Does a Food Waste Tax Work? Evidence from Quasi-Experiments in South Korea

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Abstract

Globally, one-third of food is discarded, generating lifecycle greenhouse gas emissions comparable to those from road transport. Further, waste management is among the largest municipal budget items worldwide. Exploiting plausibly exogenous unit-based food waste tax expansions in South Korea, I find that the tax substantially reduces food waste by discouraging excessive grocery purchases. Households sustain food intake despite buying less, but at the cost of additional time spent on meal production. Nonpecuniary motivations appear central to the policy's effectiveness, and the tax is likely welfare-improving because more efficient food use not only reduces externalities but also offsets time costs.

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1 Introduction

Globally, one-third of all food is discarded, generating lifecycle greenhouse gases (GHGs) comparable to emissions from the entire road transport sector (Gustavsson et al. 2011, IPCC 2014, FAO 2015). Further, waste management is often the largest municipal budget item, diverting resources from more productive investments (Kaza et al. 2018).[1] Consumer-end food waste is particularly problematic due to its high volume—responsible for 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, reducing food waste at home has become a priority for policymakers (United Nations 2015, EPA 2021).

Theoretically, a Pigouvian tax on food waste can make households internalize externalities and generate the socially optimal level of food waste (Pigou 1920).[2] Whether implementing such a tax enhances social welfare in practice, however, remains an empirical question, as it is unclear a priori which abatement strategies households will adopt, and these strategies have varying implications for welfare. For instance, while both spending time improving food storage practices and engaging in illegal dumping can reduce the tax burden, their impacts on environmental and fiscal externalities (i.e., benefits) and abatement efforts (i.e., costs) can be starkly different.

This paper provides the first empirical evidence on the welfare effect of a unit based food waste tax (hereafter "unit tax"), a quantity-based changing scheme conceptually equivalent to widely adopted Pay-As-You-Throw (PAYT) programs. To assess the benefits, I study the tax's impact on households' food purchasing, consumption, and waste, as well as the resulting changes in environmental and fiscal externalities. To evaluate the costs, I build on the insights from the

[1]Solid waste management accounts for 4%, 11%, and 19% of total municipality budget in high-, middle-, and low-income countries (Kaza et al. 2018). For instance, NYC spent $1.5 billion in 2021 alone to provide waste related services (NYC Council Finance Division 2024).

[2]Depending on the policy objective—whether to penalize the carbon content of food or to discourage food waste—a carbon tax on food may represent the first-best solution. However, as discussed in Section 6.3, this approach poses significant challenges related to technical feasibility, political acceptability, and overall effectiveness.

household production model (Becker 1965), and investigate how the tax impacts households' meal production time. Importantly, by investigating the tax's impact across different stages of food use and time allocation, I can assess its overall welfare effects while explicitly accounting for households' abatement strategies.

The empirical application exploits two waves of plausibly exogenous unit tax expansions in South Korea. Since 2005, households have been required to separate food waste from landfill waste and pay a food waste tax (unit tax on landfill waste was already in place since 1995).[3] During this initial phase, most households were charged a flat tax, while some—depending on their region and housing type—were subject to the unit tax (Wave 1 expansion). Later, with mounting concerns over food waste-driven GHG emissions and public finance burden, the central government mandated local governments to expand the unit tax to all households by 2013 (the Wave 2 expansion). However, as the physical infrastructure for unit tax collection can be costly, the unit tax rolled out over time, and 30% of households were still paying flat tax in 2017. The average tax rate after the Wave 2 expansion was 6 cents per kilogram of food waste, or $1.3 per month for a household with average waste levels ($1 = KRW 1,100 throughout the paper).

To leverage these variations, I collect four datasets on purchased, consumed, and wasted food, as well as household time usage, and match them to the unit tax status based on time, region, and housing type. For identification, I compare treated households (i.e., those with the unit tax indicator equals 1) to not-yet and never-treated households using the two-way fixed effect approach. When aggregated data is used, I compare geographic units with varying levels of treatment intensity. I also show that the results are robust to alternative estimators in the recent difference-in-differences literature (Cengiz et al. 2019, Sun and Abraham 2021, Borusyak et al. 2022).

The empirical exercises produce three key results. First, I find that the policy is highly effective: for an average household, the tax reduces annual food waste and grocery purchases by 21%

[3]Food waste separation is a necessary condition for food waste pricing. While South Korea remains unique in directly pricing food waste, many jurisdictions have adopted mandatory food waste sorting to alleviate landfill constraints and promote recycling. See Section 6.3 for details.

(49kg) and 5.5% (41kg), respectively, leading to annual savings of $3 on food waste tax and $169 on grocery expenditures. Comparing these effects in quantities (41kg vs. 49kg) suggests that purchasing less food in the first place is the primary abatement strategy, while other measures, such as illegal dumping or increased intake, account for only 16% of the observed reduction in food waste. Further, the policy effect is three times larger for perishable items (fresh vegetables and fruits) than storable items, which is plausible given that perishables are easier to become waste when not consumed in time. Importantly, these effects do not come at the cost of households' nutritional needs or "safety margins": households still maintain over 30% more food than they consume, and the tax does not reduce food or nutrient intake at home. These findings suggest that the reduction in grocery purchases primarily stems from trimming previously wasted—rather than consumed—portions of the food basket.

The estimated changes in household food usage imply a reduction of roughly 3.1 million tons of CO_2eq annually at the national level—equivalent to the emissions from 750 thousand passenger vehicles.[4] Additionally, applying the estimated waste reduction to actual municipal landfill and food waste cost data suggests potential government savings of approximately $41 million per year, net of implementation costs.

Next, I estimate the abatement cost of reducing food waste (i.e., purchasing fewer groceries), building on the household production model where households combine time and groceries to produce meals (Becker 1965). Given findings that intake does not decline after the tax, I empirically examine whether the tax leads to an increase in (1) time spent on meal production or (2) meal production productivity. I find that households spend 7.6% more time (55 additional hours per year) on meal production, incurring an annual time cost of $175.[5] Web search data further

[4] To translate changes in food usage into GHG emissions, I apply food-item–specific emissions intensities from Poore and Nemecek (2018). Further, interpreting lower purchases as avoided upstream emissions assumes that profit maximizing producers adjust output in response to the policy induced demand shock, an assumption whose plausibility is assessed in Section 6.2.

[5] To measure the time cost in monetary terms, I use the returns to shopping—money saved for additional time spent on shopping (Aguiar and Hurst 2007). More details are in Section 5.2.

indicate that households use this extra time to engage in careful meal planning and organize and store food more efficiently. However, I find no evidence that the tax increases productivity.

Lastly, I investigate the mechanism and discuss policy implications. While a large portion of the time cost is offset by grocery savings, it remains puzzling that households make such a substantial behavioral change to reduce their annual food waste tax burden by just $3. Moreover, I find that the tax elasticity of grocery demand is over an order of magnitude smaller than corresponding price elasticities (Andreyeva et al. 2010), which collectively suggest that the tax induces a considerable non-pecuniary response. This likely arises because the unit tax necessitates measurement, which naturally provides regular, salient feedback alongside direct financial incentives. Turning to the policy implication, I conduct a back-of-the-envelope cost benefit analysis and show that the unit tax reduces one ton of CO_2eq at a cost of $24 and generates over $500 million in net benefits annually.[6] These effects are driven by the tax promoting more efficient food use, which not only mitigates environmental and fiscal externalities but also offsets households' additional time costs through savings on grocery expenditures.

Related literature. This paper contributes to two different bodies of literature. First, this paper departs from earlier empirical studies on waste taxation and pricing policies in three important ways (Fullerton and Kinnaman 1996, Ek and Miliute-Plepiene 2018, Carattini et al. 2018, Bueno and Valente 2019, Ek and Söderberg 2024).[7] This is the first paper to explicitly estimate how upstream consumption changes in response to a downstream tax, contrasting with existing research that primarily examines changes at the waste disposal stage (e.g., increased recycling). Investigating the upstream effect is important because improved disposal can address only a small

[6]The cost reflects both program implementation costs and household abatement costs. To calculate benefits, I use a social cost of carbon of $190 per ton of CO_2eq (EPA 2023).

[7]There is also a literature that focuses specifically on food waste. Most of these studies evaluate non-financial interventions such as nudges or informational campaigns (see reviews by National Academies of Sciences, Engineering, and Medicine (2020)). The limited research on food-waste taxation remains predominantly theoretical (Katare et al. 2017, Hamilton and Richards 2019) or relies on stated-preference methods (Briguglio 2021).

fraction of the lifecycle environmental externalities from waste.[8] Moreover, this is the first paper to identify household abatement strategies and estimate their associated costs, a critical but rarely observed component of welfare analysis.[9] I demonstrate that the household production model offers a powerful framework for this purpose, yielding insights that extend beyond waste taxation as climate policies increasingly target household behavior (OECD 2011, IPCC 2022). Lastly, I investigate the underlying mechanism of the tax and highlight the potential role of non-pecuniary effects, in contrast to earlier studies that attribute its effects to the price channel. These novel dimensions enable a more comprehensive welfare assessment of a corrective tax on waste.

Second, this paper complements voluminous literature on the economics of climate change mitigation, which has predominantly examined conventional carbon-intensive sectors such as power, manufacturing, heating, or transportation (Andersson 2019, Gerarden et al. 2020, Reynaert 2021, Ito and Zhang 2025). In contrast, it focuses on food, a sector that remains relatively understudied despite growing recognition of its critical role in achieving climate goals.[10] Recent studies have quantified the climate benefits of food-waste recycling policies (Alacevich et al. 2021, Somers 2025), and this paper complements that work by highlighting the prevention (or the so-called "source reduction") margin.

The rest of the paper proceeds as follows. Section 2 provides background on 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 mechanism, welfare effects and additional policy implications. Section 7 concludes.

[8]For food waste, which is the largest (44%) waste category in MSW (Kaza et al. 2018), the farm-to-kitchen stage is responsible for 90% of lifecycle GHG emissions (Crippa et al. 2021).

[9]These costs are inherently difficult to quantify, as "it is hard to identify, let alone measure, the technology for pollution control and the immediate cost to households" (Pizer and Kopp 2005).

[10]Clark et al. (2020) finds that an immediate end of fossil fuel consumption is insufficient to meet the Paris Agreement's 1.5°C climate goal without changing the world's food system.

2 Waste Policies in South Korea

Wave 0 (1995-2004): unit-based tax on landfill waste. Between 1970–90, the waste quantity in South Korea increased sevenfold. To address the resulting landfill capacity problem, a national landfill waste tax was implemented in 1995. The policy had two key features. First, source-separated recyclable items such as glass bottles were picked up free of charge. Second, for other MSW (including food waste), households were required to purchase and use an official garbage bag. Prior studies found that this policy reduced the landfill waste quantity by 18% (Hong 1999).

Wave 1 (2005-2012): Waste segregation and partial implementation of the 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.[11] Also, to offset the cost of food waste management, municipalities were permitted to impose a food waste tax on households. Since the Wave 1 policy focused on *segregation* and *recycling* rather than *reduction*, the collection system was strategically designed to minimize operational costs. Consequently, food waste from apartment complexes was typically collected without measurement and residents were charged a flat tax ($1-2 per month).[12] The collection methods for non-condo residents were more varied: about half of the municipalities charged flat fees while the rest required households to purchase official food waste bags (Figure 1 (a)), which typically cost 1 cents/kg during this period. As detailed in Section 5.2, the Wave 1 expansion is utilized to study the time costs of the unit tax. [**Figure 1 Here**]

Wave 2 (2013-): Nation-wide expansion of the unit based food waste tax. Recognizing the lim-

[11]As a result, over 95% of food waste is diverted to composting or animal feed. However, these products are not particularly popular—often due to quality concerns—and in many cases, farmers can obtain them at little or no cost.

[12]In this paper, the terms “apartments” and “condominiums” are used interchangeably. Unlike in the US, where “apartment” typically refers to rental units, the term does not imply ownership status in South Korea.

itation of the Wave 1 policies in tackling externalities from food waste (see Appendix D.1 for more details about negative externalities from food waste), the central government mandated that municipalities expand the unit tax to essentially all households by 2013 (GGC 2010).[13] As a result, as Figure 1 (c) shows, there was a dramatic increase in the share of households under the unit tax between 2009 and 2017.[14] For condominium households, coverage was essentially zero prior to the Wave 2 expansion. Then it jumped sharply in 2013 and continued to rise, reaching 60% by 2017. Although the most pronounced change occurred among condo residents, Wave 2 was not driven exclusively by them: for instance, coverage among non-condo households also increased from about 80% in 2009 to nearly 100% by 2013 and remained there. Collectively, the overall share of households under the unit tax was at roughly 30% during 2009–2012 but rose steeply thereafter, reaching over 70% in 2017. Further, the map of the Wave 2 expansion in Appendix Figure F.2 (a) reveals substantial variation in the expansion across different municipalities.

The expansion occurred under two different measurement and collection regimes: typically, official trash bags for non-condo households and Smart Card (per kg) systems for condominium households (Figure 1(b)), although about 30% of municipalities relied exclusively on bag-based systems even for apartments.[15] Among municipalities that adopted Smart Card systems, some mandated their use for all apartment complexes, while others allowed individual complexes to

[13]The Wave 2 expansion was announced together with a broader package of food waste reduction plans, including general public-awareness campaigns across media outlets and support for food-sharing and donation programs (GGC 2010). However, these were neither new nor particularly binding: as the government's own assessment notes, similar encouragement and education based programs had already been implemented repeatedly at least since the early 1990s, yet had produced only limited effects (GGC 2010). Given this, the unit-tax expansion represented the headline—and the most substantive—policy change.

[14]The figure is based on 63 municipalities in the metropolitan Seoul area, aligning with the geographic scope of the empirical analysis on food usage.

[15]Each household using a Smart Card system receives a unique card to access disposal kiosks equipped with electronic scales that weigh waste and record the charge. Charges are either deducted directly from a prepaid card at the time of disposal or billed later through apartment management fees. This system allows for precise, per-kilogram billing and provides households with immediate feedback on waste quantity and cost.

opt in. Crucially, even in these opt-in cases, decisions were made by a small number of building level representatives or administrators, creating a plausibly exogenous change for the hundreds or thousands of households in each complex (Lee and Seo 2022). Because the Smart Card system is costly (approximately $1,500 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. Taken together, the Wave 2 variation reflects expansions across both collection technologies and housing types, and is unlikely to have been driven by household-level decisions.

In tandem with the extensive margin unit tax expansion, there has been a steep increase in the tax rate (Appendix Figure F.1).[16] However, the tax is still very small: a household with average waste quantity would pay $1.3 per month as a waste tax. Given the small size of the tax, its revenue covers only about 30% of food waste management costs, and local governments typically allocate substantial public funds to provide these services. For example, the City of Seoul spent $142million on food waste management in 2015 alone (Ministry of Environment 2015a).

Illegal dumping. Earlier studies have shown that waste tax policies often trigger behavioral responses like illegal dumping (Fullerton and Kinnaman 1996). In densely populated South Korea, one of the easiest ways to evade the unit tax is by discarding food waste in landfill bags, which can save both money—landfill waste tax rate is about 40% lower than the food waste tax rate—and the effort of segregation.[17] Indeed, the National Waste Assessment Statistics finds

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[16] As the unit tax is collected under two different regimes (volume vs. weight based), standardizing units is necessary to exploit tax rate variations. I follow the standardized ratio (1 liter = 0.75kg) from the Ministry of Environment Administrative Order 2015-164 (Link), which closely aligns with the average ratio of per liter vs. per kg tax rates across municipalities (0.67).

