



# Household time activities, food waste, and diet quality: the impact of non-marginal changes due to COVID-19

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## Abstract

In early 2020, a novel coronavirus quickly spread across the globe. In response to the rapidly increasing number of confirmed U.S. cases, state and local governments suggested social distancing, issued stay-at-home orders, and restricted travel, fundamentally changing how individuals allocate time. Directly impacted time activities, such as work, eating food away from home, grocery shopping, and childcare significantly impact two food-related topics: household food waste and diet quality. In order to investigate these non-marginal time changes, we predict weekly time allocated to seven activities for households in the National Food Acquisition and Purchase Survey using information from the American Time Use Survey. Jointly estimating household production functions for food waste and diet quality, we find that time events that are related to fresh produce consumption, such as increased grocery store trips and time spent in FAH activities, are related to higher diet quality, but lower food waste. While time events that are associated with quick convenient meals, such as time spent in secondary childcare and work time, are also associated with lower food waste, these events decrease household diet quality. We then predict the level of household food waste and diet quality for three COVID-19 scenarios: one where the household head is likely able to work remotely, another where the household head is likely to lose their job, and a third, where the household head is likely to be considered an essential worker. Households without children that are likely able to work remotely are predicted to have lower levels of food waste and higher diet quality, while households without children in the other two COVID-19 scenarios are predicted to have only minor differences.

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## 1 Introduction

In early 2020, a novel coronavirus (COVID-19) quickly spread across the globe, and the World Health Organization (WHO) officially declared a pandemic on March 11, 2020 (WHO, 2020). In response to the rapidly increasing number of confirmed U.S. cases, state and local governments, starting in California, issued stay-at-home orders, mandating that residents remain at home except to go to an “essential” job or shop for essential needs. With overall demand drastically decreased because of the stay-at-home orders and increased fear of virus transmission, unemployment rates rapidly increased. In a single week, a record 6.87 million new unemployment claims were filed, and the national unemployment rate reached 14.7% (BLS, 2020). In addition, over the course of just 2 months from mid-February to the beginning of April, both the Dow Jones Industrial Average and S&P 500 fell more than 30%. In response, Congress passed the Coronavirus Aid, Relief, and Economic Security Act providing \$2 trillion in various aid. Although these macroeconomic figures illustrate how widespread the economic impacts of the pandemic are, they do not convey the significant impact COVID-19 has on households’ behaviors.

Stay-at-home orders, social distancing, and travel restrictions fundamentally change how individuals allocate time. Households that previously participated in commuting to work, eating food away from home, and grocery shopping multiple times a week suddenly decreased time allocated to each of these activities to near zero. Commuting time decreased as businesses shifted to remote work, eating food away from home decreased as bars and restaurants closed, and health officials advised visiting the grocery store once every 2 weeks. In addition, schools and daycare centers closed, forcing households with children in schools or paid childcare to suddenly allocate significantly more time to own childcare.

These non-marginal changes in household time significantly impact two food-related outcomes: household food waste and diet quality. It is difficult to determine an a priori impact of COVID-19 on these outcomes because of the contrasting effects of each time category. For instance, when following stay-at-home orders and working remotely, more time can be devoted to preparing food at home (FAH), which is associated with increased consumption of fruits and vegetables and household diet quality (Monsivais et al., 2014). In contrast, less frequent food shopping trips are associated with more shelf-stable foods and lower household diet quality (Hersey et al., 2001). From the perspective of food waste, increased fruit and vegetable consumption and higher diet quality are associated with more food waste (Yu & Jaenicke, 2020), while increased purchases of shelf-stable goods and a decrease in food away from home consumption would decrease food waste. For households with children, the drastic increase in own childcare time can also impact household food waste and diet quality. The average school day is approximately

6.6 h in the United States, meaning parents are suddenly responsible for nearly a full workday's amount of childcare time. Under increased time constraints, parents may substitute out of primary ingredients and into convenience goods. To better understand how COVID-19 might have affected food waste and diet quality, this paper investigates how non-marginal changes in household time allocations impact household food waste and diet quality.

Food-waste estimates at an aggregate level range between 30 and 40% of the total food supply in the United States. Not only does this food waste amount to a significant economic loss estimated at \$160 billion (Buzby et al., 2014), but it also causes environmental damage through significant greenhouse gas emissions (FAO, 2013). To address the negative effects of food waste the USDA, EPA, and FDA introduced the "Winning on Reducing Food Waste Initiative," a joint agency initiative aiming to reduce food waste by 50% by 2030, on October 2018 (USDA, 2020). Unfortunately, the initiative does little to address food waste at the consumption stage, which constitutes the largest share of food waste in the U.S. (Griffin et al., 2009; Bellemare et al., 2017). Empirical studies on consumer food waste have often focused on the difficult task of estimating food waste rather than identifying a link between household specific characteristics and food waste (van der Werf & Gilliland, 2017). Estimation methodologies generally either consider the difference between reported purchases and food intake (Muth et al., 2011; Landry & Smith, 2019) or attempt to obtain small-scale measurements through survey or experimental design (Qi & Roe, 2016; Reynolds et al., 2014; Stefan et al., 2013). However, each of these methods has limitations due to data availability that is common throughout food waste literature (van der Werf & Gilliland, 2017).

Yu & Jaenicke (2020) overcome the data availability shortcomings "by conducting a productivity analysis of household production to obtain an input inefficiency measure that is interpreted as excess food inputs used to produce the current level of output." A major advantage of this approach is that it allows them to perform a post-estimation analysis. This analysis shows that several household characteristics, including household size, shopping with a list, and distance to primary store are associated with less food waste. In contrast, higher diet quality is associated with higher waste. While it is clear that time is an essential input in household food production that determines the efficiency of food management and utilization (Lusk & Ellison, 2017), Yu & Jaenicke (2020) do not include it in their analysis because of data limitations. Indeed, there have been no empirical studies that directly investigate how household time allocations are associated with household food waste.

In contrast, the diet-quality literature has considered household time allocations in numerous ways (Davis, 2014). Initially, time spent in FAH activities, e.g., cooking, cleaning, etc., was a primary research focus because of its direct relation to the cost of producing meals. While meals consisting of basic ingredients such as fresh whole produce, uncooked meat, and dried beans may cost less monetarily (Mackay et al., 2017; McDermott & Stephens, 2010), they require more time to prepare. This additional time is non-trivial since, on average, more than 30% of the full cost of meal production is associated with time (Raschke, 2012). Increasingly, the time-poverty literature has focused on households' struggle to balance time spent in committed activities such as work, childcare, food preparation, and other household activities (Bittman, 2002; Douthitt, 2000; Strazdins et al., 2011). Increased time

dedicated to committed activities decreases the time available to be spent in food at home activities (Hamrick et al., 2011) and makes it more difficult for households to produce healthy meals (Venn & Strazdins, 2017; Beatty et al., 2014).

Although only households with children must participate in own childcare, it is still a committed activity of interest because of the known relationship between childcare and diet quality (Scharadin & Jaenicke, 2020) and the potential relationship with food waste. With an increasing number of children eating both breakfast and lunch at school or in formal childcare, a majority of their meals may occur outside the home. Therefore, as COVID-19 suddenly closed schools and formal childcare centers, families became responsible for producing more meals. As with other committed activities, the impact on food waste is difficult to predict because additional household members are associated with lower food waste (Yu & Jaenicke, 2020), but more time in FAH production may increase food waste. Additionally, it is necessary to consider separately both primary childcare, time spent caring for the child as the primary activity, and secondary childcare, time spent providing childcare, while performing another primary activity (Folbre & Yoon, 2007; Zick & Bryant, 1996). The two types of childcare have been shown to have differing impacts on diet quality (Scharadin & Jaenicke, 2020) and the probability of a child being overweight or obese (You & Davis, 2010), potentially because secondary childcare is seen as a distraction from other tasks.

Despite this rich literature, there are two main critiques related to a lack of data containing both food purchases and time allocations (Davis, 2014). First, papers often rely on aggregate time categories, e.g., combining grocery shopping, travel to grocery shopping, food preparation and clean up, and eating into one food production term (Hamermesh, 2008). This approach limits interpretability because it is impossible to disentangle, for example, if travel to grocery shopping or meal preparation is more binding. Second, many papers concentrate on the demand for inputs (such as goods and time) rather than on outcomes (such as obesity and diet quality), which limits policy implementation (Cawley & Liu, 2012; Davis, 2014).

