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WOODWARD, JONATHAN VENESS, Ph.D. Three Essays on Economic Influences for Meal Decisions (2012)
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This dissertation focuses on two relationships: how wages and the value of time influence the decisions to spend time preparing food and eating meals, and how government food subsidies affect the types of foods that children in a household eat. Although time spent preparing food and eating regular daily meals are both known to be important to health, past research has not made it clear how increased wages may affect those decisions.

In the first essay, I develop a stylized model that illustrates how higher wages may reduce meal production time but have ambiguous effects on meal consumption time. I then examine relationships using time diary information from the American Time Use Survey (ATUS) supplemented with wage information from the Current Population Survey (CPS). Using standard and censored regression models, analyses indicate that for meal production time, women experience a negative effect from wages on weekdays, as predicted by theory, and no effect on weekends. However, men show no weekday effect and a surprising positive effect of wages on weekends, suggesting that men with a high value of weekday time may substitute weekend meal production time for weekday time. Higher wages are associated with more meal consumption time for both men and women on weekdays and weekends, indicating that consumption time is a normal good.

The second essay combines detailed data from the National Health and Nutrition Examination Survey (NHANES) on eating behaviors with wages imputed using the CPS. These allow estimation of multivariate Probit and multiple Probit models for the probability that men and women will eat each of breakfast, lunch, dinner, and snacks on weekdays and weekends. Increased wages are associated with increased probabilities of all three meals for both women and men on weekdays, with a significant effect for breakfast for men. However, on weekends,

women with higher wages are less likely to eat all three meals, particularly dinner. Similarly, although higher wage men may still be more likely to eat breakfast and dinner on weekends, they are significantly less likely to eat lunch.

The Supplemental Nutrition Assistance Program (SNAP), the National School Lunch Program (NSLP), the School Breakfast Program (SBP), and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) appear to increase food consumption among households generally and among their intended beneficiaries, much less is known about whether they help other household members. The third essay {joint with David Ribar} uses 2002-2003 data from the second Child Development Supplement of the Panel Study of Income Dynamics to examine the relationship between households' participation in the SNAP, SBP, NLSP, and WIC and individual 10 - 17 year-old children's consumption of particular food items. Analyses indicate that WIC participation by others in the household is associated with a 22 percent increase in breakfast consumption of milk and a 16 percent increase in breakfast consumption of cereal for the children in the sample, while WIC is associated with a 13 percent decrease in toast consumption. Participation in school meals is also associated with increased consumption of some foods, particularly juice, fruit, and sweet snacks. Household SNAP participation is estimated to have positive associations with some foods but negative associations with others.

THREE ESSAYS ON ECONOMIC INFLUENCES

FOR MEAL DECISIONS

by

Jonathan Veness Woodward

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Approved by

____

Committee Chair

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To my parents, Clare and Steve, who taught me to love science and learning,
and to Laura, who suggested I consider studying economics.

APPROVAL PAGE

This dissertation written by Jonathan Veness Woodward has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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TABLE OF CONTENTS

LIST OF TABLES

CHAPTER I

TIME AS AN INGREDIENT IN MEAL PRODUCTION AND CONSUMPTION

Introduction

Meals consume a substantial portion of people's time; people in the U.S. spend an average of over two hours every day on meals (Hamermesh 2007, and Table 1.1 in this paper). Underlying the total time used for meals are two important components that can behave very differently: meal production time and meal consumption time. However, past research has largely choosen to focus on only one of these components or on combined meal time, making it difficult to compare results for the two types of time. This can lead to apparent paradoxes. For example, economic theory suggests that people with higher levels of education will have higher wages and a correspondingly greater value of time, which could lead to less time spent on meals. However, Aguiar and Hurst (2007) find the opposite – more educated people spend more time on meals! Are results like this a consequence of failing to clarify the distinction between meal time that may be a cost and meal time that may be a consumption good? I examine the factors that affect the time allocated to meal production and consumption, with a particular focus on wages as an estimate of the value of time.

These factors are relevant because meal production and meal consumption time have both been found to have significant health effects. When more time is spent on meal preparation, it can result in a healthier and better balanced meal, particularly relative to meals prepared away from home (Chou et al. 2004). Similarly, for a given meal, a slower rate of consumption may result in earlier satiation and a lower risk of obesity (Stibich, 2007). Hamermesh (2009) finds that more time spent eating each day is associated with lower BMI and better health. Finally, eating meals with family members has been shown to improve communication skills in children (Ochs et al. 1992) and reduce problem behaviors in teenagers (CASA 2005), and presumably a longer meal allows more time for these benefits to come into play.

In this paper, I examine how wages and other factors such as family structure influence meal times. To motivate the separate examination of meal production and consumption times, I build upon past research by adapting the general time use models of Becker (1965) and Gronau (1977) to incorporate both of these varieties of time. In particular, I use this stylized model to illustrate how these types of time use may be affected differently by economic and demographic characteristics. A conjecture, based on my model, is that increases in an individual's monetary resources will allow that person to increase food quantity and quality while replacing preparation time with goods. In this situation, there would be a negative income effect on meal production time, but there could be a positive income effect on meal consumption time. Increasing an individual's wages would cause this type of income effect. However, higher wages also increase the opportunity cost of spending time in ways other than working. Therefore, people with higher wages will tend to substitute time working for time producing and consuming meals, leading to a negative substitution effect of wages for both sorts of meal time. If this is so, an increase in the wage rate will have both negative income and substitution effects to reduce meal production time, but positive income and negative substitution effects on meal consumption time, making the outcome ambiguous.

My empirical analysis investigates these hypotheses using the 2006-2008 American Time Use Survey (ATUS). This time diary dataset allows me to measure meal production and consumption times separately using multivariate models of the effects of imputed wages, family size, and other demographic variables. I also separate my analyses by gender, as well as weekdays and weekends. For the analyses of meal consumption times, I estimate standard linear regression models. For the analyses of meal production times, I estimate Tobit models that account for the substantial proportion of observations with censored data. As a sensitivity analysis, I also examine Two-Part and Censored Least Absolute Deviations model specifications.

These analyses of the time used producing and eating meals illuminate issues such as the apparent paradox that people with higher wages and education increase eating times, yet increased wages seem to decrease the time spent on meals. For example, similar to Hamermesh (2009), I find that men and women with higher wages spend significantly more time consuming meals each day than people with lower wages. However, higher wages are associated with women spending significantly fewer minutes producing meals on weekdays, which is consistent with my conjecture of negative substitution effects for meal production times. By demonstrating the importance of treating meal production and consumption times separately, I also hope to illuminate the possibility that production and consumption times should be considered separately for other commodities.

Theory

Becker (1965) theorized that households utilize not simply goods, but also time to produce and consume those goods. He called these consumed combinations "commodities." More formally, a commodity is produced through the combination of goods inputs with time inputs. For this analysis, I focus upon one important commodity, meals, in the context of a highly stylized model. This commodity is produced as a combination of two types of inputs: meal production time T_{MP}, and market goods and services X_M.

Meal production time T_{MP} is a form of home production. This type of time is generally considered to be primarily a cost – an input into acquiring and creating food items. Meal production includes many types of food-related activities, such as cooking, cleaning up, grocery shopping, and buying from a restaurant. Depending upon circumstances, meal production times can vary significantly. Preparing a meal from scratch requires a large amount of meal production time, while heating up a TV dinner is likely to take only a small amount. These variations are partially driven by the fact that compared to other commodities, inputs of meal production time and goods are often highly substitutable.[1]

To model the substitutable nature of meal production time and goods, I borrow the stylized home production model of Gronau (1977) for the production of meals. Prepared meals M are a function of meal production time T_{MP} and market goods and services for meals X_M,

[1] Leung et al. (1997) demonstrate a systematic tradeoff between goods and time across almost 900 recipes in Hawaii.

$$M(T_{MP}, X_M) = f(T_{MP}) + X_M \tag{1}$$

This function is additively separable, meaning that changing the quantity of time or goods does not affect the marginal productivity of the other input. If no time is spent, then *M* is equal to the purchased goods: $M(0, X_M) = X_M$. Also, I assume that $f^{'} > 0$, so additional time on meal production always increases the quantity or quality of meals, but $f'' < 0$, indicating that meal production time has diminishing returns. *M* is assumed to measure both quality and quantity of food.

These prepared meals *M* factor into a person's utility to produce well-being. A person's utility is assumed to depend on *M*, meal consumption time T_{MC}, leisure time *L*, and the consumption of non-meal goods *X*. Utility can therefore be expressed as a function, $U(M, T_{MC}, L, X)$. I assume a Stone-Geary specification for *U*,

$$U(M, T_{MC}, L, X) = (M - \gamma_1)^{\alpha_1}(T_{MC} - \gamma_2)^{\alpha_2}(L - \gamma_3)^{\alpha_3}(X - \gamma_4)^{\alpha_4} \tag{2}$$

In this function, each of the four inputs increases utility, and has productivity α, which determines how much increasing that input will improve utility. Without loss of generality, I assume that $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$. Each input also has a minimum level for subsistence, γ, which consumption must remain above for a person to survive. It is worth noting that this function is log-separable across its inputs; in particular, increasing the quantity of meals *M* will not affect the demand for T_{MC} relative to *L* and *X*, and vice versa.

In addition to meal production time, meal consumption time, and leisure time, there is a fourth possible use of time: hours worked H. For a given time interval, the four uses of time are assumed to be mutually exclusive, and over a day, their sum must equal the total time available:

$$T_{MP} + T_{MC} + L + H = T \tag{3}$$

Similarly, earnings and non-labor income must equal total expenditures on meals and other goods, with prices assumed to be constant and equal to 1 (doing so identifies the relative magnitudes of f, γ_1, and γ_4):

$$wH + N = X_M + X \tag{4}$$

Therefore, individuals will make time allocation decisions for T_{MP}, T_{MC}, L, and H, and goods allocation decisions X_M and X, to maximize utility subject to the time, budget, and production constraints. These decisions are based upon their wages, non-labor income, and the characteristics of the utility function, which includes both needs and the value placed upon quality meals, as well as factors that influence the production technologies for meals and other commodities. The mathematics of this optimization are shown in Appendix B, with the following results.

The optimal value of meal production time T_{MP}, is determined by its diminishing marginal productivity, implied by $f''(T_{MP}) < 0$. This reduced productivity means that after a certain level of meal time input, it will be more efficient for a person to work and purchase goods X_M than to spend additional time on meal production. This will occur when the marginal productivity of meal time, $f'(T_{MP})$, equals w. This makes T_{MP} an implicit function of only f and w, which I express as $T_{MP}(w)$. As I show in Appendix B, increasing wages will have a negative effect upon T_{MP}. However, because w and N are independent, there is no effect of non-labor income on meal production time.

$$\frac{\partial T_{MP}}{\partial N} = 0, \frac{\partial T_{MP}}{\partial w} = \frac{1}{f''(T_{MP})} < 0 \tag{5}$$

Since the negative wage effect is a sum of income and substitution effects, and the effect of income on production time is zero, then the substitution effect for meal production time must also be negative. This means that as wages increase, the person cuts back on meal production time and increases meal expenditures, with increased work time as the mediating variable.

Meal consumption time has an explicit solution, as shown in Appendix B:

$$T_{MC} = \alpha_2\big(T + N/w - \gamma_1/w - \gamma_2 - \gamma_3 - \gamma_4/w - T_{MP}(w) + f\big(T_{MP}(w)\big)/w\big) + \gamma_2 \tag{6}$$

Increasing non-labor income reduces the need for labor hours relative to other time, so there is a positive income effect on meal consumption time. The effect of wages on meal consumption time is ambiguous.

$$\frac{\partial T_{MC}}{\partial N} = \frac{\alpha_2}{w} > 0, \frac{\partial T_{MC}}{\partial w} = \frac{-\alpha_2(N + f(T_{MP}(w)) - \gamma_1 - \gamma_4)}{w^2} \tag{7}$$

When non-labor income is high, relative to the subsistence levels of meals and other goods, increasing wages will have a negative effect on consumption time, as it becomes more efficient to produce commodities through goods than through time. However, if the sum $N + f(T_{MP}(w)) - \gamma_1 - \gamma_4$ is negative, then the person is in the backwards-bending portion of the labor supply curve, and increasing wages will reduce labor hours and increase meal consumption (and leisure) time.

Although the results presented above are for interior solutions to the model, there are a few corner cases which can lead to different results. In particular, a person may choose not to spend any time on meal production, $T_{MP} = 0$, instead purchasing prepared food or having another household member produce the meal. For an employed individual, this will happen when the marginal productivity of meal production time is lower than the wage rate for all values of T_{MP}; in other words, $f'(0) < w$. In this case, meal production time will not be affected by changes in either income or wages, at least not unless wages fall below $f'(0)$. The results for meal consumption time are very similar to those of the interior solution.

$$T_{MC} = \alpha_2(T + N/w - \gamma_1/w - \gamma_2 - \gamma_3 - \gamma_4/w) + \gamma_2 \tag{8}$$

Increasing non-labor income will cause people to cut back on labor hours, leading to a positive income effect on meal consumption time.

$$\frac{\partial T_{MC}}{\partial N} > 0 \tag{9}$$

As with the interior solution, the effect of wages on T_{MC} is ambiguous, and will have a sign opposite of that of the expression $N - \gamma_1 - \gamma_4$.

$$\frac{\partial T_{MC}}{\partial w} = \frac{-\alpha_2(N-\gamma_1-\gamma_4)}{w^2} \tag{10}$$

Another possibility is that a person may choose not to spend any time working, $H = 0$. If non-labor income is sufficiently high relative to wages (and the minimum subsistence levels for time use $w\gamma_2 + w\gamma_3$ are sufficiently large relative to the subsistence levels for goods $\gamma_1 + \gamma_4$), then a person will select labor hours H of zero. In this case, changing the wage rate will not affect a person's total income or time use decisions, so long as wages are not increased enough to induce the person to enter the labor force. Increasing non-labor income, however, will cause a person to increase meal goods and reduce meal production time, resulting in a negative income effect for T_{MP}. There will be a corresponding increase in meal consumption time, indicating a positive effect of income on T_{MC}.

$$\frac{\partial T_{MP}}{\partial N} < 0, \frac{\partial T_{MP}}{\partial w} = 0, \frac{\partial T_{MC}}{\partial N} > 0, \frac{\partial T_{MC}}{\partial w} = 0 \tag{11}$$

Overall, this model has shown that even given a relatively simple structure, meal production and consumption time can respond quite differently to monetary inputs. Across the interior and corner cases, non-labor income has a zero or negative effect upon meal production time, but a positive effect on meal consumption time. Wages also have a zero or negative effect on meal production time, and an ambiguous influence on consumption time. It is important to remember, however, that these outcomes are the result of strong modeling assumptions that may not accurately mirror the real world. Empirical analysis is necessary to investigate these relationships.

Previous Empirical Research

Most past empirical research into meal times has focused on only a single time measure within a given paper, making it difficult to compare meal production and consumption times. For example, Zick, McCullough, and Smith (1996) considered just meal preparation time (the dominant component of meal production time), as did Florkowski et al. (2000), Aguiar and Hurst (2005), Mancino and Newman (2007), and Tashiro (2009). By contrast, Aguiar and Hurst (2007) and Hamermesh (2010) looked at meal consumption time. Finally, Hamermesh (2007) examined a summed value of meal production and consumption times. These single variable approaches present a potential problem, as looking at only one outcome can obscure the effect of factors that affect meal production and consumption in different ways.

Most of the literature on meal production time suggests that higher wages reduce time spent, as suggested by my model. Zick et al. (1996) found that mothers with higher wage rates significantly reduced meal preparation time, and also found a negative (but not statistically significant) effect for non-labor income. Similarly, Florkowski et al. (2000) found that in Bulgaria, increased household income reduced both the probability of and the time that women spent preparing meals. For people before and after retirement, Aguiar and Hurst (2005) showed that retirees spend substantially larger amounts of time preparing food. If retirement represents reduced wage opportunities, then this result is also consistent with a negative wage effect. Finally, using a sample divided by race, Tashiro (2009) found small negative effects for family income on meal production, particularly for whites.

However, Mancino and Newman's (2007) results were only partially consistent with a negative wage effect on meal production time. For higher income women, increased weekly earnings reduced food preparation time, but for low and middle income women, there was no significant effect. For men, higher household income was found to increase food preparation times! These different gender effects are difficult to explain, but may be related to a finding by Zick et al. (2008) that increasing a wife's level of education had a negative effect on her own housework time but a positive effect on her husband's time, while the husband's education had no significant effect on the housework of either spouse. If a man's weekly earnings are positively correlated with his wife's education, and he substitutes his time for hers, that could produce Mancino and Newman's result.

Rather than examining meal production time directly, Davis and You (2009) and Rashcke (2012) instead attempted to assign a monetary value to meal production; in other words, production time spent multiplied by the dollar value of that time. In the process, they estimated a person's marginal meal productivity. Since linear diminishing returns to additional meal production time were assumed, marginal productivity minus wages should be proportional to meal production time. This formulation implicitly assumes that increasing wages reduces meal production time, leaving education and age to represent underlying human capital differences. Separating by gender, Davis and You (2009) found higher levels of education increased both marginal meal productivity and wages. For women, the effect on wages was larger, but for men, meal productivity was increased more by education. More male (but not female) education was therefore correlated with increased meal production time, a result similar to Mancino and Newman (2007). Raschke (2012) studied an aggregate sample of both women and men, and his results imply that increasing levels of education lower meal production time for the combined group.

Meanwhile, greater amounts of meal consumption time have been found to correspond to higher wages and levels of education. Hamermesh (2010) found that for workers with wages, higher wages increase eating and drinking as primary activities, and seem to increase them as secondary activities while doing something else as well, although in a less statistically significant manner. Hamermesh also found that higher levels of education also increase both primary and secondary meal consumption time. Similarly, Aguiar and Hurst (2007) found that in the past few decades, college graduates have increased meal consumption time by over an hour per week, while people without a high school degree have reduced eating by around an hour and a half. This result contrasts with a relative overall increase in leisure time for less educated individuals, and suggests that better wage opportunities are increasingly leading to greater demand for meal consumption time.

In the case of aggregate food time, the sum of both meal production and consumption time, Hamermesh (2007) found that higher wages reduced time spent on food, while (controlling for wages) higher income increased time. These total meal time results could be explained as a combination of a dominant negative wage effect for meal production time and a dominant positive income effect for meal consumption time. Mancino and Newman's (2007) disparate results for male and female meal production times are puzzling, however, and suggest that men may not fit this theory. Therefore, using 2006-2008 ATUS data, I will examine measures of both meal production and consumption time separately for men and women. By examining both production and consumption time under the same models, I hope to better discern differences and similarities for how factors influence the two types of time.

Data

In order to identify the factors which influence meal times, I model meal preparation and meal consumption using data on activity times taken from the 2006, 2007, and 2008 years of the American Time Use Survey. This time-diary survey is well-suited for this analysis, as it contains a report of the primary activities each person in the survey spent his or her time on over the course of a twenty-four hour period. This makes it possible to identify not only the amount of time people spent eating, but also when they were waiting to eat, preparing or cleaning up from meals, shopping for groceries, purchasing other sorts of food, traveling to purchase food, or participating in many other activities. The 2006 through 2008 years of the ATUS also include an Eating and Health Supplement, which reports whether or not individuals were engaged in secondary eating or drinking simultaneously with another activity. This information is important as well, as people often participate in multiple activities at once, such as eating while watching television. Without data on secondary eating, those instances could be missed; this would be a problem, particularly if different types of people are more likely to multitask than others.

The ATUS, along with its extension, the Eating and Health Supplement (EHS), is a time-diary survey conducted by the Census Bureau. A subsample of households from the Current Population Survey (CPS) are contacted by telephone two to six weeks after the final CPS interview, and one individual in that household is interviewed about the use of time during the preceding 24-hour period, from 4:00 a.m. until 4:00 a.m. In addition to demographic information, the ATUS includes a detailed sequence of the activities each person participated in over the course of a day, as well as the locations where each of those activities took place. It is important to note that weekends are over-sampled, such that one half of all observations occur on a weekend. I use the sample weights included in the EHS to control for this, non-response, and other sample design characteristics, in order to make the results nationally representative.

My two categories of meal time use are meal consumption and meal production. However, each of these is itself an aggregation of more specific uses of time. I define meal production time as the sum of time spent on four activities: food preparation, purchasing groceries, purchasing food elsewhere, and time spent acquiring meal preparation services. I calculate meal consumption time using two components: primary eating and secondary eating. Table 1.1 displays the average amounts of time that men and women spend on meals on weekdays and weekends.

The first dependent variable is meal production time, the sum of four categories of time use. The first two categories are part of making one's own meals: preparing food and purchasing groceries. Food preparation itself includes time preparing meals, time presenting meals, and time cleaning up from meals, and takes an average 34 minutes per day for my sample. Purchasing groceries takes an average of six minutes (only one in six people buy groceries on a given day). The third type of meal production time is purchasing food from a non-grocery source, such as a restaurant. People spend about 75 seconds on this each day (most time in a restaurant is classified as eating and thus part of meal consumption). A fourth but trivial method of food production is using meal preparation services, on which the sample spends less than a tenth of a second on average.

For most of my analyses, my measure of meal production time excludes travel time. In principle, travel time should be included because it represents a very real cost for both purchasing groceries and eating at a restaurant. People seem to spend around 13 minutes on travel related to eating and drinking, travel to purchase groceries, and travel to purchase other food each day. The reason for excluding this component, however, is that the ATUS does not specifically ask why people are traveling. Instead of a clear description of the purpose of a trip, people are coded according to their destination (if it is not home), or their origin (if the destination is home). This may be very misleading, particularly in the case of trips with multiple destinations, so I exclude this time from my main analyses. However, in some sensitivity analyses, I consider an alternative specification for meal production time that includes travel time as well as food preparation and purchase times.

My second dependent variable is meal consumption time, of which the first part is primary eating, time that a person spends focused solely on meal consumption. In the ATUS, this is time that people spend eating and drinking, time waiting to eat, and time eating as part of a job. Time spent eating and drinking as a primary activity during the day, along with time spent waiting to eat or drink, combine for an average of 65 minutes a day for individuals in the sample. The third component, eating and drinking as part of a job, is very minor, averaging only about 25 seconds a day.

The second part of my meal consumption measure is somewhat harder to interpret: eating as a secondary activity. This can often be thought of as snacking, because secondary eating is eating that takes place at the same time as another activity. Although daily activities in the ATUS are interpreted as one primary activity per time period, the Eating and Health Supplements question people whether they were also eating during other activities, and for how long. The sample spends about 24 minutes a day on secondary eating.

It is worth noting that eating and drinking are measured differently as primary and secondary activities. The ATUS does not distinguish between primary eating and primary drinking; these are both simply recorded as "eating or drinking". However, the EHS does report secondary eating and secondary drinking separately. The ATUS Eating and Health Module includes a report of secondary drinking of beverages other than water, for which people average 61 minutes a day. However, unlike Hamermesh (2009), I do not include this time in my analysis, as secondary drinking time seems unlikely to represent a meal. It is less likely to be related to health outcomes than eating, and may have a low opportunity cost to the concurrent activity.[2]

[2] Time spent drinking alcohol may affect health, but this effect is likely to be very different than that of time spent eating.

