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 6 cents 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 $18, 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 7%, or 68 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 and cost-effective 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, 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 estimates of the benefits and costs of a unit-based food waste tax and investigates mechanisms. The empirical setting is South Korea, where food waste has been collected separately from general waste since 2005. While the majority of households were charged a monthly flat tax, some households, especially those living in non-condominium housing types, were charged a unit-based tax since then for their food waste (wave 1 expansion). With mounting concerns over

[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.

food-waste driven greenhouse gas emissions, the central government mandated local governments to expand the unit based food waste tax by 2013, through a smart card system—typically for condominium complexes—or an official trash bag—typically for other housing types (wave 2 expansion). Importantly, because the smart card system is costly, not all households received the tax treatment at the same time. The proportion of households under the tax continued to increase after 2013, and 30% of them were not facing positive marginal price even in 2017. The tax is small with an average rate of 6 cents for 1 kg or $1.3 per month for a household with average waste quantity.[3]

For empirical analysis, I collect four different datasets on purchased, consumed, and wasted food and household time usage. These rich datasets allow me to not only track the source of food waste reduction, which is crucial to determine the benefit of the policy, but also identify the abatement strategy and estimate corresponding costs. For identification, I primarily compare households that are under the tax to not-yet or never taxed households.[4] I estimate the policy effect using the two-way fixed effect approach, but I also show that the estimates are robust to alternative methods proposed in the recent difference-in-difference literature (Cengiz et al. 2019, Callaway and Sant'Anna 2021, Sun and Abraham 2021, Borusyak et al. 2022).

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 in levels (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

[3] Throughout this paper, I use exchange rate $1= KRW 1100. To put the tax size 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] I leverage the wave 2 expansion for all but time-use analysis. Because of data limitations, for the time-use analysis, I use the wave 1 expansion instead. See Section 5.2 for more details.

wasted food by 138kg CO2eq per household,[5] which in turn indicates that the program cost of reducing one ton of CO_2 is as low as \$18, 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), where households combine time and groceries to produce meals, I empirically test possible waste abatement strategies. That is, I investigate whether the tax induces (1) an increase in the time spent on meal production, (2) a change in grocery input quality, and (3) an enhancement in total factor productivity. I find that households spend 68 additional hours per year (or a 7% increase from the baseline) on meal production at home after the tax, which is worth \$168 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 2007a, 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. Given the survey results that households often forget what is stored in the fridge and make duplicate purchases (Farr-Wharton et al. 2014, Gaiani et al. 2018), organizing refrigerator could lead to a more efficient food use. 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. Taken together, results so far suggest that the tax generates a large benefit from a society's perspective by reducing GHGs, but incurs substantial time costs on households. However, households do not seem to be worse off because they can offset time costs with savings on the grocery bills.

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

[5] In monetary terms, a 138kg CO2eq reduction is worth \$7.4–\$27 depending on the social cost of carbon estimates (IWG 2021, Rennert et al. 2022).

households consider a dollar increase in the tax equivalent to a dollar increase in the grocery prices. I find that at an upper bound elasticity (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 would 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.[6] 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 poses additional difficulty in estimating the costs. I overcome these challenges by compiling multiple household-level datasets that comprehensively document food and time usage. These datasets jointly shed light on the monetary cost of time, which is crucial to estimate the monetized cost incurred on households. Understanding the abatement cost is

[6] 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. Also, Taylor (2020) estimates the cost of plastic bag regulations using an increase in the check out time at supermarkets.

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 advantageous 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 emissions from food waste (Crippa et al. 2021). Second, 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.[7] These two differences could explain why earlier works find waste pricing policies welfare-harming.[8] 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).

[7] 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.

[8] 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.

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 life cycle GHG emissions from food waste and the food waste tax policy in South Korea. Section 3 details the data sources and provides summary statistics. Section 4 and Section 5 study the benefits and costs of the tax, respectively, while Section 6 discusses mechanisms for household behavior changes. Section 7 concludes.

2 Background

2.1 Life Cycle GHG Emissions from Wasted Food and Policy Responses

Life cycle GHG Emissions from Wasted Food[9]. 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 5.1GtCO_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).[10] 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,

[9]Wasted food creates numerous environmental problems other than GHG emissions, such as biodiversity losses, soil degradation, and water depletion (EPA 2021). The social cost of carbon from wasted food, thus, is a lower bound of externality from the problem.

[10]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).

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 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,[11] but with rising income, it became increasingly difficult to find space for landfill or waste incineration sites.[12] In response, in 1995, a nation-wide tax on household waste was implemented 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 resi-

[11] 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).

[12] 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.

(a) Condominium Complex - Communal Dumpsters (b) Other Housing Types - Official Trash Bags

Figure 2.1: Waste Collection During Wave 1

dents 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)).[13] 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 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. Recognizing that the flat tax is ineffective for encouraging food waste prevention, the Green Growth Committee, a presidential

[13] 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.

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 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.[14] 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.

Figure 2.2 (b) and (d) present similar plots for the tax rate change.[15] Two things stand out from these plots. First, the tax is small. Even in 2017, the average tax rate is 8 cents per kg, which suggests that households with the average food waste quantity would pay \$20 per year. This is about 0.5% of the average annual expenditure on groceries (\$3,886) from Table 3.1. As the tax is small, it usually covers less than 50% of the operation cost for waste pick up and treatment services.[16]

Importantly, these figures are based on the intensive margin tax rate—namely, tax rate for house-

[14] 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.

[15] The tax is charged based on volume for trash bags and on weight for smart card systems. To make two different regimes comparable, I normalize everything to weight using a conversion ratio of 0.75kg/liter from an executive order of the Ministry of Environment ("2015-164").

[16] 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)).

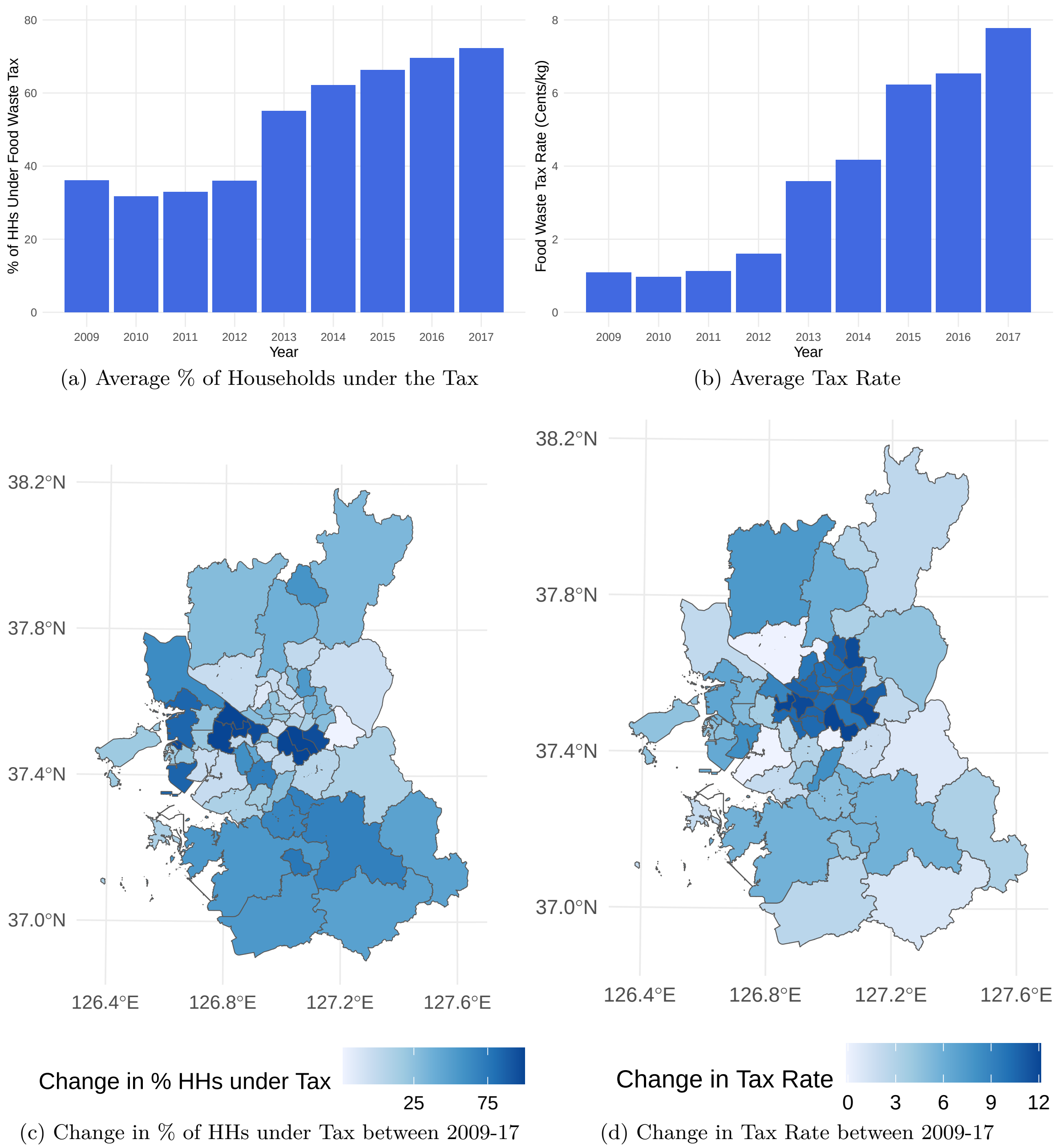


Figure 2.2: Wave 2 Expansion. Panel (a) and (b) show the overall proportion of households subject to the food waste tax and the average tax rate between 2009 to 2017 from 60 municipalities in the metropolitan Seoul area. Panel (c) and (d) show corresponding geographical distribution.

holds 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, and the average tax rate between 2014-2017 across all municipalities is 6.14 cents per kg of food waste. 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 challenging 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.[17] 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.

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

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.[18]

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 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.[19] The data also documents expenditure from restaurants, but school lunches or

[18]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.

[19]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.2, I present various exercises to test the validity of such imputations.

cafeteria purchases are excluded.

