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Abstract

We evaluate the effect of working from home on waste generated by individuals both at and away from their homes. To that end, we collect a unique dataset that matches administrative household-level waste data from Sweden with survey data on how many hours individuals work from home. A novel identification approach allows us to link waste generated away from home to the choice of location of work. Our results suggest that working from home reduces organic and residual waste by 20% and 12%, respectively.

Keywords

Environmental Policy, Working from home, Waste

JEL Classification

D12, O33, Q53, Q58

1 Introduction

In this paper, we empirically evaluate the effect of working from home on waste generated by individuals. This research question is important for two reasons. First, working from home has become increasingly widespread in the course of digitalization, Milasi et al. (2021). Second, individual waste is an underappreciated source of environmental pollution. Globally, municipal solid waste amounts to two billion tonnes annually, which corresponds to 0.74 kg per person. At least one third of it is disposed of and managed in non-sustainable ways, (Kaza et al., 2018). In 2016, solid waste caused five percent of total CO_2 emissions, excluding the impact of vehicles used for waste transportation.

It is an open question whether working from home has a positive or a negative effect on waste behaviors. While some studies argue that working from home is associated with a reduction in waste through better use of meal leftovers, (Pappalardo et al., 2020; Pires et al., 2020), improved inventory management, Bender et al. (2022), and better planning of grocery shopping, Liu et al. (2021), other studies point at negative aspects of home office such as impulse shopping due to higher exposure to online media, Lahath et al. (2021) as well as an increase in packaging due to more frequent usage of food delivery services, Liu et al. (2021). Moreover, as we argue below, a major pitfall of these findings is that the provided evidence is of descriptive nature. To date, no study has casually evaluated the overall effect of the choice of work location on waste.

However, the causal evaluation of this effect is a challenging task. First, waste generated at home is typically not observed at the household level. Therefore, most studies on waste behaviors use either aggregate measures of waste, such as municipality-level waste or self-reported measures obtained from surveys or diaries, see e.g. Alacevich et al. (2021) for references and discussion. These approaches can be problematic though. Aggregate measures of waste are hard to link to individual behaviors, which hampers establishing a causal relationship. Self-assessment survey or diary data, on the other hand, is well known to be prone to measurement error due to Hawthorne and social desirability biases. Furthermore, repetitive activities such as waste generation are characterized by decreased salience, which implies that self-assessed waste data is likely to be imprecise. Finally, survey- or diary-based studies typically do not involve a comparison of treatment and control group, so that those studies are primarily descriptive.

A second and related problem is that a large share of the waste an individual generates is generated and disposed of outside of the home. Waste disposed of in public bins, in restaurants and in professional environments such as offices, cannot be link to the individuals who have generated it. This "invisible" part of individuals' waste makes it hard to establish a causal link between choice of work location and waste.

Last but not least, selection into working from home is potentially driven by a variety of unobserved determinants of waste such as environmental preferences and awareness. Thus, a direct comparison of waste weights across individuals with different numbers of hours working from home would produce a biased estimate.

In this paper, we develop an empirical approach that allows us to deal with all aforementioned problems and estimate a causal effect of working from home on waste behaviors. The first component of this approach is to collect a unique dataset that contains the exact amount of different waste types (such as organic and nonorganic) at an *individual household level* as well as the *individual* amount of hours worked away from home for 30 months. On the waste side, we obtained the waste weight information for all households in the Swedish municipalities Partille and Varberg for the period January 2019 - June 2021. In these municipalities, waste is collected by trucks equiped with a scanner and a weighting device, so that each collection of waste produces a precise waste measurement that can be uniquely assigned to (i) the household whose bin is emptied, (ii) when the waste was collected (date and time) and (iii) the type of waste (organic, nonorganic) collected. To obtain data on the hours worked away from home, we sent a survey to all households in the two municipalities. We then matched the two types of information to obtain a balanced panel dataset which allows us to observe the choice of work location and household waste levels over time for a large number of households.

The second component of our approach is to develop an econometric strategy that deals with the selection problem and allows us to measure the unobserved part of the individual waste. This strategy consists of two steps. In a first step, we use the household-level waste and work location data to estimate the effect of working from home on the amount of waste generated and disposed of *at home*. To deal with the endogenous selection into working from home, we utilize a natural experiment triggered by the Covid pandemic. In march 2020, the Swedish government asked employers and employees to switch from working in offices to work from home whenever that was possible. A substantial share of the population followed the government recommendation, but there was a large variation in the timing of switching work location. We use this quasi-random variation and a state-of-the-art nonparametric staggered difference-in-difference estimation techniques to estimate the effect on waste generated at the household.

In a second step, we develop a novel identification approach that allows us to estimate the effect of working from home on waste generated and disposed of when individuals are *away from their homes*. The identification approach combines the estimated effects on waste at home from the first step and aggregate municipal waste data on the *total* amount of waste, that is, waste generated both at and away from home. The link between the aggregate waste data and the treatment status is established via a modified difference-in-differences approach.

Our main finding is that switching work location from the office to the home leads to a large reduction in waste. Specifically, it reduces organic waste by 20% and non-organic waste by 12% compared to baseline pretreatment levels. To put this into perspective, it is informative to compare our results with estimates of waste demand elasticity in studies evaluating Pay-As-You-Throw programs. In particular, our results suggest that working from home has a similar effect on waste as a waste price increase of roughly 20%, Valente (2020). In addition, we find that working from home has an additional beneficial effect on the dynamics of waste generation. In particular, the treated tend to shift to a larger organic/nonorganic waste ratio over time. We show that the main driver of this conversion is a disproportional relocation of waste generating activities from the working place to home: while working from home leads to an increase in organic waste disposed at the household, we fail to find such an increase in non-organic waste. Together, these findings suggest that working from home is associated with substantial beneficial changes in environmental behaviors.

A back-of-the-envelope calculation of the costs and benefits of the reduction in waste suggests that working from home leads to a 133 kg reduction of CO_2 emissions per person and year, which is roughly equal to 1.1% of the individual carbon footprint. This finding has important policy implications. In order to design favorable long-term policies, policy makers often rely on long-term projections of current trends such as e.g. the OECD Environmental Outlook.[1] Existing environmental projections do not implicitly include the effect of working from home on waste behaviors because of the uncertainty around these effects. Our estimates suggest that due to the trend towards working from home, the existing projections for CO_2 emissions have to be adjusted downwards. Furthermore, we calculate that the reduction associated with working from home leads to a reduction in the cost associated with processing waste and producing carbon dioxide. The total reduction amounts to 2.5% of the annual waste cost in the two municipalities and it is therefore also economically significant.

We contribute to the related literature in several ways. First, to the best of our knowledge, this is the first paper to *causally* identify and estimate the effect of working from home on waste generation. As pointed out, existing studies have provided descriptive evidence on the potential channels of the effect, see Iranmanesh et al. (2022) for a comprehensive literature overview. Thus, we contribute to this literature by causally quantifying the overall effect of the choice of working location. Moreover, related studies have largely evaluated waste outcomes in the context of the Covid pandemic. However, while switching to home office was a common pandemic response for many individuals, firms and governments, the pandemic

[1] See OECD (2011).

was also associated with large economic uncertainty that might itself have caused changes in consumption and waste behaviors. This compound nature of the pandemic as a treatment makes it impossible to learn about the precise mechanisms of the behavioral changes and hence the scope for policy implications is rather limited. Our paper, on the contrary, isolates the effect of remote work from the overall economic effect of the pandemic by utilizing time variation in the treatment and by making use of individual survey data on the changes in total work load.

Second, we also contribute to the waste generation literature by using more reliable data. In particular, 31 out of the 38 papers reviewed by Iranmanesh et al. (2022) use survey-data.[2] Our paper uses actual administrative records of individual waste which are not prone to measurement errors and social desirability biases. Moreover, unlike existing studies, we are able to measure changes in both organic and non-organic waste. This is important in view of estimating the overall environmental effect of the treatment.

Last but not least, this is the first paper to link individual working habits and waste disposed of away from home. Existing studies on waste generation have mainly measured the part of waste an individual disposes in the household bin, see e.g. Alacevich et al. (2021). A comparison of our results for observed and unobserved waste suggest that focusing entirely on waste generated at home would considerably underestimate the benefits of working at home.

The rest of the paper is structured as follows. Section 2 introduces the institutional set-up and describes the data. In section 3, we present our empirical strategy. In section 4, we present our main results and in section 5 a comprehensive assessment of the validity of the assumptions. Section 6 presents a cost-benefit analysis of the effect of working from home on waste. Section 7 concludes.

[2] The other use diaries or mixed method, which potentially also suffer from a social desirability bias.

