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

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Abstract

Given that lifecycle greenhouse gas (GHG) emissions from wasted food are comparable to those from road transport, promoting more efficient food use is essential for climate change mitigation. A textbook solution is penalizing food waste generation with a corrective tax, but limited evidence exists on the benefits and costs of such a policy. 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 food waste and associated lifecycle GHG emissions primarily by discouraging excessive grocery purchases in the first place. Second, building on the household production model, I show that the primary abatement strategy is spending more time on meal production. Finally, the tax appears to affect behavior mainly through non-pecuniary channels and is likely welfare-improving under mild conditions.

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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 lifecycle (Gustavsson et al. 2011, IPCC 2014, FAO 2015). 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 (Pigou 1920).[1] However, given that there are multiple abatement strategies, 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, 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 on households in proportion to the quantity of food waste generated. To examine the benefit, I study the impact of the tax on households' food usage and its implications for the lifecycle 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 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 were required 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 (the 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 (the Wave 2 expansion). Importantly, because the physical infrastructure for unit tax collection can be costly, the unit tax rolled out over time, and 30% of households were paying flat tax even in 2017. In tandem with the expansion, the tax rate has also substantially increased, but the tax is still small in absolute terms with an

[1] An alternative policy approach is imposing a carbon tax on food. While theoretically appealing, this policy faces challenges in terms of technical feasibility, political acceptability, and efficacy. More details can be found in Section 6.2.

average rate of 6 cents for 1 kg or $1.3 per month for a household with average waste quantity.[2]

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 to identify the abatement strategy and 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.[3] I also show that the results are robust to alternative methods proposed in the recent difference-in-differences literature (Cengiz et al. 2019, Callaway and Sant'Anna 2021, Sun and Abraham 2021, Borusyak et al. 2022).

The empirical exercise produces three key results. First, I find that the policy is highly effective; for an average household, the tax reduces annual food waste by 19% (46kg) and annual grocery purchase quantity by 5.5% (41kg). Comparing these effect in levels (41kg vs. 46kg) suggests that over 90% 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 less than 10%. 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 perishable items are more likely to become food waste when not consumed in time. Importantly, these effects do not come at the cost of households' nutritional needs: the tax does not reduce food and nutrient intake, 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 164kg CO_2eq per household, or 3 million ton of CO_2eq nationally, which is comparable to the emissions from 750 thousand passenger vehicles. Furthermore, the tax produces a private benefit by encouraging households to reduce their expenditure on groceries by $169 per year.

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 7.6% more time (55 additional

[2]In this paper, the exchange rate is $1 = KRW1100. Also, to put the tax size in context, $1.3 is less than 0.5% of monthly grocery spending for an average household in the sample.

[3]When aggregated data is used, I compare geographic units with different treatment intensities over time.

hours per year) on meal production after the tax, valued at $175 per year.[4] Further, web search data suggests that spending more time on organizing food is one way households use food more efficiently. In contrast, I do not find any change in grocery input quality or productivity of meal production due to the tax. Taken together, the tax seems to generates a large benefit by reducing GHGs, and its abatement costs are almost completely offset by savings on the grocery bills.

Lastly, I explore the mechanism and discuss policy implications. To rationalize the disproportionately large impact of a small tax, I first show that the price effect alone seems to explain less than 10% of the estimated tax effects under a range of plausible substitution elasticities from earlier studies (Aguiar et al. 2012). Consistent with this, I also find that the tax elasticity of grocery demand is over an order of magnitude smaller than corresponding price elasticities (Andreyeva et al. 2010). A large non-pecuniary effect likely arises from the new information generated through the measurement of food waste, which is a fundamental step in implementing the unit tax. Finally, I show that the tax is highly cost-effective—the program cost of reducing one ton of CO_2 is as low as $12—and passes the cost benefit analysis under mild conditions.

Related literature. This paper contributes to four different bodies of literature. First, I contribute to the studies exploring the effects of environmental regulation on 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 two key pillars of a welfare analysis. To that regard, perhaps the closest paper 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.[5] This has important practical implications given rising attention to the climate policies targeted at households (OECD 2011, Creutzig et al. 2018, IPCC 2022).

[4]To express the time cost in monetary terms, I 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).

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

Second, this paper departs from previous literature 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 on food, which, despite its substantial contribution to climate change, has received relatively little attention. The findings of this paper suggest that tackling consumer-driven food waste can be a highly cost-effective and 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 studies that focus on waste quantities at the disposal stage (e.g., increased recycling) (Fullerton and Kinnaman 1996, Allers and Hoeben 2010, Carattini et al. 2018, Bueno and Valente 2019, Valente 2021). Understanding the upstream effect is particularly important for food waste because the GHG emissions from the farm-to-kitchen stage are responsible for 90% of lifecycle GHG emissions from food waste (Crippa et al. 2021). Second, earlier studies underestimate the social cost of waste by an order of magnitude—even without considering the GHG emissions from the upstream—by abstracting away from the GHG emissions from waste.[6] These two differences could explain why earlier studies in general conclude waste pricing policies welfare-harming.

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

The rest of the paper proceeds as follows. Section 2 provides background on the GHG emissions from food waste and waste policy changes in South Korea. Section 3 details the data sources and provides summary statistics. Section 4 and Section 5 estimate the benefits and costs of the tax, while Section 6 discusses mechanisms and policy implications. Section 7 concludes.

[6]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 food degradation in landfills are considered, the social cost of waste is at least \$207/ton at \$190/ton of the social cost of carbon (EPA 2016, 2023).

2 Background

2.1 lifecycle GHG Emissions from Wasted Food and Policy Responses

Lifecycle greenhouse gas (GHG) emissions from wasted food are estimated at 4.4 GtCO_2eq, constituting 8% of total anthropogenic GHG emissions (FAO 2015).[7]. This is comparable to the annual emissions from the entire road transport at 5.1 GtCO_2eq each year (IPCC 2014). Two primary factors contribute to such substantial lifecycle GHG emissions from wasted food. First, producing food—even if it is ultimately wasted—results in substantial GHG emissions because food production is highly carbon-intensive.[8]. Second, food waste generates large amounts of methane when it decays in landfill, which explains why landfill is the third largest methane source in the US despite widely adopted methane-to-energy facilities (EPA 2016, Kaza et al. 2018). Notably, the relative contribution of these two sources differs by an order of magnitude: Crippa et al. (2021) shows that 90% of the lifecycle GHGs from food waste are attributable to the farm-to-kitchen stage.

Accordingly, food waste has gained significant policy attention in recent years.[9] While food waste prevention is deemed most desirable (as illustrated by the EPA's food recovery hierarchy in Appendix Figure E.1), prevailing policies in practice focus on recycling already generated wasted food (National Academies of Sciences, Engineering, and Medicine 2020).[10] A corrective tax on food waste can be a powerful alternative, as it has the potential to promote more mindful consumption habits.

2.2 Waste Policies in South Korea

Wave 0 (1995-2004): unit-based tax on landfill waste. Between 1970–90, waste quantity increased by sevenfold. To address resulting landfill capacity problem, a national landfill tax was implemented in 1995. The policy had two key features. First, source-separated recycle items such as glass bottles 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

[7] 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.

[8] This is due to several factors, including land clearing (deforestation), methane emissions from enteric fermentation in livestock, and the widespread use of nitrogen fertilizers (Springmann et al. 2018, IPCC 2019).

[9] 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).

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

advance. Prior studies found that this policy reduced the amount of waste in landfill (Hong 1999).

Wave 1 (2005-2012): Food waste segregation and partial implementation of unit-based food waste tax. In response to increasing environmental concerns over food waste in landfills, the Ministry of Environment mandated that municipalities collect food waste separately and recycle it into compost or animal feed. Also, to offset the cost of service provision, municipalities were permitted to impose a food waste tax on households. Since the Wave 1 policy focused on *segregation* rather than *reduction*, the collection system was strategically designed to minimize operational costs. Consequently, food waste from apartment complexes were typically collected without measurement and residents were charged a flat tax ($1-2 per month).[11] The collection methods for non-condo residents were more varied: about half of municipalities charged flat fees while the rest required households to purchase official food waste bags (Figure 2.1 (a)), which typically cost 1 cents/kg during this period. As detailed Section 5.2, the Wave 1 expansion is utilized to identify the abatement costs of the unit tax.

Wave 2 (2013-): Nation-wide expansion of the unit based food waste tax. With mounting concerns over GHG emissions from food waste, the central government mandated that municipalities expand the unit tax by 2013. As the Appendix Figure E.2 (a) shows, the overall fraction of households under the unit tax was around 30% between 2009 and 2012 (during the Wave 1 period) but sharply increased to over 70% in 2017, with the most dramatic change occurring in 2013.[12] Further, the map of the Wave 2 expansion in Appendix Figure E.3 (a) reveals substantial variation in the extent of expansion across different municipalities.

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 2.1 (b)).[13] 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.

[11] In this paper, the terms "apartments" and "condominiums" are used interchangeably. Unlike in the U.S., where "apartment" typically refers to rental units, in South Korea, "apartment" can refer to both rented and owned units.

[12] The figure is produced based on the 63 municipalities in the metropolitan Seoul area, an area coinciding with the empirical analysis on food usage.

[13] 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").

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

Figure 2.1: Unit Based Food Waste Tax Collection Methods

In tandem with the extensive margin unit tax expansion, there has been an eight fold increase in the tax rate over the same period (Appendix Figure E.2 (b)). 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 too small to cover the operation costs, each municipality ends up spending substantial amount of public funds to provide these services.[14]

3 Data

Food waste quantity and tax policy. I use the Unit-Based Waste Policy Yearbook from the Ministry of Environment to measure the food 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 seven households based on statistics from the City of Seoul and use per household waste quantity variable for empirical exercises.[15] The analyses leverage information from 63 municipali-

[14] 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)).

[15] The City of Seoul records food waste quantity separately for residential households and small restaurants since 2014. I use 2014 and 2015 data to calculate the conversion ratio. The data is available at https://stat.eseoul.go.kr/statHtml/statHtml.do?orgId=201&tblId=DT_201004_J070007&conn_path=I3.

ties in metropolitan Seoul area, which coincides with the geographic coverage of the grocery purchase data, from 2009 to 2015.[16] To track the fraction of households subject to the unit tax for each municipality-year, I cross reference municipality ordinances.[17] 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. Grocery purchase information comes from consumer grocery panel data from the Rural Development Administration. The survey starts in 2010 and has approximately 1000 panelists (households) each year from metropolitan Seoul area, which consists of three provinces (Seoul, Incheon, Gyeonggi-do), the fourth largest metropolitan area in the world with population over 25 million. Panelists receive a mailed journal and are required to record their monthly grocery expenditures. 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. Further, I exclude liquid items, which account for 9% of the total weight of purchased food, that can be discarded down the drain without incurring the tax. I determine the unit tax status for each household using street address information. Having a detailed address is particularly useful 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 category, expenditure, and unit price.[18]

Food intake and nutrition. I use the Korea National Health and Nutrition Examination Survey (KNHANES), waves of nationally representative cross-section survey of approximately 10,000 individuals, from the Korea Centers for Disease Control and Prevention. I use responses from metropolitan Seoul area over the 2010-2017 period that coincides with the consumer grocery purchase data. I primarily utilize the nutrition survey part of the data, 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 consumed food item. I supplement the nutrition survey with health

[16] The food waste data starts in 2009 and is replaced by another metric in 2016.

[17] For municipalities using the smart card system, I acquire a complex level implementation date through the Official Information Disclosure Act request because the system rolled out over time even within the same municipality.

[18] For shopping records with missing unit price data, I impute the missing values using price information from nearby stores. See Appendix A.2 for more details on imputation steps and validation tests.

examination results (e.g., weight or BMI). Because KHANES dataset discloses address at the community level, which is the smallest administrative unit in South Korea, I can assign the unit tax status at the household level with high precision.

Time use on food production. To investigate households' food waste abatement strategies, I use the Korean Time Use Survey from Statistics Korea, an official national statistical agency. The data documents how much time individuals (age over 10) spend on each time-use category in a given day.[19] Time spent on food production is documented in four different categories, which are cooking, cleaning up after meal, bookkeeping, and shopping. 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. Unlike the grocery or food intake data, time use data discloses respondents' address at the province—the largest sub-national administrative unit—level, which makes it challenging to assign the unit tax status. In Section **??**, I discuss how I address this limitation.