Food intake and nutrition. To understand the impact of the tax on food consumption and nutrient intake, 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 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 food consumption and resulting nutrition intake based on a 24-hour dietary recall face-to-face interview. Nutrition content is readily available for each food item consumed, and it is calculated using a standard formula based on scientific research. 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. Note, KHANES dataset discloses address at the community level, which is the smallest administrative unit in South Korea. Because the tax status could vary even within the community depending on the housing type, I assign tax status using neighborhood, time, and housing type information. At the housing type by community by year level, the tax status is near binary.

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 (age over 10) spend on each time-use category.[20] 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 two time categories—grocery shopping time and non-durable 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. The biggest limitation of this data is that the address is observed at the province, which is the largest sub-national administrative unit, level. This makes it leveraging the wave 2 expansion very challenging because finding a clean control group is difficult. That is, 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

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

without food waste tax–is not possible. 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.[21] Importantly, I track the food waste tax implementation timing separately 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.

3.2 Summary Statistics

In Table 3.1, I provide summary statistics for key variables for the empirical analysis (discussions about additional variables can be found in Appendix A.1). To make the comparison easier across different variables on food usage, I express everything in terms of per household per year except for the meal production time and calorie intake which are harder to digest in annual terms. A few points are worth noting. First, the first two rows show that food waste accounts for 48% of the overall (food and landfill) waste quantity, which is a general pattern found in many countries.[22]

Second, an average panelist purchases 837kg of groceries per year, spending roughly $4,000. To translate expenditure to quantity, I divide 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).

Third, the farm-to-kitchen GHG emissions from an average food basket are 2,823kg CO_2 equivalent. This is comparable to 7,095 miles driven by an average passenger vehicle, which is a year's

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

[22] 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.

Table 3.1: Key Variables on Food and Time Use

Variables	Min.	Max.	Mean	Std.Dev.	N
Panel A: Food Usage (Per Household, Annual)					
Food waste (kg)	39.11	948	257	88.54	420
Landfill waste (kg)	28.46	957	283	100	420
Total grocery purchase (kg)	39.89	2,562	837	333	2,880
Total grocery expenditure (USD)	199	12,953	3,886	1,600	2,880
Total GHG from grocery (kg CO2e)	91.74	9,980	2,828	1,305	2,880
Intake at Home (kg)	0.847	5,628	631	455	11,976
Intake away from Home (kg)	4.6	6,701	625	446	13,512
Panel B: Calorie Intake and Time Use (Per Capita, Daily)					
Calorie at home (Kcal)	0.68	9,635	960	597	11,976
Meal Production Time (Mins)	35.14	74.46	55.31	6.47	672

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] When compared against the grocery purchase quantity, 1kg of groceries emit 3.38 kg CO_2 equivalent. Depending on the social cost of carbon estimate, 1kg of food incurs 17-63 cents of social cost (IWG 2021, Rennert et al. 2022). Even after a tax rate increase during 2013–2017, the tax rate is only at about 13–47% of the external cost.[25]

Fourth, an average per household food intake at home is 631kg, which is 75% of the purchased food (837 kg). Next row shows the amount of food consumed away from home. It's about the same amount at 625kg. The next row shows calorie intake from food consumed at home. On average, per capita calorie intake is 960 Kcal. Given that people consume similar amount of food away from home, an average daily calorie intake is roughly 2,000 Kcal, which is on par with the recommended calorie intake (Ministry of Health and Welfare 2015).[26]

Finally, on average an adult spend 55 minutes on meal production, which includes cooking, cleaning up, keeping diary, and non-durable shopping, each day. These numbers are consistent with other

[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. 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.

[25] This is a lower bound because food waste creates negative environmental impacts other than GHG emissions.

[26] For a prime age male (female), recommended energy is 2,200–2,600 (1,800–2,100) Kcal/day.

studies that have used the time use survey to document trends in non-market working hours in Korea (Seo et al. 2021).

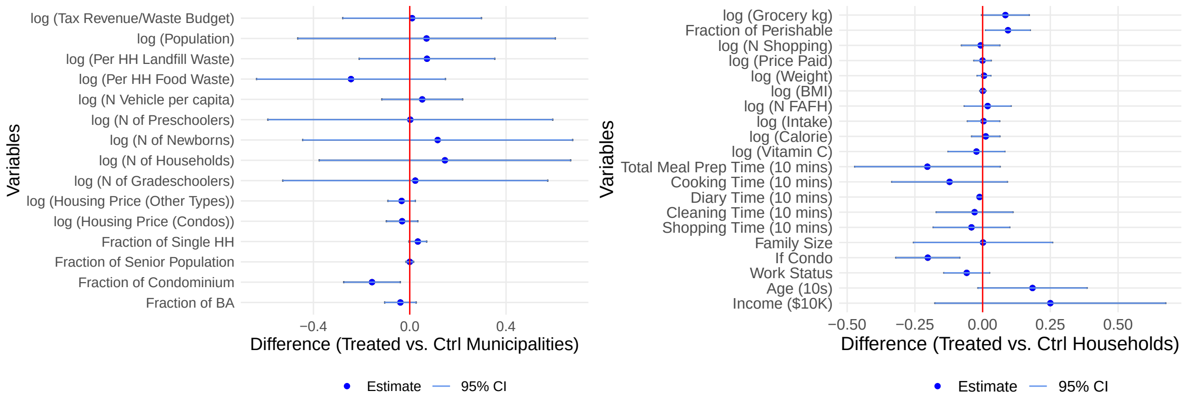
Figure 3.1 (a) and (b) present municipality-level and individual or household-level balance statistics for treated and control groups. For (a), the control group consists of bottom 10% municipalities in terms of the % of households subject to the tax in 2015, while the treated group has the rest of 54 municipalities.[27] For (b), I compare never versus ever treated households or individuals. The proportion of never treated observations are 39–68% depending on the dataset. The difference reflects the fact that the sample period for the time use analysis is 1999-2009, which is before the wave 2 expansion.

In panel (a), I show that the treated and control municipalities are highly comparable in various observed characteristics. For instance, food and landfill waste quantities are not statistically significantly different from each other. Further, numerous variables such as household size, housing price, age composition, or financial condition of local government that could be correlated with the policy status are in general highly similar to each other. One important exception is the proportion of households residing in condominium complexes. It is substantially lower for the treated municipalities, and this is not surprising given that many households living in non-condominium complexes were already treated before 2009. Indeed, Figure B.2 shows that the proportion of condominium residents in 2009 is a strong predictor of the proportion of households under the tax in 2015.

In panel (b), I present the results of the balance test for various pre-treatment outcome variables on food and time usage and demographic variables. I compare households that are eventually treated versus never treated over the sample period. Practically, I regress the ever-treated status with baseline controls described in Section 4.1 and 5.2 and year fixed effect.[28] The variables are for food purchases (quantity, expenditure, the fraction of perishable items, number of shopping trips, and price paid for 1kg of grocery), food intake, nutrition, and health (weight, BMI, intake quantity, and nutritional contents), and time use (time categories related to meal production). Consistent with panel (a), I find that observed characteristics in general are well balanced except for the condominium residency.

[27] Another potential way to define the control group would be using municipalities that did not see much expansion over the sample period. However, this could be problematic because a municipality might have started at 100 and remained at 100 over the sample period, and this "always-treated" observation can contaminate the control group.

[28] I exclude unit fixed effect because of the collinearity with the treatment status variable.



(a) Comparison of High vs. Low Expansion Municipalities

(b) Comparison of Ever vs. Never Treated Households

Figure 3.1: Comparison Between Treated vs. Control Units on Pre-treatment Outcome Variables and Demographic Characterit. Panel (a) shows the difference between treated and control municipalities. Control municipalities consists of bottom 10 percent municipalities in terms of the fraction of households subject to the tax in 2015, while the treated group has the rest of 54 municipalities. Panel (b) shows the comparison of key variables between ever and never treated households from the grocery panel, food intake, and time use data. Standard errors are clustered at the municipality level. See the text for additional details.

While the baseline characteristics seem similar between the two groups, one might still worry that households living in condominium complexes and other housing types could have different potential outcomes. I address these concerns in various ways in following sections.

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.

I also estimate an event study version of equation (1) as equation (2) where Tax_{it}^k 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.

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

The key identifying assumption is that in the absence of the food waste tax, grocery purchases of treated and control units have parallel trends. While similarities in baseline characteristics (see Figure 3.1) support this assumption, one might still worry that households in different tax expansion groups might be on different food usage trends. I address this concern in three ways.

First, I test potential pre-trend using equation (2). In estimation, 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 (Baker et al. 2021, Goodman-Bacon 2021).[29] Second, I allow for treatment heterogeneity and check pre-trend using alternative estimators proposed in the literature (Cengiz et al. 2019, Callaway and Sant'Anna 2021, Sun and Abraham

[29] 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.

2021, Borusyak et al. 2022). Third, I include province by year fixed effect to compare households with and without the treatment within a province by year.[30] This alleviate potential concerns over the comparability of households living in remote places.

To understand the impact of the tax on food intake and nutritional content, I estimate a variant of equation (1). Namely, $log(M_{ihcmt}) = \beta T_{hcmt} + \delta \mathbf{X}_{ihcmt} + \lambda_{hm} + \omega_t + \epsilon_{ihcmt}$ where subscript h indicates the housing type (condominium vs. other types) and c is community, which is the smallest administrative unit in South Korea, and the other subscripts are identical as equation (1). M_{ihcmt} represents the range of outcome variables such as intake, calories, and vitamin quantities as well as health outcomes. While the source of variation is identical as equation (1), there are three differences worth discussing. First, as the data is repeated cross section, I add municipality by housing type fixed effect instead of the household by municipality fixed effect. $\mathbf{X}_{ihcmt}$ is six individual level controls which are closely related to food intake: whether a household has a child or not, family size, income, age, sex, and working status. Second, reflecting the data structure, i indicates an individual rather than a household. Third, the tax status is assigned by combining community and housing type information. Unlike the grocery purchase data, I do not have access to the street address. However, community, which is the smallest administrative unit in South Korea, is small enough to allow me to assign a binary tax status for most of the respondents (see Appendix Figure B.3). In practice, $T_{hct} = 1$ when the fraction of households under the tax in housing type-community-year is over 75% and 0 when the fraction is below 25%. I remove observations when the fraction is 25–75% to minimize the measurement error. 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

[30] Ideally, I would include municipality by year fixed effect, but the number of observations are too small for that exercise. To see this, note that I have on average 6 unique households for a given municipality (360 households across 60 municipalities).

t. $(\%)Tax_{mt}$ is the fraction of households subject to the food waste tax.[31] $\boldsymbol{X_{mt}}$ are three municipality 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. I also check the robustness of β from equation (3) using a stacked difference-in-difference approach (Cengiz et al. 2019), which allows me to fix the control group to municipalities that are "clean", namely bottom 10% municipalities in terms of the % of households subject to the tax in 2015. 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 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.[32] 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

[31] 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$\in${condominium, other housing types, restaurant}. z_{mkt} is share of k in each municipality.