2 Setting and data

2.1 Institutional setting

Municipal solid waste in Partille and Varberg This study is based on waste data from two Swedish municipalities: Partille and Varberg. Both municipalities are located in the greater Gothenburg area and are 90 km apart from each other. Varberg has 66 000 inhabitants and of the total 290 Swedish municipalities, it is the 36th most populous. 56% of the residential buildings are detached houses (one- or two-family houses). This is higher than the national average, which is 45%. Partille has a little more than half the population of Varberg. Share of detached houses is the same as the national average.

Both municipalities apply a pay-as-you-throw pricing scheme for their waste services. Waste bins at detached houses are weighed before the waste is emptied in the waste truck. In particular, the trucks that collect the waste door-to-door are equipped with a weighing and a barcode-scanning device. When waste is collected, its weight is automatically measured and assigned to the address (and specific household(s)) via scanning the barcodes on the bins. Thus, each collection of waste produces a unique data record that contains the type and weight of waste collected, the household identifier and the date of the collection. This practice of bin weighing imply that precise waste measures are available over time at the household level.

Both Partille and Varberg apply a two-part tariff where the fixed part is determined by bin size and collection frequency and the variable part by the kilograms of waste. Partille has a policy to price its essential services low. According to Nils Holgersson's annual price review of essential services, the price for waste in Partille was 27% below the national average during 2018-2021. In contrast, Varberg had a price level that was 13% above the national average. Both Partille and Varberg have a policy to apply stable and predictable prices and during the four years, Partille increased its price by 8% per year and Varberg by 6 %. Households in both municipalities can choose to pay their bill monthly, quarterly or bi-annually.

There is heterogeneity across Swedish municipalities in terms of how households dispose of their waste, how the waste is collected and processed and what organization is responsible for the collection/processing of the different waste types. From the households' perspective, the most important distinction is between residual and organic waste, both of which are collected curbside, and the recyclable waste, which households have to take to recycle stations. All Swedish municipalities must provide curbside collection of residual and organic waste. The number and location of recycle stations is primarily determined by population size and density. In densely populated areas the maximum distance between residential houses and the closest station is often set to around 400 meters. In less densely populated urban areas, where households predominantly transport their waste by car, the distance can be up to 1000 meters.

Both Partille and Varberg offer a residual and an organic bin to all their households. About 70% of households use both these bins. 10% use a single, unsorted bin, where both residual and organic waste are thrown. About 20% of the households only have a residual bin since they dispose of their organic waste in separate compost bins. These shares are similar in the two municipalities. The different bin options cannot be combined.

Working from home during the pandemic In March 2020, the Swedish government announced a general recommendation for its population to work from home whenever possible. This recommendation remained valid until the end of September 2021. Thus, around 75% of the days during both 2020 and 2021 were subject to this recommendation.

Contrary to other countries, however, these restrictions were not mandatory and there were no lockdowns. Nevertheless, as shown below, a substantial part of employers and employees did follow the recommendation.

2.2 Data and descriptive statistics

2.2.1 Waste data

We collected waste data both at an aggregate level as well as at an individual household level.

Data on household level. We obtain waste data at the household level from the administrative registries of the waste management authorities in Partille and Varberg. The data reports the weight of each waste bin (rounded to the closest half kilogram) for each collection, from January 2019 to June 2021. The data also includes address, bin type (organic, residual or unsorted), bin size, collection frequency (the waste plan the household is on) and the date of each collection. Collection frequency can be either weekly or every fortnight. To match each bin with the respective household, we limit the analysis to single-family dwellings. Basic descriptive statistics of these variables are provided in table 1. The first row contains

Table 1: Descriptive statistics 1: total waste at the household level

Variable	Mean	Std	Median	Min	Max
Bin Size (l.)	169.40	36.52	190.00	140.00	370.00
Bin Weight (kg.)	6.69	5.33	5.50	0.00	58.00
Days between collections	13.99	0.31	14.00	7.00	14.00

Source: Partille and Varberg municipalities.

information about bin size, the second about bin weight, and the last row contains information about collection frequency, represented by the number of days between collections. In the majority of cases, households choose the two-week collection cycle. Figures 9a and 9b in appendix A show histogram of the bin weight for organic and residual waste, respectively. These histograms reveal that both waste weight distributions are right skewed with residual waste having a longer tail than organic waste.[3]

Aggregate data. We also collect municipal-level waste data for different waste types for each of the two municipalities. First, we collect annual data on recyclable waste both for

[3]In our main results, we calculate for each household and month the monthly weight for each type of waste and use this as the unit of observation of the output variable.

2018-2021, i.e. for the two years prior the pandemic and for the two years most affected by the pandemic. Table 2 contains descriptive statistics for Parille and Varberg. The first column of table 2 indicates in which year the measurement was taken. The other columns contain the weight per household of a given type of recyclable waste. Column 6 contains the total amount of recycled waste per household (i.e. the sum of columns 2-5).[4]

Table 2: Recyclable waste in Varberg and Partille, 2018-2021

Year	Glass	Paper	Metal	Plastic	Total
2018	57.88	40.09	4.55	20.84	123.35
2019	60.77	40.19	4.48	19.08	124.52
2020	58.97	43.48	4.47	18.95	125.56
2021	66.53	30.22	4.50	20.12	121.37

Recycled waste in the municipality of Partille and Varberg for the period 2018-2021. Waste is measured in kg per household and year. Numbers represent averages for the two municipalities weighted by the population size. Source: the Swedish Packaging Collection Service.

We also collect the annual amounts of organic and residual waste collected at the municipality level for Partille and Varberg. Importantly, these waste quantities include both the waste collected curbside from the households as well as waste collected from firms, restaurants and public facilities. These total quantities are displayed in table 3. Organic waste increases during the pandemic (2020-2021), and the increase is more than 10%. On the contrary, residual waste drops in both 2020 and 2021, with the total drop being around 11%. These aggregate changes are consistent with aggregate descriptive findings in other studies, see e.g. Arumugam et al. (2021)and Kasim et al. (2021). However, their interpretation is difficult, since the effect of the increased amount of work at home is conflated with changes in the consumption bundle due to the overall effect of the pandemic. We discuss this issue in detail in the identification section below.

[4]Note that newspapers are not included in paper waste. We have not considered newspapers here because of the strong paper-to-online trend in newspapers consumption.

Table 3: Organic and residual waste in Varberg and Partille, 2018-2021

Year	Organic	Residual	Total
2018	71.03	332.80	403.83
2019	68.41	361.90	430.32
2020	70.36	345.45	415.81
2021	76.09	304.65	380.73

Organic and residual waste in the municipality of Partille and Varberg for the period 2018-2021.Waste is measured in kg per household and year. Numbers represent averages for the two municipalities weighted by the population size. Source: The Swedish Waste Management Association.

2.2.2 Data on working hours away from home

To obtain individual-level data on hours worked away from home, we administered a survey. On May 24th 2021, we send a letter to all households in detached house in Varberg and Partille ($n = 21807$). The letter contained a short questionnaire printed on a paper. Individuals were asked to state (1) the total number of hours they work and (2) the number of hours worked away from home for each of the months between January 2019 and June 2021. Households were asked to return the letter with the filled questionnaire to the researchers. Inside the letter, there was a return envelope with a pre-printed address and a pre-paid stamp attached. The letter had the logo of the Ratio research institute, the institute responsible for the project.[5] The municipalities Partille and Varberg were neither involved in the survey nor aware of that it was conducted. Similarly, households were not aware that the researchers had access to their waste data. This design of the study was chosen to prevent any Hawthorne effect in the waste generation. In total, 2 375 households from the two municipalities provided complete answers and returned the questionnaire, corresponding to a response rate of 10.9%. Using the respondent's addresses, answers were matched with waste bin weights from the municipalities.

For each individual, we define two treatment variables. The first is the number of hours

[5] Ratio is an independent non-profit Swedish research institute based in Stockholm, www.ratio.se.