Recently, studies have addressed this data obstacle by predicting time use allocations for households in food-purchasing dataset samples. Using this approach, Scharadin & Jaenicke (2020) show that the committed activities of both primary and secondary childcare directly impact diet quality. In their conditional production function approach, primary childcare and food-related activities can be seen as investment activities and therefore substitutes to diet quality production, whereas secondary childcare is a distraction and therefore a substitute to food-related activities. You & Davis (2010) also predicted household time allocations to estimate the probability of a child being overweight or obese. While these studies provide a method to consider the impact of detailed time allocations on policy-relevant outcomes, care must be given to estimating the time allocations accurately. One common limitation not addressed by past studies predicting time allocations is the difference in sampling periods between the time use and food-purchasing datasets (Scharadin & Jaenicke, 2020; Hamermesh, 2007). Strict assumptions must also hold, namely that time allocations are consistent across days of the week, for these time estimations to be accurate. In contrast, You & Davis (2019) use a modified two-part model (Mullahy, 1998) and day of the week dummies to predict time use for days of the week not collected.

In this paper, we argue that time's impact on food waste and diet quality should be considered jointly because the same time constraints influencing one are likely to influence the other. Time spent working provides one specific example. Increased time working is associated with a decrease in FAH activities (Mancino & Newman, 2007; Tashiro & Lo, 2011) and an increase in food away from home events (Binkley, 2006). While both of these results are associated with a decrease in household diet quality (Barnes et al., 2016a), they may also be associated with an increase in household food waste because fresh produce requires more food preparation time (Monsivais et al., 2014) and has faster spoilage rates than shelf-stable items. Therefore, given that higher quality diets associate with increased food waste (Conrad et al., 2018; Yu & Jaenicke, 2020), it is important to consider these two issues jointly.

The starting point for the current study comes from recent research from Yu & Jaenicke (2020), which estimates household-level food waste for nearly 4000 households in USDA's National Food Acquisition and Purchase Survey (FoodAPS) and from Scharadin & Jaenicke (2020) which linked the 2010 Healthy Eating Index (HEI) for FoodAPS's households to predicted time allocations. In this study, we investigate seven committed time activities found in the American Time Use Survey (ATUS) related to working, commuting, childcare, and food-related activities and link them to both food-waste estimates and the HEI. We do the same for the number of FAH shopping trips, number of quick-service restaurant events, and number of full-service restaurant events.

We next construct three COVID-19 time scenarios: (i) One where a household head is likely able to work remotely, (ii) A second where a household head likely lost their job, and (iii) A third where a household head is likely considered an essential worker, to reflect what might have happened to households in the FoodAPS sample during the early weeks of the COVID-19 pandemic. Using our estimation results, we predict non-marginal changes in diet quality and food waste associated with these three scenarios and data subsamples based on household income and the presence of children in the household. More specifically, we find that households with children are predicted to have lower diet quality and higher food waste compared to pre-COVID-19 levels. We predict households without children but with remote work (the first scenario) will have lower levels of food waste and higher diet quality; however, households without children in the other two COVID-19 scenarios are predicted to have only minor differences. To our knowledge, this is the first paper to relate household time activities to food waste, the first to jointly estimate the impact of household time allocations on food waste and diet quality, and the first to investigate COVID-19-relevant and policy-relevant time scenarios to predict food waste and diet quality outcomes. We discuss our detailed methods and results next, along with limitations, potential long-term impacts from changes in household behavior, and policy implications of our study.

## 2 Methods

This paper builds on two previous research studies, one on household-level food waste (Yu & Jaenicke, 2020) and one on household-level diet quality and time

(Scharadin & Jaenicke, 2020). To be more precise, we follow Yu & Jaenicke's (2020) methods to estimate food waste, and incorporate these results into Scharadin & Jaenicke's (2020) household production framework that links time to the household production of diet quality, as proxied by the HEI, and now food waste as well. We begin by describing the estimation of each individual component, namely estimating household food waste, diet quality, and weekly time allocations. We then discuss the overall estimation method and how we adjust household time allocations for the COVID-19 scenarios.

## 2.1 Estimating household-level food waste

To estimate household-level food waste, we follow Yu & Jaenicke (2020) by conducting a stochastic production frontier analysis where households transform nine categories of purchased or acquired food into one metabolic energy-requirement output, along with an inefficiency term that reflects the notion that some households are more efficient than others in this production process. The output is an aggregate of the Basal Metabolic Rate for the household, which reflects the energy required to maintain steady-state body mass without physical activity. This output is calculated using the revised Harris-Benedict equations (Roza & Shizgal, 1984). The inputs reflect nine food categories already proscribed by the FoodAPS dataset.<sup>1</sup>

As in Yu & Jaenicke (2020), the stochastic production frontier is specified with a translog function and estimated via maximum likelihood after adding two error terms. One error term is assumed to follow a normal distribution to reflect white noise. The second error term follows a one-sided half normal distribution that reflects household-level output-oriented inefficiency. This output inefficiency can be converted to an input-oriented inefficiency measure, here food waste, with the help of both the quadratic formula and a strong assumption that food waste is equally proportional across all nine food categories.

## 2.2 Calculating household-level diet quality

To operationalize household-level measures of diet quality, our study uses the 2010 HEI, which measures diet quality in terms of conformance with the 2010 Federal Dietary Guidelines and can be calculated with both food consumption and purchasing data. It has been used by Scharadin & Jaenicke (2020) and many others (e.g., Guenther et al., 2013; Krebs-Smith et al., 2010; Volpe & Okrent, 2012; Guenther et al., 2014) to reflect the diet quality of the U.S. population and subpopulations. From a practical perspective, the USDA's Economic Research Service provides code to construct the 2010 HEI for the FoodAPS data.

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<sup>1</sup> Yu & Jaenicke (2020) conduct a wide array of robustness checks on how physical activity should be accounted for, the use alternative outputs, whether it matters if the food inputs are measured in grams or calories, on how endogeneity concerns might be handled, and others, all to find that household-level food waste results changed very little as assumptions over specifications changed. Thus, in this paper, we follow Yu & Jaenicke's (2020) baseline model.

### 2.3 Estimating household-level time allocations

Because no single dataset has detailed household-level food purchase information and household-level time allocation data, we impute time allocations from one nationally representative dataset into another. Following a similar approach to Scharadin & Jaenicke (2020), our procedure relies on using household characteristics in one nationally representative sample (i.e., the ATUS) to estimate time allocations and using the recovered coefficient estimates to calculate time allocations for a second sample (i.e., FoodAPS).

One complication when estimating time use variables from the ATUS into FoodAPS is that the collection timeframes are different. The ATUS collects time information for one individual in a household for a single 24-h period; however, FoodAPS collects food-purchasing information for an entire week. Some previous studies facing similar collection period inconsistencies have addressed this issue (You & Davis, 2019) while others have not (Hamermesh, 2007; Scharadin & Jaenicke, 2020). If the timeframe difference is not addressed, it is assumed that daily estimated time allocation is the same for each day of the week and that households participate in the activities each day of the week. These two assumptions are unlikely to hold for our time categories of interest, so we use a modified two-part model (Mullahy, 1998) and day of the week dummies to predict time use for each day of the week not collected.

More specifically, we estimate time allocations  $TA_{i,j,d}$  separately for each day of the week:

$$TA_{i,j,d} = \alpha_{0,j,d} + \beta_{0,j,d} \mathbf{K}_{i,ATUS} + \varepsilon_{i,j,0,d} \quad (1)$$

where  $i$  represents the household,  $j$  represents the time-use activities, and  $d$  represents the day of the week.  $\mathbf{K}_{i,ATUS}$  is a vector representing household characteristics for ATUS observations, including household annual income, average age of household members, highest education level of a household member, region of residence, residence urbanization level, and primary respondent's employment status, sex, and race. These household demographics impact time spent in household committed activities (Hamrick et al., 2011, Hamrick & Okrent, 2014) and have been used to predict daily time allocations using the ATUS (You & Davis, 2019). All household demographics are available in both the ATUS and FoodAPS sample making it possible to estimate time allocations for FoodAPS households. After recovering the estimates for  $\beta_{0,j,d}$ , we calculate

$$\widehat{TA}_{i,j,d} = \alpha_{0,j,d} + \widehat{\beta}_{0,j,d} \mathbf{K}_{i,FoodAPS} \quad (2)$$

where  $\mathbf{K}_{i,FoodAPS}$  represents the same vector of household characteristics in (1), but now for FoodAPS observations. This treatment results in a time estimate for each time activity for each day of the week. We then estimate a weekly time allocation similar to You & Davis (2019) by summing the seven daily time estimates for each time category.