[17] Illegal food waste dumping can take various forms, such as flushing it down a toilet, disposing of it in a sink, burying it, or discarding it in an unsegregated landfill bag. However, in urban South Korea, the first three are rare. Flushing or sink disposal risks costly plumbing issues, especially since food grinders are illegal. Additionally, dense cityscapes leave little space for backyard composting or illegal dumping on vacant land.

that, roughly 10% of the food waste is discarded through landfill waste bags.[18] In response, many municipalities conduct random audits and impose fines of up to $100. Given that such leakage can undermine the efficacy of the unit tax, quantifying its magnitude is crucial for assessing the policy's welfare impact. However, its illicit nature makes direct and comprehensive measurement challenging. In Section 4.2, I estimate an upper bound for illegal dumping.

3 Data

Food waste quantity. Each year, municipalities must report their food waste quantities to the Ministry of Environment, which compiles the data into the Unit-Based Waste Policy Yearbook. These figures come directly from food waste treatment facilities, where waste trucks' incoming and outgoing weights are measured to determine food waste quantities, as treatment companies are compensated based on recorded weight. This food waste quantity reflects waste generated by all non-bulk generators—both residential households and small restaurants (with areas smaller than $200m^2$)—the two groups that are subject to the food waste tax. I calculate per household food waste quantity in two steps. First, using the City of Seoul statistics, I derive a conversion ratio indicating that one restaurant generates, on average, as much food waste as seven households.[19] Second, I divide the total waste quantity by the combined number of residential households and restaurant-converted households. Also, I restrict the analysis to the 63 municipalities in the metropolitan Seoul area, which coincides with the geographic coverage of the grocery purchase data, from 2009 to 2015.[20]

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

[19] The City of Seoul has recorded food waste quantity separately for residential households and small restaurants since 2014 (https://stat.eseoul.go.kr/statHtml/statHtml.do?orgId=201&tblId=DT_201004_J070007&conn_path=I3). I use 2014–15 to calculate the conversion ratio.

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

Grocery purchase. I use consumer grocery panel data from the Rural Development Administration, collected annually since 2010. The dataset includes approximately 1,000 households per year from the metropolitan Seoul area that has a population of over 25 million. The data is collected through a mailed journal, where panelists are required to record their grocery expenditures based on shopping receipts. Each purchase is documented in detail, including variables such as type of store, shopping date and time, food item, expenditure, and unit price.[21] Additionally, the dataset includes rich demographic information including street address for each household. For the analysis, I aggregate the data at the household by year level.

I limit the sample to the balanced 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, as these can be discarded down the drain without incurring the tax. Unit tax status for each household is determined using street address information. This level of detail is particularly useful to accurately assign the tax status, because, while the unit tax status for non-condominium residents typically varies at the municipal level, condominium residents' tax status often varies at the complex level within the same municipality.

Food intake and nutrition. I use the Korea National Health and Nutrition Examination Survey (KNHANES), a nationally representative cross-section survey of about 10,000 people per year, from the Korean Centers for Disease Control and Prevention. I use responses from the metropolitan Seoul area over 2010–17 that coincide with the grocery purchase data. The data documents food intake and resulting nutritional intake estimates based on a 24-hour dietary recall face-to-face interview. It also contains health examination results from each respondent. Because KNHANES discloses addresses at the community level, which is the smallest administrative unit in South Korea, I can assign the tax status for each household with high precision. For the analysis, I aggregate the data at the individual-day level, separately for food at and away from home.

[21] 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.

Time use on meal production. I use the 1999, 2004, and 2009 Korean Time Use Survey from Statistics Korea. Conducted every five years since 1999, each survey includes approximately 30,000 respondents aged 10 and older. The survey collects two consecutive days of 24-hour time diaries (124, 137, and 144 time categories for the three waves). Time spent on food production is recorded under four specific categories: cooking, cleaning up after meals, bookkeeping, and shopping. In addition to time-use information, the survey collects rich demographic data. However, unlike grocery or food intake data, this data only discloses respondents' addresses at the province level—the largest sub-national administrative unit—which complicates assigning unit tax status at the household level. In Section 5, I discuss how I address this limitation.

Food waste tax policy and other municipality characteristics. I hand-collect data on Wave 2 policy changes at the municipality by housing type level by tracking municipality ordinances. I cross-validate this with tax rate information in the Unit-Based Waste Policy Yearbook and relevant news articles. Further, for municipalities using the Smart Card system—where the tax status can vary at the apartment complex level—I obtain complex-level implementation dates through Official Information Disclosure Act requests. For Wave 1 policy changes, I rely on a commissioned study by the Ministry of Environment that documents tax status as of 2009 (Kim et al. 2010). To collect various municipality characteristics such as the number of households by housing type, I use the Population and Housing Census, Census on establishments, and regional statistics from Statistics Korea and local governments. [**Table 1 Here**]

Summary statistics. In Table 1, I provide summary statistics for key dependent variables across all observations in the analysis sample. To contextualize different variables, I express everything in terms of per year per household.[22] Two points are worth highlighting. First, comparing the amount of total food waste with the purchased food amount suggests that 27% of the purchased

[22]Since food intake variables are annualized by multiplying daily quantities by 365, any day with zero record for a specific category (e.g., no food consumed at home on a given day) leads to a minimum annualized value of zero.

food is discarded, which is consistent with the global average (FAO 2013). Further, the consumed (526kg) and wasted (202kg) food quantity adds up to the purchased quantity (740kg), indicating that the three datasets together successfully capture an average household's food usage.

Second, using food-item specific farm-to-kitchen GHG emissions data from Poore and Nemecek (2018), I show that an average household's annual grocery purchases (740kg) generate 2,678kg CO_2eq. This corresponds to 3.6kg CO_2eq embedded in each kilogram of food waste. The resulting external cost, based solely on farm-to-kitchen stage GHG emissions, is \$0.69/kg at a social cost of carbon of \$0.19/kg (EPA 2023). The highest observed unit tax rate is less than 20% of this amount and does not even cover the costs of waste management services.

Appendix A.1 provides descriptive statistics for additional variables. Appendix A.2 reports results from various validation tests (e.g., representativeness of survey respondents and soundness of grocery panel data price imputation). Finally, Appendix A.3 reports balance test results.

4 Effect of the Unit Tax on Food Usage

4.1 Estimation Framework

Binary treatment models (food purchase and intake). I exploit the Wave 2 expansion to causally identify the effect of transitioning from a flat to unit tax on household food usage. The baseline two-way fixed effect model is in equation (1). Importantly, I exclude always-treated and non-absorbing households to minimize potential contamination of the control group (Goodman-Bacon 2021, Baker et al. 2022), resulting in a final sample of 359 households over 2010–2017.

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

Q_{imt} are various grocery purchase outcomes for household i living in municipality m at year t. Tax_{imt} is a dummy that takes 1 if a household is subject to the unit tax, regardless of whether the tax is implemented via official bags or the Smart Card system. Accordingly, equation (1) estimates the average effect of unit tax adoption, with potential heterogeneity by collection method examined separately. It has an i subscript because as described in Section 2, the treatment status could vary within a municipality. $\boldsymbol{X_{imt}}$ 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 possibility that households are likely to move when there is a life event such as starting a new job or experiencing household composition changes that can be correlated with grocery demand.

β in equation (1) and in the subsequent equations (2) and (4) capture the causal effect of unit tax adoption. That is, β may capture not only the impact of the changing price incentive (from a flat to a unit tax) but also the impact of introducing a measurement scheme, which in practice is a prerequisite for any unit tax or PAYT program implementation. As such, β represents the policy-relevant effect of adopting a unit tax system implemented in practice.[23] Which effect drives the treatment impact is an empirical question, which is discussed in Section 6.1. The approach of estimating the effect of "adopting" a new pricing scheme follows the conventions in prior evaluations of PAYT programs (e.g., Fullerton and Kinnaman (1996)), although earlier studies typically do not attempt to disentangle relative contributions.

The key identifying assumption in equation (1) is that in the absence of the unit tax, grocery purchases of treated and control households have parallel trends. While overall similarities in baseline characteristics (Appendix Figure A.3 (b)) support this assumption, one might worry about housing type specific shocks that coincide with the unit tax treatment. I show that including housing type by year instead of year fixed effects produces very similar results. Also, to investigate the plausibility of the parallel trend assumption, I estimate an event study version of equation (1) as well as alternative estimators proposed in the literature that allow treatment heterogeneity (Cengiz et al. 2019, Sun and Abraham 2021, Borusyak et al. 2022).[24]

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[23]Practically, large-scale individual metering for public services (e.g., for electricity, water, and heating) is introduced precisely to enable usage-based billing (Cowan 2009, Ito and Zhang 2025).

[24]I estimate $log(Q_{ihmt}) = \sum_{k=-7}^{6} \alpha^k Tax_{ihmt}^k + \boldsymbol{X_{ihmt}}\delta + \lambda_{im} + \omega_t + \epsilon_{ihmt}$ where Tax_{ihmt}^k takes

To understand the impact of the tax on food intake and nutrition, I estimate a variant of equation (1): $log(M_{ihcmt}) = \beta T_{hcmt} + \delta \mathbf{X}_{ihcmt} + \lambda_{hm} + \omega_t + \epsilon_{ihcmt}$ where subscript h indicates the housing type (condo vs. other types) and c is community, the smallest administrative unit in South Korea that is nested within municipality m, and the other subscripts are identical as equation (1). M_{ihcmt} are the range of outcome variables such as intake, and calories as well as health outcomes.

While the source of variation is identical to 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: income, age, sex, working status, whether someone has a child, and family size. Second, as the data does not track the same households over time, I add municipality by housing type fixed effects (λ_{hm}) instead of the household by municipality fixed effects (λ_{im}). Third, because I do not observe a street address, a binary tax status is assigned based on the community and housing type.[25] In the estimation process, I weight the regression using sample weights.

Continuous treatment models (food waste). 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 waste data is a municipality m.

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

In equation (2), W_{mt} is per household food waste quantity for m in t. The share of households under the unit tax is $(\%)Tax_{mt} = \sum_k (\%)tax_{mkt} z_{mkt}$, where $(\%)tax_{mkt}$ is the share of unit-taxed

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1 when a household is under the tax in event year $k = t - d$ where d is the policy change year. Following Baker et al. (2022), I include all event years (mechanically) available in the data (from -7 to 6) when estimating the coefficients. For presentation, I focus on event years -3 to 2, because within this window, all Wave 2 treated households are observable at every event time.

[25] 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. As Appendix Figure F.4 illustrates, the 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 does not vary within a municipality.

households in k $\in$\{condominium, non-condo, small restaurants\} and z_{mkt} is share of k for m.[26] Similar to the Tax_{imt} variable in equation (1), $(\%)Tax_{mt}$ reflects the share of households subject to the unit tax, irrespective of the collection method. $\boldsymbol{X_{mt}}$ accounts for time-varying municipality characteristics, namely educational attainment and the shares of single-person households and apartment residents. $\boldsymbol{X_{mt}}$ also includes landfill tax rate for mt to account for potential correlations between food and landfill waste tax rates. θ_m, τ_t are municipality and year fixed effects, controlling for unobserved time-invariant municipality characteristics and overall time trend.

β, the marginal effect of changes in $(\%)Tax_{mt}$, is the coefficient of interest. Since the Wave 2 expansion was mandated by the central government, endogenous selection by municipalities is unlikely. Consistent with this, the scale of the expansion appears to have been driven by external factors. As shown in Appendix Figure F.3, municipalities with a higher baseline fraction of condominium residents had greater expansion, likely due to having more capacity for growth. I also test robustness to treatment heterogeneity using recent estimator proposed by De Chaisemartin et al. (2025). In the estimation process, I use the municipality population as a weight. Throughout the analysis in Section 4, standard errors are clustered at the municipality level.

4.2 Findings

[**Table 2 Here**] *Effect of the unit tax on food waste.* I first report the effect of the unit tax on food waste quantity. In Table 2 Panel A column (1), I regress the log of food waste quantity per household on $(\%)Tax_{mt}$. The point estimate indicates that the policy effect is economically large and statistically significant: when the fraction of households subject to the unit tax changes from 0 to 100%, food waste per household decreases by 21% ($e^{-0.234} - 1 = -0.209$) or 49kg when evaluated at the average waste quantity in the pre-expansion period for low treatment intensity municipalities (235kg). Given an average tax rate of 6 cents/kg, 49kg translates into an annual savings of \$3 per household.

[26] z_{mkt} is 38% (condo), 40% (non-condo), and 22% (small restaurants) for an average municipality (Appendix Table A.1). See Section 3 for details.

To put this finding in context, I follow the PAYT literature and calculate the arc-elasticity of the tax. Using the approach in Fullerton and Kinnaman (1996), I estimate an elasticity of –0.12, larger than prior estimates of –0.08 Fullerton and Kinnaman (1996) and –0.07 Carattini et al. (2018).[27] One possible explanation is that reducing food waste provides direct financial benefits—namely, grocery savings—whereas such incentives are less evident for unsorted waste.

[**Figure 2 Here**] Figure 2 (a) illustrates results in column (1) using a 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 change in per household food waste. The fitted line suggests that municipalities with a larger increase in treatment intensity experienced a larger reduction in waste.

Recent studies find that continuous treatment difference-in-differences models with can be biased under treatment heterogeneity (Callaway et al. 2025, De Chaisemartin et al. 2025). Because $(\%)Tax_{mt}$ is inherently continuous, I examine the robustness of the main results using the estimator proposed by De Chaisemartin et al. (2025). In this framework, "switchers" ("stayers") are municipalities whose treatment intensity changes (remains constant) between periods. The results in Appendix Figure F.5 show that during the three pre-treatment years, food-waste quantities for (future) switchers and stayers evolve in parallel. At the time of treatment (event time 0), food waste among switchers falls by roughly 16% relative to stayers. This magnitude is slightly smaller but broadly consistent with the 21% reduction reported in Table 2.[28] While this robustness check is underpowered, the close alignment of the point estimate with the baseline result provides suggestive support that treatment-effect heterogeneity is unlikely to bias the main findings.

As detailed in Section 2, the Wave 2 expansion was accompanied by public-awareness campaigns. However, these policies are unlikely to confound the treatment effect for two reasons.

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[27] I assume that the difference between volume-based and weight-based elasticities follows the pattern observed in Fullerton and Kinnaman (1996).

[28] De Chaisemartin et al. (2025) impose a static treatment effect assumption, so post-treatment event time coefficients are not produced. Figures 2 (b) and Figure 5.3 (a) in Lee and Seo (2022) show treatment effects are relatively stable over time, consistent with this assumption.

First, similar outreach-based initiatives had been implemented repeatedly since the early 1990s and, according to the government's own policy review, had produced only limited and short-lived effects (GGC 2010). Second, and more importantly, nationwide media campaigns during the Wave 2 period were broad-based and applied to both treated and control municipalities, meaning these effects would be differenced out. Consistent with this interpretation, I find no evidence of reductions in other waste streams following the unit-tax expansion (Appendix Table F.1).

Finally, because the administrative food waste data record waste from both households and small restaurants together, the estimated household effect could be biased if restaurants' responses to the tax are either larger or smaller than those of households. To assess a potential bias from this, in Appendix B, I conduct a bounding exercise using two extreme scenarios and find that the estimated 21% reduction is driven primarily by household responses.

Effect of the unit tax on food purchases. To assess the social benefit of reducing food waste, I investigate its underlying sources. Column (2) of Table 2 Panel A shows that the unit tax reduces food purchase per household by 5.5% or 41kg based on the pre-tax average ($e^{-0.057} - 1 = -0.055$). Comparing 41kg to the observed reduction in food waste quantity (49kg) implies that purchasing less food in the first place is the primary abatement strategy. The comparison also implies that the upper bound of illegal dumping is 16% or 8kg.[29] 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, the 16% provides a useful benchmark.

While a 41kg reduction in grocery purchases is substantial, it does not appear to threaten households' "safety margins." As shown in Table 1, the average household purchases 740kg of food annually and consumes 526kg of them. Even after reducing purchases by 41kg, households still maintain a surplus of over 150kg—30% more than their actual consumption.