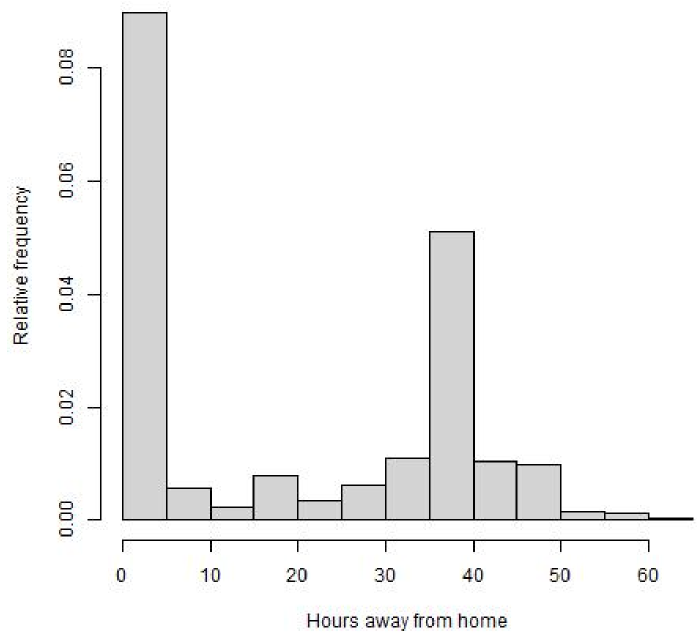


Figure 1: Histogram of hours worked away from home for the total period of observation.

away from home due to work. A histogram of the distribution of this variable is shown in figure 1. There are two particularly pronounced mass points: at 0 and at 40.

The second treatment variable is an indicator variable that takes the value 1 in the month an individual reduces the number of hours away from home in or after March 2020 and is equal to 0 otherwise. In every subsequent month after the reduction, the variable remains equal to 1.[6] Figure 2 shows the relative frequencies of the treated individuals for each month in the observation period. Month 0 corresponds to March 2020. The majority of individuals reduced their working hours away from home in March 2020. Another peak took place a year and a half later during one of the subsequent Covid-waves.

The meaning of the treatment would be conflated if the pandemic impacted not only the number of hours worked away from home but also the number of hours worked in total. However, this was not the case for the two municipalities Partille and Varberg: the share

[6] The possibility that an individual returns to working at the office is considered in section 5.1.2 below.

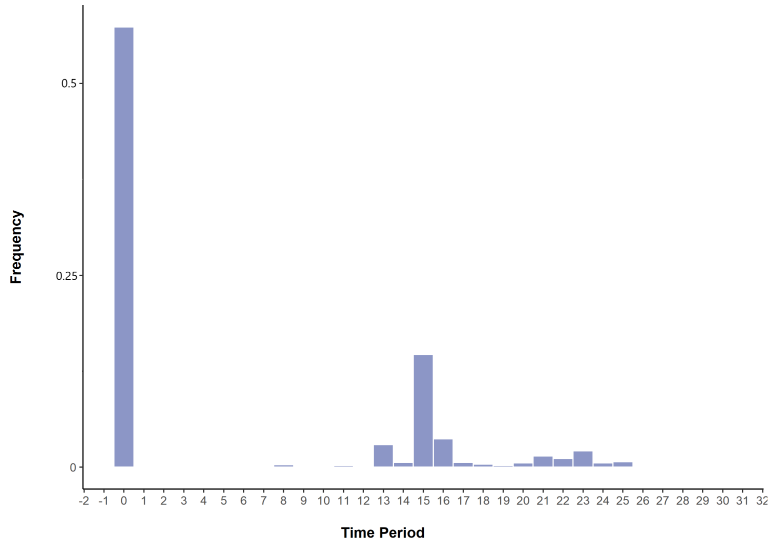


Figure 2: Timing of the treatment. Y-axis: relative frequency of the treated. X-axis: the time period. 0= January 2020.

of individuals who changed the number of hours worked in total during 2020 is roughly 2%, meaning that the interpretation of the treatment variable is not threatened through alternative channels.

2.2.3 Final sample

Our final sample consists of all households for which we have (i) complete answers to questionnaire questions and (ii) complete waste bin weights, and (iii) non-composting households. Composting households were excluded we do not observe the weight of the composted waste. We also exclude households for which we did not have waste data for the total period of observation. With this choice, our sample consists of 1983 individual households and for each household we observe the waste amount and number of hours away from home due to work in 30 periods (months).

3 Econometric framework

3.1 Notation and treatment effects of interest

Define the binary variable D_i that is equal to 1 if individual i experienced a reduction in the number of hours worked away from home due to Covid restrictions and is equal to 0 if no such reduction took place. D is our main treatment variable.[7] To define our outcome variables, let $W_i^{O,org}(d)$ denote the potential amount of *organic* waste (measured in kg.) that individual i would generate *at home* if she was subject to treatment $d \in \{0, 1\}$. The superscript O indicates that since the waste is produced at home, it is observed in our dataset.[8] Similarly, $W^{O,res}(d)$ and $W^{O,unsort}(d)$ denote the potential amount of residual and unsorted waste generated and disposed of by individual i in the household. Waste disposed of by individual i outside the household - for example through a restaurant visit or through any other type of consumption away from home - is denoted by superscript U to indicate that this waste is not observed at the individual household level. The total (observed + unobserved) waste has no superscript, e.g. $W_i^{type}(d) = W_i^{O,type}(d) + W_i^{U,type}(d)$, where "type" is either organic or residual. The corresponding realized and measured outcomes (that is, the actually produced waste) are denoted by $W_i^{O,type}, W_i^{U,type}$ and W_i^{type}.

With this notation, we define several treatment effects of interest. First, we consider the effect of an increase in the hours worked from home on each type of waste produced at home for those who were treated:

$$ATET^{O,type} = \mathbb{E}[W_i^{O,type}(1) - W_i^{O,type}(0)|D = 1]. \tag{1}$$

Studying this treatment effect is important for several reasons. First, as an individual increases hours spent at home, it is natural to expect an increase in the consumption and

[7] We also consider an alternative treatment definition based on the exact number of hours worked away from home.

[8] More precisely, it is a potential outcome that would be observed if the treatment actually takes the value d, i.e. $D_i = d$.

hence in the amount of waste generated at home. Second and more important, a comparison of $ATET^{O,org}$, $ATET^{O,res}$ and $ATET^{O,unsort}$ is potentially informative about behavioral changes associated with working from home. As an example, if working from home leads to more environmentally friendly consumption, we would expect organic waste to increase more than the other two types of waste relatively to pre-Covid baseline levels.

However, the behavioral interpretation of the treatment effects on observed (i.e. disposed of in the household bins) waste is associated with a major pitfall. In particular, a disproportionate increase in organic and nonorganic waste could also be driven by pre-existing differences in waste behaviors outside of the household. As an example, the residual waste from a meal in a restaurant could be different than the residual waste from exactly the same meal at home due to differences in packaging, while the organic waste could be similar in both cases. Under such a scenario, a transition from eating in a restaurant to eating at home would be associated with disproportionate increases in the two types of waste. Similarly, it is plausible to assume that waste-generating activities at home and out of home in general differ, which would also imply disproportionate treatment effects.

To account for this problem, we consider treatment effects on the overall (observed + unobserved) waste by an individual. The first category of treatment effects is analogous in definition to (1):

$$ATET^{type} = \mathbb{E}[W_i^{type}(1) - W_i^{type}(0)|D = 1], \tag{2}$$

where the only difference between (1) and (2) is that the latter measures the change in the overall, i.e. observed + unobserved, waste for each type (organic and residual). Next, we also consider a treatment effect that measures the change in the composition of waste resulting from the treatment *over time*:

$$ATET^{rel} = \frac{\mathbb{E}[W_{POST}^{org}(1) - W_{PRE}^{org}(1)|D = 1]}{\mathbb{E}[W_{POST}^{res}(1) - W_{PRE}^{res}(1)|D = 1]} - \frac{\mathbb{E}[W_{POST}^{org}(0) - W_{PRE}^{org}(0)|D = 1]}{\mathbb{E}[W_{POST}^{res}(0) - W_{PRE}^{res}(0)|D = 1]}, \tag{3}$$

where the subscripts PRE and POST denote periods before and during Covid. $ATET^{rel}$ measures the "conversion rate" of residual into organic waste that results over time from working at home. A large and positive $ATET^{rel}$ would indicate that even when taking the economic effect on consumption from the Covid pandemic into account, working from home results in a "conversion" of residual into organic waste. Put differently, a positive $ATET^{rel}$ means that working from home causes a positive change in the amount of organic waste relatively to residual waste over time. Thus, while (1) and (2) are static effects since they measure a single change caused by the treatment, $ATET^{rel}$ is a dynamic treatment effect.

A major problem associated with these treatment effects is that we do not observe the amount of waste a treated or nontreated individual produces away from his/her house. This makes it impossible to directly link the observed number of hours away from home with the total amount of waste that an individual generates. We address this problem in section 3.2.2 below.

3.2 Empirical strategy

3.2.1 Identification and estimation of the effect on observed waste

Estimating (1) is associated with potential endogeneity. In particular, the selection into jobs with plenty vs. few hours away from home is nonrandom. As an example, individuals with stronger pro-environmental preferences would spend c.p. a larger share of their working time at home in order to avoid CO_2-intensive commuting to work. Thus, the amount of waste generated by individuals with varying levels of hours away from home potentially captures differences in pro-environmental attitudes.