### 2.4 Estimating associations between food waste, diet quality, and time

To model the relationship between food waste, diet quality, and time, we follow the steps of Scharadin & Jaenicke (2020) who show Rosenzweig & Paul Schultz (1983)

commodity production function can be used to specify household diet quality production function and empirically estimated as a hybrid function. In our approach, we add a second commodity production function for food waste, which could alternatively be thought of as food management. More specifically, we model households as using market inputs and time to produce household commodities and maximize utility. Household diet quality, measured by the HEI, and food waste, as estimated separately using the methods previously described, are two of these commodities.

As in Scharadin & Jaenicke (2020), we specify household HEI as depending directly on purchased food items,  $X_f$ , the amount of time spent in food-at-home activities,  $T_f$ , and household characteristics,  $K$ , related to the efficiency of diet-quality production. Given that households must participate in committed activities (Kalenkoski et al., 2011) and the impact these have on food-related activities (Kalenkoski & Hamrick, 2013), the production process is conditional on time spent in committed activities. Whereas Scharadin & Jaenicke (2020) included time allocations for three categories of committed activities, we disaggregate and extend the time categories to better reflect COVID-19-related changes and to investigate time's impact at a more disaggregate level. Thus, we make the production process for HEI conditional on time spent in work-related activities,  $T_w$ , commuting,  $T_c$ , primary childcare,  $T_p$ , secondary childcare,  $T_s$ , household activities,  $T_h$ , the number of grocery store events,  $GS$ , and the number of weekly dining out events at quick-service restaurants,  $D_{QSR}$ , and full-service restaurants,  $D_{FSR}$ . Finally, we specify food waste production to be a function of the same factors.

The optimized values of purchased food items and time spent in FAH and activities,  $X_f^*$ ,  $T_f^*$ , will be determined by exogenous factors such as wages, prices, households' in-home environments, and the built environments in which the household interacts. To control for the in-home environment and household wage (Mincer, 1974), we use a vector of household demographics,  $K$ , and to control for prices and the built environment, we use geographic fixed effects,  $G$ . This vector of household demographics,  $K$ , is different from the vector used to predict household time allocations and includes household annual income, highest education level of a household member, vehicle access, number of adults in household, level of nutrition education, use of grocery shopping list, presence of a child, and race of primary respondent.  $X_f^*$  is not directly included in our estimation; however, a direct estimate of  $T_f^*$  is included in the empirical estimation because we have direct interest in this activity. Therefore, we jointly estimate the following hybrid production functions for food waste and diet quality.

$$HEI^* = H(T_f, T_w, T_c, T_p, T_s, D_{FSR}, D_{QSR}, GS, K, G) \text{ and} \quad (3)$$

$$FW^* = W(T_f, T_w, T_c, T_p, T_s, D_{FSR}, D_{QSR}, GS, K, G). \quad (4)$$

## 2.5 Predicting food waste and diet quality under COVID-19 scenarios

Using our estimation results for (3) and (4), we predict changes in household food waste and diet quality for non-marginal time changes associated with the early weeks of the COVID-19 pandemic. During this time, bars and sit-down restaurants closed, households reduced grocery store trips, and schools and childcare facilities shutdown to reduce the spread of the virus. We investigate the impact of these significant



changes by constructing three scenarios based on hypothetical assumptions about household heads: (i) they are likely able to keep their jobs and work remotely; (ii) they are likely to lose their jobs; and (iii) they are likely considered an essential worker, meaning they would keep their job and work on site.

### 2.5.1 Creating the COVID-19 scenarios

For FoodAPS households who reported being employed, several significant COVID-19 impacts will vary across households based on which scenario (remote work, unemployed, essential worker) they are assigned. The probability of being in a particular constructed scenario is based on the occupation type of the household head. However, because detailed occupation information is not available in FoodAPS, we must predict the probability a household will be in a particular scenario using the ATUS and a similar two-step process as the one used to estimate time allocations. First, we assign each occupation category in the ATUS to a COVID-19 scenario. Second, we estimate a multinomial logit model to regress the three COVID-19 scenarios on household demographics according to

$$\Pr(\text{scenario}_i = c) = \frac{e^{\beta_c \mathbf{K}_{i,ATUS}}}{\sum_{j=1}^4 \sum_{k=1}^4 e^{\beta_j \mathbf{K}_{i,ATUS}}} \quad (5)$$

where  $\mathbf{K}_{i,ATUS}$  is again a vector representing household characteristics for ATUS observations including household annual income, number of children in household, average age of household members, highest education level of a household member, region of residence, residence urbanization level, and primary respondent's sex, and race. These demographics are associated with the likelihood a household head is able to work remotely, is in the labor force, or lost their job during the pandemic (Kawaguchi & Hiroyuki, 2020, Montenovo et al., 2020). Although there are only three COVID-19 scenarios of interest, there are four used in the estimation process. Households that reported being unemployed or not in the labor force are used as the outside group in the multinomial estimation process. Finally, using the recovered parameter estimates, we calculate the probability that a FoodAPS household head is in one of the COVID-19 scenarios according to

$$\hat{\Pr}(\text{scenario}_i = c) = \frac{e^{\beta_c \mathbf{K}_{i,FoodAPS}}}{\sum_{j=1}^4 \sum_{k=1}^4 e^{\beta_j \mathbf{K}_{i,FoodAPS}}} \quad (6)$$

and assign households to the scenario with the highest predicted probability. Households with a highest predicted probability of being unemployed or not in the labor force are assigned to the essential worker scenario because no occupation related time changes are made in this group.

### 2.5.2 COVID-19 scenario time allocation assumptions

Our three COVID-19 scenarios are meant to capture the impact of the first weeks of the pandemic. During these weeks, many individuals felt the pandemic, and consequently accompanying job loss and firings, would be temporary. In addition, Congress quickly signaled that it would provide additional assistance through increased unemployment

payments, one-time stimulus checks, and increased food assistance to households negatively impacted by the economic shutdown. For these reasons, we do not alter household income in any of our scenarios and therefore changes to food behavior are due to time activity changes rather than income changes.

A number of COVID-19 restrictions will impact households in all three constructed scenarios. More specifically, to account for the closing of bars and sit-down restaurants and the recommended reduction of grocery store trips, we artificially restrict household grocery shopping events,  $GS$ , to one per week and sit-down restaurant and bar events,  $D_{FSR}$ , to zero. We do not alter the number of quick-service restaurant events,  $D_{QSR}$ , because purchasing take-out food was not restricted. We apply these restrictions to each of the three COVID-19 scenarios because they are government imposed and not conditional on job type. These are the only restrictions applied to FoodAPS households that reported being unemployed or not in the labor force during the survey collection.

