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 climate change mitigation. A textbook solution is levying a corrective tax on food waste, but limited evidence exists on the benefits and costs of such a policy. By exploiting plausibly exogenous expansions in a small food waste tax—on average 6 cents per kg—in South Korea, I report three main findings. First, the tax reduces annual food waste by 20% (53kg) and grocery purchases by 5.4% (46kg), worth $172. These estimates suggest that the avoided GHG emissions is equivalent to that from 595,000 passenger vehicles. Second, building on the household production model, I investigate abatement strategies and find that households increase time spent on meal production by 7% (60 hours), valued at $240. Finally, the tax seems to affect behavior primarily through non-pecuniary channels such as information provision or imposing a moral tax.

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1 Introduction

Globally, one-third of food is discarded, generating greenhouse gases (GHGs) comparable to those from entire road transport throughout its life cycle (Gustavsson et al. 2011, IPCC 2014, FAO 2015).[1] Consumer-end food waste is a particularly dire problem due to its high volume—up to 60% of the total food waste in developed countries—and cumulative environmental impact along the supply chain (Gustavsson et al. 2011, EPA 2021). As such, managing excessive food demand at home became an important climate policy issue (United Nations 2015, IPCC 2018, EPA 2021, OECD 2021).

Theoretically, levying a Pigouvian tax on food waste can achieve socially optimal food waste quantity at the lowest possible cost by making houseohlds internalize the externality (Pigou 1920).[2] However, given that there are multiple abatement strategy options, the welfare effect of such a tax is ambiguous a priori. For instance, while both careful meal planning or illegal dumping can reduce tax burden for households, their implications for the GHG emissions (i.e., benefits) and abatement efforts (i.e., costs) due to the tax can be starkly different.

This paper provides the first empirical evidence on the benefits and costs of a unit-based food waste tax (hereafter "unit tax"), which imposes charges in proportion to the quantity of waste generated. To examine the benefit, I study the impact of the tax on households' food usage and its implications for the life cycle GHG emissions from wasted food. To evaluate the cost, I build on the insights from the household production model (Becker 1965), and estimate how the tax impacts households' meal production time. Further, I also investigate potential mechanisms that rationalizes the effect size of a small tax and discuss whether such a policy is socially desirable.

The empirical application exploits two waves of plausibly exogenous unit tax expansions in South Korea. Since 2005, households have had to separate food waste from landfill waste and pay a small food waste tax. While the majority of households were charged a monthly flat tax, some households, depending on the region and housing type, were charged a unit tax since then (wave 1 expansion). Later, with mounting concerns over food waste driven GHG emissions, the central government mandated local governments to expand the unit tax by 2013 (wave 2 expansion). Importantly, because

[1] Food loss and waste generate 4.4 $GtCO_2eq$, or about 8% of total anthropogenic GHG emissions (FAO 2015). This is comparable to the entire road transport, which generates 5.1$GtCO_2eq$ each year (IPCC 2014).

[2] An alternative policy response is imposing a tax on food based on each food items' carbon intensity. However, taxing on food is one of the least popular policy options (Dechezleprêtre et al. 2022). Further, it might have limited effect in reducing food waste given inelastic food demand. In Section 6, I compare tax on food versus food waste.

the physical infrastructure for unit tax collection can be costly, not all households received the tax treatment at the same time even after the wave 2 expansion, and only 70% of them were paying unit tax in 2017. In tandem with the expansion, the tax rate has also substantially increased over time. But the tax is still small in absolute terms with an average rate of 6 cents for 1 kg or \$1.3 per month for a household with average waste quantity.[3]

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 compare treated (i.e., levied the unit tax) households to not-yet and never treated households using the two-way fixed effect approach.[4] I also show that the results 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). Comparing these effect in levels (46kg vs. 53kg) suggests that 86% of the observed reduction in waste is from the actual reduction (i.e., prevention) and the upper bound of illegal dumping (i.e., displacement) is only 14%. Further, the policy effect is three times larger in magnitude for perishable items (fresh vegetables and fruits) than storable items, which is plausible given that the tax makes perishable items disproportionately more expensive in expectation. Importantly, these effects do not come at the cost of households' nutritional needs: the tax has a null effect on food intake and nutrition, suggesting that the reduction in grocery purchases comes from the previously wasted—rather than consumed—part of the food basket.

The estimated changes in food usage imply that the tax reduces annual GHG emissions from wasted food by 138kg CO_2eq per household, or 2.7 million ton of CO_2eq nationally, which is comparable to the emissions from 595 thousand passenger vehicles. Furthermore, the tax produces a private benefit by encouraging households to reduce their expenditure on groceries, resulting in a savings of \$172 per year. This assists households in offsetting potential abatement costs.

[3] In this paper, the exchange rate is \$1 = KRW1100. Also, to put the tax size in context, \$1.3 is 0.4% of monthly grocery spending for an average household in the sample.

[4] Due to data limitations, I rely on aggregated data for the analyses on food waste quantity and time use. In these cases, I compare geographic units with different treatment intensities over time.

I next explore household abatement strategies, namely how households maintain food intake with 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 whether the tax affects (1) the time spent on meal production, (2) grocery input quality, or (3) productivity. I find that using more time is the primary abatement strategy: households spend 7% more time (60 additional hours per year) on meal production after the tax, valued at $240 per year.[5] Further, web search data suggests that better organizing food is an important way households trade grocery inputs with time. 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 social benefit by reducing GHGs, but incurs substantial abatement costs. Importantly, over 70% of these costs are offset with savings on the grocery bills.

Lastly, I explore the mechanism to rationalize household responses to the unit tax and discuss policy implications. To elucidate the disproportionately large impact of a small tax, I first show that the non-pecuniary effect accounts for over 90% of the estimated tax effects under a range of plausible substitution elasticity estimates from earlier studies (Aguiar et al. 2012). Further, by extending a household production model to allow disutility from food waste generation and limited awareness, I show that utility maximizing households can choose to allocate time on meal production beyond cost savings on groceries in response to the unit tax. Then, I evaluate the policy based on the cost-effectiveness metric and find that the program cost of reducing one ton of CO_2 is as low as $13, or even negative when savings on governments' waste pickup and treatment spending is considered.[6]

Related literature. This paper contributes to four different bodies of literature. First, I contribute to the studies exploring the effects of environmental regulation on household or consumer behavior. While this literature typically focuses on the efficacy (or lack of) of policies (Castledine et al. 2014, Li et al. 2014, Rivers and Schaufele 2015, Berck et al. 2016, Wichman et al. 2016, Homonoff 2018, Andersson 2019, Taylor 2019), or their abatement costs (Buck et al. 2016, Taylor 2020), I estimate both of them, which are key pillars of a welfare analysis. To that regard, perhaps the closest paper

[5]To express the time cost in monetary terms, I follow prior 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).

[6]I abstract away from a complete welfare analysis because pinpointing the exact source of non-pecuniary effect (i.e., moral tax versus information provision effects) is beyond the scope of this paper. As I discuss in Section 6.2, the tax exhibits contrasting impacts on consumer welfare depending on the origin of non-pecuniary effects.

conceptually is Davis (2008), which estimates the impact of driving ban on air quality—benefits—and additional vehicle purchases—avoidance costs. In addition to the differences in the empirical setting (ban vs. tax ; transportation vs. food waste; Mexico vs. South Korea), this paper complements Davis (2008) by presenting a framework to estimate non-monetary abatement costs (i.e., household efforts) of environmental regulation.[7] This has important practical implications given rising attention to the climate policies targeted at households (OECD 2011, Creutzig et al. 2018, IPCC 2022).

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, which is particularly relevant 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). The findings of this paper suggest that tackling consumer-driven food waste can be a highly cost-effective and potentially welfare-enhancing mitigation option.

Third, this paper extends earlier studies on waste policies in two 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 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 the upstream effect 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).[8] 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.[9] These two differences could explain why earlier works in general find waste pricing policies welfare-harming.

Lastly, this paper provides the first large-scale revealed preference-based empirical evidence on the

[7]Estimating household compliance costs to environmental regulations has been challenging. For instance, Pizer and Kopp (2005) reads, "the overwhelming focal point of the literature to date has been measurement of the direct compliance cost to firms. It is hard to identify, let alone measure, the technology for pollution control activities and the immediate cost to households of environmental regulations (p.1311)."

[8]Food is the largest (44%) waste category globally in municipal solid waste so considering upstream effect is important even if we consider food waste as a component of solid waste (Kaza et al. 2018).

[9]For instance, Repetto et al. (1992) estimates that the social cost of waste is \$5/ton due to "air and water pollution, noise, and other disamenities". However, when GHG emissions from landfill is considered, the social cost of waste is at least \$55.5/ton at \$51/ton of the social cost of carbon (EPA 2016, IWG 2021).

effect of a food waste policy. Despite heightened policy attention on food waste reduction measures in recent years, food waste studies have been largely theoretical (Hojgard et al. 2013, Katare et al. 2017, Lusk and Ellison 2017, Hamilton and Richards 2019). Existing empirical works either focus on a measurement problem (Yu and Jaenicke 2020, Smith and Landry 2021) or evaluate reduction measures based on stated preferences or smaller samples (Qi and Roe 2017, Katare et al. 2019).

The rest of the paper proceeds as follows. Section 2 provides background on the GHG emissions from food waste and the food waste 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 greenhouse gas (GHG) emissions from wasted food, encompassing both farm-to-kitchen and waste treatment stages, are estimated at 4.4 $GtCO_2eq$, constituting 8% of total anthropogenic GHG emissions (FAO 2015).[10]. This is comparable to the annual emissions from the entire road transport sector, which amounts to 5.1 $GtCO_2eq$ each year (IPCC 2014). Two primary factors contribute to such substantial GHG emissions from wasted food.

First, food production—the farm-to-kitchen stage—is among the most carbon-intensive activities, accounting for 16-27% of total GHG emissions (IPCC 2014, 2019).[11] When food is discarded, the embodied GHG throughout the supply chain is also discarded, and this "emissions in vain" explains 90% of the life cycle GHGs from food waste (Crippa et al. 2021). Second, food waste generates large amounts of methane when it decays in landfill sites. As such, emissions from solid waste disposal and treatment account for 5% of the total global GHG emissions, and landfill is the third largest methane source in the US despite widely adopted methane-to-energy facilities (EPA 2016, Kaza et al. 2018).

Consequently, reducing food waste has gained substantial attention in policy circles.[12] In partic-

[10]Wasted food has broader environmental challenges, including biodiversity losses, soil degradation, and water depletion (EPA 2021). Hence, the GHG cost represents a conservative estimate of the total social cost of wasted food.

[11]Major contributors include agricultural land expansion through deforestation, anaerobic decomposition from rice cultivation, enteric fermentation from ruminant livestock, and nitrogen fertilizer (Springmann et al. 2018, IPCC 2019).

[12]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). In the US, EPA and USDA adopted the target of cutting food waste at the retail and consumer level by 50% by 2030 (USDA and EPA 2021).

ular, policymakers oftentimes emphasize the importance of prevention (as illustrated by the EPA's food recovery hierarchy in Appendix Figure E.1), but prevailing policies in practice focus on recycling already generated wasted food (National Academies of Sciences, Engineering, and Medicine 2020).[13] This is unfortunate because the farm-to-kitchen stage is responsible for 90% of the life cycle emissions from wasted food. A corrective tax on food waste can be a powerful alternative because it has potential for waste prevention through discouraging households' excessive food purchases.

2.2 Waste Policy Changes in South Korea

Wave 0 (1995-2004): unit-based tax on landfill waste. From 1970 to 1990, waste quantity increased by over sevenfold, leading to capacity constraints in landfill space and the collection and processing infrastructure.[14] In response, in 1995, a national landfill tax was implemented. 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. With mounting environmental concerns over food waste in landfill, the Ministry of Environment mandated municipalities to collect food waste separately and recycle it.[15] Also, to recover the cost of service provision, municipalities were allowed to charge a food waste tax on households. Because the Wave 1 policy focused on *segregation* rather than *reduction*, the collection system was strategically designed to minimize operational costs. As such, for a typical municipality, food waste from condominium complexes were collected without measurement and residents were charged a flat tax ($1-2 per month). The collection methods for non-condo residents were more split: some municipalities charged flat fees while others required households to purchase official food waste bags (Figure 2.1 (a)) because it was most compatible with their existing infrastructure (Kim et al. 2010).

Importantly, households under the trash bag regime faced non-zero marginal tax rate (at maxi-

[13] Examples are encouraging donation, composting, or energy recovery.

[14] 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.

[15] After collection, food waste is converted into compost or animal feeds.

mum 1 cents/kg over the Wave 1 period) even before the Wave 2 expansion in 2013. As of 2009, 11% (50%) of municipalities in the country charged a unit tax on condominium (non-condominium) residents (Kim et al. 2010), and this variation is used to identify the policy effect on household abatement efforts (more details in Section 5.2).

Wave 2 (2013-): Nation-wide expansion of the unit based food waste tax. Given the limitation of flat tax for food waste reduction, the central government required municipalities to expand the unit tax by 2013. Figure 2.2 (a) plots the average fraction of households under the unit tax over time for 60 municipalities in the metropolitan Seoul area, which consists of three provinces (Seoul, Incheon, Gyeonggi-do).[16] As the bar graph shows, the fraction has been stable at around 30% between 2009 and 2012. The ratio is not zero over this period because, as discussed earlier, some households were required to use the official trash bag during the Wave 1 period. The fraction goes up sharply to 72% in 2017, where the most dramatic change happens in 2013. The expansion happened under two different collection regimes: typically, non-condo residents were required to use the official trash bag while condominium residents were required to use the smart card system (Figure E.7 (b)).[17]

Importantly, because the smart card system is costly (about $2,000 per kiosk), not all the households received the unit tax treatment at the same time. As such, about 30% of households did not get the treatment even in 2017, and these never-treated households form an important part of the control group in subsequent empirical exercises.