To account for possible selection biases, we utilize a natural experiment induced by the Covid pandemic in 2020. In particular, in March 2020, the Swedish government recommended that, whenever possible, individuals should work from home. As a reaction, many employers in Sweden made work from home either mandatory or optional for their employees. Our strategy is to assume that the temporal change in waste levels would have been the same for both treated (i.e. individuals, who switched either fully or partially to work from home) and nontreated individuals. This is the standard parallel trends assumption. This assumption is weaker than randomization and accounts for the possibility, that despite its unanticipated nature, the Covid shock affected disproportionately employers and employees in a way that might be related to environmental preferences.

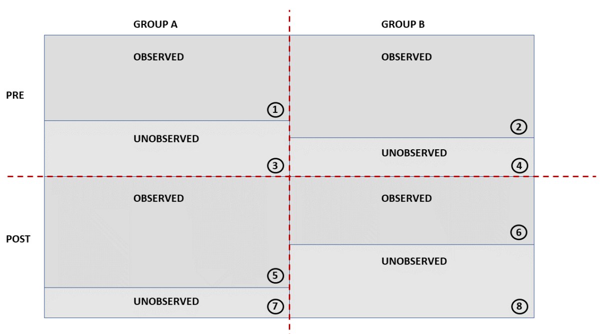
In reality, as figure 2 in section 2.2 shows, the change in the working mode did not occur simultaneously for all workers. To account for the staggered nature of the treatment, we adopt two staggered difference-in-differences (DiD) estimation approaches. The first one is the standard Two-Ways-Fixed-Effects (TWFE) estimation approach The main advantages of this approach are that (i) it is simple to implement, (ii) it allows for continuous treatment and that (iii) when correctly specified, it is efficiency. The main disadvantage of the TWFE approach is that it requires strong additional assumptions to be interpreted as a causal effect. In particular, the TWFE has been shown to be a weighted average of all possible standard 2 period $\times$ 2 groups DiD estimators, Goodman-Bacon (2021). Several studies have shown that if the corresponding effects are not constant over time and groups, the TWFE estimator may be biased, see e.g. Goodman-Bacon (2021), Borusyak et al. (2021), Sun and Abraham (2021).

To account for this possibility, we also use the nonparametric estimator by Callaway and Sant'Anna (2021), henceforth referred to as the CS estimator. It relies solely on a parallel trend assumption adapted to the multi-period setting. We provide extensive evidence for the validity of this assumption in our robustness section below.

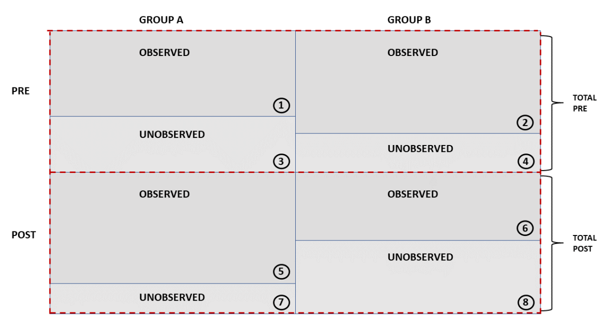
3.2.2 Identification and estimation of the effect on overall waste

Estimation of the $ATET^{type}$ and $ATET^{rel}$ needs to follow an alternative approach because both effects consider changes on waste that is partially produced away from home. In particular, per definition, individual i generates $W_i^{U,type}$ away from home, so that individual i (and in particular the treatment status of individual i) and $W_i^{U,type}$ cannot be linked directly.

To solve this problem, we develop a novel identification strategy that combines household-level data and data aggregated at a municipality and yearly level in order to link waste to treatment status. The aggregated data, as discussed in section 2.2, measures annual municipality-level amounts of the different types of waste. The main advantage of this data compared to the household-level data is that it includes the overall amount of waste produced in the municipality, that is, both the waste produced at home, as well as the waste produced outside away from home (e.g. in restaurants and firms). The main disadvantage compared to the household-level data is that we cannot distinguished how much of each waste type is produced by treated (henceforth group A) and nontreated (henceforth group B) individuals. We now demonstrate how the two sources of information can be used in an integrated approach.



(a) Quantities to be identified.



(b) Quantities identified with aggregate data only.

Figure 3: Waste pre- and during Covid. Group A denotes the treated individuals.

First, consider figure 3a which depicts the waste of any type in the two periods before and after the treatment. Taking organic waste as an example, the average amount of organic waste per household in group A in the pretreatment period $W^{O,org}_{A,PRE}$ corresponds to rectangle 1. Organic waste produced away from home $W^{U,org}_{A,PRE}$ corresponds to rectangle 3. Similar notation is used for group B and for the $POST$-treatment period, as well as for the other two types of waste (residual and unsorted). Each of these separate quantities (i.e. each rectangle) needs to be estimated from the data in order to obtain estimates for the treatment effects. In particular, under a parallel trend assumption for each type of waste, $ATET^{type}$ and $ATET^{rel}$

can be consistently estimated by standard DiD estimators

$$\hat{ATET}^{type} = \Delta W_A^{type} - \Delta W_B^{type} \qquad \text{and} \tag{4}$$

$$\hat{ATET}^{rel} = \frac{\Delta W_A^{org}}{\Delta W_A^{resid}} - \frac{\Delta W_B^{org}}{\Delta W_B^{resid}}, \tag{5}$$

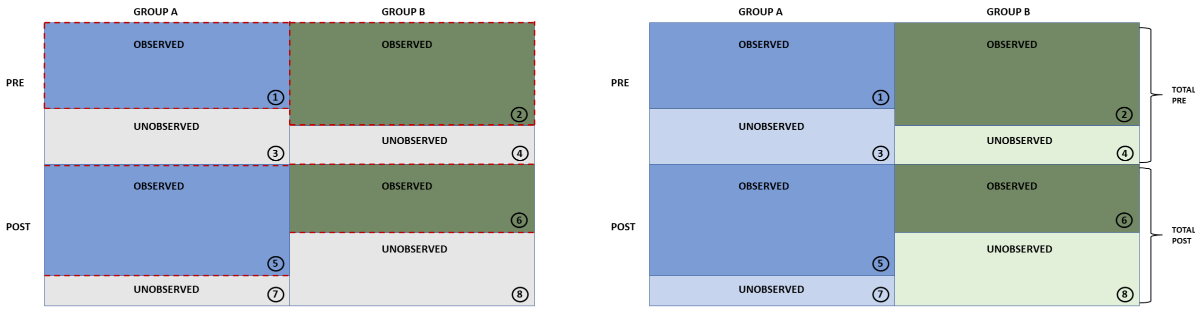
respectively, where ΔW_A^{type} denotes the difference in average amounts in two periods, for example $W_{A,POST}^{type} - W_{A,PRE}^{type}$.

Now consider 3b. It depicts the two quantities that are separately identified (i.e. measured) from the aggregate data. As indicated with red dashed lines, our aggregate data for the PRE-period consists of rectangles $1+2+3+4$, while our aggregated data for the POST-period consists of $5+6+7+8$. However, none of the separate rectangles is observed in the aggregated data. Specifically, the aggregate waste data does not allow us to assign generated waste to one of the two groups A and B. To combine the information from the aggregate data and the surveyed sample, we add the following assumptions:

Representative sample assumption. We assume that individuals in the surveyed sample are representative for the whole population in terms of waste behavior and treatment status. Under this assumption, the quantities $W_{A,PRE}^{O}$ (rectangle 1), $W_{B,PRE}^{O}$ (rectangle 2), $W_{A,POST}^{O}$ (rectangle 5), $W_{B,POST}^{O}$ (rectangle 6) are identified because they are equal to the average annual amounts of waste for the individuals from group A and B in the surveyed sample.[9] In particular, because we observe both the individual waste as well as the treatment status for all individuals from the surveyed sample, we can estimate these quantities. This is depicted in figure 4a. The darker rectangles (blue for group A and green for group B) that are separated with red dashed lines are identified under the representative sample assumption.

In addition, under the assumption of a representative sample, we also observe the shares of A and B in the population, denoted by P_A and P_B. These are simply the shares of treated

[9]Formally, $W_{A,PRE}^{O,org} = \frac{1}{12 \times N_A} \sum_{i \in A,\, t \in \{1,2,\ldots,12\}} W_{i,t}^{org}$, where $W_{i,t}^{org}$ is the monthly organic waste of individual i in month t of year 2019 and N_A is the number of individuals in group A. Similar definitions apply for all other quantities, with POST-year being year 2020.



