The Benefits and Costs of a Small Food Waste Tax and Implications for Climate Change Mitigation

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Abstract

Given that life-cycle greenhouse gas (GHG) emissions from wasted food is comparable to that of road transport, managing excessive food demand is essential for achieving climate change mitigation goals. A textbook solution is levying a corrective tax on food waste, but limited evidence exists on the benefits and costs of these taxes. By exploiting plausibly exogenous expansions in a small food waste tax—on average \$0.06 per KG—in South Korea, I document three main findings. First, the tax reduces annual food waste by 20% (53KG) and grocery purchases by 5.4% (46KG), worth \$172 for an average household, without compromising household nutritional needs. These estimates suggest that the program cost of reducing 1 ton of carbon dioxide is only \$13, or even negative when savings on the waste treatment budget is considered. Using the household production model, I then explore abatement strategies and corresponding costs and find that an average household increases their time spent on meal production by 5.5%, or 54 additional hours per year. Finally, the demand elasticity of groceries implies that the price effect explains only 5% of the reduction in grocery purchases. Instead, the tax seems to affect household behavior via non-pecuniary channels, in particular, by raising attention to food waste. The findings indicate that a small tax on food waste can be a powerful climate change mitigation tool by inducing environmentally advantageous changes in household behavior.

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1 Introduction

Globally, one-third of produced food is discarded, generating extremely large amounts—8% of the anthropogenic emissions that are comparable to that of road transport—of greenhouse gas (GHG) throughout its life cycle (Gustavsson et al. 2011, IPCC 2014, FAO 2015). While food loss can happen in all stages of the supply chain, consumer-end food waste is a particularly dire problem not only because of its high volume but also because its environmental impact of food waste is cumulative along the supply chain (EPA 2021).[1] Despite its contribution to climate change, tackling household food waste has been only at the periphery of policy discussions on climate change mitigation (IPCC 2014, Creutzig et al. 2016, 2018). However, given that even an immediate halt of fossil fuel consumption would fail to achieve the Paris Agreement's 1.5°C goal unless the current food system is changed (Clark et al. 2020), managing excessive food demand at home has become increasingly important (United Nations 2015, IPCC 2018, Springmann et al. 2018, National Academies of Sciences, Engineering, and Medicine 2020, EPA 2021, OECD 2021).

Theoretically, levying a Pigouvian tax on food waste can achieve socially optimal outcomes at the lowest possible cost (Pigou 1920). However, earlier studies show that the effect of the tax often deviates from the theoretical prediction and is a priori unclear. For instance, while taxes with high visibility can generate a much larger effect than what a standard economic theory promises (Li et al. 2014, Rivers and Schaufele 2015, Homonoff 2018, Andersson 2019), taxes with loopholes may induce behavioral responses that can seriously undermine the policy's effect (Fullerton and Kinnaman 1996, Taylor 2019). Furthermore, a focal point of most earlier works has been evaluating the policy's effect (i.e., benefit), which is important but not sufficient to understand welfare implications. That is, without identifying households' abatement strategies and corresponding costs, it is difficult to tell whether a policy is socially desirable or not.[2]

This paper provides the first large-scale evidence on the effect of a unit-based food waste tax (hereafter "food waste tax"). The empirical setting is South Korea, where a food waste tax is collected through either a smart card system (for condominium complexes) or an official trash bag (for other housing types). The tax is small with an average rate of \$0.06 for 1 KG or \$1.3 per month for a

[1]In developed countries, consumers generate 40%–60% of the total food waste quantity (Gustavsson et al. 2011).

[2]Under the neoclassical model, the tax rate is an upper bound of the abatement cost, which is a useful approximation for welfare analysis. This relationship, however, may not hold when the tax effect is a function of behavioral biases.

household with average waste quantity.[3] By exploiting plausibly exogenous expansions in food waste due to the central government's mandate, I estimate the tax effect on purchased, consumed, and wasted food quantities using the difference-in-difference approach. Then, building on the insights from the household production model (Becker 1965), I empirically test various abatement strategies such as spending more time making meals, and estimate corresponding abatement costs. I then explore to what extent household choices are consistent with the tax's price effect and investigate which class of non-pecuniary effects prevail.

The empirical analysis produces three key results. First, I find that the policy is highly effective; for an average household, the tax reduces annual food waste by 20% (53KG) and annual grocery purchase quantity by 5.5% (46KG), or spending by 4.4% ($172). Comparing the effect on wasted and purchased food quantity (46KG/53KG) suggests that 86% of the observed reduction in waste is from the actual reduction—namely, the upper bound of illegal dumping is 14%. Further, there is a remarkable difference in the policy's effect depending on the food type. The point estimate is three times larger in magnitude for perishable items (fresh vegetables and fruits) than storable items, which is plausible given that the tax makes perishable items disproportionately more expensive in expectation. Importantly, these effects do not come at the cost of households' nutritional needs: the tax has a null effect on food intake and nutrition, suggesting that the reduction in grocery purchases comes from the previously wasted—rather than consumed—part of the food basket.

The estimated changes in food usage imply that the tax reduces annual GHG emissions from wasted food by 145KG CO2eq per household,[4] which in turn indicates that the program cost of reducing one ton of CO_2 is as low as $13, or even negative when savings on governments' waste pickup and treatment spending is considered. Moreover, a $172 savings on groceries suggests that the tax generates a private benefit, which helps to offset potential abatement costs.

I next explore how households manage to keep the food intake constant while using less groceries. Building on the insights from the household production model (Becker 1965), I empirically test possible waste abatement strategies. That is, I investigate whether the tax induces a change (1) in time spent on meal production, (2) in grocery input quality, and (3) in total factor productivity. I find

[3] To put this in context, the gasoline tax in South Korea has been $2–$3 per gallon. Alternatively, $1.3 is 0.4% of monthly grocery spending for an average household in the sample.

[4] In monetary terms, a 145KG CO2eq reduction is worth $7.4–$27 depending on the social cost of carbon estimates (IWG 2021, Rennert et al. 2022).

that households spend 54 additional hours per year (or a 5.5% increase from the baseline) on meal production at home, which is worth $133 per year. To express the time cost in monetary terms, I follow recent studies on household production and use the returns to shopping—money saved for additional time spent on shopping—as a proxy for the opportunity cost of time (Aguiar and Hurst 2007, Hastings and Shapiro 2018, Nevo and Wong 2019). A wage rate, a widely used alternative, does not seem to be a good proxy in this setting given that half of the primary home food preparers in the sample are not formally employed.

Using web search data, I also provide suggestive evidence that organizing refrigerators seems to be one of the primary activities that households spend additional time on. In contrast to the estimated effect on time use, I do not find any change in input quality for groceries or total factor productivity of meal production function due to the tax. All in all, the results show that the tax seems to induce households to substitute between time and money (i.e., saving on grocery costs) without compromising their nutritional needs.

Lastly, I study why household responses to a small tax is disproportionately large. I first decompose the tax effect into price versus non-price (non-pecuniary) effects. To do so, I leverage the estimated demand elasticity of groceries from earlier works (Andreyeva et al. 2010), assuming that households perceive the tax as a grocery price change of the equivalent size. I find that at an upper bound (in magnitude) –0.8, the price effect can explain only 5% of the grocery purchases reduction from the tax. Consistent with the small price effect, I report that once the tax is in place, further rate increases have little impact on grocery purchases.

I then discuss potential non-pecuniary channels and their welfare implications. Given that carefully tracking food usage at home incurs non-trivial cognitive and time costs on households, not all of them might pay full attention to the amount of food they waste. The tax can remedy the inattention problem because taxation requires measurement, which provides feedback to households on a regular basis. This is consistent with the findings from a companion paper that the smart card system substantially reduces food waste even during the pilot period—where households start to get instant feedback on their waste generation from the system but the marginal tax rate of food waste is still effectively zero (Lee and Seo 2022).

Related literature. This paper contributes to three different bodies of literature. First, it is related to the literature studying environmental taxes on households. I document that a small food waste tax induces a large behavior change primarily through non-pecuniary channels, which contributes to generalizing earlier studies that have reported a disproportionately large effect of a corrective tax in gasoline or plastic bag contexts (Li et al. 2014, Rivers and Schaufele 2015, Homonoff 2018, Andersson 2019).

Further, and presumably more importantly, this paper estimates not only the benefit but also costs imposed on households. Despite rising attention to the environmental regulations targeted at households (OECD 2011, Creutzig et al. 2018, IPCC 2022), our understanding of the accompanying abatement cost is markedly limited primarily due to measurement challenges.[5] That is, these taxes usually induce a wide range of behavioral responses that can be captured only with multiple micro datasets. In addition, the non-monetary nature of the cost poses additional difficulty in estimations. I overcome these challenges by compiling multiple household-level datasets that comprehensively document food and time usage. Further, these datasets also jointly shed light on the monetary cost of time, which is crucial to calculate the monetized cost incurred on households. Understanding the economic cost of the policy is an important step toward a more complete welfare analysis.

Second, this paper departs from previous works on the economics of climate change mitigation. While earlier studies have primarily focused on conventional carbon-intensive sectors such as power, manufacturing, heating, or transportation (Fowlie et al. 2016, 2018, Andersson 2019, Linn and Shih 2019, Linn and McCormack 2019, Gerarden et al. 2020, Reynaert 2021), this paper focuses food, an area has been largely neglected from a GHG discussion despite its substantial contribution to climate change. Its findings suggest that tackling consumer-driven food waste can be a highly cost-effective mitigation option.

Finally, this paper extends earlier studies on waste policies in three important ways. It is the first paper to explicitly estimate how upstream consumption changes in response to a waste pricing policy. This contrasts with existing works whose empirical exercises primarily focus on identifying households' behavioral changes at the disposal stage (e.g., increased recycling) (Fullerton and Kinnaman 1996, Allers and Hoeben 2010, Carattini et al. 2018, Bueno and Valente 2019, Valente 2021). Understanding household response in the upstream stage is important because environmentally ad-

[5] An important exception—though outside of the tax setting—is Davis (2008), who studies household responses to plate-based driving restrictions in Mexico City. Davis (2008) uses the expenditure on additional vehicle purchases, one way to circumvent the regulation, to estimate the cost of regulation.

vantageous consumption pattern changes could reduce negative externality throughout the product life cycle (OECD 2000). This point is particularly important for food waste because the GHG emissions from the farm-to-kitchen stage are responsible for 90% of life cycle GHG from food waste (Crippa et al. 2021). In addition, earlier studies underestimate the social cost of waste by an order of magnitude—even without considering the GHG emissions from the upstream—by abstracting away from the GHG emissions from waste.[6] These two differences could explain why earlier works find waste pricing policies welfare-harming.[7] Last, this paper provides the first large-scale revealed preference-based empirical evidence on the effect of a food waste policy. Despite heightened policy attention on food waste reduction measures in recent years, food waste studies have been largely theoretical (Hojgard et al. 2013, Katare et al. 2017, Lusk and Ellison 2017, Hamilton and Richards 2019). Existing empirical works either focus on a measurement problem (Yu and Jaenicke 2020, Smith and Landry 2021) or evaluate reduction measures based on stated preferences or smaller samples (Qi and Roe 2017, Katare et al. 2019).

The rest of the paper proceeds as follows. Section 2 provides background information on the GHG emissions from life-cycle food waste and the food waste tax policy in South Korea. Section 3 details the data sources and provides some summary statistics. Section 4 reports the policy's effect on food usage. Section 5 presents estimation results on abatement strategies and corresponding costs, while Section 6 discusses potential explanations for household behavior changes. Section 7 concludes.

2 Background

2.1 Life Cycle GHG Emissions from Wasted Food and Policy Responses

Producing food that is ultimately wasted leaves an array of environmental footprints such as GHG emissions, biodiversity losses, soil degradation, and water scarcity (EPA 2021). This paper focuses

[6]For instance, a widely cited paper by Repetto et al. (1992) considers "air and water pollution, noise, and other disamenities" as potential non-market costs of waste (p.22), and estimates that the social cost is \$5/ton. However, when GHG emissions (mostly methane) from landfill is taken into account, the social cost of waste is at least \$55.5/ton. This number can be calculated first by multiplying GHG emissions per ton of landfill waste (1.09MMT = 148MMT/136MMT) by the social cost of carbon (EPA 2016, IWG 2021). Importantly, \$55.5/ton is after considering that about 50% of the total waste generated in the US is recycled, composted, or used for energy production.

[7]Prior literature studies unit-based pricing on municipal solid waste (MSW), which is a combination of general and food waste. However, food is the largest (44%) waste category globally in MSW and is responsible for the majority of the GHG emissions from the overall waste (Kaza et al. 2018). Thus excluding the GHGs effect from policy evaluation is also problematic for unit-based pricing on MSW as well.

on a particular environmental impact—GHG emissions, which is the primary and a well-documented source of externality from wasted food (Davies and Doble 2004, EPA 2021). Thus the environmental problem discussed below, which abstracts away from other issues, should be seen as a lower bound.

Life cycle GHG Emissions from Wasted Food. Life cycle GHG emissions from wasted food are estimated to be 4.4 $GtCO_2eq$ or 8% of the entire anthropogenic GHG emissions (FAO 2015). This is comparable to the entire road transport, which generates 5.1$GtCO_2eq$ each year. There are two reasons why emissions from wasted food is so high.

First, food production—the entire process from farm to kitchen—is one of the most carbon-intensive activities. Indeed, estimates suggest that the agricultural sector is responsible for 16-27% of the total anthropogenic GHG emissions (IPCC 2014, 2019).[8] Unfortunately, despite massive GHGs generated for food production, one third of the total produced food is never consumed, creating a so-called "emissions in vain" problem (FAO 2013). GHG intensity varies a lot by food items, and Poore and Nemecek (2018) shows that farm to kitchen GHG emissions from animal products, especially those from ruminant livestock, are 100 times more carbon intensive than their vegetable counterparts.

Second, food waste generates massive amounts of methane when it decays in landfill sites. As such, emissions from solid waste disposal and treatment account for 5% of the total global GHG emissions, and landfill is the third largest methane source in the US despite widely adopted methane-to-energy facilities (EPA 2016, Kaza et al. 2018).

Policy Responses. Addressing the food waste problem has gained a large policy attention in the past decade. For instance, United Nations Sustainable Development Goal 12.3 calls for halving per household food waste at the retail and consumer levels by 2030 (United Nations 2015). A number of national governments announced policy goals that resonate with the UN, and consequently, governments representing 15 percent of the world's population are pursuing food waste reduction actions at scale (Flanagan et al. 2019). For instance, the EPA and USDA adopted the target of cutting food waste at the retail and consumer level by 50% by 2030 (USDA and EPA 2021). In addition, state governments (e.g., New Jersey, Oregon, and Washington) have also established goals to cut food

[8] Agricultural land expansion through deforestation, anaerobic decomposition from rice cultivation, enteric fermentation from ruminant livestock, and nitrogen fertilizer usage are major contributors (Springmann et al. 2018, IPCC 2019).

waste by 50% by 2030 (EPA 2021).

Many of these policy efforts, however, focus on recycling wasted food, for instance by encouraging donation, composting, or energy recovery (National Academies of Sciences, Engineering, and Medicine 2020). While these policies could reduce environmental impacts from the waste treatment stage, they have limited effect on solving the "emissions in vain" problem. Given that carbon-intensity of the production (i.e., farm-to-kitchen) stage is an order of magnitude higher than the waste treatment stage, policies targeting source reduction is unequivocally a more effective way to reduce the GHG emissions from wasted food. A corrective tax on food waste could potentially alleviate the GHG emissions from the production stage if it induced households to reduce excessive food demand.

A conceivable alternative in response to the production stage GHG emissions is taxing food production based on carbon intensity of each product. While closer to the first-best policy, levying a carbon tax on food is one of the least popular mitigation policy options with concerns over food security and equity (Godfray et al. 2010, Dechezleprêtre et al. 2022). That is why the federal government of Canada exempted its agricultural sector from a national carbon tax (Wu and Thomassin 2018). A corrective tax on *food waste* is a practical policy alternative to a corrective tax on *food* because it does not penalize food consumption itself—rather it penalizes wasting food.

2.2 Food Waste Tax Policies in South Korea

Similar to many other parts of the world, waste management is under the jurisdiction of individual municipalities in South Korea. However, the central government has initiated a few landmark waste policy changes since the 1990s, which form the basis of identifying variations in this paper. In this section, I provide a brief overview of the evolution of waste policy in South Korea.

Wave 0 (1995-2004): starting unit-based tax on landfill waste. As the country went through fast urbanization, municipal solid waste (MSW) in South Korea grew more than seven fold between 1970 and 1990,[9] but with rising income, it became increasingly difficult to find space for landfill or waste incineration sites.[10] In response, in 1995, a nation-wide tax on household waste was implemented

[9]MSW is comprised of various items commonly disposed of after usage. These include packaging, furniture, clothing, and food scraps. MSW does not include industrial, hazardous, or construction waste (EPA 2012).

[10]For instance, the greater Seoul metropolitan area, which is home to 25 million people, has been using a single landfill site since 1992. The site is constructed on reclaimed land because creating new landfill is extremely contentious.

to reduce the amount of waste and relax the capacity constraint. The policy had two key features. First, source-separated recycled items such as empty glass bottles, aluminum cans, or milk cartons were picked up free of charge. Second, to dispose of waste that had not been recycled (including food waste), households were required to use an official garbage bag, which had to be purchased in advance. Prior studies have found that this policy was successful in reducing the amount of waste ending up in landfill (Hong 1999).