Under the remote-working scenario, we reduce commuting time,  $T_c$ , to zero; under the unemployed scenario, we reduce work time,  $T_w$ , and commuting time,  $T_c$ , to zero; and under the essential worker scenario, we do not change these household time values. Of course, under the remote and lost job scenarios, households will shift time from restricted activities to unrestricted activities. Therefore, we increase time spent in FAH,  $T_f$ , and household activities,  $T_h$ , proportionally to how the household allocated their time before COVID-19. A specific example for FAH time is provided by

$$T_{f,i,remote} = \widehat{T}_{f,i} + \left( \frac{\widehat{T}_{f,i}}{112} \right) * \widehat{T}_{c,i} \quad (7)$$

$$T_{f,i,unemployed} = \widehat{T}_{f,i} + \left( \frac{\widehat{T}_{f,i}}{112} \right) * (\widehat{T}_{c,i} + \widehat{T}_{w,i}) \quad (8)$$

where remote means the household is able to continue working from home, unemployed means the household work time is zero, and 112 is the number of awake hours per week<sup>2</sup>. For households with children, school and childcare facility closures force households to reallocate approximately 40 h per week to own childcare. In order to assess the impact of the increase in own childcare, we assign the additional 40 h of childcare according to each household's primary,  $T_p$ , and secondary childcare,  $T_s$ , ratio. Specifically,

$$T_{p,i,restricted} = \widehat{T}_{p,i} + \left( \frac{\widehat{T}_{p,i}}{\widehat{T}_{p,i} + \widehat{T}_{s,i}} \right) * 40 \quad (9)$$

$$T_{s,i,restricted} = \widehat{T}_{s,i} + \left( \frac{\widehat{T}_{s,i}}{\widehat{T}_{p,i} + \widehat{T}_{s,i}} \right) * 40 \quad (10)$$

where restricted means the value is applied to both the remote-working and unemployed scenarios. After predicting food waste and diet quality for each

<sup>2</sup> Here we assume a household sleeps for 8 h per night, therefore leaving  $16 \times 7 = 112$  waking hours per week.

household under the three scenarios, we compare means in order to discuss how COVID-19's effect on time may, in turn, impact these two outcomes, which as noted above are related to important USDA policy goals.

### 3 Data

To estimate time spent in six committed activities, we follow the approach of previous papers and use the ATUS (Hamermesh, 2007; Gelber & Mitchell, 2012; Scharadin & Jaenicke, 2020). The ATUS sample is randomly selected from a subset of completed interviews from the Current Population Survey. Respondents are interviewed about their time in the previous 24-h period, with rich information collected about how they spent their time, where they were, and whom they were with during each of 400 activities. The ATUS has continually collected time use information since 2003; however, we restrict our ATUS sample to 2 years before and 2 years after the year the FoodAPS sample was collected, 2010–2014, for two reasons. First, major time use trends are considered stable over time and are therefore traditionally pooled over multiple years (Cawley & Liu, 2012; Ng & Popkin, 2012; Fox et al., 2013). Second, despite this consistency over time, there is evidence to suggest that major economic events, such as the 2008 recession, shift time trends, particularly around food (Hamrick & Okrent, 2014, Aguiar et al., 2013).

The detailed information about household demographics is an important aspect of the ATUS that allows us to predict household time activities outside the dataset. We estimate the time use for six committed activities using household income, maximum education level in the household, region of residence, metropolitan area status, race, gender, and employment status of the primary respondent, month and day of week of the interview, and whether the interview was conducted on a holiday. In addition, because the presence of a child (Gliebe & Koppelman, 2002) and being a single-headed household (Douthitt, 2000, Harvey & Mukhopadhyay, 2007) significantly impact household time allocations, we estimate the time activities separately for four groups: single-headed households without children, single-headed households with children, multi-headed households without children, and multi-headed households with children<sup>3</sup>. We estimate time spent in work activities, commuting, grocery shopping, preparing, cleaning, and eating FAH, and household activities for all households. For households with children, we also estimate time spent in primary childcare and secondary childcare separately because of their differing impact on diet quality (Scharadin & Jaenicke, 2020) and probability of a child being overweight or obese (You & Davis, 2010).

The detailed information about household demographics and occupation category in the ATUS also allows us to estimate the multinomial logit model in (5). To

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<sup>3</sup> Although there is demographic information available on other household members, only the demographic information, i.e. race, gender, employment status, of the primary respondent is used. When partitioning by household head category, if the number of household members 18 years of age or older is greater than 1, that household is included in the multi-headed household group. If the number of household members 18 years of age or older is equal to 1 or 0, that household is included in the single-headed household group. As an example, a 17-year old living on their own would be a household with 0 members over 18-year old, but considered a single-headed household.

**Table 1** ATUS general occupation category scenario assignments

COVID-19 scenario	ATUS general occupation code and description
Able to work remotely	Management Occupations (0110), Business and Financial Operations (0111), Computer and Mathematical Science (0120), Architecture and Engineering (0121), Life, Physical, and Social Sciences (0122), Legal Occupations (0124), Sales and Related (0140), Education (0125)
Lost job	Food Preparation and Serving Occupations (0132), Travel Occupations (0200), Arts, Design, and Entertainment (0126)
Essential worker	Healthcare Practitioner (0127), Protective Services (0131), Farming, Fishing, and Forestry (0160), Installation, Maintenance, and Repairs (0180), Construction and Extraction (0170)

estimate the multinomial logit, we first assign each of the 22 general occupation categories in the ATUS to one of the three COVID-19 scenarios. Table 1 presents the COVID-19 scenario we assigned each general occupation category.

After excluding observations with known data issues, i.e., time values more than four standard deviations above the mean and missing values, we estimate time allocations for each day of the week using 45,465 ATUS observations. Table 2 presents the definition and sample means for time activities and households demographics used in the estimation of (1). Individuals in our sample spent an average of 74 min in household activities, 207 min in work activities, 15 min commuting, and 75 min in FAH activities. The average household income is about \$69,000 and the average household age is around 47 years old. In addition, a majority of respondents identify as white, female, are employed, and live in a metropolitan area. Multi-headed households with children are the largest of the sub-groups and account for about 36% of the sample, whereas single-headed households with children are the smallest of the sub-groups and account for about 6% of the sample.

For the remainder of the variables in (3) and (4), namely food waste, the HEI, household demographic controls, and geographic controls, we use the FoodAPS dataset. The Economic Research Service and the Food and Nutrition Service collected data on food item purchases acquisitions, household demographics, and location information between April 2012 and January 2013 through mixed methods of barcode scanning, receipt validation, food diaries, and telephone interviews (Page et al., 2019). Although other food-purchasing and consumption datasets are available, such as Nielsen, IRI, and NHANES, FoodAPS is unique because it contains detailed household demographic, location information, item-level nutrition information for purchased and acquired foods, and individual health characteristics. Each of these components are essential to estimating (3) and (4). Numerous studies investigating topics related to the food environment (Wilde et al., 2014; Hillier et al., 2017), nutrition education (Chang et al., 2017), diet quality (Whiteman et al., 2018; Dorfman et al., 2019; Scharadin & Jaenicke, 2020), and food waste (Yu & Jaenicke, 2020) have utilized the detailed FoodAPS data.

In order to measure household diet quality, we calculate the HEI-2010 score using both micro- and macronutrient information and Food Pattern Equivalent values for each food item in FoodAPS. The HEI score ranges from 0 to 100 and is based on 12 components, including nine adequacy components (e.g., whole fruit, whole grains,

**Table 2** Definitions and sample means for the ATUS sample

Variable name	Definition	Mean (Std.)
Household activities	Daily minutes spent in ATUS codes 020000, excluding 020200 Ex. Pet care, cleaning the house, paying bills	108.84 (0.67)
Paid work	Daily minutes spent in all ATUS codes 050000 Ex. Work, travel as part of job, paid hobbies	207.13 (1.64)
Commuting	Daily minutes spent in all ATUS code 180500 Ex. Traveling to and from work	15.14 (0.19)
Food at home activities	Daily minutes spent in all ATUS codes 020200, 110000, 180202, 181100 when in the home. Ex. Cooking dinner, washing the dishes	74.40 (0.41)
Primary childcare	Daily minutes spent in all ATUS codes 030100, 030200, 030300 Ex. Bathing a child, helping with homework	69.93 (0.89)
Secondary childcare	Daily minutes spent in all ATUS codes while also providing childcare Ex. Doing laundry, while performing childcare	238.45 (2.08)
Annual HH. income	Total annual income for HH members over 18 (\$)	69,292 (362.15)
Avg. household age	Average HH age for member over 18	47.04 (0.06)
White primary resp.	Primary respondent identified as white	0.82 (0.00)
Black primary resp.	Primary respondent identified as black	0.12 (0.00)
Asian primary resp.	Primary respondent identified Asian	0.04 (0.00)
Hispanic primary resp.	Primary respondent identified as Hispanic	0.14 (0.00)
Male primary resp.	Primary respondent identified as male	0.48 (0.00)
HH member has bachelor's degree	Highest level of education at least a bachelor's degree	0.42 (0.00)
Employed primary resp.	Primary respondent is employed	0.61 (0.00)
City	Household reside in a city center	0.26 (0.00)
Metro	Household resides in a metropolitan area	0.57 (0.01)
West	Household reside in the West Census region	0.22 (0.00)
<i>Observations: full sample</i>		45,465
Single-head no children	1 adult member, no members under 18 years old	12,309
Single-head children	1 adult member, at least one member under 18 years old	2709
Multi-head no children	>1 adult member, no members under 18 years old	14,048
Multi-head children	>1 adult member, at least one member under 18 years old	16,399