Municipality characteristics. I use Census on establishments, regional statistics (from the Statistics Korea) 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.

Summary statistics. In Table 3.1, I provide summary statistics for key dependent variables (see Appendix A.1 for descriptive statistics for additional variables). To contextualize different variables, I express everything in terms of per year per household. A two points are worth highlighting. First, comparing the amount of total food waste with the purchased food amount suggests that 28% of the purchased food is discarded, which is consistent with a global trend (FAO 2013). Further, the consumed (526kg) and wasted (206kg) food quantity adds up to the purchased quantity (740kg), indicating that the three datasets together successfully capture an average household's food usage.

Second, the farm-to-kitchen GHG emissions from an average food basket (740 kg) are 2,678kg CO_2eq, which is as large as the emissions from driving 6,849 miles with an average passenger vehi-

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

Table 3.1: Descriptive Statistics (Per Household Per Year)

Variables	Min.	Max.	Mean	Std.Dev.	N
Food waste (kg)	34.11	780	206	72.55	441
Total grocery purchase (kg)	20.97	2,213	740	307	2,872
Total grocery expenditure (USD)	119	12,312	3,658	1,534	2,872
Total GHG from grocery (kg CO_2eq)	38.03	9,912	2,678	1,270	2,872
Intake at Home (kg)	0	5,142	526	477	17,264
Intake away from Home (kg)	0	8,764	933	737	17,264
Calorie at home (1000 Kcal)	0	9,320	799	624	17,264
Meal Production Time (Hrs)	469	1,067	726	87.21	672

cle.[20] To convert food purchases to GHG emissions, I leverage food-item specific farm-to-kitchen GHG emissions data from Poore and Nemecek (2018). Also, 2,678kg CO_2eq suggests that the lifecycle social cost of 1kg of discarded food is at least \$0.69 at \$190 social cost of carbon (EPA 2023).[21] However, the highest observed unit tax rate is less than 20% of \$0.69, let alone the operation costs.

In Appendix A, I validate the data used in this paper by comparing it with external sources. For instance, I assess whether each dataset is representative of an average household in South Korea. Additionally, this section provides balance tests.

4 Effect of the Unit Tax on Food Usage

4.1 Estimation Framework

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 difference-in-differences literature (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} are various grocery purchase outcomes for household i living in municipality m at year t.

[20] Based on EPA's Greenhouse Gas Equivalencies Calculator (accessed Aug 5, 2024 at https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator).

[21] \$0.69 is a lower bound because food waste creates negative environmental impacts beyond GHG emissions.

Tax_{imt} is a dummy 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. $\boldsymbol{X_{ihmt}}$ represents time varying household characteristics: working status, income, housing type, age, and family size. I also include household by municipality fixed effect λ_{im}, which allows household characteristics to vary by municipality. This accounts 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 (Appendix Figure A.3) 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 show that allowing for the possibility of households living in different housing types responding differently (including ω_{ht} instead of ω_t) to shocks over time does not change results.[22] I also 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).

To understand the impact of the tax on food intake and nutritional content, I estimate a variant of equation (1): $log(M_{ihcmt}) = \beta T_{hcmt} + \delta \mathbf{X}_{ihcmt} + \lambda_{hm} + \omega_{ht} + \epsilon_{ihcmt}$ 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} are 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), three differences are worth pointing out. First, since food intake can vary by individual even within a household, i indicates an individual rather than a household. And $\mathbf{X}_{ihcmt}$ is individual level determinants of food intake: whether someone has a child, family size, income, age, sex, and working status. Second, as the data do not track the same individual over time, I add municipality by housing type fixed effect (λ_{hm}) instead of the household by municipality fixed effects. Third, because I do not observe a street address, a binary tax status is assigned based on the community—the smallest administrative unit in South Korea—

[22]More specifically, I estimate $log(Q_{ihmt}) = \sum_{k=-4}^{3} \alpha^k Tax^k_{ihmt} + \boldsymbol{X_{ihmt}}\delta + \lambda_{im} + \omega_{ht} + \epsilon_{ihmt}$ where Tax^k_{ihmt} 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. Thus, I impose endpoint restrictions such that $\alpha^k = \underline{\alpha}$ for $k < -4$ and $\alpha^k = \bar{\alpha}$ for $k > 3$.

and housing type.[23] In the estimation process, I weight the regression using sample weights.

Continuous Treatment Models. To estimate the impact of the tax on food waste quantity, I estimate a continuous treatment version of equation (1) because the level of observation in the food waste quantity data is municipality and the unit tax status typically varies within a 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.[24] $\boldsymbol{X_{mt}}$ 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 informs the marginal effect of changes in $(\%)Tax_{mt}$. Since the unit tax is expanded due to the central government's mandate, it is unlikely that municipalities select into expanding the unit tax. Further, as Appendix Figure E.4 shows, the magnitude of expansion is larger for municipalities with low fraction of households living in apartments, which had a larger room for expansion. 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 "clean" municipalities, namely bottom 10% municipalities in terms of $(\%)Tax_{m,2015}$. In the estimation process, I use municipality population as a weight.

4.2 Findings

Effect of the unit tax on food waste and purchases. I first report the effect of the unit tax on food waste quantity. In Panel A 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

[23] For condominium residents, I assign $T_{hct} = 1$ when the fraction of households under the tax in community-year is over 50% and 0 otherwise, which in principle can create non-trivial measurement errors. However, as Appendix Figure E.5 illustrates, community is small enough such that the distribution is bimodal with two modes at near 0 and 1 for most cases. The tax status for non-condo residents do not vary within a municipality.

[24] As discussed in section 3, 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 7 (for more details, see Section 3). Then, $Tax_{mt} = \sum_k tax_{mkt} z_{mkt}$ where tax_{mkt} is the fraction of households in k that are subject to the tax for k∈{condominium, other housing types, restaurants}. z_{mkt} is share of k in each municipality.

significant. In particular, when the fraction of households subject to the unit tax changes from 0 to 100%, food waste per household decreases by 19% ($e^{-0.209} - 1 = -0.188$) or 46kg when evaluated at the average waste quantity in the pre-tax period for low treatment intensity municipalities (244kg). In Appendix Table E.1, I report the result from the stacked DD approach. The estimated effect is consistent with Table 4.1, although the effect size is slightly attenuated at 14% ($e^{-0.152} - 1 = -0.141$).

Figure 4.1 (a) illustrates results in column (1) using binned regression. The horizontal axis is the change in the treatment intensity over time (i.e., $(\%)Tax_{m,2015} - (\%)Tax_{m,2009}$) and the vertical axis shows the corresponding change in per household food waste. The fitted line suggests that municipalities with larger increase in treatment intensity experienced a larger reduction in waste quantity.

To understand the social benefit of food waste reduction, I explore the source of observed food waste reduction. Column (2) of Table 4.1 Panel A shows that the unit tax reduces food purchase per households by 5.5% or 41kg based on the pre-tax average. Comparing 41kg to the observed reduction in food waste quantity (46kg) implies that 89% 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. 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 size of potential leakage effect—up to 11% in this case—is important.

Similarly, in column (3), I find a 4.6% reduction in grocery spending from the unit tax, which amounts to $169 savings on annual grocery bill for an average household. This finding suggests that the tax generates a private financial benefit in addition to reducing negative externalities. Further, as discussed in Section 3, purchase quantity is subject to measurement error due to missing unit price data. Finding a similar effect using expenditure strengthens the credibility of estimates in column (2). The reduction in grocery purchases after the tax treatment is consistent with external survey results (Ministry of Environment 2012).[25]

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

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

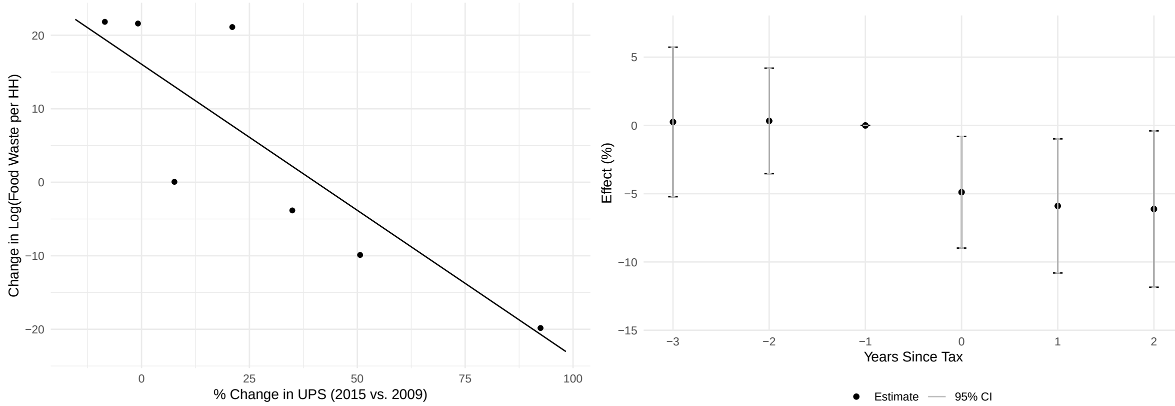
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Food Waste and Food Purchases								
(%) Unit Tax	-0.209***							
	(0.055)							
Unit Tax		-0.057***	-0.047**	-0.101***	-0.035	-0.058***	0.001	-0.061**
		(0.019)	(0.021)	(0.030)	(0.022)	(0.018)	(0.016)	(0.027)
Dependent Variable in Log	Food Waste Per HH	Grocery kg Per HH	Grocery Exp Per HH	Perishable kg Per HH	Storable kg Per HH	Kg per Trip Per HH	N Shopping Per HH	GHGs Per HH
Effect In Level	-46	-41	-169	-29	-15	-0.25	0.2	-158
Municipality FE	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality × HH FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	441	2,872	2,872	2,870	2,872	2,872	2,872	2,872
Panel B: Food Intake, Nutrition, and Health Outcomes								
Unit Tax	20.64	37.54	20.04	-52.98*	-59.3**	2.782	-1.246**	-0.332**
	(22.69)	(24.83)	(32.25)	(26.69)	(28.37)	(11.28)	(0.524)	(0.141)
Dependent Variables	Intake at Home	Calorie at Home	Vitamin A at Home	Intake out of Home	Intake out of Home (Discretionary)	Intake out of Home (Non-Disc.)	Weight	BMI
Mean of Dependent Variables	526	799	307	933	861	86	53	21
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Housing Type × Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,665	15,665	15,665	15,665	15,447	15,447	15,633	15,586

Note:
This table reports the effect of the unit tax on household food waste generation and food purchases (Panel A) and food intake (Panel B). Panel A shows the estimation results from equation (2) using municipality by year level food waste data and results from equation (1) using household level grocery panel data. Panel B 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 baseline control variables are included. Outcome variables in Panel A are in log scale while outcome variables in Panel B are in the original scale. All standard errors are clustered at the municipality level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In columns (4) and (5), 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. Columns (6) and (7) indicates that the reduction in the grocery purchases is almost entirely driven by purchasing less food per store visit, perhaps in an effort to refrain from purchasing food that will not be consumed.

In Figure 4.1 (b), I show how grocery purchase quantities change relative to the unit tax implementation timing. The point estimates before the unit tax is at 0, satisfying the parallel trend assumption. Also, the treatment effect is sharp and persistent for the next three years. In Appendix Figure E.6, I repeat the exercise using alternative estimation methods that allow treatment heterogeneity proposed in the literature (Cengiz et al. 2019, Callaway and Sant'Anna 2021, Sun and Abraham 2021, Borusyak et al. 2022). Overall, I find similar point estimates and standard errors, which suggests that the effect is robust to estimation approaches once always-treated and non-absorbing observations are removed. In Appendix Table E.2, I add housing type by year fixed effects, allowing for the possibility that households in different housing types may respond differently to national-level shocks, and find that the results are remain very similar to those in Table 4.1.