As sensitivity analyses, however, I test alternative specifications for meal consumption time, in order to determine the degree to which my definitions of consumption time are driving my results. One such specification excludes secondary eating, similar to Aguiar and Hurst (2007), leaving only primary eating and drinking. Alternatively, Hamermesh (2009) included secondary drinking in his measure of food time, and I also test the inclusion of secondary drinking in meal consumption time along with primary and secondary eating.

A person's wage opportunities are an important factor in determining the value of time, but about 22% of my sample is not employed, and lack wage data for that reason. In addition, another 9% of my sample do not report their earnings. These are unacceptably large fractions of my sample to drop, and a failure to answer wage survey questions is likely to be endogenous. Therefore, I follow the lead of Zick and Bryant (1990) and Zick and Stevens (2009) and impute wage values for my sample, an approach very similar to the two-sample two-stage least squares recommended by Inoue and Solon (2010). This process is described in greater detail in Appendix A.

Using data from the Integrated Public Use Microdata Series (IPUMS) version of the March Current Population Survey (CPS) for 2006, 2007, and 2008, I impute wage values via a three-step process. The first two steps are a maximum likelihood Heckman selection model. I estimate the probability of being employed and having wage data, and, for those people who are employed, I regress the log of wages on demographic and regional variables. Using maximum likelihood to estimate these two steps jointly controls for the fact that there may be unobserved factors which influence both employment and wages. This means the estimated coefficients on log wages should be accurate to describe people who are not employed in the employed sample, as well as those who are. Finally, in the third step I use the coefficients on the explanatory variables from the wage regression to predict log wage values for the ATUS sample for both workers and non-workers. These wage values are the predicted opportunities if a person were to work, and by calculating them for the entire sample, even those who do report wages, I avoid possible endogeneity between hours worked, time spent on meals, and wages earned. However, treating an imputed wage variable as though it were directly observed could cause the standard error associated with its effect to be underestimated; therefore, I correct for this using the method suggested by Murphy and Topel (1985).

People's meal behaviors are also likely to vary by race, ethnicity and age, as different types of food may be preferred. I classify race and ethnicity into five mutually exclusive categories: white, black, Hispanic, Asian, and other. In the ATUS, Hispanic ethnicity is reported separately from race; I count as Hispanic everyone who reports having a Hispanic ethnicity, regardless of whether the person's race is reported as white, black, Asian, or something else. For the rest of the sample, people are categorized by race, with white, as the largest group, considered to be the reference group. I restrict ages to the range of 25 to 64. These potential members of the labor force are likely to be more consistent in their behavior than age ranges for which significant fractions of the population are still in school or in retirement.

It is also important to know a household's composition, in order to identify food needs, an individual's meal production responsibilities, and other issues related to family structure. I approximate food needs by controlling for the number of children in the household; the presence of children may also affect the utility gained through meal consumption time. Children are divided into two age groups; those between zero and five, and those from age six to seventeen. The presence of a spouse or significant other may also affect food needs and utility from meals, as well as serving as an indicator of the degree of responsibility the individual has for meal preparation in the household. I also include a dummy variable for whether or not the spouse is employed, as that will affect the time the spouse has available for household tasks such as meal preparation; this variable is assumed to be zero if there is no spouse. Finally, I also control for the number of other adults in the household, besides the respondent and the spouse (if there is one).

Prices of food and preferences for time use may vary at different places and times. Therefore, I control for survey year, and whether the individual lives in the Northeast, South, Midwest, or Western census regions of the country. I also control for whether or not the person is reported as living in a metropolitan area. In addition, towards the end of 2006, the ATUS changed how secondary eating was reported, so I include an indicator for whether an individual was interviewed before or after this change.

Another factor which is correlated with meal time is the amount of time a person worked on the interview day, as work time crowds out other activities. However, as discussed in the previous section, hours worked is another choice variable determined endogenously with meal time. Furthermore, a person choosing to work more hours in order to take advantage of a high wage rate may actually be one of the key mechanisms by which wages affect meal time. Therefore, work time is not included in the main specification as an explanatory variable for meal production or consumption time. However, I do examine how including the number of minutes worked influences the results in an alternative specification.

In determining my sample, initially the 2006-2008 ATUS files contain time use data for 37,914 individuals. I restrict this sample as follows. 37,832 completed the Eating and Health supplement. Of those, 33,432 are at least age 25, and restricting to people under 65 brings the sample to 26,818. Finally, I drop all of the respondents on days identified as holidays in the ATUS, since meal patterns may be different on those days. These days include New Year's Day, Easter, Memorial Day, the Fourth of July, Labor Day, Thanksgiving Day, and Christmas Day, and dropping them leaves me with a final sample size of 26,374.

For much of my analysis, I break this sample apart into several smaller groups. I do this because different situations may lead to fundamentally different meal behaviors. The first such factor is gender; in the U.S. more responsibility for housework is often assigned to women than to men. Specialized skills and human capital can also raise a person’s efficiency at utilizing meal time and encourage one member of the family to take on a disproportionate share of the task (Becker 1985). The second axis is the day of the week; people may have more time available for preparing and eating food on weekends than they do on weekdays. I believe that both of these factors may lead not just to different quantities of time spent on meals, but to entirely different patterns of meal production and consumption. Therefore, I perform my analyses separately for each combination of men and women, weekdays and weekends.

Table 1.1 shows the average values of my dependent and independent variables for each of those combinations. Meal production time is more than twice as high for women as for men, and higher on weekends than on weekdays in both cases. Meal consumption time is about the same for women and men, and again a bit higher on weekends than weekdays. The average minutes worked are, naturally, much higher on weekdays than on weekends, and also for men than for women. On both weekdays and weekends, women have an average predicted log value for wages that equates to potential earnings of about $14 per hour, while men have a value of $22 per hour (note that these values are smaller than average wages, due to compression by the log function). The means of other variables are fairly similar for men and women on both weekdays and weekends. However, women average slightly more children, men are slightly more likely to be married, and women are more likely to have an employed spouse.

Descriptive Analysis

Tables 1.2 and 1.3 display the average levels of wages and the education completed for men and for women who engage in different quantities of meal production time and meal consumption time. Table 1.2 has four groups: people who spend no time on meal production, people who spend up to 30 minutes, people between 30 and 60 minutes, and people who spend more than 60 minutes on meal production. The columns one through four present the values for women, while five through eight display those of men. The values for education illustrate why I have chosen to perform my analyses for men and women separately. For women, only 28% spending over an hour on meal production graduated from college, while 34% of women spending less than an hour and 37% of the women not participating in meal production had done so. This pattern is reversed for women who did not attend college. However, roughly the same proportions of men from each educational category participate in each level of food production time. If education functions as a proxy for wages, then the female results suggest a negative combined income and substitution effect, as predicted, but the male values fail to demonstrate such an effect.

The pattern for imputed wages backs up these results. The women who spend larger amounts of time on meal production have lower average wages, indicating a possible negative income or substitution effect. However, average imputed wages for men are nearly flat across different amounts of meal production time, with a slight increase as production time increases.

Table 1.3, however, finds opposite effects for consumption time. The columns indicate meal consumption times for women and men of zero minutes, up to 45 minutes, 45 to 90 minutes, and over 90 minutes. Both men and women who spend over 90 minutes on meal consumption are much more likely to be college graduates than those who spend up to 45 minutes or between 45 and 90. (The same is also true for those people who spend 0 minutes on food consumption, but the sample size is extremely small.) If education causes this result by changing wages, then a positive income effect may be dominating a negative substitution effect. Longer periods of consumption time are associated with higher wages for both men and women, supporting this result, particularly for men. In an attempt to separate these effects, as well as to control for other possible variables influencing these meal times, I perform multivariate linear and non-linear analyses.

Multivariate Approach

As I discussed in the data section, many factors are likely to influence the time people spend on meals. In addition to a person's gender and whether the day is a weekday or weekend, which could be expected to change a person's entire approach towards meal times, other variables could also push meal times up or down. For example, ethnic or regional values could raise or lower meal times, dependent family members could boost meal production time but restrict meal consumption time, and people may change their priorities as they age. Since many of these variables are likely to also be correlated with wages (particularly since my wage variable is imputed), it is important to control for them in my analyses. Therefore, I perform multivariate analyses, controlling for wage, age, ethnic categories, numbers of children under six and six and older, marital status and spouse's employment status, other adults in the household, regional categories, and year.

The types of multivariate analyses I use are dictated by concern that my dependent variables may be truncated. The amount of time that a person spends on a particular activity is clearly a continuous variable, but there are constraints; it is not possible to spend fewer than zero minutes on an activity, nor can more than twenty-four hours be used in a single day. The latter constraint does not appear to be binding; no one reports eating or preparing food for all 1,440 minutes in a day. However, there are quite a number of zeros. Of the 26,818 people remaining after restricting the sample, when weighted appropriately, 32% do not spend time acquiring food.

This large numbers of zeros (32%) for meal production indicates that a limited dependent variable analysis may be most appropriate. To account for the censoring in meal production times, I use a Tobit model to predict how much time (or none) that a person spends acquiring food in a day. In this model, a person has an index representing the amount of time he or she wants to spend on meal production time. Whenever this would cause the person to spend a negative amount of time, that person spends zero time instead. This allows the expected distribution of results to match the censoring found in the data, and is consistent with the theory that people substitute money and time in the production of meals, but since a person cannot actually spend money to purchase additional time in the day, everyone who might want to do so instead bottoms out at zero meal production time.

A valuable feature of the Tobit model is that in the limiting case of no censored observations, it should produce identical coefficient estimates as linear regression; this makes it a natural extension to the linear models that form my initial analysis. When censored observations exist, however, the coefficients for the Tobit model only indicate the effects on meal production time conditional on production time being greater than zero. Therefore, I report unconditional marginal effects for the independent variables. The unconditional marginal effects are approximately equal to the conditional effects times the probability that meal production time is greater than zero, averaged over all observations.

In contrast to the censored observations for meal production, very few people spend no time on meal consumption. Although 4% spend no time on primary eating, and 45% spend no time on secondary eating, only 0.8% spend no time on either primary or secondary eating. When censoring is not present and the distribution is reasonably symmetric, ordinary least squares (OLS) is an efficient and easy to interpret way of measuring the partial correlations of the independent variables with the dependent variable. Therefore, I use OLS, with the standard weights provided in the Eating and Health Supplement to weight each observation by the probability of selection, to examine both the time spent on meal consumption and on combined daily meal time. This will estimate the best fit linear prediction for the effects of the independent variables on meal consumption times. Since an even larger fraction of people have a positive amount of total meal time, I use OLS to model that combined measure of time use as well.

A possible concern is that since wages are estimated in a separate step with its own errors, treating the imputed wage variable as though it were exact causes the standard errors to be underestimated (Murphy and Topel, 1985). In order to address this, I adapt Hole's (2006) implementation of Murphy and Topel's maximum likelihood correction for a two-step, two-sample model. Technically, the two samples are not independent, as the ATUS is a subsample of the CPS. However, since the CPS samples of women (107,454) and men (98,031) are almost 20 times larger than each of the ATUS subsamples used here, the correlation should be very small.

The corrected covariance matrix Σ equals $V_2 + V_2 * C * V_1 * C^T * V_2$, where V_1 is the covariance of the estimates from the first stage, V_2 is the covariance of the estimates from the second stage, and C is a correction matrix described in Murphy and Topel. However, the covariances generated through this method do not properly take into account either sample weighting or the marginal effects used for the Tobit model. Therefore, for each explanatory variable in the model, I calculate the ratio of the standard error estimate from Σ to the corresponding error from V_2 to get a scaling factor. (Due to the large sample sizes used in the wage imputation to calculate V_1, each of these factors is only slightly larger than 1.) I then multiply each of the weighted, robust standard errors from the Tobit meal production marginal effects by the appropriate scaling factor, and I do the same for the results of the OLS meal consumption models.

Empirical Analyses

The results of the Tobit model for meal production time are shown in Table 1.4. Columns 1 and 2 display the marginal effects for female time use on weekdays and weekends, and columns 3 and 4 show male marginal effects, while the rows represent the various control variables. The first row of column 1 indicates that on weekdays, women with higher potential wages have significantly lower meal production time, ceteris paribus. This is consistent with theory, and is probably driven in large part because a person with higher wages is more likely to enter the labor force. On weekends, however, wages do not have a statistically significant effect on a woman's meal production time. If wage opportunities are different on weekends and weekdays, and the imputed wage values represent potential weekday wages (as the majority of the CPS sample from whom wages are imputed presumably work on weekdays), then it makes sense that these imputed wages may not have much effect upon weekend time.

Meal production time for men on weekdays (column 3) is unaffected by wages, a surprising result. One possible explanation is that men may default to entering the labor force full time regardless of wage opportunities, limiting their ability to respond to different monetary incentives. A similar and even stronger result appears for weekend male meal production (column 4). On weekends, men with higher wages spend significantly more time on meal production. This counter-intuitive result could be explained by men substituting weekend time for weekday time. If weekend wage opportunities are low, men might prepare food on weekends to be eaten on weekdays. However, if that is the case, higher wages should reduce weekday production time, so then the column 3 result may still be a puzzle. Another possibility is that men with higher wages are married to women with higher wages and opportunity cost, causing substitution of inputs within the household and placing a relatively greater share of meal production on the men. A secondary analysis that splits the sample by marital status supports this hypothesis – there is a significant positive effect for married men on weekends, but not for unmarried men.

Although not a primary focus of this analysis, some of the other marginal effects for other variables on meal production time are also noteworthy. In particular, married women spend significantly more weekday time on meal production than do unmarried women; marriage has a much weaker positive effect on women’s weekend time, while married men spend significantly less time on meal production than do unmarried men.

This accentuates the importance of examining men and women separately. People with children spend significantly more time on meal production, although the effect of older children is small for men. This result confirms the expectation that caring for others and producing more food requires greater inputs of time.

Effects on meal consumption time are shown in Table 1.5. All four linear models, for women and men, weekdays and weekends, find that people with higher wages spend more time on meal consumption. In the case of women on weekdays (column 1), the effect is not statistically significant. However, for the other three columns, particularly for men, the relationship between wages and meal consumption time is large and very significant. This indicates that a positive income effect for increased wages dominates any negative substitution effect. One possible mechanism for this result is a backwards bending labor supply curve, as suggested in the theory section; people with low wages must work many hours in order to meet minimum levels of subsistence, while higher wages allow for greater amounts of leisure and consumption time. Another possibility is that increasing meal-related goods boosts the value of meal consumption time by more than increasing other goods enhances leisure time. In the first case, meal consumption time would increase at the expense of labor hours; in the second, meal consumption time crowds out other leisure time.

As with the analysis of production time, the independent variables with the most interesting effects on meal consumption time are the controls for family structure. Marriage increases meal consumption time for women and for men on weekdays. Children under six reduce weekday consumption time, particularly for men, but increase weekend consumption. This suggests that childcare responsibilities may reduce weekday leisure time. Children six and older lower women's weekday consumption time, consistent with the effect of children under six, and also reduce men's weekend consumption time, which is opposite the effect of younger children.

Alternative Model Specifications

One thing to consider for these analyses is the extent to which the results may be driven by the use of sample weights. Weights are included to make the sample nationally representative; however, if different parts of the population respond differently to factors such as wage opportunities, then the weighted outcomes may be different than would be found in the unweighted sample. In order to test this possibility, I have rerun the meal production and consumption models without weighting (for brevity, the tables are not included in this paper). The results for wages are almost identical across the weighted and unweighted analyses. However, the magnitudes and significance levels of the coefficients for ethnicities, marital status/spousal employment, and geographic regions do vary somewhat for the unweighted models.

Another concern with these analyses of production and consumption time is that meal production time is examined non-linearly using Tobit, while consumption time is modeled linearly. Part of the purpose of this paper is to examine differences in people's production and consumption time behaviors, and analyzing them with different models may make comparison of these results difficult. Furthermore, a drawback to the Tobit model for meal production time is that although it does allow for the truncation of activity times at zero, it places fairly strong restrictions on the underlying model (namely, that people decide to spend zero time according to the same normally distributed index that determines the positive amount of time that might be spent). Stewart (2009) has shown that when time use spells are positive but infrequent, Tobit estimation can generate biased results. Therefore, although examination of the meal production time distribution suggests that it may correspond to a single normal index, as a sensitivity check I estimate the linear and Tobit models for both sorts of meal time, as well as two other approaches which support censored observations: the Two-Part model and the CLAD model.

The Two-Part model predicts which people will spend time on meal production, and then identifies effects for just the sub-population that does spend such time. The advantage of this model over Tobit is that it places fewer structural restrictions; the model for the probability of spending time on meal production is independent of the model predicting the quantity of time spent. A disadvantage of this model, however, is that people who spend no time are treated differently from people who spend very little time. If participation and the amount of time are actually determined by the same process, then the Two-Part model will be inefficient and the second part is likely to be biased as well. The first part of the Two-Part model uses a Probit regression to calculate the probability that a person will spend time on meal production. Then, for the people who do participate in meal production, I use a linear model to determine which variables influence the amount of time they spend. I compute marginal effects as the derivative of the first part probability times the expected value of the second part, plus expected probability of the first part, times the derivative of the second part. However, I omit standard errors on these marginal effects due to the difficulty of computation.

The other model I use for truncated data is censored least absolute deviations (CLAD). Although the CLAD model, like Tobit, assumes the censored observations correspond to the same index as the observed data, CLAD minimizes absolute deviations instead of squared deviations to avoid over-emphasizing the missing extreme values. The CLAD model assumes that the bottom tail of the distribution is censored (at zero minutes). Therefore, to regain symmetry, CLAD effectively censors the people who spend the most time as well, so that equal numbers of observations are missing above and below. Finally, it calculates coefficients for the model that minimize the absolute differences from the observed values, and estimates standard errors through 100 bootstrap repetitions of the analysis. It is important to note that use of the CLAD model can be complicated when substantial numbers of observations are censored, such as the large fraction of men who spend no time on meal production. CLAD results are also less comparable to the other three models because the results are calculated without weighting the observations, although the other models do not change much when weighting is not included.

Tables 1.6 and 1.7 display the effects of wages on meal production and consumption time for each of the linear, Tobit, Two-Part, and CLAD models. Coefficients are shown for the linear and CLAD models, while the latent indices of the Tobit and Two-Part models indicate that for ease of comparison, displaying marginal effects is more important (due to computational difficulties, standard errors are omitted for the Two-Part model). Results are almost identical for the linear, Tobit, and Two-Part models. The CLAD analyses are not fully comparable to the others, as they are both unweighted and minimize absolute deviations rather than squared deviations. As a result, the magnitudes are somewhat different. Nevertheless, the CLAD model still finds effects with the same sign as the other three models. This suggests that my results are relatively robust across choices of models. However, I still need to consider the robustness of my independent and dependent variable definitions.

Alternative Independent Variables and Meal Time Definitions

There are a number of other potentially relevant independent variables which I excluded from my primary analyses and tables. Although non-labor income is not measured in the ATUS, household income is. However, since an important component of household income is actual earnings, it is likely to be endogenous with time use decisions and labor hours. Food stamp eligibility and receipt are also likely to be endogenous with time use decisions. Therefore, I exclude all of these variables from my primary analyses. However, alternative specifications which include these variables produce very similar results for wages and other variables of interest, indicating that my findings are not sensitive to the inclusion or exclusion of family income or food stamp receipt.

Levels of education might also be expected to influence meal times. Unfortunately, testing finds education controls to be highly correlated with wages; inclusion roughly triples the standard error for wages in each of my analyses. Fortunately, these controls are only jointly significant in one out of the eight meal production and consumption time specifications. This indicates that levels of education do not actually have much independent explanatory power. Therefore, I exclude them from my analyses to avoid concerns about collinearity.

One possible explanation for how wages appear to affect meal times is through correlation with a spouse's wage, causing a substitution of the time of one household member for another. To test this, in other analyses (again, not included in the tables here) I have split the sample by marital status and ran the analyses on each group. Single and married women had basically the same response to wages for both meal production and consumption time. By contrast, single men do not show the significant positive meal production time response to higher wages on weekends that is found in the full sample, whereas married men display an even stronger effect. These findings for women and men are consistent with Zick et al.'s (2008) finding that a husband's education has no effect on the wife's housework time, but that increasing the wife's education raises the husband's time. In addition, higher wages increase weekday meal consumption time by much more for single men than for married men. It is not clear why this should be the case, but perhaps single men have a greater amount of discretionary time available, which they only use for eating when wages are high.

As discussed in the data section, there are also other possible constructions of my dependent variables. In order to test the sensitivity of my results to the methods used to construct my variables, I test a few alternative specifications. An alternative measure of meal production time includes time travelling to purchase food or consume food, in addition to the food purchasing, meal preparation, and meal cleanup times from my main definition. Testing this definition indicates that adding travel time does not change the effects from wages or other key variables in a significant way.

In order to improve comparability to other research, I also test two alternative definitions of meal consumption time. The first includes only primary eating and drinking, and lines up with the meal consumption definition used by Aguiar and Hurst (2007). The second includes everything from the main specification, primary eating and drinking as well as secondary eating, and also includes secondary drinking, a measure which Hamermesh (2009) includes in his definitions of meal consumption. The results from the first alternative definition, the main specification, and the second alternative fall into a natural ordering. The analyses including only primary eating and drinking have much smaller standard errors and more precise effect estimates than the main specification with secondary eating, while adding secondary drinking makes the errors much larger than in my main specification. Most statistically significant effects remain the same across these definitions, including the effect of wages.

Finally, for comparison with other research and to get a sense of the overall time cost of meals, I have also tried examining total food time as a third type of dependent variable. Total food time is calculated by aggregating primary eating, secondary eating, and food production, then subtracting the overlap between secondary eating and meal production (about a minute, on average). Linear coefficients for total food time are almost identical to the sums of the effects for meal production and meal consumption. Increased wages lower total meal time for women on weekdays (although the effect is not quite significant at a five percent level), and significantly increase total meal time for women on weekends, as well as for men on both weekdays and weekends.

Work Time as an Explanatory Variable

The number of minutes worked is not included in the main specification, due to concerns about endogeneity and work time functioning as an important intermediary variable between wages and meal time. However, it may be the case that for many people, the time spent working is determined independently of both time on meals and wages. The great majority of adults are employed full time, particularly men, and may often have no real control over the number of hours they work each day. If work time is imposed exogenously, then there is no harm to including it in the model. Furthermore, if exogenous time spent working happens to be correlated with (but not caused by) potential wages (such as more highly educated people working more efficiently but also happening to take different sorts of jobs), then failing to account for work hours could bias the coefficients for wages and other variables.

Even if there is no such bias, I have hypothesized that spending additional time working may be one of the key mechanisms by which people with higher potential wage rates adjust meal times. This is supported by the observation that, for my sample, basic OLS and Tobit regressions indicate that men and women with higher imputed wages spend a higher average number of minutes working, on both weekdays and weekends, controlling for other variables in the ATUS. Therefore, running an alternative specification which includes work time could test the hypothesis that work time is an important mediating variable for the effect of wages on meal times.