Wave 1 (2005-2012): Food waste segregation and partial implementation of unit-based food waste tax. As thorny a problem as capacity constraints has been environmental problems caused by food waste treatment. For instance, it creates a massive amount of leachate and bad odor when sent to landfils. Further, moisture in food waste lowers temperatures during incineration, creating highly toxic dioxin. These factors escalated complaints from residents near waste treatment facilities, and made construction of additional facilities next to impossible. In response, the Ministry of Environment prohibited food waste disposal in landfill in 2005. Subsequently, each municipality collected food waste separately and processed it in composting or animal feed producing sites.

In a nutshell, food waste policy in the wave 1 period focused on preventing food waste from ending up in landfill sites. A practical implication is that the waste collection was designed to attain the maximum operational efficiency. For a typical municipality, therefore, condominium complex residents were asked to dispose of their food waste using standardized communal dumpsters (see Figure 2.1 (a)). Municipalities levied a flat monthly tax ($1-2 per month per household) directly on management offices, which then was collected from each household through the management fee. The collection methods for other housing types and small restaurants, in contrast, were more split: while some municipalities relied on a combination of individual household-level containers and charged flat fees, others took advantage of official trash bags similar to landfill waste (see Figure 2.1 (b)).[11] Importantly, households in municipalities with the trash bag regime were subject to the unit-based tax since 2005.

As of 2009, 11% (50%) of municipalities in the country charged a unit-based tax on condominium complex (other housing type) residents (Kim et al. 2010). Specifically, residents of other housing

[11]The majority of the food waste (70%) is from households or small restaurants (smaller than 200 m^2), whereas the rest is from bulk generators such as hotels, large restaurants, and office/school cafeterias. Since the Waste Control Act imposes responsibility on bulk generators for managing their own waste, municipalities provide waste pickup services to households and small restaurants only.

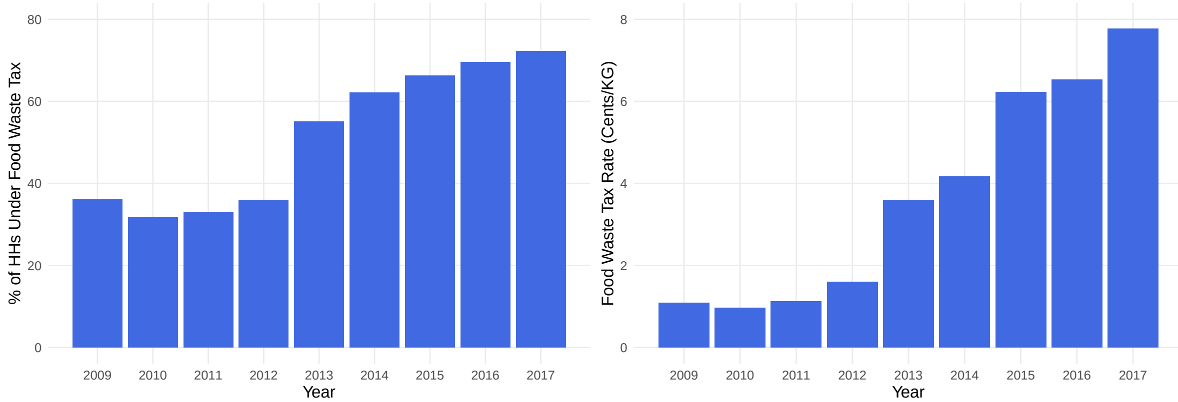
(a) Condominium Complex - Communal Dumpsters (b) Multi Unit Dwelling - Official Trash Bags

Figure 2.1: Waste Collection During Wave 1

types in the largest metropolitan cities like Seoul or Busan had a high chance of using trash bags (see Figure B.5 (a)). Consequently, there has been a substantial variation across municipalities in the fraction of households facing positive waste tax rate even before the central government driven tax expansion in wave 2. As I describe in a more detail in Section 5.2, variations from the wave 1 is used to identify the policy effect on food production labor supply decisions.

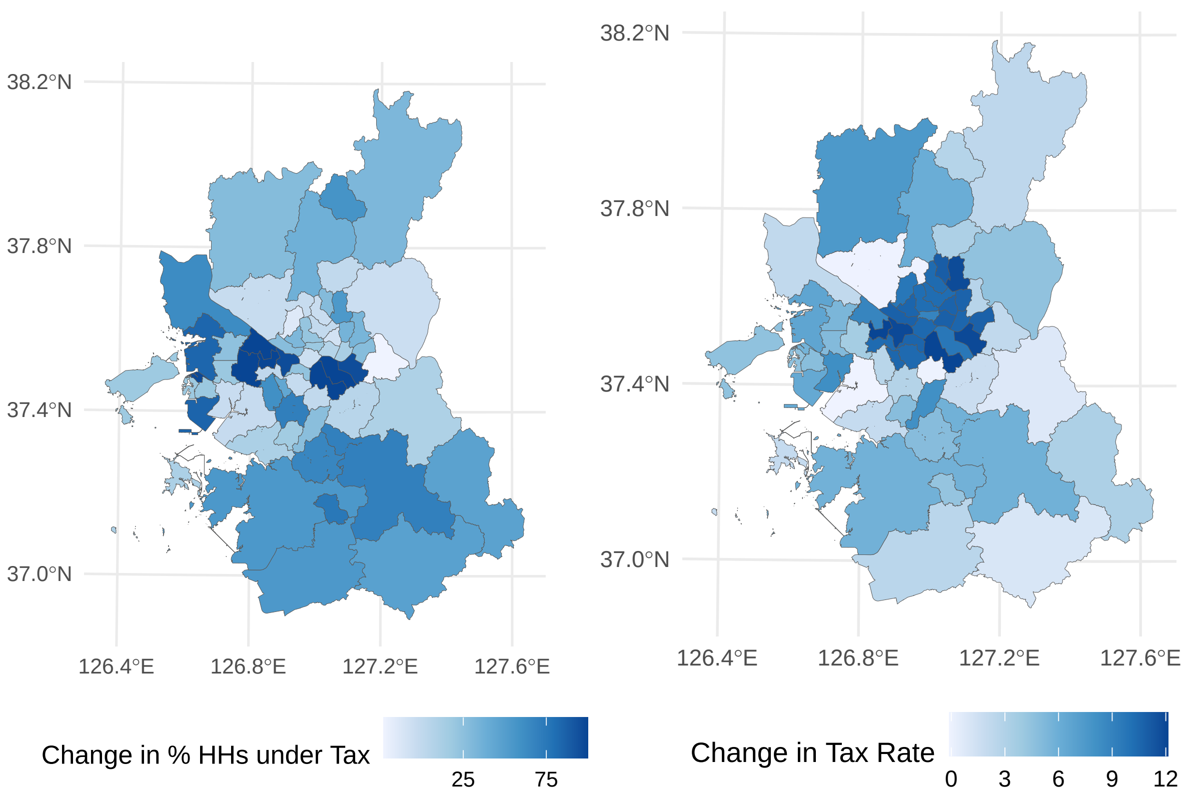
Wave 2 (2013-): Nation-wide expansion of the food waste tax policy. While converting food waste into fertilizer or animal feed is environmentally superior than dumping everything to landfill, there has been a continuing criticism about the approach from both environmental and government finance perspectives. For instance, food waste reduction through abstaining from excessive food purchase is more environmental-friendly than recycling wasted food because GHG emissions from the production stage can be avoided. Also, the government spends more than $6 billion annually for treating food waste, preventing public investments in more productive areas (GGC 2010). To fix these problems, the Green Growth Committee, a presidential committee established following the 2008 presidential election, launched an initiative in 2010 to expand the food waste tax nation wide. Subsequently, the Ministry of Environment issued a series of executive orders from 2010 to 2012 urging municipalities to impose a positive unit tax on food waste by 2013.

Figure 2.2 (a) plots the average fraction of households under the food waste tax over the sample period in the metropolitan Seoul area, which consists of three provinces (Seoul, Incheon, Gyeonggi-do) and 60 municipalities that are home to 50% of the nation's population. The wave 2 analysis



(a) % of Households under the Tax

(b) Average Tax Rate



(c) Change in % of HHs under Tax between 2009-17

(d) Change in Tax Rate between 2009-17

Figure 2.2: Wave 2 Expansion. Panel (a) and (b) show the overall proportion of households subject to the food waste tax and the average tax rate between 2009 to 2017. Panel (c) and (d) show the geographic distribution of the change in the fraction of households under the tax and tax rate between 2017 and 2009.

focuses on these areas because these 60 municipalities in three provinces near the capital city coincide with the geographical extent of the grocery purchase data. As the bar graph shows, the fraction has been stable at around 30% between 2009 and 2012. The ratio is not zero because, as discussed earlier, the majority of municipalities in Seoul was collecting food waste through official trash bags before the wave 2 expansion. Then, the fraction goes up sharply to 72% in 2017, where the most dramatic change happens in 2013.[12] Panel (c) illustrates the change in the fraction between 2017 and 2009 for each municipality. As the map shows, there is a substantial variation in the extent of expansion. As I discuss in more detail in Section 3.2, high-expansion and low-expansion municipalities do not exhibit differences in various observed characteristics. One important difference, though, is the proportion of condominium residents—high expansion municipalities had higher baseline condominium residents. This is plausible given that these municipalities had a larger room for expansion. Indeed, Figure B.3 shows that the proportion of condominium residents in 2009 is a strong predictor of the magnitude of the expansion over the sample period.

Figure 2.2 (b) and (d) present similar plots for the tax rate change. Importantly, these figures are based on the intensive margin tax rate—namely, tax rate for households under the food waste at a given point of time. It shows that an average tax rate has increased almost eight-folds between 2009 and 2017. This variation is useful because it allows me to understand the relative contribution of intensive versus extensive margin change. Panel (d) plots the change in the tax rate for each municipality between 2017 and 2009. While almost all the places have experienced an increase in tax rate, the map suggests that the rate change is highly correlated across space—for instance, the 25 municipalities in the middle of the map have experienced the highest increase. This is not a coincidence. While municipalities have jurisdiction over waste policies, they also closely coordinate with the province government. And because setting a different tax rate for different municipalities within the same province became politically more difficult as food waste tax became more salient, the Seoul Metropolitan Government required all 25 municipalities to set the same tax rate by 2017. This suggests that province government also plays an important role in shaping the food waste policy.

Outside Disposal Options. Earlier studies have documented that waste tax policies are susceptible to behavioral responses such as illegal dumping, which can seriously undermine the policy effect (Fullerton and Kinnaman 1996, Kinnaman 2006). However, measuring such a behavior has been chal-

[12] In this paper, I define food waste tax as a tax with a positive marginal price. This rules out a group-based food waste tax, a price regime that as a group, the tax is proportional to the quantity generated, but the group-level bill is evenly divided among residents (1/N pricing). Given a large size of N (in general well over 100) and small waste tax (on average less than \$0.1 per KG), a group-based food waste tax means an effectively zero marginal price. Importantly, the central government considered group-based unit pricing as a unit-based tax as well, so according to the central government's criteria, nearly 100% of households were under the unit-based tax by 2015. The central government recognizes the limitation of the group pricing but allows it, in particular as a bridge, because (1) the central government tried to minimize the plastic bag usage, which is the least expensive but environmentally less desirable way to implement unit-based tax and (2) an alternative to a plastic bag—a smart card system is costly to expand it at once.

lenging because of its illegal nature. In this paper, I use landfill waste quantity as a proxy for illegal dumping of food waste. There are a few reasons why this could be a reasonable proxy in this context. First, the unit tax rate of landfill waste is about 40% cheaper than the food waste so there is a financial incentive to do so. Further, throwing everything in a landfill waste bag can save segregation efforts. Consistent with this, the National Waste Assessment Statistic, which is a quinquennial survey conducted by the Ministry of Environment, finds that in 2012, 10% of the entire food waste is discarded through landfill waste bag.[13] Knowing this, many municipalities conduct landfill waste bag audits to levy fines which can be as large as $100. It is also worth noting that, in addition to the direct measurement through landfill waste, this paper also derives an upper bound of illegal dumping by comparing the observed reduction in food waste quantity and grocery purchase changes after the tax.

3 Data

3.1 Data Description

To understand the impact of the food waste tax on food waste generation and corresponding abatement strategies, I collect and combine five different sets of data.

Food waste and landfill waste quantity. The annual food waste and landfill waste quantity for each municipality comes from the Unit-Based Waste Yearbook by the Ministry of Environment. As the food waste tax is applied to non-bulk generators, which includes both households and small restaurants, the annual waste quantity reflects waste generated from both sources. The analysis focuses on 60 municipalities in metropolitan Seoul area, which coincides with the geographic coverage of the grocery purchase data, from 2009 to 2015.[14]

Grocery purchase. To study the impact of food waste tax on food purchase behavior, I use the consumer grocery panel data from the Rural Development Administration. The survey starts in 2010 and has approximately 1000 panelists (households) each year from metropolitan Seoul area, which

[13] Data can be accessed at https://www.recycling-info.or.kr/rrs/stat/envStatList.do?menuNo=M13020302 (Last accessed on Nov 18, 2021).

[14] The dataset starts in 2009 and is replaced by another dataset in 2016 and the time series is broken so I cannot use 2016 and beyond for the analysis.

consists of three provinces (Seoul, Incheon, Gyeonggi-do) which is a home to 50% of the nation's population. For data collection, a journal is mailed to the panelists each month, and they are required to keep the grocery and dining expenditure records for each month. I limit the sample to the balance panel of 639 households that have a non-missing shopping record at the quarterly level from 2010 to 2017. I determine the food waste tax status for each household using street address information. Having a detailed address is particularly useful in this setting because unlike non-condominium residence, whose food waste tax status varies at the municipality level, the food waste tax status for condominium complexes usually varies at the complex level. The data set documents each purchase in great detail with variables such as type of store, shopping date and time, food groups, expenditure, and unit price.[15] The data also documents expenditure from restaurants, but school lunches or cafeteria purchases are excluded.

Food intake and nutrition. To understand whether the tax affects the amount and type of food households consume, I use the Korea National Health and Nutrition Examination Survey (KNHANES) from the Korea Centers for Disease Control and Prevention. KNHANES is a repeated cross-section survey with nationally representative samples of approximately 10,000 individuals each year. I use responses from metropolitan Seoul area over the 2010-2017 period that coincides with the consumer grocery purchase data both in time and space. The survey has three main components: health interview, health examination and nutrition survey. For this paper, I focus on the nutrition survey, which documents the amount of cooking and food intake based on a 24-hour dietary recall face-to-face interview. I also supplement nutrition survey with health examination to address potential subjectivity from survey responses. For the main analysis, I use food consumed at home. One limitation of KNHANES is that the street address is not disclosed. This implies that the food waste tax status has to be approximated for condominium residents, whose status could vary at the complex level. I treat a municipality-housing type-year is subject to the tax when the fraction of households under the tax in each pair is over 2/3.

[15] About 56 percent of the observations have missing unit price information for the balance panel. In these cases, I impute the missing values using price information from the same municipality, month, store type, and food category. This recovers 64 percent of the missing price information. For values still missing, I expand the geographic region to the cluster of (5-6) nearby municipalities. This recovers an additional 17 percent of missing price information. I drop 19 percent of the observations without price information after two rounds of imputation. In Appendix A, I present various exercises to test the validity of such imputations.

Time use on food production. To investigate households' food waste abatement strategies, I use the Korean Time Use Survey, which documents how much time per day individuals older than age 10 in sampled households spend on each time-use category.[16] Time spent on food production is documented in four different categories, which are cooking, cleaning up after meal, bookkeeping, and shopping. For shopping time, I add up three time categories (travel time related to home making, grocery shopping time, and non-durable, non-grocery shopping time) to make time series comparable across different survey years. The survey has been conducted once every five years since 1999 and the number of respondents in each survey is about 30,000. It collects two consecutive days of 24-hour time diaries along with data on demographic information. Unfortunately, the address information is more restrictive than the the KNHANES data, and I can observe address only at the province level. This makes it impossible to exploit variations from the wave 2 because there is no valid control group at the province level.[17] Therefore I take advantage of the wave 1 and assign the food waste tax status at the province-housing type level. Also, to increase power, I use 16 provinces from the entire nation, rather than focusing on the Seoul metropolitan area.

Food waste tax policy. As discussed in Section 2.2, this paper takes advantage of two waves of food waste tax implementation. Information about the first wave comes from a commissioned study from the Ministry of Environment, which had surveyed food waste tax status for 234 municipalities from the entire nation as of 2009 (Kim et al. 2010). For the second wave policy change, I consult historic ordinances on food waste management for 60 municipalities in the metropolitan Seoul area.[18] Specifically, I track the food waste tax implementation timing for different housing types. For municipalities using the smart card system, I acquire implementation date information at the condominium complex level through the Official Information Disclosure Act request because the system rolled out over time even within the same municipality.