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

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 × Municipality FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	420	420	2,880	2,880
Panel B: Margins of Adjustments and GHG Implications				
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 × 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. Columns (1) and (2) in Panel A are estimated using municipality by year level food and landfill waste data based on equation (refeq:waste). The rest of the coefficients are estimated using the grocery panel data following equation (refeq:food). The grocery panel data has been aggregated to the household by year level. 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

that focuses on tax expansion through the smart card system (Lee and Seo 2022). In comparison to the column (1), which is estimated using municipality-by-year level food waste quantity data, Lee and Seo (2022) uses monthly billing data to calculate the policy effect—which is more frequent and more reliable. Lee and Seo (2022) reports a much larger 32% reduction in food waste quantity after the smart card system implementation.[33] This suggests that the estimated effect in column (1) is likely to be attenuated.

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 cheapest way to engage in illegal dumping 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 B.4 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.[34] 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.

[33] One important source of the difference seems to be the differences in data coverage: while the municipality level data used 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 smaller than Lee and Seo (2022).

[34] Note, $(\%)Tax_{m,2015} - (\%)Tax_{m,2009} < 0$ for some municipalities. This can happens when a municipality goes through a large scale urban renewal 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.

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 86% of the reduction in the observed waste quantity can be explained by purchasing less food in the first place. This is important because this adjustment represents an actual reduction, rather than a displacement of food waste.[35] 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. The reduction in grocery purchases is consistent with survey results. For instance, Ministry of Environment (2012) finds that 62% of surveyed households reported a reduction in their grocery spending after the food waste tax.[36]

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

[35] 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.

[36] 31% said $\leq$ 5%, 21% said $\geq$ 5% and $\leq$ 10%, 10% said $\geq$ 10%, and 38% said no change.

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).[37] Then I estimate equation (1) using log of GHG as an outcome variable. I find that the tax reduces GHG emissions 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, I present event study figures generated by TWFE model as equation (2) and four alternative estimators proposed in the literature (Cengiz et al. 2019, Callaway and Sant'Anna 2021, Sun and Abraham 2021, Borusyak et al. 2022). 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. Using this figure, I test parallel trend assumption and explore dynamic treatment effects while allowing for heterogeneous treatment effect. The plot is consistent with no pretrend before the tax implementation. That is, across different estimation procedures, the difference between treated and control households before the tax implementation is near zero without discernible pretrends. The figure also shows that the policy effect is relatively stable over time. In Figure B.4 (c)-(f), I plot β^k from equation (2) for other outcome variables including expenditure, perishable and storable purchase quantities. Consistent with Figure 4.1, I find clean pretrend and sharp policy effects since the first year of the treatment.

[37] 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.

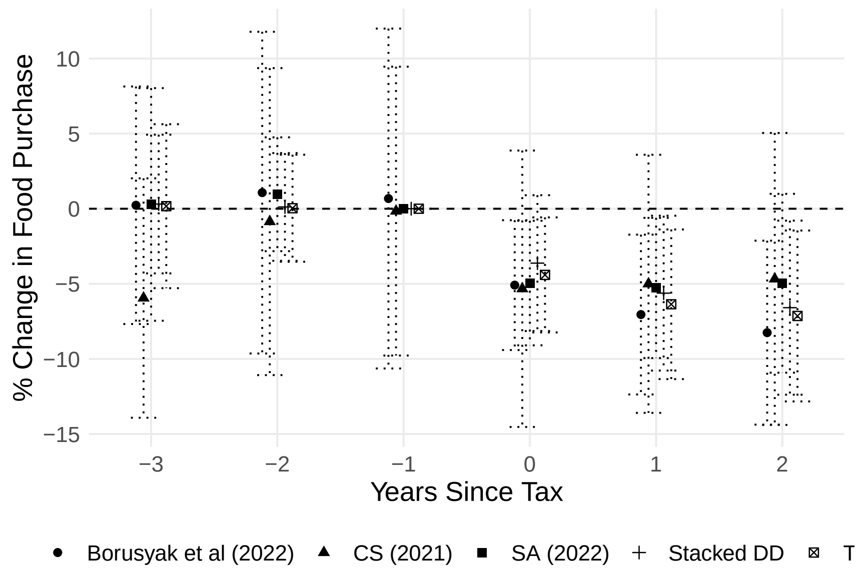


Figure 4.1: The Effect of the Food Waste Tax on Grocery Purchases. This figure overlays event study style plots estimated from five different methods: a dynamic TWFE model, a stacked difference-in-difference model a la Cengiz et al., (2019), Sun and Abraham (2021) estimator, Callaway and SantAnna (2021) estimator, and Borusyak et al., (2021) estimator. The outcome variable is log of per household annual grocery purchase (in kg). Event time is defined relative to the treatment year, namely the first year a household is subject to the food waste tax. I impose endpoint restrictions to estimate the effect using a nearly balanced panel. The bars represent 95 percent confidence intervals. Standard errors are clustered at the municipality level.

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, it allows me to understand the source of observed reduction in food waste quantity. For instance, if people consume a larger amount of food after the tax, it would suggests that changing intake quantity is an important strategy to reduce food waste. Second, given the change in the size and composition of the food basket (i.e., grocery purchases), it is important to test whether the tax has a potential nutritional or health impact.

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 do not find evidence suggesting that overall food intake quantity has changed after the tax. The estimated coefficient suggests a statistically insignificant null effect (0.35%) in quantity. Consistent with this, in columns (2) and (3), I do not find evidence for change in calorie or vitamin intake, respectively. If purchasing less perishable items implies consuming less fresh fruit or vegetable, I should find meaning reduction in vitamin intakes. However, I also find near null effects—statistically insignificant 0.3% increase.

In columns (4) and (5), I report the impact on the health outcomes, which could be interpreted as a “revealed preference” measure of food intake decisions. Consistent with no changes in food

Table 4.2: Food Waste Tax and Food Intake Changes

	(1)	(2)	(3)	(4)	(5)
Food Waste Tax	0.0035	0.0163	0.0029	-0.0143	-0.0137*
	(0.0311)	(0.0272)	(0.0604)	(0.0092)	(0.0074)
Dependent Variable in Log	Overall Intake	Calorie	Vitamin C	Weight	BMI
Year FE	Yes	Yes	Yes	Yes	Yes
Municipality × Housing Type FE	Yes	Yes	Yes	Yes	Yes
Observations	11976	11976	11976	11950	11915

Note:
This table reports the impact of the food waste tax on food intake and nutritional contents. 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

intake, I do not find evidence of significant changes on weight or BMI after the tax.[38] In Appendix Table B.2, I present results for a wider range of nutritional measures and find that the results are consistent with Table 4.2. 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.

4.3 Cost-Effectiveness of the Food Waste Tax

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. To pin down the idea, let's consider the following identity: $W = Q - C - I$, W is food waste, Q is grocery, C is intake, and I is unobserved activities that affect food waste quantity (e.g., illegal dumping). The equation suggests that in the absence of X, food waste is the difference between purchased and consumed food quantity. Given

[38] Note, the number of observations in columns (4) and (5) are slightly smaller than columns (1)-(3) 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.

findings from Section 4.2 that $\Delta C = 0$, $\Delta W = \Delta Q - \Delta I$. Further, given that $\Delta Q = 0.86 \times \Delta W < 0$, $\Delta I = -0.14 \times \Delta W > 0$. While I can take many different forms, I take a conservative stance and treat ΔI as an increase in illegal dumping to landfill, which has much higher GHG emissions than alternatives such as in-house composting or dehydration. 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.[39] Since more than 95 percent of the food waste is processed in composting or animal feed processing sites in Korea, 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.[40]

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).[41] 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%.[42] An important assumption in this calculation is that producers will respond to the tax-induced demand shock by scaling back their production.[43]

Finally, for CI_I, I use the coefficient from the national inventory report, which is 0.655 ton CO_2eq

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

[40]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.

[41]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.

[42]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.

[43]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.

(GGIRC 2015).[44] 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 and operate the smart card systems.[45] This, however, excludes spending on waste pickup and treatment services, 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 ($18.4 million per year). When I compare the cost to the total GHG reduction amount, the program costs $18 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.[46] 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.[47] 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

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

[45] These costs are inflation adjusted using 2015 as the base year.

[46] 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.

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

Table 4.3: Cost Effectiveness of the Food Waste Tax

	Items	Value
GHG Change (1000 Tonne)	GHG Reduction (from Wasted Food Production)	998
	GHG Reduction (from Waste Treatment)	72
	GHG Leakage to Landfills	-28
	Net GHG Reduction	1042
Program Cost ($ Million)	Producing Bags and Stickers (A)	8.375
	Installing Smart card System (B)	6
	Operating Smart card System (C)	4
	Total Program Cost (A+B+C)	18.375
	Savings on Waste Treatment Services (D)	-54
	Net Program Cost (A+B+C+D)	-35.625
Policy Effect	$ Per Tonne of CO_2eq Reduction (vs. A+B+C)	USD 17.6
	$ Per Tonne of CO_2eq Reduction (vs. A+B+C+D)	USD -34.2

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 mentioned 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

In this section, I identify households' abatement strategies and estimate corresponding costs. For that, I build on the insights from the household production model a la Becker (1965).[48]

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

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 $M_1 = A_1 F(Q_1, T_1)$.