Table 1.8 (analogous to Table 1.4 for the main specification) shows meal production time results including work time as an explanatory variable. I find that an additional minute worked in the day reduces meal production time for women on weekdays and weekends by about four seconds, and for men on weekdays and weekends by about two seconds. (This is a smaller fraction than the total percentage of non-work, non-sleep time spent on meal production, indicating that meal production time is relatively inelastic.) Including minutes worked in the model cuts the highly statistically significant negative wage coefficient on meal production time for women on weekdays in half; a one percent increase in wages drops production time by 6 seconds, relative to a 12 second change for the main specification in Table 1.4. However, the inclusion of work time does not change the null wage effects on meal production for women on weekends and for men on weekdays, nor does it affect the positive coefficient for male wages on weekends.

Coefficients for meal consumption time are shown in Table 1.9. An additional minute of work reduces women's consumption time by around two seconds on weekends, and reduces men's consumption time by about a second and a half on weekends. Work time has no statistically significant effect on consumption time for either women or men on weekdays. The inclusion of minutes worked in the model also has no effect on the coefficients for imputed wages for either men or women.

To test the sensitivity of these results, I run meal production and consumption analyses that include both minutes worked and a control variable whether or not work time is positive. I also run analyses using the usual number of weekly hours worked as the measure of work time. Although the coefficients for the effects of work time on meal time vary somewhat in these models, the effects for imputed wages remain pretty much the same.

These results indicate that substitution and crowding out may be taking place between work time and meal times, particularly for meal production time. Furthermore, for women on weekdays, this appears to explain about half of the effect of wages on meal production time. However, including work time in the model has no effect upon the coefficient for wages on meal production or consumption time for any of the other combinations of gender and weekday/weekend, even though wages are positively related to work time, and work time negatively affects meal times. This is puzzling, and suggests that non-linear behavior may be involved.

The explanation may lie in the precise relationship between wages and minutes worked. Although OLS and Tobit regressions indicated a simple positive connection between the two, analysis using a Two-Part model suggests that a bit more is going on. People with higher imputed wages are more likely to spend time on work on both weekdays and weekends. However, restricting the sample to the people who spent time on work, although women with higher wages still spend more time working on weekdays, higher wages have a negative effect on minutes worked for women on weekends and men on both weekdays and weekends. This suggests that these workers are in the backwards-bending portion of the labor supply curve, particularly the women and men who work on weekends.

This non-linear relationship between wages and work time could explain the unusual meal time results. Although men and weekend women with higher wages are more likely to report spending a positive amount of time working, the magnitude of that time is likely to be smaller. If the negative work effects on meal time are largely driven by the people who spend the very most time working, these may not be people with particularly high imputed wages.

Conclusion

In this paper, I have sought to establish how economic factors such as wages influence meal production and consumption times, and whether the two sorts of time respond differently. To this end, I have combined time diary information and demographic information from the ATUS with imputed wage data from the CPS. Since a significant portion of the sample spends no time on meal production, potentially biasing a linear analysis, I have estimated non-linear censored regression Tobit models for meal production time. I also estimated linear regression analyses of time spent on meal consumption and total meal time.

Overall, results for meal production time for women on weekdays are consistent with Gronau's (1977) home production theory that increased wages will cause people to substitute market goods for production time. I find that half of this effect is indeed driven by the relationship between wages and work time. This outcome also matches the effects of wages on meal preparation found in the literature. However, women on weekends and men on weekdays have no wage effect on meal production time, and men on weekends have a surprising positive effect (but one that matches the finding of Mancino and Newman 2007). I speculate that these outcomes are a result of different employment opportunities on weekdays and weekends, as well as correlation between the wages of husbands and wives. Future research could benefit from more detailed demographic data to investigate this relationship.

Meal consumption time behavior, by comparison, is fairly consistent across women and men on both weekdays and weekends. Higher expected wage opportunities have a positive effect upon meal consumption time in each case, with a large, statistically significant coefficient for women on weekends and men on weekdays and weekends. This is consistent with Becker’s (1965) theory of commodities requiring time as well as goods to consume, and my hypothesis that meal consumption time and food expenditures are complements. I find a backwards-bending labor supply curve for the workers in each of these three categories, and equation 7 in the model section predicts that higher wages for people in the backwards-bending portion of the labor supply curve will result in increased meal consumption time. Increased wages leading to increased meal consumption is also consistent with Hamermesh’s (2009) finding for the effect of actual wages on workers’ primary and secondary eating times.

This contrast between production and consumption time effects, particularly for women on weekdays, highlights why it is important to distinguish between the two types of time use if the mechanisms involved are to be understood. Combining the two into total meal time only magnifies standard errors and conceals complicated meal production behavior with simple meal consumption. Future research into meal production and consumption times would also benefit from further examination of the distinction between primary and secondary eating behaviors; although the wage effects are similar, other factors, such as ethnicity, have very different effects on these types of time. Finally, the study of income and substitution effects on meal time could be augmented by data that include a reliable measure of non-labor income.

Table 1.1. Summary Statistics

	Women		Men	
VARIABLES	Weekday	Weekend	Weekday	Weekend
Production Time	55.327	63.581	20.975	30.273
Preparing/Cooking	46.832	51.530	16.847	22.163
Buying Groceries	7.117	10.642	3.039	6.819
Consumption Time	87.866	92.511	88.585	99.763
Primary Eating	60.969	70.002	66.391	73.368
Secondary Eating	26.897	22.515	22.194	26.399
Total Meal Time	142.022	154.547	109.111	129.144
Imputed Log Wage	2.635	2.635	3.076	3.078
Minutes Worked	271.042	65.871	387.169	106.184
H.S. Drop Out	0.104	0.108	0.118	0.115
H.S. Graduate	0.287	0.289	0.312	0.315
Some College	0.277	0.273	0.253	0.243
College Graduate	0.332	0.331	0.317	0.327
Age	43.912	43.947	43.632	43.635
White	0.684	0.686	0.700	0.697
Black	0.124	0.123	0.103	0.108
Hispanic	0.133	0.135	0.144	0.143
Asian	0.041	0.037	0.033	0.032
Other	0.018	0.020	0.021	0.019
# of Children <6	0.284	0.303	0.286	0.275
# of Children >5	0.635	0.639	0.548	0.546
Married/Cohabiting	0.691	0.691	0.703	0.705
Spouse Employed	0.583	0.582	0.480	0.472
# of Other Adults	0.447	0.414	0.428	0.478
Northeast	0.173	0.176	0.184	0.187
Midwest	0.249	0.241	0.236	0.248
South	0.363	0.361	0.352	0.347
Rural	0.179	0.172	0.174	0.171
Year 2007	0.335	0.336	0.333	0.333
Year 2008	0.336	0.336	0.338	0.336
Revised E&H Quest.	0.726	0.727	0.724	0.723
Observations	7,234	7,471	5,791	5,878

Weighted Data from the 2006-2008 American Time Use Surveys and Eating and Health Supplements. Meal times are in minutes. The excluded geographic region is West, the excluded survey year is 2006.

Table 1.2. Average Characteristics by Levels of Meal Production Time

Production Time (Minutes)	Women				Men			
	T=0	0<T≤30	30<T≤60	T>60	T=0	0<T≤30	30<T≤60	T>60
Observations	3216	3518	2715	5256	5252	3260	1594	1563
Log Wage	2.653	2.654	2.650	2.604	3.051	3.093	3.108	3.109
H.S. Drop Out	0.082	0.083	0.090	0.144	0.134	0.092	0.099	0.127
H.S. Graduate	0.276	0.267	0.286	0.309	0.326	0.308	0.312	0.274
Some College	0.271	0.303	0.276	0.260	0.241	0.259	0.254	0.264
College Graduate	0.370	0.347	0.348	0.287	0.300	0.341	0.335	0.335
Weekend	0.308	0.250	0.250	0.315	0.282	0.243	0.291	0.409

Weighted data from the 2006-2008 American Time Use Surveys and Eating and Health Supplements

Table 1.3. Average Characteristics by Levels of Meal Consumption Time

Consumption Time (Minutes)	Women				Men			
	T=0	0<T≤45	45<T≤90	T>90	T=0	0<T≤45	45<T≤90	T>90
Observations	120	4085	5943	4557	99	2949	4685	3936
Log Wage	2.530	2.566	2.638	2.693	2.973	3.004	3.071	3.142
H.S. Drop Out	0.215	0.137	0.102	0.077	0.129	0.143	0.131	0.076
H.S. Graduate	0.378	0.337	0.284	0.244	0.538	0.376	0.305	0.267
Some College	0.227	0.276	0.276	0.277	0.174	0.264	0.247	0.244
College Graduate	0.180	0.250	0.339	0.402	0.159	0.216	0.316	0.413
Weekend	0.369	0.256	0.266	0.337	0.393	0.269	0.253	0.343

Weighted Data from the 2006-2008 American Time Use Surveys and Eating and Health Supplements

Table 1.4. Meal Production Time, Tobit Model

	Women		Men	
	(1)	(2)	(3)	(4)
VARIABLES	Weekday	Weekend	Weekday	Weekend
Imputed Log Wage	-17.999***	-5.150	-0.978	11.037***
	(2.805)	(3.394)	(2.625)	(3.201)
Age	0.743***	0.886***	0.265***	0.108
	(0.087)	(0.099)	(0.070)	(0.079)
Black	-3.329	-0.078	2.354	-4.057*
	(2.347)	(2.811)	(1.726)	(2.406)
Hispanic	20.456***	15.399***	-3.702**	0.443
	(2.605)	(2.953)	(1.858)	(2.465)
Asian	20.099***	32.090***	2.628	6.651
	(4.229)	(5.311)	(3.100)	(4.503)
Other	9.407	8.190	1.400	-0.468
	(6.422)	(10.431)	(3.710)	(6.212)
# of Children <6	12.536***	11.003***	5.207***	3.976***
	(1.274)	(1.425)	(1.583)	(1.053)
# of Children >5	8.787***	8.476***	1.383*	1.453**
	(0.849)	(0.896)	(0.802)	(0.705)
Married/Cohabiting	16.490***	5.839*	-9.658***	-5.842***
	(3.043)	(3.521)	(1.642)	(2.054)
Spouse Employed	1.096	8.096**	5.887***	4.741***
	(2.963)	(3.467)	(1.436)	(1.797)
# of Other Adults	-0.023	-1.117	-0.365	-2.440**
	(1.332)	(1.446)	(1.399)	(1.042)
Northeast	5.617**	-0.518	-2.746	-3.862*
	(2.402)	(2.968)	(1.885)	(2.270)
Midwest	0.086	1.620	-4.827***	-2.056
	(2.180)	(2.905)	(1.731)	(2.109)
South	-1.098	-1.336	-4.086**	-3.755*
	(2.081)	(2.470)	(1.662)	(1.988)
Rural	-0.890	-1.466	-0.192	-4.063*
	(2.209)	(2.637)	(1.558)	(2.085)
Year 2007	0.761	-1.830	-0.495	-1.701
	(3.848)	(4.058)	(2.212)	(3.512)
Year 2008	0.661	2.977	-0.052	0.956
	(3.885)	(4.042)	(2.256)	(3.511)
Revised E&H Quest.	-1.764	1.449	0.099	0.456
	(3.933)	(4.091)	(2.259)	(3.513)
Observations	7,234	7,471	5,791	5,878

Unconditional marginal effects for weighted Tobit analyses of minutes of meal production (preparing meals, cleaning up, and purchasing food).
Excluded race is White, excluded region is West, excluded year is 2006.
Standard errors in parentheses, rescaled as per Murphy and Topel (1985).
*** p<0.01, ** p<0.05, * p<0.1

Table 1.5. Meal Consumption Time, Linear Model

	Women		Men	
	(1)	(2)	(3)	(4)
VARIABLES	Weekday	Weekend	Weekday	Weekend
Imputed Log Wage	6.404	25.062***	37.154***	44.362***
	(6.793)	(4.707)	(8.561)	(9.514)
Age	-0.379	0.170	-0.296	-0.540***
	(0.254)	(0.137)	(0.195)	(0.203)
Black	-12.940**	-14.966***	-4.311	-7.785
	(5.061)	(3.713)	(6.478)	(7.955)
Hispanic	-12.886**	-4.651	-8.222*	-7.506
	(6.019)	(3.618)	(4.828)	(5.217)
Asian	14.279	14.633*	-12.865*	-11.664*
	(13.615)	(7.521)	(7.238)	(6.560)
Other	15.659	5.548	-11.512*	0.323
	(18.929)	(8.852)	(6.631)	(8.186)
# of Children <6	-6.401**	7.797***	-2.254	6.819**
	(2.929)	(2.398)	(2.534)	(2.939)
# of Children >5	-5.723***	0.615	-2.969*	-5.671***
	(1.745)	(1.443)	(1.524)	(1.516)
Married/Cohabiting	22.482	8.665*	12.467**	1.948
	(17.219)	(4.493)	(4.841)	(4.860)
Spouse Employed	-19.848	-2.454	-6.766	5.320
	(14.740)	(4.455)	(4.215)	(3.818)
# of Other Adults	7.020	-2.687*	2.005	1.210
	(6.703)	(1.603)	(2.454)	(2.534)
Northeast	-7.386	-2.908	-4.852	-5.610
	(4.521)	(3.498)	(5.142)	(6.359)
Midwest	1.518	-1.156	-5.466	-4.445
	(8.379)	(3.708)	(4.500)	(5.966)
South	-7.978*	-3.657	-5.291	-6.953
	(4.635)	(3.281)	(4.424)	(5.650)
Rural	-4.437	-6.281*	4.996	0.931
	(6.812)	(3.250)	(4.324)	(6.230)
Year 2007	5.038	10.332**	5.307	8.649
	(7.435)	(4.265)	(8.730)	(8.155)
Year 2008	9.957	6.888*	7.997	14.956*
	(6.760)	(4.113)	(8.960)	(7.940)
Revised E&H Quest.	8.573	1.747	4.531	4.823
	(5.942)	(3.845)	(8.477)	(7.477)
Constant	81.761***	10.728	-19.198	-21.165
	(21.962)	(16.505)	(24.085)	(29.485)
Observations	7,234	7,471	5,791	5,878
R-squared	0.020	0.026	0.018	0.026

Weighted linear regression for minutes of meal consumption (primary eating/drinking, eating at work, secondary eating).
Excluded race is White, excluded region is West, excluded year is 2006.
Robust standard errors in parentheses, rescaled as per Murphy and Topel (1985). *** p<0.01, ** p<0.05, * p<0.1

Table 1.6. Wage Effects on Meal Production Time Models

	Women		Men	
	(1)	(2)	(3)	(4)
MODELS	Weekday	Weekend	Weekday	Weekend
Linear	-20.394***	-6.238	-5.539*	8.319**
	(3.358)	(3.803)	(3.018)	(3.995)
Tobit	-17.999***	-5.150	-0.978	11.037***
	(2.805)	(3.394)	(2.625)	(3.201)
Two-Part	-20.075	-6.539	-5.801	8.254
CLAD	-17.160***	0.635	4.710**	23.760***
	(2.192)	(2.979)	(2.063)	(3.294)

Weighted linear regression. Unconditional marginal effects for weighted Tobit analyses. Conditional marginal effects for weighted Two-Part (Probit/Linear) model. Unweighted Censored Least Absolute Deviations (CLAD) model. Robust standard errors in parentheses. Errors are rescaled for linear and Tobit analyses as per Murphy and Topel (1985), and omitted for the Two-Part Model.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.7. Wage Effects on Meal Consumption Time Models

	Women		Men	
	(1)	(2)	(3)	(4)
MODELS	Weekday	Weekend	Weekday	Weekend
Linear	6.404	25.062***	37.154***	44.362***
	(6.793)	(4.707)	(8.561)	(9.514)
Tobit	5.540	21.688***	29.279***	36.116***
	(5.431)	(4.114)	(6.485)	(7.192)
Two-Part	6.090	24.996	36.235	44.454
CLAD	15.740***	28.333***	36.507***	39.821***
	(1.858)	(2.108)	(2.886)	(2.267)

Weighted linear regression. Unconditional marginal effects for weighted Tobit analyses. Conditional marginal effects for weighted Two-Part (Probit/Linear) model. Unweighted Censored Least Absolute Deviations (CLAD) model. Robust standard errors in parentheses. Errors are rescaled for linear and Tobit analyses as per Murphy and Topel (1985), and omitted for the Two-Part Model.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8. Meal Production Time with Minutes Worked, Tobit Model

	Women		Men	
	(1)	(2)	(3)	(4)
VARIABLES	Weekday	Weekend	Weekday	Weekend
Imputed Log Wage	-9.427***	-3.994	3.461	10.614***
	(2.876)	(3.059)	(2.674)	(2.915)
Minutes Worked	-0.060***	-0.066***	-0.031***	-0.031***
	(0.003)	(0.004)	(0.003)	(0.003)
Age	0.596***	0.745***	0.116	0.065
	(0.090)	(0.089)	(0.072)	(0.073)
Black	-2.496	0.375	1.811	-2.719
	(2.344)	(2.517)	(1.876)	(2.231)
Hispanic	23.068***	14.181***	-2.237	1.399
	(2.581)	(2.655)	(1.992)	(2.273)
Asian	20.143***	30.680***	2.907	6.057
	(4.297)	(4.634)	(3.419)	(4.136)
Other	10.348	7.126	-0.846	-0.052
	(6.665)	(9.540)	(3.859)	(5.610)
# of Children <6	8.814***	9.120***	5.507***	3.477***
	(1.280)	(1.294)	(1.653)	(0.968)
# of Children >5	7.832***	7.612***	1.794**	1.373**
	(0.847)	(0.802)	(0.858)	(0.642)
Married/Cohabiting	13.184***	3.700	-9.991***	-5.390***
	(3.131)	(3.140)	(1.762)	(1.893)
Spouse Employed	4.407	7.961**	7.336***	4.707***
	(3.048)	(3.095)	(1.542)	(1.655)
# of Other Adults	-0.211	-0.152	-1.052	-2.424**
	(1.295)	(1.285)	(1.436)	(0.966)
Northeast	5.422**	0.008	-3.524*	-3.658*
	(2.408)	(2.663)	(2.050)	(2.103)
Midwest	1.474	2.377	-5.339***	-2.285
	(2.233)	(2.624)	(1.864)	(1.946)
South	-0.296	-0.511	-4.162**	-3.808**
	(2.102)	(2.224)	(1.768)	(1.836)
Rural	0.356	-0.118	0.183	-3.221*
	(2.229)	(2.383)	(1.676)	(1.908)
Year 2007	2.576	-2.348	0.308	-1.397
	(3.903)	(3.659)	(2.397)	(3.252)
Year 2008	2.165	2.077	0.826	0.898
	(3.952)	(3.649)	(2.451)	(3.258)
Revised E&H Quest.	-3.457	2.021	-1.105	0.206
	(3.990)	(3.693)	(2.452)	(3.253)
Observations	7,234	7,471	5,791	5,878

Unconditional marginal effects for weighted Tobit analyses of minutes of meal production (preparing meals, cleaning up, and purchasing food).
Excluded race is White, excluded region is West, excluded year is 2006.
Standard errors in parentheses, rescaled as per Murphy and Topel (1985).
*** p<0.01, ** p<0.05, * p<0.1

Table 1.9. Meal Consumption Time with Minutes Worked, Linear Model

	Women		Men	
	(1)	(2)	(3)	(4)
VARIABLES	Weekday	Weekend	Weekday	Weekend
Imputed Log Wage	6.573	25.381***	38.738***	44.722***
	(6.811)	(4.690)	(8.437)	(9.515)
Minutes Worked	-0.001	-0.037***	-0.011	-0.022**
	(0.009)	(0.006)	(0.008)	(0.009)
Age	-0.382	0.129	-0.358*	-0.570***
	(0.262)	(0.137)	(0.191)	(0.204)
Black	-12.922**	-14.658***	-4.579	-7.125
	(5.028)	(3.702)	(6.578)	(7.983)
Hispanic	-12.857**	-4.578	-7.598	-6.794
	(5.957)	(3.610)	(4.740)	(5.259)
Asian	14.260	15.430**	-12.933*	-11.785*
	(13.655)	(7.438)	(7.190)	(6.553)
Other	15.666	5.132	-12.373*	0.830
	(18.930)	(8.810)	(6.711)	(8.028)
# of Children <6	-6.476**	7.263***	-2.333	6.682**
	(3.096)	(2.390)	(2.539)	(2.924)
# of Children >5	-5.747***	0.547	-2.890*	-5.614***
	(1.793)	(1.437)	(1.521)	(1.514)
Married/Cohabiting	22.408	7.792*	12.762***	2.069
	(16.835)	(4.470)	(4.829)	(4.847)
Spouse Employed	-19.790	-2.238	-6.456	5.500
	(14.435)	(4.439)	(4.283)	(3.796)
# of Other Adults	7.015	-2.199	1.769	1.103
	(6.680)	(1.602)	(2.416)	(2.557)
Northeast	-7.395	-2.601	-5.046	-5.698
	(4.497)	(3.481)	(5.120)	(6.357)
Midwest	1.542	-0.656	-5.506	-4.712
	(8.482)	(3.697)	(4.509)	(5.950)
South	-7.963*	-3.247	-5.153	-7.161
	(4.673)	(3.268)	(4.425)	(5.650)
Rural	-4.414	-5.532*	5.131	1.336
	(6.721)	(3.246)	(4.306)	(6.233)
Year 2007	5.070	9.940**	5.534	8.972
	(7.537)	(4.227)	(8.785)	(8.131)
Year 2008	9.980	6.451	8.249	15.140*
	(6.734)	(4.072)	(9.042)	(7.918)
Revised E&H Quest.	8.548	2.246	4.149	4.517
	(5.962)	(3.805)	(8.573)	(7.458)
Constant	81.779***	13.998	-17.417	-18.769
	(21.972)	(16.482)	(24.261)	(29.421)
Observations	7,234	7,471	5,791	5,878
R-squared	0.020	0.026	0.018	0.026

Weighted linear regression for minutes of meal consumption.
Excluded race is White, excluded region is West, excluded year is 2006.
Robust standard errors in parentheses, rescaled as per Murphy and Topel (1985). *** p<0.01, ** p<0.05, * p<0.1

APPENDIX A

WAGE IMPUTATION

Information on wages and salaries in the 2006, 2007, and 2008 ATUS data is missing for many individuals; in particular, people who are not employed don't earn wages. Furthermore, even for the people for whom wage data is present, a person's time use preferences and decisions could affect wages, making this variable endogenous. To get around these difficulties, I impute wages using the IPUMS files for the 2007, 2008, and 2009 March supplements of the Current Population Survey (CPS) data, as these files include people's wage and income values from the previous year. This two-sample approach both provides an estimate of potential wages for people who might not otherwise have one, and also corrects for endogeneity. My approach follows that of Zick and Stevens (2009), and is very similar to two-sample two-stage least squares, which was recommended by Inoue and Solon (2010) over Angrist and Krueger's (1992) two-sample instrumental variables technique. The key difference between my analysis and two-sample two-stage least squares is that for the first stage, I calculate the effects of explanatory variables on wages in the CPS data using a Heckman selection model rather than ordinary least squares (OLS).