and dark green and orange vegetables) and three moderation components (e.g. empty calories and sodium). Points in each component are awarded in reference to a per 1000 calories metric (or to a percent of calories metric) with a maximum score of 5 or 10 points (Guenther et al., 2013). Although the USDA and DHHS update federal dietary guidelines every 5 years (DeSalvo et al., 2016a), we calculate the HEI-2010 scores, rather than the HEI-2015 scores, because the 2010 Dietary Guidelines were in place during the FoodAPS collection period. While the HEI was originally developed to measure the diet quality of food consumption, it has been shown to be an accurate

measure of household diet quality using food purchases as well (Appelhans et al., 2017; Krebs-Smith et al., 2010; Volpe & Okrent, 2012, Guenther et al., 2014; Reedy et al., 2010). Following the approach used in Mancino et al. (2018), we calculate the HEI-2010 score for all food purchases. We exclude 102 households from the analysis because they have insufficient food purchases during the sample week to calculate the HEI.

Food-waste estimates for FoodAPS households are recovered using the productivity analysis approach used by Yu & Jaenicke (2020). As noted in their paper, the transformation of output-oriented inefficiency to input-oriented inefficiency, i.e., food waste, involves the use of the quadratic formula, and some observations do not provide solutions as real numbers. Consequently, the number of total observations with valid food waste measures is reduced to 3304.

After excluding observations with missing HEI-2010 scores, food-waste estimates, or missing covariates, we estimate (3) and (4) using 3298 observations. Table 3 presents definitions and means for the time activities and household demographics used in the estimation of (3) and (4). The first column provides estimates for the full sample, while the second and third columns provides estimates for households with children and households without children, respectively. The average household in our sample wastes approximately 32% of food purchases and has an HEI-2010 score of 51.36, matching previous estimates of both diet quality (Mancino et al., 2018) and food waste (Yu & Jaenicke, 2020). The average household with children wastes a lower percent of their food purchases and has a lower HEI-2010 score, while the opposite is true for households without children. In terms of time, the average household in our sample spends 9.7 h in FAH activities, 18.2 h working, 1.3 h commuting, and 15 h in household activities per week. Both households with and without children spend the most time in work activities, when only primary activities are considered; however, when secondary activities are considered, households with children spend more time, 36 h per week, in secondary childcare.

Table 4 presents the mean hours per week for time activities that had COVID-19 scenario assumptions imposed on them. The number of full-service restaurant and grocery store events are not included in the table because they are fixed at zero and one respectively. Time spent in food at home activities ranged between 8 h per week for households without children in the remote scenario and 12 h per week for households with children in the unemployed scenario. In general, households in the unemployed scenario saw the largest increase FAH time. As similar pattern exists for time spent in household activities, with households without children in the remote scenario spending approximately 12 h per week and households with children in the unemployed scenario spending approximately 19 h per week in the activity. Time in work-related activities is unchanged for households in the remote and essential scenarios, while time spent commuting is set equal to zero for all but the essential scenario.

The largest changes in time allocations are for primary and secondary childcare. Households with children needed to significantly increase time in own childcare as schools and daycares closed. Time spent in primary childcare nearly doubled to 21.5 and 18.6 h per week for households in the remote and unemployed scenarios respectively, whereas households in the essential scenario are estimated to spend about 8 h in primary childcare. This difference follows reality because essential

**Table 3** Definitions and sample means for the FoodAPS sample

Variables	Description	All households	Households with children	Households without children
Food waste	Estimated percent of household food waste	31.85 (0.27)	25.28 (0.29)	37.86 (0.40)
HEI-2010 score	HEI-2010 score for weekly household food purchases	51.36 (0.22)	50.25 (0.31)	52.38 (0.32)
Quick-service restaurant events	The number of purchase events at quick-service restaurants	1.41 (0.07)	1.71 (0.11)	1.11 (0.08)
Full-service restaurant events	The number of purchase events at full-service restaurants	1.15 (0.07)	1.27 (0.12)	1.26 (0.07)
Grocery events	The number of purchase events at grocery stores per week	2.73 (0.04)	2.91 (0.06)	2.56 (0.05)
FAH time	Estimated time spent cooking, cleaning, and eating food in the home in hours per week	9.71 (0.06)	10.50 (0.08)	8.98 (0.07)
Work time	Estimated time spent in income earning activities in hours per week	18.24 (0.32)	19.28 (0.44)	17.28 (0.45)
Commuting time	Estimated time spent traveling to income earning activities in hours per week	1.30 (0.02)	1.36 (0.03)	1.25 (0.03)
Household activity time	Estimated time spent household activities in hours per week	15.28 (0.10)	16.29 (0.14)	14.35 (0.12)
Primary childcare time	Estimated time spent in childcare as the primary activity in hours per week	4.96 (0.12)	10.37 (0.18)	
Secondary childcare time	Estimated time spent in childcare as the secondary activity in hours per week	17.16 (0.35)	35.90 (0.34)	
Natural log of household income	The natural log of household annual income	7.92 (0.01)	7.99 (0.02)	7.86 (0.02)
Bachelor's degree	At least one household member has at least a bachelor's degree	0.28 (0.01)	0.25 (0.01)	0.30 (0.01)
Car	Household has access to a vehicle when needed	0.87 (0.01)	0.89 (0.01)	0.85 (0.01)
Number of adults	The number of household members over 18 years old	1.95 (0.02)	2.20 (0.02)	1.73 (0.03)
MyPlate	The household is aware of the federal MyPlate guidelines	0.24 (0.01)	0.26 (0.01)	0.21 (0.01)
Grocery list	How frequently a grocery list is used on a scale from 1 (infrequent) to 5 (frequent)	3.34 (0.03)	3.28 (0.04)	3.40 (0.04)
Child	At least one household member is less than 18 years old	0.48 (0.01)	1.00 0.00	0.00 0.00
Black	Primary respondent identifies as African American	0.13 (0.01)	0.16 (0.01)	0.10 (0.01)
Asian	Primary respondent identifies as Asian	0.03 (0.00)	0.02 (0.00)	0.04 (0.01)
Hispanic	Primary respondent identifies as Hispanic	0.18 (0.01)	0.26 (0.01)	0.11 (0.01)
Observations		3,298	1,576	1,722

Table 4 Mean time allocations for time activities in COVID-19 scenarios

	All households			Households with children			Households without children		
	Remote	Unemployed	Essential	Remote	Unemployed	Essential	Remote	Unemployed	Essential
Number of quick-service restaurant events	1.93 (0.09)	1.33 (0.05)	0.93 (0.05)	1.95 (0.11)	1.30 (0.07)	1.13 (0.10)	1.91 (0.14)	1.39 (0.08)	0.85 (0.05)
Time in food at home activities	9.70 (0.12)	11.03 (0.07)	11.22 (0.09)	11.27 (0.17)	12.09 (0.07)	11.57 (0.21)	8.00 (0.12)	9.26 (0.10)	11.09 (0.10)
Time in work-related activities	26.80 (0.65)	0.00	4.77 (0.34)	22.47 (0.91)	0.00	10.90 (0.96)	31.47 (0.84)	0.00	2.43 (0.25)
Time commuting	0.00	0.00	0.36 (0.03)	0.00	0.00	0.86 (0.07)	0.00	0.00	0.18 (0.02)
Time in household activities	13.97 (0.18)	17.78 (0.12)	17.88 (0.17)	15.99 (0.26)	19.18 (0.14)	18.25 (0.41)	11.79 (0.19)	15.45 (0.16)	17.74 (0.17)
Time in primary childcare	11.18 (0.49)	11.64 (0.30)	2.30 (0.14)	21.54 (0.52)	18.64 (0.30)	8.35 (0.33)			
Time in secondary childcare	34.86 (1.33)	42.96 (0.92)	8.86 (0.45)	67.17 (0.64)	68.80 (0.44)	32.09 (0.66)			
Observations	684	1433	1181	355	894	327	329	539	854



workers continued to work on-site and therefore could not participate in primary childcare as easily. Secondary childcare also nearly doubled to about 68 h per week for households in the remote and unemployed scenario. For a similar reason to primary childcare, this increase did not happen to households in the essential scenario. These increases highlight the additional time burden of childcare during the pandemic, with households in the remote and unemployed scenarios performing some form of childcare during approximately 80% of weekly waking hours<sup>4</sup>.

