S$ ($\beta_r \in S$). $z(\beta_\gamma)$ is a vector-valued function of $\beta_r$, which is chosen to capture the shape of the probability mass function and can be represented as a logit function of higher order polynomials, splines, or step functions. $\alpha$ is a corresponding vector of coefficients. The associated log-likelihood function can be defined as:

$$LL = \sum_{n=1}^{N} \ln \left( \sum_{r \epsilon S} W(\beta_r | \alpha) \cdot L(\beta_r) \right) \tag{4}$$

The log-likelihood function was estimated using simulations in MATLAB with 5,000 random draws, following the code provided by (Train 2016).

## III.5 Results

To obtain robust WTP estimates for each attribute, this study estimates a logit-mixed logit model with polynomial, step, and spline functions. The major challenge of using LMLM is to find an appropriate functional form (Train 2016). To deal with this challenge, various numbers of degrees/steps/knots were tested from 2 to 10 with the above specification functions. Numbers of draws for the simulation procedure were tested using 2,000 and 5,000 draws. After obtaining the results for all the above specification combinations, the 9-knot-spline function with 5,000 draws was selected as the final model based on best model fit. The result of model selection metrics is available in Table A3 of the Appendix.

The mean WTP for the Texas origin attribute in the treatment group who read the adulterated honey information is $5.17 which is 12% higher than the $4.63 WTP for the control group (Table III-3). The 95% confidence interval for the Texas attribute WTP does not overlap between groups, implying that the adulteration information positively and significantly affected the WTP for Texas honey. Likewise, the WTP difference between natural and pure attributes was higher in the treatment group compared to the control group. Furthermore, the presence of negative product reviews caused a lower WTP in the treatment group than in the control group. This implies that adulteration information informed consumer reacted more to negative reviews. Moreover, the effect of negative reviews was about five times larger than those for positive reviews, implying that subjects exhibited a tendency of loss aversion for a negative product review compared to a positive review.

**Table III-3 WTP estimated by the logit-mixed logit model**

| | Overall | Control (Without adulteration info) | Treatment (With adulteration info) |
|---|---|---|---|
| Price scale | 0.425 | 0.415 | 0.435 |
| | (0.422, 0.428) | (0.408, 0.422) | (0.428, 0.442) |
| Texas | 4.896 | 4.629 | 5.17 |
| | (4.858, 4.934) | (4.552, 4.706) | (5.094, 5.246) |
| USA | 1.176 | 1.176 | 1.176 |
| | (1.176, 1.176) | (1.175, 1.177) | (1.175, 1.177) |
| Organic | 2.063 | 2.124 | 2.001 |
| | (2.052, 2.074) | (2.103, 2.145) | (1.977, 2.025) |
| Natural | 3.476 | 3.047 | 3.916 |
| | (3.445, 3.507) | (2.987, 3.107) | (3.855, 3.977) |
| Pure | 4.434 | 4.286 | 4.586 |
| | (4.408, 4.46) | (4.232, 4.34) | (4.537, 4.635) |
| Glass | 0.463 | 0.572 | 0.353 |
| | (0.448, 0.478) | (0.543, 0.601) | (0.323, 0.383) |
| Bear | -0.309 | -0.325 | -0.292 |
| | (-0.316, -0.302) | (-0.339, -0.311) | (-0.307, -0.277) |
| Positive | 2.529 | 2.64 | 2.416 |
| | (2.521, 2.537) | (2.625, 2.655) | (2.399, 2.433) |
| Negative | -15.162 | -14.884 | -15.446 |
| | (-15.258, -15.066) | (-15.071, -14.697) | (-15.643, -15.249) |
| No product | -4.192 | -5.189 | -3.171 |
| | (-4.267, -4.117) | (-5.327, -5.051) | (-3.332, -3.01) |
| Num. of subjects | 173 | 87 | 86 |
| Observations | 2,076 | 1,044 | 1,032 |

*Note: The above result uses the 9-knot-spline specification with 5,000 draws. Parentheses indicate 95% confidence interval of the estimated mean.*

**Table III-4 WTP estimated by the logit-mixed logit model (attribute-attendance)**

| | Attenders | | Non-attenders | |
|---|---|---|---|---|
| | Control | Treatment | Control | Treatment |
| Price scale | 0.6013 | 0.3593 | 0.8745 | 0.4933 |
| | (0.489, 0.714) | (0.219, 0.5) | (0.728, 1.021) | (0.301, 0.686) |
| Texas | 4.4982 | 5.3213 | 1.0716 | 6.56 |
| | (3.537, 5.459) | (3.983, 6.66) | (0.456, 1.687) | (5.373, 7.747) |
| USA | 1.4548 | 0.7259 | 1.7947 | 1.3893 |
| | (1.299, 1.61) | (0.576, 0.876) | (1.7, 1.889) | (1.074, 1.705) |
| Organic | 2.3285 | 2.297 | 2.7869 | 3.0347 |
| | (2.238, 2.419) | (1.943, 2.651) | (2.65, 2.924) | (2.783, 3.286) |
| Natural | 2.8152 | 3.9303 | 2.4426 | 6.001 |
| | (2.153, 3.477) | (2.727, 5.133) | (1.705, 3.18) | (4.868, 7.134) |
| Pure | 2.9458 | 4.5462 | 4.8276 | 4.2715 |
| | (2.355, 3.536) | (3.557, 5.536) | (4.377, 5.278) | (3.261, 5.282) |
| Glass | 0.6008 | 0.7116 | 1.5968 | 0.8466 |
| | (0.355, 0.847) | (0.285, 1.138) | (1.491, 1.703) | (0.339, 1.354) |
| Bear | 0.8057 | 0.3897 | 0.1825 | 0.1172 |
| | (0.708, 0.904) | (0.186, 0.593) | (0.117, 0.248) | (0.026, 0.208) |
| Positive | 2.2617 | 2.4126 | 2.3692 | 2.0358 |
| | (2.097, 2.427) | (2.078, 2.747) | (2.249, 2.489) | (1.651, 2.421) |
| Negative | -14.4319 | -17.8837 | -11.663 | -7.5872 |
| | (-16.437, -12.426) | (-23.186, -12.582) | (-13.011, -10.315) | (-10.244, -4.931) |
| No product | -5.6884 | -5.243 | -4.6664 | -0.745 |
| | (-7.242, -4.135) | (-9.449, -1.037) | (-6.995, -2.338) | (-6.635, 5.145) |
| Shares of subjects | 0.40 | 0.42 | 0.10 | 0.08 |
| Num. of subjects | 70 | 72 | 17 | 14 |
| Observations | 840 | 864 | 204 | 168 |

*Note: The above result uses the 9-knot-spline specification with 5,000 draws. Parentheses indicate 95% confidence interval of the estimated mean.*

To examine the effect of the certified Real Texas Honey seal the fixation count variable relative to the seal viewing was used to classify subjects into two groups: seal-observing (SO) and non-seal-observing (NSO) subjects. Subjects were classified as seal-observing if their fixation counts on the seal were above a particular cut-off value. The subject was classified as SO if she/he fixated on the product attribute at least once and this implied a cut-off value of one, following Balcombe, Fraser, and McSorley (2015);

and Van Loo, Nayga, et al. (2018). Table III-4 presents the effect on WTPs. The results indicate that NSO subjects in the control group had a $1.07 lower WTP for the Texas origin attribute ($1.07) compared to other groups (i.e., SO-control, SO-treatment, and NSO-treatment), and its 95% confidence interval does not overlap with the other three groups. Elaborating subjects who did not observe the Real Texas Honey seal and did not receive the adulteration information had significantly lower WTP for the Texas origin attribute compared to the others.

## III.6 Conclusion

This study investigates the effects of honey adulteration information, local honey labeling, and product reviews on consumers' willingness-to-pay (WTP) for honey products. This was done in a laboratory setting utilizing responses of 173 subjects participating in an eye-tracking choice experiment. The results suggest that people who received the honey adulteration information had a 12% higher WTP for honey relative to people who did not receive the adulterated honey information.