Table 3.1: Descriptive Statistics for Purchased and Discarded Food

Variables	Min.	Max.	Mean	Std.Dev.	N
Panel A: Annual Waste Generation and Food Waste Tax Policy at the Municipality Level					
Number of residential households	12,424	327,236	139,131	59,968	420
Number of restaurants (smaller than 2,152ft^2)	422	8,341	3,829	1,568	420
Number of combined households (HH)	16,824	410,646	177,425	73,329	420
Per HH food waste (KG)	39.11	948	257	88.54	420
Per HH landfill waste (KG)	28.46	957	283	100	420
Food waste fee per KG (in US Cents)	0	10.3	2.26	1.92	420
% of HH subject to tUax	0	1	0.503	0.274	420
Panel B: Annual Grocery Purchases					
Per HH total grocery purchase (KG)	39.89	2,562	837	333	2,880
Per HH perishable grocery purchase (KG)	0	1,363	296	172	2,880
Per HH storable grocery purchase (KG)	32.55	2,118	541	229	2,880
Per HH total grocery expenditure (USD)	199	12,953	3,886	1,600	2,880
Per HH number of trips	14	354	175	54.99	2,880
Per HH number of dining out	0	808	91.82	88.45	2,880
Per HH total GHG from grocery (KG CO2e)	91.74	9,980	2,828	1,305	2,880
Panel C: Demographics and Household Level Food Waste Tax Exposure					
Age	25	72	46.45	8.24	2,880
Size of family	1	9	3.61	1.09	2,880
Employment	0	1	0.475	0.499	2,880
Income (USD)	18,000	90,000	53,596	21,536	2,880
If lives in APT	0	1	0.799	0.401	2,880
If subject to tax	0	1	0.32	0.466	2,880
Per KG food waste tax	2.18	12.09	5.97	2.73	921

3.2 Summary Statistics

Table 3.1 presents summary statistics for key variables on the food usage. The variables are grouped into three categories: the first seven rows are related to the municipality level waste data, the next seven rows shed light on the household level grocery purchase behavior, and the last seven rows describe the demographic characteristics and tax exposure of the balanced panelists. Throughout the paper, outcome variables are normalized to the per household quantities because food use, for instance how much groceries to purchase, is a household (rather than individual) level decision.

A few points are worth noting. First, the waste quantity in the Unit-Based Waste Yearbook data reflects waste from both residential households and small restaurants. To calculate per household food waste quantity using this statistic, I translate restaurants into a "household" by leveraging earlier findings that a typical restaurant produces as much food waste as 10 households (Kim et al. 2010).[19] The first three rows present summary statistics for the number of residential households, restaurants, and both (residential and restaurant-converted households).

Second, per household food waste accounts for 47% of the overall (food and landfill) waste quantity, which is a general pattern found in many countries.[20] Using the average household size for the grocery panelists (3.61), the number indicates that per household food waste generation is about 76KG per year.

Third, the food waste tax is fairly small. Even at the maximum level of the waste tax (10.3 cents per KG), per household annual waste tax is less than $30.[21] This is about 0.7% of the average annual expenditure on groceries ($3,886). With the level of the tax, a typical municipality cannot even cover the waste management service operation costs.[22] When compared against the external cost, the tax level is about 30% of the external cost of wasted food from the life cycle GHG emissions.

[16] The number of time categories are 124, 137, and 144 for 1999, 2004, and 2009 survey, respectively.

[17] Within each province, some, if not every, municipalities are treated after 2013, thus finding a valid control group at the province level–namely, a province without food waste tax–is not possible.

[18] As discussed, I limit attention to the metropolitan Seoul area, which corresponds to the geographic coverage of the grocery purchase data.

[19] I also find the ratio 10 from the yearbook data using two municipalities (Jongno-gu and Dongdaemun-gu in Seoul) that allow me to infer food waste quantity separately for households and restaurants.

[20] Kaza et al. (2018) find that food and green waste is 32-56% of the total waste. In general, the proportion is higher for lower income countries.

[21] Per unit tax is based on volume for households required to use a designated waste bag. In these cases, I convert the tax using a conversion ratio of 0.75kg/liter following an executive order from the Ministry of Environment ("2015-164").

[22] For instance, Seoul Metropolitan Government spends $160/ton (or 14.5 cents per KG) for food waste pickup and treatment (https://seoulsolution.kr/ko/content/3438 (accessed on Jan 23, 2020)).

Fourth, an average panelist purchases 837KG of groceries per year. This quantity is calculated by dividing expenditure on each food item by its unit price. When compared against the amount of food waste generated, it means that 30.7% of the purchased food is discarded. This is consistent with findings from the FAO that 1/3 of the produced food is wasted globally (FAO 2013). When I split up food categories into perishable (fresh vegetable and fruits) and storable items, Table 3.1 shows that 35% of the total purchase is perishable items. To make these purchases, households make a grocery trip every two days (or 175 trips per year).

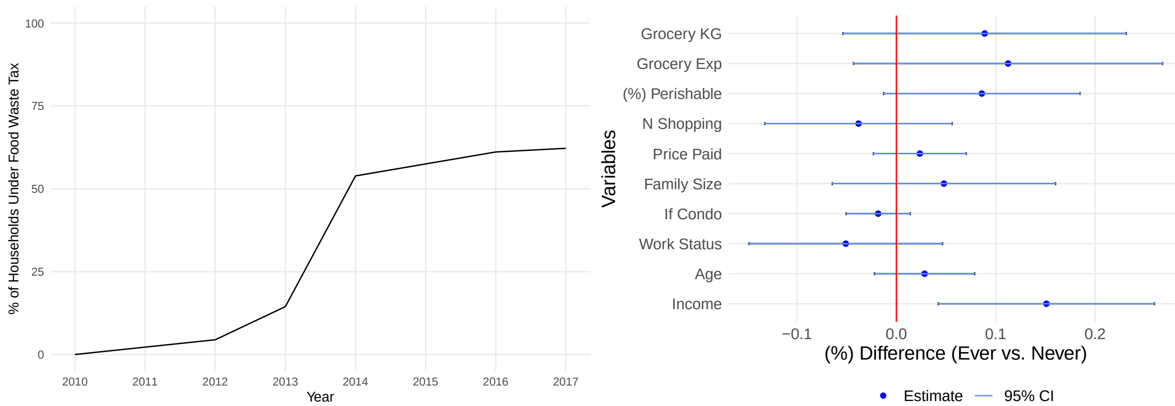
Finally, GHGs from an average food basket over the farm-to-kitchen stages are 2,823KG CO_2 equivalent. This is comparable to 7,095 miles driven by an average passenger vehicle, which is a year's worth of driving distance for many households in South Korea.[23] To calculate the GHG emissions, I convert food purchase quantity in KG to its GHG emissions using food-item specific GHG emissions estimates from Poore and Nemecek (2018).[24] The paper notes that the actual GHG emissions for a given food item varies by farming practices or climate conditions. Practically, I take the median value for all the 40 items.

In Figure 3.1 panel (a), I use the grocery sample data to show how the food waste tax has changed over time. Based on the main sample consists of 360 households over 2010-2017, plot (a) shows that the proportion of households under the tax has remained low until 2012, but increased sharply between 2013-2014, which corresponds to the wave 2 expansion period. The two end points merit further discussion: in 2010, the fraction is zero because I remove "always-treated" households from the main sample because they contaminate the two way fixed effect estimator (Baker et al. 2021, Cunningham 2021). Also, the fraction in 2017 is 61% despite the central government's mandate. As discussed earlier in Section 2.2, it is because this paper defines food waste tax as a tax that has positive marginal price, which is not necessarily the case under the central government's definition.

Panel (b) plots the balance table for various pre-treatment outcome variables and demographic variables for ever versus never treated households. These variables are related to grocery purchase patterns (purchase quantity, expenditure, the fraction of perishable items, number of shopping trips,

[23] For the calculation, I used Greenhouse Gas Equivalencies Calculator from the EPA (https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator) on Jul 16, 2021.

[24] The paper tracks GHG emissions for the 40 food items from start (extraction of resources including land use changes) to end(retail store, the point of consumer choice). For food items not mentioned in the list, I classify them into the closest item. Post-retail stages such as cooking or disposal are not considered.



(a) % of Households Under the Tax

(b) Balance Plot

Figure 3.1: Food Waste Tax Expansion and Comparison of Ever vs. Never Treated Households. Panel (a) plots the proportion of households under the unit-based tax for each year. Panel (b) shows the comparison of key variables between ever and never treated households. All variables in panel (b) except for working status and housing type dummies are log transformed. Standard errors are clustered at the municipality level. See the text for additional details.

and price paid for 1KG of grocery) and demographics. I log transformed all variables except for the working status and housing type dummy variables, and included municipality and year fixed effects whereas stadard errors are clustered at the municipality level. The results show that all the variables except for one (income) are non statistically significantly different between the two groups, adding confidence to the plausibly exogenous expansion of the tax.

4 Effect of the Tax on Food Usage

In this section, I first causally identify the policy effect on the food usage and calculate cost-effectiveness of the policy using these empirical estimates.

4.1 Empirical Strategy

Binary Treatment Models. I exploit food waste tax expansion to causally identify the effect of the tax on various behavioral determinants of food waste generation. The baseline two-way fixed effect model, which exploits the wave 2 variation, is in equation (1).

$$log(Q_{imt}) = \beta Tax_{imt} + \boldsymbol{X_{imt}}\delta + \lambda_{im} + \omega_t + \epsilon_{imt} \tag{1}$$

Q_{imt} is various grocery purchase outcome variables such as per household expenditure and quantity for household i living in municipality m at year t. Tax_{imt} is a dummy variable that takes 1 if a household is subject to the food waste tax. It has an i subscript because as described in Section 2.2, the treatment status could vary within a municipality. $\boldsymbol{X_{imt}}$ represents four household level baseline control variables: working status, income level, family size, and housing type. I also include household by municipality fixed effect λ_{im} and year fixed effect ω_t. Note, λ_{im} allows household characteristics to vary by municipality, and this is to account for the possibilities that households are likely to move when there is a life event such as starting a new job or changes in household composition that can be correlated with grocery demand. β reflects the impact of the food waste tax on grocery purchases.

In estimating equation (1), I remove always-treated and non-absorbing households to minimize potential contamination of the control group, reflecting insights from the recent literature on two way fixed effects models (Chaisemartin and D'Haultfœuille 2020, Baker et al. 2021, Goodman-Bacon 2021).[25] Further, I estimate the policy effect using a set of alternative estimators to ensure the robustness of the result (Cengiz et al. 2019, Chaisemartin and D'Haultfœuille 2020, Callaway and Sant'Anna 2021, Sun and Abraham 2021, Borusyak et al. 2022).

I also estimate an event study version of equation (1) as equation (2) where Tax^k_{it} takes 1 when a household is under the tax in event year $k = t - d$ where d is the policy change timing. I impose endpoint restrictions such that $\alpha^k = \underline{\alpha}$ for $k < -4$ and $\alpha^k = \bar{\alpha}$ for $k > 3$, where the unit of k is a year. While the restriction cannot completely rule out the change in the composition of the households at each event year, it is an attempt to strike a balance between stability of the panel composition and ability to detect change in the policy effect trend with enough event windows.

$$log(Q_{imt}) = \sum_{k=-4}^{3} \alpha^k Tax^k_{imt} + \boldsymbol{X_{imt}}\delta + \lambda_{im} + \omega_t + \epsilon_{it} \tag{2}$$

To understand potential change in the meal intake I estimate a variant of equation (1), which is $log(M_{ihmt}) = \beta T_{hmt} + \delta \mathbf{X}_{ihmt} + \lambda_m + \omega_t + \epsilon_{ihmt}$ where subscript h indicates the housing type (con-

[25] Households with a non-absorbing treatment state are removed because the treatment timing is not clearly defined. That is, a household is dropped when its tax status changes more than once. It usually happens when a household moves from a non-condominium residence (which is usually under the unit-based tax) to a condominium (many of them are not under the unit-based tax especially in earlier years) within the same municipality or when a household moves to another municipality.

dominium vs. other types) and other subscripts are the same as equation (1). M_{ihmt} represents the range of outcome variables such as intake, calories, vitamin quantities as well as health outcomes. It essentially leverages the same variation, but there are two differences due to the data structure that are worth discussing. First, T_{hmt} varies at the housing type by municipality level as opposed to the individual household level because the level of geography that I can observe in the food intake data is coarser at the municipality level. One possible approach is to assign the tax status at the municipality level. However, given that the proportion of households under the tax varies substantially by the housing type even within the same municipality (Figure B.2), I create tax variation at the housing type by municipality level. This approach not only substantially reduces potential measurement errors but also increases statistical power. In practice, $T_{hmt} = 1$ when the fraction of households under the tax in housing type-municipality-year is over 2/3 and 0 when the fraction is below 1/3. I remove observations when the fraction is between 1/3 and 2/3 because of potentially high measurement error. "Start year" in Figure B.2a corresponds to the year that the fraction of condominium residents under the tax in a given municipality exceeds 2/3. Second, as the data is repeated cross section, I add municipality fixed effect instead of the household by municipality fixed effect. $\mathbf{X}_{ihmt}$ is four household level controls which are closely related to the way households allocate time: whether a household has a child or not, family size, education level, and working status. In the estimation process, I weight the regression using sample weights.

Continuous Treatment Models. To estimate the impact of the tax on food waste quantity, I estimate a continuous treatment version of equation (1) because the level of observation in the food waste quantity data is municipality.

$$log(W_{mt}) = \beta(\%)Tax_{mt} + \boldsymbol{X_{mt}}\delta + \theta_m + \tau_t + \epsilon_{mt} \tag{3}$$

In the above equation, W_{mt} denotes per household food waste quantity for municipality m in year t. $(\%)Tax_{mt}$ is the fraction of households subject to the food waste tax.[26] $\boldsymbol{X_{mt}}$ are three munici-

[26] As discussed in section 3.2, W_{mt} captures waste quantity from both households and small restaurants, and the I factor in both households and small restaurants when constructing the $(\%)Tax_{mt}$ variable. That is, I convert small restaurants into households by using a conversion ratio from earlier studies. That is, I treat one small restaurant as 10 households (Kim et al. 2010). Then, $Tax_{mt} = \sum_k tax_{mkt} z_{mkt}$ where tax_{mkt} is the fraction of households in k that are subject to the tax for k∈{condominium, other housing types, restaurant}. z_{mkt} is share of k in each municipality.

pality specific characteristics: educational attainment, fraction of the single-person household, and fraction of the households living in condominiums. θ_m, τ_t are municipality and year fixed effects, controlling for unobserved time-invariant municipality characteristics and overall time trend.

β is the coefficient of interest, which estimates the marginal effect of changes in the fraction of the households subject to the food waste tax. I consider ϵ_{mt} as a municipality-year shock to the food waste quantity that is unrelated to the expansion of the food waste tax. Since the policy is expanded due to the central government's initiative, it is unlikely that municipalities select into expanding (implementing) the food waste tax. In the estimation process, I use municipality population as a weight.

4.2 Findings

Effect of tax on waste quantities. I first report the effect of the food waste tax on food and landfill waste quantity. Table 4.1 shows the results from estimating the equation (3). In column (1), I regress $(\%)Tax_{mt}$ on the log of per household food waste quantity. The point estimate indicates that the policy effect is economically large and statistically significant. In particular, when the fraction of households in a municipality under the tax changes from 0 to 100%, per household waste quantity goes down by 19.3% ($e^{-0.214} - 1 = -0.193$). To put this in context, I multiply the estimated coefficient by the pre-treatment food waste quantity level (268KG) and the effect size is 53KG.[27] In Appendix Table B.1 column (1), I report the result from the stacked DD estimation method. The effect size is robust to the estimation method at 17.5% ($e^{-0.192} - 1 = -0.175$).

Given the small size of the tax, the effect on the food waste quantity seems disproportionately large. To explore how plausible the effect size is, I compare the magnitude with a companion paper that focuses on tax expansion through the smart card system (Lee and Seo 2022). In comparison to this paper, which uses municipality-by-year level government statistics on food waste quantity, Lee and Seo (2022) uses monthly billing data to calculate the policy effect—which is arguably more reliable data. Lee and Seo (2022) reports a much larger 32% reduction in food waste quantity after the smart card system implementation.[28] This suggests that the estimated effect in column (1) is

[27] I use per household food waste quantity in 2009-2012 from municipalities with bottom 10% $(\%)Tax_{m,2015}$.

[28] The difference is likely to originate from the differences in data coverage: while the waste data in this paper captures waste from both households and small restaurants, data used in Lee and Seo (2022) reflects food waste generated by households only. If the tax impact on small restaurants is smaller than on households, which is plausible given that the tax is very small and thus is likely to have a tiny impact on their bottom line, the result in column (1) has to be

Table 4.1: Effect of Food Waste Tax on Waste Generation and Grocery Purhases

	(1)	(2)	(3)	(4)
Panel A: Overall Effect				
(%) Food Waste Tax	-0.2140***	0.0740		
	(0.0590)	(0.0576)		
Food Waste Tax			-0.0547***	-0.0443**
			(0.0190)	(0.0195)
Dependent Variable in Log	Food Waste Per HH	Landfill Waste Per HH	Grocery KG Per HH	Grocery Spending Per HH
In Level	-53KG	19KG	-46KG	-$172
Municipality FE	Yes	Yes	No	No
HH ID $\times$ Municipality FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	420	420	2,880	2,880
Panel B: Margins of Grocery Adjustments				
Food Waste Tax	-0.1064***	-0.0326	0.0049	-0.0495*
	(0.0331)	(0.0239)	(0.0154)	(0.0258)
Dependent Variable in Log	Perishable KG Per HH	Storable KG Per HH	Shopping Trips Per HH	GHGs Per HH
In Level	-32KG	-17KG	0.85	-138KG
HH ID $\times$ Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,880	2,880	2,880	2,880

Note:
This table presents the effect of food waste tax on waste generation and grocery purchases. All outcome variables are in log scale. I only report coefficients for the food waste tax term, but the baseline control variables are included. All standard errors are clustered at the municipality level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. See text for additional details.

likely to be a lower bound of the tax effect on food waste.