Effect of the unit tax on food intake and nutrition. Given changes in food purchase patterns, I further examine impact of the unit tax on food intake and its nutritional and health consequences. In Table 4.1 Panel B, column (1), I find that the unit tax leads to a statistically insignificant 3.8% increase in the quantity of food consumed at home. Consistent with this, columns (2) and (3) show slight increases in key nutrient intake at home following the tax. In contrast, findings in columns (4)-(6) indicate that individuals reduce their consumption of food away from home, particularly from discretionary sources like restaurants or takeout. These findings imply that individuals substitute meals away from home with meals at home after the unit tax, presumably because the tax prompts closer monitoring and timely consumption of groceries, which would be at odds with unplanned consumption of food away from home. Finally, in columns (7) and (8), I find that food intake changes cause an economically small change in weight and BMI metric. This might be attributable to reduction in food intake away from home, which typically has poorer diet quality—higher intakes of



(a) Food Waste

(b) Food Purchase

Figure 4.1: The Effect of the Unit Tax on Food Waste and Purchases. Panel (a) shows results from a binned regression estimation between the change in the fraction of households under the unit tax between 2009 and 2015 and the change in the food waste quantity per household. Panel (b) shows an event study plot for food purchase quantity. All dependent variables are log transformed.

energy, salt, and saturated fats (Gesteiro et al. 2022).

Although the food intake data do not provide information on the dollar amount spent on food items, reduction in the food consumed away from home suggests an additional financial benefit from the unit tax, beyond \$169 from Table 4.1 Panel A, column (3). Further, the fact that food intake at home do not decline after the tax implies that the reduction in grocery purchases likely comes from the previously wasted portion of the food basket rather than from the consumed portion. The findings in Section 4.2 suggest that the unit tax encourages a more efficient food use without compromising nutritional needs. But how households can maintain food intake with smaller grocery purchases? What do they do and what is the associated costs?

5 Household Abatement Strategies and Corresponding Costs

5.1 Conceptual Framework

To identify households' abatement strategies and estimate corresponding costs, I build on the insights from the household production model (Becker 1965).

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

Consider a simple meal production process in equation (3), where meal at home (M) 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 $M_1 \geq M_0$, 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, for instance, 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 estimate the impact of the unit tax on the time spent on meal production, I analyze the 1999, 2004, and 2009 Korean Time Use Survey microdata. If the time use data has detailed location information akin to the grocery or food intake data, I could have assigned the binary tax treatment status for each individual. Unfortunately, the time use data disclose respondent locations at the province—the largest sub-national administrative unit in South Korea—level only, and thus I leverage the proportion of households subject to the tax for each province-housing type as a proxy for the tax status. Importantly, as Appendix Figure E.7 Panel (b) shows, spatial and temporal variations in the Wave 2 expansion is obscured at the province-housing type level, which makes it challenging to find a clean control group. To address this, I leverage the Wave 1 expansion, where most province-housing type pairs remained untreated (Appendix Figure E.7 Panel (a)). Further, I collapse individual-level data into province-housing type-survey date-year level observations.[26]

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

[26] I show that analysis without data aggregation produces similar results.

A resulting canonical difference-in-differences estimating equation with continuous treatment is in equation (4). Time_{hpdt} is time spent on meal production activities per household for housing type by province hp on day of the week d in year t. $(\%)T_{hp,2009}$ is the proportion of households subject to the unit tax as of 2009, or the time-invariant treatment intensity, for hp. I_t is a post period indicator that takes 1 if t is 2009, and $\mathbf{X}_{hpt}$ represents the determinants of household time allocation, including factors such as whether the household has children, family size, employment status, gender, and house size, which serves as a proxy for income. 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 meal production activities. In column (1), I show that an average household spend 9.1 (7.6%) additional minutes per day or 55 additional hours per year on meal production after the unit tax. Investigating individual activities in columns (2)-(5), I find that the result in column (1) is driven by increase in meal preparation time, which include 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 as well, but the effect fails to rule out the null effect at the conventional statistical significance level.

Interestingly, I find that time spent on grocery shopping does not increase, which is consistent with findings from Table 4.1 that the tax does not increase the shopping frequency. This suggests that higher food use efficiency do not come at the cost of increased GHG emissions from more trips (i.e., more driving). Taken together, households seem to use more time to compensate for fewer groceries, and such a substitution between time and money (although by different triggers) has been well documented in earlier studies (Aguiar and Hurst 2005, 2007a). Appendix Table E.3 shows that the estimated results from household level data lead to the same conclusion.[27]

Figure 5.1 (a) visually confirms findings in Table 5.1. For this, I run binned regression between $(\%)T_{hp,2009}$ and the first difference in meal production time between 2004 and 1999 (pre period) and 2009 and 2004 (post period). The left-hand side figure shows that the change in time spent on meal production between the high versus low treatment intensity units are essentially the same, which is akin to the "no pre-trend" condition for a binary canonical difference-in-differences case. Impor-

[27] The magnitudes are slightly attenuated perhaps due to measurement errors in the binary tax status variable, which is defined as 1 if the fraction of households under the unit tax in a province-housing type is over 50%.

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

	(1)	(2)	(3)	(4)	(5)	(6)
(%) Unit Tax x Post	9.07**	7.49***	2.31	0.438**	-1.16	0.479**
	(4.03)	(2.22)	(1.39)	(0.192)	(1.37)	(0.224)
Dependent Variable	Overall Time	Prep Time	Cleanup Time	Diary Time	Shopping Time	Dollars Per Day
Province × Housing Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	672	672	672	672	672	448

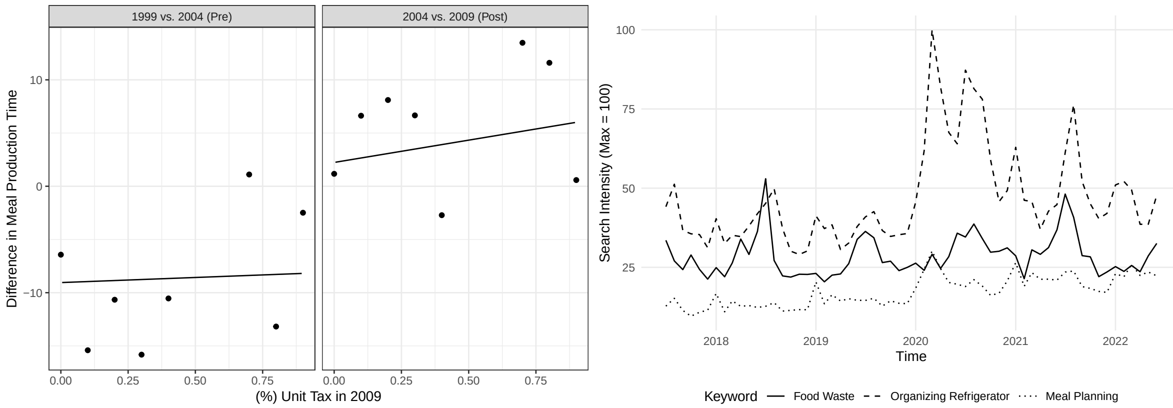
Note:
This table reports the effect of the unit tax on household meal production time by estimating equation (4) using the time use survey of 1999, 2004, and 2009 (2004 and 2009 for column (6)). I report the cofficient of interest only, but all the regressions include baseline control variables. Standard errors are clustered at the province by housing type level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

tantly, 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 utilize the additional time allocated on meal preparation, I leverage web search data from "Naver," a leading search engine in South Korea.[28] In Figure 5.1 (b), I depict web search intensity for three keywords: "food waste," "organizing refrigerator," and "meal planning," for female users aged 30–60, a demographic primarily responsible for meal preparation at home. The figure shows that search intensities for "organizing refrigerator" and "food waste" are strongly correlated over 2017–22. Further, the search intensity for "organizing refrigerator" sharply increased during COVID-19 lock down in 2020, when individuals had to prepare more meals at home. Interestingly, as Appendix Figure E.8 illustrates, such a pattern does not appear at all for other demographic groups such as men aged 30-60 or female younger than 20, which collectively suggest that organizing the refrigerator is a key strategy for reducing food waste and improving food use efficiency.[29] This finding aligns with earlier studies that identify a lack of knowledge about current food stock as a major driver of household food waste (Farr-Wharton et al. 2014, Gaiani et al. 2018).

[28] If households had perfect knowledge of food waste reduction strategies, the unit tax would simply motivate them to apply what they already know, making search data less informative for this purpose. However, survey results reveal a knowledge gap in these strategies (Ministry of Environment 2015).

[29] Because search intensities are normalized for each demographic, I cannot compare them across different groups.



(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 regression. The X-axis shows the fraction of households under the unit tax in 2009 and the Y-axis shows the first difference in meal production time for years 2004 vs. 1999 (left) and 2009 vs. 2004 (right). 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.

In Table 5.1 column (6), I estimate the abatement cost in dollars 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 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 \$175 per year per household, which almost exactly offset by savings on grocery spending (\$169 from Table 4.1) due to the unit tax.[30]

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 5.5% reduction in grocery purchases is compensated by a 7.6% increase in time use (while output level does not decrease), a large increase in productivity seems implausible.

[30] \$175 suggests that the average value of time in the context of home production is \$2.9 per hour. As a benchmark, the average market wage in South Korea for homemaking jobs in 2009 was \$4.9 per hour.

6 Discussion

6.1 Why Such a Small Tax Has Such a Large Effect on Household Behavior?

Price effect. To investigate why the unit tax has a disproportionately large impact, I first decompose the tax effect into pecuniary versus non-pecuniary effects. To pin down the size of the price effect, I calculate the predicted change in the input ratio using substitution elasticity estimates (between 1.2 and 2.6) surveyed by Aguiar et al. (2012). 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 (assuming that the value of time remains unchanged) is at maximum 1.04%. Comparing this to the a 14% change in the input ratio suggests that the price effect alone explains at maximum 7% of the observed substitution effect.

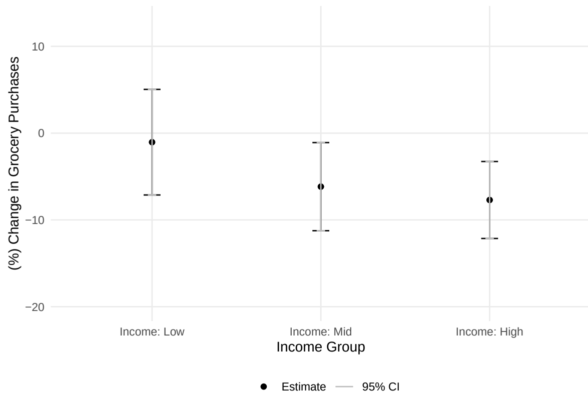
Two additional findings corroborate a small price effect. First, I leverage intensive margin tax rate changes to show that the tax elasticity of grocery purchase is -0.024 (se = 0.032),[31] more than an order of magnitude smaller than typical price elasticity of groceries (Andreyeva et al. 2010). Even after accounting for the fact that only one-third of purchased food is wasted (and thus subject to the unit tax), the starkly different impact of a dollar increase in the tax versus grocery prices suggests that the tax effect cannot be fully explained by the price channel alone (Chetty et al. 2009).

Second, in Figure 6.1, I present the differential impact of the unit tax on grocery purchases by (a) income level and (b) baseline grocery purchase quantity.[32] If the tax effect is driven by price, the effect size is likely to be largest for the lowest income group, which tends to have larger price elasticity (Andreyeva et al. 2010). However, Panel (a) suggests the opposite: while households in the low income group do not seem to change grocery purchases, households in the highest group reduce them by nearly 10%. Panel (b) provides one potential explanation: high income households, who typically purchase a large amount of food (see Appendix Figure E.9) and potentially wasted a significant portion, are primarily responding to the tax.

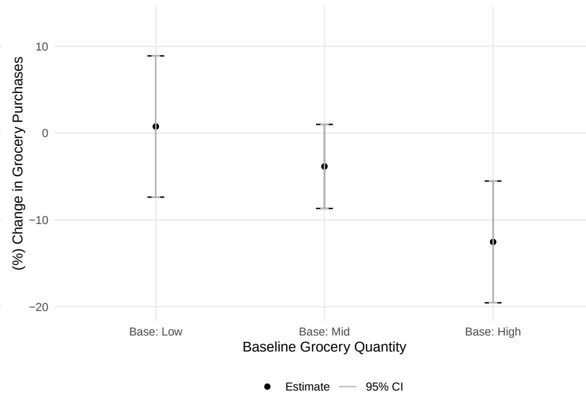
Non-pecuniary effects. The small price effect suggests that the majority of the unit tax's impact stems from non-pecuniary factors. Consistent with this, Lee and Seo (2022) finds that receiving

[31] I estimate this by replacing Tax_{imt} in equation (1) to $log(TaxRate)_{imt}$ conditional on $TaxRate_{imt} > 0$.