Similar to column (2), in column (3), I find a 4.6% reduction in grocery spending from the

[29]This is about 3% of the average waste quantity in the pre-expansion period for low treatment intensity municipalities (235kg). A small increase in landfill waste quantity after the unit tax (Appendix Table F.1) is consistent with a modest increase in illegal dumping.

unit tax, which amounts to $169 savings on annual grocery bills for an average household. This is consistent with an external survey, which found that 31%, 21%, and 10% of households reduce grocery purchases by 0–5%, 5–10%, over 10% after the unit tax (Ministry of Environment 2012a). Importantly, savings on grocery expenditures suggest that the unit 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).

In columns (4) and (5), I separately estimate the policy effect for perishable (fresh fruit and vegetable) and storable food items. If adjustment in purchases is driven by the unit tax, the policy effect should be larger for perishable items, which are easier to become waste when not consumed in time. Indeed, I find that the point estimate is nearly three times larger (in magnitude) for the perishable items. Columns (6) and (7) indicate that the reduction in grocery purchases is almost entirely driven by households buying less food per store visit, likely due to more deliberate shopping decisions, such as avoiding impulsive purchases that could lead to waste.

In Figure 2 (b), I plot grocery purchase changes relative to the unit tax timing. Pre-tax estimates are near zero, consistent with the parallel trend assumption, and the treatment effect is sharp and persistent. Appendix Figure F.6 shows similar patterns for other grocery outcomes, including (a) expenditure, (b) perishable quantities, (c) storable quantities, and (e) GHG emissions from the food basket. One exception is (d) the number of shopping trips, where coefficients are close to zero in all event times—a pattern consistent with Table 2 Panel A column (7). Appendix Figure F.7 repeats this using alternative estimation methods that allow treatment heterogeneity (Cengiz et al. 2019, 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 F.2, I add housing type by year fixed effects, allowing for the possibility of housing type specific shocks that confound with the unit tax, and find that the results remain very similar to those in Table 2.

Effect of the unit tax on food intake. How does a change in food purchases affect food intake?

In Table 2 Panel B, column (1), I find that the unit tax leads to a statistically insignificant 3.8% increase in the food consumed at home. Columns (2) and (3) also show a slightly higher key nutrient intake at home following the tax. These estimates suggest that reduced grocery purchases reflect trimming previously wasted rather than consumed portions of the food basket.

In contrast, columns (4)–(6) indicate that individuals consume less food away from home, particularly from discretionary sources such as restaurants and takeout, suggesting that the unit tax prompts a shift from meals away from home to meals prepared at home. This behavior may be driven by the tax prompting closer monitoring and more timely consumption of groceries, which can discourage unplanned food purchases and dining out. Although the food intake data do not include spending information, the reduction in food consumed away from home suggests an additional financial benefit of the unit tax beyond savings on grocery expenditures. Finally, columns (7) and (8) reveal that these changes in intake lead to a modest reduction in weight and BMI. This effect may be attributed to a decline in food consumed away from home, which is often of poorer dietary quality, with higher levels of salt and saturated fats (Gesteiro et al. 2022).

In Appendix Figure F.6 (f)-(i), I present event study plots for food intake variables. Although the estimates are underpowered, the coefficients are stable between event times –2 and –1, and the post-treatment patterns align closely with the corresponding estimates in Table 2, Panel B.

5 Household Abatement Strategies and Corresponding Costs

5.1 Estimation Framework

Section 4.2 suggests that the unit tax encourages more efficient food use without compromising nutritional needs. But how can households maintain food intake with smaller grocery purchases? What do they do and what are the associated costs? To answer these questions, I build on the insights from the household production model (Becker 1965), which has been widely used to study food waste generation and, more broadly, household meal production behaviors (Gronau 1977, Aguiar and Hurst 2007). Consider a simple meal production process in equation (3), where a meal at home (M) is produced by combining raw food input (Q), namely grocery, and time (T). This household minimizes the cost of production by choosing an optimal input mix. Suppose that before the tax, a household was producing M_0 by combining Q_0 and T_0 at a productivity level of A_0. After the unit tax on food waste, the household produces at $M_1 = A_1 F(Q_1, T_1)$.

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

From Section 4.2, I know $Q_0 > Q_1 = 0.95Q_0$ while $M_0 \leq M_1$, and the model provides two potential explanations for this empirical finding. First, households use more time to compensate for reduced grocery purchases ($T_1 > T_0$), namely, choosing a different input mix on the same isoquant curve — for instance, by planning meals more carefully or improving food storage to reduce spoilage.[30] A second possibility is a genuine increase in meal productivity ($A_1 > A_0$), namely, a shift in isoquant curve itself, allowing households to produce the same meals with fewer groceries through better techniques rather than more time.

To estimate the impact of the unit tax on time spent on meal production, I analyze microdata from the 1999, 2004, and 2009 Korean Time Use Surveys. Unlike grocery or food intake data, which provide detailed location information for respondents, the time use data report locations only at the province level—the largest sub-national administrative unit in South Korea. Consequently, the best available measure of individual households' tax status is the proportion of households subject to the tax within each province-housing type.

Importantly, because almost all province-housing types experienced substantial unit tax expansions during the Wave 2 period (Appendix Figure F.8 Panel (b)), due to the nature of the central government's mandate, identifying a clean control group during this period is particularly challenging.[31] To address this, I leverage the Wave 1 expansion, where most province-housing type

[30] To illustrate, a household can simply buy a new bag of green onions each week, letting unused stems wilt. Or, they can extend freshness by storing them in damp towels inside an airtight container, allowing purchases every 2–3 weeks instead.

[31] Identifying a control group is not a concern in Section 4, as granular location information

pairs remained untreated (Appendix Figure F.8 Panel (a)). Further, I collapse individual-level data into province-housing type-survey date-year level observations.[32]

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

A resulting canonical difference-in-differences estimating equation with continuous treatment is in equation (4). Time$_{hpdt}$ is time spent on meal production per household for housing type by province hp on day of the week d in year t. $(\%)T_{hp,2009}$ is the fraction of households subject to the unit tax as of 2009 (i.e., 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 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. Details on the meal production productivity effect estimation are in Appendix C.2.

5.2 Findings

[**Table 3 Here**] In Table 3, 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 spends 9.1 (7.6%) additional minutes per day or 55 additional hours per year on meal production after the unit tax. Investigating more granular activities in columns (2)-(5), I find that the result in column (1) is driven by higher meal preparation time, which includes cooking, preparing ingredients, and storing and organizing groceries (Statistics Korea 2009). I also find a nearly 50% increase in time spent keeping diaries, which supports meal planning, though the absolute time increase is relatively small. There is some evidence of increased cleaning time, but the effect is not statistically significant at conventional levels. Collectively, columns (2)–(4) suggest that households adopt a more

allows binary tax status assignment to each household following the Wave 2 expansion.

[32] I show that analysis without data aggregation yields similar conclusions.

deliberate approach to food management, such as auditing inventory and planning meals.

Interestingly, column (5) indicates that time spent on grocery shopping does not increase, despite presumably more careful shopping. This aligns with Section 4.2, which show that the tax does not increase shopping trip frequency. This perhaps reflects more deliberate planning—consistent with more time spent in kitchen—and efficient list-based shopping, avoiding extra time in stores. Further, unchanged trip frequency implies no additional GHG emissions from driving.

[**Figure 3 Here**] I leverage web search data from "Naver," a leading search engine in South Korea to further investigate how households utilize the additional time allocated to meal production.[33] In Figure 3 (a), I depict web search intensity for three keywords: "food waste," "organizing refrigerator hacks," and "meal planning," for female users aged 40–60, a demographic primarily responsible for meal production. Consistent with the discussion of Table 3 columns (2)-(5), the figure shows that search intensity for "food waste" is strongly correlated with both "meal planning" and "organizing refrigerator hacks" with correlation 0.72 and 0.43, over 2016–25 (excluding the anomalous COVID years (2021–22)).[34]

Importantly, as Appendix Figure F.9 shows, such a pattern does not appear for demographic groups less involved in meal production, such as men aged 40–60 or females under 20, which collectively suggests that improving food storage practices and engaging in careful meal planning are key strategies to use food more efficiently.[35] This aligns with earlier findings that some of the most common strategies consumers use to reduce food waste include: (1) properly storing food to maximize shelf life, (2) keeping a well-organized pantry, and (3) making a grocery list and engaging in meal planning (Ministry of Environment 2015b, IFIC Foundation 2019).

[33]If households had perfect knowledge of waste reduction strategies, the unit tax would simply motivate them to apply these strategies, making search data less informative for this purpose. However, survey results reveal substantial knowledge gaps (Ministry of Environment 2015b).

[34]With 2021-22, correlations are 0.62 for meal planning and 0.38 for organizing refrigerator.

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

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 2007). Appendix Table F.3 shows that the estimated results from uncollapsed data lead to a consistent conclusion.[36]

Figure 3 (b) visualizes Table 3 column (1), plotting binned regression between $(\%)T_{hp,2009}$ and the first difference in meal production time (pre: 2004 vs. 1999; post: 2009 vs. 2004). The difference for the lowest treatment intensity bin is normalized to zero for readability. The left-hand side figure shows that, before the unit tax, there was no difference in time spent on meal production over time between high- and low-treatment-intensity units, which is akin to the "no pre-trend" condition in a binary canonical difference-in-differences framework. While Appendix Figure A.3 shows a modest baseline difference in time spent on meals across treatment groups, Figure 3 (b) indicates that this difference remains stable over the pre-treatment period. In contrast, the right-hand side figure shows a positive slope, indicating that households in higher treatment intensity units spend more time on meal production after the unit tax.

In Table 3 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 measure the opportunity cost of time, I follow Aguiar and Hurst (2007) and use demographic group specific marginal returns to shopping (see Appendix C.1 for more details). I find that the cost of additional time spent on meal production is \$175 per year per household, which largely offset by savings on grocery spending (\$169 from Table 2) due to the unit tax.[37]

Finally, I present suggestive evidence indicating that the unit tax does not seem to meaningfully affect meal production productivity. While I leave details to Appendix C.2, I highlight that the likely null effect on productivity is not surprising given that productivity is measured by the

[36]Magnitudes are slightly attenuated, perhaps due to measurement errors from the binary tax status variable (=1 if over 50% of households in a province-housing type are treated.

[37]\$175 suggests that the average value of time in the home production context is \$2.9/hour. To benchmark, the average market wage in South Korea for homemaking jobs in 2009 was \$4.9/hour.

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 remains similar), a large increase in productivity seems unlikely. However, there is one caveat to this interpretation: the unit tax's impact on time use could be smaller than 7.6% for the Wave 2 expansion if improvements in meal planning tools or kitchen technologies (e.g., the proliferation of smartphones) have reduced the marginal effort required to adjust to the unit tax.[38] In this scenario, there might have been a productivity increase after the unit tax. This also has direct implications for the welfare analysis: the abatement-cost estimates in Section 6.2 would then overstate the true adjustment costs, implying that the welfare impact of the policy is likely even larger.

6 Discussion

6.1 Mechanism

Results so far indicate that households make substantial changes to their behavior after the unit tax implementation to reduce an average tax burden of just $3 per year. Although the increased time spent on meal preparation ($175) is largely offset by grocery savings ($169), such a small tax saving appears insufficient to rationalize these changes, implying that the price effect of the tax may have only a limited role in driving the overall response to the unit tax policy.

Consistent with this, I find that the tax elasticity of grocery purchase, which is estimated using the intensive margin tax rate changes, is -0.015 (se = 0.033).[39] The estimated elasticity is more than an order of magnitude smaller than typical price elasticity of groceries (Andreyeva et al. 2010), and the starkly different impact of a dollar increase in the tax versus grocery prices sug-

[38] One might worry that the Wave 1 estimate is overstated because Wave 1 introduced mandatory food waste separation in addition to unit pricing, but this is differenced out by the control households. Thus, equation (4) is capturing the incremental time use effect due to the unit tax.

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

gests that the tax effect cannot be fully explained by the price channel alone (Chetty et al. 2009).

[**Figure 4 Here**] Further, Figure 4 shows the differential impact of the unit tax on grocery purchases by (a) household income level and (b) baseline grocery purchase quantity.[40] If price-driven, the effect should be largest for low-income households, who have higher price elasticity and lower opportunity cost of time (Andreyeva et al. 2010). However, Panel (a) suggests the opposite: low-income households show no response while high-income households reduce purchases by nearly 10%. Panel (b) provides one potential explanation: households with high baseline purchases, who typically have higher income (Appendix Figure F.10) and likely wasted more, drive the response.

A small price impact suggests that a significant portion of unit tax's effect may stem from non-pecuniary channels. Since implementing a unit tax inherently requires measurement, the tax system itself provides regular, salient feedback on food waste generation, effectively functioning as an information intervention that may influence behavior beyond direct financial incentives. Consistent with this, surveys show the tax raises food waste awareness (Ministry of Environment 2012b, 2015b). Moreover, a companion paper finds that feedback alone—without a meaningful marginal price—reduces food waste by over 10% (Lee and Seo 2022).[41] Interestingly, Figure 4 (c) shows that the effect of the unit tax on grocery purchase quantities is nearly identical between Smart Card and bag based systems. Since tax rates are similar across regimes, feedback presence rather than technology appears to be the first-order determinant.

These findings align with broader research highlighting the role of monitoring and feedback in shaping environmentally friendly behaviors in other developed countries (Allcott 2011, Tiefenbeck et al. 2018). These papers find that report cards or real-time feedback reduce electricity or

[40]I categorize the 10 income levels in the grocery data into three groups (low: 1–4, medium: 5–7, high: 8–10) and baseline purchases into terciles, each interacted with Tax_{imt} in equation (1).

[41]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.

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 21% reduction in the food waste generation appears consistent with earlier research.

6.2 Welfare Effects

Empirical estimates allow me to conduct a simple cost-benefit analysis of the unit tax adoption. For this, I assume that the food production market is competitive, and thus the social welfare is determined by the tax's impact on GHG emissions, government spending, and consumer surplus. [**Table 4 Here**]

Reduction in GHG emissions. Using estimates from Table 2, Table 4 shows that the unit tax reduces lifecycle GHG emissions from wasted food by 3.1 million tons annually, equivalent to the emissions from 750 thousand passenger vehicles.[42] Importantly, this effect is almost entirely driven by avoided production (item A: 3.0 million tons), which highlights the importance of food waste prevention over recycling.[43] While details on the GHG reduction calculation are in Appendix D.2, it is worth noting that the coefficient in Table 2 column (8) is estimated using equation (1), where the outcome variable is annual GHG emissions from purchased food, constructed using food item-specific GHG intensities from Poore and Nemecek (2018). This approach ensures that the estimated effect accounts for the disproportionate reduction in more perishable (less GHG-intensive) items—thereby avoiding overstatement of the tax's GHG reduction effects.

It is important to note that the numbers in items A–C are based on two key assumptions. First, any food waste reduction not explained by lower grocery purchases will end up in landfills, which

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

[43]Item B 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).

is the worst-case GHG emissions scenario. Second, profit-maximizing farmers will scale back food production in response to the unit-tax-induced demand shock. Given the central role of Item A in overall GHG reductions, assessing the plausibility of the second assumption is crucial.

South Korean agriculture is dominated by a large number of small-scale, family-run farms with thin profit margins. As of 2015, there are 1.1 million farming households nationwide with average farmland of just 1.2 hectares (2.97 acres). While agricultural firms exist, 61% of firms have four or less employees, while only 0.7% employ more than 50 workers. As such, 45% of these firms are unprofitable, 40% earn less than $90,000 annually, and just 3% report annual profits over $450,000.[44] Given these conditions, the long-run food supply curve is likely to be flat. Consequently, (1) in response to a negative demand shock induced by the unit tax, the market is more likely to adjust through quantity rather than price, and (2) producers are likely to operate under zero profits, which supports abstracting away from producer's surplus in welfare analysis.