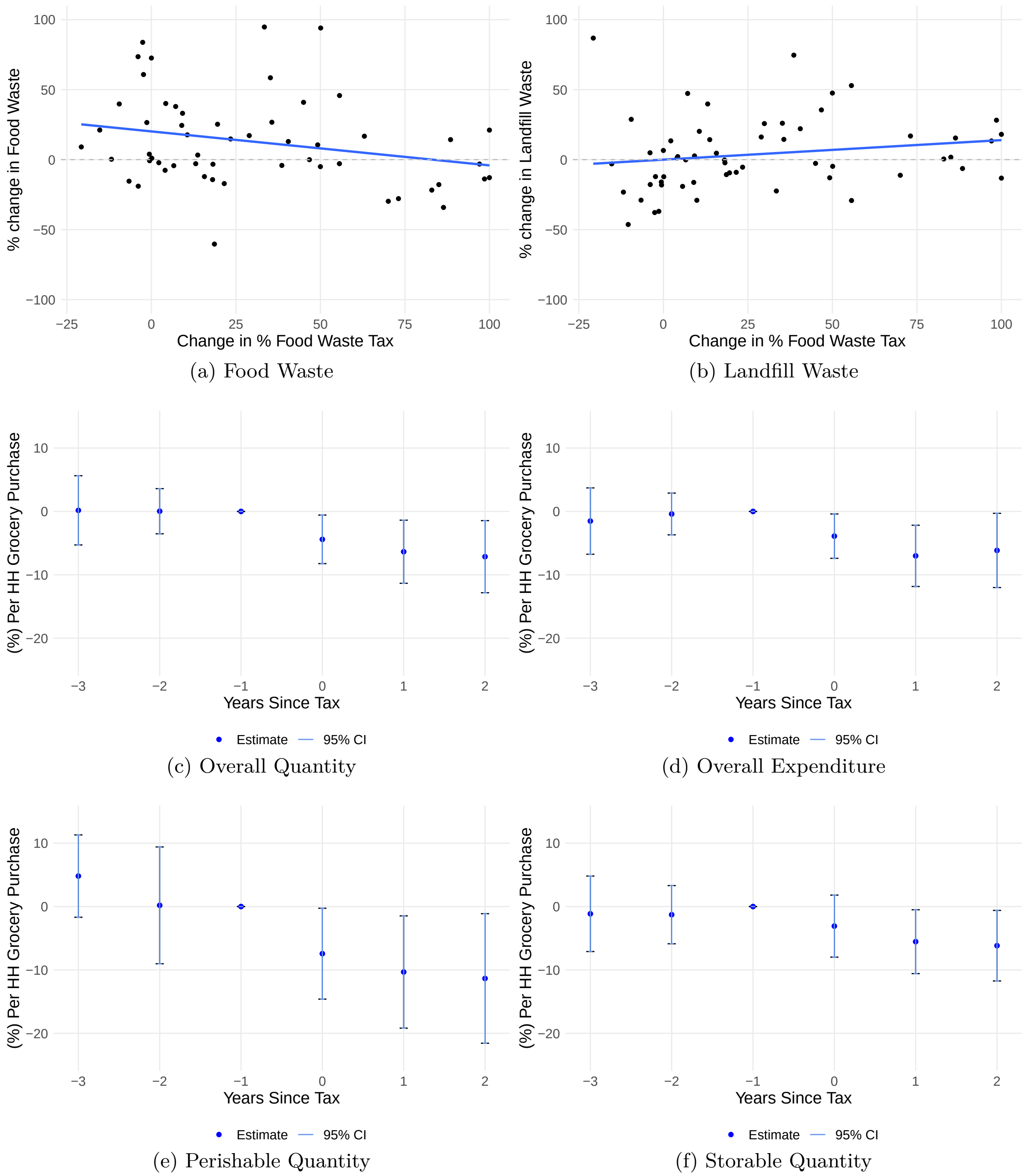
In column (2), I repeat the same analysis using landfill waste quantity per household as an outcome variable, which proxies for illegal dumping behavior. While there are a wide range of waste reduction options households can choose from—such as dehydration or in-house composting, disposal of unsegregated waste is the easiest and least costliest way to illegally dump the food waste in the urban South Korea setting. I find that the point estimate is large at 7%, but it is not precise enough to reject the null. Further, the effect size is sensitive to the choice of the estimation method. In column (2) of Appendix Table B.1, I report that the effect size is statistically insignificant 5.2%, which is over 30% smaller than Table 4.1.

Figure 4.1 panels (a)-(b) present graphical illustrations of columns (1)-(2) in Table 4.1. Recall that the identification exploits the plausibly exogenous change in the fraction of households under the food waste tax within each municipality. In each panel, the horizontal axis represents $(\%)Tax_{m,2015} - (\%)Tax_{m,2009}$ and the vertical axis shows the resulting change in per household waste quantity between the corresponding years. Dots, which represent each municipality, are evenly spread out over the x-axis, indicating that there is substantial variation in the change in the tax exposure across different municipalities.[29] The fitted line in panel (a) shows that the reduction in the food waste quantity is larger when the change in the food waste tax ratio is bigger whereas panel (b) illustrates the opposite effect for the landfill waste. Also observe that the slope of the fitted line is much steeper in panel (a), reflecting the larger coefficient (in absolute terms) of column (1) over column (2) in Table 4.1.

Effect of the tax on grocery purchases. I then turn to the impact of the tax on grocery purchases, which is the key determinant of the tax effect on the life cycle GHG emissions from wasted food. Columns (3) and (4) from Table 4.1 Panel A show the estimated coefficients from equation (1) on overall grocery purchase quantity and expenditure. Specifically, column (3) suggests that the tax encourages households to purchase less food by 5.5% or 46KG based on the pre-treatment period average. Comparing 46KG to the observed reduction in food waste quantity (53KG) implies that

smaller than Lee and Seo (2022).

[29] Note, $(\%)Tax_{m,2015} - (\%)Tax_{m,2009} < 0$ for some municipalities. This can happens when a municipality goes through a large scale gentrification that converts thousands of multi dwelling units to a large condominium complexes. Because the fraction of households under the tax is lower for condominiums, the negative growth can happen despite the central government's expansion initiative.



(a) Food Waste

(b) Landfill Waste

(c) Overall Quantity

(d) Overall Expenditure

(e) Perishable Quantity

(f) Storable Quantity

Figure 4.1: The Effect of the Food Waste Tax on Waste Quantity and Grocery Purchases. Panels (a) and (b) show the food waste tax effect on the food and landfill waste quantity. The horizontal axis is the change in the proportion of household subject to the food waste tax between 2009 and 2015 and the vertical axis is the change in the food (panel a) and landfill (panel b) waste quantity per household. Each dot represents each municipality. Panels (c)-(f) show event study plots for the overall grocery quantity, overall grocery spending, perishable purchase quantity, and storable purchase quantity, respectively. All dependent variables are log transformed. See the text for additional details.

86% of the reduction in the observed waste quantity can be explained by purchasing less food in the first place, which amounts to the actual reduction, rather than displacement of food waste.[30] Given the lack of consensus on the extent of illegal dumping induced by waste pricing (Bel 2016), which critically determines the desirability of the policy, being able to bound the potential leakage effect is important.

A similar effect size is detected from expenditure as well in column (4). Namely, I find a 4.4% reduction in grocery spending which amounts to $172 savings on annual grocery bill for an average household. This finding suggests that the tax generates a private benefit, which helps to offset potential abatement costs. Further, as discussed in section 3.1, purchase quantity is subject to measurement error due to missing unit grocery price information. Finding a similar effect using expenditure, which does not have the measurement issue, thus adds credibility to the estimates in quantity.

In Panel B of Table 4.1 columns (1) and (2), I separately estimate the policy effect for perishable (fresh fruit and vegetable) and storable food items. The point estimates show that the effect size is over three times larger for the perishable items, which is plausible given that the tax makes perishable items disproportionately more expensive because of their low storability.

In column (3), I study if reduction in grocery purchase reflects a more frequent grocery shopping trips. Given that one of the important reasons behind food waste generation is a prediction error on in-house food demand, households might reduce per trip purchase quantity while taking more frequent trips. The estimated coefficient suggests a 0.5% increase in trip frequency, which seems neither economically nor statistically significant. Understanding this channel is important from the climate change policy perspective, because if reduction in grocery purchase is primarily driven by more frequent trips, it might induce additional GHG emissions from those trips. The results suggest that this possibility is not a major concern in this context.

In column (4), I estimate the impact of the tax on the GHG emissions from the food basket. For this, I convert each row of shopping records into GHG emissions by matching each grocery item to the grocery-specific GHG emissions estimates from Poore and Nemecek (2018).[31] Then I estimate equation (1) using log of GHG as an outcome variable. I find that the tax reduces GHG emissions

[30] A 5.5% reduction out of the entire food basket can be seen as a 18% reduction in the previously wasted part of the food basket, which is on average 30.7%. A key assumption here is that food intake quantity remains the same, which I empirically show in Table 4.2.

[31] They choose 40 products that account for 90% of global protein and calorie consumption. Their assessment begins with inputs (farmers' choices) and ends at retail, covering both fresh and processed foods.

from grocery purchases by 5%. Using pre-tax average quantity of GHG emission from food basket, I can translate 5% to 138KG CO2eq per household, which is worth \$7-\$26 depending on the social cost of carbon estimates (IWG 2021, Rennert et al. 2022). This estimate is useful to evaluate the benefit of the policy in Section 4.3.

In Figure 4.1 (c)-(f), I plot β^k from equation (2) for a list of outcome variables. To produce these figures, I impose end point restriction such that $\beta_k = \underline{\beta}$ for $k < -4$ and $\beta_k = \bar{\beta}$ for $k > 3$, where the unit of k is a year. Because the sample is unbalanced in event time, these endpoint coefficients give unequal weight to households that experienced the food waste tax early or late in the sample. For this reason, I focus the analysis on the event-time coefficients falling within $k = [-3, 2]$ that are identified off of a nearly balanced panel.

Consistent with Table 4.1, panel (c) shows a clear reduction in the quantity purchased after the food waste tax. Importantly, the plot has no pre-trend, which satisfies the parallel trend assumption. In panel (d), I repeat the same exercise using overall expenditure, rather than KG, as an outcome variable. As mentioned earlier, weight measure is subject to the measurement error from missing unit price information. Panel (d) closely mirrors the pattern in panel (c), putting additional credibility to the results in KG. In panels (e) and (f), I split up the analysis into perishable and storable items. The difference in magnitude between perishable and storable items are evident from these two figures.

In Appendix Figure B.4, I estimate the impact of tax on overall grocery purchase quantity and overall expenditure using five different estimation methods proposed in the literature. I find similar point estimates and standard errors as Table 4.1, which suggests that the effect is robust to estimation approaches once always-treated and non-absorbing observations are removed.

Effect of tax on food intake and nutrition. Understanding the impact of the tax on food intake is important for at least two reasons. First, given the change in the size and composition of the food basket (i.e., grocery purchases), the tax might have a potential nutritional or health impact. Second, exploring whether there's a change in food intake also allows me to test whether people reduce excessive food demand without compromising their biological needs.

In Table 4.2, I report the impact of the food waste tax on food intake and nutritional consequences using the food intake and nutrition survey data. In column (1), I find that the overall quantity of

Table 4.2: Food Waste Tax and Food Intake Changes

	(1)	(2)	(3)	(4)	(5)	(6)
Food Waste Tax	-0.0058	-0.0051	-0.0164	-0.0068	-0.0115	-0.0040
NA	(0.0334)	(0.0283)	(0.0522)	(0.0704)	(0.0167)	(0.0085)
Dependent Variable in Log	Overall Intake	Calorie	Vitamin A	Vitamin C	Weight	BMI
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,103	14,103	14,103	14,103	13,327	13,285

Note:
This table reports the impact of the food waste tax on food intake and nutrition qualities. All outcome variables are in log scale. I report the cofficient of interest only, but all the regressions include baseline control variables. Standard errors are clustered at the municipality level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. See text for additional details.

food consumed at home does not change due to the tax. The estimated coefficient suggests a statistically insignificant null effect (-0.6%) in quantity. Consistent with no change in overall food intake quantity, there is no change in the calorie level as column (2) shows. In columns (3) and (4), I explore the tax impact on vitamin A and C, respectively. If purchasing less perishable items implies substitution between perishable and storable items, I should find reduction in vitamin intakes. However, I also find near null effects—statistically insignificant 1.6% and 0.7% reductions.

In columns (5) and (6), I report the impact on the health outcomes. Although the food intake data is produced out of a 24-hours dietary recall interview, which is more credible than self-reporting based survey, there could still be a chance of systemic bias. Investigating the health outcomes are useful because these are error-free and more objective measures that capture the impact of food intake. Consistent with no changes in food intake, I do not find any effect of the tax on weight or BMI.[32] Taken together, households do not seem to reduce the amount of food they consume (namely, they eat the same amount of food). Rather, the reduction seems to come mostly from previously wasted part of the food basket.

[32]Note, the number of observations in columns (5) and (6) are slightly smaller than columns (1)-(4) because not everyone who had participated in the food intake survey participated in the health examination, which requires them a separate trip to an examination center.

4.3 Cost-Effectiveness of the Food Waste Tax

As section 4.2 shows, the food waste tax reduces observed food waste quantity, where 86% of it is explained by grocery purchase adjustments. This means that the upper bound of food waste displacement is 14%. In calculating the policy effect, I take a conservative stance and treat the unexplained part as illegal dumping to landfill. This ignores the fact that some households might engage in activities other than illegal dumping such as in-house composting, dehydration, or additional food intake, which have lower GHG emissions than landfill.

In this section, I use cost-effectiveness, namely the program cost to reduce 1 ton of CO_2 to evaluate the policy. While this metric is different from the social welfare, which is based on the social cost rather than the program cost, cost-effectiveness is widely used among policy makers, and is a good stepping step towards a more complete welfare analysis. I first discuss the GHG reduction effect from the tax and compare it with the program cost.

Reduction in the life cycle GHG emission from food waste. When the observed food waste quantity is reduced due to the tax, life cycle GHG emissions can change for three reasons. First, the quantity of legitimately discarded food waste (W) will change. Second, the quantity of food produced (Q) will change because households purchase less food than before. An assumption is that producers will respond to the tax-induced demand shock by scaling back their production.[33] Lastly, the quantity of illegally dumped food waste (I), which I assume it ending up in landfill, will change. These three sources have different carbon intensity, and thus the overall change in life cycle GHG emissions should multiply changes in each quantity by their carbon intensity ($\Delta \mathrm{CO}_2 = \Delta W \times CI_W + \Delta Q \times CI_Q + \Delta I \times CI_I$ where CI_X stands for carbon intensity of X).

Estimates from Table 4.1 inform ΔW, ΔQ, and ΔI. For the carbon intensity, I use the following estimates. For CI_W, I use the per unit methane and nitrous oxide emissions from the national carbon inventory report (GGIRC 2015), which are based on 2006 IPCC Guidelines.[34] Since more than 95 percent of the food waste is processed in composting or animal feed processing sites in Korea,

[33] This assumption is unlikely to be true in the short-run when supply curve is near vertical. However, profit-maximizing retailers will reduce inventory in response to the demand shock, and producers are likely to respond in the longer-run as the supply curve gets flatter. Appendix Figure B.8 shows how rice producers have responded to a continuing reduction of rice demand due to dietary changes. The plot clearly illustrates large reductions in production quantity and crop land over time. Given that rice production is one of the most protected crop in South Korea, supply responses for other products are likely to be more sensitive.

[34] Methane and nitrous oxide are two major non-CO_2 GHGs.

GHG emissions is 0.19 ton CO_2eq per ton of food waste, which is less than 1/3 of that of food waste in landfill.[35]

For CI_Q, I convert each row of shopping records into GHG emissions by matching each grocery item to the grocery-specific farm-to-kitchen GHG emissions estimates from Poore and Nemecek (2018).[36] As Table 3.1 suggests, food production is highly carbon intensive activity: 1 ton of average food basket is responsible for 3.38 ton of CO_2eq. After the conversion, I estimate equation (1) using log of GHG as an outcome variable. Panel B column (4) of Table 4.1 shows that per household GHG emission from grocery purchases has decreased by 4.1%.[37]

Finally, for CI_I, I use the coefficient from the national inventory report, which is 0.655 ton CO_2eq (GGIRC 2015).[38] Note that CI_I is 3-4 times larger than CI_W, which implies that food waste tax might be welfare harming if most of the observed reduction comes from illegal dumping.