[32] For these exercises, I first create a dummy variable for income groups by categorizing the 10 income levels in the grocery panel dataset into three groups: low (levels 1-4), medium (levels 5-7), and high (levels 8-10). Similarly, a categorical variable for baseline grocery purchase is created by dividing households into three groups, each representing one-third of the purchase quantity distribution in 2010. These variables are interacted with Tax_{imt} in equation (1).



(a) Tax Impact on Groceries by Income Level



(b) Tax Impact on Groceries by Baseline Quantity

Figure 6.1: Heterogeneous Treatment Effect. These figures illustrate the differential impact of the tax on grocery purchases by including an interaction term between the unit tax dummy and categorical variables for (a) income level and (b) baseline grocery purchase quantities.

feedback on food waste generation alone seems to reduce food waste quantity by over 10% (or over a quarter of the full effect size of the unit tax).[33]

Earlier studies suggest that non-pecuniary effects may arise from either information provision or an emotional tax or subsidy effect. Per information provision, it is well documented that a large part of household food waste is attributable to a lack of recognition and monitoring of inefficient food usage.[34] Introducing a unit tax could remedy the situation, as the tax system inherently involves measurement of food waste when it is disposed of. This process provides regular feedback on the amount of waste generated, prompting households to be more mindful of their food usage. Alternatively, the unit tax might create an emotional disincentive for generating food waste or offer a moral incentive for reducing it (Glaeser 2006, Allcott et al. 2019a). This effect is likely to occur when the tax directly influences social norms or culture surrounding food waste (Allcott et al. 2019b).

6.2 Policy Implications

The estimates in Sections 4 and 5 allow me to quantify key elements of the costs and benefits of the unit tax, with the exception of non-pecuniary effects, which can directly influence consumer

[33] Lee and Seo (2022) studies the Wave 2 unit tax expansion with a particular emphasis on the smart card system. Since this system is new, residents typically had a one-month pilot period during which households receive instant feedback on their waste generation via the smart card system, but the marginal tax rate remains effectively zero.

[34] 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, National Academies of Sciences, Engineering, and Medicine 2020).

Table 6.1: Cost Effectiveness of the Unit Food Waste Tax

	Items	Value
GHG Change (1000 Ton)	Avoided Production (A)	3020
	Avoided Food Waste Treatment (B)	167
	Increased Food Waste in Landfill (C)	63
	Net GHG Effect (A+B-C)	3123
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)	-79
	Net Program Cost (D+E+F+G)	-43
Cost Effectiveness ($/Ton of CO_2eq)	(D+E+F)/(A+B+C)	12
	(D+E+F+G)/(A+B+C)	-14

surplus positively or negatively. Given this limitation, I begin by assessing the policy based on cost-effectiveness—the program cost to reduce 1 ton of CO_2. I then show that, under mild conditions, the policy could improve welfare, though the magnitude is not quantifiable. This section concludes with discussions on external validity and comparison to alternative tax designs.

Cost effectiveness. Using estimates from Table 4.1, Table 6.1 shows that the unit tax reduces life-cycle GHG emissions from wasted food by 3.1 million tons, which equivalent to the emissions from 750 thousand passenger vehicles (for more details, see Appendix C). Importantly, this effect is almost entirely driven by avoided production (item A: 3.0 million ton), which highlights the importance of implementing food waste policies that prioritize prevention over recycling.[35] Note, this exercise relies on two assumptions. First, profit-maximizing farmers will scale back food production in response to the unit-tax induced demand shock.[36] Second, any food waste reduction not explained by lower grocery purchases will end up in landfills, which is the worst-case scenario in terms of GHG emissions.

For the annual program cost, I take into account both the operating (item D and F in Table 6.1) and capital cost (item E in Table 6.1) of the unit tax system.[37] The combined program cost (items

[35]The GHG reduction effect from waste treatment can be much larger in other countries. In South Korea, nearly all food waste is processed at specialized facilities, which generate significantly less GHG than food waste in landfills. However, this practice is an exception rather than the norm; for instance, in the U.S., 50% of total food waste ended up in landfills in 2018 (EPA 2020).

[36]A similar assumption is made in Deschênes et al. (2017).

[37]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).

D+E+F) amounts to $36 million per year.[38] Comparing this cost to the total GHG reduction, the program costs $12 per tonne of CO_2 reduced. However, the $36 million program cost does not account for significant waste pickup and treatment cost savings from the unit tax. That is, since food waste tax revenue covers less than 50% of operational costs, local governments spend a large portion of their budget to provide these services.[39] Assuming a constant marginal cost, a 19% reduction in food waste after the unit tax saves $79 million per year nationwide. When these savings are considered, the government's cost to reduce one additional tonne of CO_2 becomes negative.

Welfare effects. 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. The extended household production model in Appendix D suggests that the former should factor in (1) grocery savings ($169), (2) additional time costs ($175), and (3) non-pecuniary effects of the unit tax. For the reduction in external costs, I multiply per households net GHG reduction (0.164 ton per year from Appendix C) with the up-to-date social cost of carbon $190 for emission year of 2020 (EPA 2023). Taking these three numbers suggest that the tax increases social welfare by $25 per household without considering the non-pecuniary effects.

Allcott et al. (2019a) shows that purely informational nudges, which help households to make more informed decisions, directly improve consumer welfare, whereas nudges that induce moral taxes, which can evoke guilt for a certain behavior, directly reduce consumer surplus. In Appendix D, I show that even if the non-pecuniary effect stems from a moral tax, the unit tax can be welfare improving under some mild conditions. Specifically, unless the unit tax induces a more than double increase in the "moral tax rate", the negative effect on consumer surplus has to be less than $25. Further, because food waste reduction generates important co-benefits such as preventing biodiversity losses, soil degradation, and water depletion, the unit tax perhaps can pass the cost benefit analysis even if there is a more dramatic increase in the moral tax rate.

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 price. For example, Homonoff (2018) reported a 40% reduction in the

[38] I exclude spending on waste pickup and treatment services, which must be provided regardless of the tax policy.

[39] For instance, the Seoul Metropolitan Government spent $136 million in 2015 on these services. Similarly; Kaza et al. (2018) reports that waste treatment accounts for 5-20% of the municipality budget in many countries.

usage of plastic bags in the US following the implementation of a 5-cent bag tax. Relatedly, Iizuka and Shigeoka (2022) report that imposing a small (e.g., $2) co-payment can reduce the likelihood of doctor visits by 5%. Second, given that the unit tax effect is driven by a non-pecuniary channel, earlier studies on information interventions or nudges also provide valuable benchmarks (Allcott 2011, Ferraro and Price 2013, Costa and Kahn 2013, Tiefenbeck et al. 2018, 2019). These papers find that report cards or real-time feedback reduce electricity or water consumption by 2–22% where the frequency of feedback seems to be an important determinant of effect size. Given that households dispose of their food waste 2–3 times per week on average, a 19% reduction in the food waste generation appears consistent with earlier research.

Tax on food or food waste. While lifecycle GHG emissions vary substantially across food items—for example, beef is 100 times more carbon intensive than vegetable to produce (Poore and Nemecek 2018)—the unit based food waste tax imposes a uniform tax rate for every wasted food. Given this limitation, a tax on food based on its carbon intensity can be considered an alternative policy to reduce food waste. While theoretically appealing, implementing such a tax is difficult for three reasons.

First, unlike CO_2 where emissions can be measured based on fossil fuel usage (due to emissions are proportional to fuel consumption), there is no straightforward method to measure non-CO_2 GHG emissions from food production (Timilsina 2022). For instance, emissions from growing beef or rice depends heavily on agricultural practices, which are extremely costly to measure. Second, taxing food consumption itself rather than penalizing wasting food is likely to be politically contentious with concerns over food insecurity and regressivity (Godfray et al. 2010, Dechezleprêtre et al. 2022).[40] Third, tax saliency literature 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 (Finkelstein 2009, Chetty et al. 2009). Given these considerations, a unit based tax on food waste is a practical yet potentially more powerful policy apparatus than taxing food. Further, given that the unit tax effect is mostly from the extensive margin, a low tax rate that is likely politically feasible should produce a similar effect size as an "optimal" tax rate.

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

7 Conclusion

Given that lifecycle GHG emissions from wasted food is comparable to that of road transport (IPCC 2014, FAO 2015), managing excessive food demand has become increasingly important for climate change mitigation. 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 6% as well as grocery spending by $169.

Building on the insights from the household production model, I show that spending more time on meal production is the primary abatement strategy and an average households spend 7.6% more time on meal production after the unit tax. However, the time cost is almost completely offset by savings from fewer grocery purchases. Finally, I find that over 90% of the unit tax effect can be explained by non-pecuniary effects, which likely arise from regular feedback produced by measurement of food waste, which is inherent to the implementation of the unit tax. Also, I show that the policy is highly cost-effective in reducing GHGs and is likely welfare improving under mild conditions.

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A Data Appendix

A.1 Detailed Descriptive Statistics

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

Variables	Min.	Max.	Mean	Std.Dev.	N
Panel A: Food Waste					
Number of residential households	4,993	420,976	128,226	76,591	441
Number of restaurants (smaller than 2,152ft^2)	315	13,899	4,775	2,613	441
Number of combined households (HH)	7,198	518,269	161,655	93,299	441
Food waste (kg)	34.11	780	206	72.55	441
Landfill waste (kg)	36.12	878	263	101	441
Panel B: Food Purchases					
Total grocery purchase (kg)	20.97	2,213	740	307	2,872
Perishable grocery purchase (kg)	0	1,363	296	173	2,872
Storable grocery purchase (kg)	15.55	1,553	443	187	2,872
Total grocery expenditure (USD)	119	12,312	3,658	1,534	2,872
Number of trips	10	354	171	54.43	2,872
Total GHG from grocery (kg CO_2eq)	38.03	9,912	2,678	1,270	2,872
Panel C: Food Intake and Nutrition					
Intake (kg)	34.45	8,764	1,460	752	17,264
Intake at Home (kg)	0	5,142	526	477	17,264
Intake away from Home (kg)	0	8,764	933	737	17,264
Discretionary Intake (kg)	0	8,764	861	723	17,009
Non-discretionary Intake (kg)	0	2,705	86.06	208	17,009
Calorie at home (1000 Kcal)	0	9,320	799	624	17,264
Calorie away from Home (1000 Kcal)	0	11,156	1,097	860	17,264
Vitamin A (g)	0	26,164	307	520	17,264
Weight (kg)	7.92	128	53.33	18.16	16,240
Panel D: Meal Production Time					
BMI	11.39	40.96	21.35	4.02	16,192
Meal Production Time (Hrs)	469	1,067	726	87.21	672
Cooking Time (Hrs)	243	562	403	47.26	672
Cleaing Time (Hrs)	98.85	304	216	29.06	672
Diary Time (Hrs)	0	60.83	6.17	5.86	672
Shopping Time (Hrs)	14.36	276	101	40.23	672
Non-food Home Making Time (Hrs)	365	1,217	653	97.43	672

Table A.1 presents summary statistics for a full set of 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, I treat a restaurant as seven households based on statistics from the City of Seoul. The first three rows present summary statistics for the number of residential households, restaurants, and both (residential and restaurant-converted households). The fourth and fifth rows jointly show that food waste accounts for 44% of the overall (food and landfill) waste quantity, which is a general pattern found in many countries.[41]

The second panel presents descriptive statistics for grocery purchases. An average panelist purchases 740kg of groceries per year, spending $3,658. 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 28% 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 40% of the total purchase is perishable items. To make these purchases, households make a grocery trip every two days (or 171 trips per year).