Consistent with this, Appendix Figure F.11 shows that after the Wave 2 expansion in 2013, the production of vine fruits—such as watermelon, Korean melon, and tomato, which tend to generate larger amounts of food waste—sharply declined relative to that of tree fruits—such as apple, grape, and peach—which typically result in minimal or no food waste.[45] Indeed, industry groups have cited the food waste tax as a key driver of the decline in watermelon demand and subsequent production (Yoon 2013, Wee 2017).

Government spending. Since food waste tax revenue covers about 30% of food waste management costs for a typical municipality, local governments spend a large portion of their budget to provide these services—for instance, the Seoul Metropolitan Government spent $142 million in 2015 alone (Ministry of Environment 2015a). Assuming a constant marginal cost, a 21% reduction in food waste after the unit tax saves $78 million per year nationwide even after accounting

[44]Data for farm sizes, employees, and finances can be accessed at Link 1, Link 2, Link 3.

[45]Both production statistics and fruit classifications are obtained from the Ministry of Food, Agriculture, Forestry and Fisheries. See links for tree fruits and vine fruits.

for increased landfill costs under the worst-case leakage scenario. For a complete impact on the government budget, the unit tax implementation costs need to be considered as well. In Table 4, I take into account both the operating (item D and F) and capital cost (item E) of the unit tax system.[46] The combined program cost (items D+E+F) amounts to $36 million per year. Taken together, the unit tax saves government spending on food waste by $41 million per year.

Household abatement costs.[47] A standard household production model suggests that consumer utility loss due to the tax is $6 per year per household: households spend $175 more on time but save $169 on groceries.[48] Thus, the household abatement cost at the national level (19.1 million households) is $115 million (Item H). Note, $6 does not take into account food waste tax payment because it is a pure transfer between government and households.

It is worth emphasizing that under the standard model, households would have been better off maintaining their pre-tax meal production practices. From the household's perspective, shifting time and food inputs incurs a cost of $6 but yields only $3 in tax savings. This implies that the behavioral changes induced by the unit tax likely generate non-pecuniary benefits worth at least $3 per household per year. While in theory this non-pecuniary benefit could arise either from an increase in utility when adopting the new behavior—positive experiences associated with preventing food waste (e.g., warm glow)—or from a decrease in utility when failing to adjust—negative emotions tied to generating waste (e.g., guilt), strong taxpayer support for the unit tax suggests that the non-pecuniary effect is more likely to reflect the former.[49] Importantly, when

[46]For items D and G, I use the 2015 Unit-Based Waste Policy Yearbook, which is the first year with a 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).

[47]For a more formal discussion, see Appendix E.

[48]Recall that the time cost is estimated using variation from the Wave 1 expansion. If, as discussed in Section 5.2, the marginal time required to adjust to the unit tax has decreased over time, the time cost associated with the Wave 2 expansion may be lower than $175.

[49]For instance, support for the tax has increased over time, with the share of survey respon-

reducing food waste yields not only tax savings but also a moral subsidy (e.g., warm glow), the effective abatement costs may be lower than \$115 million (Allcott and Kessler 2019). While survey evidence supports this interpretation, fully distinguishing between these explanations is beyond the scope of this paper. Therefore, I take a conservative approach and retain the \$115 million estimate for policy evaluation.

Overall impacts. Table 4 provides two key metrics to assess the welfare effect of the unit tax. First, the abatement cost per ton of CO_2eq is \$24, which is calculated by dividing the total economic cost (government spending and household abatement costs) by the total GHG reduction due to the policy. Notably, \$24 per ton indicates that the unit tax is one of the most cost-effective GHG mitigation measures (Gillingham and Stock 2018). Second, the net benefit of the policy is \$515 million per year. For benefit, I monetize the value of reduced GHG emissions using a social cost of carbon of \$190 per ton of CO_2eq (EPA 2023). From this, the household abatement cost of \$115 million is subtracted. Importantly, the \$515 million likely underestimates the true benefits of the policy, as it does not account for additional environmental benefits of food waste prevention, such as reduced biodiversity loss, soil degradation, and water depletion (EPA 2021).

6.3 Policy Considerations

Designing Food Waste Taxes. Depending on the policy objective—whether to penalize the carbon content of food or to discourage food waste—a carbon tax on food may be the first-best solution, as the food waste tax applies a uniform rate to all discarded food, regardless of its carbon intensity. However, despite its theoretical appeal, implementing a carbon tax on food is challenging and likely less effective than a food waste tax for at least three reasons.

First, unlike CO_2, where emissions can be measured based on fossil fuel usage (as emissions are proportional to fuel consumption), there is no straightforward method to measure non-CO_2

dents in favor rising from 57% in 2010 to 70% in 2014. Moreover, 85% of respondents agreed that a food waste tax is necessary to reduce waste (Ministry of Environment 2015b).

GHG emissions from farms (Timilsina 2022). For example, emissions from producing beef depend heavily on agricultural practices, which can vary significantly even at the individual farm level and 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 (Dechezleprêtre et al. 2022). Indeed, while over 70 countries have implemented carbon pricing as of 2024, the agricultural sector remains exempt in all cases, largely due to political oppositions (World Bank 2025). Moreover, the importance of non-pecuniary effects of the food waste tax—combined with its relatively small price effect—suggests that governments can further enhance its political feasibility by adopting a lower, more palatable tax rate without significantly compromising its effectiveness.

Third, tax saliency literature suggests that the food tax, which is likely to be reflected in the final price consumers pay rather than charged separately, might not have as strong effects as a food waste tax, unless the food price increase is substantial (Chetty et al. 2009). For instance, using food demand elasticities, Wirsenius et al. (2011) finds that a 16% increase in the prices of ruminant meat would be required to reduce GHG emissions comparable to the estimated GHG reduction effect of the unit tax (6%). Given these considerations, a unit based tax on food waste is likely to be a more realistic and effective policy tool than taxing food.

Implementing Food Waste Tax in Other Jurisdictions. Food waste separation is a necessary precondition for implementing food waste pricing. A growing number of jurisdictions around the world have adopted mandatory food waste sorting policies—similar to the Wave 1 period—to ease landfill pressure and promote organic waste recycling, including US states (California, Vermont) and cities (Seattle), major Chinese cities, and countries such as France and Sweden Symons (2024). These developments indicate that many jurisdictions have already established the institutional foundation—separate collection and enforcement capacity—needed for unit-based food-waste pricing. In such settings, food-waste taxation could represent a natural progression from sorting mandates, analogous to how landfill pricing schemes have expanded to roughly one-quarter to one-third of municipalities across developed economies (Bel 2016).

7 Conclusion

The lifecycle GHG emissions from wasted food are comparable to those of road transport (IPCC 2014, FAO 2015). Additionally, waste treatment is the largest budget item for many municipalities worldwide, often diverting resources from more productive investments (OECD 2000, Kaza et al. 2018). As a result, addressing food waste has become a critical priority for both climate change mitigation and public finance management. While imposing a corrective tax on food waste generation is a textbook solution, limited evidence exists on its welfare effects.

Leveraging plausibly exogenous food waste tax expansions in South Korea, I show that the tax reduces annual food waste and grocery purchases by 21% (49kg) and 5.5% (41kg), respectively, saving $3 in waste taxes and $169 in grocery expenditures per household per year. This enhanced efficiency in food use suggests an annual reduction of 3.1 million tons of CO_2eq (GHG emissions) and $41 million in government spending. However, these efficiency gains come with costs: households spend more time on meal production, worth $175 per household per year.

I show that a significant portion of the tax effect is driven by non-pecuniary factors, likely due to the information and feedback on food waste generation from measurement—a necessary condition for unit taxation implementation. Finally, I show that the tax is highly cost-effective in reducing GHG emissions, as abatement costs are largely offset by grocery savings. Overall, the findings demonstrate that the unit tax generates substantial welfare gains.

While the results provide new quasi-experimental evidence on the behavioral and welfare effects of unit-based food waste taxation, several limitations remain. First, because of data constraints on spatial coverage, the Wave 2 analysis focuses on the Seoul metropolitan area. Although the sample is broadly representative of the average South Korean household, more geographically diverse dataset would allow for a more robust analysis. Second, the paper cannot fully identify the sources of the non-pecuniary effects of the tax; disentangling them remains an important topic for a more comprehensive welfare calculation. Third, the analysis is static by design and does not capture the dynamic nature of food purchasing, storage, and usage decisions; incorporating intertemporal considerations could explain why households over-purchase.

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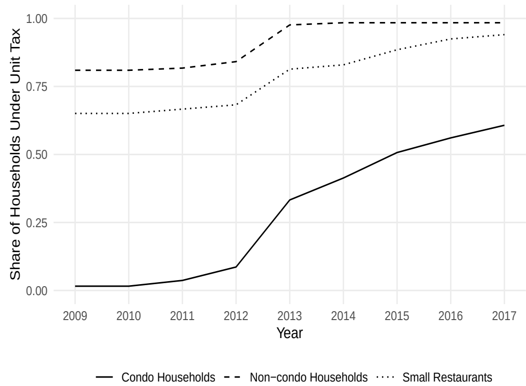
Tables and Figures

(a) Official Trash Bags

(b) Smart Card System



(c) Share of Households under the Unit Tax by Type

Figure 1: Unit Based Food Waste Tax Collection Methods and Expansion Trend. Panels (a) and (b) show pictures of two different food waste tax collection methods. Panel (c) plots the share of households subject to the food waste tax by household type from 2009 to 2017, using data from 63 municipalities in the Seoul metropolitan area.

Table 1: Descriptive Statistics (Per Household Per Year)

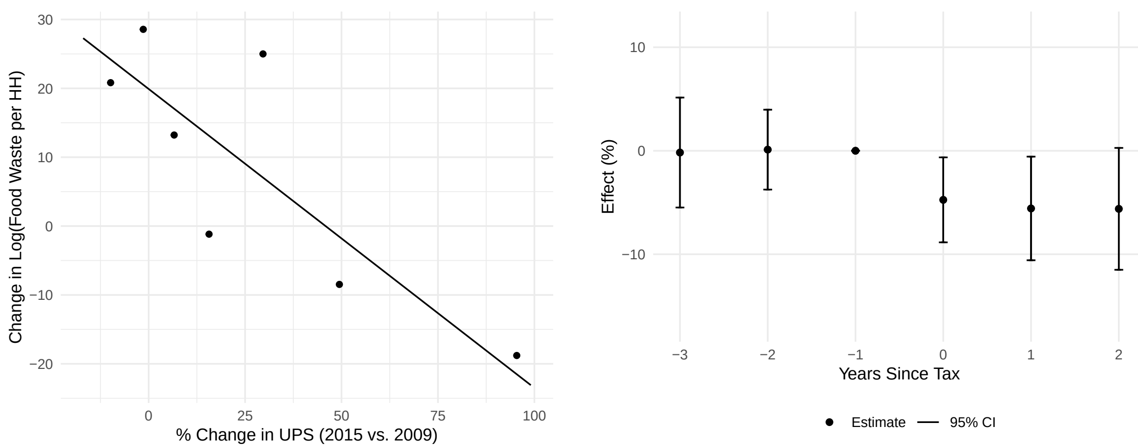
Variables	Min.	Max.	Mean	Std.Dev.	N
Food waste (kg)	33.51	737	202	69.88	441
Total grocery purchase (kg)	20.97	2,213	740	307	2,872
Total grocery expenditure (USD)	119	12,312	3,658	1,534	2,872
Total GHG from grocery (kg CO_2eq)	38.03	9,912	2,678	1,270	2,872
Intake at Home (kg)	0	5,142	526	477	17,264
Intake 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

Note:
This table presents descriptive statistics for the key outcome variables. Food-waste quantities are sourced from the Unit-Based Waste Policy Yearbook. Food-purchase data come from the grocery panel, food intake and nutrition data come from KNHANES, and meal-production time comes from the time use survey.

Table 2: The 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	-0.231***							
	(0.053)							
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)
Dep. Vars 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	-49	-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
Muni. × 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 Dep. Vars	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
House Type × Muni. 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 level food waste data and results from equation (1) using household level grocery panel data. Panel B shows the estimation results from 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.



(a) Food Waste

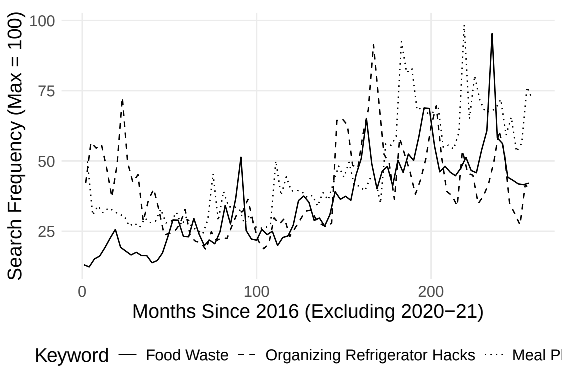
(b) Food Purchase

Figure 2: 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.

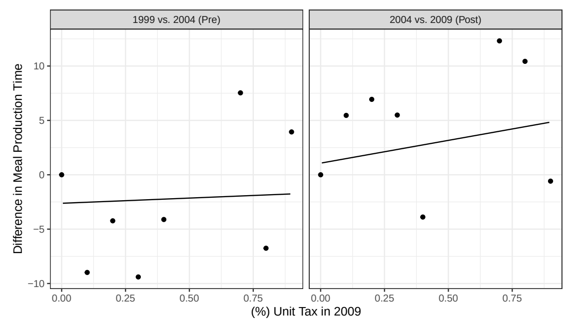
Table 3: The Effect of the Unit Tax on Household Meal Production Time

	(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 Mins	Prep Mins	Cleanup Mins	Diary Mins	Shopping Mins	Dollars Per Day
Mean of Dependent Variable	119	66	36	1	17	5
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 coefficient of interest only, but all the regressions include baseline control variables. Standard errors are clustered at the province by housing type level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

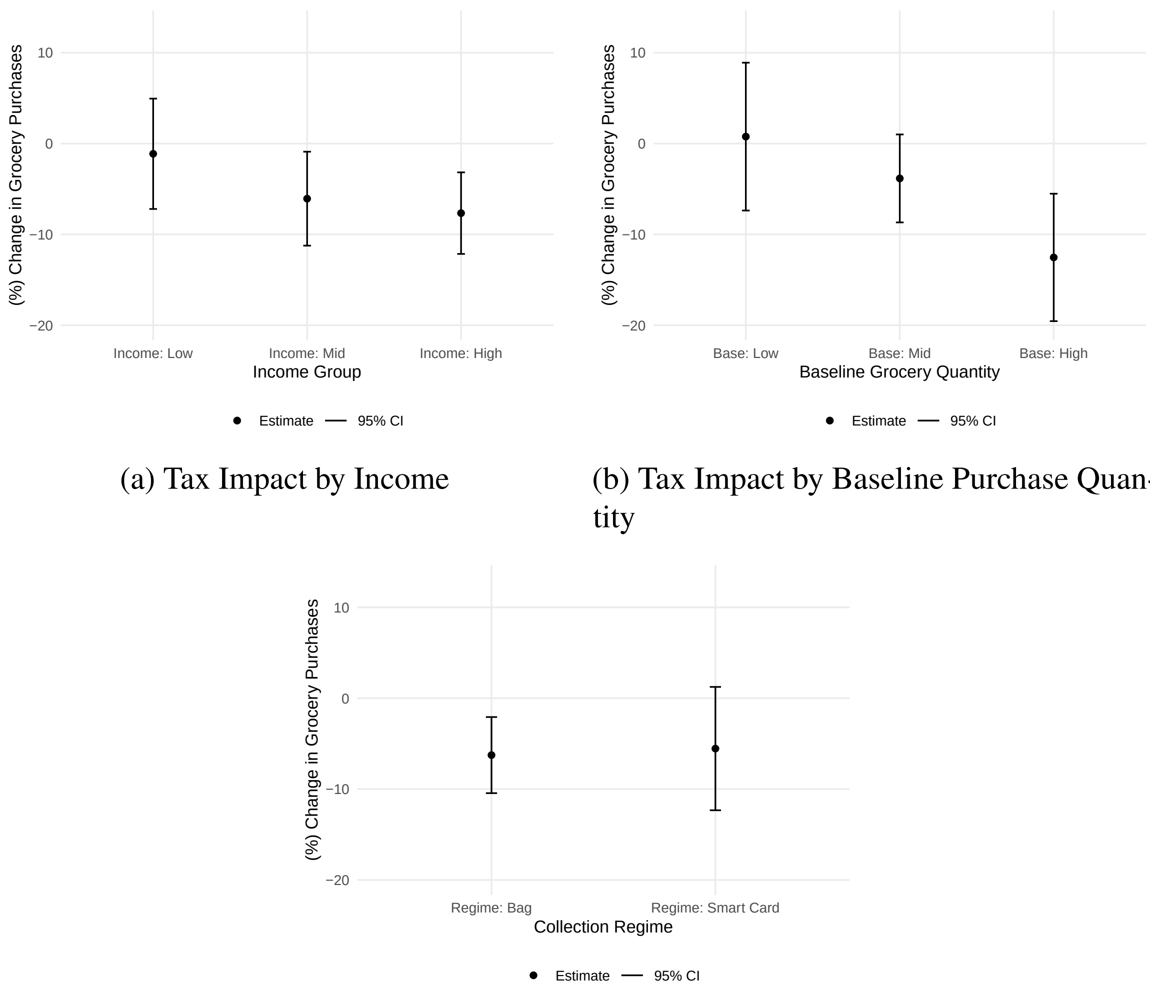


(a) Search Intensity



(b) Unit Tax and Time Spent on Meal Production

Figure 3: The Effect of the Unit Tax on Time Use. Panel (a) presents the trend in web search intensity for three food waste-related keywords among female users aged 40-60 on Naver, South Korea's dominant search engine, from Jan 2016 to Feb 2025, excluding the COVID period from Jan 2020 to Dec 2021. Panel (b) shows the impact of unit tax on time spent on meal production using binned regressions. The X-axis is the share of households under the unit tax in 2009 and the Y-axis is the first difference in meal production time for years 2004 vs. 1999 (left) and 2009 vs. 2004 (right).