In tandem with the extensive margin unit tax expansion, municipalities have substantially increased the tax rate over time. Figure 2.2 (b) shows that there has been an eight fold increase in the tax rate over the same period. However, the tax is still very small: a household with average waste quantity would pay $1.3 per month as a waste tax, which is about 0.5% of the corresponding grocery spending. As the tax is small, the tax revenue cannot cover the waste pickup and treatment service budget, and thus each municipality spends substantial amount of budget to provide these services.[18]

Outside Disposal Options. Earlier studies have documented that waste tax policies are prone to be-

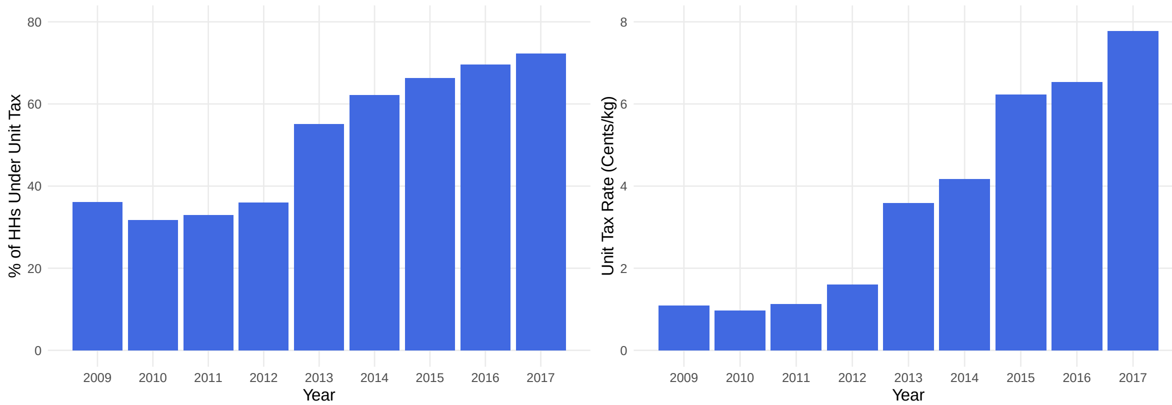
[16] I show policy change from the metropolitan Seoul area because empirical exercises on food usage, which exploits the Wave 2 expansion, focuses on this region due to data limitation.

[17] To make two units (i.e., volume for bags and weight for smart card systems) comparable, I convert volume to weight using a conversion ratio of 0.75kg/liter from an executive order of the Ministry of Environment ("2015-164").

[18] For instance, the City of Seoul 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)).

(a) Official Trash Bags
(b) Smart Card System

Figure 2.1: Unit Based Food Waste Tax Collection Methods



(a) Average % of Households under the Unit Tax
(b) Average Tax Rate

Figure 2.2: Wave 2 Expansion. Panel (a) and (b) show the fraction 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.

havioral 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, discarding 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.[19] Knowing this, many municipalities conduct landfill waste bag audits to

[19] Data can be accessed at https://www.recycling-info.or.kr/rrs/stat/envStatList.do?menuNo=M13020302 (Last

levy fines which can be as large as $100. It is also worth noting that, in addition to the direct measurement based on landfill waste, I also derives an upper bound of illegal dumping by comparing the observed reduction in food waste quantity and grocery purchase changes after the tax.

3 Data

I compile multiple data sets on households' food and time usage. In this section, I describe each data source and provide descriptive statistics.

3.1 Data Description

Waste quantity and tax policy. I use the Unit-Based Waste Policy Yearbook from the Ministry of Environment to measure the waste quantity and to track unit tax policy changes. Each year, municipalities are required to report detailed information on various aspects of their waste management including the amount of food and landfill waste quantity, tax rate, tax regime (flat vs. unit tax), waste collection methods, and government spending for waste service provision. 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. Thus, I convert one restaurant to 10 households based on a conversion factor from Kim et al. (2010) and use per household waste quantity variable for empirical exercises. The analyses leverage information on 60 municipalities in metropolitan Seoul area, which coincides with the geographic coverage of the grocery purchase data, from 2009 to 2015.[20] To track the unit tax policy change, I cross reference historic ordinances.[21] Information on policy changes during the Wave 1 period, which predates the Unit-Based Waste Policy Yearbook, comes from a commissioned study from the Ministry of Environment. This study surveyed food waste tax status as of 2009 for all municipalities in the country (Kim et al. 2010).

Grocery purchase. To study the impact of unit tax on food purchase behavior, I use the consumer grocery panel data from the Rural Development Administration. The survey starts in 2010 and has

accessed on Nov 18, 2021).

[20]The dataset starts in 2009 and is replaced by another dataset in 2016, resulting in a discontinuity in the time series. Consequently, data from the year 2016 onward cannot be employed for the analysis.

[21]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.

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 unit tax status for each household using street address information. Having a detailed address is particularly useful in this setting because unlike non-condominium residents, whose unit tax status vary at the municipality level, the unit tax status for condominium residents usually vary 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.[22] The data also documents expenditure from restaurants, but school lunches or cafeteria purchases are excluded.

Food intake and nutrition. To understand the impact of the tax on food consumption at home, 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. While the survey has three main components: health interview, health examination and nutrition survey, I focus on the nutrition survey, which documents food consumption—both at and away from home—based on a 24-hour dietary recall face-to-face interview. The data also contains nutrition content for each food item consumed by applying a standardized formula developed by the agency. I also supplement nutrition survey with health examination results (e.g., weight or BMI) to address potential subjectivity from survey responses. 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 for condominium residents, I assign a binary tax status using community, time, and housing type information.

[22] 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.

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.[23] 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 leveraging the Wave 2 expansion difficult because finding a clean control group is difficult. That is, within each province, some, if not every, municipalities are treated after 2013, and thus finding a province without unit tax is not possible. Therefore I take advantage of the Wave 1 and assign the unit tax status at the province-housing type level. Also, to increase power, I use all 16 provinces rather than focusing on three provinces in the Seoul metropolitan area.

Municipality characteristics. I use Census on establishments, regional statistics (from the Statistics Office) and Statistics Yearbook from local governments to collect various municipality characteristics. These variables, which are closely related with waste generating behavior, include number of restaurants, condominium, and non-condominium households, education level, and fraction of single-person household for each year and municipality.

3.2 Summary Statistics

In Table 3.1, I provide summary statistics for key variables for the empirical analysis (more detailed discussion with additional variables can be found in Data Appendix A.1). To contextualize different variables on food usage, I express everything in terms of per year per household except for the meal production time and calorie intake which are easier to digest in per daily per capita. A few points are worth noting. First, the first three rows show that 30.7% of the purchased food is discarded and food waste accounts for 48% of the overall (food and landfill) waste quantity. These patterns are consistent with experiences from other countries (FAO 2013, Kaza et al. 2018).

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

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 CO_2eq)	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 Usage (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

Second, the farm-to-kitchen GHG emissions from an average food basket (837 kg) are 2,823kg CO_2eq, which is calculated by I multiplying food-item specific GHG intensity from Poore and Nemecek (2018) to food item specific purchase quantity.[24] To put this quantity in perspective, 2,823 CO_2eq 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.[25] Alternatively, 2,823kg CO_2eq suggests that the social cost of 1kg of food is at least 17-63 cents (IWG 2021, Rennert et al. 2022), which implies that the unit tax rate is only at about 13–47% of the external cost.[26]

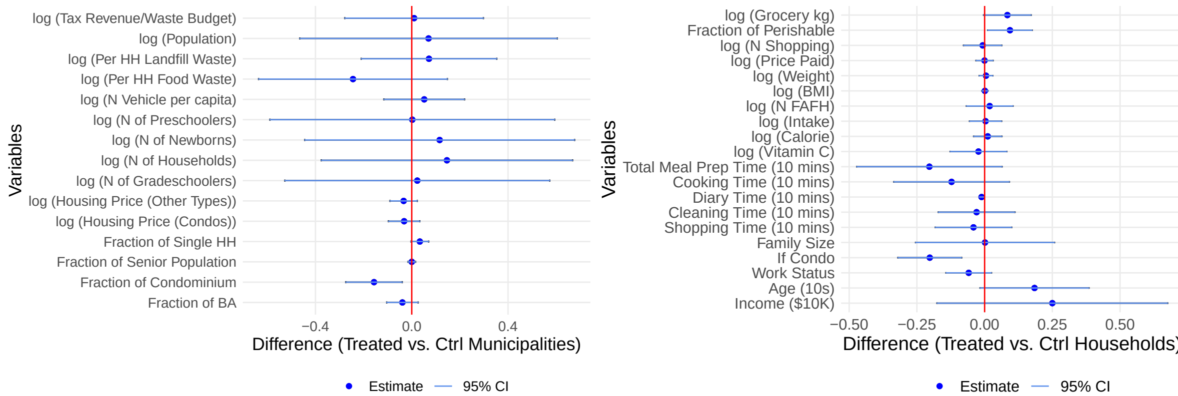
Third, the data on food intake indicates that, on average, an individual consumes 960 Kcal per day from food consumed at home. Because food waste is the difference between purchase (837 kg) and intake (631 kg), the implied waste quantity accounts for 25% of the purchases. This is slightly lower than 30.7% from a direct comparison of waste and purchase quantity, but the difference is small enough to suggests that three different datasets on food purchase, waste, and intake effectively capture average food use patterns of Korean households. Finally, on average an adult spend 55 minutes on meal production, which is consistent with findings from other studies (Seo et al. 2021).

Balance plot. In Figure 3.1, I show various balance test results to investigate if there are baseline

[24] Poore and Nemecek (2018) estimate the distribution of farm-to-kitchen GHG emissions for the 40 food items. Practically, I take the median GHG intensity for each item. Also, when an item is not in the list, I match it to the closest item on the list.

[25] 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.

[26] 17-63 cents is a lower bound because food waste creates negative environmental impacts beyond GHG emissions.



(a) High vs. Low Expansion Municipalities

(b) 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 for observed characteristics in 2009. Control municipalities consists of bottom 10 percent municipalities in terms of the fraction of households subject to the unit 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.

differences between the treated and control observations. In Panel (a), I compare differences at the municipality level using the waste data. Here, the control group consists of bottom 10% municipalities in terms of the % of households subject to the unit tax in 2015, while the treated group has the rest of 54 municipalities.[27] I show that the treated and control municipalities are highly comparable in various observed characteristics in 2009, which is the first year in the waste quantity sample. 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 fiscal condition are highly similar to each other. One important exception is the proportion of condominium residents. It is substantially lower for the treated municipalities, and this is not surprising given that many non-condo residents were required to use trash bags before 2009.

In panel (b), I compare ever versus never treated households or individuals for various food and time usage and demographic variables in the pre-treatment 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,

[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.

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.

While the baseline characteristics seem similar between the two groups, one might still worry that households might differ in unobserved characteristics by housing type, and thus have different potential outcome trajectories. I address these concerns in various ways in following sections.

4 Effect of the Tax on Food Usage

In this section, I 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 the Wave 2 unit tax expansion to causally identify the effect of the tax on household food usage. The baseline two-way fixed effect model is in equation (1). Importantly, I remove always-treated and non-absorbing households to minimize potential contamination of the control group, building on the insights from the recent literature on two way fixed effects models (Baker et al. 2021, Goodman-Bacon 2021).

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

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 unit 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 unit tax on grocery purchases.

The key identifying assumption is that in the absence of the unit tax, grocery purchases of treated and control households have parallel trends. While similarities in baseline characteristics (Figure 3.1) support this assumption, one might still worry that unobserved characteristics might be different by housing type, a key predictor for the unit tax status. I address this concern in three ways.

First, I test potential pre-trend using a dynamic version of equation (1).[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 2021, Borusyak et al. 2022). Third, as a robustness check, I repeat the analysis with housing type by year fixed effects to account for unobserved heterogeneity of households by housing type.

To understand the impact of the tax on food intake and nutritional content, I estimate a variant of equation (1): $log(M_{ihcmt}) = \beta T_{hcmt} + \delta \mathbf{X}_{ihcmt} + \lambda_{hm} + \omega_t + \epsilon_{ihcmt}$ 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} is 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, because how much food to eventually consume is an individual decision, i indicates an individual rather than a household. $\mathbf{X}_{ihcmt}$ is 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, as the data is repeated cross section, I add municipality by housing type fixed effect (λ_{hm}) instead of the household by municipality fixed effect in equation (1). 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 E.5). 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 with the fraction between 25–75% to minimize the measurement error. In the estimation process, I weight the regression using sample weights.

[29] More specifically, I estimate $log(Q_{imt}) = \sum_{k=-4}^{3} \alpha^k Tax^k_{imt} + \boldsymbol{X_{imt}}\delta + \lambda_{im} + \omega_t + \epsilon_{it}$ where Tax^k_{it} takes 1 when a household is under the tax in event year $k = t - d$ where d is the policy change year. Because the sample is unbalanced in event time, coefficients near the endpoint give unequal weight to households that experienced the unit tax early or late in the sample. For this reason, I impose endpoint restrictions such that $\alpha^k = \underline{\alpha}$ for $k < -4$ and $\alpha^k = \bar{\alpha}$ for $k > 3$.

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.

$$log(W_{mt}) = \beta(\%)Tax_{mt} + \boldsymbol{X_{mt}}\delta + \theta_m + \tau_t + \epsilon_{mt} \tag{2}$$

In equation (2), W_{mt} denotes per household food waste quantity for municipality m in year t. $(\%)Tax_{mt}$ is the fraction of households subject to the unit tax.[30] $\boldsymbol{X_{mt}}$ 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 (2) 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 the unit tax on waste quantities. I first report the effect of the unit tax on food waste quantity. In column (1), I regress $(\%)Tax_{mt}$ on the log of food waste quantity per household. 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 unit tax changes from 0 to 100%, food waste per household decreases by 19.3% ($e^{-0.214} - 1 = -0.193$) or 53kg when evaluated at the average quantity in the pre treatment period (268kg).[31] In Appendix Table E.1 column (1), I report

[30] As discussed in section 3.2, W_{mt} captures waste quantity from both households and small restaurants. To address this, I convert small restaurants into households by using a conversion ratio of 10 from 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, restaurants}. z_{mkt} is share of k in each municipality.

[31] 268kg is the average waste quantity per household in the 2009-2012 period from the municipalities with bottom 10% $(\%)Tax_{m,2015}$.