The third panel presents descriptive statistics on food intake, nutrition, and body metrics. To make the comparison with Panel A and B easier, I converted per capita daily intake quantities to per household annual intake quantities.[42] The first three rows in Panel C indicate that an average household intakes 1,460kg of food and about 40% of them are consumed at home. Importantly, the total intake quantity is consistent with statistics from a government agency.[43] The next two rows show that only about 10% of food consumed away from home is non-discretionary, such as meals at school or office cafeterias, suggesting that there is potentially a large room for food usage adjustments in response to the unit tax. The next row shows that an average household acquires 799,000 Kcal of calories per year (equivalently 826 Kcal per day per person) from food consumed at home.

Finally, Panel D documents annual time spent (in hours) on meal production for an average household—the total amount of time spent by any adult (age over 19). The first row shows that an average household spends two hours per day on meal production. From the second to fifth rows, I split up meal production into smaller time categories, and find that over 85% of the meal production time is time spent inside of kitchen—preparing ingredients, storing groceries, cooking, setting table, and doing the dishes (Statistics Korea 2009). Households spend another 100 minutes per day on other home making activities, including 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.[44]

A.2 Data Validation

Assessing the representativeness. The empirical exercises in this study draw on three distinct household-level datasets. To evaluate the representativeness of the survey respondents, I compare key demographic characteristics with benchmark data, such as the Census or other national-level surveys. Specifically, for age, family size, and housing type (if residing in an apartment) I use the Population and Housing Census, respectively. For employment and income, I use nationally representative survey data "Economically Active Population Survey" and "Household Income and Expenditure Survey (HIES)", respectively.

[41] 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.

[42] An average household size in the sample is 2.65.

[43] See https://www.khidi.or.kr/kps/dhraStat/result5?menuId=MENU01657&gubun=age1&year=2017 accessed on Aug 5, 2024.

[44] 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.

Table A.2: Sample Moments vs. Benchmarks

Variables	Mean	SD	Benchmark
Panel A: Grocery Panel			
Age	46.97	8.37	46.14
Housing Type (if APT)	0.54	0.5	0.5
Family Size	3.52	1.18	3.05
If Working	0.55	0.5	0.5
Monthly Income (USD)	3633	1782	3563
Panel B: Food Intake			
Age	39.79	22.95	38.14
Housing Type (if APT)	0.5	0.5	0.5
Family Size	2.91	1.26	2.65
If Working	0.59	0.49	0.6
Monthly Income (USD)	3105	2196	3217
Panel C: Time Use			
Age	35.81		35
Housing Type (if APT)	0.4	0.49	0.45
Family Size	2.69	1.14	2.95
If Working	0.61	0.49	0.58
Monthly Income (USD)	2515	2581	2536

Appendix Table A.2 Panel A presents this comparison for the grocery purchase dataset. To ensure a meaningful benchmark, I restrict the benchmark data to match the demographic profile of the grocery panel, namely (1) 97% of the panelists are female, and (2) the age range is limited to 25–72. The results in Panel A indicate that the grocery panel data largely align with the benchmark. For example, the average age in the grocery panel is 47, closely mirroring the Population Census average of 46.1. The most notable discrepancy arises in family size: the grocery panel reports an average family size of 3.52, while the Population Census indicates an average of 3.05. This difference likely stems from the fact that the grocery panel did not survey single-person households until 2017, the final year of my sample. In empirical exercises, I control for family size to minimize the potential bias from different family sizes.

In Panel C, I compare the time use data to benchmarks from the 1999–2009 period. Again, sample means closely align with benchmarks, suggesting that the time use data successfully represents an average household's time usage pattern.[45]

Additional validation tests for the grocery panel data. 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,

[45]The time use survey provides age data for individuals aged 10 and older, while for those younger than 10, it records only the number of preschoolers in each household. To estimate the mean age of the entire population, I assume an average age of 3 years for preschoolers. Although this assumption enables the calculation of the overall average age, determining the standard deviation requires further assumptions about the variance in the ages of preschoolers. This limitation has minimal impact to the conclusion since the comparison of sample means indicates that the time use survey already closely mirrors the Population Census.

it could still be the case that households forget or skip reporting. Second, as discussed in section 3, 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.

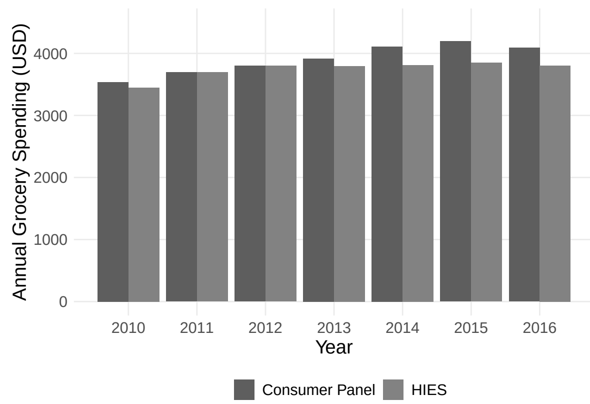
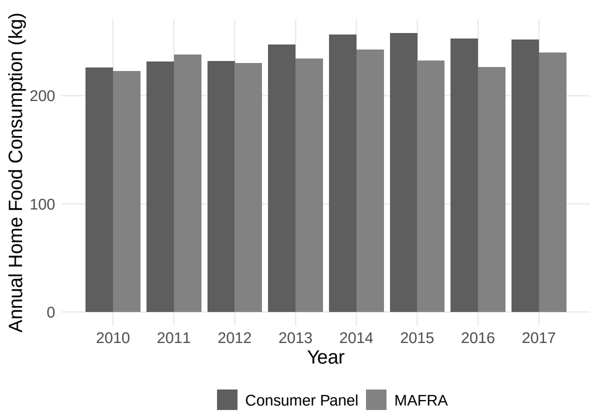
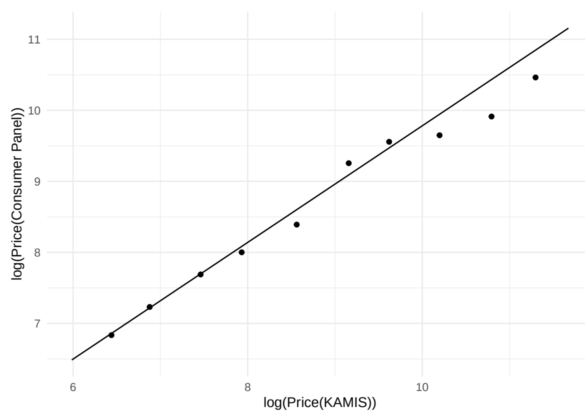


Figure A.1: Consumer Panel Data Validation (Total Expenditure). This figure compares the overall household spending from the comsumer panel data and the Household Income and Expenditure Survey.

For the first issue, I compare overall spending amount (in dollars) from an average panelist to household spending information from HIES, a nationally representative survey of over 7,000 households. I use total grocery expenditure net of liquid categories (cooking oil and diary) from urban households with family size larger or equal to two to make it comparable to the consumer panel. Figure A.1 shows that annual grocery expenditure from these two different surveys are very close to each other over the 2010–16 period.[46]



(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.

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

[46] 2017 is excluded because the grocery panel 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.

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.

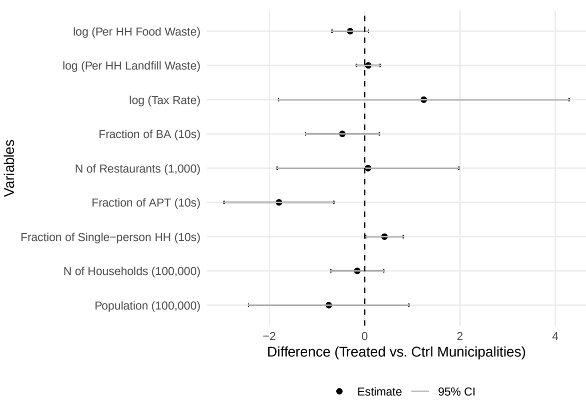
To test the validity of this procedure, I compare the per household grocery purchase in kg from the grocery panel and per household food consumption statistics from the Ministry of Agriculture, Food and Rural Affairs (MAFRA). Importantly, the consumption statistic does not distinguish food that is actually 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 binned scatterplot between the unit price information from the grocery panel and the price information from KAMIS (Korea Agricultural Marketing Information Service) website, which is an official source, maintained by the Korea Agro-Fisheries & Food Trade Corporation. The figure suggests that the imputed price is highly correlated with the actual price.

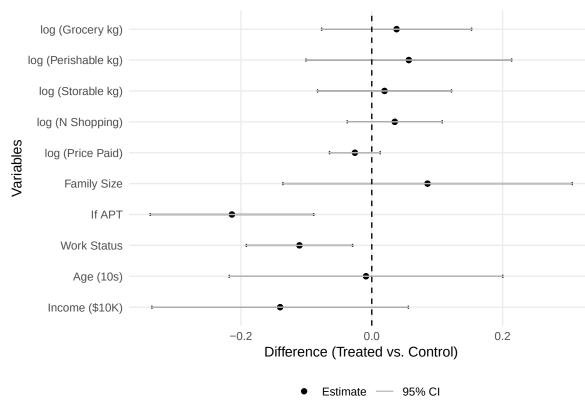
A.3 Balance Tests

Balance plot. In Appendix Figure A.3, I show various balance test results to investigate if there are baseline 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% or 7 municipalities in terms of the % of households subject to the unit tax in 2015, while the treated group has the rest of 56 municipalities. 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 demographic variables show similarities. One important exception is the fraction of apartment residents. It is substantially lower for the treated municipalities, and this is not surprising given that many non-apartment residents were required to use trash bags during the Wave 1 expansion. In panels (b)–(d), I compare ever versus never treated households or individuals for various food and time usage and demographic variables in the pre-treatment period. Consistent with panel (a), I find that observed characteristics in general are well balanced except for the housing type (i.e., fraction of apartment residents). While the baseline characteristics seem similar between the two groups, one might still worry that households might differ in unobserved characteristics by housing type. To account for this, I include housing type specific fixed effects in empirical analyses except.[47]

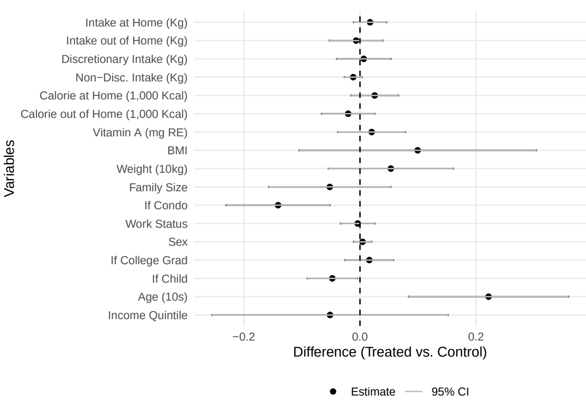
[47] I cannot implement this with food waste because the data is observed at the entire municipality level.



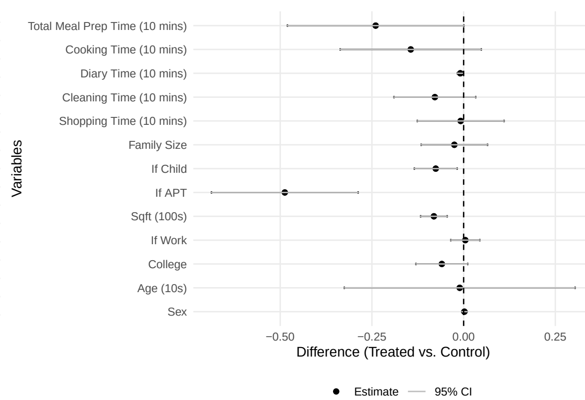
(a) Balance: Food Waste



(b) Balance: Grocery



(c) Balance: Intake



(d) Balance: Time Use

Figure A.3: Balance Plots. These figures compare treated vs. control units on pre-treatment outcome variables and demographic characteristics. 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. Panels (b)–(d) show the comparison of key variables between ever and never treated households from the grocery panel, food intake, and time use data.

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).[48] The choice seems more appropriate than wage, which is frequently used to measure the opportunity cost of time, especially within the household production context—over half of the primary meal preparers in the sample are not formally employed and thus wage is not well defined.[49]

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. To express the value of time on an hourly basis, rather than per shopping trip, I adjust the estimated value by multiplying the number of trips per hour.