## 4 Results

We first discuss the results from the joint estimation of (3) and (4) for the full FoodAPS sample and the sub-sample results for households with at least one child under 18 years old and for households with no children under 18 years old. Table 4 presents the results for all three of these estimations. Afterwards, we present and discuss the results of the three COVID-19 scenarios in Table 5. Results for the multinomial logit regression used to predict the COVID-19 scenario for each household are presented and briefly discussed in Appendix A.

### 4.1 Food waste and diet quality joint estimation

The first few rows of Table 5 show how food-purchasing events and predicted time directly related to food activities influence food waste and diet quality. The number of quick-service restaurant events, number of grocery store events, and time spent in FAH activities are all negatively related to food waste. In general, each of these signs follow intuition. For example, each additional grocery store visit per week is expected to reduce food waste by 0.79 percentage points, a result that echoes previous literature suggesting increased shopping frequency decreases the probability that food, especially fresh produce, will spoil (Lee, 2018). In addition, each additional hour spent in FAH activities is expected to reduce food waste by 1.60 percentage points. The more time a household allocates to preparing, cooking, and cleaning-up meals at home, the less likely that food purchased at the beginning of the week will go unused. Both quick-service restaurant and full-service restaurant events are negatively associated with food waste, but only quick-service restaurant events are statistically significant. Households may plan quick-service restaurant events into their food plan for the week, i.e. getting take out on a particularly busy night, thus avoiding purchasing excess food.

We find similar trends for quick-service restaurant and full-service restaurant events with regard to diet quality. An additional quick-service restaurant event per week is associated with an expected decrease of household HEI by 0.51 points. An additional full-service restaurant event is also expected to decrease household HEI, but this decrease is not statistically significant. The negative relationship follows past literature that has shown increased food away from home consumption decreases diet

<sup>4</sup> Assuming that an individual devotes 8 h to sleeping each night, there are 16 waking hours for each day of the week. Households in the remote and unemployed scenarios perform approximately 88 h of total childcare. Therefore,  $88/(16 \times 7) = 0.78$ .

Table 5 Results for the joint estimation of (3) and (4) for the full FoodAPS samples and children subsamples

	All households		Households with children		Households with no children	
	Waste	HEI	Waste	HEI	Waste	HEI
Grocery events	-0.79*** (0.10)	0.44*** (0.10)	-0.77*** (0.12)	0.39*** (0.14)	-0.68*** (0.17)	0.63*** (0.16)
FAH time	-1.60*** (0.24)	0.23** (0.11)	-0.77** (0.35)	0.21 (0.41)	-2.79*** (0.40)	0.3 (0.38)
Quick-service restaurant events	-0.51*** (0.12)	-0.38* (0.21)	-0.38*** (0.14)	-0.31* (0.16)	-0.54*** (0.18)	-0.42** (0.21)
Full-service restaurant events	-0.12 (0.14)	-0.2 (0.14)	-0.25 (0.16)	-0.04 (0.18)	-0.02 (0.21)	-0.24 (0.20)
Work time	-0.26*** (0.08)	-0.08 (0.08)	-0.14* (0.08)	-0.07 (0.10)	-0.43*** (0.16)	-0.05 (0.15)
Commuting time	1.99* (1.11)	1.04 (1.11)	-0.27 (1.14)	1.05 (1.35)	4.15* (2.16)	0.51 (2.04)
Household activity time	0.37*** (0.14)	0.03 (0.14)	-0.06 (0.18)	0.12 (0.21)	0.90*** (0.25)	0.07 (0.23)
Primary childcare time	0.23*** (0.07)	0.17** (0.07)	0.25*** (0.07)	0.23*** (0.08)		
Secondary childcare time	-0.10** (0.04)	-0.15*** (0.04)	-0.17*** (0.03)	-0.17*** (0.04)		
Natural log of household income	7.33*** (0.35)	1.33*** (0.35)	4.74*** (0.41)	0.96** (0.48)	9.47*** (0.55)	1.35*** (0.51)
Bachelor's degree	4.58*** (0.58)	3.48*** (0.58)	3.01*** (0.75)	3.74*** (0.88)	6.26*** (0.86)	2.94*** (0.81)
Access to car	0.79 (0.69)	1.29* (0.69)	-0.08 (0.86)	1.11 (1.02)	0.12 (1.00)	1.67* (0.94)
Aware of MyPlate	0.61 (0.51)	1.69*** (0.51)	0.36 (0.59)	1.70** (0.69)	1.33* (0.79)	1.68** (0.75)
Uses grocery list	0.36** (0.15)	0.43*** (0.15)	0.51*** (0.18)	0.42** (0.21)	0.13 (0.23)	0.65*** (0.22)
Child in household	-6.67*** (1.04)	1.77* (1.04)				
Observations	3298	3298	1576	1576	1722	1722
R-squared	0.497	0.249	0.443	0.312	0.526	0.334

Standard errors in parentheses

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

quality (Mancino et al., 2009). In contrast to their relation to food waste, the number of grocery store events and amount of time spent in FAH activities are positively related to household HEI. On average, an additional grocery store event per week is expected to increase household HEI by 0.44 points and each additional hour per week of FAH time is expected to increase HEI by 0.23 points. These results follow past literature suggesting that frequent shopping trips are associated with more fresh produce purchases (Pechey & Monsivais, 2015) and that converting that produce into meals requires additional preparation time compared to more processed food options.

Considering non-food committed activities, time spent commuting is positively related to food waste, while time spent working is negatively related. Each additional hour of commuting per week is associated with an increase of about 2 percentage points of food waste. We speculate that households with longer commutes may be more likely to deviate from their original food plan because there are more eating options available along the longer route home. In contrast, each additional hour spent working is expected to decrease food waste by 0.26 percentage points. It is possible that increased work time may affect the composition of food purchases; that is household heads with long work hours may purchase more shelf stable food knowing they will have less time to prepare meals. Furthermore, increased work time may increase the probability that a household adheres to a food plan by decreasing opportunities to deviate during more flexible non-committed time. Hours per week in household activities is not significant for diet quality or food waste.

Time spent in primary childcare is positively related to diet quality and secondary childcare is negatively related to diet quality, a result consistent with Scharadin & Jaenicke's (2020) findings. Although the estimated coefficients are relatively close in magnitude, an increase of 0.17 points per additional hour of primary childcare and a decrease of 0.15 points per additional hour of secondary childcare, households often spend significantly more time in secondary childcare, making the overall impact larger. Similar relationships exist between both childcare types and food waste. Namely, an additional hour in primary childcare is expected to increase food waste by 0.23 percentage points and an additional hour of secondary childcare is expected to decrease food waste by 0.10 percentage points. These relationships can be explained by the same intuition. A household participating in more primary care is likely to purchase more nutritious perishable items, which are associated with higher levels of diet quality because both are considered investments in the child. More nutritious perishable items also increase food waste. In contrast, more time in secondary childcare is associated with distracted and stressed decision making, leading to more shelf-stable processed good purchases. These goods are associated with lower diet quality and less food waste.

The direction of each of these relationships is consistent across the subsamples of households with and without children. However, there are differences in statistical significance for time spent in FAH, commuting, and household activities in relationship to food waste. For households with children, time spent in primary and secondary childcare seems to dominate the relationship for HEI. Although, the number of quick-service restaurant and grocery store events remains significant, time spent in childcare is the only time allocation statistically significant. A similar but weaker effect is present in relation to food waste for households with children. While primary and secondary childcare remain highly significant, time spent in household

activities, FAH activities, and commuting are no longer significant. These results suggest that having a child and participating in childcare fundamentally changes how households allocate time, and therefore impacts their food-waste and diet-quality decisions.