(a) Identified quantities under the representative sample assumption.

(b) Fully identified waste quantities.

Figure 4: Identification of observed and unobserved waste.

and nontreated in the surveyed sample.

However, the representative sample is not sufficient to identify all quantities of interest. To see why, note that any two quantities $W^U_{A,PRE}, W^U_{B,PRE}$ that satisfy

$$W^O_{A,PRE} + W^O_{B,PRE} + W^U_{A,PRE} + W^U_{B,PRE} = rec\,1 + rec\,2 + rec\,3 + rec\,4 \tag{6}$$

are potential candidates for the true unobserved values.

The representative sample assumption would be violated if the decision to participate in the survey is systematically related to unobserved factors of waste behavior and working habits. In section 5 below, we provide extensive evidence that this is not the case.

Equal change assumption: we assume that *for the nontreated*, the components of waste generated at home and away from of home exhibit equal trends over time. Formally, we assume that for each type of waste, it holds

$$\Delta W^U_B = \Delta W^O_B. \tag{7}$$

Using the enumeration of the rectangles, the assumption implies $r6 - r2 = r8 - r4$. Thus, this is a modified parallel trends assumption.

The equal change assumption would be violated if the economic and behavioral reasons behind the time trend in waste generation differ for the observed and unobserved components of individual waste. As an example, the economic uncertainty associated with the Covid pandemic would have a stronger negative effect on unobserved organic waste than on the observed organic waste if dining away from home is more strongly affected than eating at home. In section 5 below, we study the effect of potential violations of the equal change assumption. Our results suggest that even a substantial violation of this assumption leaves the main results unaffected. The intuition is that ΔW_B^O is very small compared to other quantities used to estimate the treatment effects, so that even a very large mismatch between ΔW_B^U and ΔW_B^O has little impact on the estimates.

Zero-Waste assumption. We assume that individuals who switched due to the pandemic to at least part-time working from home (i.e. the treated) produce all of their waste at home. Formally, the assumption implies that for each type of waste, $W_{A,POST} = W^O_{A,POST}$. In figure 4a, this amounts to assume that rectangle 7 contains no waste. The intuition behind this assumption is that individuals that work at least half a day from home are likely to have their meals at home.

While this assumption appears to be strong, we provide a theoretical result that if the representative sample assumption is satisfied, the Zero-Waste assumption is void and its violation not affect the results, see lemma 1 in section 5 below. A violation of the equal change assumption does not affect this invariance result.[10]

Under these assumptions, we can state the following result:

Proposition 1 *Under the parallel trends, representative sample, zero-waste and equal change assumptions, the treatment effects $\hat{ATET}^{type}$ and $\hat{ATET}^{rel}$ are identified from the data.*

Proof of proposition 1. Identification of the treatment effects under these three assumptions has the following steps (waste type superscripts are omitted for notational simplicity):

[10]Nevertheless, we adopt the Zero-Waste assumption because it makes the exposition of our identification approach substantially easier. The final estimate, however, does not depend on the assumption. We provide a detailed discussion in section 5.

1. Identification of $W_{B,POST}$: the aggregated municipal waste, W_{POST} is equal to

$$W_{POST} = P_A W_{A,POST} + P_B W_{B,POST}. \tag{8}$$

$W_{B,POST}$ is observed from the aggregate data, while P_A and P_B are observed from the individual waste data because of the representative sample assumption. In addition, because of the Zero-Waste assumption, $W_{A,POST}$ is identified from the household-level data (and equal to $W^O_{A,POST}$). Solving for $W_{B,POST}$, we obtain

$$W_{B,POST} = (W_{POST} - P_A W_{A,POST})/P_B, \tag{9}$$

where due to the assumptions, the r.h.s. of (9) is fully observed. This identifies the total post-treatment waste of group B, $W_{B,POST}$. It corresponds to the sum of the rectangles 6 and 8.

2. Identification of $W^U_{B,POST}$ (rectangle 8): because of the representative sample assumption, we observe $W^O_{B,POST}$ (rectangle 6). Using the result from the previous step, we can identify the waste of group B produced outside of the home, that is, $W^U_{B,POST}$.

3. Identification of $W^U_{B,PRE}$ (rectangle 4): using the equal change assumption (7), we can write

$$W^U_{B,PRE} = W^U_{B,POST} + W^O_{B,PRE} - W^O_{B,POST}. \tag{10}$$

The r.h.s. of equation (10) consists of terms that are fully identified. In particular, $W^O_{B,PRE}, W^O_{B,PRE}$ are observed because of the representative sample assumption, while $W^U_{B,POST}$ was identified in the previous step.

4. Identification of $W_{A,PRE}$ and $W_{B,PRE}$: due to the previous steps, the total of waste produced by group B in the pre-covid period is identified and equal to $W_{B,PRE} =$

$W^U_{B,PRE} + W^O_{B,PRE}$. Next, using a decomposition equivalent to (8) but for the pre-treatment period, we obtain

$$W_{A,PRE} = (W_{PRE} - P_B W_{B,PRE})/P_A, \tag{11}$$

where the l.h.s of (11) is fully observed. Thus, $W_{A,PRE}$ is observed.

Repeating this procedure for the different types of waste, we have identified all components necessary to compute the treatment effects. ■

4 Main results

4.1 Estimates of the effect of working from home on *observed* waste

We start by presenting the estimates of the effects of working from home on waste that is generated at the household level, i.e. $ATET^{O,type}$ presented in equation (1).

Results obtained with approach 1. Consider first the TWFE estimation results, which are presented in table 4. Each column corresponds to a separate regression with a different definition of the dependent variable. In specification 1, the dependent variable is the average amount of total household waste per month. In specifications 2, 3, 4, the dependent variable is defined analogously for organic waste, residual waste and unsorted waste, respectively. In all four specifications, the treatment variable is defined as the hours worked away from home H_i.

All four estimates are negative, and the estimates of specifications 1, 2 and 4 are also statistically significant at the 1% significance level. To study their implications, consider first the estimate in specification 1. The coefficient indicates that if the model is correctly specified, an increase of one hour in the hours worked away from home will lead to a decrease in total monthly household waste of 60 gram. Thus, a switch from full time 40-hours work in the office to full time work at home corresponds to an increase in total waste of 2.4 kg per month and household. Similarly, a reduction in the hours away from home equal to the pre-pandemic standard deviation of the hours away from home (19.68 hours) corresponds to an increase of 1.18 kg in total waste per month and household. To put these amounts of waste into perspective, recall that the average amount of waste per household and individuals is $2 \times 6.69 = 13.38$ kg per month (twice the fortnight-weight). Thus, the two amounts above correspond to an increase of 18% and 8% in total waste per household and month, respectively.

Columns (2), (3) and (4) suggest that this change in total waste is large driven by a change in organic waste. In particular, for households which have both organic and residual bins, an increase of one hour away from home leads to a decrease in the organic waste of roughly 40 gram, which is equal to 2/3 of the total change. Residual, on the contrary, amounts only to a small portion of the total change, and the corresponding effect is not statistically significant. For households that have only an unsorted bin, the effect is again negative and significant and of somewhat larger magnitude than the effect on total waste. One possible reason for the larger effect estimate is selection into bin type. In particular, the group of individuals with unsorted bins would be more affected by the switch to home office if the choice of the bin was driven by working habits in the first place.

Results obtained with approach 2. Table 5 contains the results obtained with the nonparametric CS estimator. As before, each column represents a specification with a different outcome variable. All total ATT effects are positive and the first two specifications yield statistically significant effects. Standard errors are cluster-robust and obtained with the multiplier bootstrap method. Note that the treatment variable is now D, which is equal to 1 when an individual experienced *a reduction* of the hours away from home (and not the number of hours away from home as in the previous specification). Thus, the positive effects in all specifications are consistent with the negative effects in table 4. As an example, the coefficient in specification (1) implies that a reduction in the hours away from home leads

Table 4: Regression Results - TWFE

	Dependent variable: Bin Wight			
	1	2	3	4
	Total Waste	Organic	Residual	Unsorted
β^{TWFE}	-0.061^{***}	-0.039^{***}	-0.011	-0.164^{***}
	(0.014)	(0.008)	(0.014)	(0.043)
Observations	35,430	19,320	24,060	690
Adjusted R^2	-0.033	-0.032	-0.036	-0.052

Notes: The TWFE regression estimator has been used for all four model specifications. The treatment variable is W_i and is defined as the number of hours worked away from home. The dependent variable in specification (1) is the total waste weight per household and month, in specification (2) the organic waste weight, the residual waste weight in specification (3) and the unsorted in specification (4). The standard errors are indicated in brackets and are clustered at the household level.Statistical significance is denoted with the standard asterix system: *p<0.1; **p<0.05; ***p<0.01.

to an average increase in the total waste per household and month of roughly 1.1 kg. This coefficient is somewhat lower than the β^{TWFE} and reflects the averaging of the treatment variable. Similar conclusions can be made for organic waste. The estimates for residual and unsorted waste are not significant.