(a) Tax Impact by Income

(b) Tax Impact by Baseline Purchase Quantity

(c) Tax Impact by Collection Regime

Figure 4: 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) household income level, (b) baseline grocery purchase quantities, (c) collection regime.

Table 4: The Welfare Effect of the Unit Based Food Waste Tax

	Items	Value
GHG Change (1000 Ton)	Avoided Production (A)	3020
	Avoided Food Waste Treatment (B)	177
	Increased Food Waste in Landfill (C)	100
	Net GHG Effect (A+B-C)	3097
Government Spending ($ Mn)	Producing Bags and Stickers (D)	12
	Installing Smart Card System (E)	17
	Operating Smart Card System (F)	7
	Spending on Waste Services (G)	-78
	Total Gov. Spending (D+E+F+G)	-41
Household Abatement Costs ($ Mn)	Reduction in Consumer Surplus (H)	115
Total Abatement Costs/Ton of CO_2eq	(D+E+F+G+H)/(A+B-C)	24
Net Benefit ($ Mn)	(A+B-C) $\times$ \$190 - (D+E+F+G+H)	515

Online Appendix

Does a Food Waste Tax Work? Evidence from Quasi-Experiments in South Korea

Seunghoon Lee

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 non-condo (residential) households	4,811	190,384	65,452	41,381	441
Number of condo households	176	233,256	62,774	46,082	441
Number of restaurants (smaller than $200m^2$)	492	14,418	5,166	2,848	441
Number of combined households (HH)	8,437	518,269	164,387	94,562	441
Food waste (kg)	33.51	737	202	69.88	441
Landfill waste (kg)	35.76	837	258	98.14	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
BMI	11.39	40.96	21.35	4.02	16,192
Panel D: Meal Production Time					
Meal Production Time (Hrs)	469	1,067	726	87.21	672
Cooking Time (Hrs)	243	562	403	47.26	672
Cleaning 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)	411	1,338	784	116	672

Appendix Table A.1 presents summary statistics for a full set of food and time use variables, which are grouped into four categories: wasted, purchased, consumed food, and time use. Each panel merits attention. For Panel A, it is worth highlighting that the waste quantity in the Unit-Based Waste Yearbook reflects waste from all non-bulk generators, namely both residential households and small restaurants. To calculate per household food waste quantity, I treat a restaurant as seven households based on a conversion ratio derived from statistics from the City of Seoul (e.g., the mean number of restaurant in Panel A (5,166) is treated as 36,162 "household equivalents"). The first four rows present summary statistics for the number of non-condo (residential) households, condo households, restaurants, and both (residential and restaurant-converted households). Dividing the first to third rows with the fourth row indicate that the share each type is 38% (condo), 40% (non-condo), and 22% (small restaurants) for an average municipality. The fifth and sixth rows together indicate that food waste constitutes 44% of the total waste quantity (including food and landfill waste), aligning with global trends. For many countries, food and green waste typically make up 32-56% of total waste (Kaza et al.(2018)Kaza, Yao, Bhada-Tata, and Woerden).

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 also consistent with global trends that 1/3 of the produced food is wasted (FAO(2013)). Panel B also shows that 40% of the total purchases are perishable items like fresh fruits and vegetables. 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 facilitate the comparison with Panels A and B, I multiply per capita daily intake quantities with the average household size in the sample (2.65) and 365 and convert them to per household annual intake quantities. The first three rows in Panel C indicate that an average household intakes 1,460kg of food, which is consistent with external statistics from a government agency, and about 40% of them is consumed at home.[1] 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 the annual time spent (in hours) on meal production for an average household—the sum 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 (or 45 minutes per day per adult). From the second to fifth rows, I split up meal production into more granular time categories, and find that over 85% of the meal production time is time spent inside of the kitchen—preparing ingredients, storing groceries, cooking, setting the table, and doing the dishes (Statistics Korea(2009)). In addition to meal production, Households spend over two hours per day on other homemaking activities, including cleaning, laundry, and organizing/sorting (or 50 minutes per day per adult). 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)Seo, Ki, and Koh).

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 these survey respondents, I compare key demographic characteristics with a few benchmark datasets. For age, family size, and housing type (if residing in an apartment) I use the Population and Housing Census as benchmarks. For employment and income, I use nationally representative survey data "Economically Active Population Survey" and "Household Income and Expenditure Survey (HIES)", respectively.

First, I discuss the results of the grocery panel data. Notably, since 97% of the panelists are female and the age range is restricted to 25–72, I similarly restrict the external data to these demographic characteristics for meaningful comparisons. Appendix Table A.2 Panel A shows that the grocery panel data largely align with the benchmark. For instance, the average age of grocery panel participants is 47, closely match-

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

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

ing the Population Census average of 46.1. Similar alignment is observed in housing type and working status. The most notable discrepancy is in family size, though the difference is modest relative to the standard deviation. This disparity is likely attributable to the exclusion of single-person households from the grocery panel until 2017, the final year of my sample.

In Panel B, I repeat the analysis using food intake data, finding that the sample means align even more closely with the benchmarks. In Panel C, I extend the comparison to time use data, using benchmarks from the 1999–2009 period. Here too, the sample means show strong alignment with the benchmarks.[2] Taken together, Appendix Table A.2 indicates that the food and time use data effectively represent an average household in South Korea.

Additional validation tests for the grocery panel data. There are two additional potential concerns about the grocery panel data. First, the data might capture only a subset of the panelists' purchases because households fail to keep a record of every single spending. Although the Rural Development Agency compensates panelists $50 per month and replaces unreliable panelists, it could still be the case that households forget or skip reporting. Second, as discussed in section 3, I impute unit prices for shopping records with missing information. In this section, I investigate the validity of the consumer panel data from these two aspects.

[2] The time use survey provides age data for individuals aged 10 and older, while for younger children, 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 mean age, estimating the standard deviation is not feasible without additional assumptions about age variance among preschoolers. Nonetheless, this limitation has minimal impact on the conclusions, as the comparison of sample means demonstrates that the time use survey closely aligns with the Population Census.

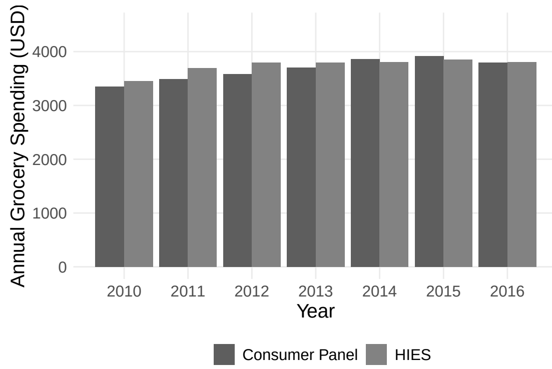
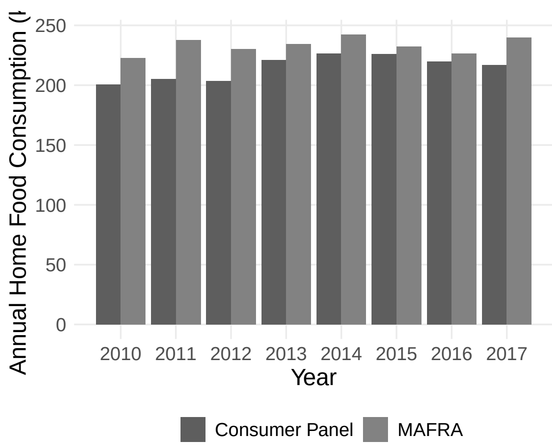
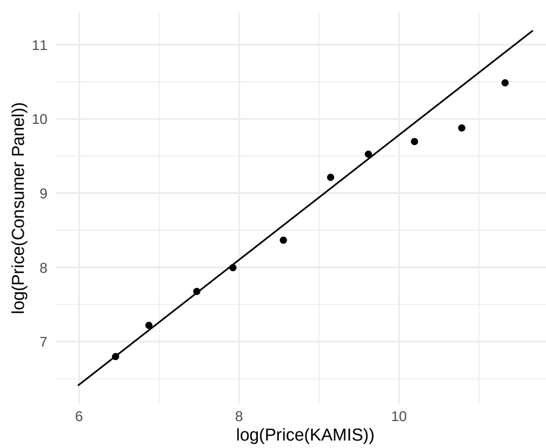


Figure A.1: Consumer Panel Data Validation (Total Expenditure). This figure compares the overall household spending from the consumer panel data and the Household Income and Expenditure Survey.

For the first issue, I compare the overall spending amount (in dollars) from an average panelist to household spending information from the Household Income and Expenditure Survey (HIES), which was used in Appendix Table A.2. I use total grocery expenditure net of liquid categories (cooking oil and dairy) from urban households in HIES with family sizes larger or equal to two to make it comparable to the consumer panel. Appendix Figure A.1 shows that annual grocery expenditures from these two different data are very close to each other over the 2010–16 period.[3]



(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 the missing unit price information issue, I conduct two rounds of imputations using a similar approach to (Golan et al.(2001)Golan, Perloff, and Shen). Specifically,

[3]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.

I first use the median unit price of the same food category from the same type of stores (e.g., farmer's markets, supermarket chains, and mom and pop stores) located in the same municipality and month. This successfully imputes 64% of the missing price information. For the second round, I expand the geographic scope to a cluster of 5-6 adjacent municipalities and repeat the same exercise. This recovers another 17% of the missing price information. By dividing the total expenditure by the unit price, I back out the quantity purchased.

To test the validity of this procedure, I compare the per household grocery purchase (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 meals consumed within a home from (Han(2018)).

Panel (a) of Appendix Figure A.2 shows the result. From 2010 to 2017, the amount of food purchased between the consumer panel and MAFRA official statistics are very closely related. This adds credibility to the unit price imputation. In Panel (b), I present a binned scatterplot comparing unit prices from the grocery panel with benchmark unit prices obtained from KAMIS (Korea Agricultural Marketing Information Service), where prices are surveyed by the government from selected representative stores. The figure suggests that the two prices are highly correlated.

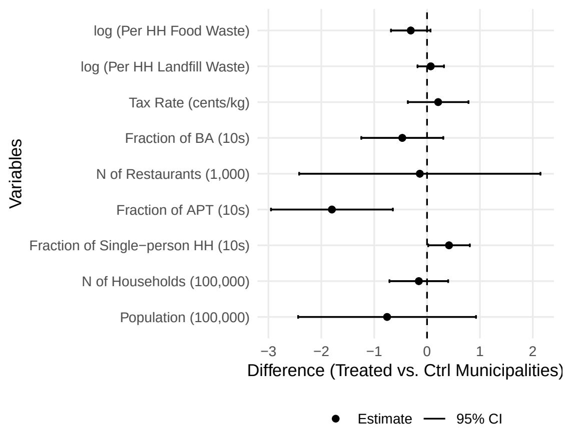
A.3 Balance Tests

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. Specifically, I estimate a series of binary treatment regressions on various outcome variables. When variables are in levels, I rescale them to improve comparability across measures. For example, in Panel (b), income is reported in units of $10,000, so a coefficient of 0.1 corresponds to an income difference of $1,000.

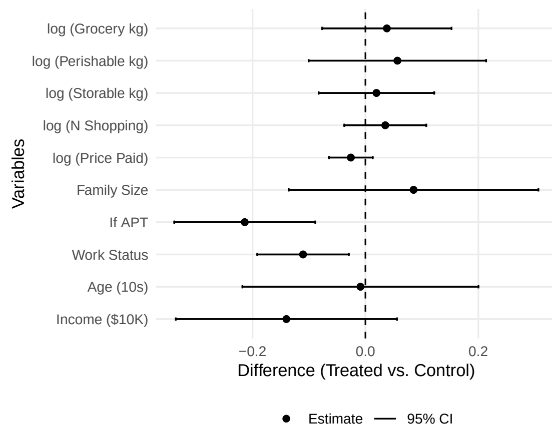
In Panel (a), I compare differences at the municipality level using the food waste data. Here, the control group consists of the bottom 10% or 7 municipalities in terms of the share of households subject to the unit tax in 2015, while the treated group has the rest of 56 municipalities. I show that the treated and control municipalities are highly comparable in various observed characteristics in 2009, which is the first year in the food waste 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 a non-trivial number of 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 when feasible.[4]

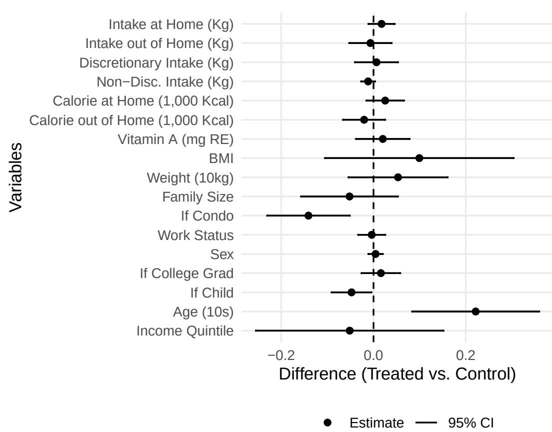
[4] I cannot implement this with food waste analysis because the data is observed at the entire municipality level.