The Heckman selection model for wages that I use here consists of two equations. The first is a Probit style model that predicts the probability of working/receiving a wage, while the second is a linear regression that estimates the value of the log of wages, conditional on the person working. Although I am primarily interested in the results for wages from the second equation, they may yield biased estimates of potential wages for non-workers if there exists heterogeneity in wage offers between people who choose to work relative to those who do not. Therefore, the error terms of the two equations are assumed to be jointly normally distributed; unobserved factors that influence a person's probability of having a job may also affect the wages that person could receive. Heckman's (1979) original suggestion for this model is two calculate the equations in two steps, sequentially. However, estimating them simultaneously using maximum likelihood is more efficient (Cameron and Trivedi 2005), and so I take that approach here.

Starting with the 2007, 2008, and 2009 March supplements of the CPS, I restrict the sample to individuals between ages 25 and 64 (to match my ATUS sample). Since most individuals in the CPS do not report hourly earnings, I instead calculate hourly wages as annual wage and salary income from the previous year, divided by the number of weeks worked and by the usual hours worked per week. I drop the approximately 1% of my sample with top-coded earnings (primary wage source greater than $200,000 or secondary wage source greater than $35,000), the 1% with allocated earnings data, and the 0.1% with top-coded usual weekly hours. After calculating real hourly wages in 2006 dollars, I also drop the 0.7% who make less than $2.80 per hour, and the 0.2% who make $100 or more per hour. Within this final sample, people with positive values for wages, weeks worked, and hours worked (the latter two categories overlap perfectly) are considered to be employed (75% of the remaining sample), while someone with a value of zero for any of those is not employed (25%).

Again following the structure of Zick and Stevens (2009), I calculate the probability of working and wage effects for men and women separately. My explanatory variables include several demographic characteristics. Using the average values of age for men and women in the restricted sample, I calculate a centered age variable, which I include in the analysis, as well as the centered age variable squared. This centering allows me to avoid the collinearity problems of age and age squared. I also control for three of four educational categories: did not complete high school, high school graduate, and some college, leaving college graduates as my excluded category. Finally, I include indicator variables for Hispanic and black non-Hispanic ethnicities.

I also control for the person's state of residence, year, and whether or not the person lives in a rural area or not, as well as interactions between state and rural status. People are defined as rural residents if they either do not live in a metropolitan area, or if their metropolitan area is not identified. Although the latter may seem ambiguous, in practice there are only four states with unidentified people – Colorado, Louisiana, Nevada, and Utah, and none of these states contain people reported as not living in a metropolitan area. Therefore, as these are known to be states with large rural areas, it seems reasonable to assume that unidentified individuals must represent the rural population. Alternatively, since there is no overlap between states with non-metropolitan residents and unidentified residents, the controls for those four states can be thought of as a control for not identifying metropolitan status. Apart from those four, the District of Columbia, New Jersey, and Rhode Island report no rural residents of any sort in the sample. Massachusetts has only 42 men and 61 women in rural areas, followed by

Maryland, with 134 men and 157 women.

In contrast to this large number of state and rural indicators, Zick and Stevens (2007) control only for which of the four geographic areas of the country (Northeast, South, Midwest, or West) a person lives in, as well as whether or not an area is rural. I test the explanatory power of state controls versus regional controls, and find that states together have significantly more explanatory power than regions over log wages, at a 0.01% significance level. The interactions between state and rural status are also jointly significant at that level for both men and women. Therefore, I choose to include all of these in the wage imputation model.

In order to predict the probability of a person being employed (with an observed income), I also include three variables which should affect the decision to work but not the wages received when working. The first two of these exclusion restrictions are the number of the person's own children in the household under five years old, and the number of his or her own children who are five or older. I control for these separately, as children not yet old enough to enter kindergarten may affect parental employment differently from those who are old enough. The amount of non-labor income available may also affect the need to work, which I approximate as the sum of income from interest, income from dividends, and income from rent, adjusted for inflation. Table A2 shows the results.

These three variables as exclusion restrictions generate rho, the correlation between the error terms of the selection and log wage equations of 0.19 for women, and -0.73 for men. In this case of women, this suggests that women with higher potential wages are more likely to work – an intuitive result. For men, however, the correlation is quite negative, indicating that in at least some cases, men with higher potential wages are less likely to be employed. This is a bit surprising, but can be explained in terms of a high fraction of men working, regardless of the level of wages they might receive. This leaves labor force non-participation to be driven by such things as early retirement, full-time education that continues past age 25, etc., which may be correlated with relatively high wages.

Lambda, the product of the correlation rho and the variance of the wage model, captures how much the variation in the selection model influences the log wage equation, and corresponds to the coefficient on the inverse Mills ratio in a two-step Heckman model. I find this value to be 0.10 for women, very similar to the inverse Mills ratio coefficient of 0.12 found by Mulligan and Rubinstein (2008) for women in the CPS from 1995-1999 (contrasted with their 1975-79 CPS finding of -0.08), and a bit smaller than the coefficient for labor force participation found by Baffoe-Bonnie (2009) of 0.22 for white females in the NLSY. For men, I found a value of -0.43, greater in magnitude than Baffoe-Bonnie's labor force participation selection term of -0.10 for white males, but the same sign, although he found a positive result of 0.17 for black males. Note, however, that Baffoe-Bonnie calculated separate selection models for labor force participation and hiring, so the outcomes are not fully comparable to my single model for employment.

Using the coefficients on independent variables estimated in the equation for the log of wages, I then impute log wage values by multiplying those coefficients by the observed values of the explanatory variables for participants in the ATUS. This allows me to use the ATUS data to estimate a model for meal time use that includes the log of wages as an explanatory variable. This is effectively identical to the two-sample two stage least squares approach discussed in Inoue and Solon (2010). Since most of the variables in the wage equation also appear as variables explaining time use, it is necessary to have a source of identifying variation. In this case, identifying variation is provided by the state-level geographic controls, as well as their interaction with the rural variable. Economic opportunities may vary significantly from state to state, but it seems reasonable to expect patterns of time-use to be relatively constant within the larger geographic regions.

The CPS sample and the ATUS sample used for imputing wages are very similar, as can be seen in Table 1.A.1 below. The fraction of the sample inhabiting each of the state and rural interaction cells is very similar as well, including the empty rural cells of the District of Columbia, New Jersey, and Rhode Island, so the inability to estimate coefficients for those variables is not a problem. One possible concern is that the large negative coefficient on lambda in the wage regression for men causes the average imputed log wages to be significantly larger than the average actual log wages for employed men. In an attempt to account for this variation, I also perform a linear regression for log wage without controlling for selection, shown in Table 1.A.2. The results for women are almost identical for the Heckman and linear models. For men, most of the coefficient effects are similar across the two models, with age being the main exception; the Heckman model finds maximum wages at age 61, while linear regression indicates that wages are maximized at just age 50.

Table 1.A.1. Weighted Variable Means

	Women			Men		
VARIABLES	CPS-Full	CPS-Emp	ATUS	CPS-Full	CPS-Emp	ATUS
% Employed	0.697	1.000		0.796	1.000	
Log(Wage)		2.714			2.930	
Impute Wage (Heckman)	2.633	2.667	2.635	3.067	3.070	3.077
Impute Wage (OLS)	2.683	2.714	2.684	2.915	2.930	2.929
H.S. Drop Out	0.106	0.069	0.106	0.128	0.110	0.116
H.S. Grad	0.291	0.277	0.288	0.316	0.306	0.314
Some College	0.288	0.303	0.275	0.258	0.262	0.248
Black	0.125	0.130	0.123	0.107	0.098	0.105
Hispanic	0.135	0.120	0.134	0.154	0.161	0.143
Age	44.001	43.130	43.930	43.650	42.525	43.634
Northeast	0.185	0.189	0.174	0.179	0.180	0.186
Midwest	0.219	0.229	0.245	0.221	0.225	0.242
South	0.367	0.362	0.362	0.361	0.357	0.350
Year 2007	0.333	0.335	0.335	0.334	0.335	0.333
Year 2008	0.336	0.335	0.336	0.335	0.334	0.337
Rural	0.158	0.154	0.175	0.160	0.149	0.173
Nonlabor $	1,343.71	1,274.21		1,511.87	1,442.33	
# children<Age 5	0.188	0.164		0.181	0.204	
#children>=Age 5	0.835	0.825		0.693	0.737	

This table displays the weighted means for people in the full sample of the 2007, 2008, and 2009 March CPS data, those who were employed with positive wages in that data, and the values for members of the 2006, 2007, and 2008 ATUS and E&H survey. Excluded education category is college graduates, excluded race is white, the excluded region is West, and the excluded year is 2006.

Table 1.A.2. Heckman Maximum Likelihood and Linear Models of Log Wage

	Women			Men		
	Heckman M.L.		Linear	Heckman M.L.		Linear
VARIABLES	Log(Wage)	Employment	Log(Wage)	Log(Wage)	Employment	Log(Wage)
Centered Age	0.004***	-0.020***	0.005***	0.012***	-0.021***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Centered Age	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.001***
Squared	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High School	-0.817***	-0.850***	-0.771***	-0.569***	-0.687***	-0.695***
Drop Out	(0.012)	(0.018)	(0.009)	(0.009)	(0.019)	(0.009)
High School	-0.536***	-0.350***	-0.520***	-0.399***	-0.368***	-0.461***
Graduate	(0.006)	(0.013)	(0.006)	(0.006)	(0.014)	(0.006)
Some	-0.342***	-0.147***	-0.336***	-0.279***	-0.221***	-0.312***
College	(0.006)	(0.013)	(0.006)	(0.006)	(0.015)	(0.006)
Black	-0.076***	0.125***	-0.082***	-0.160***	-0.206***	-0.202***
	(0.007)	(0.016)	(0.007)	(0.009)	(0.018)	(0.008)
Hispanic	-0.143***	0.018	-0.142***	-0.209***	0.183***	-0.168***
	(0.008)	(0.016)	(0.008)	(0.008)	(0.019)	(0.007)
Constant	2.995***	0.926***	3.031***	3.401***	1.177***	3.332***
	(0.024)	(0.048)	(0.023)	(0.023)	(0.055)	(0.022)
rho		0.190***			-0.735***	
		(0.027)			(0.010)	
lambda		-0.100***			-0.432***	
		(0.014)			(0.008)	
R-squared			0.234			0.255

Predicted log wages in the 2007-2009 waves of the March CPS. Rho is the correlation between the two stages, while lambda is the product of rho and the error variance of the wage equation. Excluded education category is college graduates, and the excluded race is white. Year, state, rural, and state*rural interaction terms are omitted. Robust standard errors are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX B

THEORETICAL MODEL SOLUTION

Suppose meals, meal consumption time, leisure time, and other goods are all factors in a Stone-Geary Utility function $U(M, T_{MC}, L, X) = (M-\gamma_1)^{\alpha_1}(T_{MC}-\gamma_2)^{\alpha_2}(L-\gamma_3)^{\alpha_3}(X-\gamma_4)^{\alpha_4}$. The alphas are the relative intensities of each commodity in the production of utility, while the gammas are the various subsistence levels of consumption. Meals M are produced using meal production time and meal goods following Gronau's (1977) home production model, $M(T_{MP}, X_M) = f(T_{MP}) + X_M$. Meal production time has positive but decreasing marginal returns in the creation of meals, $f' > 0$, $f'' < 0$, and $f(0) = 0$. Time use is subject to the constraint ($T_{MC} + T_{MP} + L + H = T$), while income equals expenditures ($wH + N = X_M + X$), with the assumption that prices are equal to 1. Then the Lagrangian equation for utility is:

1. £$= U(M, T_{MC}, L, X) + \lambda_1(T - T_{MC} - T_{MP} - L - H) + \lambda_2(wH + N - X_M - X)$, with choice variables $T_{MP}, T_{MC}, L, H, X_M, X$.

In that order, the following first order conditions hold, assuming an interior solution:

2. $U_M(M, T_{MC}, L, X) * M_T(T_{MP}, X_M) - \lambda_1 = 0$
$\Rightarrow \alpha_1(M-\gamma_1)^{\alpha_1-1}(T_{MC}-\gamma_2)^{\alpha_2}(L-\gamma_3)^{\alpha_3}(X-\gamma_4)^{\alpha_4} * f'(T_{MP}) = \lambda_1$

3. $U_T(M, T_{MC}, L, X) - \lambda_1 = 0$
$\Rightarrow \alpha_2(M-\gamma_1)^{\alpha_1}(T_{MC}-\gamma_2)^{\alpha_2-1}(L-\gamma_3)^{\alpha_3}(X-\gamma_4)^{\alpha_4} = \lambda_1$

4. $U_L(M, T_{MC}, L, X) - \lambda_1 = 0$
$\Rightarrow \alpha_3(M-\gamma_1)^{\alpha_1}(T_{MC}-\gamma_2)^{\alpha_2}(L-\gamma_3)^{\alpha_3-1}(X-\gamma_4)^{\alpha_4} = \lambda_1$

5. $-\lambda_1 + w\,\lambda_2 = 0 \Rightarrow \lambda_1 = w\,\lambda_2$

6. $U_M(M, T_{MC}, L, X) * M_X(T_{MP}, X_M) - \lambda_2 = 0$
$\Rightarrow \alpha_1(M-\gamma_1)^{\alpha_1-1}(T_{MC}-\gamma_2)^{\alpha_2}(L-\gamma_3)^{\alpha_3}(X-\gamma_4)^{\alpha_4} * 1 = \lambda_2$

7. $U_X(M, T_{MC}, L, X) - \lambda_2 = 0$
$\Rightarrow \alpha_4(M-\gamma_1)^{\alpha_1}(T_{MC}-\gamma_2)^{\alpha_2}(L-\gamma_3)^{\alpha_3}(X-\gamma_4)^{\alpha_4-1} = \lambda_2$

Using 2, 5, and 6, $U_M(M, T_{MC}, L, X) * M_T(T_{MP}, X_M) = \lambda_1 = w\,\lambda_2 = wU_M(M, T_{MC}, L, X) * M_X(T_{MP}, X_M)$, implying that $M_T(T_{MP}, X_M) = wM_X(T_{MP}, X_M)$ and

8. $f'(T_{MP}) = w$, so T_{MP} is an implicit function only of *w*, denoted T_{MP} (*w*).

By 3, 4, 5, and 7, $U(M, T_{MC}, L, X) * \alpha_2 (T_{MC} - \gamma_2)^{-1} = U(M, T_{MC}, L, X) * \alpha_3 (L - \gamma_3)^{-1} = \lambda_1 = w\, \lambda_2 = wU(M, T_{MC}, L, X) * \alpha_4 (X - \gamma_4)^{-1}$, so

9. $(X - \gamma_4)/\alpha_4 = w(L - \gamma_3)/\alpha_3 = w(T_{MC} - \gamma_2)/\alpha_2$

Using the constraints to solve for H yields:

10. $wT_{MC} + wL + X = wT + N - wT_{MP} - X_M$

11. $w(T_{MC} - \gamma_2) + w(L - \gamma_3) + (X - \gamma_4) = wT + N - w\gamma_2 - w\gamma_3 - \gamma_4 - wT_{MP} - X_M$

12. $\left(\frac{\alpha_2+\alpha_3+\alpha_4}{\alpha_4}\right)(X - \gamma_4) = wT + N - w\gamma_2 - w\gamma_3 - \gamma_4 - wT_{MP} - X_M$

13. $(X - \gamma_4) = \left(\frac{\alpha_4}{\alpha_2+\alpha_3+\alpha_4}\right)(wT + N - w\gamma_2 - w\gamma_3 - \gamma_4 - wT_{MP} - X_M)$

Now we just need to solve for *Xm*, using 6 and 7:

14. $U_M(M, T_{MC}, L, X) * M_X(T_{MP}, X_M) = \lambda_2 = U_X(M, T_{MC}, L, X)$

15. $\alpha_1(X - \gamma_4) = \alpha_4(M - \gamma_1)$

16. $(M - \gamma_1) = f(T_{MP}) + X_M - \gamma_1 = \left(\frac{\alpha_1}{\alpha_2+\alpha_3+\alpha_4}\right)(wT + N - w\gamma_2 - w\gamma_3 - \gamma_4 - wT_{MP} - X_M)$

17. $\left(\frac{\alpha_1+\alpha_2+\alpha_3+\alpha_4}{\alpha_2+\alpha_3+\alpha_4}\right)(X_M - \gamma_1) = \left(\frac{\alpha_1}{\alpha_2+\alpha_3+\alpha_4}\right)(wT + N - \gamma_1 - w\gamma_2 - w\gamma_3 - \gamma_4 - wT_{MP}) - f(T_{MP})$

18.
$(X_M - \gamma_1) = \left(\frac{\alpha_1}{\alpha_1+\alpha_2+\alpha_3+\alpha_4}\right)\left(wT + N - \gamma_1 - w\gamma_2 - w\gamma_3 - \gamma_4 - wT_{MP} - \left(\frac{\alpha_2+\alpha_3+\alpha_4}{\alpha_1}\right) f(T_{MP})\right)$

19. $(X - \gamma_4)/\alpha_4 = w(L - \gamma_3)/\alpha_3 = w(T_{MC} - \gamma_2)/\alpha_2 = \left(\frac{1}{\alpha_1+\alpha_2+\alpha_3+\alpha_4}\right)\left(wT + N - \gamma_1 - w\gamma_2 - w\gamma_3 - \gamma_4 - wT_{MP} + f(T_{MP})\right)$

20. $T_{MC} = \left(\frac{\alpha_2}{\alpha_1+\alpha_2+\alpha_3+\alpha_4}\right)\left(T + N/w - \gamma_1/w - \gamma_2 - \gamma_3 - \gamma_4/w - T_{MP}(w) + f\big(T_{MP}(w)\big)/w\right) + \gamma_2$

Now all of our choice variables are in terms of the exogenous constraints w, N, and T. We can find the signs of the income and wage effects. Using 8,

21. $\frac{dT_{MP}}{dN} = T_{MP}^{'}(w) * \frac{dw}{dN} = T_{MP}^{'}(w) * 0 = 0$

22. $f'(T_{MP}) = w \Rightarrow f^{''}(T_{MP}) * \frac{dT_{MP}}{dw} = 1 \Rightarrow \frac{dT_{MP}}{dw} = \frac{1}{f^{''}(T_{MP})} < 0$

The income effect on meal production time is zero, while the wage effect is negative; since the wage effect is a sum of income and substitution effects, we can surmise that the substitution effect of increased wages on meal production time must be negative as well. Using 20,

23. $\frac{dT_{MC}}{dN} = \left(\frac{\alpha_2}{\alpha_1+\alpha_2+\alpha_3+\alpha_4}\right) * \frac{1}{w} > 0$

24. $\frac{dT_{MC}}{dw} = \left(\frac{\alpha_2}{\alpha_1+\alpha_2+\alpha_3+\alpha_4}\right)\left(-\frac{N}{w^2} + \frac{\gamma_1}{w^2} + \frac{\gamma_4}{w^2} - \frac{dT_{MP}}{dw} + \left(\frac{f'(T_{MP})}{w}\right)\frac{dT_{MP}}{dw} - \left(\frac{f(T_{MP}(w))}{w^2}\right)\right)$
$= \frac{-\alpha_2(N+f(T_{MP}(w))-\gamma_1-\gamma_4)}{w^2(\alpha_1+\alpha_2+\alpha_3+\alpha_4)}$

There is a positive income effect on meal consumption time in this case. The effect of wages could be either positive or negative, depending upon the magnitude of $N + f(T_{MP}(w))$ relative to $\gamma_1 + \gamma_4$. This represents the backwards bending portion of the labor supply curve; if merely meeting subsistence requirements for goods requires all non-labor income and some earned income, then increasing the wage rate will allow a person to cut back on labor hours and increase meal consumption time.

It is also possible to perturb the Meal function M so that $\frac{dT_{MP}}{dN} < 0$. (For example, if X_M has slight returns to scale, such as M = $f(T_{MP}) + X_M{}^{1.01}$, then $f^{'}(T_{MP}) = 1.01 * w * X_M{}^{0.01}$. Increasing N will boost X_M, forcing $f^{'}(T_{MP})$ to rise and T_{MP} to fall, without much effect on the rest of the variables.)

Corner cases:

The results above hold for interior solutions. As structured, T_{MC}, L, X must all be greater than zero (so long as the corresponding γ's are non-negative). However, the other three choice variables T_{MP}, H, X_M can potentially be equal to zero, and in those corner cases, the partial statics may be different.

1. H = 0. $T_{MP} > 0, X_M > 0$. The wage is insufficient to motivate the individual to enter the labor force. The individual divides T between T_{MP}, T_{MC}, L, and N between X_M, X. $\frac{dT_{MP}}{dN} < 0, \frac{dT_{MC}}{dN} > 0$. Will happen when $X_M + X \leq N$, or:

$(\alpha_1 + \alpha_4)(wT - w\gamma_2 - w\gamma_3 - wT_{MP}(w)) \leq (\alpha_2 + \alpha_3)\big(N - \gamma_1 - \gamma_4 - f(T_{MP}(w))\big)$

2. $T_{MP} = 0$. $f^{'}(0) < w \implies$ no time will be spent on meal production. $T_{MC} = \left(\frac{\alpha_2}{\alpha_1+\alpha_2+\alpha_3+\alpha_4}\right)(T + N/w - \gamma_1/w - \gamma_2 - \gamma_3 - \gamma_4/w) + \gamma_2$. $\frac{dT_{MC}}{dN} = \frac{\alpha_2}{w(\alpha_1+\alpha_2+\alpha_3+\alpha_4)} > 0$, $\frac{dT_{MC}}{dw} = \frac{-\alpha_2(N-\gamma_1-\gamma_4)}{w^2(\alpha_1+\alpha_2+\alpha_3+\alpha_4)}$ is ambiguous and will have the opposite sign from $N - \gamma_1 - \gamma_4$. Could rule out this case by assumption, $f^{'}(0) > w$.

3. $X_M = 0$. $f^{'}(T_{MP}) > w$. All of $wH + N$ is needed for spending on X. $\frac{dT_{MP}}{dN} > 0, \frac{dT_{MC}}{dN} > 0$. $\frac{dT_{MP}}{dw}$ and $\frac{dT_{MC}}{dw}$ are ambiguous, and will have the opposite sign from $N - \gamma_4$. (18 provides the conditions for this to happen.)

4. $H = 0$. $T_{MP} = 0$. T is used for T_{MC}, L, while N is used for X_M, X. $\frac{dT_{MC}}{dN} = 0, \frac{dT_{MC}}{dw} = 0$.

5. $H = 0$. $X_M = 0$. All of N is needed for spending on X. Neither w nor N will affect meal production or consumption time.

CHAPTER II

WHO SKIPS BREAKFAST, LUNCH, OR DINNER?