From Section 4.2, I find that $Q_0 > Q_1 = 0.95Q_0$ while $M_1 = M_0$, and the model provides three potential explanations for this empirical finding. 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 same amount of meal using smaller amount of grocery ($A_1 > A_0$). 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, this could be true if households purchase pre-cut products such as peeled fruits, which suggests that the amount of edible parts in a grocery basket could be similar even after the tax. 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. In contrast to grocery purchase and food intake data that allow me to observe detailed address of households, the time use survey reveals lo-

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

cation information of each respondent only at the province level, which is the largest sub-national administrative unit in South Korea. And because the tax status is changing at a sub-province level, I cannot tell whether a household is under the tax or not with certainty.

Given this limitation, I take a pseudo-panel approach, which translates individual level repeated cross section data into aggregated panel data (Deaton 1985, Bellemare et al. 2018). Specifically, I collapse the individual level data by taking weighted average of household level data for each province p by housing type h by survey date d by year t cell. In generating cells, I leverage the housing type and survey date information as well because housing type is a strong predictor of food waste tax status, and households spend time differently depending on the date of a week.

Further, the data limitation imposes a challenge in identifying the policy effect using the wave 2 expansion because it is hard to find a clean control over the wave 2 period. Appendix Figure B.5 Panel (b) shows, between 2009 and 2014 (wave 2 expansion started in 2013), essentially all province-housing type pairs have expanded the tax status. In contrast, Panel (a) shows that I have a large number of clean controls for the period of 1999 to 2009. 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. Since the treatment happens at the same time during Wave 1, the empirical design is a canonical difference-in-difference with continuous treatment as opposed to the staggered adoption design.

$$Time_{hpdt} = \beta(\%)T_{hp,2009}I_{hpt} + \delta\mathbf{X}_{hpt} + \alpha_{hp} + \lambda_t + \omega_d + \epsilon_{hpdt} \tag{5}$$

Specifically, I estimate equation (5), where $(\%)T_{hp,2009}$ is the proportion of households within $hp, 2009$ cell subject to the tax, I_{hpt} is a variable that takes 1 in the 2009, and $\mathbf{X}_{hpt}$ are control variables which are closely related to the way households allocate time: whether a household has a child or not, family size, working status, sex, and the size of house, which proxies for income.[49] In the estimation process, I weight the regression by the number of households in hpt. Standard errors are clustered at the province by housing type, which corresponds to the unit of treatment.

[49] 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)
Panel A: Time Spend on Home Meal Production (in Minutes)					
(%) Food Waste Tax x Post	3.927**	2.681**	0.7765	0.2100**	0.2595
	(1.673)	(1.067)	(0.5774)	(0.0875)	(0.5405)
Dependent Variable	Overall	Prepping	Cleaning	Diary	Non-durable Shopping
Province × Housing Type FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Survey Date FE	Yes	Yes	Yes	Yes	Yes
Observations	672	672	672	672	672
Panel B: Value of Time Spend on Home Meal Production					
(%) Food Waste Tax x Post	3.478*	0.1568***			
	(1.942)	(0.0551)			
Unit of Dependent Variable	Minute	Dollars Per Day			
Province × Housing Type FE	Yes	Yes			
Year FE	Yes	Yes			
Survey Date FE	Yes	Yes			
Observations	448	448			
Panel C: Other Abatement Strategies (Input or TFP Change)					
Food Waste Tax	-0.0028	0.0103	0.0016	-0.0306	-0.0044
	(0.0820)	(0.0114)	(0.0439)	(0.0350)	(0.0350)
Dep. Var in Log (TFP: in Level)	TFP	Grocery Price	N of FAFH	Intake FAFH	Calorie FAFH
HH ID × Municipality FE	No	Yes	No	No	No
Municipality × Housing Type FE	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Observations	28	2,880	13493	13512	13512

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. Panel A and B are estimated using the pseudo-panel approach as equation (refeq:time). In panel C, I test other potential abatement strategies. For column (1), I link three datasets on food and time usage to estimate the TFP difference between tax and no-tax group. Column (2)-(5) are estimated using grocery purchase and food intake data. 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)-(5)) level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

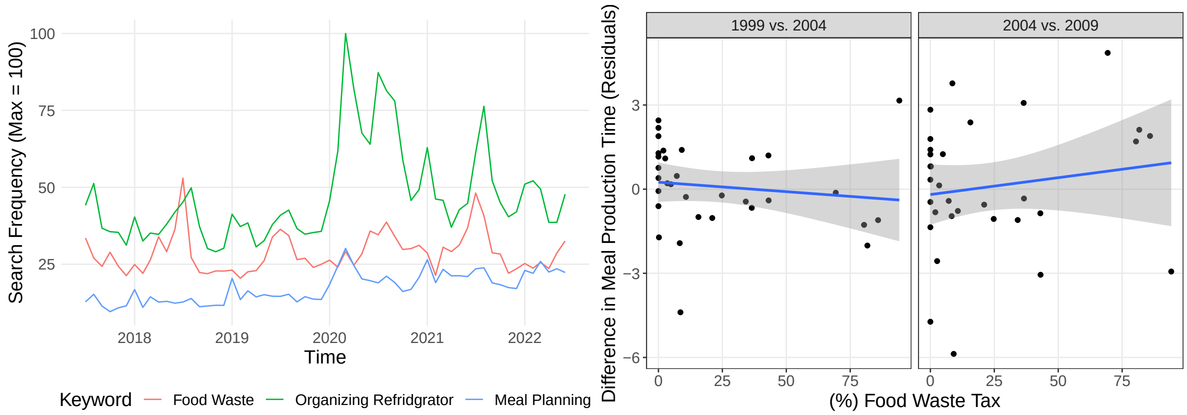
In Panel A of Table 5.1, I estimate the change in the time spent on home meal production activities. Specifically, I focus on four different stages of meal production: preparation, clean up, keeping diary, and shopping. While the first three categories remain constant over the different waves of survey, shopping category has changed over time. To make it comparable across different years, I standardize it to non-durable shopping time, which include not only food shopping but non-food groceries or beauty and health items.

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 3.9 additional minutes per day after the tax. When compared against the average minutes spent on home production, this amount to a 7% increase. Since an average household in the sample has 2.88 adults, household level increase is 11 minutes per day or 68 additional hours per year. Using more time in meal production while purchasing less groceries to maintain food intake is consistent with earlier studies that have found households maintain consumption level despite expenditure fluctuates by making substitution between money (grocery spending) and time (Aguiar and Hurst 2005, 2007a).

In columns (2)-(5), 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). I also find a statistically significant increase in time spent on keeping diaries, which could help households with meal planning. I also find suggestive evidence of increased time spent on cleaning or non-durable products shopping, but the effect fails to rule out the null effect at the conventional statistical significance level.

To understand what exactly households are doing in those additional hours, I use web search data and find that organizing refrigerator seems to be one of the important activities households are engaging.[50] In Figure 5.1 (a), 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

[50] 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.



(a) Search Intensity

(b) Effect of Tax on Time Spent on Meal Production

Figure 5.1: Internet Search Keywords related to Meal Production and the Effect of the Tax on Time Use. Panel (a) 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 from Naver, a dominant search engine in South Korea. In Panel (b), each dot represents a province by housing type (condominium vs. other types) paris. The X-axis shows the fraction of households under the tax and the Y-axis shows the first difference in meal production time for years 2004 vs. 1999 (left) and 2009 vs. 2004 (right). Meal production time variable is residual of baseline controls and province by housing type, year, and survey date fixed effects. The fitted line is produced using OLS and grey area represents the 95 percent prediction interval. See the text for additional details.

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. Organizing refrigerator has a potential to significantly improve efficiency in food usage given survey findings that households tend to forget what is inside of the fridge and often make duplicate purchases (Farr-Wharton et al. 2014, Gaiani et al. 2018). 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.[51]

Figure 5.1 (b) provides visual representation of the tax effect on the time spent on meal production. To produce these figures, I first calculate residuals of time spent on meal production using five baseline control variables and province by housing type, year, and survey date fixed effects. Then, I take the average of residuals for each province and housing type ("pair") by year over survey dates.

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

Finally, I take the first difference between 2004 and 1999, and 2009 and 2004, which correspond to pre and post treatment periods, respectively.

The left-hand side figure shows that the difference in time spent on meal production between 1999 and 2004 between high and low fraction pairs are essentially the same. However, the right-hand side figure shows that the slope is much steeper after the treatment. Namely, after the tax implementation, households in the high fraction pairs are spending more time in meal production that those in the low fraction pairs.

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 (2007a) 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.[52] 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 2007a). 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 Aguiar and Hurst (2007a) 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 (2007a) is to what extent Korean households are similar to the US households. One of the key findings in Aguiar and Hurst (2007a) 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).[53] Consistent with Aguiar and Hurst (2007a), I find that the value of time has an

[52] 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 over half of the primary meal preparers in the sample are not formally employed.

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

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 at a househohold level 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.[54] As the time use data has income variable from 2004 and onward, for this exercise, I limit the analysis 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 similar 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 \$0.16 per day per adult. Multiplying this with the average number of adults in households (2.88) and by 365 suggests that the cost of abatement is \$168 per year per household. In Section 4.2, I show that the savings from purchasing less groceries is \$172 per year per household, which suggests that the savings from grocery spending almost completely offsets abatement costs in terms of time.

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

[54] For the tax status, I use 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 tax (no tax) status. When a household belongs to a pair with the fraction between 1/3 and 2/3, I remove them to minimize the measurement error.

that input's cost share and the scale elasticity (Syverson 2004).[55] Practically, I compute TFP based on the following equation: $TFP_c = m_c - a_q q_c - a_t t_c$ where m_c is log of food intake quantity for cell c, a is cost share of each input and q_c and t_c are log of input quantities. 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 (2007a) similar to earlier section.[56]

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 a small (if anything) effect on the food consumed away from home both in terms of quantity and nutritional contents. These findings make sense given that switching

[55] 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.