## 4.2 Food waste and diet quality for COVID-19 scenarios

Table 6 presents the average percent of household food waste and HEI-2010 score for each of the three COVID-19 scenarios. The baseline scenario represents each of the FoodAPS households pre-COVID-19, and therefore reflects households' average estimated food waste and HEI without any changes. Each FoodAPS household is assigned to either the remote, unemployed, or essential scenario using the highest predicted probability from the multinomial logit estimation. Given the significant impact of time spent in childcare and household income on food waste and HEI outcomes, we estimate each scenario separately for households with and without children and households above and below 185% of the poverty threshold. We chose 185% of the poverty threshold

**Table 6** Predicted food waste and diet quality under COVID-19 scenarios

	185% or below of PT		Above 185% of PT	
	Household food waste (%)			
<i>Children</i>				
Baseline	21.94	(0.21)	30.08	(0.36)
Remote	27.67 <sup>a</sup>	(0.79)	31.54 <sup>a</sup>	(0.56)
Unemployed	21.73 <sup>b</sup>	(0.25)	26.62 <sup>a,b</sup>	(0.46)
Essential	24.43 <sup>a,b,c</sup>	(0.42)	31.18 <sup>c</sup>	(1.01)
<i>No children</i>				
Baseline	31.91	(0.42)	42.33	(0.41)
Remote	25.53 <sup>a</sup>	(1.49)	38.15 <sup>a</sup>	(0.83)
Unemployed	30.38 <sup>a,b</sup>	(0.76)	43.65 <sup>a,b</sup>	(0.68)
Essential	33.92 <sup>a,b,c</sup>	(0.52)	44.08 <sup>a,b</sup>	(0.60)
	Household HEI-2010 score			
<i>Children</i>				
Baseline	48.60	(0.24)	52.62	(0.34)
Remote	45.62 <sup>a</sup>	(0.75)	58.36 <sup>a</sup>	(0.61)
Unemployed	43.40 <sup>a,b</sup>	(0.30)	47.26 <sup>a,b</sup>	(0.44)
Essential	47.66 <sup>a,b,c</sup>	(0.47)	50.97 <sup>a,b,c</sup>	(0.85)
<i>No children</i>				
Baseline	50.54	(0.34)	53.77	(0.28)
Remote	60.31 <sup>a</sup>	(1.93)	52.94	(0.58)
Unemployed	51.01 <sup>b</sup>	(0.63)	54.82 <sup>a,b</sup>	(0.43)
Essential	50.80 <sup>b</sup>	(0.44)	52.97 <sup>b,c</sup>	(0.46)

<sup>a</sup>denotes difference from baseline at 95% level.

<sup>b</sup>denotes difference from remote at 95% level.

<sup>c</sup>denotes difference from unemployed at 95% level.

because it is a common threshold when considering low-income households eligible for federal assistance programs (Ver Ploeg et al., 2015, Todd & Benjamin, 2016).

Households with children that are likely able to continue working either remotely or as an essential worker are predicted to increase food waste regardless of income level; however, the difference is lower for households above 185% of the poverty line. Households in these scenarios must significantly increase time spent in own childcare, mostly secondary childcare, while still allocating time to other activities at pre-COVID-19 levels. Increased time spent in secondary childcare without any time compensation leads to less efficient meal planning and preparing and increased food waste. In contrast, households in the unemployed scenario are able to partially absorb the increase in own childcare because of the reduction in work hours, allowing them to maintain or reduce their level of food waste.

Households without children below 185% of the poverty line, except for essential workers, are expected to reduce food waste. Households that are likely able to work remotely are expected to decrease food waste by about 6.5 percentage points, while households that are likely to become unemployed are expected to decrease food waste by 1.7 percentage points. These households are able to partially reallocate time related to commuting and, for the unemployed group, working to FAH activities, reducing food waste. In contrast, food-waste predictions for households with no children vary substantially depending on the scenario and income level. Households predicted to be essential workers are expected to increase food waste. These households maintain their normal time allocations but visit the grocery store less frequently. Similar trends exist for households without children above 185% of the poverty line, the comparison group with the most amount of food waste. Households assigned to the unemployed scenario are expected to increase food waste by 1.3 percentage points if they are above 185% of the poverty line, but decrease food waste by 1.5 percentage point if they are below 185% of the poverty line. This difference could stem from the closing of full-service restaurant: Higher income households have more food away from home events and thus the impact of decreasing full-service restaurant events to zero is more pronounced.

For households with children, all but one scenario predicts lower diet quality compared to the baseline. Households below 185% of the poverty threshold are expected to reduce their HEI score by 3.3, 5.2, and 0.9 points, respectively, depending on whether they are assigned to the remote, unemployed, and essential worker scenarios. Households above 185% of the poverty line are expected to reduce their HEI scores by 5.4 and 1.6 points, respectively if they are assigned to the unemployed or essential worker scenarios. Although households are invested in the long-term well-being of their children, secondary childcare may overwhelm their diet-quality goals. Households become more focused on the short term because of the additional burden of secondary childcare and therefore are more likely to purchase shelf-stable or convenience goods that are associated with lower diet quality. Only households that are likely able to work remotely and above 185% of the poverty threshold are expected to have a higher HEI score. Income is positively associated with food away from home consumption; therefore, in the baseline scenario these households may have more food away from home events than households below the poverty line. As a result, when full-service restaurant closed, the increase in FAH meals was larger, increasing HEI score.

In general, the diet quality of households without children is impacted less than those with children. Households below 185% of the poverty line assigned to the remote

scenario are expected to have a diet quality statistically different from the baseline scenario. These households are expected to increase their HEI score by almost 10 points. This very large HEI increase highlights the role time constraints play in household meal production. Lower income households are often constrained by both money and time and, therefore relaxing one of the constraints can have a significant impact. The lack of difference in the HEI score between the baseline and remote scenario for households above 185% of the poverty threshold, compared to the statistically significant difference for households assigned to the unemployed scenario, may further illustrate the relationship between money and time in meal production. When households are less constrained by income, additional time is expected to have less of an impact on diet quality. As a result, only very large increases in available time, i.e. losing a your job, will result in changes from the baseline.

## 5 Discussion

This paper builds on two past studies, one predicting food waste using a production efficiency approach (Yu & Jaenicke, 2020) and the other investigating how time spent in select committed activities impacts household diet quality (Scharadin & Jaenicke, 2020). To overcome data obstacles, we use the ATUS to estimate weekly time allocations for time activities related to diet quality and food waste for FoodAPS households. We then jointly estimate the impact of the time activities on household food waste and diet quality, extending past research that considered the topics separately. Finally, we use our estimation results to predict how three COVID-19 scenarios are expected to impact household diet quality and food waste for households with and without children and below and above 185% of the poverty threshold.

In general, we find similar interpretations for time events related to food waste and diet quality. Time events that are likely to increase fresh produce consumption, such as increased grocery store events and time spent in FAH activities, are related to higher diet quality and lower food waste, while time events that are associated with lower produce consumption, such as time spent in secondary childcare and work time, are negatively related to both diet quality and food waste. In contrast, we find that commuting and other household activities are only related to food waste. One explanation is that these activities increase the probability that a household deviates from a meal plan. Depending on their alternative choices, it is possible for households to deviate without significantly decreasing their overall HEI score. However, it is likely that a deviation will lead to increased food waste, especially if food items in their original meal plan are perishable.

In addition to the differences between food waste and diet quality, there are differences within time categories that highlight the importance of including disaggregate time categories. For example, if all food activities were considered a single time category, the unique effects of grocery shopping and meal preparation would cancel each other out. In addition, disaggregating food away from home into the number of quick-service restaurant and full-service restaurant events allows us to more accurately model the COVID-19 scenarios and capture the increased impact of quick-service restaurant events on diet quality and food waste.

One explanation for the increased impact of quick-service restaurant is that quick-service restaurant events are often less nutritious and can be a convenient alternative to a full-service restaurant event or making a meal. Therefore, additional quick-service restaurant events could likely decrease a household's diet quality while also decreasing food waste by avoiding preparing FAH. Another important disaggregation is the distinction between primary and secondary childcare. While time spent in primary childcare is positively related to both food waste and diet quality, secondary childcare is negatively related to both.