For the honey product origin information, this study finds that people who did not receive the adulterated honey information that observing the Real Texas Honey seal lead to a higher WTP for the Texas origin attribute. On the other hand, for those not observing the seal the WTP was only affected by the adulteration information. Thus, either receiving the adulterated honey fact information or observing the Real Texas Honey seal increased the WTP for Texas honey. The results also show that negative review information exerted a much larger reduction on the WTP than was the WTP increase that arose from positive reviews (Tables III-3 and III-4).

There are a few limitations to this study that also lead to research needs. First, the generalizability of the experimental results might be biased by the non-incentive-compatible design and research could explore these issues in other settings. Moreover, since the study focuses on investigating how subjects react to the local honey seal, product reviews, product attribute information, a table format presentation of choice sets was used in the eye-tracking experiment rather than presenting product packages. Both approaches have advantages and disadvantages. The table format presentation lays out information in an organized way, which is more frequently seen in an online shopping environment but not in onsite grocery shopping situations. On the other hand, presenting product packages could reflect a more realistic onsite grocery shopping scenario, but the information of interest will be less salient to subjects. Research comparing WTP under both approaches could be pursued. Besides, this study defines a subject as paying attention to the Real Texas Honey seal if the number of fixations was larger than one, following Balcombe, Fraser, and McSorley (2015) and Van Loo, et al. (2018). However, this threshold may seem arbitrary, and additional research might be done to develop a more rigorous definition. Finally, people's WTP response to adulteration information may vary by the passage of time. The treatment effect of the adulteration information may diminish as time pass. Nevertheless, this study is not able to capture such effect. Future work can develop panel experimental studies that conduct an experiment multiple times to track the same group of subjects within a certain time period.

The findings of this study have a number of important implications for future practice to food policy makers and honey marketers.

1. Food retailers may want to find means of addressing negative product reviews, since they can substantially impact consumers' WTP.
2. For imported honey, there may need to be a way of labeling the products as ones that are not adulterated. More generally avoiding negative media information on country specific honey can lower price discounts and this likely holds for other products.
3. When firms determine their pricing strategies for honey products, they can potentially raise price premiums by informing consumers on production location and desirable product attributes.

Taken together, well-framing food product information through media and labeling information could make products more attractive and lucrative, while poorly choosing or informing on product attributes plus and not managing negative consumer reviews could significantly harm the profitability of food products. This study also hints that one can possibly nudge consumers to make food choices that can benefit the environment through media and labeling information. Similar study design in a field experiment setting would be worth developing to verify the external validity of relevant information effects.

CHAPTER IV

# RICE, CARBON DIOXIDE, CLIMATE CHANGE, AND FEEDING THE FUTURE

## IV.1 Introduction

Globally rice is the most widely consumed staple food crop (Food and Agriculture Organization 2014; 2016), and population growth is increasing rice demand. But there are risks to future productivity arising from climate change and carbon dioxide mitigation action (Sinnarong et al. (2019); Kirschbaum 2011). Threats are also arising from diminishing levels of research investment (Andersen et al. 2018; Pardey et al. 2016; Alston and Pardey 2006). Without substantial rice productivity increases, billions may struggle from malnutrition and food insecurity, particularly in developing countries. Additionally, this can lead to conflict and societal instability (Brück and d'Errico 2019). To quantify the CO2 and climate risks, the research reported here studies the impacts of climate change, CO2 fertilization, and research investment on growth in rice yields.

Climate conditions are key determinants of agricultural productivity and production variability (Selvaraju, Gommes, and Bernardi 2011). For rice, Sinnarong et al. (2019) find an increase in temperature can reduce yields and increase their variability. Also, CO2 atmospheric concentration increases can enhance crop yields for select crops, including rice (Kirschbaum 2011). Technical advances as stimulated by research investments is another crucial determinant of productivity and can offset possible negative impacts of climate change (McCarl, Villavicencio, and Wu 2008; Miao, Hennessy, and Babcock 2012; Villavicencio et al. 2013). The conventional way of modeling yield growth due to technological advanced is to use time as a proxy (McCarl, Villavicencio, and Wu

2008; Attavanich and McCarl 2014). However, given the steady advance of $CO_2$, this approach captures not only technological advance but also $CO_2$ influences (Attavanich and McCarl 2014). As such one can easily overestimate the rate of yield growth and ignore the fact that climate change mitigation would lessen the $CO_2$-induced yield enhancement. Thus, it is important, particularly for $CO_2$ sensitive crops like rice, to partition out the $CO_2$ effect. But to do this, one must overcome a collinearity issue between time as a proxy for technological progress and dynamically increasing $CO_2$ emissions (where the correlation with time is generally above 95%). To do this for U.S. corn, wheat, sorghum, and cotton, Attavanich and McCarl (2014) combined U.S. reported yields with free air carbon dioxide enrichment (FACE) experiment data. In turn, they found that $CO_2$ concentration increases biased upwards estimated rates of technological progress by as much as 40%.

In the research to date that this study has identified, there has not been a joint study on the rice yield effects of climate, research investment, and $CO_2$ fertilization. This study addresses that on observed Asian rice yields along in an effort to shed light on future rice productivity and needed research investment.

## IV.2 Empirical Methodology

To estimate the effect of climate, $CO_2$ fertilization, and research investment on rice yield growth this study does econometric estimation of observed rice yields, FACE results, climate conditions, and atmospheric $CO_2$ concentrations. To do this, a rice yield production function is assumed as in Just and Pope (1979) and Chen, McCarl, and

Schimmelpfennig (2004) among others. In particular, following Attavanich and McCarl (2014), the rice yield functional form is expressed as:

$$log(y_{it}) = f(X_{it}, \beta) + \mu = f(X_{it}, \beta) + h(X_{it}, \alpha)\varepsilon_{it} \quad (1)$$

where $y_{it}$ denotes Food and Agriculture Organization (FAO) and FACE experiment reported rice yields in country $i$ in year $t$; $X_{it}$ is a set of explanatory variables in country $i$ in year $t$, including mean precipitation, mean annual average maximum temperature, and a drought measure, global CO2 concentration, percent of land under irrigation, and time (including both linear and quadratic terms). In alternative model specifications, instead of using the time trend variable, AGRD spending variables (including both current and one-year lagged terms) are used to capture technical advance driven by agricultural research expenditure. The research and development expense includes FAO estimates of salary-related expenses, basic and applied research expenses, experimental development costs, operating and program costs, and capital investments by government, nonprofit, and higher education agencies. A dummy variable indicating whether a particular observation is an observation in the FACE data is also included in the covariates. Other time-invariant unobservable effects and their association with climate variation are controlled by country fixed effects and their interaction terms with precipitation, temperature, and the drought index.

To correct for heteroscedasticity and estimate the effects of climate and other effects on rice yield variance, a three-step feasible generalized least squares (FGLS) method is employed (as discussed in Just and Pope 1979; and Attavanich and McCarl 2014). The empirical estimation procedure is as follows:

First, estimate $log(y_{it}) = f(X_{it}, \beta) + \mu$ by using pooled ordinary least squares (OLS) and obtain residuals ($\hat{\mu}$).

Second, estimate the residuals as a function of X $log(\hat{\mu}^2) = g(X, \gamma) + u$ and obtain fitted values $\widehat{log(\hat{\mu}^2})$ and calculate $\sqrt{exp(\widehat{log(\hat{\mu}^2}))}$.

Lastly, $log(y_{it}) = f(X_{it}, \beta) + \mu$ is estimated using weighted least squares (WLS) with $\sqrt{exp(\widehat{log(\hat{\mu}^2}))}$ as weights. The FGLS approach can address the heteroscedasticity issue where yield variability is impacted by climate.

## IV.3 Data

A list of data sources is presented in Table IV-1 and additional information on exact data used follows:

- The rice yield data of 24 Asian countries are from FAO rice yield data from 1961 to 2016 (Food and Agriculture Organization 2020). The study also uses FACE experiment-based rice yield data from experiments in Japan and China (Hasegawa et al. 2013; Sun et al. 2014; Jing et al. 2016), which are presented in Table IV-2.
- Country-level climate data came from the Climatic Research Unit (CRU), University of East Anglia (2020). Taiwan weather data were collected from the Taiwanese Central Weather Bureau (2020).
- The global CO2 concentration data are from Meinshausen et al. (2011). Drought based data were incorporated using the SPEI Global Drought measure from the associated web page (Vicente-Serrano et al. 2010).