[56] More specifically, I multiply the elasticity of price with respect to shopping time ($\alpha_s = 0.1$ from Aguiar and Hurst (2007a)) with the average shopping expenditure ($23) in my grocery panel data, which gives the average opportunity cost of time for home production ($2.3/hour).

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.

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.[57] 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.[58]

[57] 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.

[58] 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).

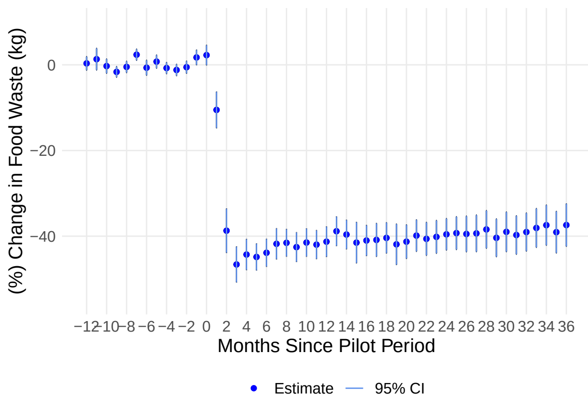
Consistent with a small price effect, I find that the tax elasticity is -0.024 ($se = 0.03$), which is neither economically nor statistically significant. Importantly, I estimate this by replacing Tax_{imt} in equation (1) to $log(TaxRate)_{imt}$ conditional on the unit tax is in place. I limit my attention 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).

6.2 Non-pecuniary Effect of the Tax

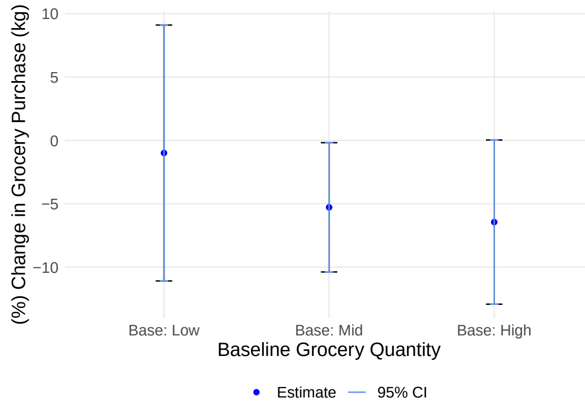
Given a small price effect, the tax seems to affect household behaviors primarily through non-pecuniary channels. In this section, I explore two potential explanations and discuss their welfare implications.

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 af-



(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 using monthly billing data. The plot is reproduced from Lee and Seo (2022). 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.

ter 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.[59] 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 feedback 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

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

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, respectively, using age, income, family size, location, and year.[60] 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 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 in-

[60]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.

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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

creased 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.[61]

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

[61] 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).

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.

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 $18 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 Data Appendix

A.1 More Details on Data Source and Descriptive Statistics

Table A.1: Descriptive Statistics for Food and Time Use

Variables	Min.	Max.	Mean	Std.Dev.	N
Panel A: Food Waste (Annual, Per Household)					
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
Food waste (kg)	39.11	948	257	88.54	420
Landfill waste (kg)	28.46	957	283	100	420
Panel B: Food Purchases (Annual, Per Household)					
Total grocery purchase (kg)	39.89	2,562	837	333	2,880
Perishable grocery purchase (kg)	0	1,363	296	172	2,880
Storable grocery purchase (kg)	32.55	2,118	541	229	2,880
Total grocery expenditure (USD)	199	12,953	3,886	1,600	2,880
Number of trips	14	354	175	54.99	2,880
Total GHG from grocery (kg CO2e)	91.74	9,980	2,828	1,305	2,880
Panel C: Food Intake and Nutrition (Annual, Per Household)					
Intake at Home (kg)	0.847	5,628	631	455	11,976
Intake away from Home (kg)	4.6	6,701	625	446	13,512
Panel D: Food Intake, Nutrition, and Health (Daily, Per Capita)					
Calorie at home (Kcal)	0.68	9,635	960	597	11,976
Vitamin C at home (mg)	0	1,577	37.79	53.36	11,976
Weight (kg)	8.19	132	57.95	18.83	11,950
BMI	11.78	42.34	22.43	4.18	11,915
N of Food Away from Home (Per Month)	1	60	20.03	15.83	13,493
Panel D: Time Use in Meal Production (Daily, Per Capita)					
Meal Production Time (Mins)	35.14	74.46	55.31	6.47	672
Cooking Time (Mins)	19.65	42.7	29.69	3.36	672
Cleaing Time (Mins)	5.7	25.75	15.93	2.27	672
Diary Time (Mins)	0	4.82	0.407	0.452	672
Shopping Time (Mins)	0.721	21.29	9.29	3.39	672
Non-food Home Making Time (Mins)	30.39	83.4	47.81	7.4	672

Table A.1 presents summary statistics for key variables on the food and time usage. The variables are grouped into four different categories: wasted, purchased, consumed food, and time use. Each panel merits discussion. For panel A, 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).[62] The first three rows present summary statistics for the number of residential households, restaurants, and both (residential and restaurant-converted households). The fourth and fifth rows

[62] 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.

jointly show that food waste accounts for 48% of the overall (food and landfill) waste quantity, which is a general pattern found in many countries.[63]

The second panel presents descriptive statistics for grocery purchases. An average panelist purchases 837kg of groceries per year, spending roughly $4,000. To translate expenditure to quantity, I divide 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 A.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).

The last row of the panel shows that the GHGs from an average food basket generated 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.[64] 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).[65] When compared against the grocery purchase quantity, 1kg of groceries emit 3.38 kg CO_2 equivalent. Depending on the social cost of carbon estimate, 1kg of food incurs 17-63 cents of social cost (IWG 2021, Rennert et al. 2022). Even after a tax rate increase during 2013–2017, the tax rate is only at about 13–47% of the external cost. Notably, this is based on a lower bound external cost estimate because food waste creates negative environmental impacts other than GHG emissions.

The third panel presents descriptive statistics on food intake and nutrition. To make the comparison with Panel A and B easier, I converted per capita daily intake quantities to per household annual intake quantities. Reflecting the data structure, the values reflect per capita daily intake. The first row indicates that an average per capita daily food intake at home is 0.59kg. Using the average household size of the sample (2.9), this suggests that an annual food intake at home is 625kg, which is 74% of the purchased food in Panel B. Next row shows the amount of food consumed away from home. It's about the same amount at 0.51kg per day. In Panel D, I present food intake and nutrition quality per capita on a daily basis. I choose not to convert this to annual per household level because of difficulty in interpretation. The first row shows calorie intake from food consumed at home. On average, per capita calorie intake is 960 Kcal. Given that people consume similar amount of food away from home, an average daily calorie intake is roughly 2,000 Kcal, which is on par with the recommended calorie intake (Ministry of Health and Welfare 2015).[66] Consistent with this, the average BMI is 22.43, which is within the normal weight range (18.5–22.9). I can draw similar conclusions for vitamin intakes as well. On average, individuals acquire about half of the recommended vitamin from food consumed at home (Ministry of Health and Welfare 2015). The last row shows the monthly number of food consumption away from home. In contrasts to food intake and nutrition survey, which is constructed from the food dietary interview, this metric is measured using a survey questionnaire. The question asks how often they consume food away from home and provides a list of categories (as large as twice per day to as small as less than once per month). I convert each

[63] 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.

[64] 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.

[65] 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. 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.

[66] For a prime age male (female), recommended energy is 2,200–2,600 (1,800–2,100) Kcal/day.

category into numeric values, and find that individuals on average eat 20 times away from home in a month. This is inconsistent with food intake results that individuals consume about half of their food away from home, which is not surprising given the variable is capped at 60.

Panel E documents daily time spent (per minute) on meal production for individuals aged over 19. The first row shows that on average each adult spend 55 minutes on meal production each day. From the second to fifth rows, I split up meal production into smaller time categories, and find that more than half of the meal production time is dedicated to the actual cooking, which includes activities such as preparing ingredients, storing groceries, cooking, and setting table (Statistics Korea 2009). For shopping time, I use time spent on non-durable shopping to maintain consistency over survey periods, so 9.66 minutes are likely to be an overestimate for grocery shopping. Individuals spend another 49 minutes on average on other home making activities, which include cleaning, laundry, and organizing/sorting. These numbers are consistent with other studies that have used the time use survey to document trends in nonmarket working hours in Korea (Seo et al. 2021). Further, the number of hours spent on home making is comparable to that of the US. For instance, Aguiar and Hurst (2007b) finds that in 2003, an individual in the US spent 118 minutes per day on various home making activities.[67]

A.2 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.[68] 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 A.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.

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

[67] These activities include "core" nonmarket work, which consists of meal production, laundry, indoor household cleaning, and "obtaining goods and services", which include grocery shopping, shopping for other household items, running errands, and buying goods online. They also include corresponding travel times in calculation.

[68] 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.