Table 4.1: Effect of the Unit Tax on Household Food Usage

	(1)	(2)	(3)	(4)	(5)
Panel A: Food and Landfill Waste Generation					
(%) Unit Tax	-0.2140***	0.0740			
	(0.0590)	(0.0576)			
Dependent Variable in Log	Food Waste Per HH	Landfill Waste Per HH			
In Level	–53kg	19kg			
Municipality FE	Yes	Yes			
Year FE	Yes	Yes			
Observations	420	420			
Panel B: Food Purchases and GHG Emissions					
Unit Tax	-0.0547***	-0.0443**	-0.1064***	-0.0326	-0.0495*
	(0.0190)	(0.0195)	(0.0331)	(0.0239)	(0.0258)
Dependent Variable in Log	Kg Per HH	Spending Per HH	Perishable kg Per HH	Storable kg Per HH	GHGs Per HH
In Level	–46kg	–$172	–32kg	–17kg	–138kg
HH ID $\times$ Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,880	2,880	2,880	2,880	2,880
Panel C: Food Intake, Nutrition, and Health Outcomes					
Unit 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
Housing Type $\times$ Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	11976	11976	11976	11950	11915

Note:
This table reports the effect of the unit tax on household waste generation (Panel A), food purchases (Panel B), and food intake (Panel C). Panel A shows the estimation results for equation (2) using municipality by year level food and landfill waste data. Panel B shows the estimation results for equation (1) using household level grocery panel data. Panel C shows the estimation results for a variant of equation (1) using individual level food intake data. I only report coefficients for the unit tax term, but the baseline control variables are included. All outcome variables are in log scale. All standard errors are clustered at the municipality level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the result from the stacked DD approach. The effect size is similar at 17.5% ($e^{-0.192} - 1 = -0.175$). A disproportionately large effect of a small unit tax on food waste quantity is consistent with findings from a companion paper (Lee and Seo 2022).[32]

In column (2), I show the impact of the unit tax on landfill waste quantity per household, which proxies illegal dumping behavior. The estimated effect 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 E.1, I report that the effect size is statistically insignificant 5.2%, which is over 30% smaller than Table 4.1 column (2).

Figure E.6 presents graphical illustrations of columns (1)-(2). Recall that the identification exploits the plausibly exogenous change in the fraction of households under the unit tax. In each panel, the horizontal axis represents $(\%)Tax_{m,2015} - (\%)Tax_{m,2009}$ and the vertical axis shows the corresponding change in per household waste quantity. Dots, which represent each municipality, are evenly spread out over the x-axis, indicating that there is substantial variation in the unit tax exposure change across different municipalities.[33] The fitted line in panel (a) shows that the reduction in the food waste quantity is larger when the change in the food waste tax ratio is bigger whereas panel (b) illustrates the opposite effect for the landfill waste. Also observe that the slope of the fitted line is much steeper in panel (a), reflecting the larger coefficient (in absolute terms) of column (1) over column (2) in Table 4.1.

Effect of the unit tax on grocery purchases. To explore the source of observed food waste reduction, I turn to the impact of the unit tax on grocery purchases. Column (3) of Table 4.1 Panel A shows that the implementation of unit tax reduces food purchase per households 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 (i.e., prevention) rather than displacement. Conversely, the upper bound of illegal dumping is 14% of the observed reduction in food waste. 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.

[32]Lee and Seo (2022) focuses on the unit tax expansion via a smart card system. Using monthly billing data from Gwangju Metropolitan city, Lee and Seo (2022) reports a 32% reduction in food waste quantity due to the treatment.

[33]Note, $(\%)Tax_{m,2015} - (\%)Tax_{m,2009} < 0$ for some municipalities. This can happens when a municipality experiences a large scale urban renewal that converts a large number of multi dwelling units to condominium complexes.

Similarly, in column (4), I find a 4.4% reduction in grocery spending from the unit tax, which amounts to $172 savings on annual grocery bill for an average household. This finding suggests that the tax generates a private financial benefit, which helps households 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 values. Finding a similar effect using expenditure, which does not have the measurement issue, adds credibility to the estimates in quantity. The reduction in grocery purchases after the tax treatment is consistent with external survey results. For instance, Ministry of Environment (2012) finds that 62% of surveyed households reported a reduction in their grocery spending after the unit tax.[34]

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. If adjustment in food purchases is driven by the unit tax, the policy effect should be larger for perishable items, which are more likely to become food waste when not consumed in time. Indeed, I find that the point estimate is over three times larger (in magnitude) for the perishable items.

In Figure 4.1 presents the event study figures and illustrates that the results are in line with the parallel trends assumption: irrespective of the method used, the coefficients on the years prior to the unit tax treatment are all close to zero without showing discernible pretrends. Figure 4.1 also sheds light the treatment effect dynamics: all the estimated coefficients show persistent treatment effects in the post periods. In Figure E.6 (c)-(f), I plot β^k from TWFE event study 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.

Effect of the unit tax on food intake and nutrition. Understanding the impact of the unit tax on food intake is important for at least two reasons. First, it helps to further pin down the source of observed reduction in food waste. That is, I can test if the 14% of observed food waste reduction—the part not explained by reduction in grocery purchases—is attributable to higher food intake. Second, given the change in the size and composition of the food basket (i.e., grocery purchases), there might be health implications, which might affect the welfare calculation.

In Table 4.1 Panel C, I report the impact of the unit tax on food intake and nutritional conse-

[34] Reported reduction in grocery purchases is less than 5%, 5–10%, over 10% for 31%, 21%, and 10% of respondents. 38% reported no change.

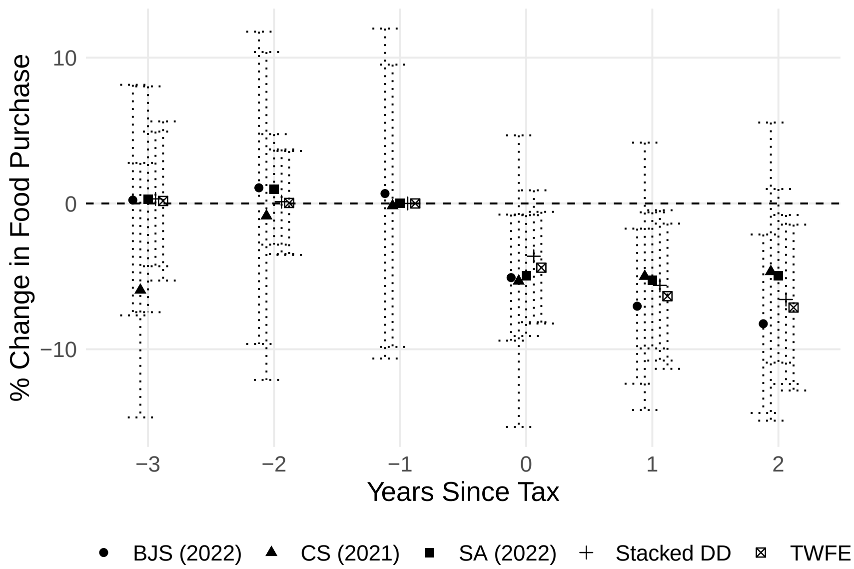


Figure 4.1: The Effect of the Food Waste Tax on Grocery Purchases. This figure overlays event study style plots estimated from five different methods: a dynamic TWFE model, a stacked difference-in-difference model a la Cengiz et al., (2019), Sun and Abraham (2021) estimator, Callaway and SantAnna (2021) 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.

quences. In column (1), the point estimate suggests a statistically insignificant null effect of the unit tax on overall intake quantity (0.35%). Consistent with this, column (2) indicates that calorie intake do not change after the tax. Further, given that the tax's impact on grocery purchases is driven by a reduction in perishable items, there is concern about potential health implications. In column (3), however, I do not find evidence for a statistically significant reduction in vitamin intake.

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 intake, I do not find evidence of significant changes on weight or BMI after the tax.[35] In Appendix Table E.2, I present results for a wider range of nutritional measures and find that the results are consistent with Table 4.1. Taken together, households do not seem to reduce the amount of food they consume (namely, they eat the same amount of food). Instead, the reduction in grocery purchases seems to come mostly from previously wasted part of the food basket. Little change in food intake from a small unit tax is plausible given widely documented persistence of food habits (Atkin 2016).

[35] The number of observations in columns (4) and (5) are slightly smaller than (1)-(3) because not everyone in the food intake survey participated in the health examination, which requires a separate trip to an examination center.

The discussion so far suggests that the tax is beneficial for both government—GHG reductions—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).

$$M = AF(Q, T) \tag{3}$$

Consider a simple meal production process as equation (3), where meal at home is produced by combining raw food input (Q), namely grocery, and time (T). This household aims to minimize the cost of production by choosing an optimal input mix. Suppose that before the tax, household was producing M_0 by combining Q_0 and T_0. Suppose that the corresponding productivity was A_0. Further posit that after the tax τ is imposed on food waste, household produces at $M_1 = A_1F(Q_1, T_1)$.

From Section 4.2, I find that $Q_0 > Q_1 = 0.95Q_0$ while $M_1 = M_0$, and the model provides three potential explanations for this empirical finding. First, household use more time to maintain meal quantity ($T_1 > T_0$). Second, the unit 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 ($Q_1 \neq 0.95Q_0$). The last case can happen when households purchase pre-cut products such as peeled fruits after the unit tax, and thus edible parts of of a grocery basket do not change. I empirically test these potential abatement strategies using data on food intake and nutrition, time use, and grocery prices.

5.2 Findings

To empirically examine the impact of the unit tax on the time spent on meal production, I analyze the microdata from the Korean Time Use Survey, by leveraging the Wave 1 variation. Before reporting the results, I first discuss the empirical approach. Unlike grocery purchase and food intake data, which afford detailed household address information, the time use survey only discloses respondent locations at the province level, the largest sub-national administrative unit in South Korea.

Since the unit tax status changes at a sub-province level, the data limitation imposes a challenge in assigning the tax status to individual survey respondents. To address this issue, I take a pseudo-panel approach and collapse individual-level repeated cross-section data into province by housing type by survey date by year level (Deaton 1985, Bellemare et al. 2018). I leverage the housing type (i.e., condominium or not) and survey date information because housing type is a strong predictor of the unit tax status, and household time use varies depending on the day of the week.

Moreover, the data limitation implies that identifying the policy effect using the Wave 2 expansion is difficult due to the lack of clean control groups over the period. As Appendix Figure E.7 Panel (b) shows, between 2009 and 2014 (the Wave 2 expansion started in 2013), nearly all province-housing type pairs had expanded the unit tax. In contrast, Panel (a) illustrates that there are a large number of untreated province-housing type pairs over the period of 1999 to 2009 because, as discussed in 2.2, the majority of municipalities imposed a flat tax during that time. Consequently, I analyze time use data for three survey years (1999, 2004, and 2009), leveraging the Wave 1 expansion.

Given that the treatment occurs simultaneously during Wave 1, rather than in a staggered fashion, the empirical design follows a canonical difference-in-differences approach with continuous treatment, as equation (4).

$$Time_{hpdt} = \beta(\%)T_{hp,2009}I_t + \delta\mathbf{X}_{hpt} + \alpha_{hp} + \lambda_t + \omega_d + \epsilon_{hpdt} \tag{4}$$

Here, Time_{hpdt} is time spent on meal production activities for an average adult living in housing type by province hp on day of the week d in year t. $(\%)T_{hp,2009}$ is the proportion of households under the unit tax as of 2009, which is after the Wave 1 expansion in 2005, for a housing type by province hp. This term captures the time-invariant treatment intensity, which determines the treatment group status. I_t is a post period indicator that takes 1 if t is 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 a house, which proxies for income.[36] 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.

In Table 5.1, I estimate the impact of the unit tax on the time spent on home meal production activities. Specifically, following the time categories of the time use data, I separately estimate the policy effect for these four different stages: preparation, clean up, keeping diary, and shopping.[37] In column (1), I show that an average adult spend 3.9 additional minutes per day or a 7% more on meal production, which is the sum across four different categories, after the unit tax. Given that an average number of adults for households in the sample is 2.56, a 3.9 minutes increase per adult translates into a 10 minutes increase per household per day or 61 additional hours per year. The finding suggests that households use more time to compensate for fewer groceries, and such a choice has been well documented in earlier studies (Aguiar and Hurst 2005, 2007a).

In columns (2)–(5), I investigate the impact of the tax on individual meal production stages. 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 cooking, preparing ingredients, storing and organizing groceries, and setting the table (Statistics Korea 2009). I also find a statistically significant increase in time spent on keeping diaries, which facilitates meal planning. There is evidence of increased time spent on cleaning or non-durable products shopping as well, but the effect fails to rule out the null effect at the conventional statistical significance level.

Figure 5.1 (a) visually confirms findings in Table 5.1 by plotting the relationship between treatment intensity and time spent on meal production for pre and post treatment periods. For this, I create binned scatterplots as the following: first run equation (4) without $(\%)T_{hp,2009}$ term and collect residuals. Then, average residuals for each province by housing type by year. Finally, I take the first difference between 2004 and 1999, and 2009 and 2004, which correspond to pre and post treatment periods—given that the wave 1 expansion happened in 2005 and plot them against the treatment intensity in 2009 ($(\%)T_{hp,2009}$).

[36] Monthly income variable started in 2004 so I use the size of a house as a proxy for income.

[37] The shopping category in the survey 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.