Cost-Effectiveness. Table 4.3 summarizes the cost-effectiveness of the policy for the metropolitan Seoul area, which consists of three provinces (Seoul, Incheon, Gyeonggi-do). As described in Section 3.1, I limit the analysis in Section 4.2 to this area because the geographical coverage of the grocery panel data is these three provinces. I first calculate the annual net GHG reduction effect of the tax using estimates from Table 4.1 and carbon intensity estimates. Reflecting different carbon intensity levels for waste treatment (W), production of wasted food (Q), and illegal dumping (I), the GHG reduction effect is dominated by reduction in wasted food production. This finding emphasizes the importance of studying households' upstream responses in evaluating a waste policy. Further, it suggests that waste policies focusing on prevention can have an order of magnitude larger effect than reuse or recycle policies.

For the cost, I consider the cost necessary to implement the unit-based tax. For instance, local governments spend substantial amount of budget on producing bags and stickers and also to install the smart card systems. This, however, excludes spendings on waste pickup and treatment services,

[35]However, a series of investigative news articles pointed out that a large fraction of "fertilizers" or "animal feeds" are actually illegally dumped in empty lot because of their low quality. In this case, the external cost would be much higher, justifying a more aggressive waste reduction measures.

[36]Poore and Nemecek (2018) choose 40 products that account for 90% of global protein and calorie consumption. Their assessment begins with inputs (farmers' choices) and ends at retail, covering both fresh and processed foods.

[37]An alternative approach would be evaluating the GHG reduction effect at the mean of pre-treatment GHG emissions. This approach overestimates the policy effect because the policy effect is primarily driven by perishable items, which have lower carbon intensities than storable items.

[38]I rely on default method which could be less accurate but allows comparison across different waste disposal methods (Hiraishi et al. 2000).

Table 4.3: Cost Effectiveness of the Food Waste Tax

	Items	Value (1000 Tonne, $ Million)
GHG Change	GHG Reduction (from Wasted Food Production)	998
	GHG Reduction (from Waste Treatment)	73
	GHG Leakage to Landfills	-28
	Net GHG Reduction	1043
Program Cost	Producing Bags and Stickers (A)	8.25
	Installing Smart card System (B)	5
	Total Program Cost (A+B)	13.25
	Savings on Waste Treatment Services (C)	-54
	Net Program Cost (A+B+C)	-40.75
Policy Effect	$ Per Tonne of CO_2eq Reduction (vs. A+B)	USD 12.7
	$ Per Tonne of CO_2eq Reduction (vs. A+B+C)	USD -39.1

which have to be provided irrespective of the food waste tax. The third row summarizes the direct program cost—fiscal cost to implement the tax policy ($13.25 million per year). When I compare the cost to the total GHG reduction amount, the program costs $13 to reduce one additional tonne of CO_2.

This, however, does not take into account that providing waste treatment service is costly. For instance, Seoul Metropolitan Government alone spent $136 million (or 14.5 cents per KG) for waste treatment in 2015.[39] When food waste quantity decreases after the tax, it generates savings on waste treatment spending as well. Assuming that the marginal cost of waste treatment service is constant, the estimated waste treatment budget savings from 20% reduction in food waste from the three provinces is $54 million per year.[40] Interestingly, when savings on waste treatment is taken into account, the program cost is negative. In other words, the program not only reduces GHG emissions but also saves government spending.

Note, the cost-effectiveness measure is calculated against the GHG reduction effect only, but there are additional benefits of food waste reduction such as improvement in environmental amenity or enhancing food security (Bajželj et al. 2014, Hiç et al. 2016). This implies that the benefit discussed in terms of GHG reduction is likely to be a lower bound of the benefit of food waste reduction.

In addition, CI_W in South Korea could be substantially lower than many other countries. As men-

[39] Financial burden from waste treatment is not unique to South Korea. Kaza et al. (2018) shows that waste treatment is responsible for 5-20% of municipality budget for many countries.

[40] This number has factored in a higher spending due to the increased landfill waste quantity.

tioned earlier, almost all food waste is treated in a food waste processing sites, which contributes to a small GHG emissions from the treatment stage. If I compare that to the US, for instance, in 2018 alone, 50% of the total food waste ended up in landfill sites (EPA 2020), which suggests that the benefit of the food waste reduction could be even larger.

The discussion so far suggests that the tax is beneficial for both government—GHG reductions and waste treatment budget savings—and households—reduction in grocery spending without hurting nutritional needs. But how households can maintain food intake with smaller grocery purchases? What do they do and what is the corresponding cost?

5 Household Abatement Strategies and Corresponding Costs

5.1 Conceptual Framework

Findings from the earlier section suggests that a tiny tax on food waste leads to a substantial reduction in the amount of food waste, and the majority of the reduction can be explained by grocery purchase adjustment. In this section, I estimate the cost of tax-induced behavior change based on the insights from the household production model a la Becker (1965).[41]

$$U = u(M, L, X), \text{ where } M = AF(Q, T) \tag{4}$$

Equation (4) illustrates household's food waste generation problem. A representative household maximize their utility by consuming meal (M), leisure (L), and numeraire (X). Meal is produced at home using raw food input (Q), namely grocery, and time (T). This household optimizes over Q, T, and L. Suppose that before the tax, household was producing M_0 of meal by combining Q_0 of grocery and T_0 of time. Suppose that the corresponding productivity was A_0. Further posit that after the tax τ is imposed on food waste, household produces at $M_1 = A_1F(Q_1, T_1)$.

From Section 4.2, I find that $Q_0 > Q_1 = 0.95Q_0$. Given this finding, the model suggests that there are four possibilities. First, household use less grocery input and produce less meal ($M_1 < M_0$). Second, food waste tax might have increased the productivity, allowing households produce the

[41] Food waste generation problem has been frequently modeled building on Becker (1965). See for instance, Hojgard et al. (2013) and Lusk and Ellison (2017).

same amount of meal using smaller amount of grocery ($A_1 > A_0$). This could happen if measurement, which is a prerequisite for taxation, generates useful information. Third, input quality for grocery might have changed, allowing households to produce the same amount of meal using "smaller" amount of grocery inputs ($Q_1 \neq 0.95Q_0$). For instance, households might respond to the food waste tax by purchasing pre-cut products such as peeled fruits. If this is true, the amount of edible parts in a grocery basket could be similar even though the observed grocery purchase quantity is lower after the food waste tax. (4) $T_1 > T_0$ meaning that households use more time to compensate for less food input. Lastly, households could have compensated lower grocery input with higher time input ($T_1 > T_0$). For instance, households can spend time on meal planning, organizing the refrigerator, or freezing leftover food for reuse. Indeed, earlier studies have found that households maintain consumption level despite expenditure fluctuates by making substitution between money (grocery spending) and time (Aguiar and Hurst 2005, 2007). I empirically test these potential abatement strategies using data on food intake and nutrition, time use, and grocery price.

5.2 Findings

Food waste tax and time use. To empirically test whether the tax affects time spent on meal production, I leverage the Korean Time Use Survey micro data. I estimate a variant of equation (1), which is $\text{Time}_{ihpt} = \beta T_{hpt} I_{hpt} + \delta \mathbf{X}_{ihpt} + \alpha_{hp} + \lambda_t + \epsilon_{ihpt}$ where subscript h is the housing type (condominium vs. other types), p is province, the largest sub-national administrative unit which is the most granular location information disclosed for time use data, and other subscripts are the same as equation (1). Similar to the food intake data, I do not observe survey respondents' street address so I assign the tax status based on the fraction of households under food waste tax for each pair of province and the housing type. Specifically, when a household lives in a province-housing type pair with the fraction over 2/3 (below 1/3), I assign it into a treatment (control) group status. I remove households when they live in a pair with the fraction between 1/3 and 2/3 because of potentially high measurement error.

This data limitation imposes a challenge in leveraging the wave 2 expansion for the time use analysis because 12 out of 34 provinces-housing type pairs have fraction of households under the tax between 1/3 and 2/3 as Appendix Figure B.5 Panel (b) shows. In contrast, Panel (a) shows that there are only five such cases for the wave 1 period. Thus, I take advantage of the wave 1 expansion for this analysis. Because the time use data is conducted every five years, I have three survey years (1999, 2004, and 2009) prior to the wave 2 expansion in 2013. Since wave 1 started in 2005, I have only single post year, and thus the empirical design is a canonical difference-in-difference case as opposed to the staggered adoption. As such, T_{hpt} is the tax treatment group status, which takes 1 if the fraction of household under the tax in housing type-province in 2009 is over 2/3 and 0 when the fraction is below 1/3. I_{hpt} is a variable that takes 1 in the 2009. $\mathbf{X}_{ihpt}$ are four household level controls which are closely related to the way households allocate time: whether a household has a child or not, family size, working status, and the size of house, which proxies for income.[42] In the estimation process, I weight the regression using sample weights.

In Panel A of Table 5.1, I estimate the change in the time spent on home meal production activities. Specifically, I focus on four different stages of meal production: preparation, clean up, keeping diary, and shopping. While the first three categories remain constant over the different waves of survey, shopping category has changed over time. To make it comparable across different years, I standardize it to non-durable shopping time.

In column (1), I estimate the tax impact on overall meal production time, which is the sum across four different stages. I find that an average adult spend 3.2 additional minutes per day after the tax. When compared against the average minutes spent on home production, 3.2 minutes amount to a 5.5% increase. Since an average household in the sample has 2.55 adults, household level increase is 8.2 minutes per day or 49.6 additional hours per year. In column (2), I repeat the same analysis for non-food homemaking activities such as cleaning or doing laundry. Although statistically insignificant, I find suggestive evidence that households reduce non-food homemaking to spend more time on food production.

In Figure 5.1, I present an event study plot that corresponds to the result in column (2). Because there is only one post period, I do not create an event year variable. Rather, I estimate $\text{Time}_{ihpt} = \beta_{1999} T_{hpt} I_{1999} + \beta_{2009} T_{hpt} I_{2009} + \delta \mathbf{X}_{ihpt} + \alpha_{hp} + \lambda_t + \epsilon_{ihpt}$ where I_{1999} and I_{2009} are indicator variables for year 1999 and 2009 (2004 is omitted). The depicted effects in Figure 5.1 corresponds to β_{1999} and β_{2009}. The figure shows that β_{1999} is near null, which suggest that there was no difference in meal production time between the control and treated group observations before the wave 1 expansion. In 2009, however, I find a clear and sharp increase in meal production time and the magnitude coincides

[42] Monthly income variable started in 2004 so I use square feet of property as a proxy for income.

Table 5.1: Household Abatement Strategies

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Time Spend on Home Meal Production (in Minutes)						
Tax Treated Group x Post	3.161***	-1.581	2.085***	0.3856	0.0606	0.6301
	(1.120)	(1.399)	(0.7159)	(0.3826)	(0.0429)	(0.4436)
Dependent Variable	Overall	Non-food Homemake	Prepping	Cleaning	Diary	Non-durable Shopping
Province × Housing Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	146,531	146,531	146,531	146,531	146,531	146,531
Panel B: Value of Time Spend on Home Meal Production						
Tax Treated Group x Post	3.363**	0.1293***				
	(1.512)	(0.0454)				
Unit of Dependent Variable	Minute	Dollars Per Day				
Province × Housing Type FE	Yes	Yes				
Year FE	Yes	Yes				
Observations	88,272	88,272				
Panel C: Other Abatement Strategies (Input or TFP Change)						
Food Waste Tax	-0.0028	0.0103	0.0191	-0.0257	0.0020	0.0105
	(0.0820)	(0.0114)	(0.0248)	(0.0366)	(0.0376)	(0.1001)
Dep. Var in Log (TFP: in Level)	TFP	Grocery Price	N of FAFH	Intake FAFH	Calorie FAFH	Vitamin A FAFH
HH ID × Municipality FE	No	Yes	No	No	No	No
Municipality FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Observations	28	2,880	14,085	15,922	15,922	15,922

Note:
This table empirically tests potential household abatement strategies. Panel A explores whether households compensate by investing more time in food production. In panel B, I estimate the cost of spending more time on home production. In panel C, I investigate other potential abatement strategies. I report the cofficient of interest only, but all the regressions include baseline control variables. Standard errors are clustered at the province by housing type (Panel A, B) and municipality (Panel C columns (2)-(6)) level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. See text for additional details.

with column (2).

In columns (3)-(6), I investigate the impact of the tax on more granular meal production activities. The estimated coefficients suggest that the increase in overall meal production time is driven by increase in meal preparation time, which describes activities such as preparing ingredients, storing and organizing groceries, setting the table, and making baby formulas (Statistics Korea 2009).

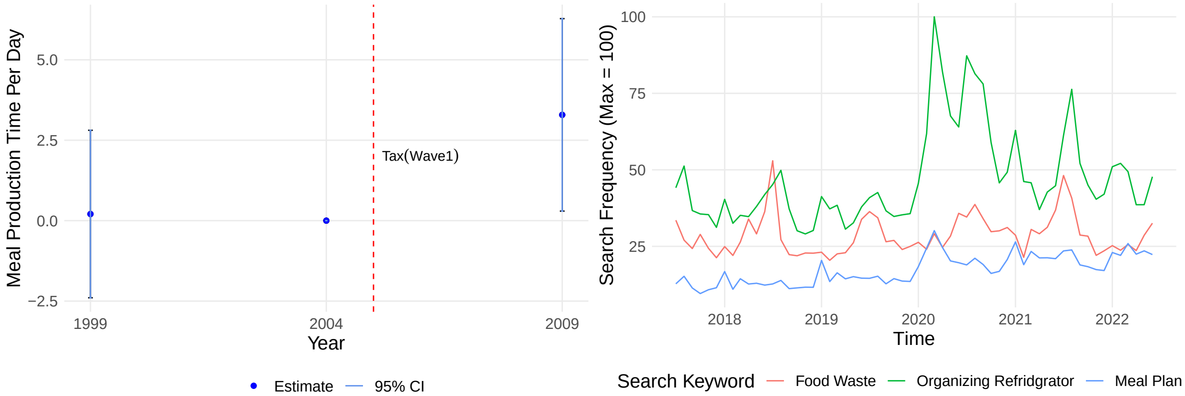
Indeed, web search results suggest that organizing refrigerator is one of the most common strategies for households to reduce food waste.[43] In Figure 5.1 (b), I present web search frequency plots for "food waste", "organizing refrigerator", and "meal planning" for female aged 30-60. This figure has two interesting patterns. First, the search frequency for organizing refrigerator and food waste are similar to each other while it is difficult to find such a similarity between food waste and meal planning. Second, search frequency for all three keywords, but in particular for organizing refrigerator, sharply increased in March 2020, which was the initial COVID-19 spike in South Korea. These patterns suggest that organizing refrigerator is deemed one of the primary way to more efficiently use groceries. In Appendix Figure B.6, I reproduce the figure for male aged 30-60 and female below 20 years old, which are less engaged in meal production. Interestingly, I do not find any relationship between food waste and organizing refrigerator in these figures, which is consistent with the conjecture that organizing refrigerator is key to reduce food waste.[44]

Food waste tax and the cost of time use. In Panel B of Table 5.1, I estimate the monetized cost of changing behavior. A crucial step in this exercise is to determine the value of time for home production activities. For this, I follow Aguiar and Hurst (2007) and use the marginal return on shopping, which informs how much money households can save by spending more time on shopping activities, to put a dollar value on time.[45] A key assumption in this approach is that the value of time of the shopper is the same as that of the person undertaking home production (Aguiar and Hurst 2007). The marginal return on shopping is calculated by multiplying the elasticity of price with respect to shopping time and average spending amount. For the elasticity, I take the central estimate from

[43]Given the survey results that households are not readily aware of food waste reduction strategies (Ministry of Environment 2015), the additional time on meal production is likely to be spent on new activities. To this regard, web search data provides useful information on how households might actually spend the additional time on.

[44]Because search intensities are normalized for each population group, I cannot compare search intensities across different panels.

[45]Numerous earlier works have used market wage as a price of time. However, this is less ideal to study the meal production decisions especially given that 35% of time use survey adult respondents do not work in the labor market.



(a) Effect of Tax on Time Spent on Meal Production (b) Search Intensity

Figure 5.1: Effect of the Tax on Time Use and Learning About Actual Behaviors from Internet Search Keywords. Panel (a) is an event study plot for the effect of the tax on meal production time where the dependent variable is daily meal production time in minutes. Panel (b) shows the trend in web search intensity for three food waste related keywords (food waste, organizing refrigerator, and meal planning) for female users aged 30-60 between July 2017 and Jun 2022. See the text for additional details.

Aguiar and Hurst (2007) rather than estimating it because the grocery panel data does not have a UPC code. This limitation is critical because without a UPC code, it is difficult to ensure that the estimated elasticity is not contaminated by switching between products.

One potential concern for using the elasticity from Aguiar and Hurst (2007) is to what extent Korean households are similar to the US households. One of the key findings in Aguiar and Hurst (2007) is that the price of time substantially varies with age and income. That is, the value of time is highest in the middle age, which usually involves disproportionately large responsibilities at work and home. Similarly, the value of time is higher for higher income groups. To test if the Korean consumers exhibit similar characteristics, in Appendix Figure B.7, I create bin scatter plots between age and the opportunity cost of time (in Panel A) and income decile and the opportunity cost of time (in Panel B).[46] Consistent with Aguiar and Hurst (2007), I find that the value of time has an inverse-U shape with age and is positively correlated with income.