Using our estimation results, we predict how three COVID-19 scenarios may impact household diet quality and food waste. In general, there are more statistically significant changes for households with children compared to households without. The increased impact of COVID-19-related changes for households with children highlights the additional burden that school and childcare closures have on these households. Under these conditions, households struggle to provide an additional 40 h of own childcare. Given that a majority of this time will be secondary childcare, convenience foods become a more attractive option. These results may be of particular interest to policy makers investigating COVID-19 impacts on households participating in the Supplemental Nutrition Assistance Program because, in addition to other obstacles that low-income households face, a majority are households with children (Cronquist, 2019). Limiting the number of grocery store trips to meet COVID-19 guidelines also has the opportunity to disproportionately impact low-income households. Bulk buying groceries once every 2 weeks may decrease the amount of fresh produce and increase the amount of canned, frozen, and dry goods households will purchase, in turn leading to a decrease in diet quality and food waste. However, low-income households may not have the income to purchase multiple weeks of food at once or have the storage space to accommodate a large purchase.

When interpreting these results, there are a number of limitations to consider. First, our model predicts changes in food waste and diet quality using observations from past behavior. Therefore, the predicted scenarios are not able to capture changes in preferences around recent trends, such as baking bread at home or creating "focaccia gardens" (Nierenberg, 2020). We are also not able to capture the impact of stockpiling decisions made in the early weeks of the pandemic. Households stockpile shelf-stable goods, such as canned soup and dry pasta, which are often higher in sodium and less nutritious. Therefore, we may expect lower food waste and lower diet quality in scenarios that included stockpiling. However, the overall impact is difficult to predict because households may also become more health conscious, considering healthy eating as an additional preventative measure against COVID-19, and consume more frozen fruits and vegetables.

Our analysis does also not account for intrahousehold time reallocation that may occur during the pandemic. Although we partition the sample while estimating time allocations, we focus solely on the demographics of the household head while predicting COVID-19 scenarios. This approach assumes that only the primary respondent in the survey affects time allocations. This, of course, may not be true. For example, one household member may lose their job, while the other continues to be employed as an essential worker. If the primary respondent is the essential worker in this example, our approach would predict little change in time

allocations. In reality, household time allocations would change because the other household member is now unemployed. A complete analysis of intrahousehold time allocations requires more in-depth analysis that considers demographic information on spouses similar to You & Davis (2019).

A final limitation is that we do not change household income in the COVID-19 scenarios. From a conceptual standpoint, we assume households believe the loss of income to be temporary or covered by government assistance policies. As a result, although household income will change in the unemployed scenario, engrained household behaviors centered around income level might not change significantly and households would continue to act as if their old level of income is accurate. From a practical standpoint, variation in state unemployment benefit calculations and increased federal unemployment assistance make estimating household income in the unemployment scenario operationally difficult. Therefore, we choose to focus solely on how time activity changes lead to changes in food waste and diet quality.

Although we do not alter the value of household income in the COVID-19 scenarios, we do allow income level to impact our predictions by estimating household diet quality and food waste for households above and below 185% of the poverty threshold. One particularly interesting result highlighted by the income disaggregation is the estimated increase in diet quality for households below 185% of the poverty threshold with no children and able to work remotely. These households have a significant increase in predicted diet quality, while comparable households above 185% or with children see little expected change. In addition, these households are expected to decrease food waste by more than comparable households. This suggests additional flexibility allowed by remote working is particularly beneficial for lower income households, highlighting the role the interaction between income and time plays in household food decisions. While economic literature has long called for the time to be incorporated in food assistance policy (Venn & Strazdins, 2017, Davis, 2014), our predictions suggest that remote working may help increase diet quality and decrease food waste for low-income households in absence of formal inclusion into benefit calculations.

Our study provides a first look at what the “new normal” may be surrounding diet quality and food waste. Although our COVID-19 scenarios are partially based on temporary virus restrictions, past research suggests that major events, such as the 2008 financial crisis (Hamrick & Okrent, 2014), can change long-term time trends around food. In addition, many companies are beginning to explore the benefits of allowing employees to work remotely after the pandemic ends. If businesses are able to decrease overhead costs, increase employee satisfaction, and maintain productivity, remote working may become commonplace, rather than an exception. Finally, households may develop a preference for online shopping platforms while trying to avoid grocery store visits. If delivery is financially possible, households may be able to purchase less shelf stable food and more fresh produce without incurring the additional time cost of numerous grocery trips. The Food and Nutrition Service is exploring this type of time saving service by extending the SNAP Online Purchasing Pilot to six additional states since April 2019. Future research should investigate whether COVID-19 motivates long-term changes in time trends and how that impacts household decision making around food.



## Compliance with ethical standards

**Conflict of interest** The authors declare no competing interests.

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## 6 Appendix A. Multinomial logit estimation results

Information in FoodAPS is not sufficiently detailed to assign households directly to a COVID-19 scenario. Therefore, we predict the probability a household will be in a particular COVID-19 scenario using the ATUS and a similar two-step process as the one used to estimate time allocations. First, we assign each of the 22 general occupation categories in the ATUS to one of the three COVID-19 scenarios. This assignment is detailed in Table 1 of the main text. Second, we estimate a multinomial logit model to regress the three COVID-19 scenarios on household demographics. Results for the multinomial logit regression used to predict the COVID-19 scenario for each FoodAPS household are presented below in Table 7.

Table 7 shows that key predictive demographics follow intuition. A household's level of income and education are positively associated with the probability that a household head is employed in an occupation assigned to the remote work scenario. In contrast, income and education are negatively associated with the probability a household head is employed in an occupation assigned to the unemployed or essential worker scenarios. Occupations that are able to work remotely, e.g. management positions, often have higher salaries and require more formal education than positions with high COVID-19 unemployment rates, e.g. food service positions, or essential worker positions, e.g. construction positions. If a household lives in a city, the household head is more likely to be employed in an occupation assigned to the remote work or unemployed scenarios. This makes sense because there are more office and food service positions in urban areas. Being male increases the probability of being assigned to the essential scenario. Many occupations considered essential under COVID-19 restrictions, e.g. construction, protective services, etc., have traditionally higher male employment rates. Given the intuitive interpretation of key demographic variables, we are confident that the multinomial logit estimation process provides a good prediction of which scenario a household would face under COVID-19 restrictions.

Table 7

Table 7 Average marginal effects for the multinomial logit regression

	Remote worker	Unemployed	Essential worker
Log of annual income	0.0506*** (0.003)	-0.0411*** (0.003)	-0.0042 (0.004)
Highest level of education in household is "some college"	0.0312*** (0.006)	-0.0210*** (0.006)	-0.0108** (0.005)
Highest level of education in household is a BA	0.2280*** (0.005)	-0.1330*** (0.005)	-0.0914*** (0.005)
Household resides in a city center	0.0199*** (0.007)	0.0276*** (0.007)	-0.0485*** (0.006)
Household resides in an urbanized area	0.0021 (0.006)	0.0285*** (0.006)	-0.0334*** (0.005)
Number of children between 13 and 18 years old	-0.002 (0.004)	-0.0103*** (0.004)	0.0106*** (0.003)
Number of children 12 years old or younger	-0.0006 (0.002)	-0.0067*** (0.002)	0.0107*** (0.002)
Average household age	-0.0008*** 0.000	-0.0005*** 0.000	-0.0009*** 0.000
Primary respondent identifies as male	-0.0347*** (0.004)	-0.0714*** (0.004)	0.1074*** (0.004)
Primary respondent identifies as black	-0.009 (0.017)	-0.019 (0.017)	0.0291* (0.015)
Primary respondent identifies as Asian	-0.01 (0.018)	-0.0061 (0.019)	0.0138 (0.017)
Primary respondent identifies as Hispanic	-0.0657*** (0.007)	0.0260*** (0.006)	0.0339*** (0.006)
Household resides in the Midwest Census Region	-0.0067 (0.007)	0.0015 (0.007)	0.0055 (0.006)
Household resides in the South Census Region	0.0064 (0.006)	-0.0116* (0.006)	0.0054 (0.006)
Household resides in the West Census Region	0.0127* (0.007)	-0.0113 (0.007)	-0.0006 (0.006)
Observations	37,910	37,910	37,910

Standard errors in parentheses

Outside group is households not in the labor force

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

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