Table 5.1: The Effect of the Unit Tax on Household Meal Production Time

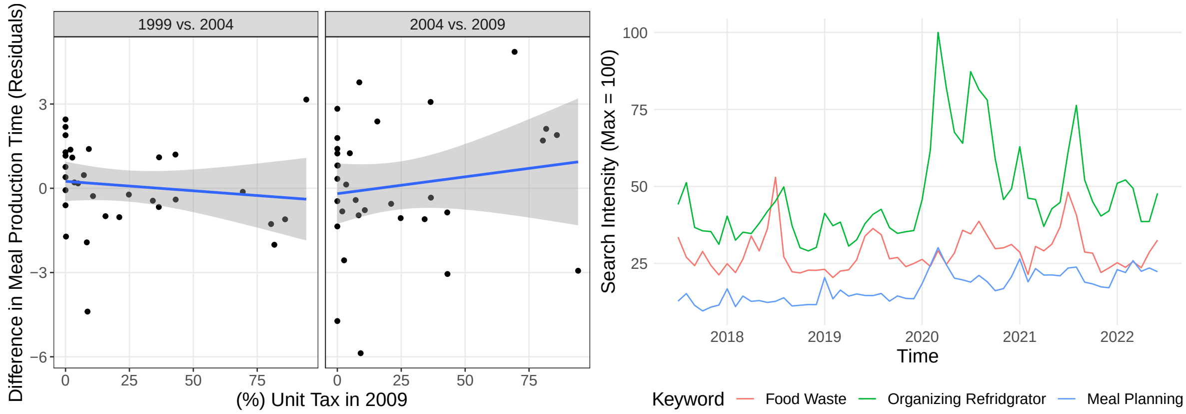
	(1)	(2)	(3)	(4)	(5)	(6)
(%) Unit Tax x Post	3.927**	2.681**	0.7765	0.2100**	0.2595	0.2569**
	(1.673)	(1.067)	(0.5774)	(0.0875)	(0.5405)	(0.1199)
Dependent Variable	Overall	Prepping	Cleaning	Diary	Non-durable Shopping	Dollars Per Day
Province × Housing Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	672	672	672	672	672	448

Note:
This table reports the effect of the unit tax on household meal production time. The coefficients are produced by estimating equation (4) using the time use survey of 1999, 2004, and 2009. 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 level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The left-hand side figure shows that the difference in time spent on meal production between 1999 and 2004 between the high versus low treatment intensity units are essentially the same, which is analogous to the "no pre-trend" condition for a binary canonical difference-in-differences case. Importantly, the post period (2004 vs. 2009) shows a positive slope, which suggests that households in the high treatment intensity units are spending more time in meal production than their low treatment intensity counterparts after the unit tax.

To explore how households allocate the additional time spent on meal preparation, I leverage web search data from "Naver," a prominent search engine in South Korea.[38] In Figure 5.1 (b), I depict web search intensity for three keywords: "food waste," "organizing refrigerator," and "meal planning," focusing on females aged 30–60, a demographic largely responsible for meal preparation at home. Two noteworthy patterns emerge from this figure. First, the search intensity for organizing the refrigerator and food waste closely align, while a similar correlation is less evident between food waste and meal planning Second, search intensity for all three keywords, but in particular for organizing refrigerator, experiences a sharp spike in March 2020, which was the initial COVID-19 lock down

[38] The value of internet search data in comprehending household activities during the additional hours is contingent upon the baseline knowledge level of households regarding food waste reduction strategies. Perfect knowledge would render internet search data less informative, as the unit tax would merely encourage households to implement existing knowledge. However, survey results indicate a knowledge gap in food waste reduction strategies (Ministry of Environment 2015).



(a) Unit Tax and Time Spent on Meal Production

(b) Search Intensity

Figure 5.1: The Effect of the Unit Tax on Time Use. Panel (a) shows the impact of unit tax on time spent on meal production using binned scatterplots. Each dot represents a province by housing type (condominium vs. other types) pairs. The X-axis shows the fraction of households under the unit 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. Panel (b) shows the trend in web search intensity for three food waste related keywords (food waste, organizing refrigerator, and meal planning) for female users aged 30-60 between July 2017 and Jun 2022 from Naver, a dominant search engine in South Korea.

period in South Korea.

In Appendix Figure E.8, I plot the same figure for male aged 30-60 and female below 20 years old groups. I do not find any relationship between food waste and organizing refrigerator in these figures, which further highlights the role of organizing refrigerator.[39] These patterns suggest that households consider organizing the refrigerator as a primary way to optimize their grocery usage. This aligns with survey findings indicating that households often forget the contents of their fridge, leading to duplicate purchases (Farr-Wharton et al. 2014, Gaiani et al. 2018).

In Table 5.1 column (6), I estimate the corresponding abatement cost by regressing equation (4) using the value of time spent on meal production as an outcome variable. To put a dollar value on time spent, I follow Aguiar and Hurst (2007a) and calculate the opportunity cost of time using the demographic group specific marginal returns to shopping (see Appendix B.1 for more details). I find that the cost of additional time spent on meal production is \$0.26 per day per adult or \$240 per year per household (scale up using the average number of adults in households (2.56) and the number of

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

days per year).[40] In Section 4.2, I show that the savings from purchasing less groceries is \$172 per year per household. While this estimate suggests that over 70% of the abatement costs are offset by savings on groceries, it raises a question why households allocate seemingly "too much" additional time in meal production after the unit tax. In Section 6, I show that this choice can be consistent with utility maximization when non-pecuniary effect explains the majority of the tax effect.

Finally, I find that the other two possibilities—higher productivity in meal production and input (grocery) quality change—do not seem to explain household abatement strategies. While I leave details of these exercises to Appendix B.2, I highlight that the null effect on productivity is not surprising given that the productivity is measured by the residual in the production function. That is, when a 5% reduction in grocery purchases is compensated by a 7% increase in time use (while output level is constant), a large increase in productivity seems implausible by construction.

6 Discussion

Findings from earlier sections raise a few puzzles: why such a small tax has such a large impact on household behavior? Why households seem to spend too much additional time on meal production? What is the welfare effect of the unit tax? To answer this question, I first decompose the tax effect into pecuniary versus non-pecuniary effects. Then, using an augmented household production model, I show that utility maximizing households can choose to spend additional time in meal production that goes beyond grocery savings when the tax has a direct impact on consumer surplus. Finally, I discuss policy implications.

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

Price effect. To pin down the size of the price effect, I calculate the predicted input ratio change under a range of previous substitution elasticity estimates from Aguiar et al. (2012), which is between 1.2 and 2.6. Given that the average unit tax rate is equivalent to a 0.4% increase in the grocery price, the predicted change in the input ratio (in the absence of time price change) is at maximum 1.04%. Comparing this to the a 13% change in the input ratio suggests that the price effect alone explains at maximum 8% of the observed substitution effect.

[40] \$240 suggests that on average, the value of time is \$4 per hour. This number seems plausible given that the average market wage for homemaking jobs in 2009 was \$4.9 per hour.

Two additional findings corroborate a small price effect. First, I leverage intensive margin tax rate changes to show that the tax elasticity of grocery purchase is -0.024 (se = 0.03), over an order of magnitude smaller than typical price elasticity of groceries (between –0.27 and –0.81) from Andreyeva et al. (2010).[41] If the tax effect is solely attributed to the price channel, the impact of a dollar increase in the tax and grocery prices should not be as markedly different. The stark difference between extensive versus intensive margin effects suggests that introducing *a* unit tax might be more important than imposing the *right* tax rate.

Second, in Figure 6.1, I present the differential impact of the unit tax on grocery purchases by income level (panel (a)) and baseline grocery purchase quantity (panel (b)).[42] If the tax effect is driven by price, the effect size should be the largest for the lowest income group, which tends to be more price elastic (Andreyeva et al. 2010). However, the point estimates in panel (a) suggest the opposite: while households in the low income group do not change grocery purchases at all, households in the highest group reduce them by nearly 10%. Panel (b) provides one potential explanation for the results in Panel (a): high income households used to purchase a large amount of food (and potentially wasted a significant portion of it) are responding to the tax, which again cannot be explained by the price effect. Appendix Figure E.11 clearly shows that baseline purchase quantity is highly correlated with income.

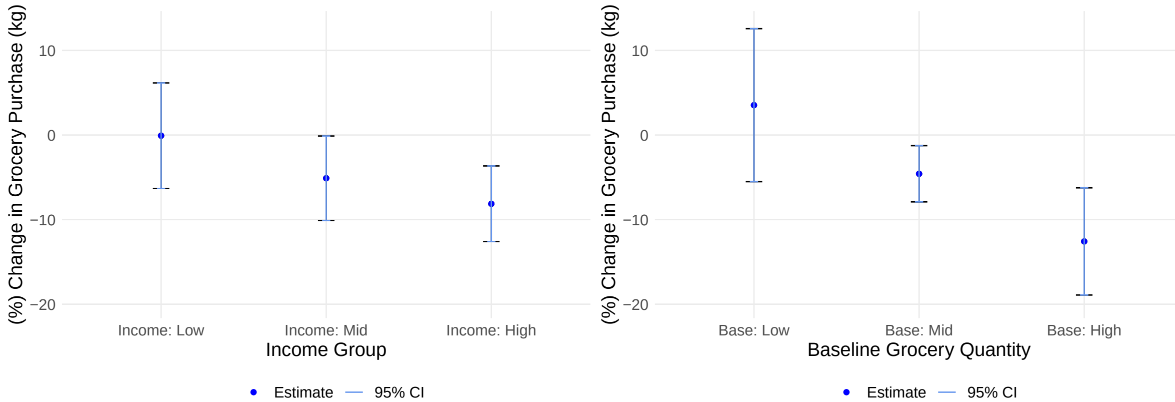
Non-pecuniary effects. Findings from a companion paper provides more direct evidence of the non-pecuniary effect. Lee and Seo (2022) zooms into the smart card system based unit tax implementation. The paper finds that even during the pilot period, where households start to get instant feedback on their waste generation but the marginal tax rate is still effectively zero, the waste quantity decreases by over 10% (or 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 insufficient time for households to adjust their behaviors.[43]

Earlier studies suggest that the non-pecuniary effect may stem from either information provision

[41] I estimate this by replacing Tax_{imt} in equation (1) to $log(TaxRate)_{imt}$ conditional on $log(TaxRate)_{imt}$ defined. I do not use extensive margin variation to avoid capturing the zero-price effect (Shampanier et al. 2007, Iizuka and Shigeoka 2022).

[42] For these exercises, I first create dummy variables for income groups, categorized as low (monthly income below \$2,954), medium (monthly income between \$2,954 and \$4,318), and high (monthly income above \$4,318). Similarly, dummy variables for grocery purchases in 2010 are created, classified into low (bottom 33%), medium (middle 33%), and high (top 33%). These variables are then interacted with Tax_{imt} in equation (1).

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



(a) Tax Impact on Groceries by Income Level (b) Tax Impact on Groceries by Baseline Quantity

Figure 6.1: Heterogeneous Treatment Effect. Panel (a) illustrates the differential impact of the tax on grocery purchases based on the income level. Panel (b) repeats the same exercise using baseline grocery purchase quantities. See the text for additional details.

or imposing an emotional tax on food waste generation. For the former, it is well documented that not all households pay full attention to their food usage. For instance, households tend to forget the contents of their refrigerator and make duplicate purchases (Farr-Wharton et al. 2014, Gaiani et al. 2018) or underestimate the amount of the food they waste (Neff et al. 2015, NRDC 2017). This imperfect awareness is attributed to limited attention spans and the absence of systematic feedback on food waste generation or lack of information (National Academies of Sciences, Engineering, and Medicine 2020). Introducing a unit tax could remedy the situation as taxation inherently necessitates the measurement of food waste amounts, offering households new information on a regular basis. This increased frequency enables households to identify and potentially minimize avoidable waste.

An alternative explanation is that the unit tax might impose an emotional tax on food waste generation by directly sending a signal that generating food waste is not desirable (Glaeser 2006). Rees-Jones and Rozema (2020) shows that introducing a corrective tax is typically accompanied by provision of information, persuasive appeals, and alternative non-price interventions, all of which might discourage undesirable behaviors. Indeed, at least since the mid-2000s, both central and local governments have undertaken extensive public awareness campaigns to promote food waste reduction (Ministry of Environment 2006).

6.2 Rationalizing Overcompensating Behavior

Insights from a standard household production model suggests that household can save money on groceries by investing more time in meal production. However, it cannot explain why households may choose to allocate time on meal production beyond grocery savings. This seemingly irrational behavior can be rationalized when I extend the standard model to allow for distastes for food waste generation and limited awareness. While a more formal treatment is in Appendix D, the key insights suggest that a utility maximizing household can choose to "overcompensate" when the tax generates new information that helps households making a choice that they would have made under better information (the information channel) or when the tax increases the emotional cost of generating waste (the moral tax channel).

Importantly, depending on the source of such a choice, the welfare effect of the unit tax can be starkly different. If the information (moral tax) channel prevails, it can directly increase (decrease) consumer utility. One approach to formally test relative importance of these two channels is to estimate households' willingness to pay (WTP) for the unit tax regime. That is, to the extent that households value measurement and feedback provided by the unit tax(or the value of information outweighs any moral tax imposed), their WTP for the regime should be positive (Allcott and Kessler 2019). While estimating the WTP parameter is beyond the scope of this paper, survey results indicate that households, in general, are supportive of the tax (Ministry of Environment 2015). For instance, the proportion of survey respondents in favor of the tax has risen from 57% in 2010 to 70% in 2014. Moreover, over 85% of them answered that food waste tax is necessary to reduce food waste.

Indeed, many of food waste campaigns—an important source of moral tax effect—typically utilize media outlets such as TV, radio, or social media, reaching both households with and without the unit tax. Considering that the empirical analyses in preceding sections employ a difference-in-differences design, the impact of accompanying interventions is likely to cancel out, unless there exists a substantial interaction effect between an awareness campaign and the unit tax.[44] While these findings qualitatively suggests that the moral tax channel may not fully explain the policy effect,

[44]Even without accompanying policies, the unit tax may directly send a signal to households that generating food waste is not desirable, and impose an emotional tax. Previous studies on conventional or electric cigarette reported the impact of corrective tax on social norms or risk perceptions (Durkin et al. 2021, Abouk et al. 2023).

these are not convincing enough to determine the relative importance between two channels.

6.3 Policy Implications

To test whether the unit based food waste tax is socially desirable or not, I need to the benefit and cost estimates. While estimates in Sections 4 and 5 allow me to pin down a large part of benefits and costs of the policy, without understanding the mechanism behind the non-pecuniary effect, which can directly affect consumer surplus either positively or negatively, I cannot draw a strong conclusion about the welfare effect.

Given the limitation, I primarily focus on discussing the cost-effectiveness—the program cost to reduce 1 ton of CO_2—of the unit tax, which is a widely used metric for policy evaluation. In addition, I discuss under which conditions, the policy is likely to pass the cost benefit analysis. This subsection concludes with discussions on external validity and comparison with alternative policy measures.