Because the time use data does not have information on grocery spending, I merge time use data with the grocery panel data using demographic characteristics—income (low if monthly income is below USD 1818), family size (1-2, 3-4, and above), age (20-30, 30-50, and above), and the tax status. As the time use data has income variable from 2004 and onward, for this exercise, I limit the analysis

[46]The opportunity cost of time is calculated by multiplying 0.1, which is the elasticity from Aguiar and Hurst (2007) and average spending per shopping trip.

to 2004 and 2009 time use survey data. Loosing 1999 does not seem to affect the result much. In column (1) of Panel B in Table 5.1, I find that the effect of the tax on meal production time is almost identical to the column (1) in Panel A. In column (2), I estimate the effect of tax on the value of time spent on meal production. As the outcome variable is the price of meal production time per day, the estimated coefficient indicates that the cost of changing behavior (i.e., spending more time on meal production) is \$0.13 per day per adult. Multiplying this with the average number of adults in households (2.55) and by 365 suggests that the cost of abatement is \$133 per year per household. In Section 4.2, I show that the savings from purchasing less groceries is \$172 per year per household. Comparison between two point estimates suggests that choosing to use more time input can be financially beneficial for households.

TFP change in home production. I also investigate if the tax can enhance total factor productivity in the home production process. If this is the case, the tax can generate savings on grocery bills for households while reducing GHG emissions at a low (or no, depending on the magnitude of TFP increase) cost. In column (1) of Table 5.1, I explore the tax impact on the TFP.

This exercise is implemented in three steps. In Step 1, I merge datasets on food intake (output), grocery purchases, and time use (two inputs) using demographic characteristics. Specifically, I use income (low if monthly income is below USD 1818), family size (1-2, 3-4, and above), age (20-30, 30-50, and above), and the tax status to create cells. I take the average value for food intake, grocery purchases, and time use.

In Step 2, I estimate TFP for each cell. For this, I use the factor share approach, which exploits the first order condition of cost minimization that an input's output elasticity equals the product of that input's cost share and the scale elasticity (Syverson 2004).[47] For estimation, I run the following regression: $TFP_c = m_c - a_q q_c - a_t t_c$ where a is cost share of each input and c indicates each cell. The factor share for grocery (a_q) and time (a_t) are calculated by dividing the value of each input by total production cost. To assign a dollar value for the time input, I follow Aguiar and Hurst (2007) similar to earlier section.[48]

[47] One potential drawback of the factor share approach is its assumption that the cost of adjustment is zero (De Loecker and Syverson 2021). While this might be of a serious concern for firms substituting between labor and capital, less so is true for home production where households substitute between time and groceries, which are much more flexible than the firm setting.

[48] More specifically, I multiply the elasticity of price with respect to shopping time ($\alpha_s = 0.1$ from Aguiar and Hurst (2007)) with the average shopping expenditure (\$23) in my grocery panel data, which gives the average opportunity

In Step 3, I estimate a regression model $TFP_c = \beta Tax_c + \delta \mathbf{X}_c + \epsilon_c$ where c indicates each demographic cell. One caveat in this model is that there is only a single period (2009-2010) that three datasets overlap, which implies that the tax variation is cross-sectional. The estimated β is in column (1), and is near null, suggesting that the TFP barely changed due to the food waste tax. This is not surprising given that the TFP is essentially capturing the residual in the production function. Because a 5% reduction in grocery purchases is accompanied by a 5.5% increase in time use, by definition there is likely to be a little room for a large TFP increase.

Input quality change. Another potential explanation for using less food input and maintaining the intake quantity is a change in input quality. For instance, if households purchase pre-cut products to reduce food waste at home, and purchase the same amount of *edible* parts, it is not surprising at all that the intake quantity remains constant. To explore this possibility, I regress the impact of the tax on unit price per KG of purchased food using grocery panel data following equation (1). Column (2) in Panel B of Table 5.1 shows that the change in the paid price is near null—if anything a 1 percent increase. This economically small effect indicates that change in grocery quality is not likely to be the primary abatement strategy.

In columns (3)-(6), I explore if households consume more food away from home after the taxation. While no change in food intake quantity is for the food consumed at home, it is still worth investigating whether there is a spillover effect to the consumption of food away from home. The estimated coefficients suggest that the tax has very small effect on the food consumed away from home both in terms of quantity and nutritional contents. These findings make sense given that switching to food away from home to avoid the tax is an extremely costly way to engage in abatement.

6 Why Such a Small Tax Has Such a Large Effect?

Findings from earlier sections pose a puzzle: why such a small tax has such a large impact on household behavior? To answer this question, I first decompose the tax effect into pecuniary versus non-pecuniary effects. Then, I investigate potential non-pecuniary effects of the tax.

cost of time for home production ($2.3/hour).

6.1 Price Effect of the Tax

One possible explanation for the disproportionately large tax effect is that households are extremely elastic to the tax. To test this possibility, I focus on the grocery purchase behavior. To start, I calculate the implied demand elasticity of groceries using the tax introduction and compare it with the estimates from prior works. For this, let's suppose that households perceive a dollar increase in tax identical to a dollar increase in food price. Then, using the average tax rate, average fraction of wasted groceries, average grocery price, and the estimated policy impact (a 5.4% reduction from Table 4.1 Panel A column (3)), I can show that the implied tax elasticity is –14.[49] This is in a sharp contrast to a large body of prior works that have shown that food demand is inelastic (Tiffin and Tiffin 1999, Andreyeva et al. 2010).

To quantify the contribution of the price effect, namely movement along the curve effect, I calculate the predicted quantity change using price elasticity estimates from Andreyeva et al. (2010), which has surveyed 160 studies on the price elasticity of demand for major food categories. Specifically, I take the median values from various food categories, which range from –0.27 to –0.81. Given that the average tax rate is equivalent to a 0.4% increase in the grocery price, the predicted quantity change under these elasticities is between –0.1% to –0.32%. Comparing this to the 5.4% reduction in grocery quantity from the tax implementation suggests that the price effect can explain at maximum 5% of the total tax effect, while the rest can be explained by the shift in the curve effect.[50]

Consistent with a small price effect, I find that the tax elasticity is -0.024 (se = 0.03), which is neither economically nor statistically significant. Importantly, I estimate this by replacing Tax_{imt} in equation (1) to $log(TaxRate)_{imt}$ conditional on the unit tax is in place. I limit my attention to the intensive margin effect because there might be a non-pecuniary effect of tax that turns on when a unit based tax starts. This is surprising given that the range of tax rates in this plot is larger than the marginal tax rate change due to the introduction of the unit-based tax (namely, from 0 to an average rate of 6 cents per KG).

[49] The average price for one KG of grocery is \$4.67 while the average tax rate conditional on the unit taxation is \$0.06 per KG of food waste. Given that an average household dispose about 30% of the purchased grocery, effective tax rate per KG of food is $0.06 \times 0.3 = \$0.018$. Then, the percentage change in price due to the tax is $\frac{0.018}{4.67} \times 100 = 0.38\%$. Dividing 0.38% with the percentage change in grocery purchase after the tax (5.4%) yields an elasticity of 14.2.

[50] Another way to see this is the following: the average tax rate is \$0.06 per KG of wasted food, which is 1.3% of the average grocery price households pay for the wasted portion of the food basket. At $\epsilon_p = -0.8$, the predicted reduction in the wasted part due to the tax is 1KG. However, the actual reduction was 17.4% (5.4/0.31).

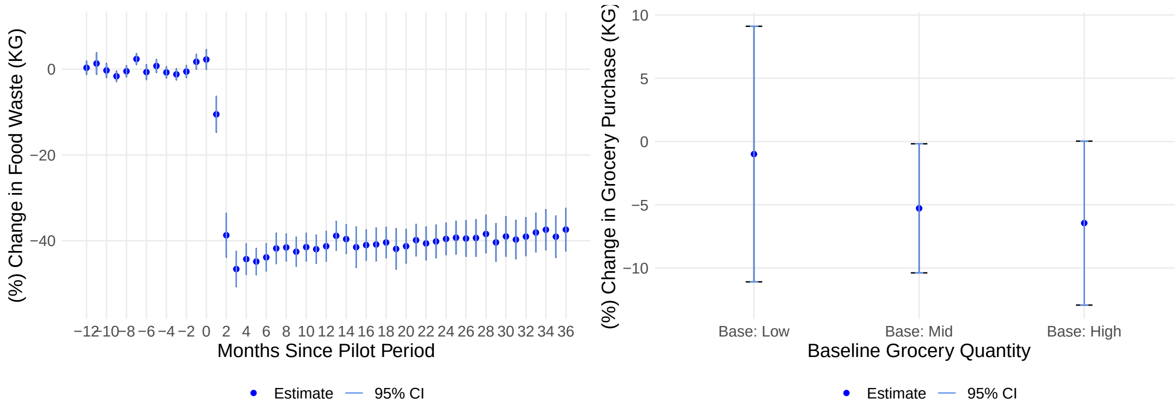
6.2 Non-pecuniary Effect of the Tax

Given a small price effect, the tax seems to affect household behaviors primarily through non-pecuniary channels. In this section, I explore two potential explanations and discuss their welfare implications.

Raising attention. Earlier studies on households' food waste generation behavior (in the absence of any interventions) have pointed out that not all households pay full attention to their food usage. For instance, households tend to forget what is in their refrigerator and make duplicate purchases (Farr-Wharton et al. 2014, Gaiani et al. 2018) or underestimate the amount of the food that they waste (Neff et al. 2015, NRDC 2017). Such imperfect recognition may arise given that households have limited attention span and there is no systematic feedback on food waste generation (National Academies of Sciences, Engineering, and Medicine 2020). Imposing a tax could remedy the situation because taxing cannot happen without measuring the amount of food waste. Measurement creates new information for households, which might help them recognize they were generating unnecessarily large amount of food waste. Given the frequency of food waste disposal for an average households, which is 2-3 times per week, the tax is likely to substantially raise households' attention food usage.

In a companion paper, we zoom into the introduction of the smart card system to estimate the lower bound of the measurement effect (Lee and Seo 2022). Specifically, we exploit the pilot period, where households start to use the smart card system and get instant feedback on their waste generation but the marginal tax rate is still effectively zero. Figure 6.1 (a), which is reproduced from Lee and Seo (2022), shows the change in the food waste quantity since the pilot period (i.e., event time is 0 when pilot period starts). We find that the waste quantity decreases by over 10% right after the introduction of the smart card system, which amounts to 25–30% of the full-fledged effect size. This is likely to be a lower bound of the measurement effect because the pilot period, which is usually less than a month, might be too short to capture the full effect if it takes time for households to adjust their behaviors.[51] The finding that getting feedback alone reduces waste quantity suggests that households might not have been fully aware of the food waste they generate in the absence of the tax. The effect from the pilot period is much larger than a widely used report card intervention which leads to 2-5% reduction in energy or water uses, presumably because the frequency of feed-

[51] Also, there might be an interaction effect between price and measurement effect.



(a) Tax and Waste Quantity (Smart Card System) (b) Tax Impact on Groceries by Baseline Quantity

Figure 6.1: The Effect of Tax by Timing and Baseline Grocery Purchases. Panel (a) shows the change in the food waste quantity starting from the pilot period of the smart card system. Panel (b) illustrates the differential impact of the tax on grocery purchases based on the baseline grocery purchase quantities. See the text for additional details.

back is much higher in the food waste tax setting (Allcott 2011, Ferraro and Price 2013, Costa and Kahn 2013). Consistent with the conjecture, the pilot period effect is smaller than real-time feedback interventions (Tiefenbeck et al. 2018).

I provide two additional sets of evidence that are consistent with the hypothesis that a subset of households have an attention gap. In Figure 6.1 (b), I estimate the differential tax effects by baseline grocery purchase quantity. I split the sample using the grocery purchases in 2010 and estimate the policy effect for each group using equation (1). Figure 6.1 (b) suggests that the effect size differs substantially depending on the baseline grocery purchases. Specifically, for the high and middle baseline group (above the 0.67 quantile and between the 0.33 and 0.67 quantile, respectively), the reduction is –5 to –6%. Surprisingly, I find no reduction in purchases from the low purchase group after the tax, presumably because they were already using their food efficiently by paying attention to their food use. Consistent with this, in Appendix Figure B.9, I cannot rule out that the tax has null effect on grocery purchases for low income households.

Another evidence is in Table 6.1, which shows the marginal products of one additional dollar spent for two inputs before and after the tax. If households had limited attention to food usage, and inadvertently used too much food and too little time in the absence of the tax, then the optimality condition—the marginal products of additional dollar should be identical for two inputs—might not have been satisfied. To test this, I merge food intake data with grocery purchase and time use data,

Table 6.1: Marginal Product of Meal Production Inputs

	(1)	(2)
Grocery Expenditure	0.0129	
	(0.0127)	
Grocery Expenditure × Food Waste Tax	0.0046	
	(0.0155)	
Labor Time Value		0.1268***
		(0.0094)
Labor Time Value × Food Waste Tax		-0.0564***
		(0.0144)
Year FE	Yes	Yes
Municipality FE	Yes	No
Province × Housing Type FE	No	Yes
Observations	530	577

Note:
This table reports the marginal product of grocery and time in dollar terms. Outcome variables are annual intake quantity per household (in KG). I report the cofficient of interest only, but the food waste tax term is fully interacted. Standard errors are clustered at the municipality (column (1)) or province by housing type (column (2)) level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. See text for additional details.

respectively, using age, income, family size, location, and year.[52] Then, I regress food intake quantity level on grocery and time use (both in monetary terms) interacted with the tax status.

The estimated coefficients in column (1) suggest that one additional dollar spent on grocery produces 0.013 additinal KG of food before the tax, and the marginal product increases to 0.018 after the tax. Similarly, in column (2), I report that one additional dollar spent on time produces 0.13 additional KG of food before the tax, but the marginal product reduces to 0.07 after the tax. Using these estimates, I report that the ratio of marginal products before the tax ($\frac{MP_{Labor}}{MP_{Grocery}}$) is 9.8 before the tax, but is reduced by more than half to 4. This finding suggests that households were using too much food and too little time inputs before the tax, but they make substantial adjustments after the tax. One caveat is that these results should be taken as suggestive evidence because panel variations might not be able to fully account for potential endogeneity in grocery and time input choices.

Imposing moral tax. An alternative possibility is that the food waste tax might have affected households behavior like a "moral tax" (Glaeser 2006). Indeed, at least since the mid-2000s, the

[52]Instead of merging all three datasets together, I merge it separately for intake and grocery, and intake and time use because there is only one period (2009-2010) where all three datasets are available.

central and local governments have carried out numerous public awareness campaigns to promote food waste reduction, which might have imposed emotional costs for generating food waste (Ministry of Environment 2006).

One way to test the moral tax effect is estimating the tax's direct impact on households' utility. While there is no data available on the direct utility impact of the tax, results from an annual survey on food waste tax suggest that households, in general, are supportive of the tax (Ministry of Environment 2015). For instance, the proportion of survey respondents supporting the tax has increased from 57% in 2010 to 70% in 2014. Also, over 85% of them have responded that food waste tax is needed to reduce food waste. Given these results, moral tax is not likely to be the dominating non-pecuniary channel.[53]

Further, these campaigns are usually carried out via media outlets (TV, radio, or social network advertisement), which is affecting both households with and without the tax. Given the difference-in-difference research design, moral tax effect is likely to have been cancelled out unless there is a large interaction effect between an awareness campaign and the tax.

Implications for welfare analysis. The cost-effectiveness rubric discussed in Section 4.3 is constructed using the net GHG reduction effect of the tax and the program cost of the policy implementation. While this is informative for policymakers, this metric fails to reflect other determinants of social welfare. For a more complete welfare analysis, we need to factor in two additional elements. First piece is the net private cost from the policy, which is the difference between savings on grocery bills and household abatement costs such as time cost. Second piece is a potential change in direct utility due to, for instance, a moral tax effect. While the findings in Section 4.2 and 5.2 provide information to calculate the impact of tax on net private cost, this paper does not have enough evidence to pin down (or rule out) the moral tax effect.

While I defer a more complete welfare analysis that considers for future works, it is still useful to note that the tax seems to generate net private benefit for households. For instance, taking the reduction in grocery expenditure for an average household ($172) and the increased time cost ($133), the tax seems to generate $51 net private benefit per year. When multiply this with the number of households in the greater Seoul area (7.23 million), the net private gain can be as large as GHG

[53]In a follow-up work (Lee and Seo 2022), we design a survey to elicit households' willingness-to-pay for the smart card system. With this estimate, we can more directly test the moral tax effect (Allcott and Kessler 2019).

reduction and waste budget savings effect.