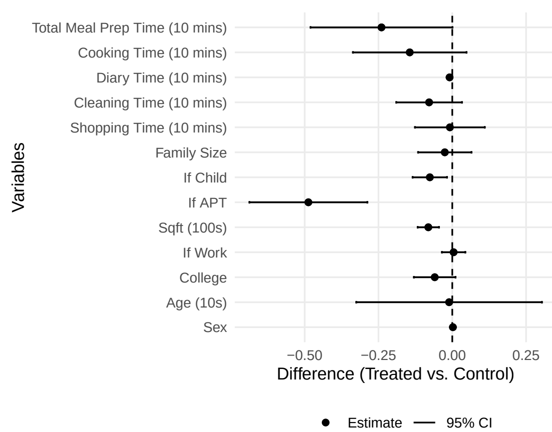
(a) Balance: Food Waste



(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 by estimating separate regressions for each variable. 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 Bounding Exercise on the Waste Reduction Effect

Recall that restaurants account for roughly 22% of "household equivalent" units in the sample (Appendix Table A.1). Also, the total food waste from restaurants can be decomposed into the waste intensity (waste per meal sold) and the number of meals sold. In the first extreme, assume that the waste intensity remains constant. Then, any reduction in restaurant food waste should come from the reduction in meals sold. Table 2, Panel B, column (5) suggests that the quantity of meals sold declined by 7% after the unit tax, which implies that waste from restaurants should have declined by 7%. Combining this 7% with the observed 21% overall reduction and the 22% restaurant share yields an implied 25% decline in household food waste. Thus, in this case, the 21% estimate is conservative for households. In the second extreme, suppose that after the unit tax, restaurant waste intensity fell dramatically, say by 30%. Although there is little empirical evidence quantifying food waste intensity changes in restaurants, industry reports suggest that investing in capital-intensive, high-tech kitchen management systems can reduce food waste intensity by roughly this magnitude (Filimonau and De Coteau(2019)). Under this deliberately aggressive assumption and combining it with the 7% decline in restaurant food consumption, the implied reduction in restaurant food waste is approximately 35% $(1 - 0.7 \times 0.93) \times 100$. Even in this case, the implied household reduction remains about 17% because restaurants are only 22% of the household equivalent. That said, small restaurants are unlikely to achieve such large reductions in waste intensity due to the unit tax: reducing waste often entails real business risks (e.g., lowering inventory can jeopardize sales; shrinking portion sizes may reduce customer satisfaction), supplier relationships limit flexibility in order sizes, sourcing costs may rise when order quantities decrease, and high staff turnover makes it difficult to sustain operational changes (Filimonau et al.(2020)Filimonau, Todorova, Mzembe, Sauer, and Yankholmes).

C Details on Household Abatement Strategies

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

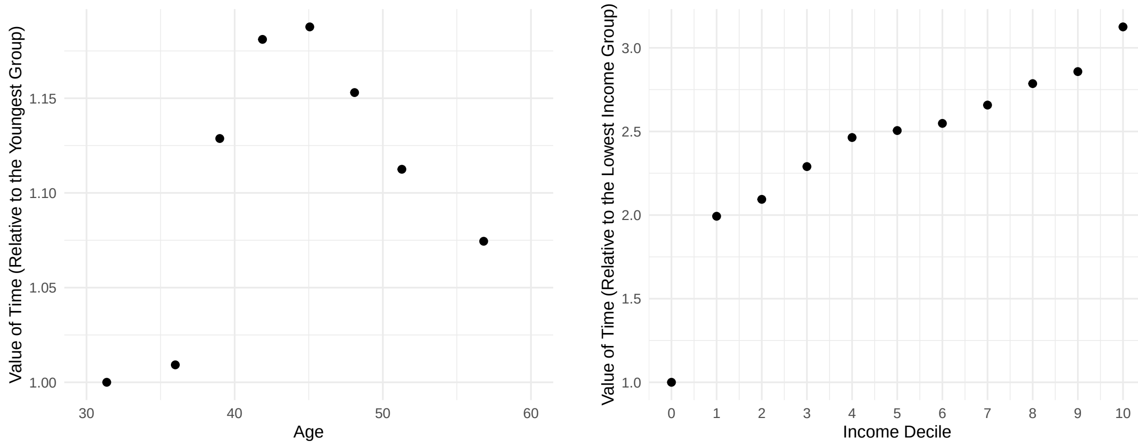
In Table 3 column (6), I estimate the impact of unit tax on household abatement costs. For this, I need to express the outcome variable in equation (4) in the dollar value of time spent in meal production. A crucial step in this exercise is to pin down the opportunity cost of time, and I use the *marginal 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(2007), Hastings and Shapiro(2018), and Nevo and Wong(2019). 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.[5]

Aguiar and Hurst (2007) demonstrates that the marginal return on shopping can be calculated by multiplying (i) the elasticity of price with respect to shopping frequency and (ii) the average spending per shopping trip. To convert this value into an hourly basis rather than per shopping trip, I adjust the product of (i) and (ii) by dividing it by (iii) the average time spent per shopping trip.

For (i), the elasticity, I assume it is consistent across households and use the headline estimate of 0.1 from Aguiar and Hurst (2007).[6]

[5] Aguiar and Hurst (2007) points out two additional concerns: (1) the observed wage may not be the marginal return to labor (due to nonlinear wage schedules, human capital accumulation on the job, etc.), and (2) individuals may not be able to adjust labor hours freely at the margin.

[6] I choose not to estimate the elasticity because the grocery panel data does not have a UPC code.



(a) Age and Value of Time

(b) Income and Value of Time

Figure C.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.

For (ii), the average spending per shopping trip, I rely on the grocery panel data, as the time use data does not include spending information. I begin by calculating spending per shopping trip for each demographic cell, where cells are defined by income level (low if monthly income is below $1,818), family size (1–2, 3–4, and 5 or more), and age group (20–30, 30–55, and 55 or older). Next, I aggregate the time use data using the same demographic categories and merge it with the grocery panel data to calculate (iii), the average number of shopping trips per hour for each cell. Then, I calculate the value of time for each cell by taking the product of the three objects. Finally, I merge the VOT estimates with the time use data based on demographic characteristics. Note, as the time use data has an 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 (2007) is to what extent Korean households are similar to US households. One of the key findings in Aguiar and Hurst (2007) is that the price of time substantially varies with age and income. That is, the opportunity cost of time is highest in middle age, which usually involves disproportionately large responsibilities at work and home. Similarly, the value of time is higher for higher income groups. To explore if the Korean consumers exhibit similar characteristics, in Appendix Figure C.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 (2007), I find that the value of time has an inverse U shape with age and is positively correlated with income.

C.2 Testing Productivity Change

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,

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.

Table C.1: The Effect of Unit Tax on Productivity

	(1)	(2)
Constant	0.579	0.718
	(0.076)	(0.114)
Unit Tax	0.005	-0.007
	(0.112)	(0.086)
Income: High		-0.044
		(0.092)
Family Size: 3-4		-0.055
		(0.098)
Family Size: 5+		0.082
		(0.117)
Age: 30-55		0.039
		(0.103)
Age: 55+		-0.427
		(0.108)
N. Obs	30	30

Note:
This table reports the effect of the unit tax on meal production productivity. For this, I link three datasets on food and time usage to estimate the TFP difference between tax and no-tax group. Column (1) does not include any controls while column (2) controls for income, family size, and age. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

depending on the magnitude of the productivity increase) abatement costs.

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 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)).[7] 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_t are cost share of each input and q_c and t_c are log of input quantities. The factor shares for grocery (a_q) and time (a_t) are calculated by dividing the value of each

[7]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.

input by the total production cost. To assign a dollar value for the time input, I follow Aguiar and Hurst (2007) similar to the earlier discussion in Appendix C.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 (1) the sample size is small at 30 and (2) the tax variation is cross-sectional. Given these limitations, the results in Appendix Table C.1 are suggestive at best, but the estimated null effects are 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 little room for a large TFP increase.

D GHG from Food Waste and its Welfare Implications

D.1 Negative Externalities from Food Waste

Lifecycle greenhouse gas (GHG) emissions from wasted food are estimated at 4.4 $GtCO_2eq$ per year, constituting 8% of total anthropogenic GHG emissions (FAO(2015)). This is comparable to the annual emissions from the entire road transport at 5.1 $GtCO_2eq$ (**?**). These substantial emissions stem from two key factors. First, food production is highly carbon-intensive, driven by activities such as land clearing (deforestation), enteric fermentation in livestock, and the use of nitrogen fertilizers (IPCC(2019)). Second, food waste generates large amounts of methane when it decays in landfill.[8] 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.

In addition to greenhouse gas (GHG) emissions, food waste imposes a significant fiscal externality. MSW management is often the largest budget item for many municipalities, accounting for 4%, 11%, and 19% of the total municipality budget in high-, middle-, and low-income countries (Kaza et al.(2018)Kaza, Yao, Bhada-Tata, and Woerden). For example, New York City spent $1.5 billion in 2021 alone on waste-related services (NYC Council Finance Division(2024)). Similarly, South Korea allocated $1 and $0.5 billion to landfill and food waste management in 2015 (Ministry of Environment(2015a)). Given that food waste constitutes the largest portion of global MSW at 44% (Kaza et al.(2018)Kaza, Yao, Bhada-Tata, and Woerden), reducing food waste could alleviate fiscal pressures and redirect public funds toward more productive areas worldwide.

In addition to the GHG emissions and government spending, food waste causes additional externalities such as biodiversity losses, soil degradation, water depletion, bad odor, and urban space constraints throughout its lifecycle (EPA(2021)). Hence, the GHG and fiscal costs represent a conservative estimate of the total social cost of wasted food.

Given these large externalities, reducing food waste has gained significant policy attention in recent years.[9] While food waste prevention (the so-called "source reduction") is deemed most desirable (Appendix Figure D.1), prevailing policies such as encouraging donation, composting, or energy recovery focus on recycling already generated wasted food (National Academies of Sciences, Engineering, and Medicine(2020)). A corrective tax on food waste can be a powerful alternative to those existing policies, as it has the potential to prevent excessive food purchases in the first place.

[8] Indeed, landfill is the third largest methane source in the US despite widely adopted methane-to-energy facilities (Kaza et al.(2018)Kaza, Yao, Bhada-Tata, and Woerden, EPA(2016)).

[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)).

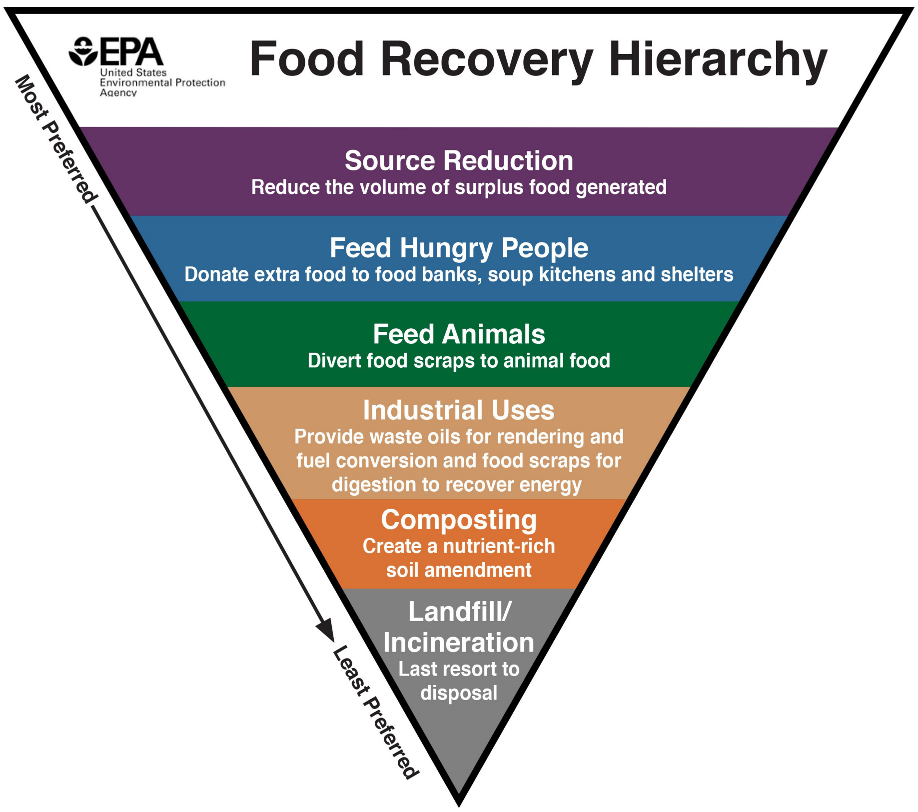


Figure D.1: Food Recovery Hierarchy

D.2 Calculating the Net GHG Reduction Effect for Welfare Analysis

To calculate the change in net GHG emissions from wasted food due to the unit tax, I consider changes in GHG emissions from three different sources: emission reductions from avoided food production; emission reductions from avoided food waste treatments; and emission increases due to leakage. To quantify each effect, I use per household estimates from Table 2 and scale up to the national level by multiplying them with the number of total households in South Korea (19.1 million).

First, for the avoided food production, I directly take the estimated effect from Table 2 Panel A column (8). To produce results in column (8), I first convert each row of shopping records in the grocery panel data into GHG emissions by matching each grocery item (e.g., 0.5kg of tomato) to the item-specific farm-to-kitchen GHG emissions estimates (e.g., 0.7 kg CO_2eq per 1kg of tomato) from (Poore and Nemecek(2018)).[10] Then I estimate equation (1) using the 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. When multiplying 158 kg CO_2eq with the number of households, the national GHG reduction from the production stage is 3 million tons CO_2eq per year.

Second, for the avoided food waste treatment, I multiply the reduced food waste quantity with the corresponding GHG emission intensities. Since more than 95 percent of the food waste is processed in composting or animal feed processing sites in Korea, the intensity is less than 1/3 of that of food waste in landfills at 0.19 ton CO_2eq per ton of food waste (GGIRC(2015)). Given the amount of food waste reduction for an average household (49kg), the reduction in GHG emissions from the waste treatment stage is 0.009 ton CO_2eq per household or 0.18 million tons nationally.

Lastly, for the emission increases due to leakage, I first assume that the reduced food waste (49kg) not attributable to the reduction in grocery purchases (41kg) ends up in landfill. Then, I multiply the increased food waste quantity in landfills after the unit tax with the corresponding GHG emission intensities. Then, I multiply 8kg with the GHG intensity of food waste in landfill (0.655 ton CO_2eq) from the national inventory report (GGIRC(2015)).[11] The resulting increased GHG emissions from leakage is 0.005 ton CO_2eq per household or 0.1 million tons nationally. Taking three sources together, the net annual GHG reduction effect of the unit tax is 0.162 ton CO_2eq per household or 3.1 million ton CO_2eq nationally.

E Estimating Household Abatement Costs

E.1 Standard Household Production Model

First, I examine household choices within a standard household production model to underscore the necessity of accounting for non-pecuniary effects. The utility function is given by $U = X + \delta L + v(M)$, where U consists of numeraire X, utility from leisure δL (δ is the marginal value of time), and utility from meal quantity $v(M)$, where M is produced by combining time input T and raw food input Q (i.e., $M = F(T, Q)$). The quasilinear functional form reflects the fact that expenditures on groceries and time spent on meal production constitute a relatively small fraction of the total budget and time endowment (see Table 1).

A consumer is subject to two constraints: $X + PQ + \tau(Q - M) = I$ where P is the price of grocery, I is total income, τ is the food waste tax rate, and $Q - M$ is the quantity of food waste, and $T + L = \bar{T}$ where $\bar{T}$

[10] Poore and Nemecek(2018) reports 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 a food item in the grocery panel data is not included in Poore and Nemecek(2018), I match it to the closest item.

[11] I use the "default method" which could be less accurate but allows comparison across different waste disposal methods (Hiraishi et al.(2000)Hiraishi, Nyenzi, Miguez, Bhide, and Pipatti).

is total non-working time. By plugging in two budget constraints into the utility function, the household's problem reduces to $U = v(M) + I - PQ - \tau(Q - M) + \delta(\bar{T} - T)$.