Cost effectiveness. To calculate the cost effectiveness, I first calculate the annual reduction in the national GHG emissions from food waste leveraging estimates from Table 4.1 (for more details, see Appendix C). For this, I consider three components: emission reductions from avoided production, which is 86% of the observed food waste reduction (item A: 2.6 million ton); emission reductions from avoided waste treatments (item B: 0.2 million ton); and emission increases due to leakage, which is 14% of the observed food waste reduction (item C: 0.09 million ton).[45] There are two assumptions in this exercise. For the avoided production calculation, I assume that suppliers scale back their production in response to the unit tax driven demand shock.[46] For the leakage, I consider the worst case scenario (in terms of GHG emissions) and assume that all 14% end up in landfill. In calculating these numbers, I multiply the per household effect size by the number of total households in South Korea (19 million).

The total (items A+B+C) reduction in the GHG emissions due to the unit tax throughout the life cycle of food waste is 2.7 million ton, which is comparable to the emissions from 595 thousand

[45] The GHG reduction effect from the food waste treatment can be much larger in other countries. In South Korea, nearly all food waste is treated in a food waste processing sites, which generates substantially smaller amount of GHG than food waste in landfill. Such a practice is an exception than a norm: for instance, in the US, 50% of the total food waste ended up in landfill sites in 2018 (EPA 2020).

[46] Testing this assumption is beyond the scope of this paper. However, economic theory suggests that profit-maximizing producers are likely to respond to such a demand shock especially in the long run. Consistent with this, Appendix Figure E.10 shows even rice—the most heavily subsidized crops in South Korea—producers have responded to a dwindling demand due to dietary changes.

Table 6.1: Cost Effectiveness of the Unit Food Waste Tax

	Items	Value
GHG Change (1000 Ton)	Avoided Production (A)	2637
	Avoided Food Waste Treatment (B)	192
	Increased Food Waste in Landfill (C)	88
	Net GHG Effect (A+B-C)	2741
Program Cost (\$ Million)	Producing Bags and Stickers (D)	12
	Installing Smart card System (E)	17
	Operating Smart card System (F)	7
	Total Program Cost (D+E+F)	36
	Budget Savings on Waste Services (G)	-72
	Net Program Cost (D+E+F+G)	-35
Cost Effectiveness (\$/Ton of CO_2eq)	(D+E+F)/(A+B+C)	13
	(D+E+F+G)/(A+B+C)	-13

passenger vehicles. Importantly, the majority of the GHG reduction effect comes from the farm-to-kitchen stage, which is responsible for 90% of the life cycle GHG emissions from wasted food. This emphasizes the importance of (1) implementing food waste policies that can encourage prevention rather than recycling and (2) evaluating food waste policies' impact throughout the life cycle.

For the annual program cost, I consider the cost necessary to implement the unit tax such as cost of producing bags or installing and operating the smart card systems.[47] I exclude spending on waste pickup and treatment services, which have to be provided irrespective of the unit tax status. The combined program cost (items D+E+F) amounts to \$36 million per year. When I compare the cost to the total GHG reduction amount, the program costs \$13 to reduce one additional tonne of CO_2.

The \$36 million program cost, however, does not take into account that providing waste treatment service is costly. Given that the food waste tax contributes to less than 50% of the operational costs, the Seoul Metropolitan Government, for instance, expended \$136 million (equivalent to 14.5 cents per kg) in 2015 to deliver these services.[48] As the quantity of food waste decreases following the implementation of the unit tax, it results in fiscal savings for governments. Assuming a constant marginal cost of waste treatment services, the annual waste treatment budget savings resulting from the 19.3% reduction in food waste amount to \$72 million nationally. When factoring in these savings

[47] For items D and G in Table 6.1, I use the 2015 Unit-Based Waste Policy Yearbook, which is the first year with detailed cost breakdown. For E and F, I use smart card system installation data from Korean Environment Corporation (https://www.citywaste.or.kr/EgovPageLink.do?link=/ucwmsNew/portal/sysInfo/sysInfo06, accessed on Dec 5, 2023).

[48] This situation is not unique to South Korea; Kaza et al. (2018) notes that waste treatment accounts for 5-20% of the municipality budget in many countries.

on waste treatment, the government cost to reduce one additional ton of CO_2 becomes negative.

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.

Conditions for welfare improvement. Assuming that production is perfectly competitive, the welfare effect of the unit tax can be calculated by the sum of the change in consumer's utility and external costs. For the change in consumer's surplus for an average household, I take the point estimates for grocery savings ($172) and additional time costs ($240). For the reduction in external costs, I multiply per households GHG reduction (0.143 ton per year) with the up-to-date social cost of carbon $190 for emission year of 2020 (EPA 2023).[49] Taking these three numbers suggest that the tax lowers social welfare by $41 per household.

There are at least three different possibilities for this policy to pass the cost benefit analysis. First, when the co-benefit of food waste reduction is large, the policy can pass the cost benefit analysis. While estimating the impact of food waste reduction on preventing biodiversity losses, soil degradation, and water depletion in dollars seem onerous, the existing estimates suggest that the economic value of these co-benefits can be substantial (Hornbeck 2012, Hanley and Perrings 2019, Perez-Quesada et al. 2023). Second, the benefits can exceed the costs when the social cost of carbon is over $480/ton. While this number is over twice larger than $190, EPA (2023) suggests that the social cost of carbon can be much higher even in the near future.[50] Lastly, as the discussion in Appendix D indicates, when the non-pecuniary effect is mostly driven by the information rather than moral tax impact, the tax can be welfare improving.

External validity. To explore external validity, I compare findings of this paper to two different strands of literature. First, this paper aligns with prior research that has identified a disproportionately large effect of a small tax. For example, Homonoff (2018) reported a 40% reduction in the usage of plastic bags in the US following the implementation of a 5-cent bag tax. Second, given that the unit tax effect is driven by a non-pecuniary channel, earlier studies on information interventions

[49]For this, I divide the net GHG reduction from Table 6.1 by the number of households in South Korea (19 million).
[50]For instance, the social cost of carbon for 2030 under a 1.5% discount rate is $380.

or nudges provide valuable benchmarks (Allcott 2011, Ferraro and Price 2013, Costa and Kahn 2013, Tiefenbeck et al. 2018, 2019). These papers generally find that treatments such as report cards or real-time feedback reduce electricity or water consumption. While the reported effect sizes vary considerably (between 2–22%), the frequency of feedback (1–2 times per month for report cards vs. real time) seems to be crucial. Given that households dispose of their food waste 2–3 times per week on average, the findings of this paper appear consistent with earlier research.

Tax on food or food waste. While life cycle GHG emissions vary substantially across food items—for example, beef production can be 100 times more carbon intensive than vegetable production (Poore and Nemecek 2018)—the unit based food waste tax imposes a uniform tax rate for every food item. Given this limitation, a tax on food based on its carbon intensity might considered as an alternative policy option to reduce food waste.[51]

While theoretically appealing, such a tax is hard to implement in practice for multiple reasons. First, unlike CO_2 where emissions can be easily measured based on fossil fuel usage (due to emissions being proportional to the carbon content within each fossil fuel), there is no straightforward method to measure non-CO_2 GHG emissions from agricultural activities (Timilsina 2022). For instance, emissions from growing beef or rice depends heavily on agricultural practices or baseline physical characteristics, which are extremely costly to measure. This is a major drawback because 48% of GHG emissions from the food sector are non-CO_2 GHGs (Crippa et al. 2021). Even if we could overcome the measurement problem during the production stage, there are additional feasibility issue. Introducing a food tax is likely to be politically contentious with concerns over food insecurity and regressivity (Godfray et al. 2010, Dechezleprêtre et al. 2022).[52]

Further, insights from tax saliency literature (e.g., Finkelstein (2009); Chetty et al. (2009)) suggest that the food tax, which is likely to be reflected in the final price consumers pay, might not have as strong effect as a food waste tax, which is charged independently. Given these considerations, a uniform rate per unit tax on food waste is a practical yet potentially more powerful policy apparatus than a food tax.

[51] A third option would be imposing a unit-based food waste tax with varying tax rates—where the tax rate is determined by production stage carbon intensity for each food item. This policy is attractive because it strongly discourages households from wasting carbon-intensive food without necessarily restricting food intake. However, such a tax seems unrealistic due to prohibitively high measurement costs.

[52] Indeed, the federal government of Canada exempted its agricultural sector from a national carbon tax (Wu and Thomassin 2018).

7 Conclusion

Given that life-cycle GHG emissions from wasted food is comparable to that of road transport (IPCC 2014, FAO 2015), managing excessive food demand has become increasingly important. While imposing a corrective tax on food waste generation is a textbook solution, limited evidence exists on its benefits and costs. By leveraging two waves of plausibly exogenous small food waste tax expansions in South Korea, I show that the tax promotes more efficient food use, which reduces GHG emissions from food waste by 5%.

Building on the insights from the household production model, I empirically test household abatement strategies and estimate corresponding costs. Results indicate that households increase time spent on meal production to compensate for a lower grocery input. This incurs non-trivial abatement costs, but savings from fewer grocery purchases seem to offset a large part of the cost increase. Finally, using the substitution elasticity over meal production, I find the price effect explains less than 10% of the estimated change in grocery and time usage. I also discuss non-pecuniary channels with an emphasis on the role of measurement, which is not only a prerequisite for taxation but also generates new information, and their welfare implications.

These results have several policy implications. First, the stark difference between extensive versus intensive margin effects suggests that introducing *a* unit tax might be more important than imposing the *right* tax rate. Second, the unit tax is as a cost-efficient and a more politically palatable climate change mitigation policy, with a remarkably high cost effectiveness and consensus on the desirability of food waste reduction (Ministry of Environment 2015, Neff et al. 2015). While I also present conditions for the policy to pass the cost benefit analysis, I defer a more complete welfare analysis to future studies. Third, food waste policies should focus on prevention rather than recycling since over 90% of GHG emissions are from the farm-to-kitchen stage. Fourth and finally, reducing food waste generates co-benefits such as enhancing food security. 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), a unit based 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 CO_2eq)	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 E: 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).[53] The first three rows present summary statistics for the number of residential households,

[53] 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.

restaurants, and both (residential and restaurant-converted households). The fourth and fifth rows 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.[54]

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.[55] 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).[56] 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).[57] 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

[54] 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.

[55] 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.

[56] 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.

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

a list of categories (as large as twice per day to as small as less than once per month). I convert each 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.[58]

A.2 Grocery Purchase Data Validation

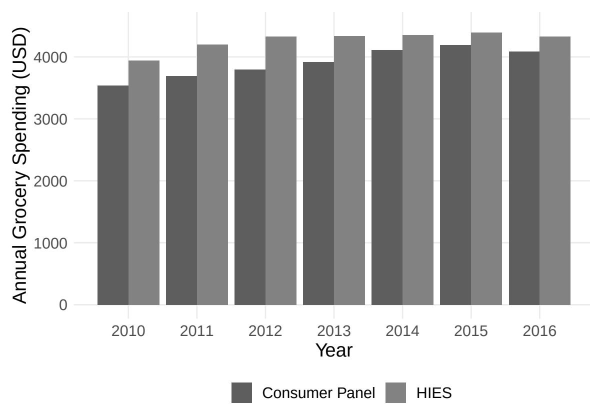


Figure A.1: Consumer Panel Data Validation (Total Expenditure). This figure compares the overall household spending from the comsumer panel data and the Household Income and Expenditure Survey. See the text for additional details.

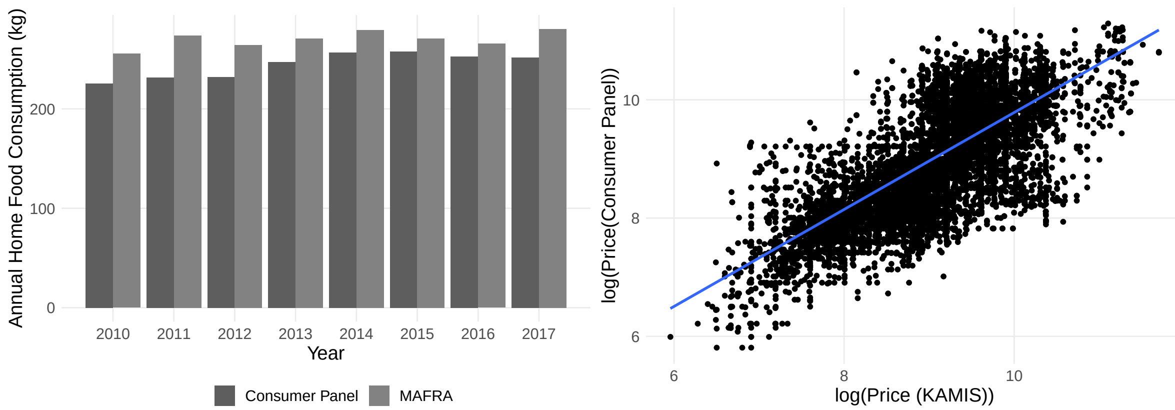
There are two potential concerns with the grocery panel data. First, the data might capture only a subset of the panelists' shopping behavior. This can happen when households fail to keep the record of every single spending. Although the Rural Development Agency compensates panelists $50 per month and 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

[58]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.

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.[59] 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.



(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.

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

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

[59]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.

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.

B Details on Household Abatement Strategies

B.1 Calculating the Dollar Value of Increased Time Spent on Meal Production

In Table 5.1 column (6), I estimate the impact of unit tax on household abatement costs. For this, I need to express the outcome variable in equation (4) in dollar value of time spent in meal production. A crucial step in this exercise is to pin down the opportunity cost of time, and I use the *marginal returns to shopping*—how much money households can save by spending more time on searching for cheaper items—as the value of time following Aguiar and Hurst (2007a). The choice seems more appropriate than wage, which is frequently used to measure the opportunity cost of time, especially within the household production context. Theoretically, the observed wage might be different from the marginal return to labor due to, for instance, nonlinear wage schedules, inability to adjust labor hours freely at the margin or human capital accumulation effects from the job (Aguiar and Hurst 2007a). Empirically, over half of the primary meal preparers in the sample are not formally employed and thus wage is not well defined.