External validity. With all the empirical estimates and potential explanations of mechanism, it is worth briefly discussing external validity of the results. Two issues are particularly critical: 1) can other countries or cities introduce a food waste tax given the current institutional and physical infrastructure and 2) if implementable, to what extent the effect size would be similar. For the first issue, imposing a food waste tax requires segregating and pricing food waste, both of which are widely used already. For instance, California, Vermont, and the city of Seattle have mandatory organic waste segregation policies (Sandson and Leib 2019). In addition, one-fourth to one-third of municipalities in developed countries already have waste pricing on landfill waste (Bel 2016). These facts suggest that many parts of the world already have a necessary institutional infrastructure. Regarding the second issue, the effect size depends on the status quo food waste quantity and reasons for waste generation. In the US, for instance, the average household spends $1,866 per year on food it never consumes, which is somewhat higher than in South Korea. More generally, over half of the total wasted food is generated by consumers in developed countries (EPA 2021), suggesting that there is an enormous mitigation potential. Further, given that many households in the US underestimate the amount of food they waste (Neff et al. 2015), limited attention to wasted food is not likely to be confined to Korean households.

7 Conclusion

Given that an immediate end of fossil fuel consumption is insufficient to meet the Paris Agreement's 1.5° climate goal without changing the world's food system (Clark et al. 2020), managing excessive food demand has become increasingly important. While a textbook solution is imposing a corrective tax on food waste generation, there is limited evidence on the benefits and costs of it. By leveraging two waves of expansions in a small food waste tax in South Korea I first show that the tax encourages more efficient food use. Households reduce the amount of wasted food primarily by purchasing less food in the first place, but without compromising food intake quantity or nutrition quality.

Building on the insights from the household production model, I next empirically test various waste abatement strategies that can explain how households maintain food intake with less grocery purchases. I find that after the tax is imposed, households increase their time spent on meal production to compensate for lower grocery input. Finally, using the grocery demand elasticities from the literature, I find that the price effect (or "move along the curve effect") can explain only 5% of the grocery purchase adjustments. I also discuss potential non-pecuniary channels with a particular focus on raising households' attention on food waste through a regular feedback.

These results have several policy implications. First, a food waste tax is a low-hanging fruit climate change mitigation policy measure as the policy costs a remarkably low program cost of $13 in reducing one ton of CO_2. Recent discussions at the United Nations Climate Change Conference emphasize the importance of finding affordable mitigation options, and food waste tax can play an important role to that regard. In addition to cost-efficiently reducing GHG, the policy seems to also generate net private benefit, although I defer a more complete assessment of the welfare effect to future studies. Second, government policies should focus on preventing rather than recycling food waste since over 90% of GHG emissions from wasted food are from the farm-to-kitchen stage.

Third, taxing food waste is arguably politically less contentious in comparison to other measures on food use, because households in general agree that reducing food waste is desirable (Ministry of Environment 2015, Neff et al. 2015). Fourth and finally, reducing food waste generates co-benefits beyond GHG emission reductions by, for example, contributing to enhancing food security and improving environmental qualities by reducing pollutants other than GHG. Further, given that the world needs to feed 9.6 billion people in 2050, which is projected to be extremely challenging without converting forests to arable land (Bajželj et al. 2014), food waste tax is an important starting point that can induce more efficient and sustainable food use.

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A Grocery Purchase Data Validation

There are two potential concerns with the grocery panel data. First, the data might capture only a subset of the panelists' shopping behavior. This can happen when households fail to keep the record of every single spending. Although the Rural Development Agency compensates panelists $50 per month and replaces unreliable households, it could still be the case that households forget or skip reporting. Second, as discussed in section 3.1, I impute unit price information for shopping records with missing information. In this section, I investigate the validity of the consumer panel data from the two aspects.

For the first issue, I compare overall spending amount (in dollars) from an average panelist to household spending information from Household Income and Expenditure Survey (HIES). HIES is administered by Statistics Korea and aims at understanding the income and expenditure of Korean households. The data surveys 7,200 households, covering the universe of household spending items from food to housing. I use grocery and liquor (excluding tobacco) purchase information from urban households with family size larger or equal to two to make it comparable to the consumer panel.

Figure A.1 shows the comparison between two different data sources from 2010 to 2016.[54] Two points are worth discussing. The level of spending is approximately $4,000 per year from both surveys. This corresponds to the average household grocery spending from Table 3.1. Also, the two time series exhibit a very similar pattern. In a given year between 2010 and 2016, the grocery panel captures 88% to 95% of the household spending documented in the HIES.

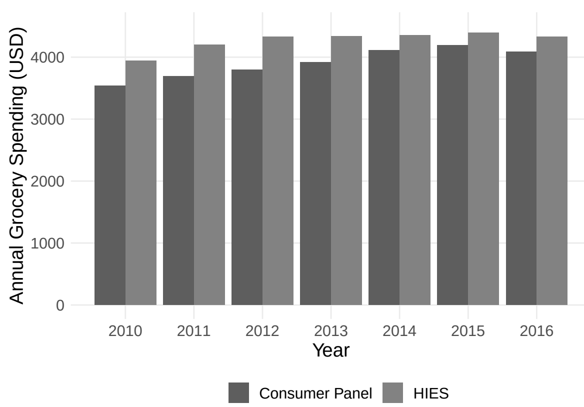


Figure A.1: Consumer Panel Data Validation (Total Expenditure). This figure compares the overall household spending from the comsumerillustrate the validity of the consumer panel data on three different dimensions including total expenditure, total quantity purchased, and grocery price. See the text for additional details.

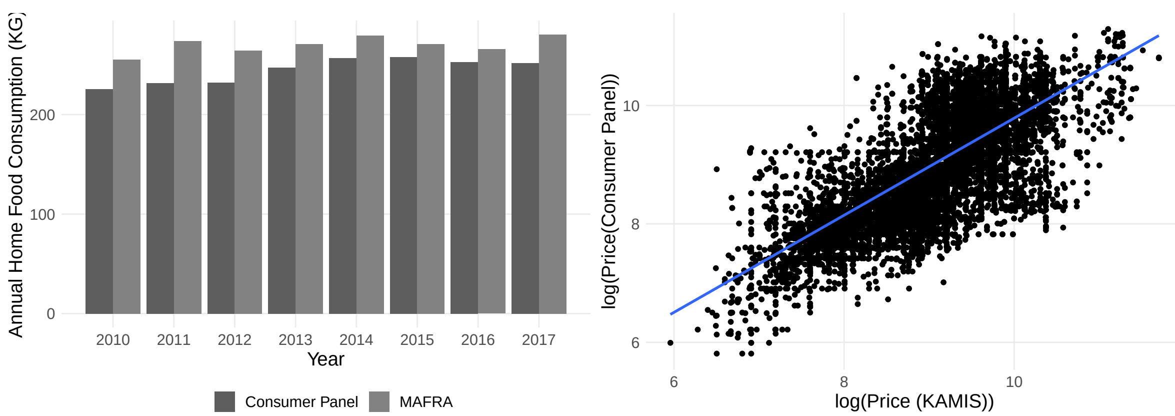
To address the second issue, namely missing unit price information issue, I conduct two rounds of imputations using a similar approach to Golan et al. (2001). Namely, I first use the median unit price of the same food category from the same type of stores (e.g., farmer's market, supermarket chains, and mom and pop stores) located in the same municipality and month. This successfully imputes 64% of the missing price information. For the second round, I expand the geographic scope to a cluster of 5-6 municipalities and repeat the same exercise. This recovers another 17% of the missing price information. By dividing the total expenditure with the unit price, I back out the quantity purchased.

To test the validity of this procedure, I compare the per household grocery purchase in KG from the grocery panel and per household food consumption statistics from the Ministry of Agriculture,

[54]2017 is excluded because the HIES sample has changed to include a single-person household. The balanced grocery panel does have a very small number of single-person households so I did not use 2017.

Food and Rural Affairs (MAFRA). Importantly, the consumption statistic does not distinguish food that is actually consumed or eaten versus leftover. As the MAFRA data covers food consumption from both home and outside (e.g., restaurants, cafeteria, etc), I adjust it using the fraction of meal consumed within home from Han (2018).

Panel (a) of Figure A.2 shows the result. From 2010 to 2017, the amount of food purchased between the consumer panel and MAFRA official statistic are very closely related. This add credibility to the unit price imputation. In panel (b), I provide additional evidence by comparing the unit price information from the grocery panel to the price information from KAMIS (Korea Agricultural Marketing Information Service) website, which is an official source, maintained by the Korea Agro-Fisheries & Food Trade Corporation. Each dot in the scatter plot represents logged price of each food category at the municipality by year by market type from the consumer panel (on the y-axis) and the KAMIS data (on the x-axis). The correlation is over 0.8, suggesting that the imputed price is highly correlated with the actual price.



(a) Total Quantity Purchased

(b) Price

Figure A.2: Consumer Panel Data Validation (Quantity and Unit Price). These figures illustrate the validity of the consumer panel data based on total quantity purchased and grocery price. See the text for details.

B Additional Tables and Figures

Table B.1: Effect of Food Waste Tax on Waste Generation (Stacked DD)

	(1)	(2)
(%) Food Waste Tax	-0.1920***	0.0517
	(0.0600)	(0.1461)
Dependent Variable	Food Waste Per HH	Landfill Waste Per HH
Observations	2,646	2,646
Year × Stack FE	✓	✓
Municipality × Stack FE	✓	✓

This table presents the effect of food waste tax on waste generation using the stacked DD approach. I only report coefficients for the food waste tax term, but the baseline control variables are included. All standard errors are clustered at the municipality level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. See text for additional details.

Back to 4.2.

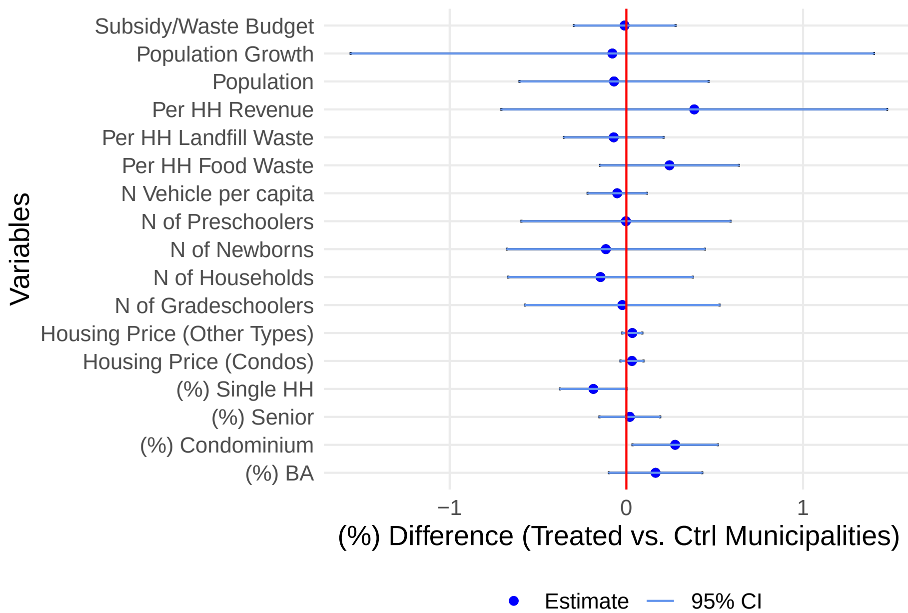
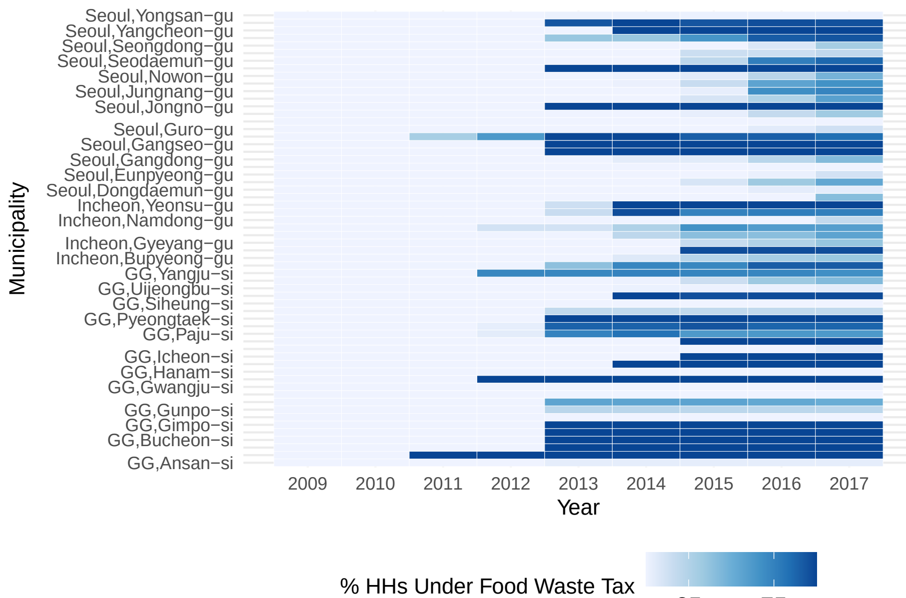
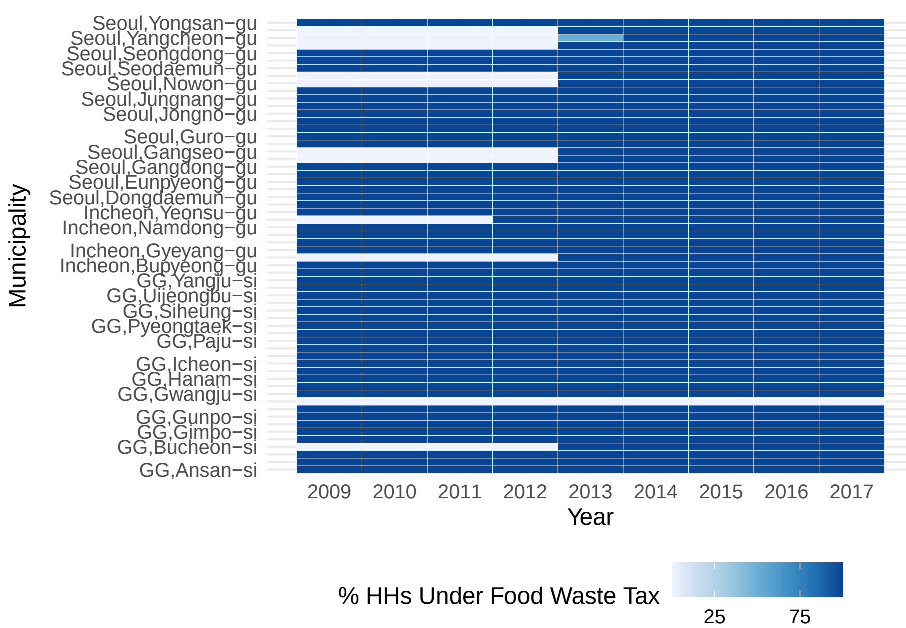


Figure B.1: Wave 2 Expansion and Municipality Characteristics. This figure compares pre-treatment characteristics for high-expansion versus low-expansion municipalities.

Back to 3.2.



(a) Condominium



(b) Other Housing Types

Figure B.2: Wave 2 Expansion by Housing Type. Panel (a) and (b) plot the proportion of condominium and other housing types residents under the unit-based tax for each municipality-year. See the text for additional details.

Back to 2.2.