For the elasticity, I assume that it is identical across different households and take the headline estimates (0.1) from Aguiar and Hurst (2007a).[50]

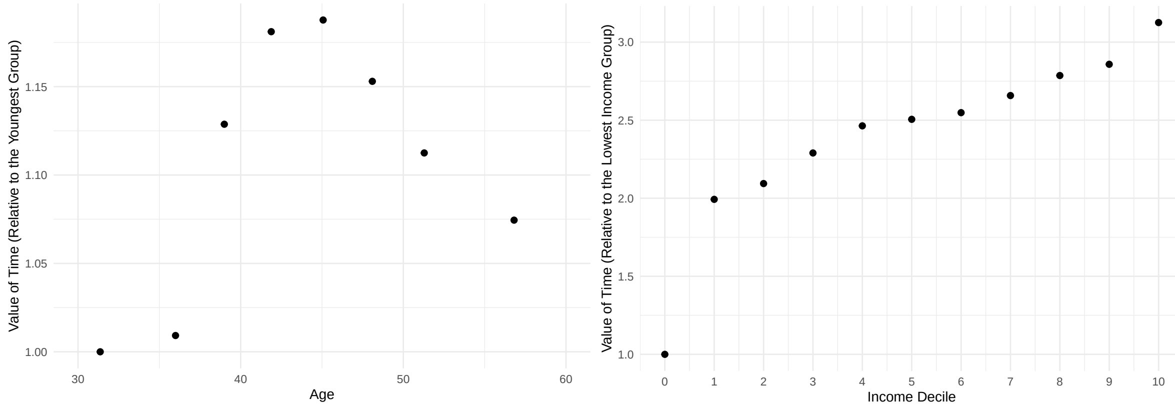
For the average spending per shopping trip, I use information from the grocery shopping data because the time use data do not have information on spending. I start by aggregating the grocery panel data by demographic characteristics—income (low if monthly income is below USD 1,818), family size (1-2, 3-4, and above), and age (20-30, 30-50, and above)—and calculate spending per shopping trip for each demographic cell. Then, I aggregate the time use data using same set of demographic characteristics and merge it with the average spending information to calculate the average number of shopping per hour for each cell. Then, I calculate the value of time for each cell by taking the product of elasticity (0.1), average spending per trip, and average number of trips per hour. Finally, I merge the VOT estimates with the time use data based on demographic characteristics. Note, 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.

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 B.1, I create bin scatter plots between (a) age and (b) income decile against the value of time, normalized with the lowest group's value. 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.

[48] Hastings and Shapiro (2018) and Nevo and Wong (2019) also used returns to shopping to measure the opportunity cost of time.

[49] Aguiar and Hurst (2007a) also raise theoretical concerns about using wages as a measure of the opportunity cost of time.

[50] 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).



(a) Age and Value of Time

(b) Income and Value of Time

Figure B.1: Value 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.

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 of the production function) using demographic characteristics. I use demographic variables including income, family size, age, and the tax status 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).[51] 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_q and a_c are 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.

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) 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 5.5% reduction in grocery purchases is accompanied by a 7.6% increase in time use, by construction there is likely to be a little room for a large TFP increase.

[51] One potential drawback of the factor share approach is in 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.

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

	(1)	(2)
Unit Tax	-0.007	0.010
	(0.086)	(0.012)
Dep. Var in Log (TFP: in Level)	TFP	Grocery Price
HH ID × Municipality FE	No	Yes
Year FE	No	Yes
Observations	30	2,872

Note:
This table reports the effect of the unit tax on other abatement channels. For column (1), I link three datasets on food and time usage to estimate the TFP difference between tax and no-tax group. Column (2) 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 municipality (column (2)) level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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) 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.

C Calculating the Net GHG Reduction Effect

To calculate the change in net GHG emissions from wasted food due to the unit tax, 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. To quantify each effect, I first use estimates from Table 4.1. When necessary, I convert the estimated effects in kg to GHG using source specific carbon intensity. In calculating these numbers, I multiply the per household effect size by the number of total households in South Korea (19 million).

For the avoided food production, I directly take the estimated effect from Table 4.1 Panel A column (8). This estimate does not need a conversion because it is already measured in GHG (158kg per year). To produce this, I first convert each row of shopping records into GHG emissions by matching each grocery item to the item-specific farm-to-kitchen GHG emissions estimates from Poore and Nemecek (2018).[52] Then I estimate equation (1) using log of GHG as an outcome variable. I take this approach instead of an alternative—multiplying reduced grocery purchase quantity and carbon intensity of average food basket—to allow food basket composition changes due to the unit tax.

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 CO_2eq per ton of food waste, which is less than 1/3 of that of food waste in landfill. Given the amount of food waste reduction for an average household (46kg), reduction in GHG emissions from the waste treatment stage is 0.009 ton CO_2eq per household.

Lastly, for the carbon intensity of additional food waste in landfill (leakage), I use the coefficient from the national inventory report, which is 0.655 ton CO_2eq (GGIRC 2015).[53] Given that the leakage size of 5kg per household (i.e., the reduction in the observed food waste quantity not attributable to the reduction in grocery purchases), increased GHG emissions from leakage is 0.003 ton CO_2eq per household. Taken three sources together, the net GHG reduction effect of the unit tax is 0.164 ton CO_2eq per household.

[52] 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.

[53] 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

Setup. To understand the impact of non-pecuniary channels on consumer surplus, I extend a standard household production to allow disutility on food waste generation building on the model in Allcott and Kessler (2019). In equation (5), the utility function is quasilinear such that U is sum of utility from meal quantity $v(M)$, numeraire X, utility from leisure δL, and distaste for food waste generation $\mu(Q-M)$. The functional form choice reflects the fact that money spent on groceries and time spent on meal production is relatively small portion of the total budget and time endowment (see as Table 3.1). Also, to focus on the non-pecuniary effect, equation (5) abstracts away from the price effect of the tax.

In equation (5), 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. 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.

$$U = v(M) + X + \delta L - \mu(Q - M) \tag{5}$$

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

By plugging in two budget constraints into the utility function, the two equations reduce to equation (7).

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

The impact of moral tax on consumer surplus. Given that pure information provision unambiguously increases consumer surplus, I focus on deriving conditions for the unit tax to increase consumer surplus under the assumption that the non-pecuniary effect is driven by moral tax. Posit that before the unit tax, households chose Q_0 and L_0 to attain the utility level of $U_0 = v(M_0) + I - PQ_0 + \delta L_0 - \mu W_0$ where $W = Q - M$. Now suppose that the unit tax increases μ to $\mu' > \mu$. If this household maintains their choice of Q and L, utility is $U_0' = v(M_0) + I - PQ_0 + \delta L_0 - \mu' W_0$. If households change their choice to (Q_1, L_1), utility becomes $U_1 = v(M_1) + I - PQ_1 + \delta L_1 - \mu' W_1$. Using estimates from Sections 4 and 5, I know that $v(M_1) \geq v(M_0)$, $-P(Q_1 - Q_0) + \delta(L_1 - L_0) = -6$, $W_1 = 0.8W_0$, and $W_0 = 240$. Plugging these values in suggests $U_1 - U_0' = -6 + 48\mu'$ has to be larger than 0 (because households adjust food and time usage), namely $\mu' > \frac{1}{8}$.[54] Also, because $\mu' > \mu$, we know that $\mu < \frac{1}{8}$ should hold. Now, to understand the impact of the tax on consumer welfare due to the moral tax effect, I can subtract U_1 from U_0 as in equation (8).

$$U_1 - U_0 = -6 + 240(\mu - 0.8\mu') \tag{8}$$

Given that the monetized impact of unit tax on grocery savings, additional time costs, and GHG reductions suggests a surplus of \$25 per household, the sign of the overall welfare effect hinges on whether $U_1 - U_0 = -6 + 240(\mu - 0.8\mu') < -25$. To proceed, let's write $\mu' = \alpha\mu$ where α captures the magnitude of change in μ due to the unit tax. Then, observe that $\frac{d(U_1 - U_0)}{d\mu} = 240 - 192\alpha$, which implies that when $\alpha < 1.25$ (namely, μ increases by less than 25% from the unit tax), $U_1 - U_0$ is smaller (larger in magnitude) when $\mu = 0$ and when $\alpha > 1.25$, $U_1 - U_0$ is smaller when $\mu = \frac{1}{8}$, the largest possible value. More generally, I can express the largest consumer surplus loss due to the

[54] For simplicity, I assume $v(M_1) = v(M_0)$. However, the likelihood that the unit tax enhances consumer surplus is higher if I instead allow $v(M_1) > v(M_0)$.

moral tax effect with respect to a range of α values.

Appendix Figure D.1 shows that as long as the increase in μ from the unit tax is not "too large" (more specifically, less than 105%), the direct loss in consumer surplus is always less than \$25. This indicates that the unit tax is likely to be welfare improving under some mild conditions even if the non-pecuniary effect is entirely driven by the moral tax effect.

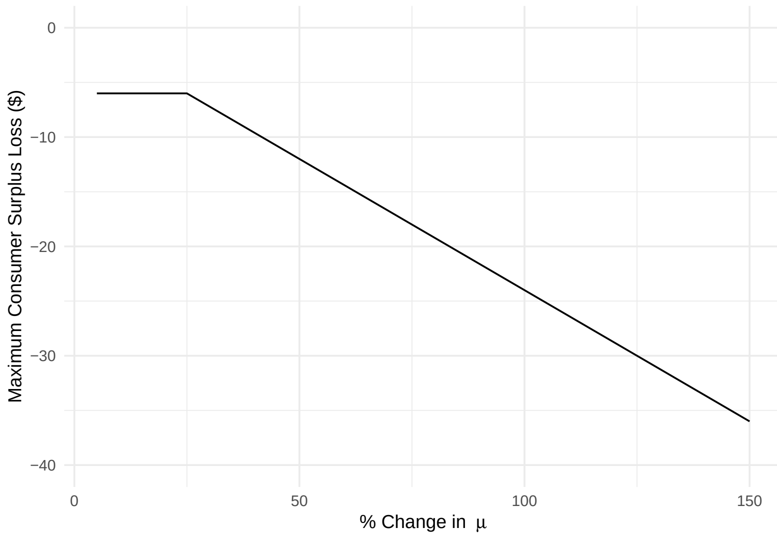


Figure D.1: Losses in Consumer Surplus from the Moral Tax Effect. This figure illustrates the impact of the non-pecuniary channel on consumer surplus under the moral tax scenario using equation (8).

E Additional Tables and Figures

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

	(1)	(2)
(%) Unit Tax	-0.206***	-0.152**
	(0.044)	(0.066)
Baseline Controls	No	Yes
Observations	3,136	3,136
Year × Stack FE	✓	✓
Municipality × Stack FE	✓	✓

This table presents the effect of the unit tax on food waste generation using the stacked DD approach. I only report coefficients for the food waste tax term, but the baseline control variables are included in column (2). 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: Unit Tax and Food Purchases (Alternative Specification)

	(1)	(2)	(3)	(4)	(5)	(6)
Unit Tax	-0.047**	-0.042*	-0.099***	-0.022	-0.052***	-0.057**
	(0.020)	(0.022)	(0.031)	(0.023)	(0.017)	(0.028)
Dependent Variable in Log	Grocery kg Per HH	Grocery exp Per HH	Perishable kg Per HH	Storable kg Per HH	Grocery kg per HH per Trip	GHGs Per HH
In Level	-35	-152	-28	-10	-0.23	-147
Municipality × HH ID FE	Yes	Yes	Yes	Yes	Yes	Yes
If APT × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,872	2,872	2,870	2,872	2,872	2,872

Note:
This table reports the impact of the unit tax on food purchases with a specification that allows housing type specific annual shocks. 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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Table E.3: The Effect of the Unit Tax on Household Meal Production Efforts (Alt Specification)

	(1)	(2)	(3)	(4)	(5)	(6)
Unit Tax Group x Post	7.60***	5.80***	1.65	0.123	0.027	0.382**
	(2.67)	(1.40)	(1.00)	(0.125)	(1.01)	(0.185)
Dependent Variable	Overall Time	Prep Time	Cleanup Time	Diary Time	Shopping Time	Dollars Per Day
Province × Housing Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,348	82,348	82,348	82,348	82,348	49,531

Note:

This table reports the effect of the unit tax on household meal production effort using household level data. A binary unit tax group status is assigned based on the fraction of households subject to the unit tax in 2009 (1 if the ratio is over 50

Back to 5.2.