The marginal return on shopping is calculated by multiplying (1) the elasticity of price with respect to shopping frequency and (2) average spending per shopping trip. In this case, because time per trip may not be constant, I scale it up to an hour using inverse of time spent per trip. I also note that the result is very similar when I calculate the marginal return on shopping using (1) the elasticity of price with respect to shopping time and (2) average spending per shopping time.

For the elasticity, I assume that it is identical across different households and take the central estimates from Aguiar and Hurst (2007a) (columns 2 for elasticity with respect to shopping frequency and 4 for elasticity with respect to shopping time from Table 3).[60] For the average spending per shopping trip

Because the time use data do not have information on spending, I impute predicted values by merging the time use data with the grocery panel data. Specifically, I start by merging time use data with the grocery panel data at a household level using demographic characteristics—income (low if monthly income is below USD 1,818), family size (1-2, 3-4, and above), age (20-30, 30-50, and above), and the tax status.[61] 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.[62] Then I aggregate the individual level time use survey with imputed spending information to housing type by province by survey date by survey year level.

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 opportunity cost 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 E.9, I create bin scatter plots between age and the opportunity cost of time (in Panel A) and income decile and the opportunity

[60] I choose to not to estimate the elasticity because the grocery panel data does not have a UPC code. Without a UPC code, I cannot tell whether the observed relationship between shopping time and paid price is due to price differences for the identical product or product differences between stores (e.g., Coke vs Pepsi).

[61] 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.

[62] Loosing 1999 does not seem to affect the result. When I compare the impact of unit tax on overall time spent on meal production using 1999, 2004, and 2009 survey years versus only the latter two years in Panel A of Appendix Table B.1, the result is strikingly similar.

Table B.1: The Effect of Unit Tax on Time Use and Other Abatement Channels

	(1)	(2)
Panel A: Time Spend on Home Meal Production (in Minutes)		
(%) Unit Tax x Post	3.927**	3.478*
	(1.673)	(1.942)
Sample	1999,2004,2009	2004,2009
Province × Housing Type FE	Yes	Yes
Year FE	Yes	Yes
Survey Date FE	Yes	Yes
Observations	672	448
Panel B: Other Abatement Strategies (Input or TFP Change)		
Unit Tax	-0.0028	0.0103
	(0.0820)	(0.0114)
Dep. Var in Log (TFP: in Level)	TFP	Grocery Price
HH ID × Municipality FE	No	Yes
Municipality × Housing Type FE	No	No
Year FE	No	Yes
Observations	28	2,880

Note:
This table reports the effect of the unit tax on household meal production time (Panel A) and other abatement channels (Panel B). The coefficients in Panel A are produced by estimating equation (4) using the time use survey of 1999, 2004, and 2009 for column (1) and 2004 and 2009 for column (2). For Panel B column (1), I link three datasets on food and time usage to estimate the TFP difference between tax and no-tax group. Column (2) is estimated using grocery purchase 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) and municipality (Panel B column (2)) level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

cost of time (in Panel B).[63] Consistent with Aguiar and Hurst (2007a), I find that the value of time has an inverse-U shape with age and is positively correlated with income.

B.2 Testing Productivity Change and Input Quality Change

TFP change in home production. I test if the unit tax has an impact on meal production productivity, which I measure using the total factor productivity (TFP). If this is the case, the tax can generate both private and social benefits at a low (or no, depending on the magnitude of the productivity increase) abatement cost.

This exercise is implemented in three steps. In Step 1, I merge datasets on food intake (output of the production function), grocery purchases, and time use (two inputs) using demographic characteristics. I use the same set of demographic variables (income, family size, age, and the tax status) as in the exercise in Panel A of Table B.1 to create cells and merge data. Then I calculate the average value for food intake, grocery purchases, and time use for each cell.

In Step 2, I estimate TFP for each cell by calculating the residual of the production function. For this, I use the factor share approach, which exploits the first order condition of cost minimization that an input's output elasticity equals the product of that input's cost share and the scale elasticity (Syverson 2004).[64] 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 discussion in Appendix B.1.[65]

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) in Panel B of Table B.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 7% increase in time use, by construction 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, with the idea that such an input quality change will increase unit price change. Column (2) in Panel B of Table B.1, which is produced using grocery panel data with equation (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.

[63] 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.

[64] 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.

[65] 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).

C Calculating the GHG Reduction Effect

To calculate the life cycle GHG reduction from wasted food, I consider change in GHG emissions from three different sources: emission reductions from avoided production; emission reductions from avoided waste treatments; and emission increases due to leakage. Estimates from Table 4.1 inform change in quantity for component. To convert the quantity in kg to GHG, I need source specific carbon intensity.

For carbon intensity of food waste treatment stage, I use the per unit methane and nitrous oxide emissions—two major non-CO_2 GHGs from food waste treatment—from the national carbon inventory report (GGIRC 2015), which are based on 2006 IPCC Guidelines. 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 $\mathrm{CO_2}$eq per ton of food waste, which is less than 1/3 of that of food waste in landfill.

For the carbon intensity of additional food waste in landfill, I use the coefficient from the national inventory report, which is 0.655 ton $\mathrm{CO_2}$eq (GGIRC 2015).[66] Note that food waste in landfill produces 3-4 times larger GHG than adequately treated food waste, which implies that unit tax could be welfare harming if most of the observed reduction comes from illegal dumping.

Finally, for the avoided production part, it is beneficial to start by revisiting the overarching approach. One way to calculate GHG reductions from avoided production is multiplying reduced grocery purchase quantity and carbon intensity of average food basket. I deliberately avoided this approach to prevent overestimation of the GHG reduction effect that arises from two factors: (1) carbon intensity varies substantially by food type and (2) the unit tax impact on grocery purchases is primarily driven by perishable items, which tend to have lower carbon intensities. Note, while I can in principle take a similar approach for waste treatment stages as well, but this is not feasible because of data limitation—food waste is not collected by different food type. Further, it has second-order importance because waste treatment stage's contribution to the overall emissions is small.

Consequently, I take an alternative approach as following. I first 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), which chooses 40 products that account for 90% of global protein and calorie consumption and assesses GHG emissions from the farm to kitchen stage. Then I estimate equation (1) using log of GHG as an outcome variable.

[66] I use the "default method" which could be less accurate but allows comparison across different waste disposal methods (Hiraishi et al. 2000).

D Extended Household Production Model

I extend a standard household production model to allow for distastes for food waste generation to (1) rationalize increased meal production time and (2) derive welfare implications.

Setup. Consider the utility maximization problem in equation (ref{eq:utilmax}). Here, utility is dependent on meal quantity M, which is produced by combining raw food input Q and meal production time T, numeraire (X), and leisure time (L). A consumer is subject to two constraints: $X + PQ = I$ where P is price of grocery and $T + L = \bar{T}$ where $\bar{T}$ is total non-working time.

$$U = U(M, X, L) \tag{5}$$

$$s.t. \;\; X + PQ = I \;\text{ and }\; T + L = \bar{T} \tag{6}$$

Building on the model in Allcott and Kessler (2019), I extent the standard household production model that allows disutility on food waste and limited awareness on food waste quantity. By plugging in the budget constraint into this augmented utility function, household chooses M and Q to maximize equation (7). δ is the marginal value of time, μ is marginal disutility from food waste, which captures not only environmental concerns but also any other non-monetary disutilities, such as feelings of inadequacy in homemaking. λ is limited awareness parameter, which can be smaller than 1 (if $\lambda = 1$, a household is fully aware of the food waste quantity). λ can be smaller than 1 in the absence of measurement. Two additional points are worth noting. First, I assume a quasilinear utility function for simplicity. The choice reflects the fact that money spent on groceries and meal production time is relatively small portion of the total budget and non-working time (see as Table 3.1). Second, to focus on the non-pecuniary effect, equation (7) abstrats away from the price effect of the tax.

$$U = u(M) + I - PQ + \delta(\bar{T} - T) - \mu\lambda(Q - M) \tag{7}$$

Rationalizing the 7% increase in meal production time. Now suppose that the unit tax is imposed. First we consider the information provision effect. For that, posit that $\lambda < 1$ before the unit tax. Households chose Q_0, M_0 and achieved the utility level of U_0. Posit that the unit tax is imposed. Because tax cannot happen without measurement, households receive new information on their waste generation and λ becomes 1. Then, $U_1 - U_0 = u(M_1) - u(M_0) - P(Q_1 - Q_0) + \delta(L_1 - L_0) - \mu(W_1 - \lambda W_0)$ where $W = Q - M$. Estimates from Sections 4 and 5 suggest that $u(M_1) = u(M_0)$, $-P(Q_1 - Q_0) + \delta(L_1 - L_0) = -68$, and $W_1 = 0.8W_0$. Then to rationalize additional time spent on meal production, I need to show $U_1 - U_0 = -68 - \mu W_0(\lambda - 0.8) > 0$ or $\mu W_0(\lambda - 0.8) > 68$ under some μ, λ. This can happen when μ is large and $0.8 < \lambda < 1$.

Next, we consider the moral tax effect. For that, posit that $\lambda = 1$ before the unit tax, and the unit tax increases μ to $\mu' > \mu$. Then, $U_1 - U_0 = -68 + W_0(\mu - 0.8\mu')$ after simplification as before. μ' such that $\mu < \mu' < 1.25\mu$ rationalize additional time spent on meal production through the moral tax channel.

Interpretation and welfare implications. Insights from a standard household production model suggests that household can save money on groceries by investing more time in meal production. However, it cannot explain why households can choose to allocate time on meal production beyond grocery savings. This seemingly irrational behavior can be explained by the augmented household production model that allows for distaste for food waste and limited awareness. This model shows that utility maximizing households can choose to allocate "too much" time on meal production that goes beyond grocery.

Importantly, depending on the reason behind such a choice, the welfare effect of the unit tax can be starkly different. If the tax affects households through the awareness channel, it can directly increase consumer utility because the new information empowers households to allocate resources in a manner more closely aligned with their utility function. In other words, new information helps households making a choice that they would have made under better information. If the moral tax effect is prevalent instead, it will directly reduce consumer utility because it increases the emotional cost of generating waste. From a modeling perspective, the effect is similar to an increase in the tax rate.

E Additional Tables and Figures

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

	(1)	(2)
(%) Unit 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 E.2: Food Waste Tax and Food Intake Changes (Other Health and Nutritional Measurements)

	(1)	(2)	(3)
Panel A: Health Outcome and Micronutrients 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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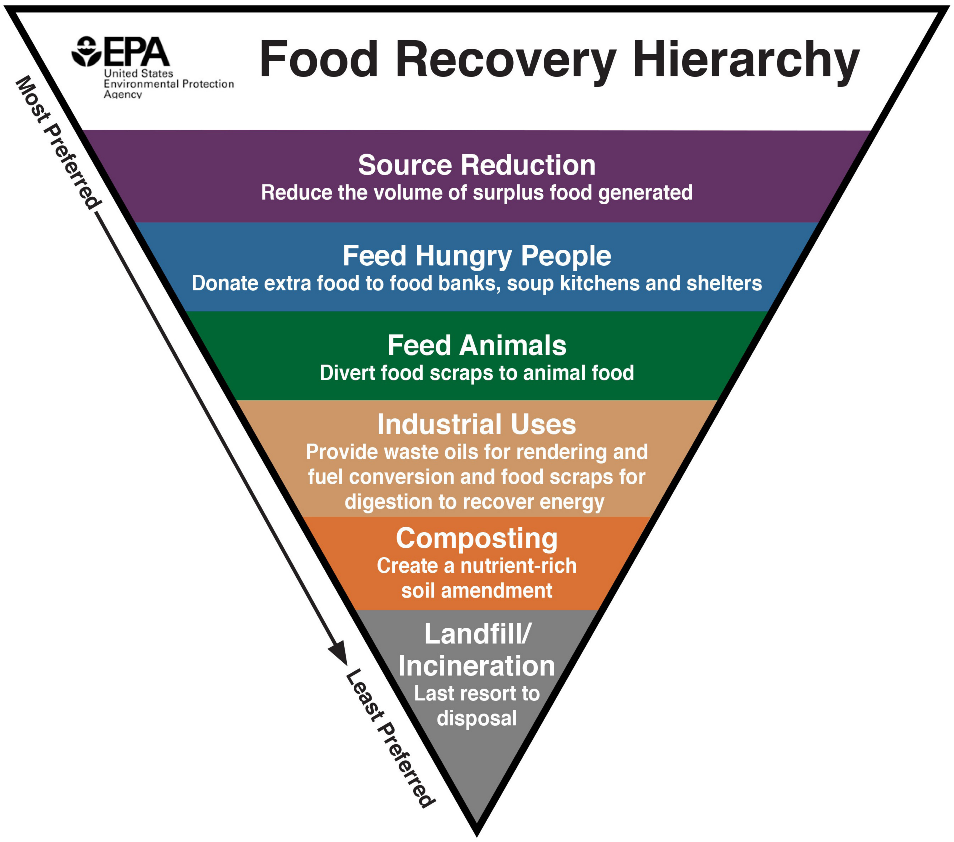