- In addition to using time trends to capture technological progress from 1961 to 2016, this study also captures the technological effect by an alternative variable, research and development (AGRD) expenditure data from ASTI (2020), Taiwan National Statistics (2020), and the World Bank (2020). Since AGRD spending data is only available after 1981, this research studies the effect of AGRD spending on rice yields from 1981 to 2016. Some countries have missing AGRD observations during the study period. Thus, only periods with complete observations are considered in the analysis.

The summary statistics of the above data are provided in Table IV-3.

**Table IV-1 Data sources**

| Variables | Duration | Sources |
|---|---|---|
| Rice yields (ton/hectare) | 1961-2016 | Food and Agriculture Organization of the United Nations (2020) |
| Precipitation (mm) | 1961-2016 | Climatic Research Unit (CRU), University of East Anglia (2020), Taiwanese Central Weather Bureau (2020) |
| Temperature (Celsius) | 1961-2016 | Climatic Research Unit (CRU), University of East Anglia (2020), Taiwanese Central Weather Bureau (2020) |
| SPEI | 1961-2016 | Vicente-Serrano et al. (2010) |
| Irrigation rate | 1961-2016 | Food and Agriculture Organization (2020) |
| Global $CO_2$ concentration (ppm) | 1961-2100 | Meinshausen et al. (2011) |
| Agricultural R&D expenditure | 1981-2016 | ASTI (2020), Taiwan National Statistics (2020), World Bank (2020) |
| FACE data | 1998-2003, 2007-2008, 2010 | Hasegawa et al. (2013); Sun et al. (2014); Jing et al. (2016) |

**Table IV-2 FACE data**

| Year | Country | Area | $CO_2$ (ppm) | Rice yields ($g/m^2$) |
|---|---|---|---|---|
| 1998 | Japan | Shizukuishi | 642.0 | 679.2 |
| 1999 | Japan | Shizukuishi | 629.9 | 838.4 |
| 2000 | Japan | Shizukuishi | 578.5 | 797.9 |
| 2001 | China | Wuxi | 577.5 | 1182.9 |
| 2002 | China | Wuxi | 562.4 | 1103.8 |
| 2003 | China | Wuxi | 574.4 | 971.7 |
| 2007 | Japan | Shizukuishi | 570.0 | 546.0 |
| 2008 | Japan | Shizukuishi | 576.0 | 672.0 |
| 2010 | Japan | Tsukuba | 585.0 | 642.0 |

Sources: (Hasegawa et al. 2013; Sun et al. 2014; Jing et al. 2016)

**Table IV-3 Summary statistics**

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Yield (ton/hectare) | 1,608 | 3.25 | 1.63 | 0.39 | 11.83 |
| Precipitation (mm) | 1,608 | 1,422.13 | 930.44 | 53.10 | 4,945.30 |
| Mean temperature (Celsius) | 1,608 | 23.67 | 7.17 | 6.95 | 32.75 |
| SPEI (-: drought, +: wet) | 1,608 | -0.99 | 5.80 | -17.20 | 16.21 |
| CO2 concentration (ppm) | 1,608 | 356.71 | 31.02 | 317.64 | 642.00 |
| Irrigation rate | 1,608 | 20.70 | 16.90 | 0.00 | 76.20 |
| AGDR (mil. USD) | 468 | 87.28 | 212.8 | 0.02 | 1,917.28 |

## IV.4 Empirical Investigation and Results

This section first explores intertemporal and geographical variation in rice yields and AGRD expenditures. Moreover, it examines rice yield growth with and without separating out the effects of CO2 concentration. Then forecasted impacts of projected climate change and CO2 concentration on yield growth under different mitigation scenarios are explored. Finally, the end of this section examines how much AGRD expenditure needs to change to offset climate change and CO2 mitigation effects.

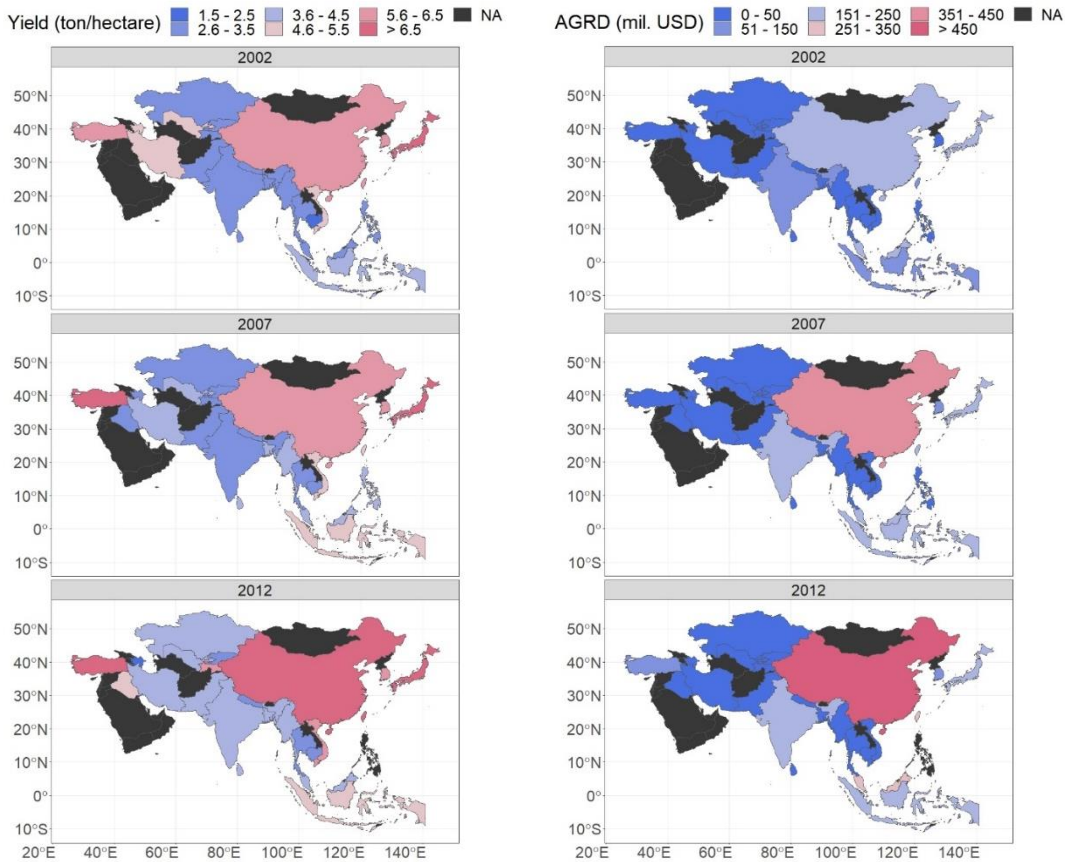


**Figure IV-1 Temporal and geographical variations in Asian rice yields and AGRD expenditures**

### *IV.4.1 Trends in Rice Yields and AGRD*

Figure IV-1 shows temporal and geographical variations in Asian rice yields and AGRD expenditure. Overall, rice yields have steadily increased in the past decade, particularly in East Asia, Turkey, Indonesia, and Vietnam, as shown in the left-panel. On the other hand, the right-panel shows relatively stagnant AGRD expenditures across most Asian countries except China.

### *IV.4.2 Estimating CO2 and Climate Effects*

The fundamental interest of this research is estimating CO2 and climate effects. For CO2, this study has a problem separating it from time effects as concentrations have been rising at a virtually constant rate with a correlation with time in the data set without the FACE additions of 0.9936. This does not allow for independent CO2 effect identification. Nevertheless, the global CO2 concentration and the time trend variable reflect very different forces. The former enhances rice yields through the CO2 fertilization effect; the latter captures the effects of technological progress (e.g., advances in rice varieties, farming practices, equipment, etc.). Furthermore, disentangling time and CO2 are important, and their correlation may change in the future under climate mitigation efforts. Including FACE rice yield data decreases the correlation between the global CO2 concentration and the time trend variable because CO2 is independently varied within the FACE observations. Thus, CO2 concentration does not systematically advance with time. When including FACE data, the correlation with time falls from 0.9936 to 0.8335.