Introduction

The consumption of three regular daily meals has been repeatedly found to be associated with better health outcomes among children and adults. Skipping breakfast is associated with increased risk of obesity (Ma et al., 2003; Hallfrische et al., 1982). Young adults who eat breakfast also have better daily meal quality (Deshmukh-Taskar et al., 2010). Moreover, greater numbers of daily meals, particularly three or more relative to two or fewer, are connected to lower obesity rates (Fabry and Tepperman, 1970; Ma et al., 2003). On a psychological note, the consumption of family dinners seems to lead to a reduction of problem behaviors in teenagers (CASA Report, 2009). These issues make it important to know what influences the consumption of the three regular daily meals: breakfast, lunch, and dinner. In this paper, I use data from the National Health and Nutrition Examination Survey (NHANES) to examine how wages and other demographic factors affect whether or not working age adults eat each of those three meals or snacks.

A person's decision to eat a meal is likely to be influenced by the costs and benefits of that meal, many of which are economic. Becker's (1965) theory of household production and time use suggested that the costs of consuming a commodity such as a meal take two forms: time costs and monetary costs. At least as far as the participation decision goes, the monetary cost of eating a meal is likely to mainly be an issue for a person suffering substantial financial hardship. However, since there are only twenty-four hours in a day, time costs could be a problem for anyone. The opportunity cost of time is likely to be more acute for people with a high wage. Consistent with this idea, Hamermesh and Lee (2007) found perceptions of time shortages and time stress to be more acute for households with higher earnings, which leads to an expectation that those households might be more likely to skip activities such as meals. Similarly, Devine et al. (2009) showed that long or unusual work hours often resulted in missed meals for parents.

Although the costs are primarily economic, the benefits of eating a meal are likely to be driven more by health and social concerns. More educated individuals may be better aware of the many health benefits to eating multiple regular meals. Keski-Rahkonen et al. (2003) found that parents in Finland with higher education and higher SES were more likely to eat breakfast. Aguiar and Hurst (2007) also found that the amount of time people spend on eating has been increasing over time for college graduates relative to people with less education. Individuals have been found to eat more in the company of others (DeCastro, 1997), which suggests they may also be more likely to eat a meal when family members are present. These varied results leave ambiguity in how factors, particularly wages and the value of time, influence a person's probability of eating a meal.

To examine how economic and demographic factors influence a person's decision to eat meals, I use data on working age adults from the continuous waves of the NHANES. The NHANES consists of repeated cross-sectional interview and physical examination data gathered from American families in biennial waves. I use information from the 1999-2000, 2001-2002, 2003-2004, 2005-2006, and 2007-2008 waves for my analysis. To measure meal participation, I rely upon the NHANES dietary recall interview, of which a particular strength is the multiple-pass method which first asked people what they ate, then which meal they were eating it for, and finally attempted to assign a time to each eating occasion. Other relevant data collected in the NHANES include demographic information and a great array of information about health and health behaviors.

Unfortunately, although the NHANES includes many useful variables, it does not have a measure of wages or the value of a person’s time. Additionally, a person’s actual wages are likely to be endogenous to his or her patterns of time use decisions. Therefore, to add a measure of wages not caused by an individual’s time use behavior, I calculate imputed wages using estimates derived from the Current Population Survey (CPS). This imputation is performed using a maximum likelihood Heckman selection method, with marital status and the number of children as exclusion restrictions for the labor force participation equation, and a full set of interactions of gender, age, ethnicity, and education to identify wage effects for workers.

To identify which factors do cause people to miss meals, I estimate separate binary probability models for whether or not a person consumes breakfast, lunch, and dinner. These analyses are split by whether the person was male or female, and also whether the interview day was a weekday or weekend. Important control variables include the imputed wage rate as a proxy for the value of a person's time, ethnicity, the individual's level of education, marital status, and a quadratic function of age.

Using these models, I find that the decision to eat or skip a meal depends heavily upon which meal it is, as well as the person's gender and the day of the week. Women with higher potential wages are more likely to report eating meals on weekdays, but significantly less likely to eat meals, particularly dinner, on weekends. Men with higher wages are more likely to eat meals on weekdays, particularly breakfast, but are less likely to eat lunch on weekends. These associations between higher wages and lower relative probabilities on weekends of lunch or dinner are surprising. The financial cost of a meal (a reason for a low wage individual to choose not to eat) should be about the same on weekdays and weekends, while the time cost (a reason for a high wage person to skip a meal) could be higher on weekdays, since work is likely to take away time that could be used for other activities on those days.

Previous Research

Despite the importance of eating regular meals, previous research into why people skip meals has been sparse, particularly for adults. Williams (2002) stated that "the reasons for skipping breakfast are not known" when describing breakfast eaters in Australia. One possibility is that people with a higher value of time, such as those with higher wages, choose to limit the number of times they eat, causing them to compress the necessary calories into fewer meals or snacks. Alternatively, people with inadequate financial resources might not be able to afford the full complement of meals.

The idea that a high value of time leads to cutting back on activities comes from the time-stress literature. Hamermesh and Lee (2007) found that for a given work schedule, households with higher income report greater feelings of time pressure and shortages of time. They speculate that this is due to a higher shadow price of time; in other words, households with higher income have more consumption to fit into the same amount of time. Conversely, holding income constant, Kalenkoski et al. (2011) found employed adults were more likely to be "time poor." If meals are relatively time intensive, then increased time stress could cause people to skip meals at times of the day when opportunity costs are high.

Past research has found a number of reasons for skipping meals that seem to support the time stress hypothesis. These include a lack of time for breakfast (Williams 2002, Howden 1993), pressure to work through lunch (SHRM 2009), or long or unusual work hours (Devine et al., 2009). An experiment by Waterhouse et al. (2005) found that highly structured days increased the probability that college students missed meals. The other economic explanation for meal skipping, however, is that a shortage of money may make it impossible to buy the food needed for a meal. A lack of food available to consume is one reason people reported for skipping breakfast (Howden 1993). Similarly, Keski-Rahkonen et al. (2003) found that Finns with more education and higher employment SES eat breakfast more often. They also found that people who exercise more and get more than six hours of sleep are more likely to report eating breakfast regularly. If exercise and sleep reduce the available time for meals, this suggests that time constraints may be less important than a commitment to healthy behaviors.

Alternatively, those could simply have been people with more available time, which they divided between exercise, sleep, and meals.

A third possibility is that work may provide daily structure that influences meal consumption. Research into shift work suggests that people working a regular daytime shift are more likely to eat meals that day. Duchon and Keran (1990) found that night shift workers are more likely to skip breakfast or lunch than day shift workers, resulting in 0.2 fewer meals eaten per day. Along the same lines, Lennernas et al. (1995) found that 3-shift workers rearrange nutrient intake among different meals or snacks, depending upon the shift worked. Lennernas et al. (1995) and Waterhouse et al. (2003) also discovered that nutrient intakes on average were lower on days off than on work days. Waterhouse et al. (2003) report that meal decisions were often made based on habit and available time rather than appetite. This supports the time stress hypothesis that less time can mean fewer meals, but also indicates that reductions of available time may increase the probability of eating a meal if a specific block of time is left available for the person to eat.

These competing influences of time and money constraints make the effect of wages on meal participation difficult to predict. Higher wages will reduce the degree to which money is a constraint on meals, but may increase the time cost. This dilemma can be illustrated with a stylized theoretical model.

Stylized Model

Becker's (1965) household production model suggests that people use both a vector of goods inputs and a vector of time inputs to create commodities, the items that are ultimately consumed. For the meal commodity, the vector of goods may represent different sorts of ingredients and sources of food; it is not the focus here. The elements of the vector of time inputs, meanwhile, include time that people spend preparing food as well as the amounts of time spent eating each meal of the day. The functional form for the production of commodities is important. If goods and time perfectly substituted for each other in the commodity production functions, then commodities would fall into two categories: those produced entirely with goods, and those produced entirely with time. However, in practice almost all commodities require both goods and time to be used together, as complements. Hamermesh and Lee (2007) assume that goods and time are perfect complements, and I use a modified form of their model here.

Treating goods and time as perfect complements for a given meal, we are interested in the decision for whether or not to eat each of the meals of breakfast, lunch, and dinner. A person is considered to have eaten a meal if they spend any time consuming it. Time spent on each of these meals could be considered to be an element of a day’s meal consumption commodity; however, for simplicity I treat each meal as a separate commodity, and develop a generalized model which can be used for the consumption decision of any single meal. Furthermore, although in actuality meal decisions are connected, relevant results can be more straightforwardly derived here by assuming that the utility gained from eating a given meal is independent of the consumption of other meals that day. Since even one minute of eating counts as a meal, we can expect a meal to be eaten if the marginal utility of the first portion consumed is higher than the marginal utility of any other commodity that could be produced with the same amount of time and goods. Therefore, our essential question is whether or not the quantity consumed of a given meal will be greater than zero.

If only a single meal is being considered, then an individual's optimization problem is simple:

(1) Maximize Utility $U(M, C)$

Where *M* is the amount consumed of the meal commodity and *C* is a composite commodity of all other goods. If time and goods are perfect complements in the production of M and C, then optimal levels of time T_M, T_C and goods X_M, X_C will be in a fixed linear proportion to each other. Without loss of generality, these can be treated as linear functions of the respective commodities *M* and *C*.

(2) $T_M = t_M M,\ T_C = t_C C,\ X_M = b_M M$, and $X_C = b_C C$

The individual's choices are subject to the constraints (a) that the total time spent on all commodities cannot exceed the total time *T* an individual has available minus hours worked *H* and (b) that the total expenditure cannot exceed earnings *Hw* (hours worked times the hourly wage) plus non-labor income *N*.

(3) $\sum T_i = T - H$

(4) $\sum p_i X_i = Hw + N$

Therefore, using the equations from (2) to substitute for T_i and X_i, these constraints can be rewritten as

(5) $t_M M + t_C C = T - H$

(6) $p_M b_M M + p_C b_C C = Hw + N$

Optimizing utility subject to these constraints, the individual chooses *M* and *C* to maximize the Lagrangean

(7) $L = U(M, C) + \mu(Hw + N - p_M b_M M - p_C b_C C) + \lambda(T - H - t_M M - t_C C)$

Here, the Lagrange multipliers for money and time are μ and λ, respectively. The Kuhn-Tucker first order condition for *M* states that

(8) $U_M - \mu * p_M * b_M - \lambda * t_M \leq 0$

and if $U_M - \mu * p_M * b_M - \lambda * t_M < 0$, then the meal commodity, *M*, must equal zero. In other words, a person will choose not to eat a meal if the marginal utility of eating (U_M) is less than the sum of the utility cost of the money ($\mu * p_M * b_M$) and the time ($\lambda * t_M$) that would be required to eat. We can examine equation (8) to identify some factors that will affect meal consumption and to suggest variables to be considered in an analysis of why a person chooses to eat or skip a particular meal.

The shadow value of money (μ) is a measure of the opportunity cost of spending money on food. This cost is likely to be greatest when the total amount of money is small; in other words, the person is suffering from financial hardship. If this is a primary factor in the person choosing not to eat a given meal, then they are suffering from food hardship. Therefore, people with low income are likely to have the highest value of (μ), and may be the least likely to eat a given meal, particularly if the prices (p_M) and necessary amounts of food for that meal (b_M) are also high.

The shadow price of time (λ) represents the opportunity cost of spending time on food. Since goods and time are assumed to be perfect complements in the production of commodities, individuals with higher incomes are likely to have a higher value for time; this can lead to time stress, where people do not have enough time to complete all of their activities. More critically, holding income constant, a high wage may increase the cost of time spent on things other than working, and lower the probability of eating a meal. This tradeoff between labor and "leisure" is somewhat mitigated in this model, because goods and time are assumed to be perfect complements for a given commodity. Instead, people with higher wages may spend less non-labor time on time-intensive commodities, and more non-labor time on goods-intensive commodities. The shadow price of time could also be higher if a person has less total time available for one particular meal. Someone who sleeps late may have no time for breakfast, or a person with a demanding job might work through lunch. Finally, men and women could have different household responsibilities, causing the opportunity cost of a meal to differ by gender.

A related consideration is the time cost of a meal (t_M). This value really represents two quantities: the time it takes to prepare or acquire food, and the time it takes to eat. Like the quantity of goods required (b_M), the time required for a meal is a function of the meal production technology used, and is likely to vary across meals and weekdays/weekends. For example, on a workday a person might purchase a ready-made lunch from a restaurant, while on a weekend lunch may have to be prepared from scratch.

Finally, although those factors can influence the costs of eating, it is also important to consider the benefit of eating an additional meal. Many things may raise the marginal utility of eating (U_M). For example, the presence of family members could make eating a particular meal more desirable. Also, although I have assumed that meals are independent, having skipped or expecting to skip another meal could increase the benefit from eating this one.

Overall, then, the expected effect of wages is ambiguous. Higher wages lower the effective monetary cost of eating through the shadow price of money (μ), but increase the cost of time (λ); these are basically the income and substitution effects for wages. Although a person's value of μ should remain constant across different meals and weekdays and weekends, meals such as lunch on workdays may involve a different meal production technology than other meals. This could effectively change the quantity and price (b_M and p_M) of goods needed for a meal, and therefore the relative importance of money. Meanwhile, non-work days effectively have a smaller value of work hours (H), lowering the shadow price of time, and possibly making wages less important on those days.

Data

To examine the relationship between wages and meal participation empirically, I use data from the Center for Disease Control's National Health and Nutrition Examination Survey. Variables collected from American families through English and Spanish language interviews and physical examinations include demographic information, twenty-four hour recall of foods and meals eaten, and a great array of information about health and health behaviors, weighted so as to be representative of the US population. Starting in 1999, the NHANES became "continuous," and consists of repeated cross-sectional data gathered in biennial waves. Data are available from five waves: 1999-2000, 2001-2002, 2003-2004, 2005-2006, and 2007-2008. The first two waves contain meal consumption data for a single day per individual; the last three waves have two days of meal data for a majority of the sample.

The initial NHANES sample has 51,623 individuals, around ten thousand from each wave. Approximately a thousand people from each wave did not participate in the twenty-four hour food recall interview[3], leaving the sample at 46,361 people, and a total of 70,979 person*day observations of meal behavior; the dietary recall sample weights compensate for these lost observations. Of these people, children and the elderly are likely have substantially different meal behavior from working age adults. Imputed wages may not be a good measure of a person's opportunity costs below age 25, when people could still be in school, or at age 65 or older, when people are likely to have retired. Therefore, I drop these younger and older people from the sample as well; since

[3] The people omitted from the sample also include 1-3 individuals each year who did complete the food recall interview, but reported eating no foods.

the NHANES oversamples children, this reduces the sample to 15,127 individuals and 23,459 observations. Some of these people lack data for specific variables needed in my analyses, particularly those from the 1999-2000 wave. Marital status is missing for 327 people and 332 observations, education is missing for a further 9 people and 11 observations, and 7 people and 7 observations are missing sample weights. Finally, since I use the two-day sample weights for the 2003-2008 observations, which do not exist for the 976 people who did not participate in the follow-up dietary interview over the telephone, I drop those people as well. This leaves a final sample of 13,808 individuals and 22,133 person*day observations.

I use this sample to measure people's participation in the meals of breakfast, lunch, and dinner. However, the NHANES measures people's food consumption through a multiple-pass approach that does not specifically collect that information. Instead, people are first asked to recall which foods they ate on the previous day, midnight to midnight. They are then asked to name the meals they ate those foods for, and what time those foods were eaten. People are encouraged to recall if there were any foods forgotten in earlier passes through the day. Using this combination of meal names and times, I assemble a list of meals eaten by each person, as shown in Table 2.1. I then use this list to construct a consistent mapping of meal names across multiple waves of the NHANES to breakfast, lunch, and dinner.

To construct this mapping, I follow Kant et al.'s (2006) definition of breakfast. People who describe themselves as eating food for "breakfast," "brunch," or "desayano" are counted as eating breakfast. I define "lunch" and "almuerzo" as lunch, and "dinner," “supper,” and “cena” are classified as dinner. Other words chosen are considered to be neither breakfast, lunch, nor dinner; I describe these eating occasions with the catch-all term of snack.

However, as a sensitivity analysis, I also consider the breakfast definition used in Kant et al. (2008) and the meal definitions of the USDA report, *What We Eat in America*[4]. Those define “breakfast,” “desayuno,” and “almuerzo” as breakfast, and the USDA report treats “lunch,” “brunch,” and “comida” as lunch. Research into the meaning of these words indicates that “almuerzo” is used consistently in Latin America to describe lunch, while “comida” simply means food. In the case of brunch, the modal time in 1999-2002 is 10 a.m., while the median is 11 a.m. In 2003-2008, the modal time is 11 a.m., while the median ranges from 11 a.m. to noon. These times could describe either breakfast or lunch, so I stick with the methodology of Kant et al. (2006) for consistency.

One of the most important individual characteristics that influences meal consumption in my analysis is a person’s wage rate. This serves as an estimate of the value of his or her time, as well as of the opportunity cost that person must pay when choosing to eat rather than to work. Wages also influence a person’s ability to afford food. Unfortunately, although the NHANES includes many useful variables, it does not have a measure of wages or the value of a person’s time. Additionally, a person’s actual wages are likely to be endogenous to his or her patterns of time use decisions. For example, a person who eats regular meals might be healthier and more productive,

[4] http://www.ars.usda.gov/Services/docs.htm?docid=18349

causing them to receive a higher wage. Therefore, in order to provide a measure of wages for the NHANES sample, as well as to compensate for possible endogenous wages, I employ a model-based procedure to impute wages using data from the 1999-2008 March waves of the Current Population Survey (CPS) and coefficient estimates from a maximum likelihood Heckman selection model of wages and employment. This is very similar to a two-sample two-stage least squares approach; I discuss the model and data in further detail in Appendix A: Wage Imputation.

To estimate the imputation model, I use the Stata joint (two-equation) maximum likelihood Heckman selection procedure to estimate the determinants of wages separately for men and women in the CPS. The first part of this model uses a Probit equation to estimate coefficients for labor force participation, with non-labor income, the number of family children age four or under, and the number of family children age 5-18 as exclusion restrictions to identify varied probability of participating in the second equation. The second equation is a linear regression on wages for the employed portion of the CPS sample. The covariance of the error terms for these joint equations is statistically quite significant, indicating that the probability of labor force participation is correlated with wages, and suggesting that the selectivity-corrected Heckman model is appropriate. Coefficients from the second equation are then used to predict wages for people in the NHANES sample.

The independent variables that appear in the Heckman equations for both labor force participation and wages are a complete set of categorical variables describing the full interactions between pairs of years (1999-2000, 2001-2002, 2003-2004, 2005-2006, 2007-2008), ethnicity (non-Hispanic white, non-Hispanic black, and Hispanic), categories of education (did not attend high school, attended but did not complete high school, high school graduate, some college, and college graduate), and five-year age categories. Those variables also appear in the meal participation equations in my main analysis, so the effects of imputed wages are implicitly being identified by the interactions between those variables, such as how relative wage opportunities shift over time. These variable interactions explain a small but extremely statistically significant portion of wages in a linear model, indicating that the instruments have sufficient strength.

Returning to the NHANES data, I use a number of other independent variables to examine factors that influence a person's probability of participating in each of the three meals. One characteristic with extremely wide-reaching effects on behavior is gender; for example, men and women may have different responsibilities for housework and childcare, affecting both their ability to respond to wage opportunities and the time available to eat meals. Therefore, I not only control for gender, but instead perform conditional analyses separately for women and men. Similarly, the day of the week influences how people spend their time in many ways, so I also analyze weekdays and weekends separately.

Several other characteristics may also affect the decision to eat a given meal. Important personal characteristics include age, ethnicity, and education. I control for age with both a linear and quadratic term. Ethnicity is separated into three groups, with indicator variables for Hispanics and non-Hispanic black individuals, leaving everyone else in the default group. I also use dummy variables to control for levels of education: no high school, attended high school but did not graduate, graduated from high school (or the equivalent), and attended college but did not graduate, with college graduates as the default group.

More situational controls include a dummy variable for marital status, as married people may engage in social interaction that increases the benefits from eating, while introducing economies of scale that decrease the monetary and preparation costs. Larger households could affect meal behavior in the same way, so I also include a variable for the number of people living in the household. Similarly, people might eat different meals at different times of year, so I use an indicator variable for whether the interview was in the "winter" (November through April) or "summer" (May through October). Meal behaviors have been shown to trend over time (Popkin and Duffey 2010, Kant and Graubard 2006), so I control for which survey wave a person was interviewed for: 1999-2000, 2001-2002, 2003-2004, 2005-2006, or 2007-2008. Finally, people may respond differently to varying interview techniques, so I control whether a given interview was conducted in person on the first interview day or over the phone on the second day.

In order to control costs, the NHANES does not pick people randomly from the entire United States. Instead, each year the survey selects fifteen counties to serve as primary sampling units. Within those locations, the NHANES randomly chooses households, from which one resident is extensively interviewed about many things, including their foods consumed. Since locations and households both vary in size and composition, the resulting sample, as-is, does not accurately represent the U.S.

population. People who live in low population regions or households are more likely to be selected to participate in the survey. On top of these effects, the NHANES also deliberately oversamples minorities, some ranges of age, and pregnant women.

In order to correct for these varied selection probabilities, the NHANES provides sampling weights for the participants from each wave of the food consumption interview; use of these weights adjusts the sample demographics to match the national population. Since the people in the 2003-04, 2005-06, and 2007-08 waves are effectively sampled twice, I apply the additional correction of dividing the weights from each of those years by two. This should make the weighted sample descriptive of not just the country, but also across the years 1999-2008.

Descriptive Analysis

Table 2.2 displays the weighted fractions of women and men who eat breakfast, lunch, and dinner on weekdays and weekends. Eighty-six percent of women eat breakfast on weekdays, 82% eat lunch, and 93% eat dinner. Similarly, the proportion of women eating breakfast on weekends is also 86%, but only 71% eat lunch on weekends, and 91% eat dinner. The same fraction of women eats snacks on both weekdays and weekends, 92%.

Men are a bit less likely than women to eat meals on either weekdays or weekends. On weekdays, 82% eat breakfast, 79% eat lunch, and 92% eat dinner. Breakfast increases slightly on weekends, to 83%, but lunch falls to 67% and dinner to 90%. Snack consumption falls slightly from 93% on weekdays to 92% on weekends.

These percentages for women and men indicate that although most people eat a given meal, there is a substantial proportion for each meal that does not. This variation may be explainable through differences in individual characteristics for the people who skip meals. Therefore, I next investigate the average values of wages and other demographic characteristics for people who skip breakfast, lunch, dinner, and snacks relative to those of the population as a whole.

The columns of Table 2.3 show weighted averages for the dependent and independent variables for women. The first column represents the means for all women in the sample, while the second, third, fourth, and fifth columns display averages for women who did not eat breakfast, lunch, dinner, and snacks, respectively. Women who skip any of those meals (columns 2, 3, 4, and 5) have lower expected wages than the sample as a whole (column 1). They also have lower levels of education, and are less likely to be married. Relatively fewer women report eating lunch and dinner on weekends than on weekdays, as well.