Figure E.1: Food Recovery Hierarchy

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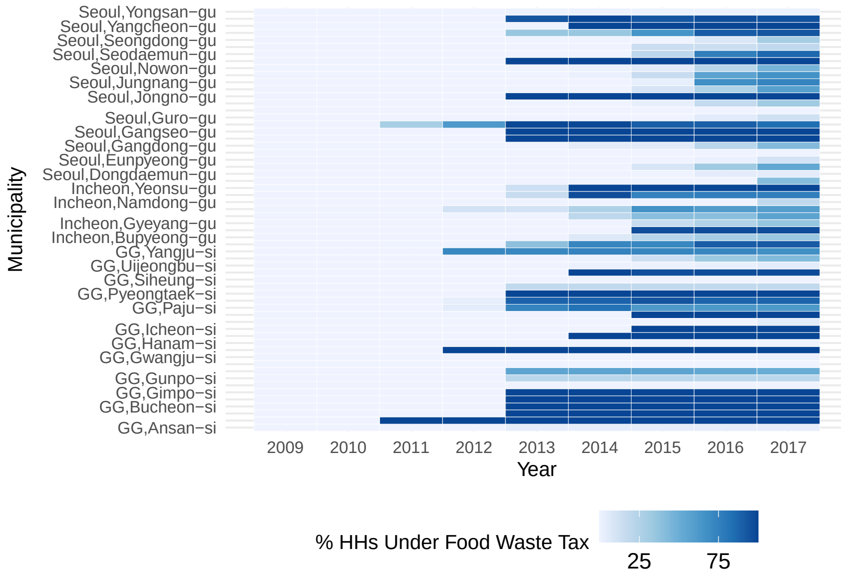
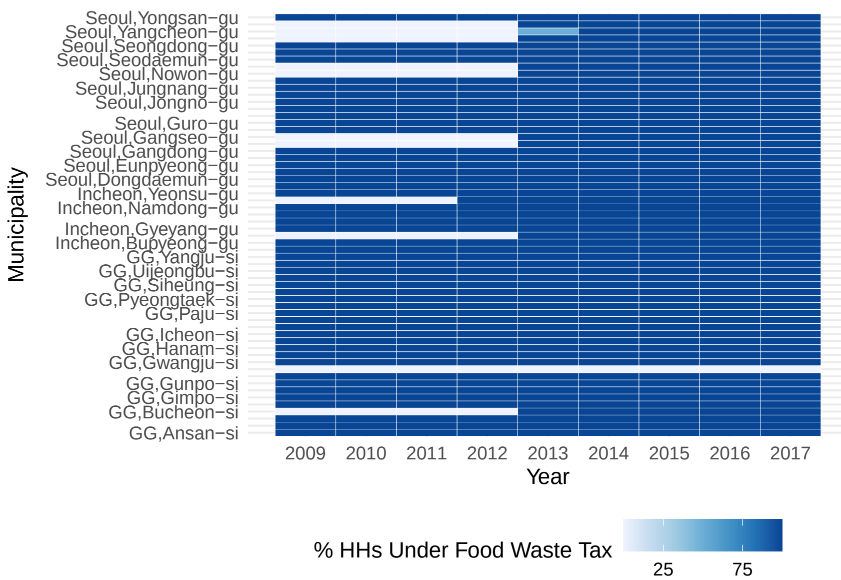


(a) Condominium



(b) Other Housing Types

Figure E.2: Wave 2 Expansion by Housing Type. Panel (a) and (b) plot the proportion of condominium and other housing types residents under the unit-based tax for each municipality-year (2009-2017) for 60 municipalities in the metropolitan Seoul area.

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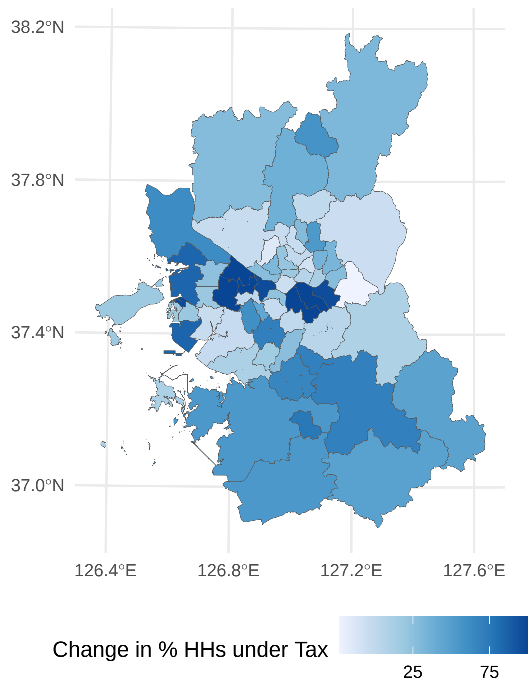
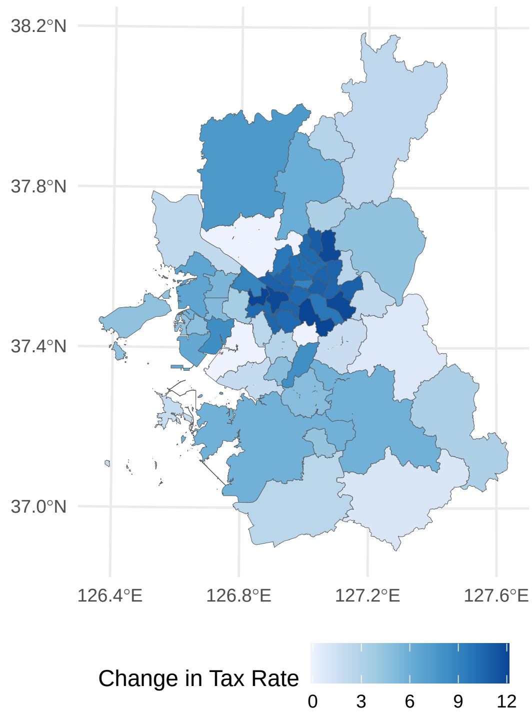


(a) Change in % of HHs under Tax between 2009-17



(b) Change in Tax Rate between 2009-17

Figure E.3: Wave 2 Expansion Map. Panel (a) and (b) plot the change in the proportion of households under the tax and the change in the tax rate between 2017 and 2009 for 60 municipalities in the metropolitan Seoul area.

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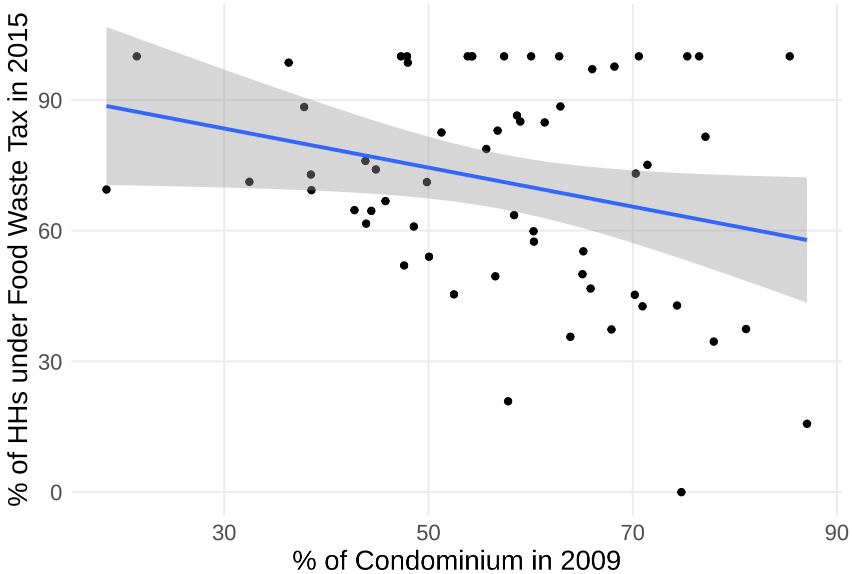

Figure E.4: This figure shows the relationship between the proportion of households living in condos in 2009 and the proportion of households under the tax 2015. Each dot represents a municipality and fitted line is produced using OLS. Grey area represents 95 percent prediction interval. See the text for additional details.

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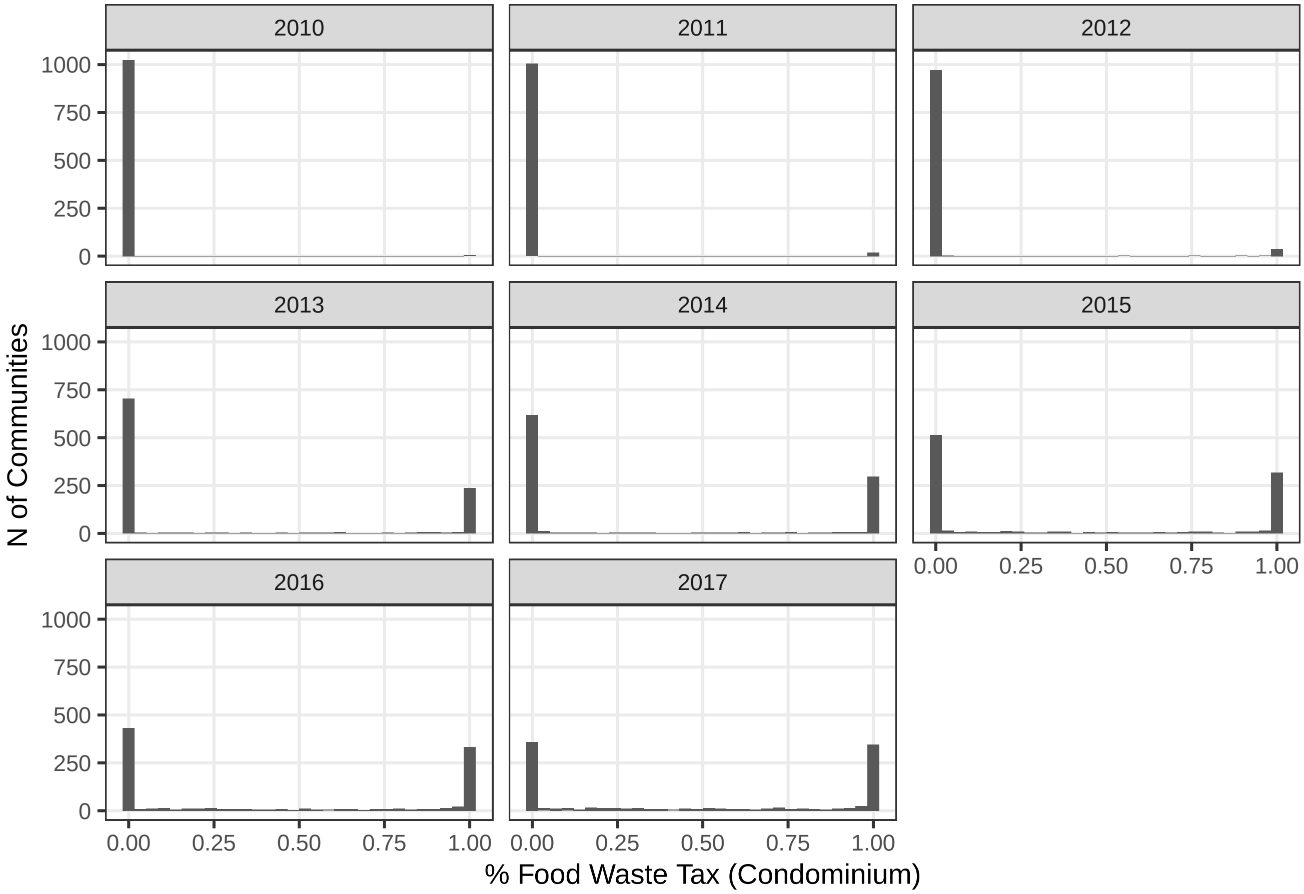

Figure E.5: Distribution of the Fraction of Condominium Residents Under the Tax at the Community Level for 2010-2017. These panels illustrate the distribution of the fraction of condominium residents under the food waste tax at the community (the smallest administrative unit in South Korea) level for years 2010-2017. The data is from 1028 communities within three provinces in the metropolitan Seoul area.

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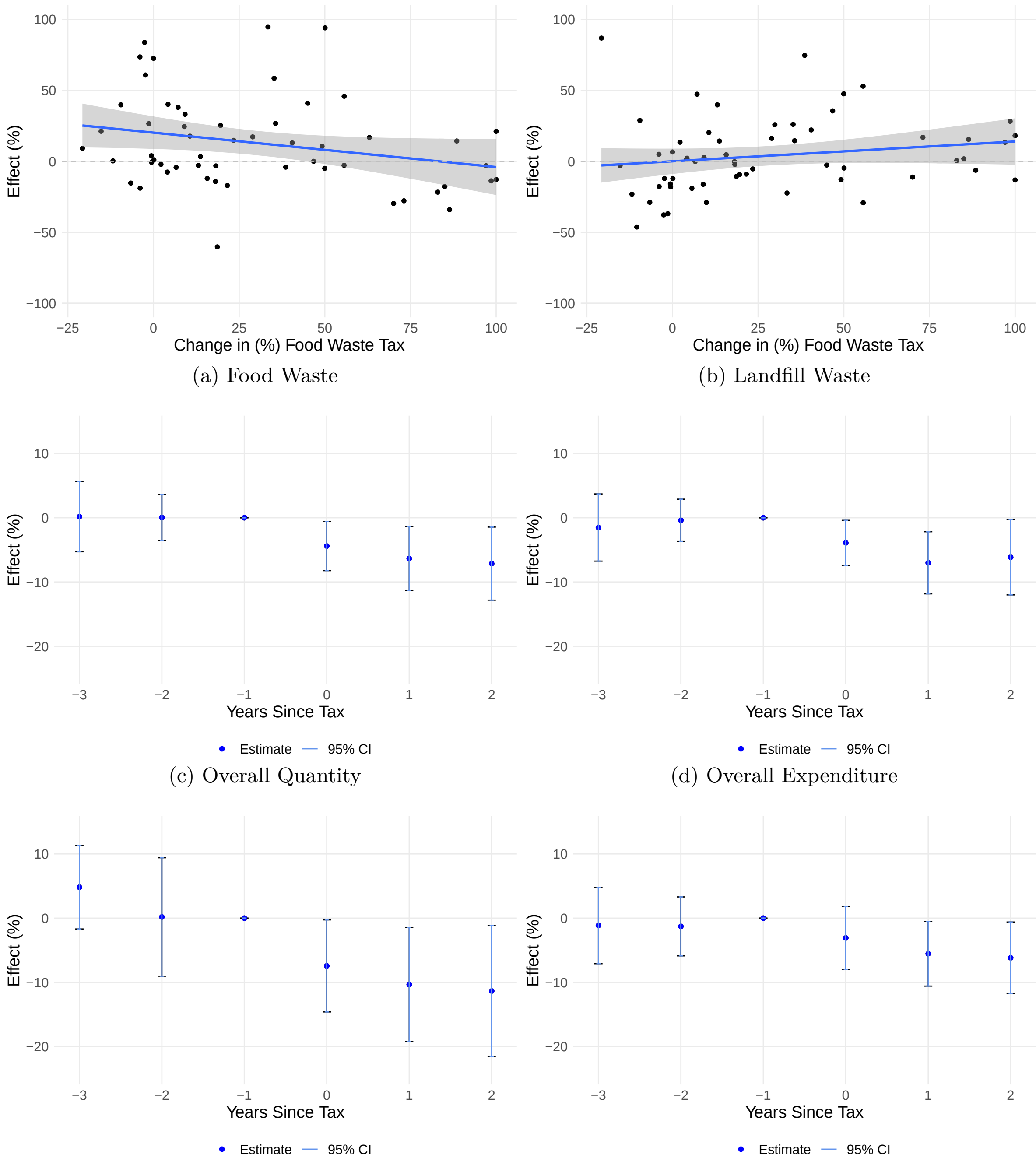

(a) Food Waste (b) Landfill Waste

(c) Overall Quantity (d) Overall Expenditure

(e) Perishable Quantity (f) Storable Quantity

Figure E.6: The Effect of the Food Waste Tax on Waste Quantity and Grocery Purchases. In (a) and (b), the horizontal axis is the change in the fraction of households under the tax between 2009 and 2015 and the vertical axis is the change in the food and landfill waste quantity per household. Each dot represents a municipality and fitted line is produced using OLS. Grey area represents 95% 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. All dependent variables are log transformed.