Table IV-4 shows the result of both the time trend model and the AGRD expenditure model, as estimated by OLS with heteroscedasticity-consistent standard errors (OLS-HC) and the FGLS approach. Models 1 to 4 use linear and quadratic time trend terms to proxy for the technological effect. Models 5 to 8 use the AGRD expenditure variable to reflect the technological effect. Breusch-Pagan tests reject the hypothesis of the existence of homoskedasticity across all model specifications. Thus, the OLS-HC and FGLS approaches are used for correcting heteroscedasticity. The significant coefficients of the time trend and AGRD spending variables represent yield growth over time due to varietal improvement, altered management and other forces. Also, note the magnitude of those coefficients is larger when the global CO2 concentration variable is not included, implying that omitting the explicit CO2 fertilization effect biases upward the yield growth estimates. Overall, CO2, irrigation rate, and the specific FACE observations positively influence rice yields.

For the impact of climate factors on rice yields, although the coefficients of precipitation, average max temperature, and SPEI are not significant in Table IV-4, some of their interaction effects with the country-dummies are significant. Figure IV-2 and Table B2 show parsimonious models that do not include fixed effects and their interaction effects with climate variables and give an overall climate effect across the study countries. The result indicates that the coefficients of precipitation and average max temperature are significantly negative, implying that a high volume of precipitation and high temperature have a negative impact on rice yields.

**Table IV-4 Effects of climate, CO2, and technological progress on rice yields**

| | Time trend | | | | AGRD expenditure | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS-HC (w/o CO2) | OLS-HC (w/ CO2) | FGLS (w/o CO2) | FGLS (w/ CO2) | OLS-HC (w/o CO2) | OLS-HC (w/ CO2) | FGLS (w/o CO2) | FGLS (w/ CO2) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Precipitation (log mm) | -0.037 | -0.044 | 0.028 | 0.032 | -0.653 | -0.668 | -0.524 | -0.565 |
| | (0.153) | (0.152) | (0.125) | (0.127) | (0.763) | (0.773) | (0.834) | (0.871) |
| Max. Temperature (log Celsius) | -0.637 | -0.660 | -0.644 | -0.658 | -1.736 | -1.728 | 0.401 | -0.300 |
| | (0.735) | (0.737) | (0.798) | (0.829) | (3.837) | (3.847) | (3.531) | (3.688) |
| CO2 (log ppm) | | 1.623 | | 1.090 | | 0.230 | | 1.128*** |
| | | (1.973) | | (0.777) | | (0.604) | | (0.177) |
| SPEI (-: drought, +: wet) | 0.004 | -0.054 | 0.007* | -0.056 | 0.027 | 0.007 | 0.023 | 0.050 |
| | (0.004) | (0.116) | (0.004) | (0.054) | (0.019) | (0.324) | (0.018) | (0.099) |
| Irrigation rate (percentage) | 0.003*** | 0.003*** | 0.005*** | 0.005*** | 0.010** | 0.009* | 0.007*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.004) | (0.005) | (0.002) | (0.001) |
| Time trend (Sequence of 1 to 56) | 0.012*** | 0.006 | 0.013*** | 0.010*** | | | | |
| | (0.002) | (0.006) | (0.001) | (0.002) | | | | |
| Sq. time Trend (Sq. Sequence of 1 to 56) | 0.00002 | -0.00001 | -0.00000 | -0.00003 | | | | |
| | (0.00003) | (0.0001) | (0.00001) | (0.00003) | | | | |
| AGRD (log mil. USD) | | | | | -0.031 | -0.034 | -0.020 | -0.027 |
| | | | | | (0.060) | (0.061) | (0.018) | (0.018) |
| 1-yr lagged AGRD (log mil. USD) | | | | | 0.116* | 0.110* | 0.120*** | 0.070*** |
| | | | | | (0.061) | (0.065) | (0.017) | (0.018) |
| FACE dummy | 0.235** | -0.477 | 0.179** | -0.210 | 0.278*** | 0.179 | 0.250*** | -0.249** |
| | (0.111) | (0.886) | (0.088) | (0.389) | (0.099) | (0.304) | (0.058) | (0.107) |
| log(CO2) × SPEI | | 0.010 | | 0.011 | | 0.003 | | -0.004 |
| | | (0.020) | | (0.009) | | (0.054) | | (0.016) |
| Constant | 2.521 | -6.702 | 2.141 | -4.123 | 10.208 | 8.921 | 3.281 | -1.228 |
| | (2.724) | (11.516) | (2.858) | (5.356) | (11.479) | (12.040) | (13.042) | (13.605) |
| Breusch-Pagan test(p-value) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Num. of countries | 33 | 33 | 33 | 33 | 24 | 24 | 24 | 24 |
| Observations | 1,608 | 1,608 | 1,608 | 1,608 | 410 | 410 | 410 | 410 |
| Adjusted R2 | 0.803 | 0.803 | 0.933 | 0.937 | 0.858 | 0.857 | 0.986 | 0.990 |

Note: *p<0.1; **p<0.05; ***p<0.01. All models include country fixed effects, and their interaction with precipitation, temperature, and SPEI. The null hypothesis of Breusch-Pagan test is the existence of homoskedasticity

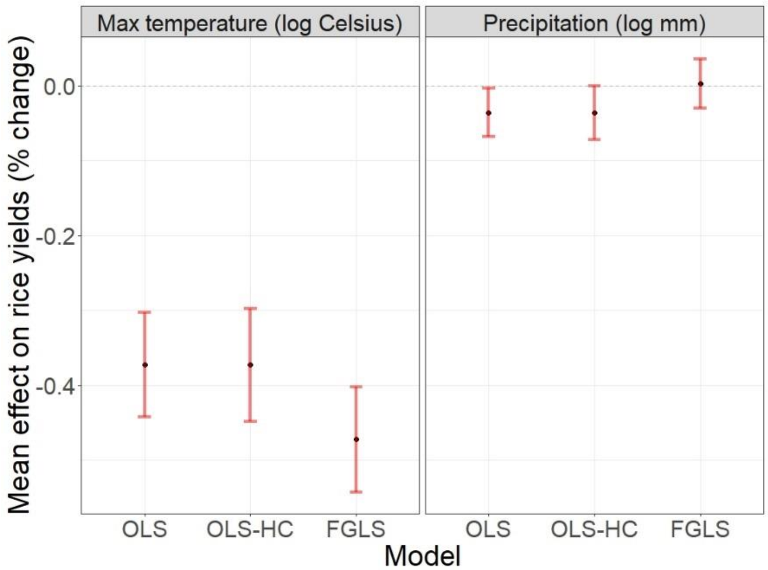


**Figure IV-2 Climate effect on rice yields**

The estimates with and without the CO2 fertilization effect can be used to examine CO2 effects on yield growth. Specifically, this section examines the case where CO2 remained at the 1990-level versus the case where it has grown steadily since then. The resultant projections are in Figure IV-3, where the solid line represents the rice yield trajectory at the observed CO2 growth level, and the dashed line indicates the rice yield trajectory with CO2 held at the 1990-level. Both scenarios are estimated using Model 8 of Table IV-4. The only difference between these two in-sample projection scenarios is using different CO2 concentration levels. The finding shows that the rice yield growth from 1981 to 2016 is 16% with CO2 concentration held at the 1990-level and is 33% with observed CO2 concentration growth. The resulting 17% difference implies that the CO2 fertilization effect has been responsible for 17% of the rice yield growth in the past two decades. Namely, 52% (=17%/33%) of the observed rice yield growth is attributed by with factoring in the CO2 influence.