Table 5: Regression Results - CS Estimator

	Dependent variable: Bin Weight			
	(1)	(2)	(3)	(4)
	Total Waste	Organic	Residual	Unsorted
ATT	1.080^{**}	0.837^{**}	0.185	1.030
	(0.527)	(0.427)	(0.426)	(1.790)
Observations	35,430	19,320	24,060	690

Notes: The CS estimator has been used for all four model specifications. The standard errors, indicated in brackets, are cluster-robust and the asterisks next to the point estimates denote the statistical significance level (*p<0.1; **p<0.05; ***p<0.01).

Implications. There are three main takeaways from the above empirical results. First, working more from home leads to an increased amount of waste disposed of in the household bins. A likely explanation is that this increase has been caused by consuming more food at home. While eating at a restaurant or in the office causes no waste at home, eating at home is associated with additional packaging and food waste in the home bins.

Second, both approaches suggest that the increase in total waste at the household level is largely driven by an increase in organic waste. As an example, the TWFE estimates for the effect on organic waste are more than twice as large in magnitude than the corresponding estimates for residual and unsorted waste. Similar conclusion can be made for the CS-estimates: the estimate for the effect on organic waste is roughly four times larger than the coefficient for the effect on residual waste.

4.2 Estimates of the effect of working from home on ***overall*** waste

We now present estimates of the effects on overall waste, that is, on observed (i.e. generated at home O) and unobserved waste (U). In particular, we consider the effects $ATET^{type}$ from equation (2) and $ATET^{rel}$ from equation (3). [11]

Consider first the treatment effects $ATET^{type}$ from equation (2). Our estimate for the effect on organic waste $ATET^{org}$ is equal to -14.04 kg per year (-1.17 kg per month) and household. To put this into perspective, this effect amounts to a 20.5% reduction in organic waste relative to the pre-Covid levels. Similarly, $ATET^{res}$ is equal to $-44.25\,(-3.69)$ kg per year (month) and household, which is equivalent to a 12.2% reduction in residual waste compared to pre-Covid levels. Thus, both estimates suggest that work from home leads to a substantial decrease in waste.

Finally, the estimate of the effect $ATET^{rel}$ is positive and equal to 1.585. The interpretation of this treatment effect is that over time, individuals who worked from home during the pandemic turned some of their residual waste into organic waste, as compared to the control group.

Implications. Overall, our estimates point to a substantial decrease in all types of

[11] Since the estimates are constructed from data at an aggregate level and hence for the whole population of interest, no statistical confidence levels can be generated.

waste due to working at home and to a shift from residual to organic waste. These results are consistent with descriptive evidence based on diaries and surveys that point towards behavioral changes such as better use of food leftovers, better management of inventories, and less impulse purchases, see e.g. Pires et al. (2020) for evidence from an online survey and Iranmanesh et al. (2022) for a literature review. Moreover, our results suggest that these positive changes in underlying pro-environmental behavior offset possible negative effects of remote work such as increased online purchases of packed food.

Rermark. The above estimated effects are not offset by an increase in recycled waste. In particular, as table 2 in section 2.2 reveals, all categories of recycled waste exhibit a decrease in the Covid year 2020, while there is a "rebound" increase in 2021 associated with returning to pre-Covid number of working hours away from home.

5 Analysis of the validity of the assumptions

5.1 Assumptions necessary to identify the effect on observed waste

5.1.1 The parallel trends assumption

We now provide both graphical and statistical evidence for the plausibility of the parallel trends assumption. Consider first figure 5. On the x-axis, calendar time is displayed. The black vertical line denotes March 2020, the month in which the government recommendation to work at home was announced. All periods before March 2020 represent pretreatment periods. The y-axis displays the average total waste weight per individual and month. The upper (violet) line reports the average waste weight for the treatment group, while lower line reports the average waste weight for the control group.[12] For both groups, average waste follows a roughly cyclical pattern that is most likely driven by seasonal differences in consumption. The pointwise difference in both curves is almost constant throughout and roughly equal to 3.5 kg., which is reflected in the parallel way both curves are aligned to

[12]The control group here is defined as those individuals who never reduce their hours away from home.

each other.

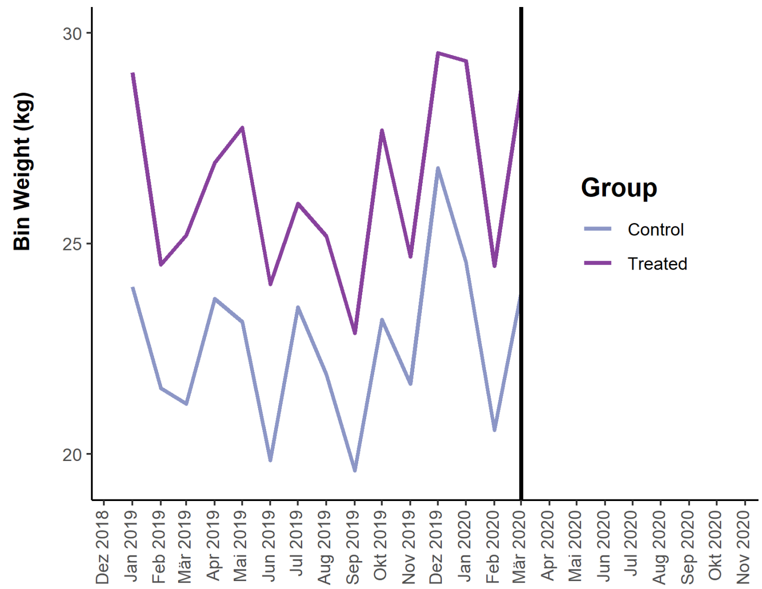


Figure 5: Average monthly household waste for treated (violet curve) and nontreated (blue curve) groups

Next, we estimate placebo treatment effects for the total waste using the nonparametric CS estimator.[13] To be specific, for each household, the placebo treatment variable changes value a pre-specified number of periods, say l, before the actual realization of the treatment for that household. Importantly, within a given estimation procedure, the time lag l of the placebo treatment is common for all units of observation. We follow this procedure for $l = 1, 2, 3, 4$. That is, we estimate the placebo treatment effect for the -1 to -4, periods, where the actual treatment is obtained in period 0. The results are shown in table 6. The first column contains the lagged period for which the placebo treatment is estimated. The second column contains the placebo estimate. The third and fourth column contain the estimates for the left and right 95 % confidence bounds, respectively. In all 4 cases, the estimated confidence interval contains the point 0, which indicates that the effect estimates are not statistically significant.

Thus, both the graphical and the statistical approaches suggest that pretreatment trends

[13] We follow similar procedure using the TWFE estimator and all placebo effects are close to zero and nonsignificant.

Table 6: Placebo estimation procedure with the nonparametric CS estimator

Period	Placebo ATET	Lower confidence bound	Upper confidence bound
-1	0.95	-0.51	2.41
-2	0.32	-0.97	1.61
-3	0.92	-0.24	2.08
-4	-0.38	-1.24	0.48

Placebo testing for 5 pretreatment periods for the effect ontotal waste per. Each row contains the estimation for one placebo test for a given number of lagged periods. Estimations are conducted with the CS estimator.

can be assumed to be parallel. This provides indirect evidence for the validity of the parallel trends assumption.

5.1.2 Assessing the impact of the staggered adoption assumption

The CS estimation approach requires that an individual who is treated remains treated thereafter. However, many of the individuals who reduced their hours away from home eventually increased them again, see figure 10 in appendix A. To account for possible biases of the result, we restrict the time horizon to exclude such "reverse-treated" individuals. In particular, we reestimate the model including only the first 27, 22 and 15 periods (instead of using all 30 periods). The results for these three specifications are displayed in tables 7, 8 and 9 in appendix B.1, respectively. Coefficient signs, magnitudes and significance remain very robust and similar to our main CS estimates.

5.2 Assumptions necessary to identify the effect on overall (observed and unobserved) waste

5.2.1 The "representative sample" assumption

We provide evidence for this assumption in two different ways. First, we compute the average monthly waste observed at the household both for all households in the two municipalities and for the surveyed sample.[14] Figure 6 shows the estimated averages. The x-axis displays each month in the year, while the y-axis measures the average waste weight for that month for each of the two groups. The solid curve represents the waste of the surveyed sample, while the dashed curve represents the waste of the full population. The figure shows that on average, waste observed at the household follows very similar patterns for the full population and the surveyed sample.