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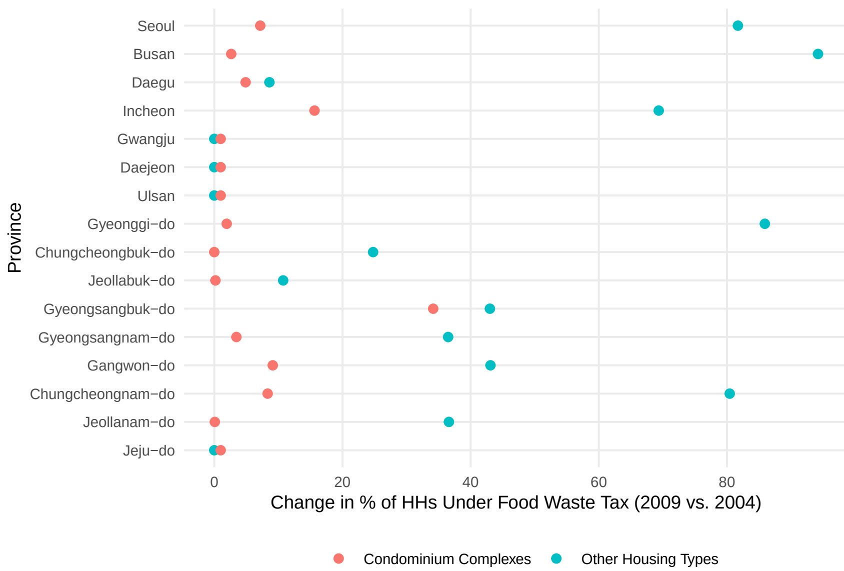
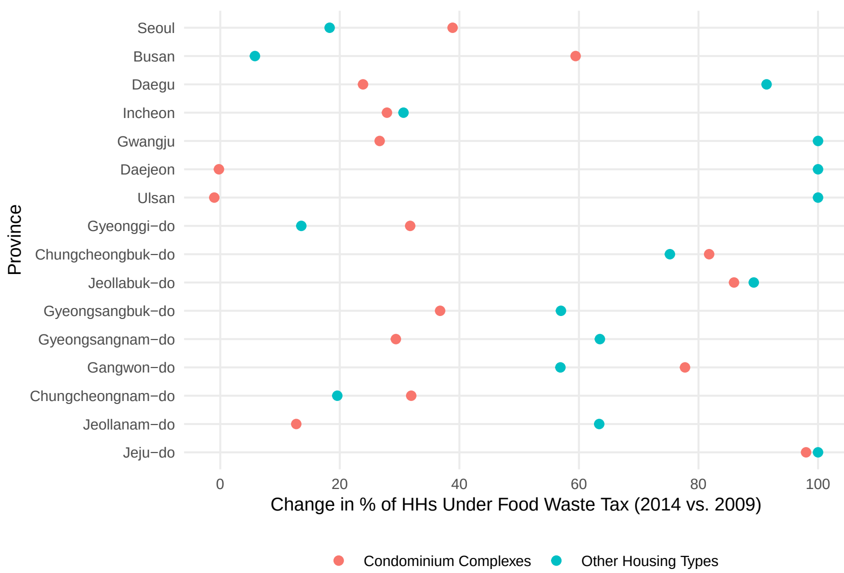


(a) 2004 vs. 2009



(b) 2009 vs. 2014

Figure E.7: 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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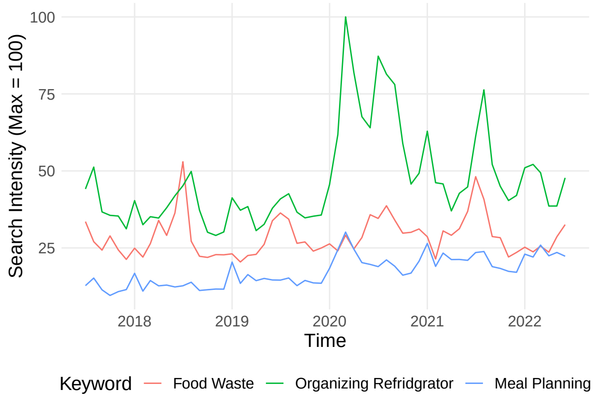
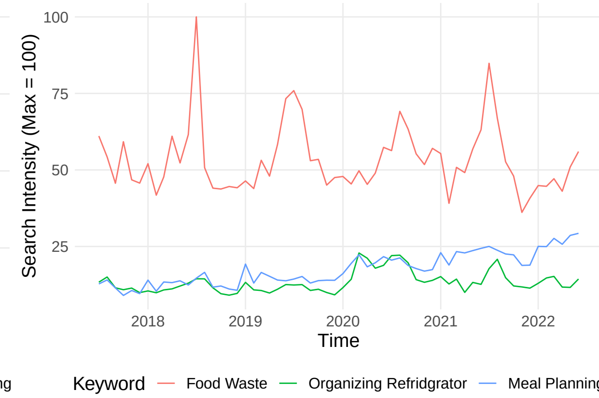
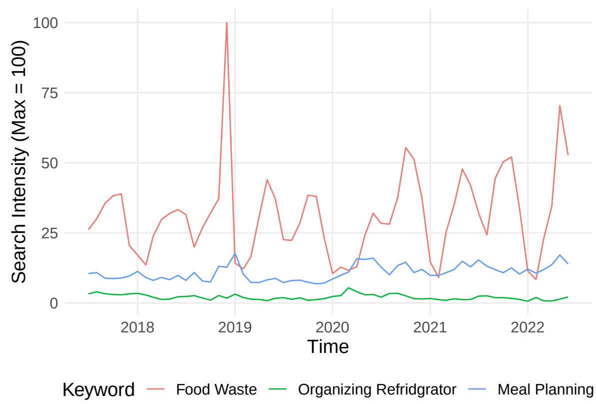


(a) Female Age 30-60



(b) Male Age 30-60



(c) Female Age Below 20

Figure E.8: 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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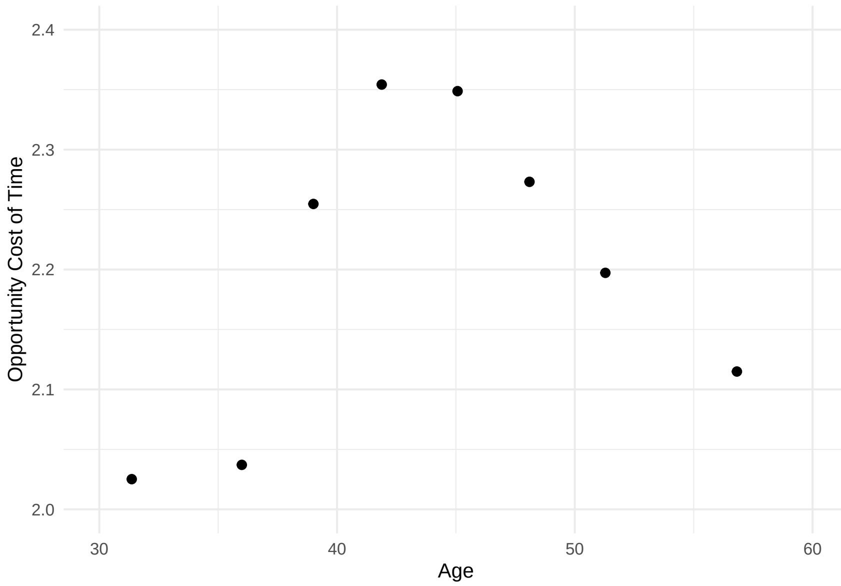
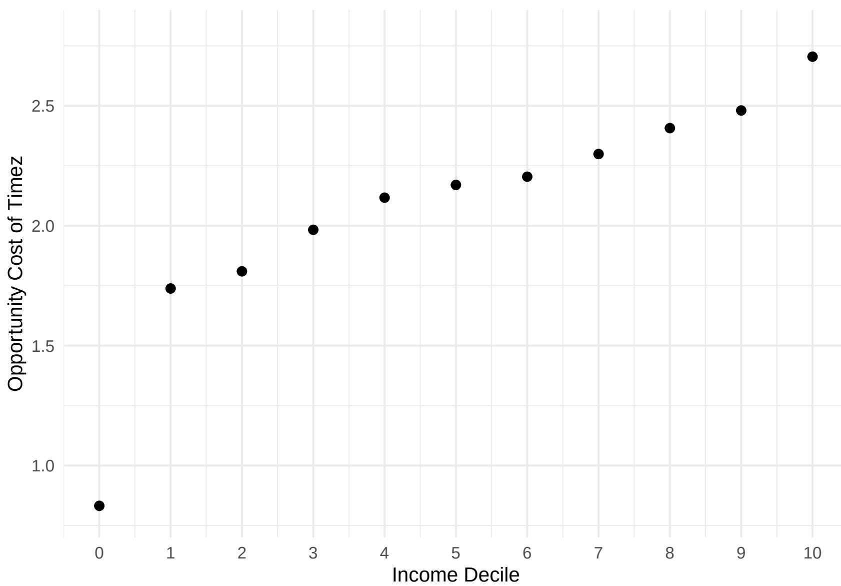


(a) Age and Opportunity Cost of Time



(b) Income and Opportunity Cost of Time

Figure E.9: 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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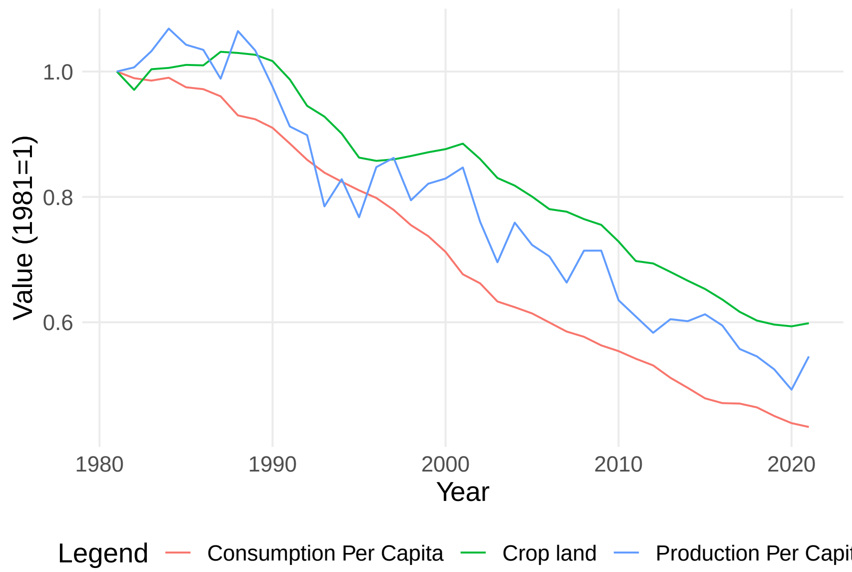

Figure E.10: Rice Production over Time. This figure shows how rice consumption per capita, production per capita, and rice crop land have changed over time in South Korea. Data comes from Statistics Korea. See the text for additional details.

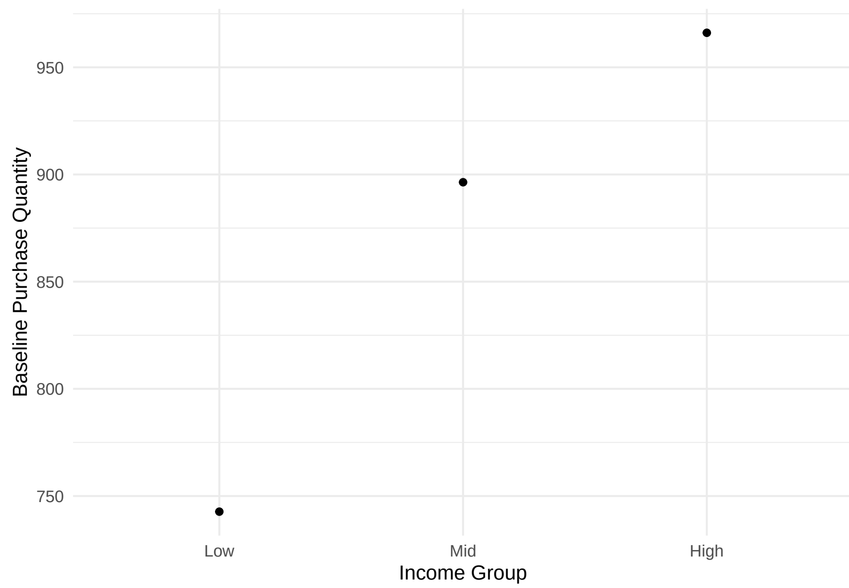

Figure E.11: Correlation Between Baseline Purchase Quantity and Income. This figure shows the relationship between household income and baseline (year = 2010) grocery purchase quantity using the grocery purchase panel data.

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