A few robustness checks are conducted in the Appendix. Since previous studies suggest that the effect of AGRD on crop yields likely has lagged effects (Villavicencio et al. 2013; Huffman and Evenson 2006), Model 5-8 of Table IV-4 include AGRD one-year lagged term. Figure B1 shows the difference in predicted rice yields with and without adding the lagged AGRD term. Although there are some deviations between the two models, overall predictions are closely aligned. In addition, note that productivity and contemporaneous AGRD expenditure are potentially endogenous (Doraszelski and Jaumandreu 2013). To explore the unbiased contemporaneous effect of AGRD on rice yields in Model 5 – 8 of Table IV-4, a Two-stage Least Squares model is conducted using one-year lagged term as an instrument variable (IV). Table B1 shows the IV estimation results, indicating that the coefficients of AGRD expenditure without and with including the CO2 variable are 0.091 and 0.088, respectively. This finding also confirms that omitting the CO2 fertilization effect can bias upward the yield growth induced by AGRD.

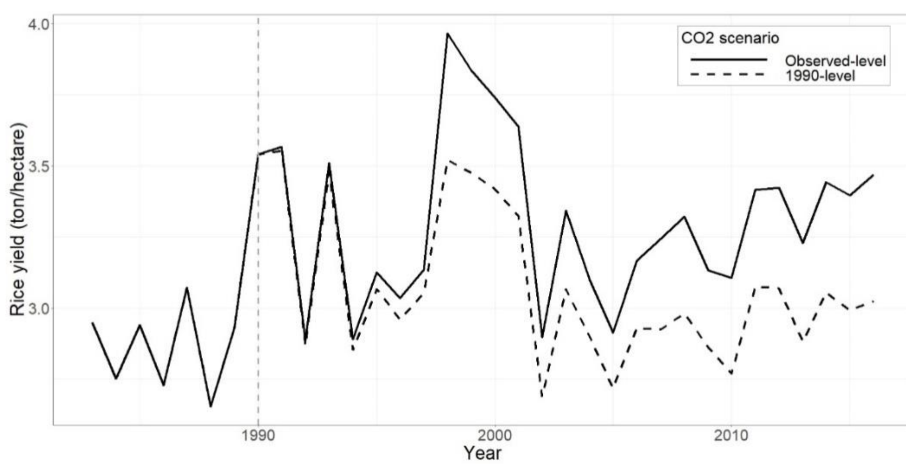


**Figure IV-3 Difference in predicted past rice yields under different CO2 levels**

Note: the above line chart is estimated by the FGLS approach, which is presented in Table IV-4. The black dashed line indicates the fitted rice yield trajectory given other variables at the yearly average level and CO2 at the 1990-level in the post-1990 period. The solid line represents the observed rice yield trajectory. The vertical gray dashed line denotes the starting point of applying different assumed CO2 levels.

*IV.4.3 Scenario Forecasting of the Impact of Climate Change and AGRD on Rice Yields*

As found above, both climate factors and CO2 concentration influence rice yields. The estimated equations can project climate change scenario effects on rice yields. To do this, the following analysis uses CMIP5 climate projections under the Representative Concentration Pathway (RCP) scenarios RCP4.5, RCP6.0, and RCP8.5 and their associate CO2 levels (IPCC 2013). The climate model used is the Community Earth System Model version 1 couples with the Community Atmospheric Model version 5 (CESM1-CAM5) (Neale et al. 2012). The projection of SPEI uses the maximum length of dry spell using the Community Climate System Model 4.0 (CCSM4) from the Coupled Model Intercomparison Project Phase 5 (CMIP5)(Gent et al. 2011). The projections of climate change and CO2 impacts are developed using Model 8 in Table IV-4.

Increases in the AGRD expenditure growth can stimulate rice yield growth, offsetting the effects of climate change and CO2. The average growth rate of AGRD expenditure is 6% across the sample countries over the study period. The following scenario analysis uses 6% as a benchmark growth rate and shows the corresponding AGRD expenditure under optimistic growth (9%), mild growth (3%), and no growth. Figure IV-4 shows a case under varying the above growth rates in AGRD expenditures. With 9% AGRD growth, the rice yields are expected to significantly increase by 224% and 98% in 2100 compared to the 2016-level under the RCP8.5 and RCP4.5 scenarios, respectively. On the other hand, under a no AGRD growth scenario, the year 2100 rice yields are expected to only increase by 102% and 23% under the RCP8.5 and RCP4.5 scenarios, respectively. The above forecast finding shows that rice yields are expected to be highly affected by the degree of mitigation and the amount of AGRD expenditure. Nevertheless, the world population in 2100 is projected to be 10.9 billion, which is 46% growth compared to the 2016-level (United Nations 2019). It will be challenging to feed the future if there is no AGRD growth with ambitious mitigation.

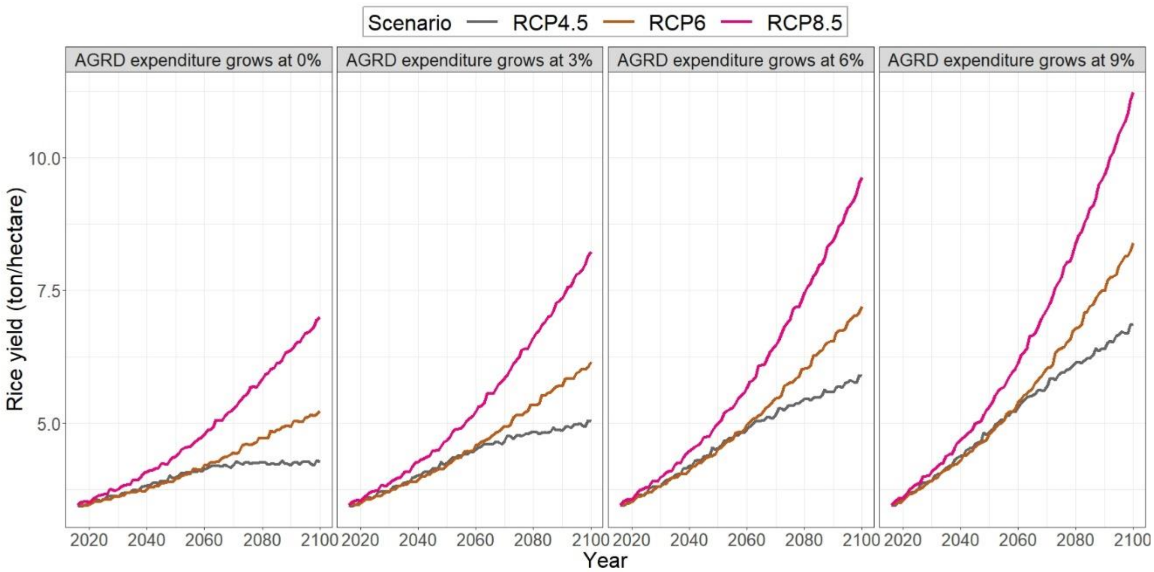


**Figure IV-4 Rice yield forecast under different AGRD spending scenarios**

Note: the forecasting result is estimated using the FGLS approach (Model 8 of Table IV-4) with the CMIP5 projection data mentioned in Section IV.4.3.

*IV.4.4 Offsetting Effects by Increasing AGRD*

The forecast results in Figure IV-4 indicate a need for more AGRD investment to offset climate and CO2 effects if we are to feed the projected future. Figure IV-5 presents the correspondingly annual AGRD expenditures under the different AGRD expenditure growth scenarios. The corresponding AGRD spending at 3% growth is estimated to be 246 million USD in 2030 and 652 million USD in 2060, resulting in 30% and 50% rice yield growth in 2060 under RCP4.5 and RCP 8.5, respectively. The AGRD spending at 9% growth is 586 million USD in 2030 and 9,971 million USD in 2060, leading to 53% and 77% rice yield growth in 2060 under RCP4.5 and RCP8.5, respectively. Thus, with higher levels of CO2 mitigation having adequate supplies to meet future food demand requires increased R&D spending.