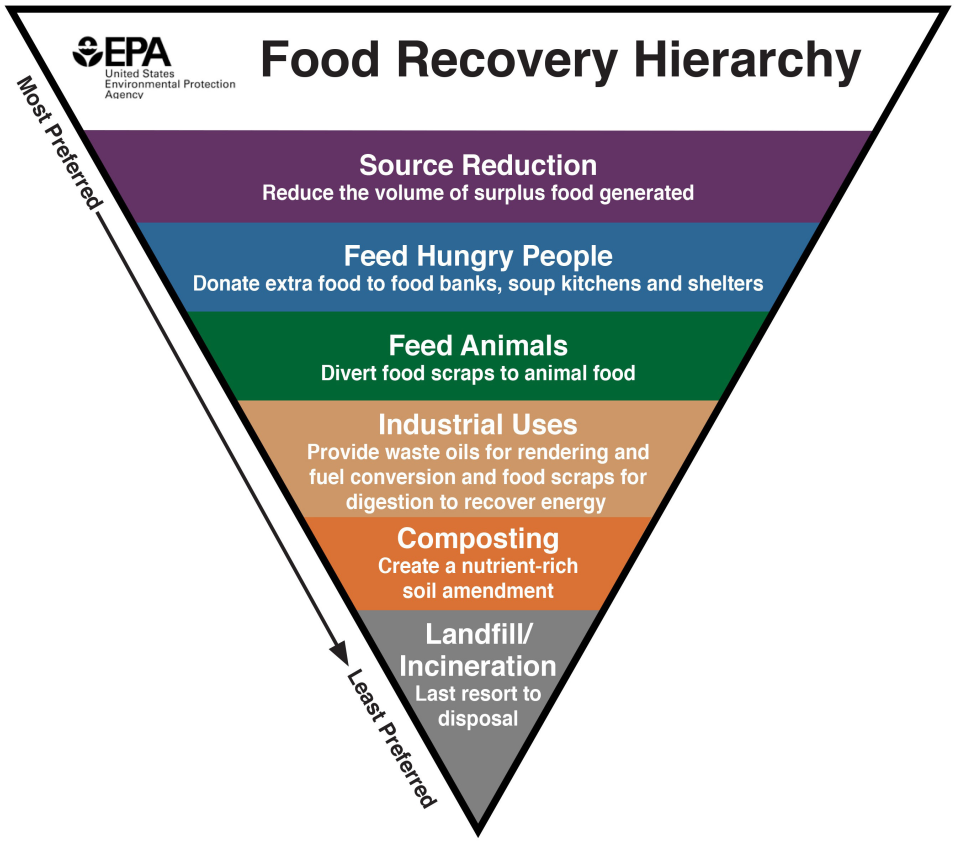
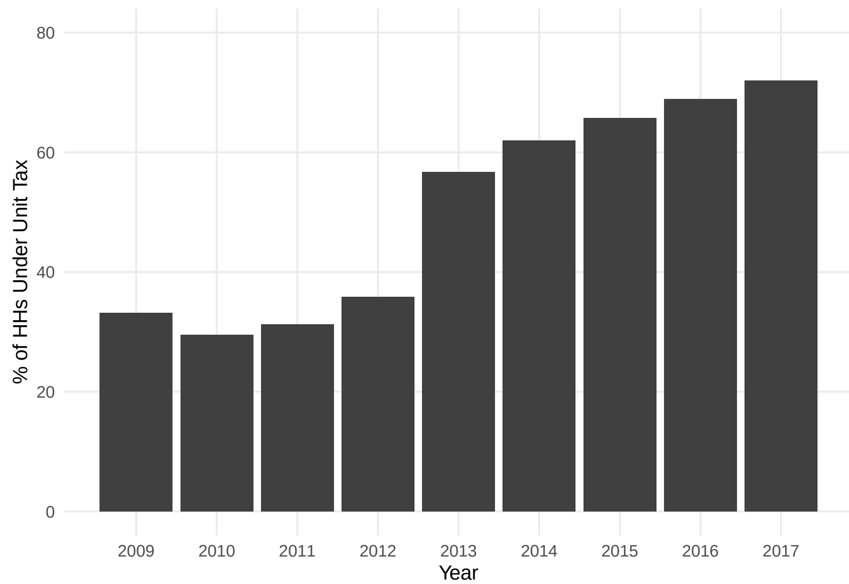
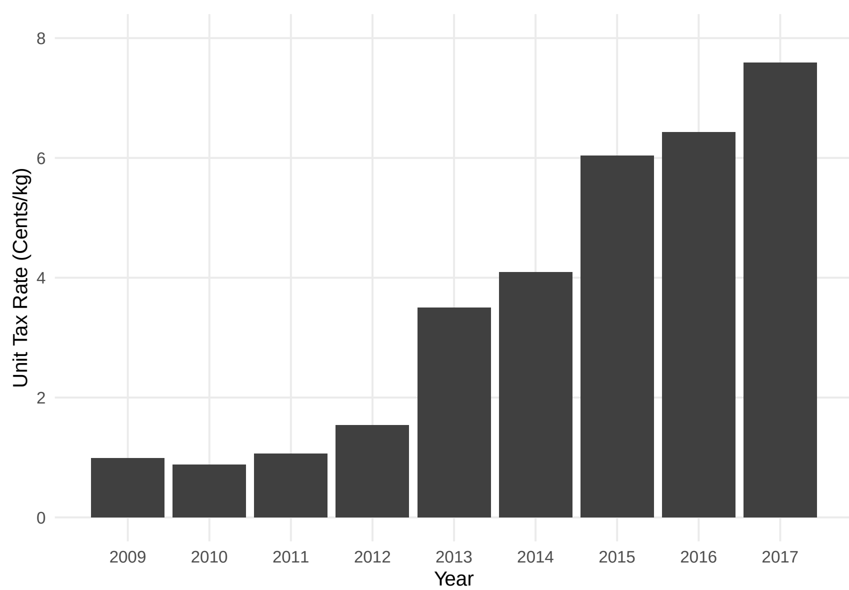


Figure E.1: Food Recovery Hierarchy

Back to 2.1.



(a) Average % of Households under the Unit Tax



(b) Average Tax Rate

Figure E.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 63 municipalities in the metropolitan Seoul area.

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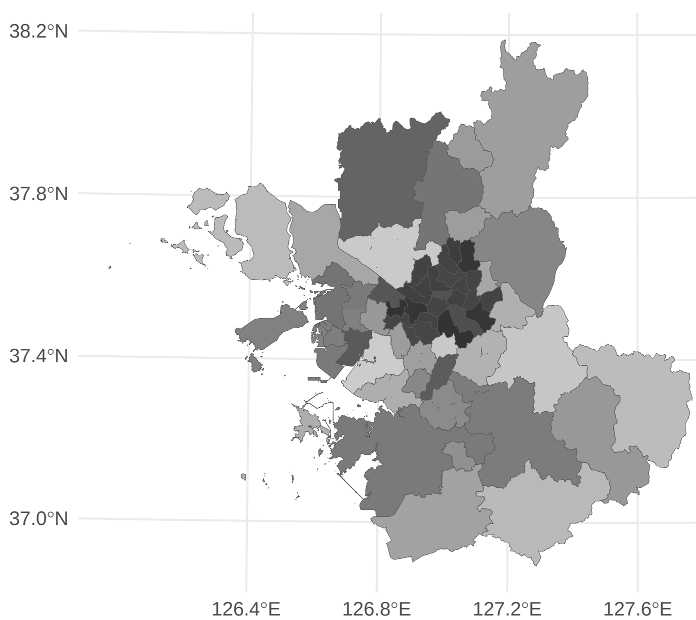
(a) Change in % of HHs under Tax between 2009-17



(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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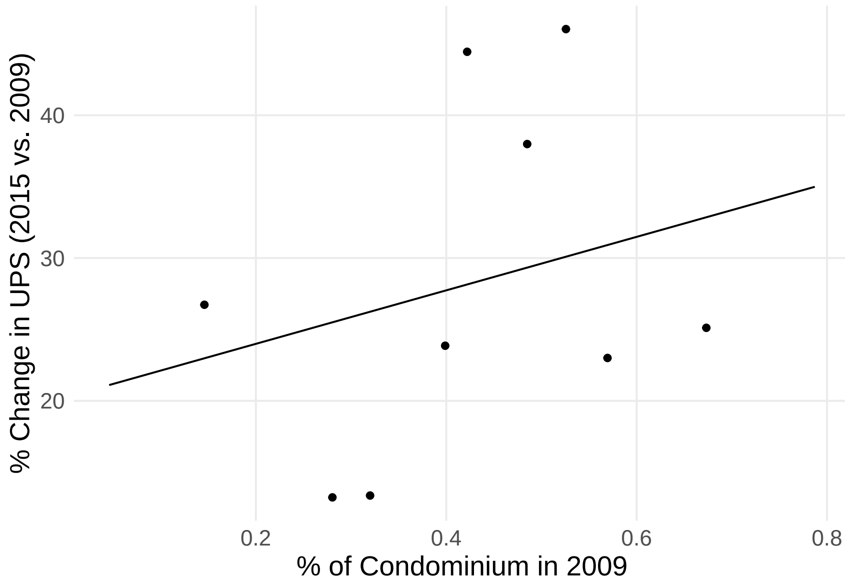

Figure E.4: This figure shows the relationship between the proportion of households living in condos in 2009 and the change in the proportion of households under the tax between 2009 and 2015 using binned regression.