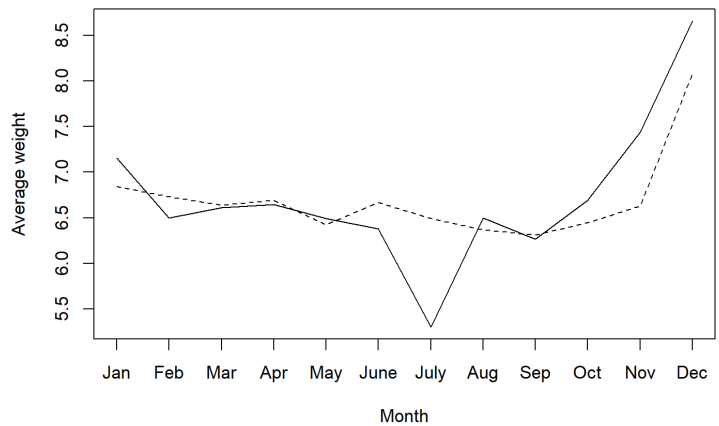


Figure 6: Comparison of monthly average waste per household for household in the surveyed sample (solid curve) and all households in the two municipalities (dashed curve) groups

Second, we compare the share of treated in the surveyed sample and in the whole population. As above, for the survey sample we can compute this share directly from our survey data. The estimated share amounts to roughly 35%. For the total population, we do not dispose of individual data on hours working at home. To overcome this problem, we use aggregate level statistics about work habits during the Corona pandemic in Sweden, collected by Statistics Sweden.[15] In particular, individuals were asked whether they had to work from home due to Covid pandemic. The share of individuals who answered the question with

[14]We are able to compute these averages from individual household waste data because we observe the household waste for every household in the two municipalities (and not only for the surveyed sample).

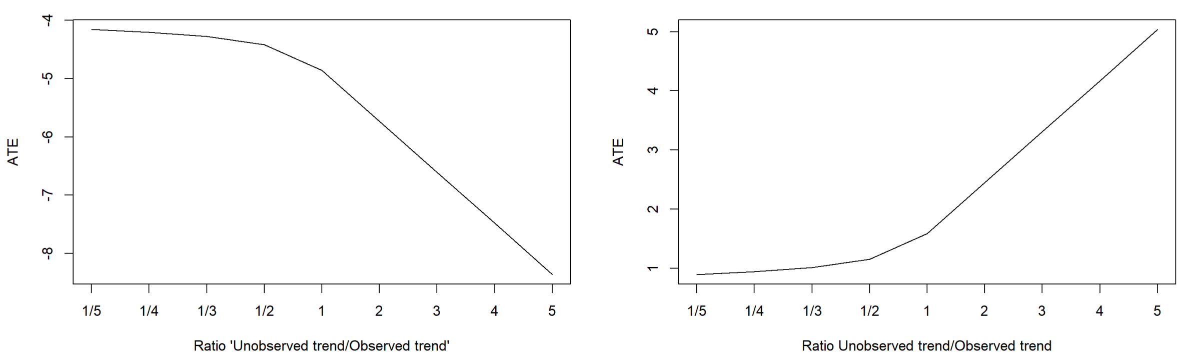
[15]Detailed information can be obtained (in Swedish) under: https://www.scb.se/pressmeddelande/ny-statistik-sa-manga-har-jobbat-hemifran-under-pandemin/.

“yes” in 2020, our POST-treatment period, is equal to 34.5%, which is very close to the estimate obtained with the sample of surveyed individuals.

Thus, the above results provide strong support for the validity of the “representative sample” assumption.

5.2.2 The “equal change” assumption

Next, we study the “Propotional effect” assumption (7). This is a nontestable assumption and without individual data on the treatment status for the whole population, it is even difficult to provide indirect evidence for its validity. Instead, we provide an assessment of the impact of potential violations of this assumption on the final estimates through a sensitivity analysis. In particular, in a first step, we assume that $\frac{\Delta W_B^{U,type}}{\Delta W_B^{O,type}} = a^{type}$ where a^{type} is some constant. $a^{type} = 1$ is equivalent to the equal change assumption. Then, in a second step, we estimate the treatment effects for different choices of the constants a^{org}, a^{res}.



(a) $ATET^{org} + ATET^{res}$ (b) $ATET^{rel}$.

Figure 7: Assessment of violations of the equal change assumption. a^{org} is varied

Figure 7 shows the results from the sensitivity analysis for which a^{org} was varied and a^{res} was held constant. Consider first figure 7a. On the x-axis, the different choices of a^{org} are measured. As an example, $a^{org} = \frac{1}{5}$ means that the unobserved trend is simulated to be 5 times smaller than the observed one, while $a^{org} = 5$ means the reverse, i.e. the unobserved trend is simulated to be 5 times larger. The y-axis measures the effect on the total waste, $ATET^{org} + ATET^{res}$. For all choices of a^{org}, the estimated effect is negative and varies between 4 and 8 kilo reduction in the total waste per month. Analogous scenarios are simulated for the two ATEs separately and yield very similar (i.e. negative) results. Next, consider figure 7b. The y-axis displays estimated relavite conversion ATEs ($ATET^{rel}$) corresponding to each value of a^{org}. The estimated ATET remains positive for any choice of the constant. Very similar results are obtained when (1) only a^{res} or (2) simultaneously a^{org}, a^{res} are varied and we omit them.

Thus, the above results from the sensitivity analysis suggest that very large violations of the equal change assumption do not change the direction of the results and they remain consistent with our main results. Intuitively, the main reason for this insensitivity result is that for group B, both observed and overall waste vary very little between the PRE- and POST-covid periods.

5.2.3 The "Zero-Waste" assumption

Finally, we study the importance of the Zero-Waste assumption, $W^{type}_{A,POST} = W^{O,type}_{A,POST}$. It turns out that under the representative sample assumption, the Zero-Waste assumption is dispensable.

Lemma 1 *Suppose that for each type of waste, the representative sample assumption holds. Then $ATET^{type}$ and $ATET^{rel}$ do not depend on $W^{type}_{A,POST}$.*

To see this, suppose first that the equal change assumption holds. Then, following the steps of proposition 1, we get for each type of waste

$$W_{A,POST} - W_{A,PRE} = \frac{2P_B \times (W^O_{B,PRE} - W^O_{B,POST}) - W_{PRE}}{P_A} \tag{12}$$

and the right hand side does not depend on $W_{A,POST}$ (or equivalently, on $W^O_{A,POST}$). Since both $ATET^{type}$ and $ATET^{rel}$ depend on $W_{A,POST} - W_{A,PRE}$ and not only on $W_{A,POST}$, the estimates are insensitive to violation of the Zero Waste assumption. Similarly, the independence result remains valid for any violation of the proportional impact assumption, i.e. for any choice a^{org}, a^{res}.

6 Cost-benefit analysis

We now perform back-of-the-envelop calculations of the CO_2 emission reduction and the cost savings that result from the decrease in waste triggered by working at home. To calculate the former, we use calculations by the IVL research institute[16] of life-cycle benefit of reducing different waste streams. These calculations can be found in Miliute-Plepiene et al. (2019) (in Swedish). According to this study, reducing the general or residual waste by 1 kg is equivalent to reducing the emission of CO2 by 2.3 kg, while reducing the organic waste by 1 kg is equivalent to reducing the emission of CO2 by 2.2 kg. Combining these estimates with our estimates of $ATET^{type}$, we obtain an annual reduction of $44.25 \times 2.3 + 14.04 \times 2.2 = 132.66$ per household. This corresponds to 57.68 kg CO_2 annual reduction per individual.[17] To put this number into perspective, note that the annual carbon dioxide emissions per capita in Sweden in 2019 (the pretreatment period) were roughly 5.2 tones.[18] Thus, working from home is estimated to decrease the individual carbon footprint by 1.1%.

To calculate the cost savings of the reductions in waste, we assume that the public cost of one kg CO_2 emissions is equal to the the CO_2 tax, which is 1.2 SEK/kg.[19] This is a conservative value since it does not include health and other environmental benefits resulting from reducing the CO_2 emissions. To determine the total value of the savings due to a reduction in the CO_2 tax, we first multiply the number of treated households ($0.35 \times (7145 + 16316) = 8211$ households) by the average annual household CO_2 savings (132.66 kg) and then multiply this number by the Swedish CO_2 tax/kg. To this number, we add the savings from waste processing, which are calculated as $8211 \times (44.25 + 14.04) \times 2.15$,

[16]www.ivl.se/english/startpage.html

[17]Number of individuals per household in the two municipalities were 2.322 in 2018, 2.310 in 2019, 2.295 in 2020 and 2.286 in 2021.