Posit that before the unit tax, households chose Q_0 and T_0 to attain $U_0 = v(M_0) + I - PQ_0 + \delta(\bar{T} - T_0)$. Now suppose that the unit tax τ is imposed. If households maintain their choice of Q and T, utility is $U_0' = v(M_0) + I - PQ_0 + \delta(\bar{T} - T_0) - \tau(Q_0 - M_0)$. If households change their choice to (Q_1, L_1), utility becomes $U_1 = v(M_1) + I - PQ_1 + \delta(\bar{T} - T_1) - \tau(Q_1 - M_1)$. Households will change their choice if $U_1 - U_0' = v(M_1) - v(M_0) - P(Q_1 - Q_0) - \delta(T_1 - T_0) - \tau(Q_1 - M_1 - (Q_0 - M_0)) > 0$. Estimates from Sections 4 and 5 indicate that $P(Q_1 - Q_0) = -169$, $\delta(T_1 - T_0) = 175$, and $\tau(Q_1 - M_1 - (Q_0 - M_0)) = -3$, which implies that $U_1 - U_0' = -3$.[12] Finally, the utility loss from the unit tax (i.e., household abatement cost) is represented by $U_1 - U_0 = -6$, ignoring the tax payment because it is a pure transfer between households and government.[13]

Importantly, $U_1 - U_0' = -3$ implies that households would have been better if they maintained their input mix (Q_0, M_0). These suggest that household behaviors may be difficult to fully explain without accounting for non-pecuniary effects of the unit tax.

E.2 Extended Household Production Model

To allow non-pecuniary effect of the unit tax, I extend a standard household production model building on Allcott and Kessler (2019). In particular, $U = v(M) + I - PQ - \tau(Q - M) + \delta(\bar{T} - T) + N$, where N is a moral utility from food waste generation. While describing the non-pecuniary effect as moral utility seems appropriate in this context—where wasting food is generally viewed as undesirable—other behavioral mechanisms, such as habit formation, may also explain the effect within a similar modeling framework (Hussam et al.(2022)Hussam, Rabbani, Reggiani, and Rigol).

Suppose that the unit tax changes moral utility. While theory suggests that ΔN may reflect a moral "tax" for generating food waste—which directly reduces the utility from maintaining (Q_0, T_0)—or a moral "subsidy" for reducing food waste from some baseline—which directly increases the utility from changing the input mix to (Q_1, T_1)—the overwhelming taxpayer support for the unit tax (Lee(2014), Ministry of Environment(2015b)) suggests that the latter is more likely in this setting.

Now, let $U_0 = v(M_0) + I - PQ_0 + \delta(\bar{T} - T_0) + N_0$ is the baseline utility level with moral utility. If households maintain their input choice after the tax, $U_0' = v(M_0) + I - PQ_0 - \tau(Q_0 - M_0) + \delta(\bar{T} - T_0) + N_0'$ and if they change the input mix, $U_1 = v(M_1) + I - PQ_1 - \tau(Q_1 - M_1) + \delta(\bar{T} - T_1) + N_1$. Now, utility maximizing households change their behavior after the tax when $U_1 - U_0' = -3 + N_1 - N_0' \geq 0$, which implies $N_1 - N_0' \geq 3$. Because the tax invokes moral subsidy, N_0 will not change when households maintain their initial input mix (i.e., $N_0 = N_0'$), which in turn suggests that household abatement cost $U_1 - U_0 = -6 + N_1 - N_0 \geq -3$, which is smaller than the benchmark case that does not take into account the non-pecuniary effect.

[12]While Table 2 shows a statistically insignificant but small increase in food intake, $v(M_1) \approx v(M_0)$ under a standard concave utility function ($v' > 0$ and $v'' < 0$). This follows from the household production model's optimality condition ($v'(M) = \frac{P}{f_Q}$), which suggests that the baseline M will be a level with low marginal utility. That is, grocery price P is relatively low in comparison to household budget and f_Q seems to be relatively low when I approximate it using the average productivity (i.e. roughly 70% of purchased food is consumed).

[13]U_1, not U_0' is relevant because households choose to change their input mix.

F Additional Tables and Figures

Table F.1: Effect of the Unit Tax on Landfill Waste Generation

	(1)	(2)
(%) Unit Tax	0.032	0.030
	(0.054)	(0.058)
Baseline Controls	No	Yes
Fixed-Effects:		
Municipality FE	Yes	Yes
Year FE	Yes	Yes
Observations	441	441

Note:
This table presents the effect of the unit tax on landfill waste generation using equation (2). 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table F.2: The Effect of the Unit Tax on 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 grocery panel data with a specification that allows housing type specific shocks. All outcome variables are in log scale. I report the coefficient of interest only, but all the regressions include baseline control variables. Standard errors are clustered at the municipality level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table F.3: The Effect of the Unit Tax on Meal Production (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 time use survey 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 percent and 0 otherwise). I report the coefficient of interest only, but all the regressions include baseline control variables. Standard errors are clustered at the province by housing type level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

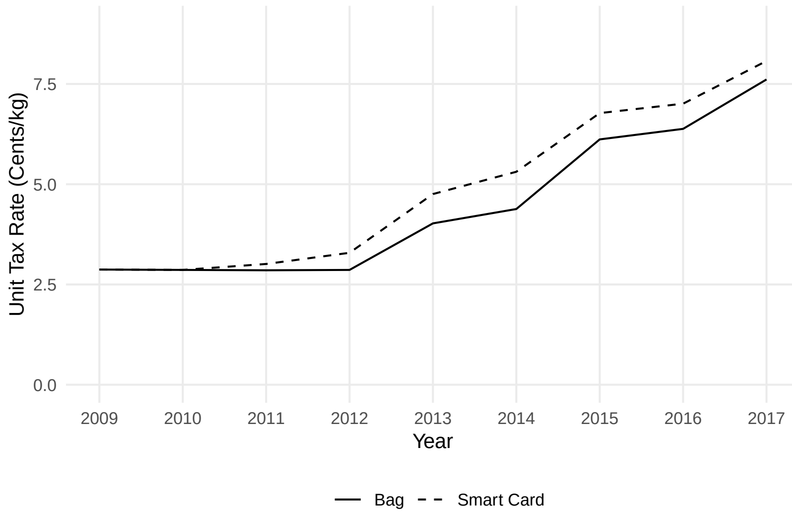
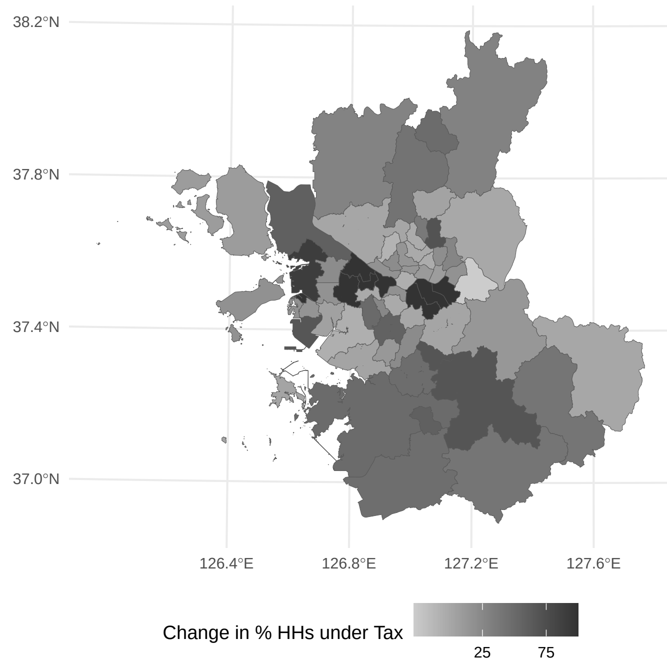
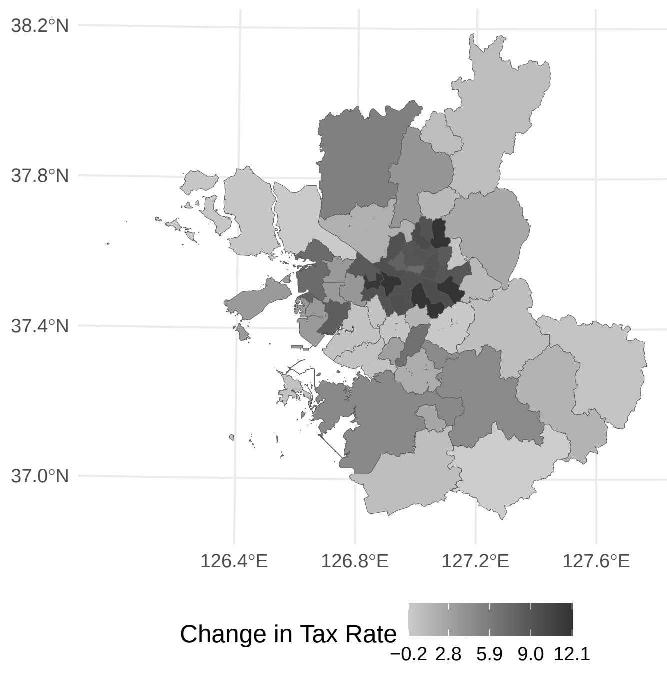


Figure F.1: Tax Rate Changes by Collection Method During the Wave 2 Expansion. This figure plots the average food waste tax rate by collection method from 2009 to 2017 for 63 municipalities in the Seoul metropolitan area. Bag based tax rates are converted to a per kg equivalent using the Ministry of Environment's standardized conversion of 1 liter = 0.75 kg.



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



(b) Change in Tax Rate between 2009-17

Figure F.2: 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 63 municipalities in the metropolitan Seoul area.

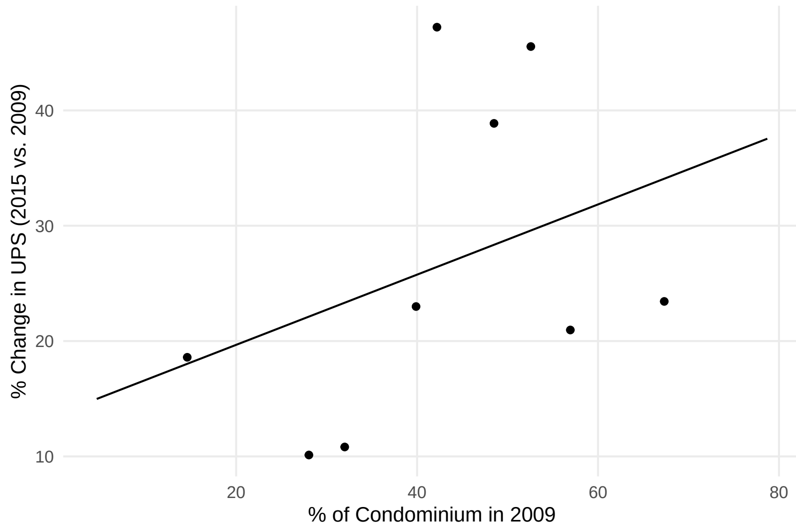


Figure F.3: This figure shows the relationship between the share of households living in condos in 2009 and the change in the proportion of households under the tax between 2009 and 2015 using a binned regression.

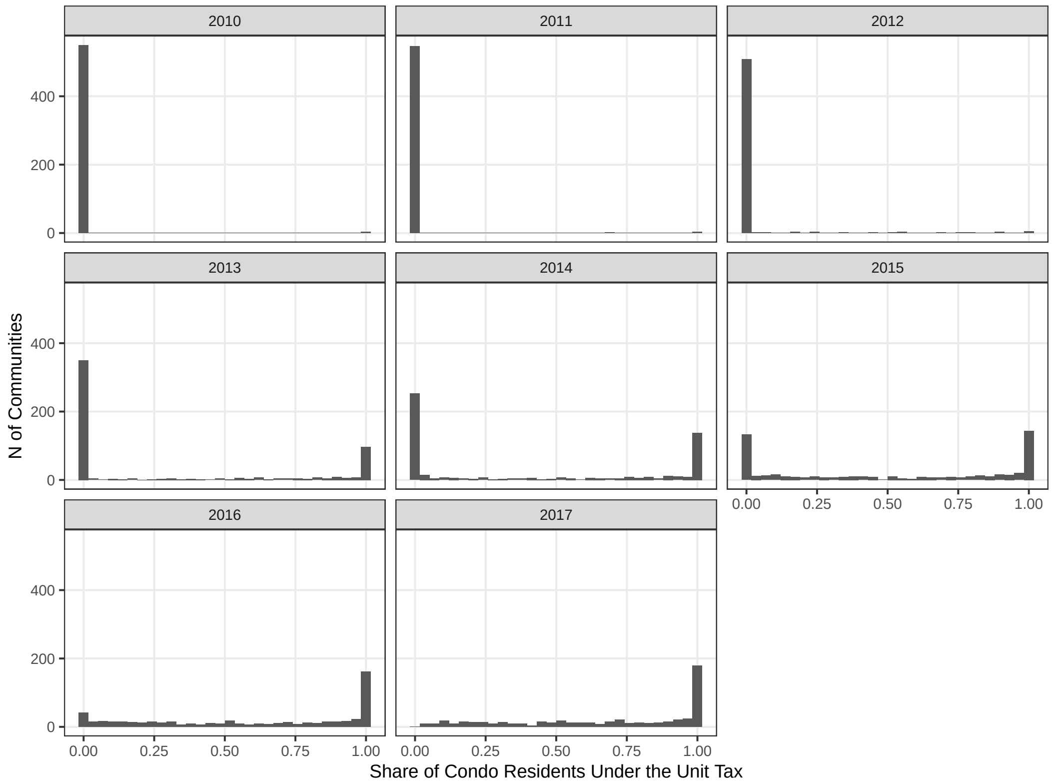


Figure F.4: Share of Condominium Residents Under the Unit Tax at the Community Level for 2010–17. These panels illustrate the share of condominium residents under the unit tax at the community (the smallest administrative unit in South Korea) level for years 2010–17. The data is from 1028 communities from the metropolitan Seoul area.

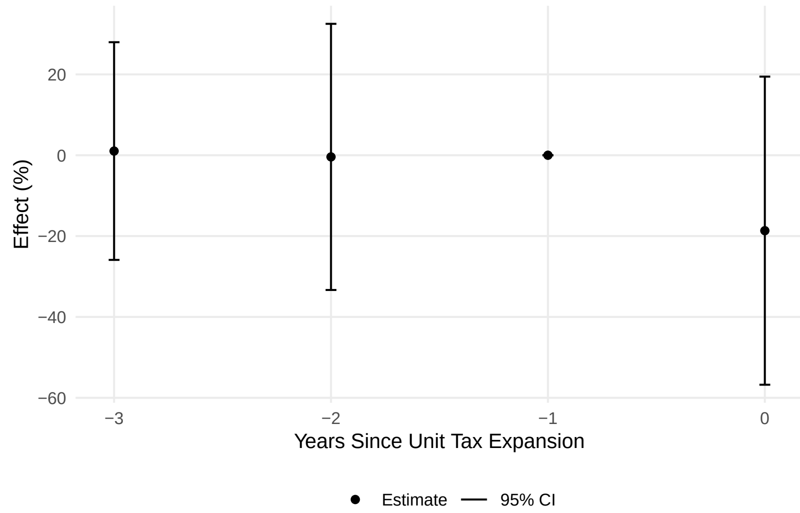
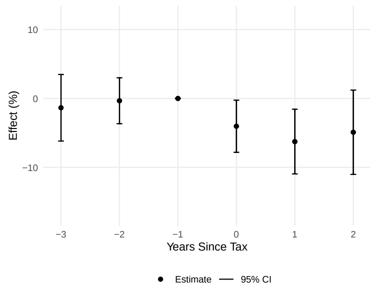
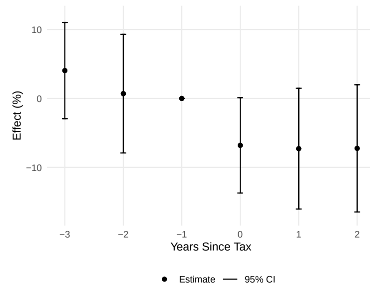


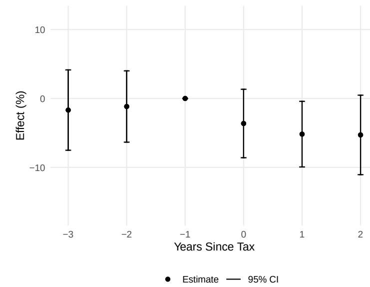
Figure F.5: The Effect of the Food Waste Tax on Food Waste Quantity. This figure plots the impact of food waste tax expansion (increase in treatment intensity) on food waste quantity using methods in de Chaisemartin et al. (2025). The outcome variable is log of per household food waste quantity. Event time is defined relative to the treatment expansion year. The bars represent 95 percent confidence intervals. Standard errors are clustered at the municipality level.