The columns of Table 2.4 display similar weighted variable means for men. Interestingly, all of the relationships mentioned above for women also apply to men. In particular, wages appear to be lower for men who skip meals than for the full sample. An important question, then, is whether the positive association between wage opportunities and meal participation holds for women and men on both weekdays and weekends after other factors are controlled for.

Multivariate Approach

In order to determine the connections between each of the variables and meals after the other factors have been accounted for, I conduct a multivariate analysis of meal participation. These are separate binary probability models (Probit) for the decision to participate in each of the four meal categories (breakfast, lunch, dinner, and snacks). The sample is split by gender and by weekday/weekend, as those categories may prompt fundamentally different meal behaviors. Each observation is weighted as described previously, and standard errors are clustered by individual (relevant for the people in the 2003-2008 surveys who were interviewed on two separate days). Important control variables include the wage rate as a proxy for the value of a person's time, ethnicity, a quadratic function of age, marital status, household size, the individual's level of education, whether or not the interview was conducted over the phone, and the season and survey wave.

A possible concern is that since wages are estimated in a separate step with its own errors, treating the imputed wage variable as though it were exact causes the standard errors to be underestimated (Murphy and Topel, 1985). In order to address this, I adapt Hole's (2006) implementation of Murphy and Topel's maximum likelihood correction for a two-step, two-sample model. The independence of the NHANES and CPS samples simplifies the relevant algebra.

The corrected covariance matrix Σ equals $V_2 + V_2 * C * V_1 * C^T * V_2$, where V_1 is the covariance of the estimates from the first stage (the Heckman model wage coefficients), V_2 is the covariance of the estimates from the second stage (the Probit model), and C is a correction matrix described in Murphy and Topel. However, the covariances generated through this method do not properly take into account either sample weighting, clustering, or marginal effects. Therefore, for each explanatory variable in the model, I calculate the ratio of the standard error estimate from Σ to the corresponding error from V_2 to get a scaling factor. I then multiply each of the weighted, robust standard errors for the marginal effects on meal participation by the appropriate scaling factor. Due to the large sample sizes used in the wage imputation to calculate V_1, this increases the various standard errors by amounts ranging between one and ten percent of the initial value.

Empirical Results

Table 2.5 shows compiles the marginal effects of the wage variable on the probabilities of women and men eating breakfast, lunch, dinner, and snacks on weekdays and weekends. Values represent the average marginal effect for a one unit change in the log of imputed wages on the expected probability of a person consuming a meal of that particular type. The first row of the table displays the effects for women on weekdays. Large standard errors mean that none of the relationships between wages and breakfast, lunch, dinner, or snacks are statistically significant. However, they do all appear to be positive.

The results for women eating meals on weekends are displayed in the second row of Table 2.5. Again, the standard errors for breakfast and lunch obscure any connection between wages and meal consumption, although here the signs suggest that such a correlation might be negative. In the case of dinner, the relationship with wages is negative (at a 0.10 significance level); a 1% increase in wages is associated with a decrease in the probability of weekend dinner of 0.319 percentage points. At the same time, however, the probability of eating snacks increases by 0.212 percentage points, at a 0.01 significance level. This may indicate that women with higher wages are less likely to be able to find the time to eat formal meals, and snack instead.

The third row displays the results for men on weekdays. A 1% increase in wages is associated with a 0.221 percentage point increase in the probability of breakfast, at a 0.10 significance level. Wages also have modest positive but statistically insignificant connections with the probability of eating food for both lunch and dinner. Conversely, that 1% wage increase corresponds to a 0.076 percentage point decrease in the probability of snacking. This is a relationship which could be observed if men with higher wages are more likely to follow a structured schedule with opportunities for breakfast, lunch, and dinner, but not snacks.

Similarly, the results for men on weekends are shown in the fourth row of Table 2.5. As with weekdays, wages may be positively associated with the probability of eating both breakfast and dinner. These effects are relatively large, but not quite statistically significant. Similarly, wages still have a statistically insignificant negative correlation with snacking. However, unlike weekdays, men with higher wages on weekends are significantly less likely to eat lunch (at a 0.05 significance level). A 1% increase in wages corresponds to a lower probability of lunch of 0.216 percentage points.

As can be seen in the full specifications for the Probit models, Tables 2.6-2.9, other independent variables also appear to influence the probability of eating meals. Both genders of blacks and Hispanics are less likely to eat any given meal (except for breakfast for Hispanics) or to snack on either weekdays and weekends. Also, increasing levels of education are generally associated with higher probabilities of eating meals, with statistically significant results for men's lunches, and for women on weekends; however, female college graduates are less likely to snack on weekends. This corresponds to the theory that more highly educated individuals are better informed about the health benefits of eating regular meals. Married men and women are more likely to eat each of the three meals, but not particularly more likely to eat snacks. This is consistent with the idea that there are lower individual marginal costs and greater benefits to eating meals together. However, controlling for marital status, household size only appears to positively affect the probability of men eating lunch on weekends.

One interesting result is the effect of the "telephone" variable, which indicates whether the interview was conducted on the first day, in person, or on a later day, over the phone. The results suggest that, holding other factors constant, people were a few percent more likely to report eating a given primary meal in the phone interview, and less likely to eat snacks. This suggests that people responding over the telephone reported a greater fraction of meals as breakfast, lunch, or dinner. This may be a result of the fact that a list of the possible responses for meal names was made available to respondents. Although it is unfortunate that the results were not identical for in person and telephone interviews, the fact that the probability of meals did not decrease over the telephone is good news for surveys conducted entirely using the phone, such as the ATUS.

Finally, using the existence of multiple days of data for individuals from the last three waves of the NHANES, I also perform random effects Probit analyses on the data, using the same controls. The results, not presented here, are very similar to those of the normal weighted probit. However, there appears to be significant variation in meal probabilities both within and across individuals. In general, the unexplained standard deviation within individuals (sigma) appears to be slightly more than twice the unexplained deviation across individuals (rho).

Estimating Meal Probabilities Together

One concern with examining meals individually is that meals are not independent; people do not ignore breakfast when deciding whether or not to eat lunch. One way to account for this is to allow for correlation in the probabilities of eating breakfast, lunch, dinner, and snacks. I estimate a Probit model with multiple dependent variables for participation in these four meal categories simultaneously.[5] This model is set up in the same way as the individual Probit models of the main specification, except that the error terms for the four meals follow a joint Normal distribution.

Linking these four types of meals may improve the results in a variety of ways. First, if there are significant correlations between meals, then accounting for this should improve the efficiency of the results, particularly if there are unobserved factors that make a person more or less likely to report participating in meals generally. Second, this

[5] I calculate this model using the mvprobit command with 100 repetitions in Stata, which relies upon the GHK simulator to estimate *M*-dimensional Normal distributions.

model reports the correlations between meals; when these are negative, they provide an estimate of the degree to which people substitute between meals. This joint model can be thought of as having the Probit models for individual meals nested within it, where they restrict the correlations between meals to be zero. Testing these restrictions with a likelihood ratio test rejects the hypothesis that meals are uncorrelated, for both genders on both weekdays and weekends, at a 0.1% level of significance.

The marginal effects of wages and other independent variables on the probabilities of eating each meal are displayed in Tables 2.10, 2.11, 2.12, and 2.13. These analyses split the sample along gender and weekday/weekend lines, and are analogous to the main specification Tables 6 through 9. Both the signs and magnitudes of the marginal effects for wages in the multinomial Probit model are very similar to the results from the regular Probit. This is reassuring, since it suggests those results are relatively robust. However, the standard errors for these marginal effects are fairly different, larger in some cases and smaller in others, resulting in different effects being statistically significant. Also, unlike the regular Probit, due to computational difficulties I do not correct the multinomial Probit errors to account for wages being imputed, so they are likely to be underestimated by between one and ten percent (the range by which the Murphy and Topel correction increased the regular Probit standard errors).

In Table 2.10, the wage effects are again positive for all four meals for women on weekdays, but still not statistically significant. For Table 2.11, women on weekends, dinner retains its statistically significant negative wage effect, and wages are still significantly positive for snacks, although the magnitudes change somewhat. In the case of men on weekdays in Table 2.12, a reduced standard error enhances the significance of the positive wage effect for breakfast, but the error for snacks increases, eliminating the significant effect of wages in that case. Finally, for men on weekends in Table 2.13, although the magnitudes change very little, the positive wage effects for breakfast and dinner become statistically significant in the multiple Probit model, while the negative wage effect on lunch loses significance.

Correlations between meals suggest that women on weekdays substitute between snacks and the other three meals, but that breakfast is a complement to both lunch and dinner. On weekends, women substitute between lunch and dinner as well as substituting between snacks and other meals. For men on weekdays, breakfast and dinner tend to be eaten together, while dinner and snacks are substitutes. Men on weekends behave in the same way as women on weekends, substituting between lunch and dinner and between snacks and other meals.

Another way to look at multiple meals simultaneously is to assume that people select particular meal patterns for a day. Therefore, I test a model that assumes a person considers each possible collection of meals as a single unit, and then chooses between them. For example, a person might plan for a schedule including breakfast, lunch, and dinner, and compare it to an alternative schedule that includes only breakfast and dinner or only lunch and dinner. The person will have reasons for preferring each possible schedule, and pick the one that he or she likes the best.

I estimate this model using a multinomial Logit approach. In the multinomial Logit model, there is a separate latent variable y_k^* for each of the *k* possible outcomes y_k.

For each latent variable y_k^*, I calculate a set of coefficients β_k for the independent variables *x* which determine how they influence preferences for that outcome, as well as a stochastic error term ε_k that follows an extreme value distribution. This relationship is modeled linearly: $y_k^* = x\beta_k + \varepsilon_k$. The person is observed to participate in the pattern of meals y_k that has the largest value of y_k^*.

I consider the five different types of schedules defined by Siega-Riz et al. (1998). A person may eat all three meals, he or she may eat lunch and dinner but not breakfast, breakfast and dinner but not lunch, breakfast and lunch but not dinner, or the person may only eat one or zero meals in a day. Only a relatively small fraction of the population skips any given combination of two meals, and less than half a percent of the sample chooses not to eat any of the three. Therefore, more reliable estimates are garnered by grouping these behaviors together.

Table 2.14 shows the fractions of people that eat each combination of meals, as well as the marginal effects of log wages on the probabilities of eating those combinations. In almost every case, men are more likely to skip eating meals than women, and both men and women are less likely to eat meals on weekends than on weekdays. The effects of increasing wages are more nuanced, and relatively similar to those for individual meals in Table 2.5. Women on weekdays with higher wages are more likely to eat all three meals, and less likely to skip any combination of meals, although none of these results are statistically significant. On weekends, women with higher wages are less likely to eat all three meals or to skip only lunch, more likely to skip only breakfast or only dinner, and significantly more likely to skip two or more meals. Men with higher wages are significantly more likely to eat all three meals on weekdays, and significantly less likely to skip breakfast. Finally, on weekends, men with higher wages are significantly more likely to skip only lunch, and significantly less likely to skip only breakfast. This suggests that those meals are treated as substitutes, with higher wage men having a preference for skipping lunch over breakfast.

Finally, I investigate the possibility that people may make meal decisions individually, but consider the other meals that they are eating when doing so. This is consistent with the idea that people are short-sighted, and react to their past behavior and expected future behavior, but do not expect their current actions to change what they will do. This model is estimated with Probit similarly to the main specification, but includes additional controls for the effects of other meals eaten in the day. The breakfast model controls for lunch and dinner, the lunch model controls for breakfast and dinner, the dinner model controls for breakfast and lunch, and the snacking model controls for breakfast, lunch, and dinner.

The signs, magnitudes, and significance levels of the marginal effects for wages in this model are nearly identical to those of the main specification in Table 2.5. The only substantive change is the wage effect for men snacking on weekdays; while still negative, it is no longer statistically significant. The effects of eating other meals, meanwhile, are quite similar to the correlations found by the multiple Probit models in Tables 2.10 through 2.13. Breakfast is positively affected by and positively affects lunch and dinner for women on weekdays, while the probability of snacking is negatively affected by all three other meals. For women on weekends, lunch and dinner negatively affect each other, and snacks are again negatively affected by all three other meals. Breakfast and dinner positively affect each other for men on weekdays, while dinner reduces the probability of snacking. Finally, men on weekends are much the same as women on weekends; lunch and dinner negatively affect each other, and eating lunch and dinner also negatively affects the probability of snacking.

Sensitivity Tests

Some possible sources of concern with these results are the constructions of the meal variables and the imputed wage variable. To address the possibility of incorrectly identified meals, I evaluate the basic Probit models again, using the FDA's definitions of breakfast and lunch, to see if those affect my results. The results for breakfast and lunch under those definitions seem fairly similar, although statistical significance is lost for men on weekdays and weekends. However, the significance of the Hispanic ethnicity increases. This is relevant because a major reason for differences between the FDA definitions and the Kant et al. (2006) definitions of my primary specification is the classification of various Spanish meals. If we assume, a priori, that Hispanics are more likely than not to have similar meal patterns to people of other ethnicities, then this suggests than the FDA classifications may be less reliable, since they exacerbate those differences.

I also estimate the models using definitions of meals based upon the times at which they are eaten. In this classification, there are no snacks. Any eating or drinking occasion that begins in the span from 4 a.m. up to but not including 11 a.m. is classified as breakfast, meals that begin at 11 a.m. up until almost 4 p.m. are considered to be lunch, and meals beginning from 4 p.m. up to but not including 11 p.m. are treated as dinner. Meals before 4 a.m. or beginning at or after 11 p.m. fall into a special "nighttime" category. The reclassification of snacks leads to a high probability of eating each type of meal; the probability of breakfast is 89%, lunch is 93%, and dinner is 98%, although nighttime meals are eaten by only 15% of the sample.

These time-defined meals appear to have little connection to imputed wages. On the whole, this is not surprising, since it aggregates meals and snacks, and with the exception of women on weekdays, the wage coefficients for meals and snacks were generally of opposite signs. The only statistically significant wage coefficient is for women eating lunch on weekdays; a 1% rise in wages corresponds to a 0.104 percentage point increase in the probability of lunch. No particularly noteworthy trends are apparent in other independent variables, although married and more highly educated individuals are still generally more likely to eat breakfast, lunch, and dinner defined this way.

In terms of testing the imputed wage variable, if the exclusion restrictions for the Heckman selection model are not sufficiently strong or valid, then imputed wages from that model will not be reliable. However, tests of different combinations of exclusion restrictions (with the exception of home ownership, which may be too highly correlated with wage rates) yield relatively consistent levels of explained variation and correlation between the wage equation and labor force participation, which is an encouraging sign.

In order to further determine the possible sensitivity of the meal participation results to the construction of the wage variable, I estimate marginal effects for Probit models using three other definitions for wages. First, instead of using a selection model, I use the average values of log wage for labor force participants in the CPS to impute wages for people with the same combination of gender, age, ethnicity, education, and year in the NHANES. This linear estimate of log wages yields similar results to those found in my main specifications. The signs and magnitudes remain roughly the same for all 16 log wage coefficients; those for women eating dinner remain statistically significant, but none of the coefficients for men are.

I also estimate models for meal participation using linear wage (as opposed to log wage), imputed both through a Heckman selection model, and via OLS, as described above. The magnitudes of the coefficients for non-logged wage are very different from those for log wages, of course. However, with the exception of a statistically insignificant positive result for lunch for women on weekends in the linear model, the signs for each model's coefficient are identical to those of log wages. This consistency across specifications indicates that my results are not particularly sensitive to the exact method of imputation used.

Another possibility is that the two constraints of money and time might affect people differently at different points in the wage distribution. In this case, wages could have a non-linear effect on meal participation. To test this possibility, I run two quadratic specifications in wage. First, I include wage squared in the model. This massively magnifies the standard errors for wages, blotting out all statistical significance, except for strong opposing signs between wage and wage squared for lunch for women on weekends and men on weekdays. Even there, however, the combined marginal effect of wage is negative for the entire distribution. These large standard errors indicate that wage and wage squared are too highly correlated.

To address this issue, I also test a model that includes centered wage squared, instead; this is computed by subtracting the average level of imputed wage for a person's gender and weekday/weekend status from the person's wage to get a centered wage value, then squaring that value. In this model, the coefficients and significance for wages are almost identical to those found in Tables 2.6-2.9, while the coefficients for centered wage squared are generally statistically insignificant. These results suggest that non-linear effects are not particularly important for wages.

A final concern I address is that of weighting. As discussed in the data section, the NHANES data is gathered according to a complicated sample design with considerable oversampling for some demographic groups. In order to obtain nationally representative results, my analyses weight the data appropriately and cluster the standard errors. However, this leads to some observations being weighted almost a thousand times more heavily than others, which raises questions about the extent to which the results are driven by the weighting. To investigate these questions, I rerun the Probit models for meal participation without weights or clustering. The signs of the marginal effects of wages on meals with this specification are relatively similar to those of the primary, weighted specification. However, very few of the results are statistically significant; only the positive snack effect for women on weekends and the positive breakfast effect for men on weekends remain. This suggests that the relationships between meals and wages in the weighted specification may be driven by people with higher individual weights:

members of groups that were not oversampled, or individuals from the 1999-2002 waves with a single dietary interview day.

Discussion

Overall, the results found for wages on weekdays and weekends are surprising. Ex ante, theory predicted that either the income effect of an increased ability to afford food would give wages a positive effect on meal participation, or else the substitution effect of a higher cost of time would link wages to meal skipping. Which effect would dominate was unclear. Either way, however, the income effect could be expected to remain constant across weekdays and weekends, while weekend time would be less strained for people working on weekdays. Therefore, higher wages would be expected to have a more positive effect on weekends than on weekdays.

This is not what I found. Instead, increased wages are associated with increased probabilities of breakfast, lunch, and dinner for both women and men on weekdays. However, on weekends, women with higher wages are less likely to eat all three meals, with a highly significant result for dinner. Similarly, men with higher wages are significantly less likely to eat lunch on weekends. This outcome is surprising, and also seemingly not consistent with the result I found in my meal production and consumption time paper – namely, that women and men with higher wages spend more time eating on weekends.

One possible explanation for this discrepancy could be that higher wage individuals are more likely to work, and employed people opt for less structured meal consumption on weekends, as suggested by Waterhouse et al. (2003). In this case, they might still eat, but think of their eating occasions as snacks rather than breakfast, lunch, or dinner. If snacks require a relatively low ratio of preparation time to goods consumed, this corresponds to Becker's (1965) theoretical result that people with a higher value of time will prefer to consume goods-intensive commodities. Consistent with this theory, I find significantly higher probability of snacking for women with higher wages on weekends, and significantly lower probability for higher wage men snacking on weekdays.[6] Investigating meals jointly, I also find strong negative correlations between eating snacks and other meals, and these correlations are greater on weekends, further supporting the idea that people often substitute between snacks and eating breakfast, lunch, and dinner.

The joint meals analyses also yield interesting information about substitution between breakfast, lunch, and dinner. Within the context of a single weekday, after controlling for other factors, people who eat breakfast are more likely to eat dinner, and women eating breakfast are also more likely to eat lunch. This suggests that rather than substituting, people's weekday meal decisions are driven by some common factor, such as a preference for regular meals. On weekends, the situation is different; breakfast has no correlation with other meals, while people who skip lunch are less likely to skip dinner. A possible explanation here is that weekend eating schedules are less structured, leading people to eat when hungry and not worry too much about which meal is being

[6] However, women have a consistent positive wage effect on snacking, while men have a consistent negative effect, so the two genders clearly approach snacks differently. This is perhaps a result of different meal preparation responsibilities. My meal production and consumption paper finds wages to have an overall negative effect upon women's meal production time, and an overall positive effect on men's meal production time.

eaten.[7] This theory of weekend substitution is also supported by the greater negative correlation found on weekends between snacks and other meals.

Increasing wages do not appear to have a great effect on women's meal patterns. However, men with higher wages are less likely to skip breakfast yet eat lunch and dinner. On weekdays, higher wage men choose to eat all three meals rather than skip breakfast. On weekends, though, men with higher wages do not appear likely to eat many more meals; instead, they are less likely to skip breakfast and more likely to skip lunch. One possible explanation for this behavior is that higher wage men are more likely to have breakfast as a weekday routine, which carries over to the weekend, and are then less interested in weekend lunches.

Overall, then, I do not find that greater wage opportunities on weekdays crowd out regular meals on those days. Instead, it seems that the increased structure of work days may relatively increase the probability that higher wage women and men eat breakfast, lunch, and dinner, and decrease the probability that men snack. On weekends, women with higher wages may snack rather than eat other meals, and men with higher wages prefer to skip lunch instead of breakfast. Future research may benefit from focusing on how the structure of daily schedules affects meals, or examine how meal contents differ across weekdays and weekends, and between meals and snacks.

[7] Analyses of meal timing using data from both the NHANES and the American Time Use Survey show a much smoother distribution throughout a weekend day than is found on weekdays.

Table 2.1. Meal Names in the NHANES

Meal Name	99-00	01-02	03-04	05-06	07-08	Meal ID
Breakfast	1,729	2,473	2,099	2,342	2,699	Breakfast
Lunch	1,500	2,150	1,839	2,015	2,360	Lunch
Dinner /	1,915	2,758	1,836	1,998	2,207	Dinner
Supper			526	569	780	Dinner
Brunch	134	192	108	102	153	Breakfast?
Snack /	4,401	5,929	3,732	4,107	4,695	Snack
Drink			1,481	2,377	2,738	Snack
Infant Feeding	1	0	0	0	0	None
Ext. Consumpt.	432	705	453	1,513	1,654	Snack
Desayuno	226	205	171	320	460	Breakfast
Almuerzo	199	137	137	214	276	Lunch?
Comida	301	274	193	287	320	Snack?
Merienda	128	105	71	165	232	Snack
Cena	344	278	232	346	420	Dinner
Entre Comida	153	243	70	84	134	Snack
Botana	49	71	65	143	176	Snack
Bocadillo	28	80	92	74	140	Snack
Tentempie			6	11	24	Snack
Bebida			98	304	468	Snack
Other	2	11	1	3	0	Snack
Don't Know	1	1	0	0	0	Snack
Missing						
Total Meals	11,543	15,612	13,210	16,974	19,936	

This table indicates the English and Spanish meal names in the five waves of NHANES data. Counts are the number of meals of that type eaten by people in the final sample. Meal ID indicates the Breakfast/Lunch/Dinner identity assigned to that meal in this paper.

Table 2.2. Meal Participation Rates on Weekdays and Weekends

	Women		Men	
VARIABLES	Weekdays	Weekends	Weekdays	Weekends
Breakfast	0.86	0.86	0.82	0.83
Lunch	0.82	0.71	0.79	0.67
Dinner	0.93	0.91	0.92	0.90
Snack	0.93	0.92	0.92	0.92
Observations	8,005	3,736	6,953	3,439

Weighted average values for meal participation in the 1999-2008 NHANES.