[18]See https://www.statista.com/statistics/449823/co2-emissions-sweden/.

[19]See https://www.upphandlingsmyndigheten.se/

where the price of waste processing per kg waste is 2.15 SEK. We thus calculate that the total value of the savings for the two municipalities resulting from waste reduction due to working from home is equal to 2 336 286 SEK (285 211 USD as of December 31st 2020). To put this into perspective, this reduction is equal to 2.5% of the total cost for waste processing in the two municipalities for 2020 (91.8 M SEK).

7 Conclusion

In this paper, we study the effect of working from home on waste generated by individuals. Using a unique dataset on household-level waste and a novel identification approach, we find that working from home decreases individual organic waste by 20% and residual waste by 12%. These reductions are substantial from economic and environmental perspectives. While we quantify the total effect on each type of waste, the precise mechanisms are yet to be determined, which is a promising path forward for future research.

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A Descriptive statistics

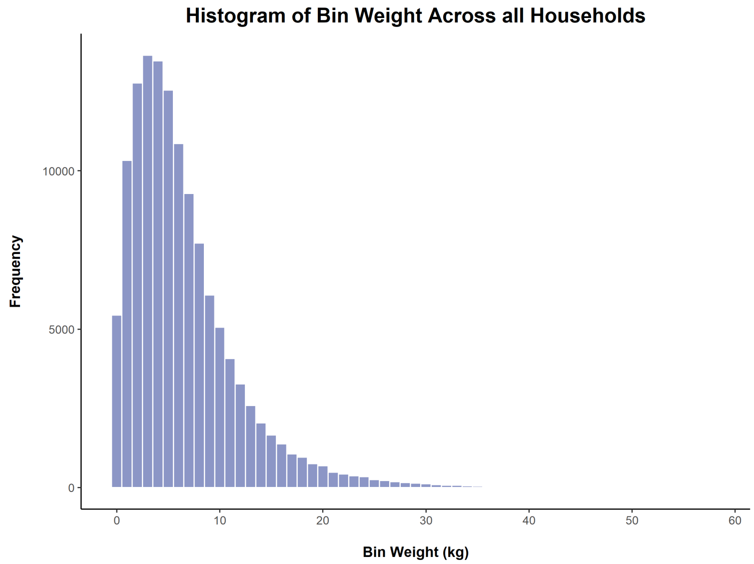
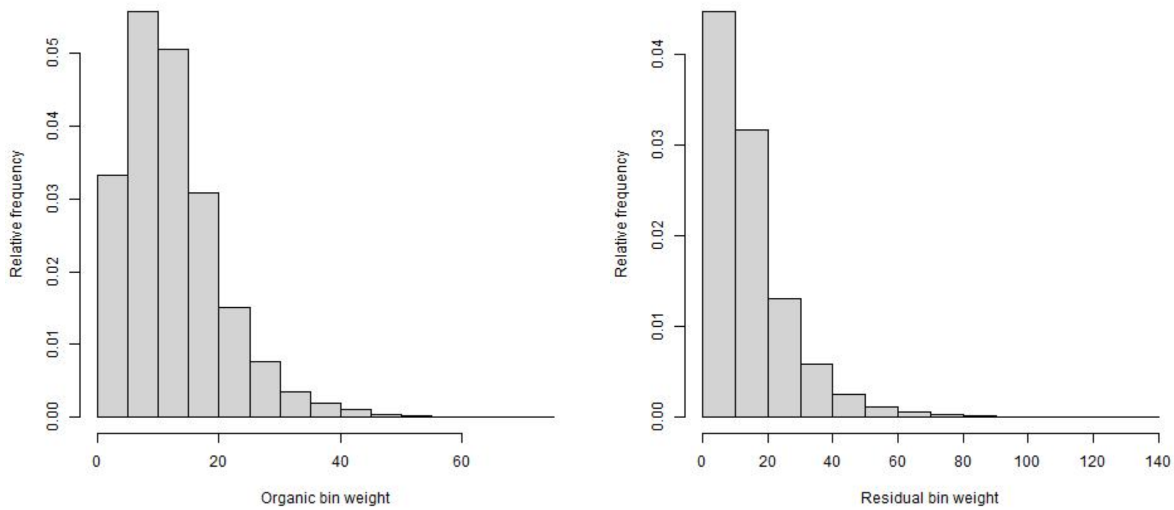


Figure 8: Histogram of Bin Weight Across all Households.

B Assessment of the validity of the assumptions

B.1 Assessing the impact of the staggered adoption assumption



(a) Organic waste. (b) Residual waste.

Figure 9: Histograms of bin weight for the total period of observation.

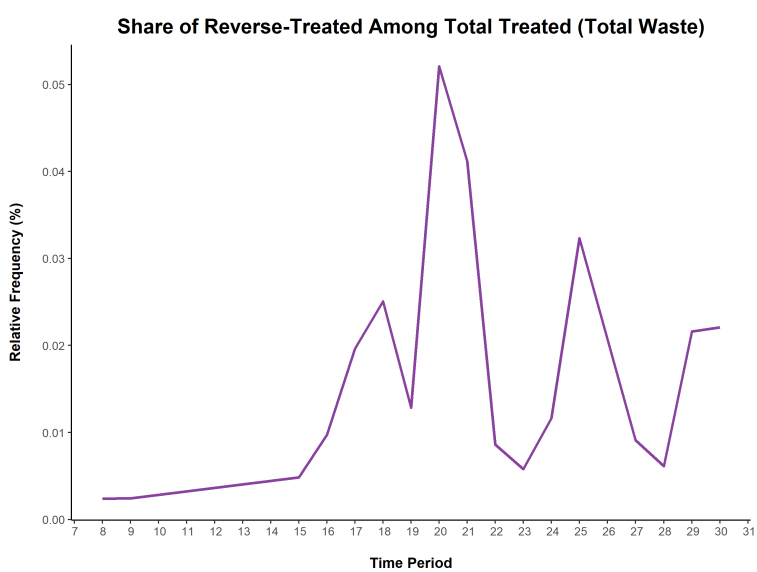


Figure 10: The share of individuals returning to their pre-covid number of hours away from home (the so called "reversed treated") on the total number of treated individuals for every point in time.

Table 7: Robustness Check - Violation of the Staggered Treatment Assumption (1)

	Dependent variable: Bin Weight			
	(1)	(2)	(3)	(4)
	Total Waste	Organic	Residual	Unsorted
ATT	1.170**	0.899**	0.278	0.838
	(0.517)	(0.376)	(0.448)	(1.610)
Observations	31,887	17,388	21,654	621
Number of Households	1,181	644	802	23
Time Periods	27	27	27	27

Notes: The CS estimator has been used for all four model specifications. The time period considered for all models covers January 2019 to March 2021. The standard errors, indicated in brackets, are cluster-robust and the asterisks next to the point estimates denote the statistical significance level (*p<0.1; **p<0.05; ***p<0.01).

Table 8: Robustness Check - Violation of the Staggered Treatment Assumption (2)

	Dependent variable: Bin Weight			
	(1)	(2)	(3)	(4)
	Total Waste	Organic	Residual	Unsorted
ATT	1.010*	0.683*	0.158	0.996
	(0.541)	(0.400)	(0.464)	(1.380)
Observations	25,982	14,168	17,644	506
Number of Households	1,181	644	802	23
Time Periods	22	22	22	22

Notes: The CS estimator has been used for all four model specifications. The time period considered for all models covers January 2019 to October 2020. The standard errors, indicated in brackets, are cluster-robust and the asterisks next to the point estimates denote the statistical significance level (*p<0.1; **p<0.05; ***p<0.01).

Table 9: Robustness Check - Violation of the Staggered Treatment Assumption (3)

	Dependent variable: Bin Weight			
	(1)	(2)	(3)	(4)
	Total Waste	Organic	Residual	Unsorted
ATT	1.010*	0.683*	0.158	0.996
	(0.541)	(0.400)	(0.464)	(1.380)
Observations	25,982	14,168	17,644	506
Number of Households	1,181	644	802	23
Time Periods	22	22	22	22

Notes: The CS estimator has been used for all four model specifications. The time period considered for all models covers January 2019 to October 2020. The standard errors, indicated in brackets, are cluster-robust and the asterisks next to the point estimates denote the statistical significance level (*p<0.1; **p<0.05; ***p<0.01).