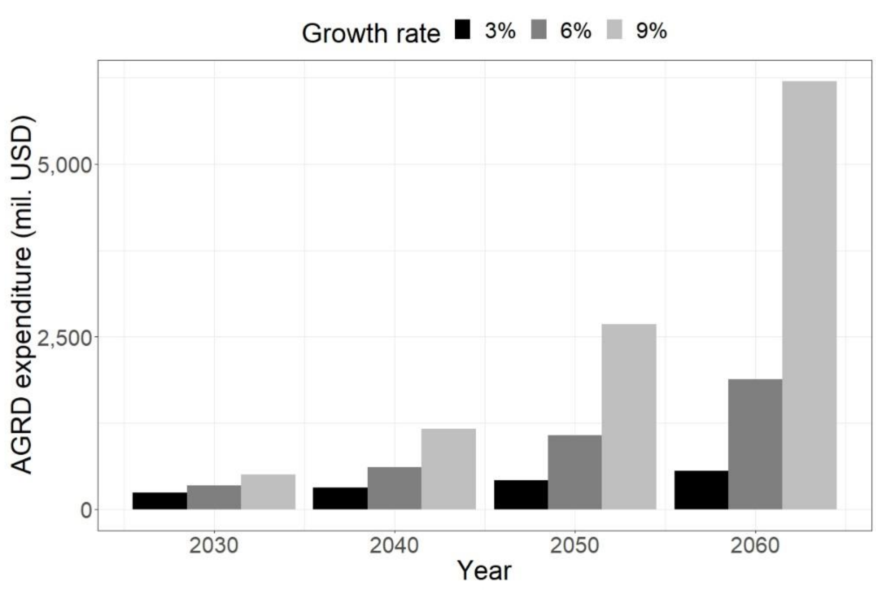


**Figure IV-5 Required annual AGRD expenditure under different growth scenarios**

Note: the average growth rate of AGRD expenditure is 6% across the sample countries over the study period. This scenario analysis uses 6% as a benchmark growth rate and shows the corresponding AGRD expenditure under optimistic growth (9%), and mild growth (3%).

## IV.5 Conclusion

This essay reported on an investigation of the impacts of climate, CO2 fertilization, time-technological progress, and research investment on Asian rice yield increases over time. The findings suggest that while Asian rice yields increased by 33% over 1981 to 2016, that around 52% of the observed yield increases were due to increases in atmospheric CO2, as found in Attavanich and McCarl (2014) for other crops.

The estimation result shows that the future rice yields are influenced by climate and CO2 simultaneously. The result also shows that a high volume of precipitation and high temperature have a negative impact on rice yields, implying that climate change and CO2 mitigation are found to be yield depressing factors. At the end of this century, the projected population growth is about 46%. Nevertheless, under the RCP4.5 scenario without AGRD growth the rice yield growth is expected to marginally increase by about half of this 23% portending food security issues. However, under an optimistic 9% AGRD growth scenario then yields increase by 98%. To meet food demand growth through rice yield growth, the AGRD growth must maintain at 3% under RCP6, implying that the corresponding annual AGRD spending needs to increase substantially if more ambitious mitigation action taken.

The current work has some limitations that suggest possible research directions. Previous studies suggest that the effect of AGRD on crop yields takes place with a substantial lag after the AGRD expenditure is realized. The lag is possibly as long as 25 years (Villavicencio et al. 2013; Huffman and Evenson 2006). However, incorporating such lags would cause us to need to drop observations. Due to the limited Asian country

AGRD data, this study had to make a trade-off between the number of AGRD lagged terms and estimation efficiency. Redoing the research a longer time series and more AGRD data would provide more informative results and policy implications. Additionally, the current work does not explicitly consider the effect of fertilizers and time-varying soil quality on rice yields. Adding observations on fertilizer usage and soil quality data and then redoing the research on rice yield effects would be helpful to further identify the role of CO2, climate and other factors.

The finding of the CO2 fertilization effect in this study implies that we are not doing as well in increasing rice yields as might otherwise appear. Namely, around 52% of the current yield increases appear to be coming from CO2, and this could go away given aggressive mitigation. Substantial CO2 mitigation coupled with future climate change causes negative impacts on rice yield growth in the absence of increasing investments in rice research. Thus, to feed the future while mitigating CO2 to levels less than that found in RCP6.0 likely causes a need for added investment in agricultural research and development.

# CHAPTER V

# CONCLUSIONS

This dissertation consists of three essays reporting on studies that investigate the impacts of market information, environmental policies/practices, and environmental change. A difference-in-difference econometric approach, laboratory experiment, and a historical econometric estimation are used to identify impacts of the events and information of interest. The associated policy implications are also discussed in each essay.

The first essay evaluates the effects of unit-based pricing (UBP) of municipal solid waste and a mandatory recycling (MR) policy in Taiwan on waste reduction, recycling, illegal dumping, and waste tourism incidents. It is analyzed using a difference-in-difference approach over different cities in Taiwan where the policy has been implemented or not. The results suggest that the UBP policy curbed the quantity of unsorted waste and increased disposal of biodegradable waste but did not significantly increase recycling unless the MR policy was not in place. In contrast, the MR policy effectively boosted biodegradable waste and recycling but did not necessarily decrease the amount of unsorted waste. There was a temporary increase in illegal dumping following the UBP policy. No evidence indicates that waste was shipped to nearby urban municipalities that had no UBP policy but that there was an increase in waste moving into a neighboring rural municipality without the policy.

The second essay reports on an investigation on how honey consumers' willingness-to-pay reacts to food product adulteration, product origins, and review information. It was done using choice experiments as influenced by honey product information. Certified local honey seal, honey adulteration information, and product reviews were considered. Their effect was investigated in an eye-tracking supported choice experiment. The results show that honey adulteration or labeling location information independently increase WTP, and negative product reviews cause a much larger reduction in WTP than the increase produced by positive product reviews. The results also suggest that while adulteration information or a certified local honey seal has a positive effect on WTP that they are substitutes with the result occurring from one or the other but no WTP boost from consumers receiving both forms. These results have both policy and behavioral implications regarding consumer responses to complex food information in grocery shopping environments.

The third essay explores the growth in yields of Asian rice, where rice is arguably the most important food crop. Given projected population growth, land availability, and food demand, increases in rice crop productivity is vital to future food security. Climate change, CO2, and research investment are factors influencing future productivity. This study econometrically investigates the productivity impacts of climate, CO2 fertilization, and research investment on Asian rice yields. To allow identification of CO2 effects, the study integrates FAO reported yield data with free air carbon dioxide enrichment (FACE) field experimental data. The finding shows that CO2 accumulation has made a significant contribution to rice yield growth in the three past decades, amounting to about a 52% of the yield increase. The result also shows that a high volume of precipitation and high temperature have a negative impact on rice yields, implying that climate change and CO2 mitigation are found to be yield depressing factors. The analysis of this essay finds that a high level of $CO_2$ mitigation raises a need for more investment in agricultural research and development to maintain needed productivity growth.

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APPENDIX A

EXPERIMENT INFORMATION AND ESTIMATION MODEL SELECTION

**Table A1 Product reviews and corresponding subjects' evaluation**

| | **Positive review.** This honey has a great taste and rich flavor with a mild honey aroma. It's quite thick and takes time to move from one side of the container to the other. Love this honey! | **Negative review.** Its taste is odd and seems more like corn syrupy. This honey is like a diluted honey, runny and watery. It even has a sour smell. Not a pleasant experience… |
|---|---|---|
| **Extremely positive** | 117 (66%) | 0 (0%) |
| **Somewhat positive** | 49 (28%) | 4 (2%) |
| **Neither positive nor negative** | 6 (3%) | 4 (2%) |
| **Somewhat negative** | 4 (2%) | 32 (18%) |
| **Extremely negative** | 1 (1%) | 137 (78%) |

*Note: We asked how subjects feel the above honey product reviews collected and revised from Amazon in the survey questions. Counts of subjects and percentages of total subjects are presented in parentheses. The result shows that most subjects have positive feelings for the positive review, so do for the negative review. Thus, we rule out the possibility that subject misread or misunderstand the product reviews.*