Table 2.3. Variable Means for Women

VARIABLES	(1) All	(2) No Breakfast	(3) No Lunch	(4) No Dinner	(5) No Snack
Breakfast	0.86	0.00***	0.83***	0.76***	0.89**
Lunch	0.79	0.73***	0.00***	0.76	0.86***
Dinner	0.92	0.86***	0.91	0.00***	0.95***
Snack	0.93	0.94**	0.95***	0.95***	0.00***
Imputed Log Wage	2.53	2.42***	2.43***	2.37***	2.45***
	(0.32)	(0.29)	(0.30)	(0.30)	(0.30)
White	0.70	0.59***	0.58***	0.50***	0.60***
Black	0.12	0.21***	0.19***	0.21***	0.20***
Hispanic	0.13	0.15***	0.17***	0.25***	0.15*
Other Race	0.05	0.05	0.05	0.03*	0.05
Age	43.65	40.51***	44.17*	43.54	43.21
	(11.68)	(11.19)	(11.59)	(11.38)	(11.82)
Married	0.68	0.58***	0.61***	0.57***	0.65
Household Size	3.15	3.38***	3.25**	3.37***	3.25
	(1.62)	(1.75)	(1.75)	(1.79)	(1.64)
No High School	0.05	0.08***	0.08***	0.12***	0.06
H.S. Drop Out	0.12	0.18***	0.19***	0.22***	0.18***
H.S. Graduate	0.23	0.26**	0.27***	0.28**	0.25
Some College	0.32	0.32	0.31	0.25***	0.33
College Graduate	0.28	0.15***	0.15***	0.13***	0.19***
Weekday	0.71	0.71	0.61***	0.64***	0.69
Weekend	0.29	0.29	0.39***	0.36***	0.31
Winter	0.39	0.45***	0.40	0.44**	0.43*
Summer	0.61	0.55***	0.60	0.56**	0.57*
Telephone Interview	0.34	0.28***	0.30***	0.32	0.36
Year 1999-2000	0.16	0.21***	0.19***	0.20*	0.23***
Year 2001-2002	0.21	0.23*	0.22	0.25**	0.24
Year 2003-2004	0.20	0.20	0.19*	0.19	0.32***
Year 2005-2006	0.21	0.17***	0.20	0.19	0.10***
Year 2007-2008	0.22	0.19**	0.21	0.18***	0.11***
Observations	11,741	1,745	2,915	1,121	858

Weighted variable means for women from the 1999-2008 waves of the NHANES. Columns represent (1) all women in the sample, (2) women who did not eat breakfast on the preceding day, (3) women who did not eat lunch on the preceding day, and (4) women who did not eat dinner on the preceding day. Unweighted standard deviations are in parentheses for the three non-Boolean variables. Statistically significant differences between meal skippers and the full sample are indicated by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.4. Variable Means for Men

VARIABLES	(1) All	(2) No Breakfast	(3) No Lunch	(4) No Dinner	(5) No Snack
Breakfast	0.83	0.00***	0.80***	0.74***	0.85
Lunch	0.75	0.71***	0.00***	0.74	0.78
Dinner	0.92	0.88***	0.92	0.00***	0.96***
Snack	0.92	0.93	0.93	0.96***	0.00***
Imputed Log Wage	3.00	2.89***	2.93***	2.87***	2.97**
	(0.30)	(0.28)	(0.28)	(0.28)	(0.29)
White	0.71	0.64***	0.63***	0.52***	0.61***
Black	0.11	0.15***	0.15***	0.19***	0.16***
Hispanic	0.13	0.15**	0.17***	0.24***	0.16**
Other Race	0.05	0.06	0.04	0.04	0.07
Age	43.28	40.00***	43.76*	42.81	42.43
	(11.43)	(11.41)	(11.50)	(11.73)	(11.94)
Married	0.71	0.63***	0.64***	0.61***	0.68
Household Size	3.12	3.18	3.06	3.25*	3.18
	(1.64)	(1.72)	(1.76)	(1.81)	(1.71)
No High School	0.05	0.08***	0.09***	0.11***	0.05
H.S. Drop Out	0.12	0.18***	0.18***	0.20***	0.12
H.S. Graduate	0.25	0.28**	0.28***	0.29*	0.27
Some College	0.29	0.27	0.28	0.25**	0.29
College Graduate	0.29	0.19***	0.17***	0.16***	0.27
Weekday	0.70	0.70	0.60***	0.64***	0.69
Weekend	0.30	0.30	0.40***	0.36***	0.31
Winter	0.40	0.44**	0.42	0.50***	0.45**
Summer	0.60	0.56**	0.58	0.50***	0.55**
Telephone Interview	0.34	0.29***	0.29***	0.28***	0.36
Year 1999-2000	0.16	0.20***	0.17	0.20**	0.19*
Year 2001-2002	0.22	0.23	0.26***	0.24	0.26*
Year 2003-2004	0.20	0.21	0.20	0.18	0.28***
Year 2005-2006	0.21	0.18***	0.18***	0.19	0.12***
Year 2007-2008	0.21	0.19**	0.19**	0.19	0.14***
Observations	10,392	1,958	2,954	1,071	846

Weighted variable means for men from the 1999-2008 waves of the NHANES. Columns represent (1) all men in the sample, (2) men who did not eat breakfast on the preceding day, (3) men who did not eat lunch on the preceding day, and (4) men who did not eat dinner on the preceding day. Unweighted standard deviations are in parentheses for the three non-Boolean variables. Statistically significant differences between meal skippers and the full sample are indicated by: *** p<0.01, ** p<0.05, * p<0.1

Table 2.5. Imputed Wage Marginal Effects on Meal Consumption for Women and Men

Subsample	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Women				
Weekdays	0.059	0.063	0.079	0.053
	(0.100)	(0.127)	(0.048)	(0.067)
Weekends	-0.122	-0.050	-0.319*	0.212***
	(0.164)	(0.209)	(0.183)	(0.058)
Men				
Weekdays	0.221*	0.067	0.055	-0.075*
	(0.132)	(0.122)	(0.074)	(0.041)
Weekends	0.339	-0.228**	0.210	-0.062
	(0.209)	(0.114)	(0.161)	(0.060)

Marginal effects of imputed wages on meal probabilities from weighted Probit models (full specifications in Tables 6-9) in the 1999-2008 waves of the NHANES. Standard errors in parentheses are rescaled as per Murphy and Topel (1985). *** p<0.01, ** p<0.05, * p<0.1

Table 2.6. Probit Estimates of the Determinants of Meal Consumption for Women on Weekdays

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	0.059	0.063	0.079	0.053
	(0.100)	(0.127)	(0.048)	(0.067)
Black	-0.041**	-0.090***	-0.036***	-0.030**
	(0.019)	(0.022)	(0.011)	(0.014)
Hispanic	0.025	-0.049**	-0.033***	-0.011
	(0.020)	(0.022)	(0.012)	(0.012)
Other Race	0.007	-0.039	-0.002	-0.001
	(0.020)	(0.032)	(0.015)	(0.021)
Age/10	-0.076*	-0.075	-0.072***	0.019
	(0.046)	(0.050)	(0.022)	(0.042)
Age Squared/100	0.013**	0.007	0.008***	-0.002
	(0.005)	(0.005)	(0.003)	(0.005)
Married	0.050***	0.027	0.023***	-0.009
	(0.012)	(0.017)	(0.007)	(0.008)
Household Size	-0.001	-0.006	-0.001	0.003
	(0.005)	(0.005)	(0.003)	(0.002)
No High School	-0.105	-0.153	-0.018	0.013
	(0.113)	(0.140)	(0.064)	(0.072)
H.S. Drop Out	-0.058	-0.137	-0.003	-0.004
	(0.092)	(0.123)	(0.057)	(0.067)
H.S. Graduate	-0.039	-0.111	-0.008	-0.010
	(0.068)	(0.091)	(0.040)	(0.048)
Some College	-0.046	-0.076	0.003	-0.012
	(0.050)	(0.060)	(0.027)	(0.035)
Summer	0.027**	-0.016	-0.003	0.008
	(0.013)	(0.013)	(0.005)	(0.007)
Telephone Interview	0.024**	0.035**	0.002	-0.017*
	(0.010)	(0.014)	(0.007)	(0.009)
Year 1999-2000	-0.032	-0.032	-0.013	-0.085***
	(0.022)	(0.026)	(0.011)	(0.024)
Year 2001-2002	-0.014	-0.017	-0.025**	-0.070***
	(0.018)	(0.018)	(0.011)	(0.018)
Year 2003-2004	-0.013	0.000	-0.014	-0.081***
	(0.019)	(0.019)	(0.010)	(0.016)
Year 2005-2006	0.016	-0.027*	-0.012	0.001
	(0.014)	(0.015)	(0.010)	(0.012)
Observations	8,005	8,005	8,005	8,005

Weighted marginal effects on meal probabilities for women interviewed on weekdays in the 1999-2008 waves of the NHANES. Excluded categories are white, college graduates, winter, and 07-08. Rescaled standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.7. Probit Estimates of the Determinants of Meal Consumption for Women on Weekends

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	-0.122	-0.050	-0.319*	0.212***
	(0.164)	(0.209)	(0.183)	(0.058)
Black	-0.105***	-0.137***	-0.082***	-0.012
	(0.030)	(0.030)	(0.031)	(0.010)
Hispanic	-0.026	-0.092***	-0.116***	0.016
	(0.027)	(0.033)	(0.031)	(0.011)
Other Race	-0.038	-0.055	0.065*	-0.014
	(0.036)	(0.042)	(0.039)	(0.012)
Age/10	0.080	-0.129	0.052	-0.027
	(0.080)	(0.103)	(0.077)	(0.031)
Age Squared/100	-0.004	0.013	-0.005	0.003
	(0.008)	(0.011)	(0.008)	(0.003)
Married	0.015	0.047**	0.015	0.006
	(0.020)	(0.023)	(0.019)	(0.007)
Household Size	-0.003	0.011	0.004	-0.004
	(0.005)	(0.007)	(0.005)	(0.003)
No High School	-0.264	-0.182	-0.390**	0.180***
	(0.170)	(0.205)	(0.177)	(0.057)
H.S. Drop Out	-0.244	-0.224	-0.348**	0.149***
	(0.157)	(0.179)	(0.158)	(0.049)
H.S. Graduate	-0.206*	-0.111	-0.241**	0.123***
	(0.116)	(0.127)	(0.114)	(0.033)
Some College	-0.118*	-0.119	-0.135*	0.072***
	(0.071)	(0.081)	(0.072)	(0.022)
Summer	0.026*	-0.018	0.019	0.002
	(0.014)	(0.022)	(0.019)	(0.007)
Telephone Interview	0.043**	0.031*	-0.010	-0.017**
	(0.021)	(0.017)	(0.023)	(0.008)
Year 1999-2000	-0.058*	-0.025	-0.058*	-0.022**
	(0.030)	(0.026)	(0.029)	(0.010)
Year 2001-2002	-0.047*	-0.030	-0.064***	-0.040***
	(0.026)	(0.029)	(0.024)	(0.011)
Year 2003-2004	-0.030	-0.010	-0.011	-0.037***
	(0.021)	(0.026)	(0.023)	(0.010)
Year 2005-2006	-0.037	0.013	-0.011	-0.001
	(0.028)	(0.029)	(0.019)	(0.012)
Observations	3,736	3,736	3,736	3,736

Weighted marginal effects on meal probabilities for women interviewed on weekends in the 1999-2008 waves of the NHANES. Excluded categories are white, college graduates, winter, and 07-08. Rescaled standard are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.8. Probit Estimates of the Determinants of Meal Consumption for Men on Weekdays

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	0.221*	0.067	0.055	-0.075*
	(0.132)	(0.122)	(0.074)	(0.041)
Black	-0.008	-0.070***	-0.051***	-0.040***
	(0.025)	(0.023)	(0.011)	(0.008)
Hispanic	0.086**	-0.040	-0.043***	-0.044***
	(0.039)	(0.030)	(0.016)	(0.011)
Other Race	-0.061*	-0.014	-0.011	-0.027
	(0.035)	(0.049)	(0.028)	(0.019)
Age/10	0.027	-0.136**	0.002	0.062**
	(0.063)	(0.064)	(0.037)	(0.031)
Age Squared/100	-0.001	0.012*	-0.002	-0.006*
	(0.007)	(0.006)	(0.004)	(0.003)
Married	0.041**	0.064***	0.045***	0.008
	(0.019)	(0.016)	(0.012)	(0.009)
Household Size	-0.000	0.004	-0.003	-0.001
	(0.006)	(0.005)	(0.004)	(0.003)
No High School	-0.054	-0.208***	-0.042	-0.022
	(0.091)	(0.067)	(0.038)	(0.030)
H.S. Drop Out	-0.052	-0.212***	-0.044	-0.031
	(0.067)	(0.054)	(0.034)	(0.025)
H.S. Graduate	-0.025	-0.132***	-0.035	-0.031*
	(0.055)	(0.045)	(0.026)	(0.018)
Some College	-0.019	-0.115***	-0.013	-0.011
	(0.041)	(0.034)	(0.022)	(0.017)
Summer	0.042**	0.004	0.025**	0.013*
	(0.017)	(0.016)	(0.011)	(0.008)
Telephone Interview	0.025	0.034***	0.017*	-0.020**
	(0.016)	(0.013)	(0.010)	(0.009)
Year 1999-2000	-0.049**	-0.009	-0.020	-0.048***
	(0.023)	(0.024)	(0.015)	(0.014)
Year 2001-2002	-0.018	-0.070***	-0.008	-0.053***
	(0.026)	(0.021)	(0.015)	(0.012)
Year 2003-2004	-0.031	-0.029	-0.013	-0.041***
	(0.029)	(0.018)	(0.017)	(0.012)
Year 2005-2006	0.005	-0.003	-0.015	0.003
	(0.025)	(0.018)	(0.012)	(0.009)
Observations	6,953	6,953	6,953	6,953

Weighted marginal effects on meal probabilities for men interviewed on weekdays in the 1999-2008 waves of the NHANES. Excluded categories are white, college graduates, winter, and 07-08. Rescaled standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.9. Probit Estimates of the Determinants of Meal Consumption for Men on Weekends

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	0.339	-0.228**	0.210	-0.062
	(0.209)	(0.114)	(0.161)	(0.060)
Black	-0.029	-0.123***	-0.036	-0.058***
	(0.035)	(0.028)	(0.022)	(0.011)
Hispanic	0.022	-0.070**	-0.051*	-0.021
	(0.049)	(0.035)	(0.031)	(0.020)
Other Race	-0.003	-0.010	-0.013	-0.050**
	(0.050)	(0.053)	(0.053)	(0.023)
Age/10	-0.030	-0.004	-0.036	0.051
	(0.081)	(0.079)	(0.063)	(0.036)
Age Squared/100	0.006	0.002	0.001	-0.005
	(0.009)	(0.008)	(0.007)	(0.004)
Married	0.074***	0.091***	0.030	0.008
	(0.024)	(0.025)	(0.024)	(0.012)
Household Size	0.005	0.019**	0.000	-0.002
	(0.007)	(0.008)	(0.008)	(0.004)
No High School	0.076	-0.377***	0.061	-0.062
	(0.132)	(0.072)	(0.103)	(0.040)
H.S. Drop Out	0.110	-0.216***	0.042	-0.044
	(0.113)	(0.065)	(0.084)	(0.032)
H.S. Graduate	0.089	-0.187***	0.041	-0.050**
	(0.086)	(0.051)	(0.067)	(0.025)
Some College	0.084	-0.103***	0.031	-0.051***
	(0.058)	(0.037)	(0.046)	(0.016)
Summer	-0.020	-0.015	0.026	-0.008
	(0.024)	(0.022)	(0.018)	(0.010)
Telephone Interview	0.062**	0.022	0.028	-0.031**
	(0.027)	(0.020)	(0.023)	(0.015)
Year 1999-2000	-0.043	-0.081**	-0.036	-0.044**
	(0.042)	(0.033)	(0.033)	(0.019)
Year 2001-2002	-0.041	-0.056*	-0.039	-0.040**
	(0.041)	(0.031)	(0.029)	(0.018)
Year 2003-2004	-0.040	-0.014	0.011	-0.061***
	(0.039)	(0.034)	(0.029)	(0.021)
Year 2005-2006	-0.012	0.008	0.001	0.011
	(0.033)	(0.036)	(0.021)	(0.017)
Observations	3,439	3,439	3,439	3,439

Weighted marginal effects on meal probabilities for men interviewed on weekends in the 1999-2008 waves of the NHANES. Excluded categories are white, college graduates, winter, and 07-08. Rescaled standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.10. Multiple Probit Estimates for Meal Consumption for Women on Weekdays

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	0.065	0.064	0.098	0.051
	(0.112)	(0.120)	(0.073)	(0.081)
Black	-0.044***	-0.096***	-0.045***	-0.036***
	(0.015)	(0.016)	(0.011)	(0.011)
Hispanic	0.027	-0.052**	-0.041***	-0.012
	(0.019)	(0.020)	(0.012)	(0.014)
Other Race	0.007	-0.041	-0.001	-0.002
	(0.025)	(0.031)	(0.021)	(0.022)
Age/10	-0.080	-0.080	-0.091***	0.026
	(0.053)	(0.057)	(0.034)	(0.038)
Age Squared/100	0.013**	0.008	0.010***	-0.003
	(0.006)	(0.006)	(0.004)	(0.004)
Married	0.054***	0.028**	0.028***	-0.011
	(0.012)	(0.013)	(0.008)	(0.009)
Household Size	-0.002	-0.006	-0.002	0.004
	(0.004)	(0.005)	(0.003)	(0.003)
No High School	-0.111	-0.163	-0.026	0.006
	(0.102)	(0.109)	(0.067)	(0.075)
H.S. Drop Out	-0.060	-0.146	-0.007	-0.012
	(0.092)	(0.099)	(0.062)	(0.068)
H.S. Graduate	-0.040	-0.118*	-0.012	-0.017
	(0.065)	(0.071)	(0.044)	(0.048)
Some College	-0.048	-0.080*	0.002	-0.016
	(0.043)	(0.047)	(0.030)	(0.032)
CORRELATIONS	**Breakfast**	**Lunch**	**Dinner**	**Snack**
Lunch	0.092**			
	(0.039)			
Dinner	0.183***	-0.005		
	(0.043)	(0.045)		
Snack	-0.143***	-0.191***	-0.134**	
	(0.041)	(0.048)	(0.061)	
Observations	8,005	8,005	8,005	8,005

Weighted marginal effects on meal probabilities for women interviewed on weekdays in the 1999-2008 waves of the NHANES. Excluded categories are white and college graduates; season and year are also controlled for. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.11. Multiple Probit Estimates for Meal Consumption for Women on Weekends

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	-0.111	-0.061	-0.237**	0.361***
	(0.132)	(0.183)	(0.098)	(0.104)
Black	-0.095***	-0.136***	-0.060***	-0.021
	(0.019)	(0.026)	(0.017)	(0.016)
Hispanic	-0.023	-0.092***	-0.084***	0.029
	(0.022)	(0.032)	(0.018)	(0.018)
Other Race	-0.036	-0.054	0.042	-0.026
	(0.030)	(0.045)	(0.031)	(0.022)
Age/10	0.072	-0.119	0.043	-0.043
	(0.064)	(0.089)	(0.051)	(0.050)
Age Squared/100	-0.004	0.012	-0.004	0.005
	(0.007)	(0.010)	(0.006)	(0.005)
Married	0.013	0.047**	0.011	0.012
	(0.016)	(0.021)	(0.014)	(0.012)
Household Size	-0.003	0.010	0.002	-0.007*
	(0.005)	(0.007)	(0.004)	(0.004)
No High School	-0.239**	-0.190	-0.288***	0.309***
	(0.121)	(0.169)	(0.089)	(0.099)
H.S. Drop Out	-0.221**	-0.229	-0.254***	0.256***
	(0.109)	(0.150)	(0.081)	(0.085)
H.S. Graduate	-0.186**	-0.114	-0.178***	0.211***
	(0.078)	(0.108)	(0.058)	(0.060)
Some College	-0.106**	-0.120*	-0.100**	0.125***
	(0.052)	(0.072)	(0.039)	(0.040)
CORRELATIONS	Breakfast	Lunch	Dinner	Snack
Lunch	-0.030			
	(0.0044)			
Dinner	0.051	-0.208***		
	(0.057)	(0.045)		
Snack	-0.134**	-0.206***	-0.226***	
	(0.059)	(0.052)	(0.069)	
Observations	3,736	3,736	3,736	3,736

Weighted marginal effects on meal probabilities for women interviewed on weekends in the 1999-2008 waves of the NHANES. Excluded categories are white and college graduates; season and year are also controlled for. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.12. Multiple Probit Estimates for Meal Consumption for Men on Weekdays

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	0.192**	0.066	0.053	-0.092
	(0.090)	(0.093)	(0.058)	(0.062)
Black	-0.007	-0.066***	-0.043***	-0.049***
	(0.021)	(0.022)	(0.014)	(0.014)
Hispanic	0.074***	-0.038	-0.037**	-0.055***
	(0.025)	(0.026)	(0.016)	(0.019)
Other Race	-0.053*	-0.013	-0.010	-0.033
	(0.030)	(0.036)	(0.024)	(0.023)
Age/10	0.023	-0.130**	0.002	0.078**
	(0.052)	(0.054)	(0.034)	(0.040)
Age Squared/100	-0.001	0.012**	-0.002	-0.008*
	(0.005)	(0.006)	(0.004)	(0.004)
Married	0.035**	0.061***	0.040***	0.010
	(0.015)	(0.016)	(0.010)	(0.010)
Household Size	-0.000	0.004	-0.003	-0.001
	(0.005)	(0.005)	(0.003)	(0.004)
No High School	-0.045	-0.198***	-0.033	-0.024
	(0.064)	(0.067)	(0.041)	(0.042)
H.S. Drop Out	-0.044	-0.203***	-0.036	-0.038
	(0.053)	(0.057)	(0.033)	(0.036)
H.S. Graduate	-0.021	-0.126***	-0.030	-0.037
	(0.041)	(0.044)	(0.025)	(0.027)
Some College	-0.016	-0.110***	-0.011	-0.012
	(0.030)	(0.034)	(0.020)	(0.021)
CORRELATIONS	Breakfast	Lunch	Dinner	Snack
Lunch	0.033			
	(0.038)			
Dinner	0.116***	-0.064		
	(0.043)	(0.044)		
Snack	-0.068	-0.051	-0.190***	
	(0.047)	(0.049)	(0.054)	
Observations	6,953	6,953	6,953	6,953

Weighted marginal effects on meal probabilities for men interviewed on weekdays in the 1999-2008 waves of the NHANES. Excluded categories are white and college graduates; season and year are also controlled for. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.13. Multiple Probit Estimates for Meal Consumption for Men on Weekends