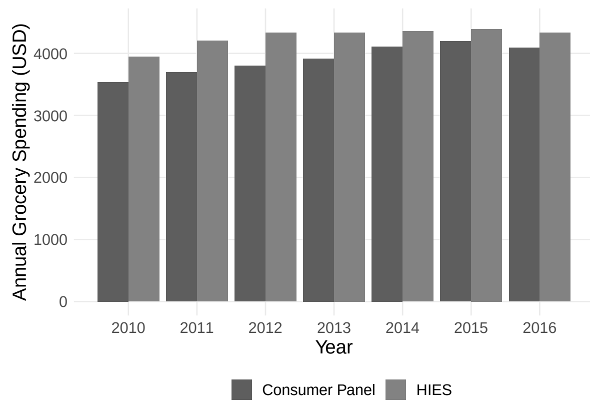
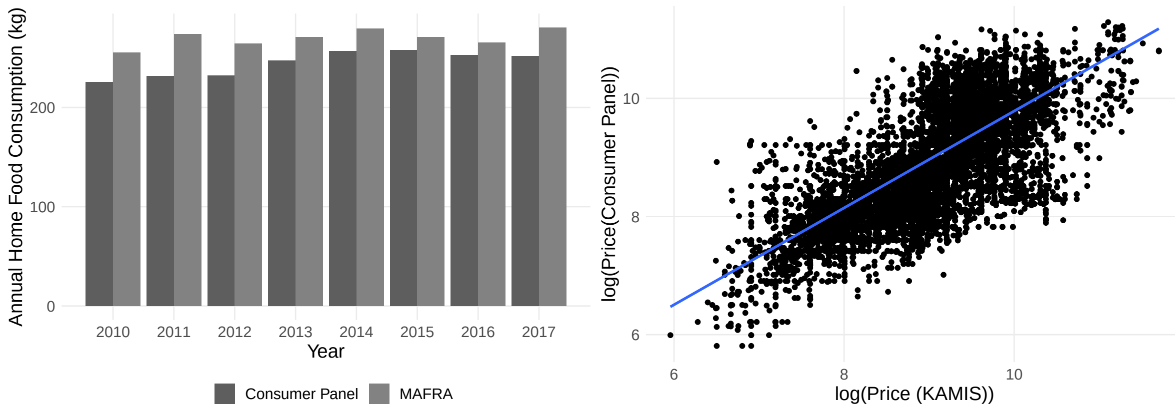


Figure A.1: Consumer Panel Data Validation (Total Expenditure). This figure compares the overall household spending from the comsumer panel data and the Household Income and Expenditure Survey. See the text for additional details.

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, 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 (Purchase Quantity and Unit Price). These figures examine 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	-0.1833***	0.0347
	(0.0596)	(0.1534)
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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table B.2: Food Waste Tax and Food Intake Changes (Other Health and Nutritional Measurements)

	(1)	(2)	(3)
Panel A: Health Outcome and Mineral \& Vitamin Intake			
Food Waste Tax	-0.0105	0.0714	0.0018
	(0.0057)	(0.0647)	(0.0340)
Dependent Variable in Log	Waist Circumference	Vitamin A	Potassium
Year FE	Yes	Yes	Yes
Municipality × Housing Type FE	Yes	Yes	Yes
Observations	11913	11976	11976
Panel B: Other Nutrients Intake			
Food Waste Tax	0.0215	0.0808	0.0090
	(0.0295)	(0.0439)	(0.0284)
Dependent Variable in Log	Protein	Fat	Carbohydrate
Year FE	Yes	Yes	Yes
Municipality × Housing Type FE	Yes	Yes	Yes
Observations	11976	11976	11976

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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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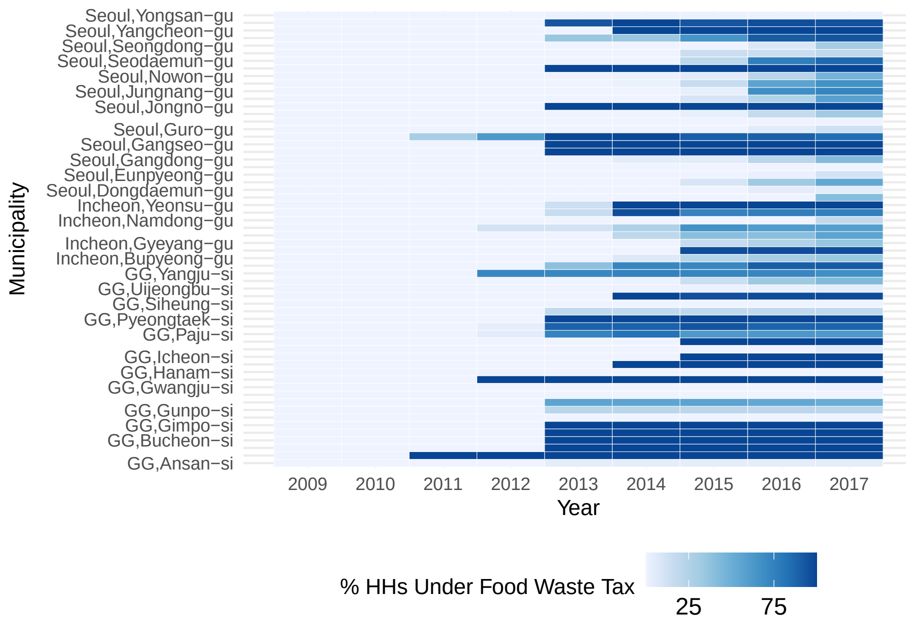
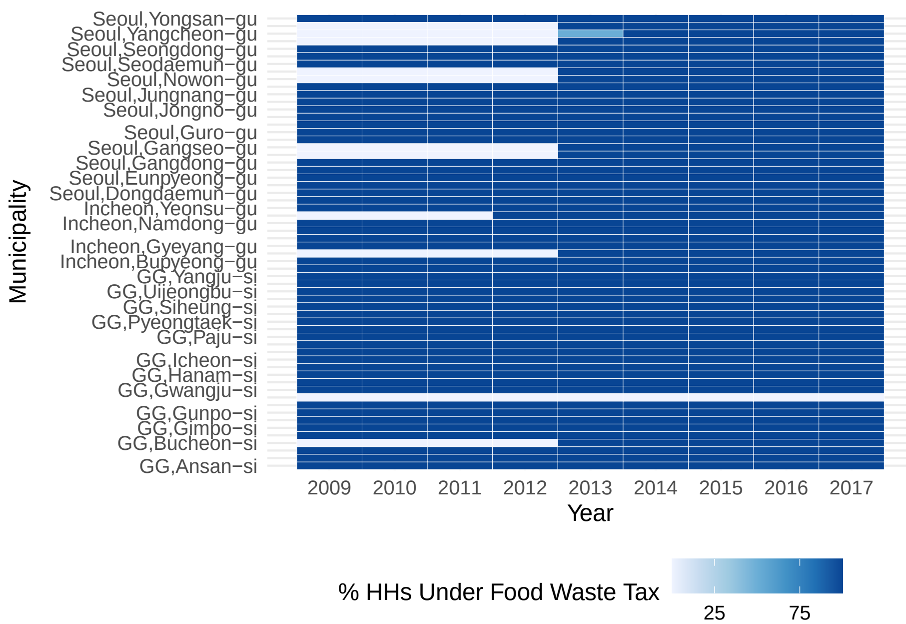


(a) Condominium



(b) Other Housing Types

Figure B.1: 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 (2009-2017) for 60 municipalities in the metropolitan Seoul area.

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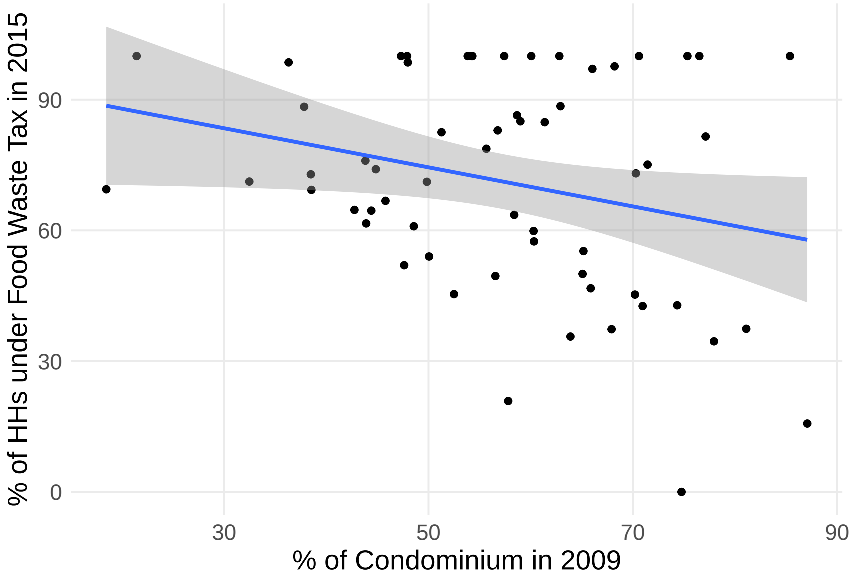

Figure B.2: This figure shows the relationship between the proportion of households living in condos in 2009 and the proportion of households under the tax 2015. Each dot represents a municipality and fitted line is produced using OLS. Grey area represents 95 percent prediction interval. See the text for additional details.