**Table A2 Description of self-reported variables**

| Variable name | Description |
|---|---|
| **[Honey preferences]** ***How important are the following factors to you when making honey purchasing decision?*** **(1 if not important at all – 5 if extremely important)** | |
| ***honey_price*** | Importance of price attribute |
| ***honey_taste*** | Importance of taste attribute |
| ***honey_nutrition*** | Importance of nutrition attribute |
| ***honey_cont*** | Importance of container attribute |
| ***honey_size*** | Importance of size attribute |
| ***honey_brand*** | Importance of brand attribute |
| ***honey_origin*** | Importance of origin attribute |
| ***honey_pure*** | Importance of pure attribute |
| ***honey_raw*** | Importance of raw attribute |
| ***honey_organic*** | Importance of organic attribute |
| ***honey_natural*** | Importance of natural attribute |
| **[Subject attitudes]** ***Use the scale to indicate how much you agree or disagree with the following statements.*** **(1 if strongly disagree - 5 if strongly agree)** | |
| ***prot_env*** | It is important to protecting the environment to you personally |
| ***eco_prod*** | You are ready to buy environmentally friendly honey products even if they cost a little bit more. (e.g. organic, non-GMO, local honey, etc.) |
| ***label_real*** | Current labels on honey products allow you to identify real product information |
| ***know_natural*** | **= 1 if subjects answer (3) in the following question;**<br>**= 0 if otherwise.**<br>According to your understanding, what does a honey product labeled "natural" mean?<br>(1) A honey product hasn't included artificial or synthetic ingredients, such as all color additives regardless of source. (2) A honey product wasn't made in a field where uses pesticides. (3) A honey product hasn't been processed or manufactured, such as thermal technologies, pasteurization, or irradiation |
| ***know_pure*** | **= 1 if subjects answer (1) in the following question;**<br>**= 0 if otherwise**<br>Pure honey is visibly thick and will take noticeable time to move from one side of a container to another while fake honey will simply run, though not as quickly as water does. (1) True. (2) False. (3) I don't know. |
| ***know_organic*** | **= 1 if subjects answer (2) in the following question;**<br>**= 0 if otherwise**<br>There is no real organic honey because honey bees can fly to wherever they like. (1) True. (2) False. (3) I don't know. |
| ***know_local*** | **= 1 if subjects answer (3) in the following question;** |

| | |
|---|---|
| | **= 0 if otherwise**<br>Local honey means that (1) Honey products are sold by a local company. (2) Honey products are bottled in that local area, but pollination service could occur in somewhere else. (3) Honey products made by local honey bees, namely pollination service only occurs in the local area. |

**Table A3 Model selection of the logit-mixed logit model**

| No. draws | Degree/level/knot | Polynomial | | Step | | Spline | |
|---|---|---|---|---|---|---|---|
| | | LL | Chi-square | LL | Chi-square | LL | Chi-square |
| 5000 | 2 | 1333.12 | - | 1345.11 | - | 1317.58 | - |
| | 3 | 1318.69 | 28.86 | 1326.93 | 36.36 | 1305.92 | 23.32 |
| | 4 | 1310.81 | 15.76 | 1312.95 | 27.96 | 1297.84 | 16.16 |
| | 5 | 1319.06 | -0.74 | 1309.48 | 6.94 | 1258.69 | 94.46 |
| | 6 | 1298.72 | 39.94 | 1279.71 | 66.48 | 1279.27 | -41.16 |
| | 7 | 1294.42 | 48.54 | 1253.82 | 51.78 | 1251.03 | 15.32 |
| | 8 | 1299.64 | 38.1 | 1217.47 | 72.7 | 1206.23 | 104.92 |
| | 9 | 1263.39 | 110.6 | 1197.14 | 40.66 | 1191.09 | 30.28 |
| | 10 | 1282.31 | -37.84 | 1213.95 | -33.62 | 1206.17 | -30.16 |
| 2000 | 2 | 1351.34 | - | 1361.3 | - | 1348.67 | - |
| | 3 | 1349.77 | 3.14 | 1323.63 | 75.34 | 1320.09 | 57.16 |
| | 4 | 1311.11 | 80.46 | 1326.84 | -6.42 | 1302.38 | 35.42 |
| | 5 | 1314.37 | -6.52 | 1324.71 | -2.16 | 1278.43 | 47.9 |
| | 6 | 1284.91 | 52.4 | 1296.07 | 55.12 | 1272.06 | 12.74 |
| | 7 | 1265.38 | 91.46 | 1278.65 | 34.84 | 1222.7 | 111.46 |
| | 8 | 1264.34 | 2.08 | 1232.94 | 126.26 | 1219.84 | 5.72 |
| | 9 | 1246.85 | 37.06 | 1260.52 | -187.8 | 1211.65 | 22.1 |
| | 10 | 1244.4 | 4.9 | 1229.32 | 7.24 | 1229.63 | -13.86 |

*Note: 9-knot-spline function with 5,000 draws was selected as the final model since it had the best model fit in terms of log-likelihood values.*

APPENDIX B

ROBUSTNESS CHECK

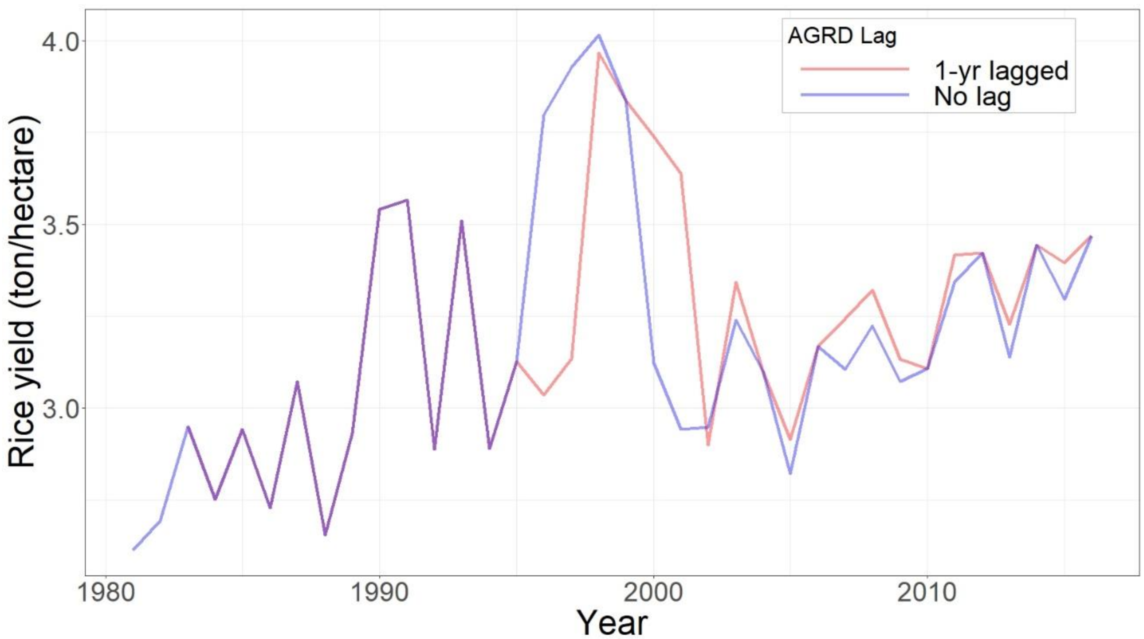


**Figure B1 Predicted past rice yields with and without a lagged term**

Note: the above line chart is estimated by the FGLS approach, which is presented in Table IV-4. The red line indicates the fitted rice yield trajectory included the AGRD one-year lagged term. The purple line represents the fitted rice yield trajectory without including the AGRD one-year lagged term.