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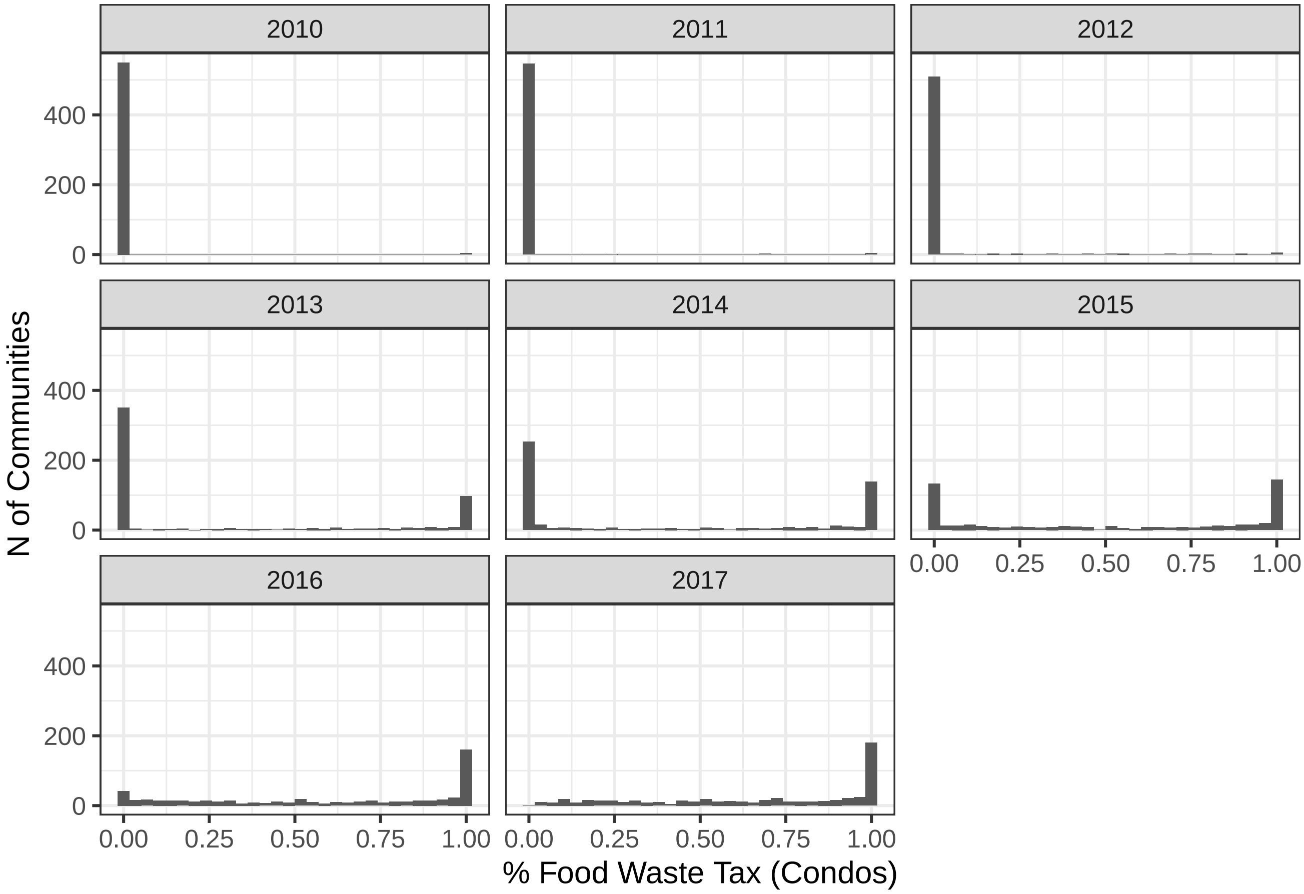
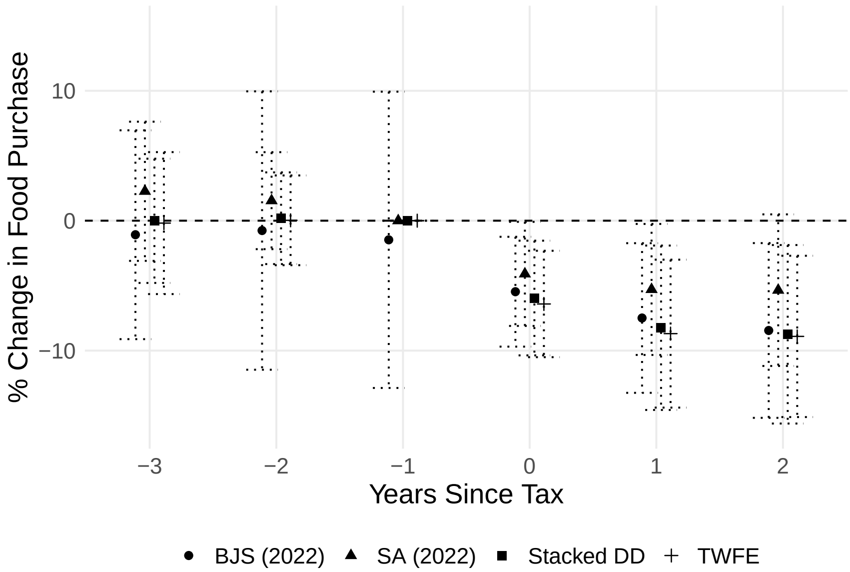
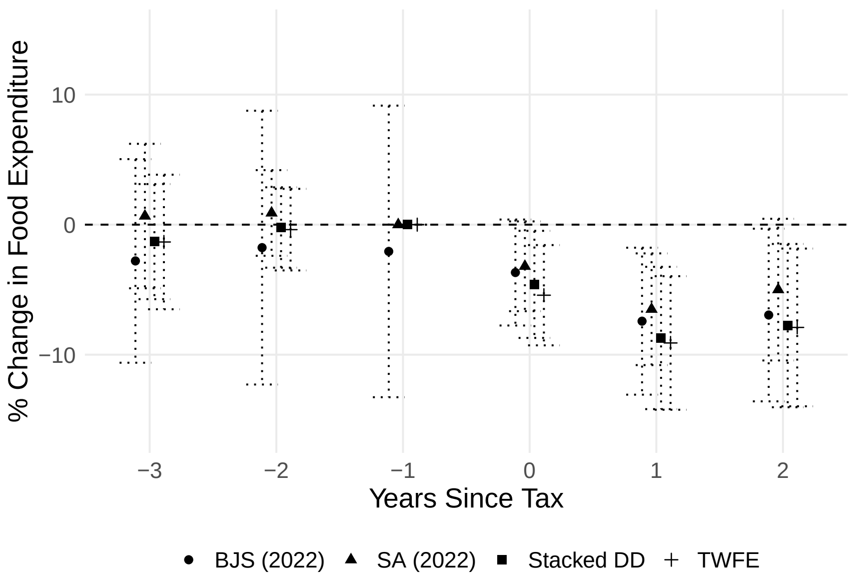


Figure E.5: Distribution of the Fraction of Condominium Residents Under the Tax at the Community Level for 2010-2017. These panels illustrate the distribution of the fraction of condominium residents under the food waste tax at the community (the smallest administrative unit in South Korea) level for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

Back to 4.1.



(a) Overall Quantity



(b) Overall Expenditure

Figure E.6: 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 (a) log of per household annual grocery purchase (in kg) and (b) log of per household annual grocery spending (in USD). 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.

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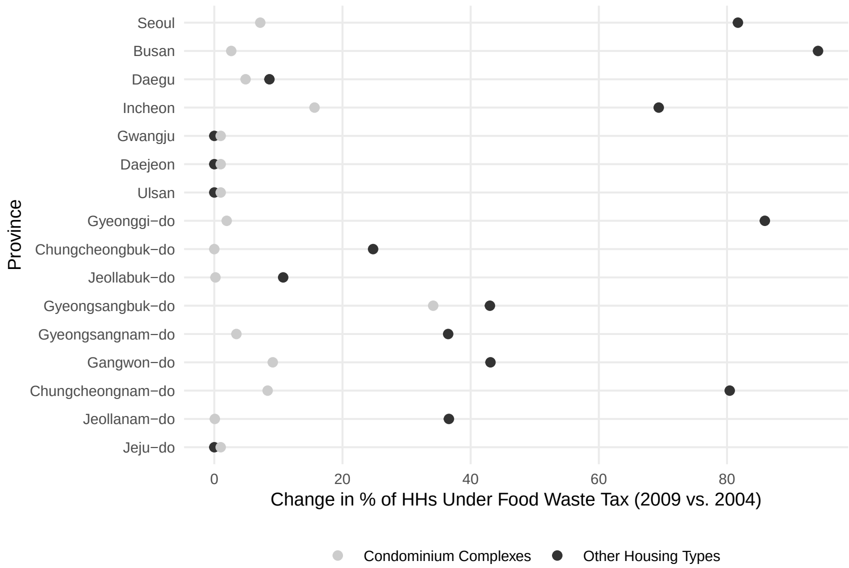
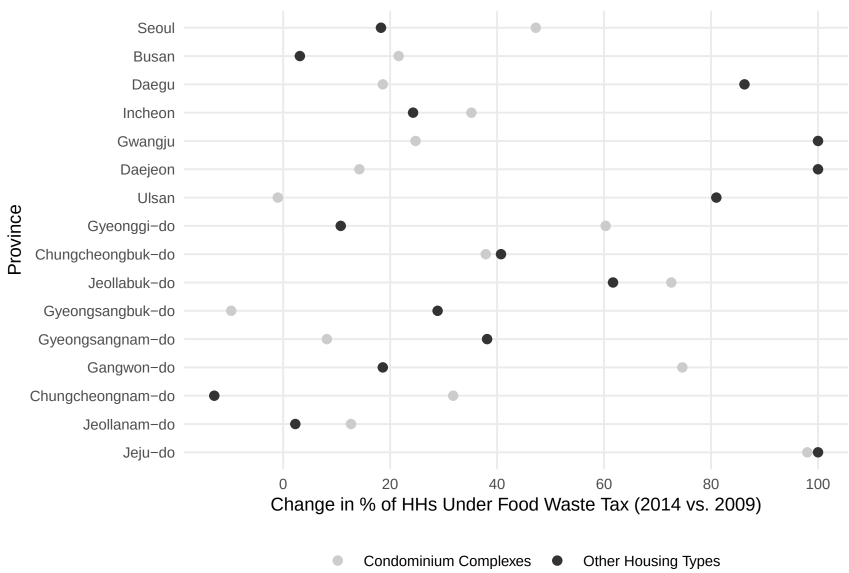


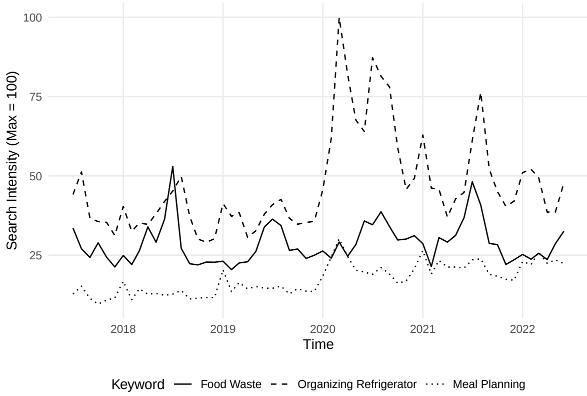
(a) 2004 vs. 2009



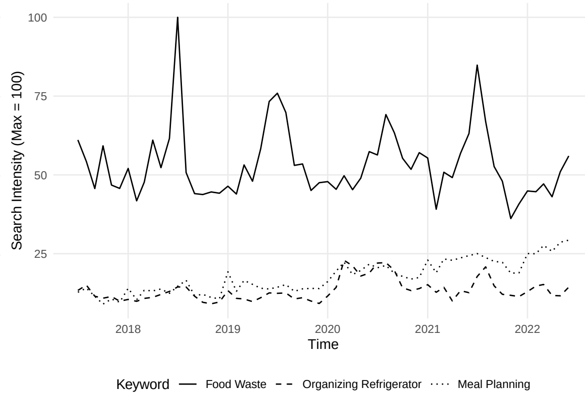
(b) 2009 vs. 2014

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).

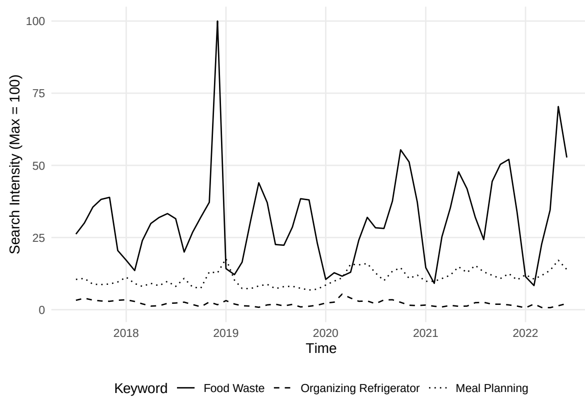
Back to 2.2 or 5.2.



(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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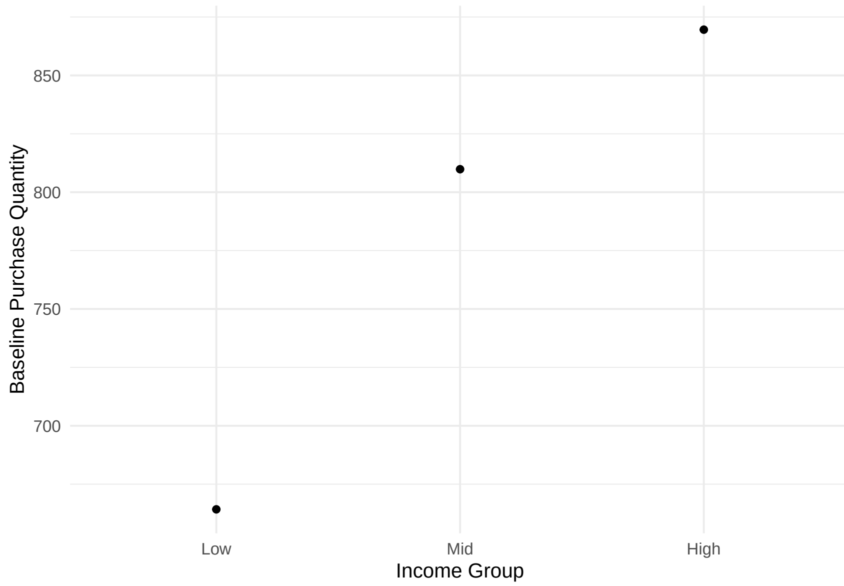

Figure E.9: Correlation Between Baseline Purchase Quantity and Income. This figure shows the relationship between household income and baseline (year = 2010) grocery purchase quantity using the grocery purchase panel data.

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