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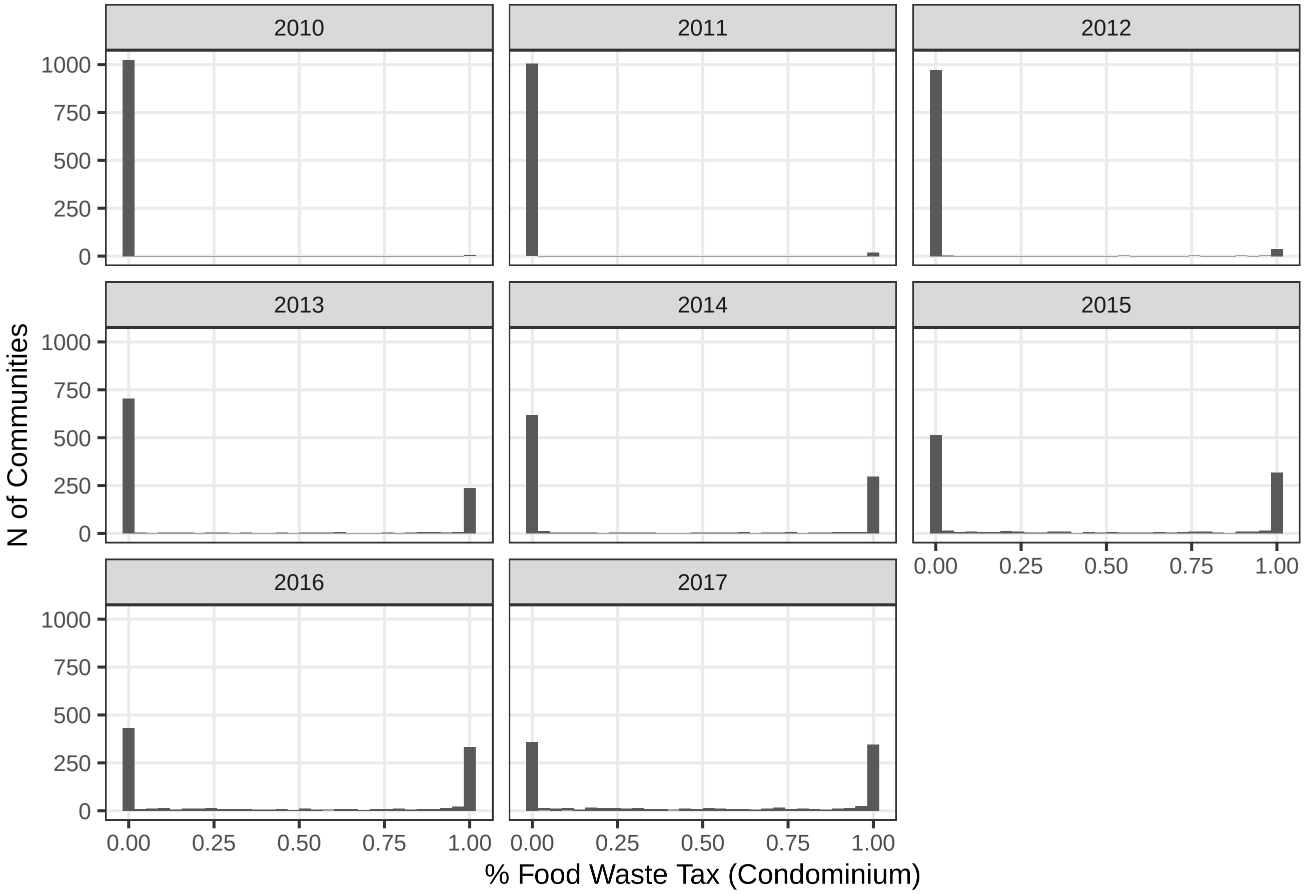

Figure B.3: Distribution of the Fraction of Condominium Residents Under the Tax at the Community Level for 2010-2017. These panels illustrate the distribution of the fraction of condominium residents under the food waste tax at the community (the smallest administrative unit in South Korea) level for years 2010-2017. The data is from 1028 communities within three provinces in the metropolitan Seoul area.

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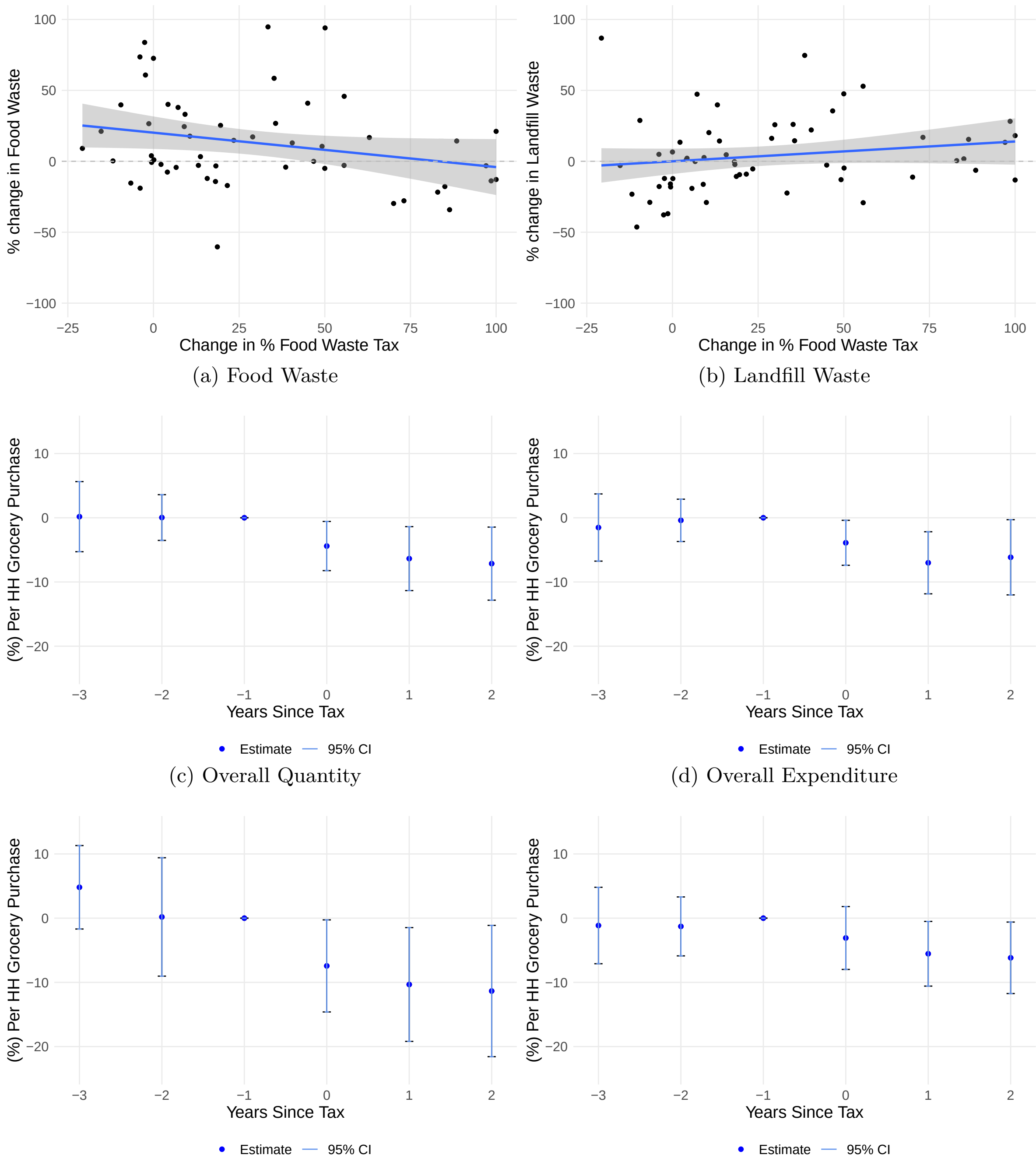

(a) Food Waste (b) Landfill Waste

(c) Overall Quantity (d) Overall Expenditure

(e) Perishable Quantity (f) Storable Quantity

Figure B.4: 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 a municipality and fitted line is produced using OLS. Grey area represents 95 percent prediction interval. Panels (c)-(f) show event study plots from TWFE estimation for the overall grocery quantity, overall grocery spending, perishable purchase quantity, and storable purchase quantity, respectively. All dependent variables are log transformed.

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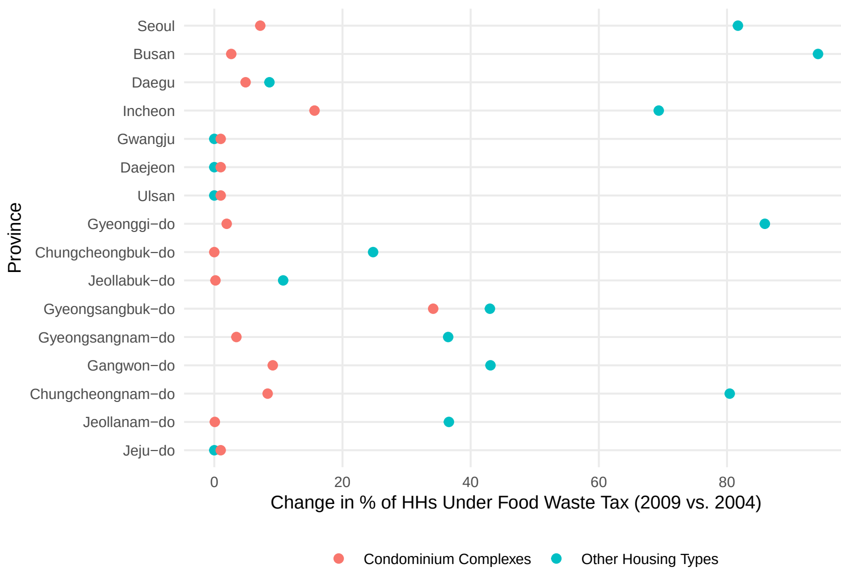
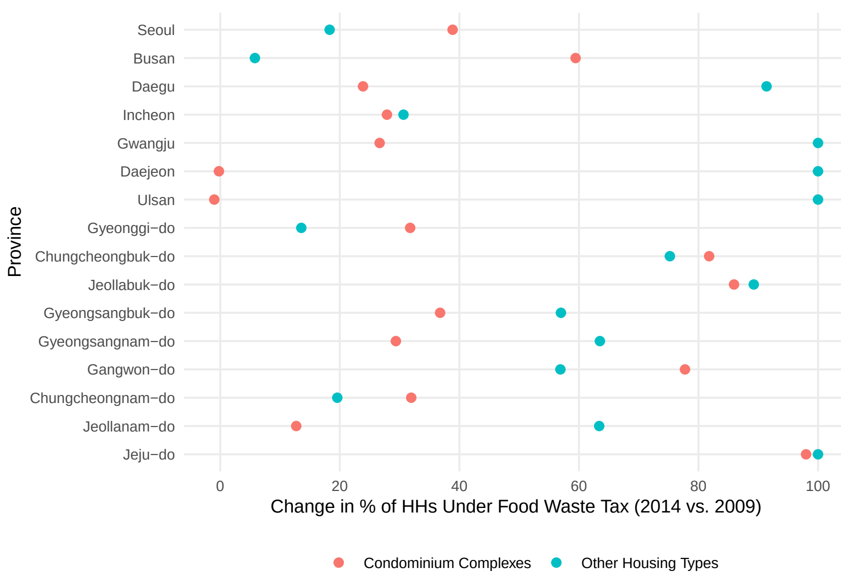


(a) 2004 vs. 2009



(b) 2009 vs. 2014

Figure B.5: Change in the 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 two different housing types. Panel (a) illustrates the change between 2004 and 2009 (the Wave 1 effect) while panel (b) is the change between 2009 and 2014 (the Wave 2 effect).