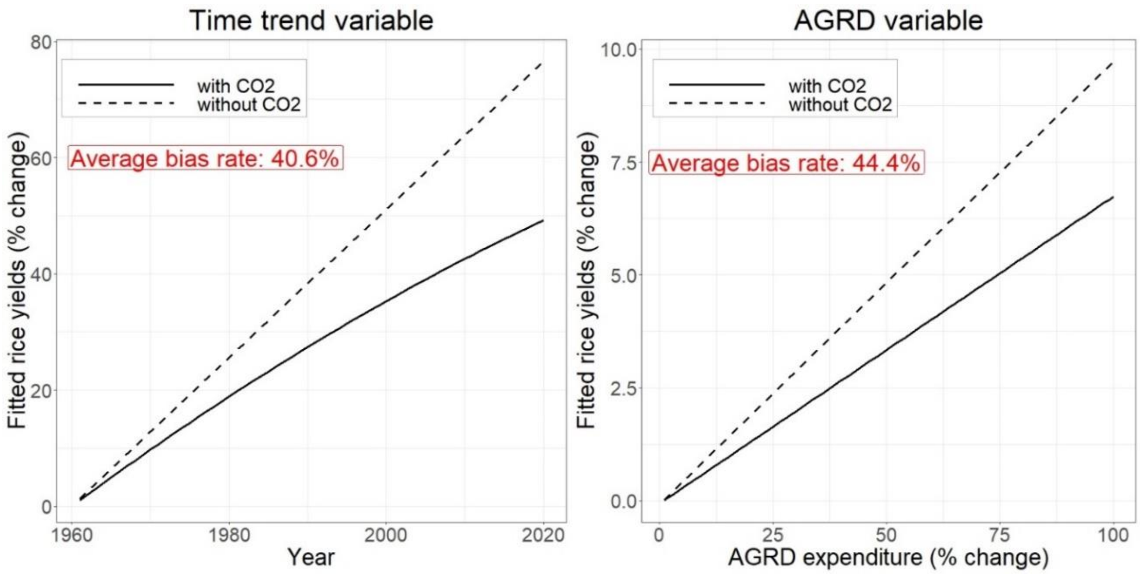


**Figure B2 Difference in the coefficients of the AGRD expenditure variable**

Note: the above line charts are estimated OLS with heteroscedasticity-consistent standard errors (OLS-HC) and the third stage FGLS, which are presented in Table 4, respectively. The dashed lines indicate that given other variables constant, the trajectory of the AGRD effects on rice yields across different change rates of AGRD when the CO2 variable is omitted. The solid lines represent that given other variables constant, the trajectory of the AGRD effects on rice yields across different change rates of AGRD when the CO2 variable is included in the model. The discrepancies between the solid and dash lines show the CO2 effect has been responsible for a substantial amount of past rice yield growth. Namely, actual pure technological progress driven by AGRD is substantially smaller than what we observe. The boost from CO2 ranges from 40.6% to 44.4%.

**Table B1 Effects of climate, CO2, and technological progress on rice yields (IV)**

| | w/o CO2 | | w/ CO2 | |
|---|---|---|---|---|
| | 1st stage: AGRD | 2nd stage: Yield | 1st stage: AGRD | 2nd stage: Yield |
| | (1) | (2) | (3) | (4) |
| Precipitation (log mm) | -0.573 | -0.582 | -0.669* | -0.586 |
| | (0.350) | (0.678) | (0.350) | (0.681) |
| Max. Temperature (log Celsius) | -2.213 | -1.465 | -2.113 | -1.470 |
| | (1.412) | (3.175) | (1.437) | (3.176) |
| CO2 (log ppm) | | | 1.154** | 0.089 |
| | | | (0.572) | (0.546) |
| SPEI (-: drought, +: wet) | 0.007 | 0.026 | 0.198 | -0.017 |
| | (0.009) | (0.017) | (0.148) | (0.259) |
| Irrigation rate (percentage) | 0.013*** | 0.008** | 0.009* | 0.008* |
| | (0.005) | (0.003) | (0.005) | (0.004) |
| 1-yr lagged AGRD (log mil. USD) | 0.950*** | | 0.903*** | |
| | (0.018) | | (0.030) | |
| AGRD (log mil. USD) | | 0.091*** | | 0.088*** |
| | | (0.017) | | (0.029) |
| FACE dummy | 0.011 | 0.276*** | -0.531** | 0.244 |
| | (0.036) | (0.087) | (0.263) | (0.275) |
| log(CO2) × SPEI | | | -0.032 | 0.007 |
| | | | (0.025) | (0.043) |
| Constant | 9.553* | 9.040 | 3.060 | 8.547 |
| | (5.205) | (9.255) | (6.279) | (9.787) |
| Weak IV test(p-value) | - | 0 | - | 0 |
| Endogeneity test(p-value) | - | 0.012 | - | 0.02 |
| Observations | 410 | 410 | 410 | 410 |
| Adjusted R2 | 0.996 | 0.855 | 0.996 | 0.855 |
| F Statistic | 1,041.729*** (df = 98; 311) | - | 1,031.563*** (df = 100; 309) | - |

Note: *p<0.1; **p<0.05; ***p<0.01. The above results are estimated with heteroscedasticity-consistent standard errors (OLS-HC). The null hypothesis of Weak IV test is the existence of weak IV. The null hypothesis of endogeneity test is the existence of endogeneity using the Wu-Hausman test.

**Table B2 Effects of climate, CO2, and technological progress on rice yields (without fixed effects)**

| | Time trend | | | | AGRD expenditure | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS-HC (w/o CO2) | OLS-HC (w/ CO2) | FGLS (w/o CO2) | FGLS (w/ CO2) | OLS-HC (w/o CO2) | OLS-HC (w/ CO2) | FGLS (w/o CO2) | FGLS (w/ CO2) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Precipitation (log mm) | -0.008 | -0.007 | -0.004 | -0.003 | -0.039** | -0.036* | 0.013 | 0.003 |
| | (0.013) | (0.013) | (0.011) | (0.011) | (0.019) | (0.018) | (0.017) | (0.017) |
| Max.Temperature (log Celsius) | -0.374*** | -0.377*** | -0.512*** | -0.504*** | -0.365*** | -0.373*** | -0.491*** | -0.472*** |
| | (0.032) | (0.032) | (0.035) | (0.035) | (0.039) | (0.039) | (0.035) | (0.036) |
| CO2 (log ppm) | | 2.370 | | 2.804 | | 0.607* | | 0.485 |
| | | (3.202) | | (2.577) | | (0.349) | | (0.295) |
| SPEI (-: drought, +: wet) | 0.002 | 0.141 | 0.002 | 0.087 | 0.001 | 0.330 | -0.001 | 0.284 |
| | (0.002) | (0.176) | (0.002) | (0.158) | (0.003) | (0.264) | (0.002) | (0.182) |
| Irrigation rate (percentage) | 0.010*** | 0.010*** | 0.009*** | 0.009*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Trend (Sequence of 1 to 56) | 0.008*** | 0.002 | 0.013*** | 0.005 | | | | |
| | (0.003) | (0.010) | (0.002) | (0.008) | | | | |
| Sq. Trend (Sq. Sequence of 1 to 56) | 0.00002 | -0.0001 | -0.00003 | -0.0001 | | | | |
| | (0.00004) | (0.0001) | (0.00004) | (0.0001) | | | | |
| AGRD (log mil. USD) | | | | | 0.092*** | 0.091*** | 0.085*** | 0.086*** |
| | | | | | (0.005) | (0.005) | (0.005) | (0.005) |
| FACE dummy | 0.592*** | -0.491 | 0.433*** | -0.858 | 0.260*** | -0.058 | 0.156* | -0.069 |
| | (0.158) | (1.411) | (0.129) | (1.222) | (0.095) | (0.193) | (0.089) | (0.150) |
| log(CO2) × SPEI | | -0.024 | | -0.014 | | -0.055 | | -0.048 |
| | | (0.030) | | (0.027) | | (0.044) | | (0.031) |
| Constant | 1.804*** | -11.846 | 2.166*** | -14.013 | 2.516*** | -1.092 | 2.532*** | -0.336 |
| | (0.119) | (18.423) | (0.125) | (14.829) | (0.113) | (2.071) | (0.119) | (1.765) |
| Breusch-Pagan test(p-value) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Num. of countries | 33 | 33 | 33 | 33 | 25 | 25 | 25 | 25 |
| Observations | 1,608 | 1,608 | 1,608 | 1,608 | 468 | 468 | 468 | 468 |
| Adjusted R2 | 0.347 | 0.347 | 0.419 | 0.409 | 0.522 | 0.526 | 0.588 | 0.589 |

Note: *p<0.1; **p<0.05; ***p<0.01. The null hypothesis of Breusch-Pagan test is the existence of homoskedasticity.