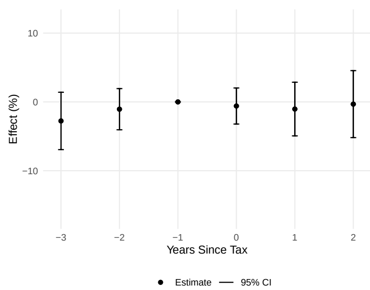
(a) Overall Expenditure



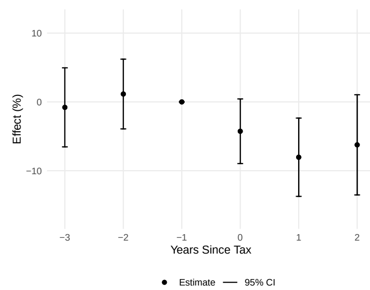
(b) Perishable Quantity



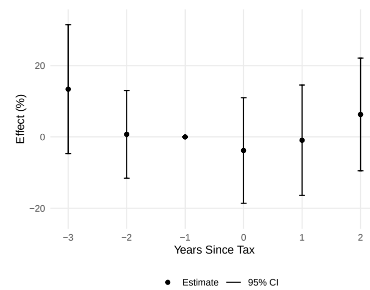
(c) Storable Quantity



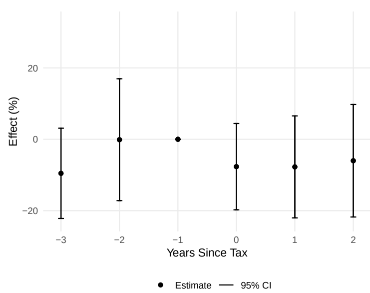
(d) Number of Trips



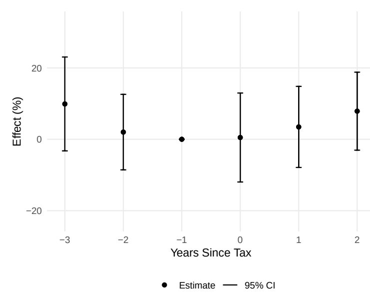
(e) GHG Emissions



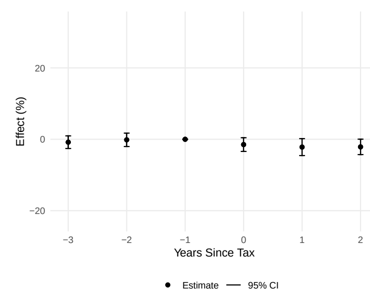
(f) Intake at Home



(g) Intake out of Home (Discretionary)

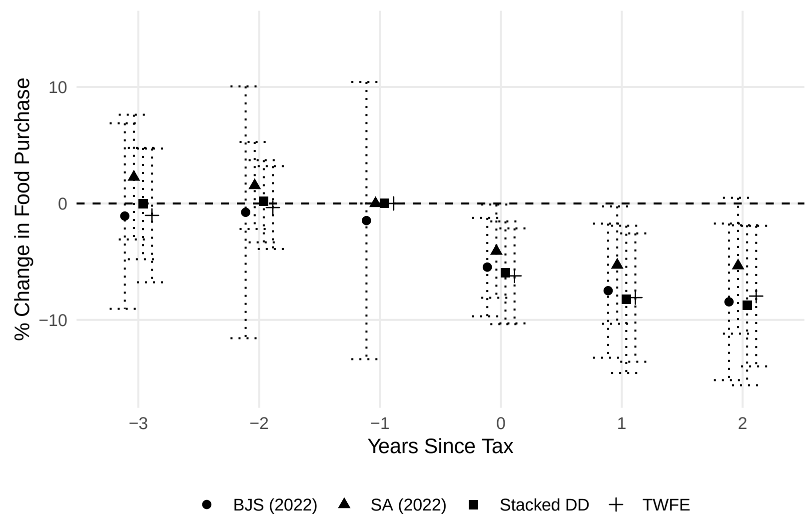


(h) Calorie at Home

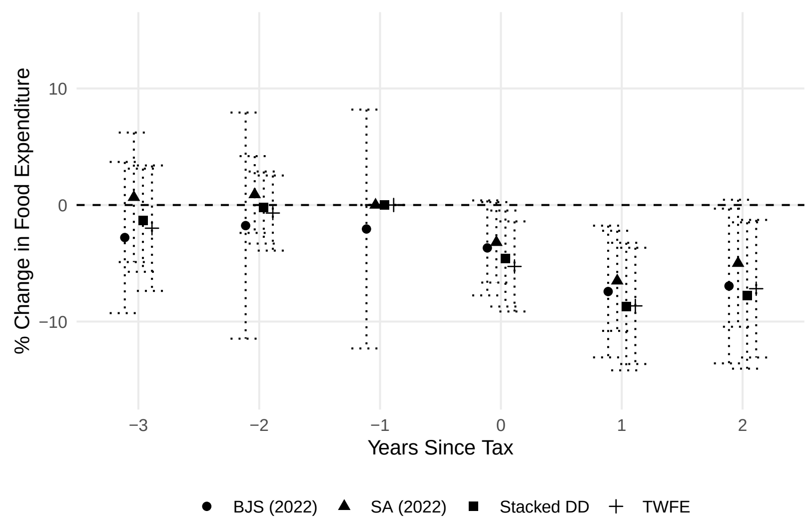


(i) BMI

Figure F.6: The Effect of the Food Waste Tax on Grocery Purchases and Food Intake. These figures show the unit-based food waste tax policy effect on the grocery purchases and food intake. Panels (a)-(e) show event study estimates for additional variables (all in logs) related to food purchases. Panels (f)-(i) show event study estimates for food intake variables. Panels (f)-(i) are estimated in levels, and coefficients are divided by the mean of dependent variables to express in percentages. Standard errors are clustered at municipality. The bars correspond to a 95% confidence interval.

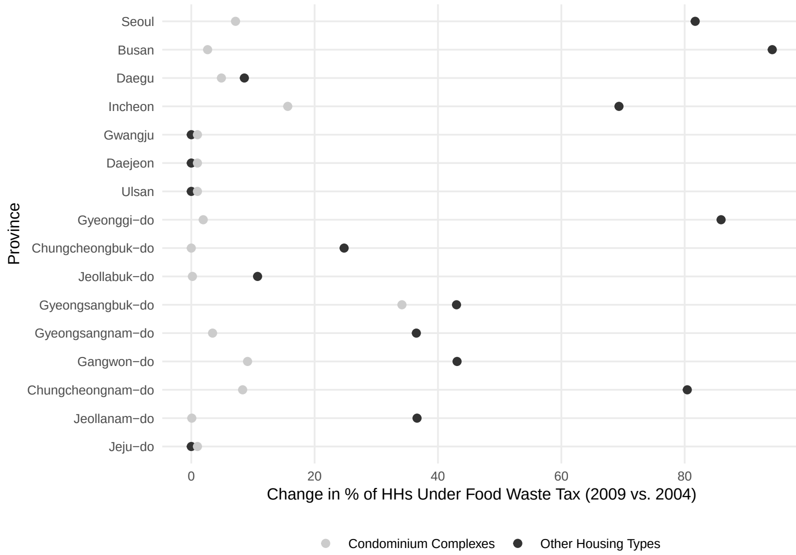


(a) Overall Quantity

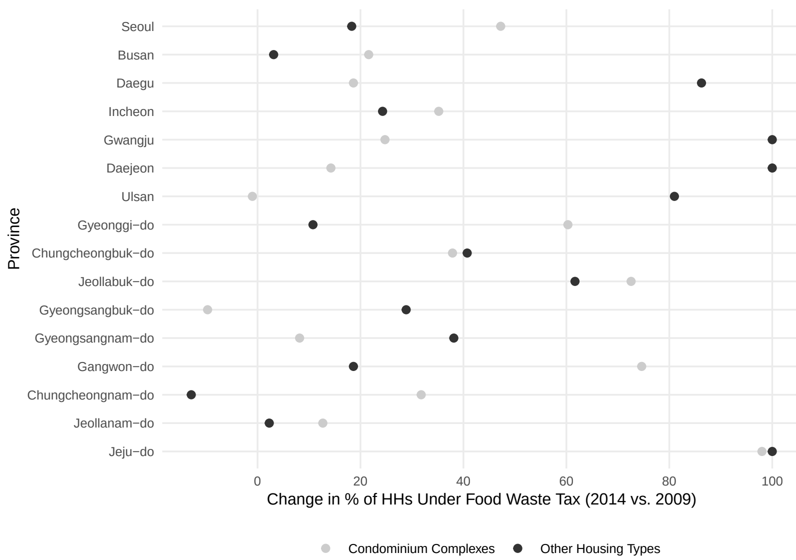


(b) Overall Expenditure

Figure F.7: The Effect of the Food Waste Tax on Grocery Purchases. This figure overlays event study style plots estimated from four different methods: a dynamic TWFE model, a stacked difference-in-differences model a la Cengiz et al., (2019), Sun and Abraham (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. The bars represent 95 percent confidence intervals. Standard errors are clustered at the municipality level.

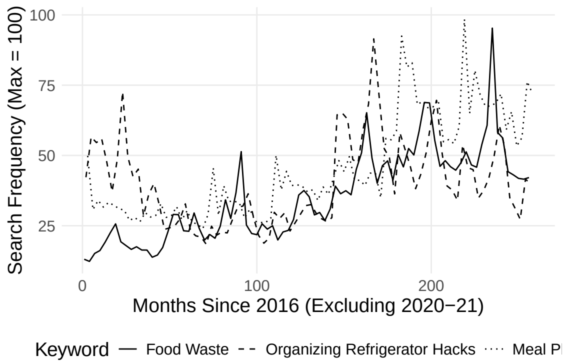


(a) 2004 vs. 2009

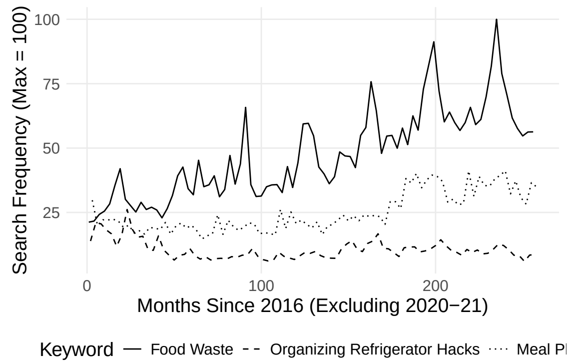


(b) 2009 vs. 2014

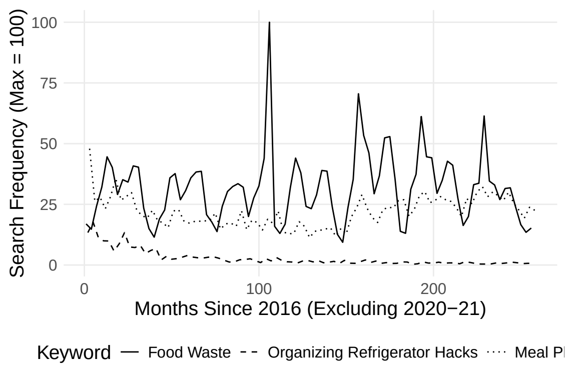
Figure F.8: Change in the Share of Households under the Unit Tax at the Province Level. These figures show the share of households under the unit tax at the province level for two different housing types. Panel (a) illustrates the change between 2004 and 2009 (the Wave 1 effect) while panel (b) is the change between 2009 and 2014 (the Wave 2 effect).



(a) Female Age 40-60



(b) Male Age 40-60



(c) Female Age Below 20

Figure F.9: Search Trends by Demographic Groups. These figures show trends in web search intensity for three food waste-related keywords ("food waste", "organizing refrigerator hacks", and "meal planning") across different demographic groups on Naver, South Korea's dominant search engine, from Jan 2016 to Feb 2025, excluding the COVID period (Jan 2020–Dec 2021). The Y-axis is normalized based on the maximum search intensity for each group over the 2016–25 period. Panel (a) represents females aged 40–60, panel (b) represents males aged 40–60, and panel (c) represents females under 20.

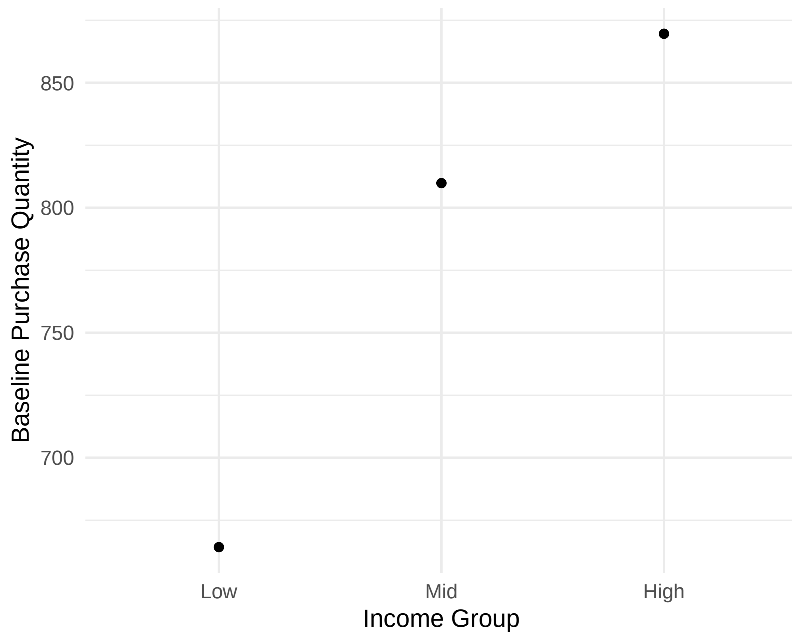


Figure F.10: Correlation Between Baseline Purchase Quantity and Income. This figure shows the relationship between household income and baseline (year = 2010) grocery purchase quantity using the grocery purchase panel data.

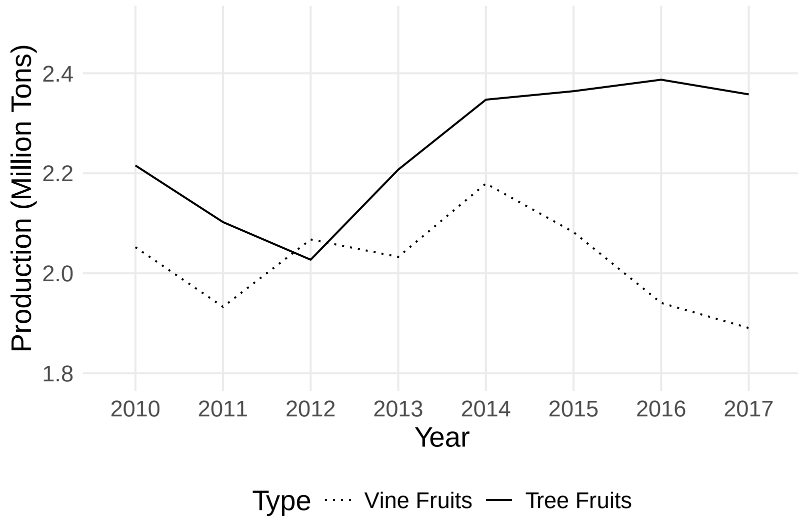


Figure F.11: Fruit Production over Time by Fruit Types. This figure illustrates the changes in fruit production before and after the wave 2 unit tax expansion in South Korea, distinguishing between tree fruits (e.g., apples, grapes, and peaches) and vine fruits (e.g., watermelon, Korean melon, and tomato). The data is sourced from Statistics Korea.

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