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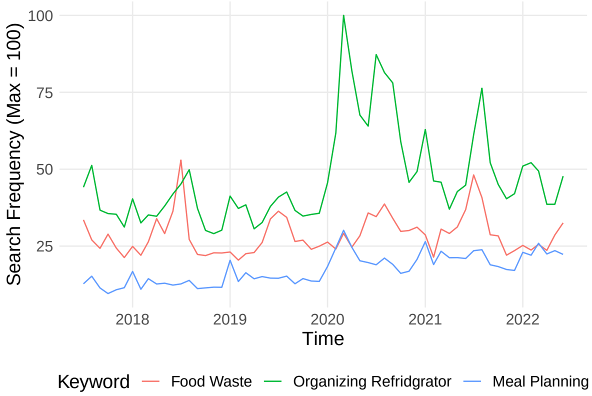
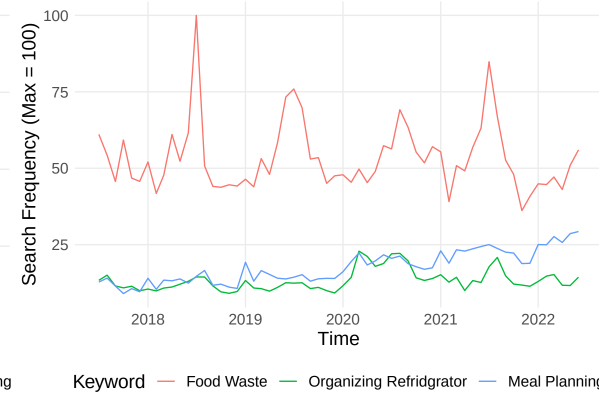
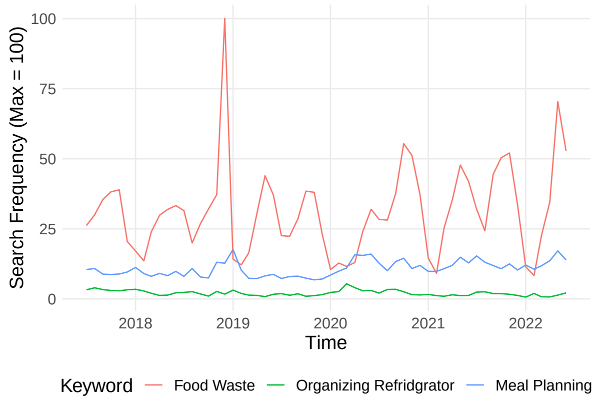


(a) Female Age 30-60



(b) Male Age 30-60



(c) Female Age Below 20

Figure B.6: Trends in Internet Search Keywords. 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 from Naver, a dominant search engine in South Korea. Y-axis has been normalized based on the maximum search intensity over the five years period for each demographic group. Panel (a) is for female age between 30-60, panel (b) is for male age between 30-60, and panel (c) is for female age below 20.

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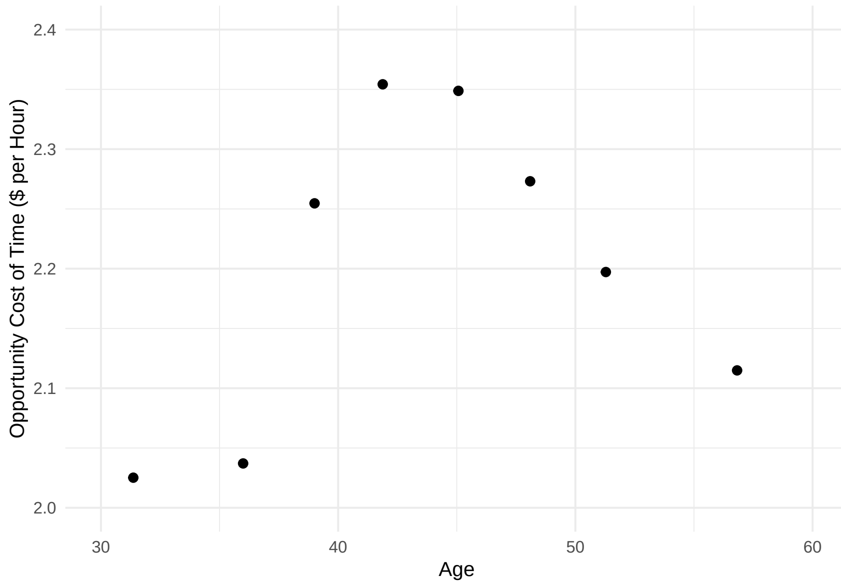
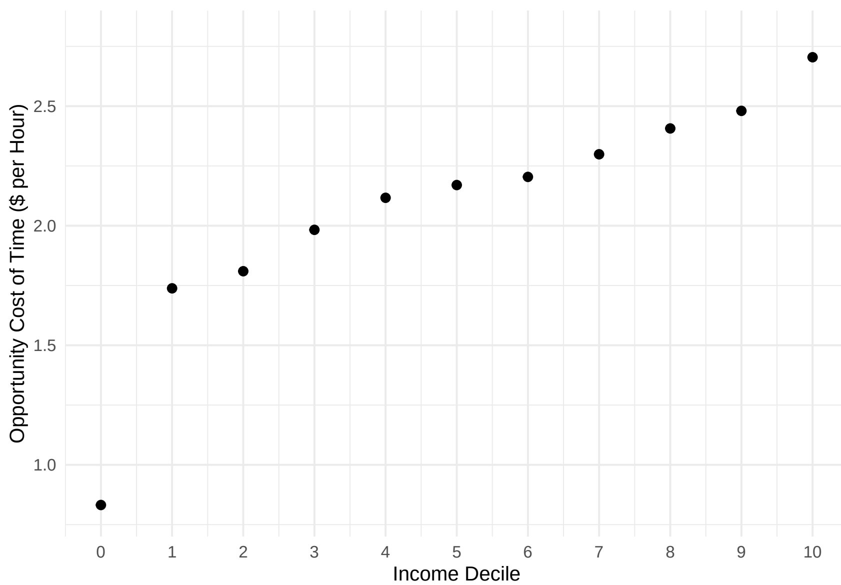


(a) Age and Opportunity Cost of Time



(b) Income and Opportunity Cost of Time

Figure B.7: Opportunity Cost of Time by Demographic Characteristics. These figures show the binscatter plots between opportunity cost of time and age (Panel A) and income level (Panel B) using the grocery panel data. Opportunity cost of time is calculated by multiplying the returns to shopping (elasticity between time and money from shopping) from Aguiar and Hurst (2007a) and average spending per shopping trip

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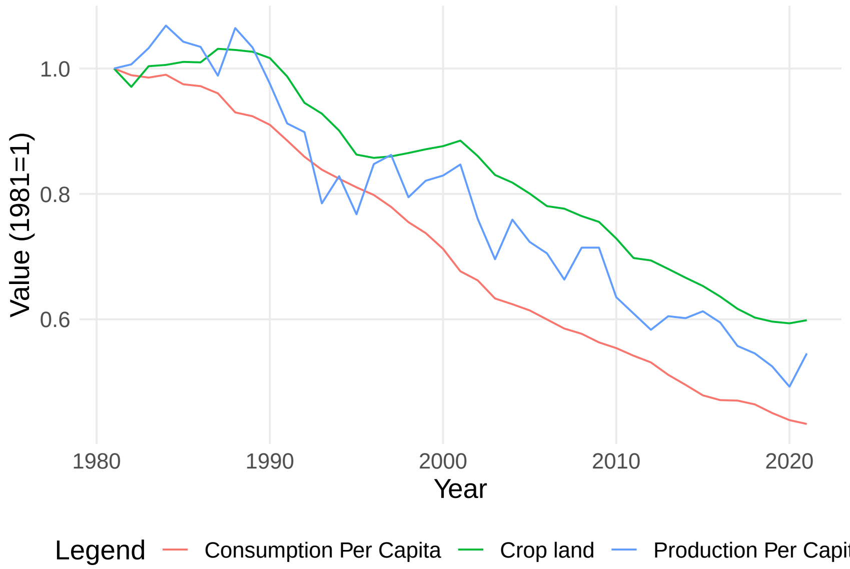

Figure B.8: Rice Production over Time. This figure shows how rice consumption per capita, production per capita, and rice crop land have changed over time in South Korea. Data comes from Statistics Korea. See the text for additional details.

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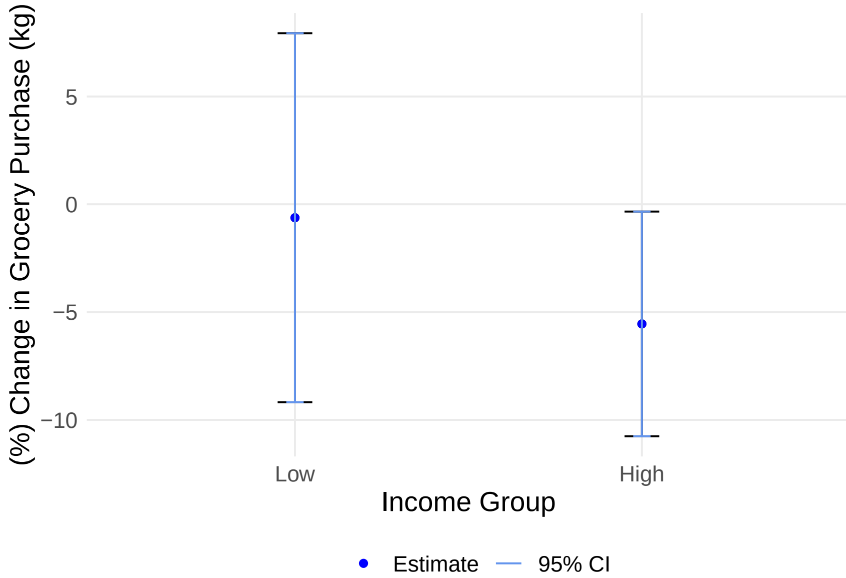

Figure B.9: The Effect of the Tax on Grocery Purchases by Baseline Grocery Quantity. This figure shows how the effect size varies by income group. See the text for additional details.

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