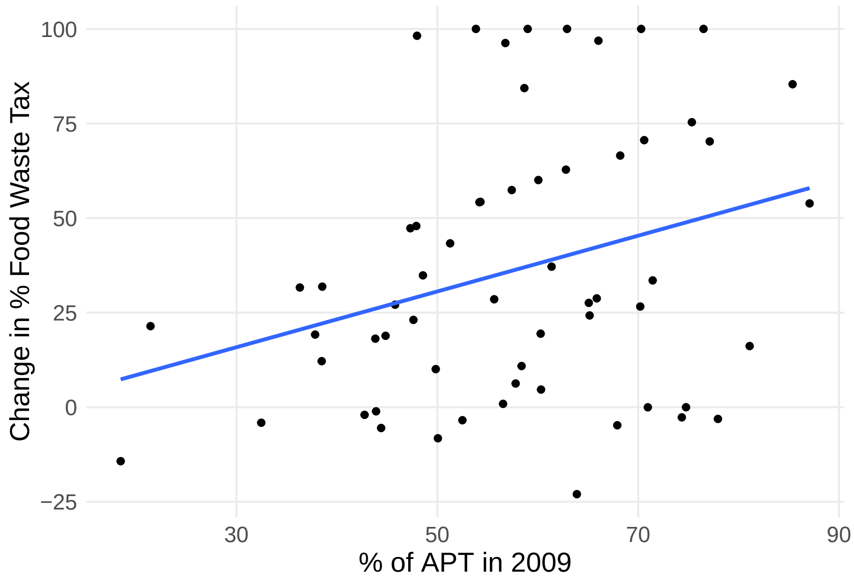
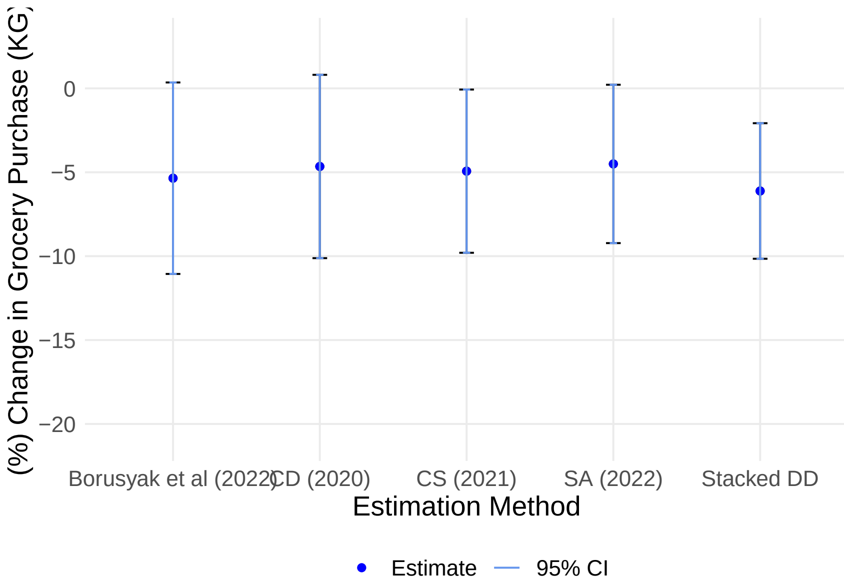
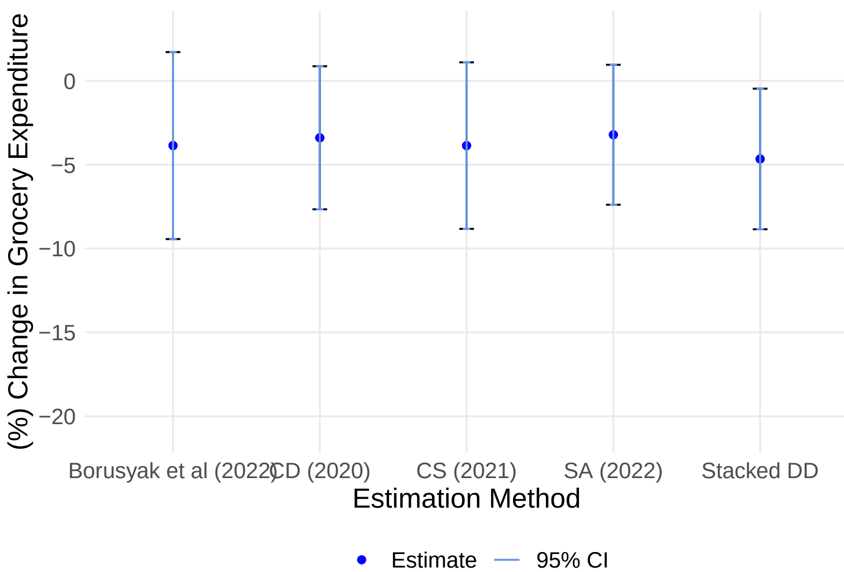


Figure B.3: This figure shows the relationship between the proportion of condos in 2010 to the change in the fraction of households under food waste tax between 2010 and 2015. Each dot represents each municipality. See the text for additional details.

Back to 2.2.



(a) Grocery Quantity



(b) Grocery Expenditure

Figure B.4: Alternative Estimators for the Tax Effect on Grocery Purchases. This figure plots the impact of food waste tax on grocery purchase quantity (Panel A) and expenditure (Panel B) using five different estimation approaches. See the text for additional details.

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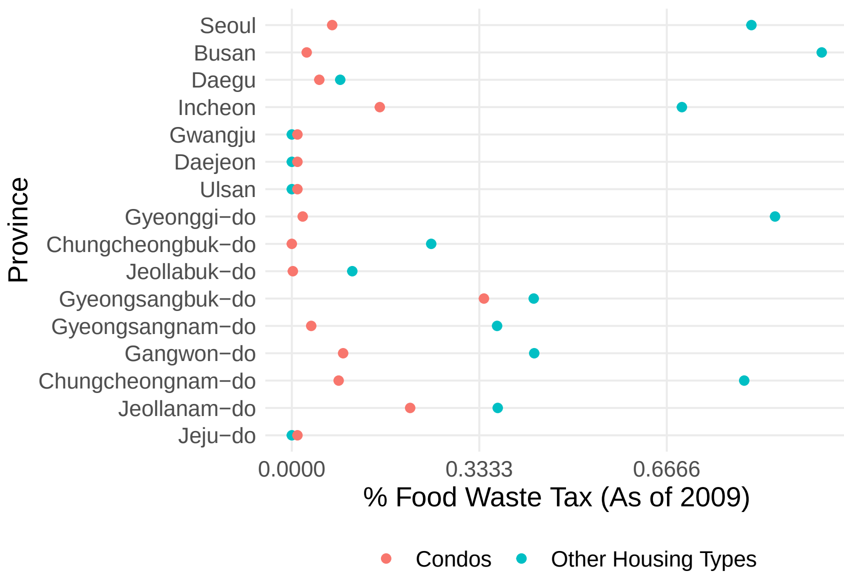
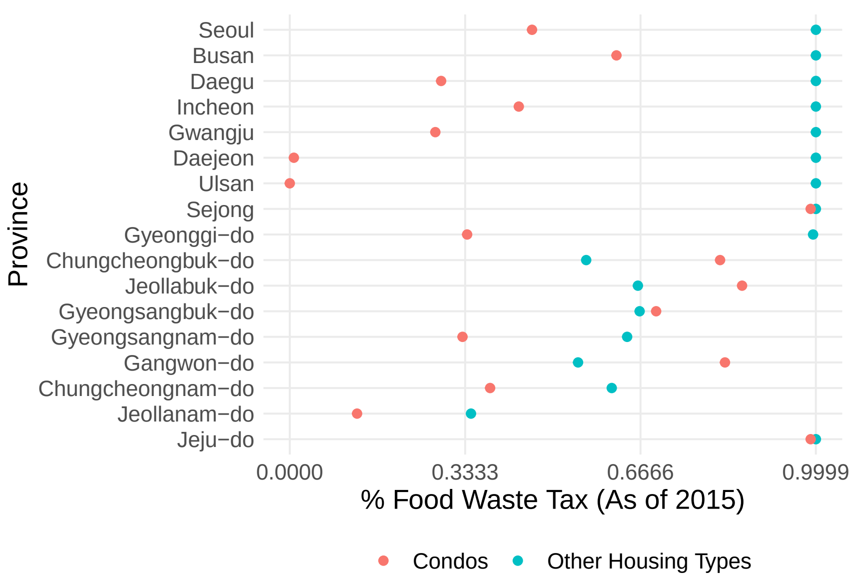


(a) 2009



(b) 2014

Figure B.5: Proportion of Households under Food Waste Tax at the Province Level. These figures show the proportion of households under the food waste tax at the province level for aparement complexes and other housing types. Panel (a) is for the wave 1 period (as of 2009) while panel (b) is for the wave 2 period (as of 2014). See the text for additional details.

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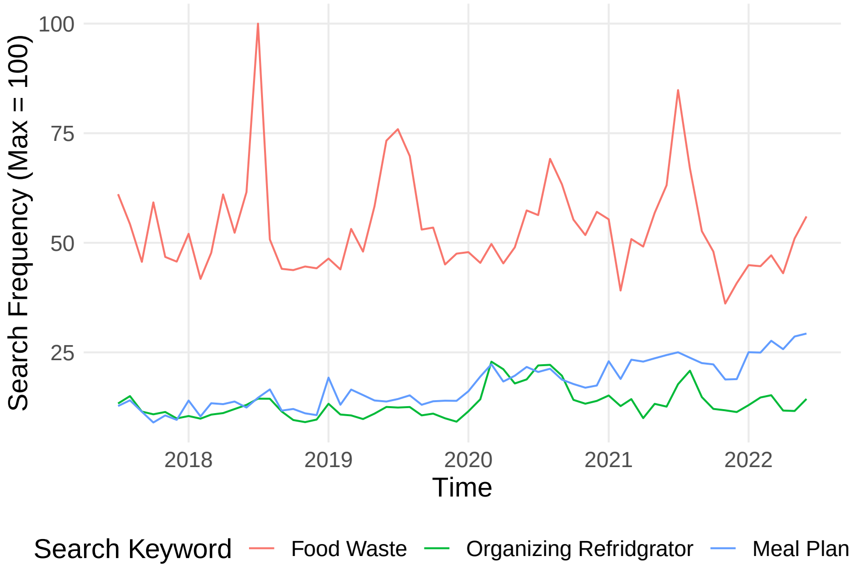
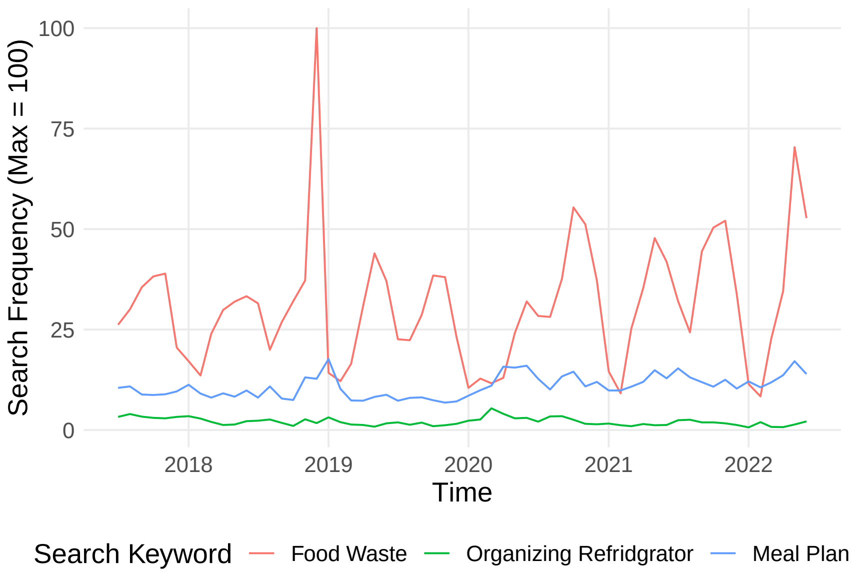


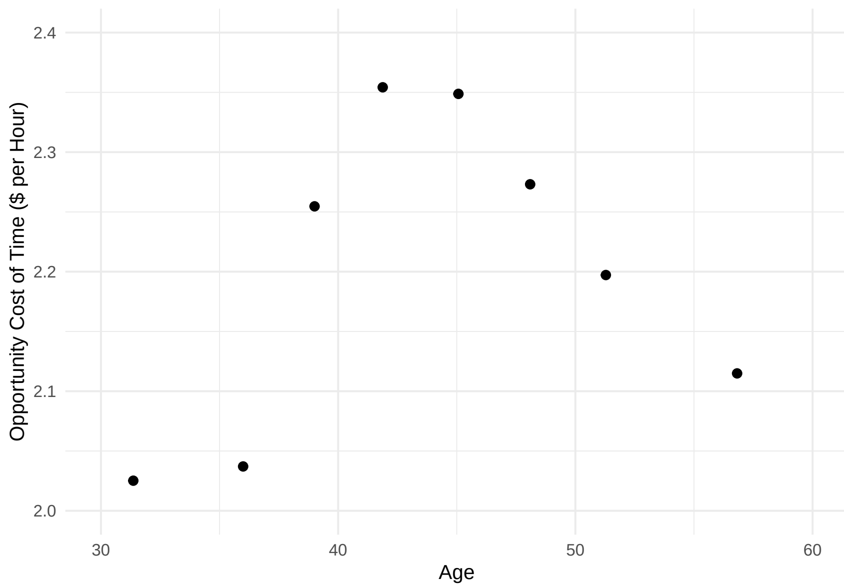
(a) Male Age 30-60



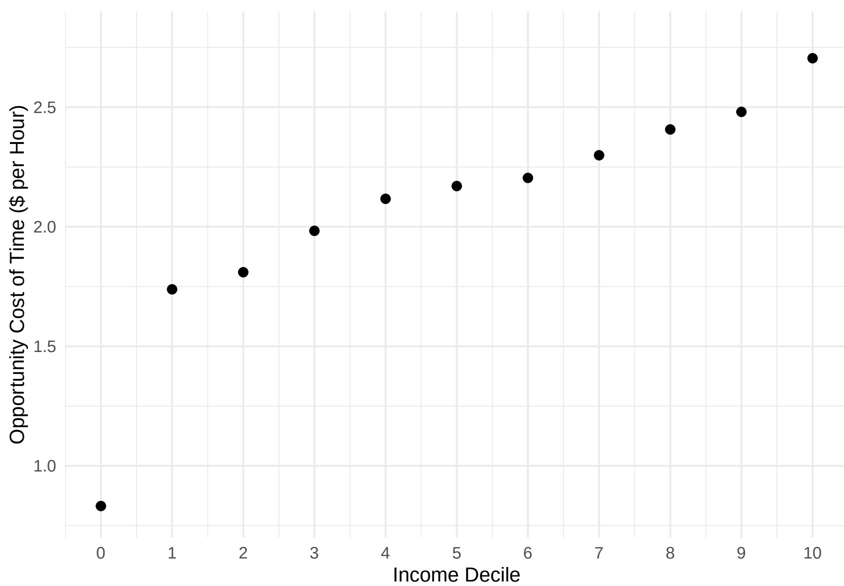
(b) Female Age Below 20

Figure B.6: Trends in Internet Search Keywords and Food Waste Abatement Strategies. These figures show the trend in web search intensity for three food waste related keywords (food waste, organizing refrigerator, and meal planning) for different population groups between July 2017 and Jun 2022. Y-axis has been normalized based on the maximum search intensity over the five years period for each demographic group. Panel (a) is for male age between 30-60, and panel (b) is for female age below 20. See the text for additional details.

Back to 5.2.



(a) Age and Average Spending



(b) Income and Average Spending

Figure B.7: Average Spending and Demographic Characteristics. These figures show the binscatter plots between average spending and age (Panel A) and income level (Panel B) using the grocery panel data. See the text for additional details.

Back to 5.2.

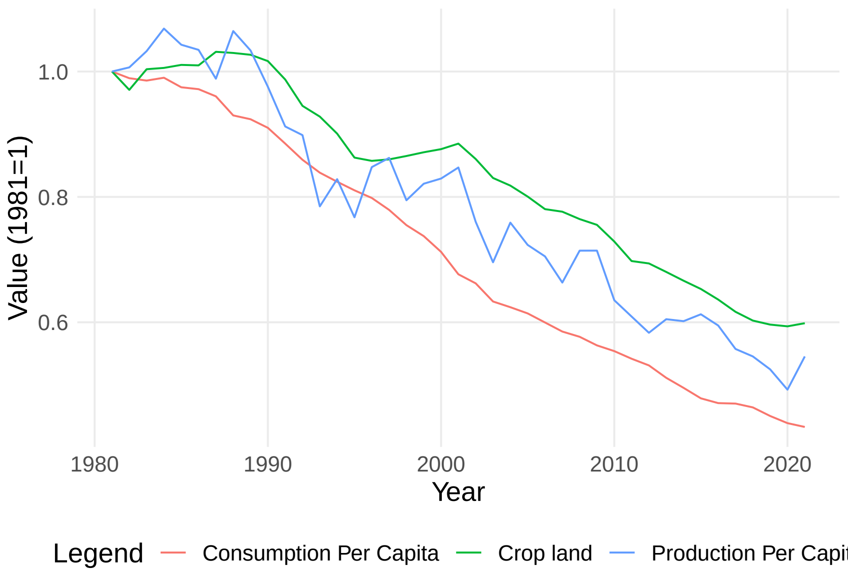


Figure B.8: Rice over Time. This figure shows how rice consumption per capita, production per capita, and rice crop land have changed over time. See the text for additional details.

Back to 4.3.

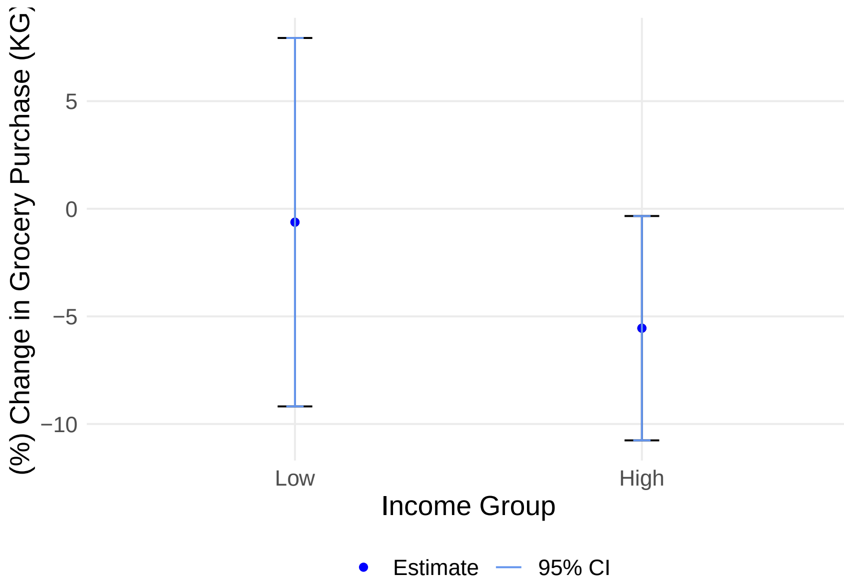


Figure B.9: The Effect of the Tax on Grocery Purchases by Baseline Grocery Quantity. This figure shows how the effect size varies by income group. See the text for additional details.