VARIABLES	(1) Breakfast	(2) Lunch	(3) Dinner	(4) Snack
Imputed Log Wage	0.280**	-0.253	0.162*	-0.070
	(0.121)	(0.163)	(0.089)	(0.085)
Black	-0.024	-0.136***	-0.028	-0.066***
	(0.027)	(0.035)	(0.021)	(0.019)
Hispanic	0.018	-0.078*	-0.039*	-0.024
	(0.032)	(0.041)	(0.024)	(0.023)
Other Race	-0.002	-0.013	-0.014	-0.061**
	(0.040)	(0.052)	(0.031)	(0.024)
Age/10	-0.024	-0.003	-0.027	0.062
	(0.069)	(0.086)	(0.050)	(0.046)
Age Squared/100	0.005	0.002	0.001	-0.006
	(0.007)	(0.009)	(0.005)	(0.005)
Married	0.061***	0.100***	0.023	0.009
	(0.019)	(0.026)	(0.015)	(0.014)
Household Size	0.004	0.021***	-0.000	-0.002
	(0.006)	(0.007)	(0.005)	(0.005)
No High School	0.063	-0.417***	0.049	-0.072
	(0.086)	(0.117)	(0.064)	(0.062)
H.S. Drop Out	0.091	-0.239**	0.033	-0.051
	(0.071)	(0.095)	(0.052)	(0.051)
H.S. Graduate	0.074	-0.206***	0.032	-0.058
	(0.055)	(0.072)	(0.040)	(0.038)
Some College	0.069*	-0.114**	0.023	-0.059**
	(0.041)	(0.053)	(0.030)	(0.029)
CORRELATIONS	Breakfast	Lunch	Dinner	Snack
Lunch	0.039			
	(0.044)			
Dinner	0.041	-0.118**		
	(0.063)	(0.051)		
Snack	-0.104*	-0.135***	-0.231***	
	(0.058)	(0.051)	(0.071)	
Observations	3,439	3,439	3,439	3,439

Weighted marginal effects on meal probabilities for men interviewed on weekends in the 1999-2008 waves of the NHANES. Excluded categories are white and college graduates; season and year are also controlled for. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.14. Multinomial Logit Model for the Pattern of Meals Eaten

	Women on Weekdays			Women on Weekends		
	All Meals			All Meals		
Percent Eating Wage Effect	0.673 +0.193 (0.172)			0.557 -0.274 (0.218)		
	No Breakfast	No Lunch	No Dinner	No Breakfast	No Lunch	No Dinner
Percent Eating Wage Effect	0.089 -0.029 (0.075)	0.136 -0.055 (0.112)	0.039 -0.077 (0.051)	0.083 +0.115 (0.118)	0.229 -0.057 (0.212)	0.059 +0.082 (0.078)
	No Meals or 1 Meal			No Meals or 1 Meal		
Percent Eating Wage Effect	0.062 -0.032 (0.096)			0.073 +0.134* (0.081)		

	Men on Weekdays			Men on Weekends		
	All Meals			All Meals		
Percent Eating Wage Effect	0.613 +0.301** (0.135)			0.513 +0.083 (0.178)		
	No Breakfast	No Lunch	No Dinner	No Breakfast	No Lunch	No Dinner
Percent Eating Wage Effect	0.116 -0.204** (0.092)	0.157 -0.022 (0.096)	0.041 -0.031 (0.055)	0.092 -0.220** (0.112)	0.239 +0.260* (0.137)	0.052 -0.004 (0.083)
	No Meals or 1 Meal			No Meals or 1 Meal		
Percent Eating Wage Effect	0.073 -0.043 (0.042)			0.104 -0.119 (0.091)		

Weighted multinomial Logit model for people choosing to eat all three meals of breakfast, lunch, and dinner, eating lunch and dinner but not breakfast, eating breakfast and dinner but not lunch, eating breakfast and lunch but not dinner, or eating at most one meal. Percent Eating displays the fraction of the subsample making that meal choice, while Wage Effect shows the marginal effects of a one-unit change in the log wage variable on the probability of making that choice. Other demographic controls include ethnicity, age, household characteristics, education, and the time of the interview. Wage standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

APPENDIX A

WAGE IMPUTATION

Unfortunately, information on wages and salaries is not available in the NHANES for 1999-2008. Furthermore, even if it were, many people are not employed, and for those who are, time use preferences and decisions could affect wages, making this variable endogenous. To get around these difficulties, I impute wages using the IPUMS files for the 2000-2009 March supplements of the Current Population Survey (CPS) data, as these files include people's wage and income values from the previous year. This two-sample approach both provides an estimate of potential wages for people who might not otherwise have one, and also corrects for endogeneity. My approach follows that of Zick and Stevens (2009), and is very similar to two-sample two-stage least squares, which was recommended by Inoue and Solon (2010) over Angrist and Krueger's (1992) two-sample instrumental variables technique. The key difference between my analysis and two-sample two-stage least squares is that for the first stage, I calculate the effects of explanatory variables on wages in the CPS data using a Heckman selection model rather than ordinary least squares (OLS).

The Heckman selection model for wages that I use here consists of two equations. The first is a Probit style model that predicts the probability of working/receiving a wage, while the second is a linear regression that estimates the value of the log of wages, conditional on the person working. Although I am primarily interested in the results for wages from the second equation, they may yield biased estimates of potential wages for non-workers if there exists heterogeneity in wage offers between people who choose to work relative to those who do not. Therefore, the error terms of the two equations are assumed to be jointly normally distributed; unobserved factors that influence a person's probability of having a job may also affect the wages that person could receive. Heckman's (1979) original suggestion for this model is two calculate the equations in two steps, sequentially. However, estimating them simultaneously using maximum likelihood is more efficient (Cameron and Trivedi 2005), and so I take that approach here.

Starting with the 2000-2009 March supplements of the CPS, I restrict the sample to individuals between ages 25 and 64 in the preceding year (to match the NHANES sample). Since most individuals in the CPS do not report hourly earnings, I instead calculate hourly wages as annual wage and salary income from the previous year, divided by the number of weeks worked and by the usual hours worked per week. I drop the approximately 1% of my sample with top-coded earnings (primary wage source greater than $200,000 or secondary wage source greater than $35,000), the 1% with allocated earnings data, and the 0.1% with top-coded usual weekly hours. After calculating real hourly wages in 2004 dollars, I also drop the 0.7% who make less than $2.80 per hour, and the 0.2% who make $100 or more per hour. Within this final sample, people with positive values for wages, weeks worked, and hours worked (the latter two categories overlap perfectly) are considered to be employed (75% of the remaining sample), while someone with a value of zero for any of those is not employed (25%).

Again following the structure of Zick and Stevens (2009), I calculate the probability of working and wage effects for men and women separately. My explanatory variables are the two-year period of the interview, race/ethnicity, education, and age category. I identify the interview period as which pair of years the preceding year fell into (1999-2000, 2001-2002, 2003-2004, 2005-2006, or 2007-2008). Ethnicity is defined as whether the person reports as Hispanic, non-Hispanic black, or something else. Education has five possible outcomes: did not attend high school, attended but did not graduate from high school, graduated from high school, attended but did not graduate from college, and college graduate. Finally, people's ages are grouped into eight different five-year categories, based on how old the person was in March of the preceding year (25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64).

Individually, these variables can also be expected to influence meal participation, and need to be included in those models. This would make an imputed wage variable collinear with those categories. However, people of different ages, ethnicities, and levels of education may earn different amounts of money in different years. Therefore, the terms used in the wage imputation models here consist of not just year, ethnicity, education, and age, but instead the full set of interactions for each possible combination of outcomes for these variables. This results in 600 distinct indicator variables.

In order to predict the probability of a person being employed (with an observed income), I also use three variables which should affect the decision to work but not the wages received when working. The first two of these exclusion restrictions are the number of the person's own children in the household under five years old, and the number of his or her own children who are five or older. I control for these separately, as children not yet old enough to enter kindergarten may affect parental employment differently from those who are old enough. The amount of non-labor income available may also affect the need to work, which I approximate as the sum of income from interest, income from dividends, and income from rent, adjusted for inflation.

These three variables as exclusion restrictions generate rho, the correlation between the error terms of the selection and log wage equations of 0.20 for women, and -0.70 for men. In this case of women, this suggests that women with higher potential wages are more likely to work – an intuitive result. For men, however, the correlation is quite negative, indicating that in at least some cases, men with higher potential wages are less likely to be employed. This is a bit surprising, but can be explained in terms of a high fraction of men working, regardless of the level of wages they might receive. This leaves labor force non-participation to be driven by such things as early retirement, full-time education that continues past age 25, etc., which may be correlated with relatively high wages.

The product of the correlation rho and the variance of the wage model captures how much the variation in the selection model influences the log wage equation, and corresponds to the coefficient on the inverse Mills ratio in a two-step Heckman model. I find this value to be 0.11 for women, very similar to the inverse Mills ratio coefficient of 0.12 found by Mulligan and Rubinstein (2008) for women in the CPS from 1995-1999 (contrasted with their 1975-79 CPS finding of -0.08), and a bit smaller than the coefficient for labor force participation found by Baffoe-Bonnie (2009) of 0.22 for white females in the NLSY. For men, I found a value of -0.41, greater in magnitude than Baffoe-Bonnie's labor force participation selection term of -0.10 for white males, but the same sign, although he found a positive result of 0.17 for black males. Note, however, that Baffoe-Bonnie calculated separate selection models for labor force participation and hiring, so the outcomes are not fully comparable to my single model for employment.

Using the coefficients for each combination of values of the categorical variables, I find the expected value of log wages for each of the 600 categories for women and for men. I use these to impute log wage values for respondents in the NHANES. This allows me to use the NHANES data to estimate a model for meal participation that includes the log of wages as an explanatory variable. This is effectively identical to the two-sample two stage least squares approach discussed in Inoue and Solon (2010). Since most of the variables in the wage equation also appear as variables explaining time use, it is necessary to have a source of identifying variation. In this case, identifying variation is provided by the interactions between the categorical variables. There may be a substantial range of variation in economic opportunities for different combinations of ethnicity, education, age, and especially year, whereas meal decisions are unlikely to change in the same way within these subcategories.

The CPS sample and the NHANES sample used for imputing wages are fairly similar, as can be seen in Table 2.A.1 below. However, there are some important differences between the surveys. For one thing, although both surveys strive to be nationally representative, the NHANES samples from only fifteen counties a year. Furthermore, the NHANES deliberately oversamples older adults. Finally, I adjust each two-year block of CPS data to have identical total weight, but do not so adjust the NHANES. Since the U.S. population has been increasing over time, and also since I drop a number of NHANES observations with poor data from 1999-2000, this means that the NHANES emphasizes later years more heavily than the CPS does.

Table 2.A.1. Weighted Variable Means

	Women			Men		
VARIABLES	CPS-Full	CPS-Emp	NHANES	CPS-Full	CPS-Emp	NHANES
% Employed	0.693	1.000		0.800	1.000	
Log(Wage)		2.626			2.865	
Impute Wage (Heckman)	2.542	2.575	2.534	2.993	2.993	3.001
Impute Wage (Linear)	2.596	2.626	2.590	2.852	2.865	2.854
H.S. Drop Out	0.072	0.052	0.117	0.082	0.070	0.118
H.S. Grad	0.309	0.297	0.232	0.318	0.309	0.249
Some College	0.285	0.303	0.321	0.256	0.263	0.288
College Graduate	0.291	0.323	0.283	0.293	0.315	0.292
Black	0.134	0.140	0.123	0.116	0.108	0.107
Hispanic	0.129	0.115	0.126	0.143	0.148	0.129
Age 30-34	0.135	0.141	0.128	0.137	0.150	0.128
Age 35-39	0.149	0.156	0.140	0.148	0.160	0.148
Age 40-44	0.152	0.163	0.140	0.153	0.161	0.140
Age 45-49	0.141	0.150	0.144	0.142	0.145	0.140
Age 50-54	0.120	0.121	0.136	0.119	0.115	0.141
Age 55-59	0.098	0.086	0.099	0.096	0.082	0.094
Age 60-64	0.078	0.046	0.094	0.074	0.046	0.084
Year 2001-2002	0.200	0.201	0.206	0.200	0.202	0.220
Year 2003-2004	0.200	0.198	0.204	0.200	0.199	0.203
Year 2005-2006	0.200	0.198	0.210	0.200	0.198	0.208
Year 2007-2008	0.200	0.199	0.222	0.200	0.197	0.212
Non-Labor Income ($)	1,250.30	1,177.76		1,460.085	1,389.61	
# Children<Age 5	0.193	0.169		0.196	0.220	
# Children>=Age 5	0.906	0.904		0.768	0.817	

This table displays the weighted means for people in the full sample of the 2000-2009 March CPS data, those who were employed with positive wages in that data, and the values for members of the 1999-2000, 2001-2002, 2003-2004, 2005-2006, and 2007-2008 NHANES survey. The excluded education category is did not attend high school, excluded race is white, excluded ages are 25-29, and the excluded time period is 1999-2000.

CHAPTER III

IS INDIVIDUALLY-TARGETED FOOD ASSISTANCE SHARED AMONG FAMILY MEMBERS?

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Abstract

The Supplemental Nutrition Assistance Program (SNAP), the National School Lunch Program (NSLP), the School Breakfast Program (SBP), and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) share a common goal of helping people with limited financial means obtain better diets than they could otherwise afford, but the programs differ in terms of the groups that they target and the types of assistance they provide. While the programs appear to increase food consumption among households generally and among their intended beneficiaries, we know much less about whether they help other people. This investigation uses 2002-2003 data from the second Child Development Supplement of the Panel Study of Income Dynamics to examine the relationship between households' participation in the SNAP, SBP, NLSP, and WIC and individual 10 - 17 year-old children's consumption of particular food items. Our analyses indicate that WIC participation by others in the household is associated with a 22 percent increase in breakfast consumption of milk and a 16 percent increase in breakfast consumption of cereal for the children in our sample,

while WIC is associated with a 13 percent decrease in toast consumption. Participation in school meals is also associated with increased consumption of some foods, particularly juice, fruit, and sweet snacks. Household SNAP participation is estimated to have positive associations with some foods but negative associations with others.

Introduction

The U.S. Department of Agriculture is responsible for several large food assistance programs. The programs with the greatest expenditures are the Supplemental Nutrition Assistance Program (SNAP, formerly the Food Stamp Program), the National School Lunch Program (NSLP), the School Breakfast Program (SBP), and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) (Oliveira, 2010). These programs share a common goal of helping people with limited financial means obtain better diets than they could otherwise afford, but they differ in terms of the groups that they target and the types of assistance they provide. The SNAP is intended to help low-income households generally, while the other three programs help specific groups. The NSLP and SBP are intended to improve nutritional outcomes for low-income school-age children, while WIC is intended to assist low-income pregnant, breastfeeding, and postpartum women and low-income infants and children up to age five.

A substantial amount of research has investigated whether and by how much these programs improve nutritional outcomes among their intended beneficiaries. Fox *et al.* (2004) have summarized much of this research. They report, for instance, that studies of the SNAP indicate that each dollar of food assistance increases households' food spending, food consumption, and dietary intakes. Similarly, studies generally indicate that WIC increases dietary intakes among pregnant and post-partum women, infants, and young children and that the NSLP and SBP increase food consumption among school children. We know much less, however, about whether targeted assistance, such as the SBP, NSLP, and WIC, affects outcomes for non-targeted household members.

This investigation uses 2002-2003 data from the second Child Development Supplement (CDS-II) of the Panel Study of Income Dynamics (PSID) to examine the relationship between households' participation in the SNAP, SBP, NLSP, and WIC and individual 10 - 17 year-old children's consumption of particular food items. The CDS-II is useful for this research because it includes information on food consumption, participation in food assistance programs, household economic and demographic circumstances, and other characteristics. The variety of measures allows us to control for many observed characteristics of households in multivariate analyses.

Background

Social scientists conceptualize that targeted and non-targeted food assistance may affect individual household members' food consumption in a number of ways. The first and intended manner is by increasing the amount of food available to the targeted beneficiaries. Indeed, there is evidence across a vast number of studies that all of the programs are associated with increased food consumption and higher intakes of at least some nutrients for their intended beneficiaries (Fox, Hamilton, and Lin, 2004). However, the evidence, especially regarding WIC, is far from conclusive and many of the associations are modest in size (Besharov and Germanis, 2000).

The programs may also increase the availability of food for non-targeted individuals living in assistance households. Especially relevant for our study are the foods from a family's WIC package. The packages contain particular types of foods—at the time of our study, formula, infant cereal and baby foods for beneficiaries who are infants and juice, milk, regular cereal, eggs, and legumes for beneficiaries who are mothers or small children (Oliveira and Chandran, 2005). While it is doubtful that infant foods would be consumed by older children or other household members, the non-infant food items might be available to and eaten by others. This would have the effect of raising food consumption among the non-targeted beneficiaries and lowering it among the targeted beneficiaries. This latter effect would undermine the goals of WIC.[8]

A second way in which food assistance participation could affect different household members' food outcomes is through its effect on overall household income. Expenditures that might have gone toward meals for targeted beneficiaries might be redirected toward food consumption for other household members. Social scientists have long recognized that household expenditures are fungible. If a household allocates positive amounts of its own money to food in the absence of program benefits, it has the flexibility to reduce those expenditures (and increase other expenditures) should it

[8] Similar effects can occur in households in which some but not all of the people are members of a SNAP assistance unit. They are also possible in school meal and summer food service programs with "backpack" features.

receive program benefits. For example, Long (1991) reported that households reduced their other food expenditures by 61 cents for each dollar's worth of NSLP benefits. Fox *et al.* (2004) summarize research that indicates that households' propensity to spend SNAP assistance on food consumption is substantially less than dollar-for-dollar.

Oliveira and Chandran (2005) and VerPloeg (2009) have suggested that the nutrition education components of WIC and other programs represent a third way by which participation in targeted programs can affect different household members' food consumption. The educational components may increase adults' awareness of their households' nutritional needs causing them to allocate more money toward food expenditures. The educational components could also help adults to use food more efficiently and to monitor children's consumption more carefully. Each of these effects could result in more food consumption.

In addition to these causal explanations for associations between food assistance participation and different household members' food consumption, we must also recognize that non-causal mechanisms, including reverse causality and spurious correlations owing to omitted characteristics, may lead to associations. Participation in the SBP, NSLP, WIC and SNAP each require active steps by households. Households with stronger preferences regarding food consumption or with greater food needs would be more motivated and more likely to participate in these programs than other households. The observed association between food assistance and food consumption could reflect these underlying characteristics.

A number of studies have either directly or indirectly examined the possible substitution between food assistance and non-targeted household members' food consumption. Among the indirect studies, Oliveira and Gundersen investigated the relationship between WIC participation and young children's food consumption, comparing outcomes for targeted and non-targeted children in WIC-receiving households. Oliveira and Gundersen were concerned about the selectivity of WIC eligibility and participation and posited that non-targeted children in WIC-receiving households could serve as a suitable control group for targeted children. The researchers found that the consumption of several nutrients was higher among targeted children than non-targeted children in these households. Interestingly, however, the estimates from their study also indicated that intakes of several nutrients for their control group of non-targeted children living in WIC households were lower than the intakes for children of similar ages living in income-eligible but non-participating households. This latter comparison suggests that non-targeted children do not benefit from household WIC participation (Oliveira and Gundarsen, 2000).

Arcia *et al.* also examined substitution indirectly. The researchers estimated multivariate models of households' expenditures on all foods, groceries, and meals away from home that included indicators for WIC receipt and interactions of the WIC indicator with the numbers of children and adults in the household. They interpreted the coefficients on the interactions as indirect measures of sharing. The estimates, however, did not yield any evidence of sharing (Areia, Crouch, and Kulka, 1990).

Ishdorj *et al.* investigated substitution more directly, examining calcium intakes among targeted family members in WIC households, non-targeted family members in WIC households, and others in income-eligible, non- WIC households and employing multivariate estimation procedures that accounted for the endogeneity of WIC participation. Ishdorj *et al.* failed to uncover evidence of substitution, finding that calcium intakes were lower among non-targeted family members in WIC households than among others in non-WIC households (Ishdorj, Jensen, and Tobias, 2008).

In contrast to these results, Oliveira and Chandran (2005) were able to detect evidence of substitution between young targeted and non-targeted children in their consumption of WIC-approved cereal and juice. VerPloeg (2009) examined food consumption behaviors associated with the Healthy Eating Index (HEI) among children aged 5 - 17 years who lived in households that did and did not receive WIC. The key advantage of VerPloeg's study design was that it was limited to children who were necessarily non-targeted for WIC by virtue of their ages. She found evidence of substitution in grains, fruits, cholesterol, and the total HEI. She also found that food intakes were higher if the children lived in households with multiple WIC recipients rather than a single recipient and in households with non-infant recipients rather than infant recipients.

Rose *et al.* (1998) investigated another form of substitution, examining the effects of household SNAP, WIC and NSLP participation on nutrient intakes of children aged 1 - 4 years. The researchers found that NSLP participation by other children in the household was associated with higher intakes of iron and zinc. Bhattacharya *et al.* (2006) examined the SBP and found that children's participation was associated with adults' eating behavior.

Data

For this study, we examine food consumption among children who were respondents in the second (2002-2003) wave of the Child Development Supplement to the Panel Study of Income Dynamics. The PSID is a national, longitudinal survey, which began with 5000 households in 1968. Since then, those households and the new households formed from the original sample members and their descendants have been followed in annual interviews through 1997 and biennial interviews thereafter. In 1997, a supplemental set of interviews, the CDS-I, was conducted to collect information on 3563 children in PSID families aged 0 - 12. Five years later, a second wave, the CDS-II, was conducted with 2907 of the CDS-I children.

The instruments in the CDS-II included a Child Interview (CI) that was administered directly to the focal children and a Primary Caregiver (PCG) interview that was administered to one of the child's guardians. Respondent children to the CI who were ten years or older were asked about foods usually consumed for breakfast and over the preceding week[9].

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[9] A third supplement, the CDS-III, was fielded in 2007. The CDS-III also asked about children's breakfast and weekly food consumption. However, our analysis of the CDS-III indicated that its food data were unreliable.

Of the children who participated in the CDS-II, about a third (956) were five to nine years old and, thus, too young to answer the questions about food consumption. A further 207 age-eligible children did not complete the CI, leaving 1744 children with information on food outcomes. For our analysis dataset, we combine information from the CI for these children with available information from the PCG interview and with household economic and demographic information from later waves of the PSID. We drop some children whose households did not participate in later waves of the PSID. Because of our interest in studying the effects of the NLSP and SBP, we also drop children who were not enrolled in elementary or secondary school or were older than 17 years. We also drop children with item non-response for food consumption or program participation. The final analysis sample includes 1582 children aged 10 - 17 years for the breakfast consumption analyses and slightly fewer observations for the weekly food consumption analyses.

We use responses from two sets of CDS questions to analyze children's eating behaviors. The first asked, "What do you usually have for breakfast on a weekday morning?" Children could indicate (yes/no) whether they consumed milk, coffee, juice, cereal, toast, fruit, eggs, meat, snack food, or other food. The second question asked how often children ate particular foods in a week. "Think about all of the food that you ate last week, including meals and snacks at home, at school, at restaurants, and anywhere else. How many days last week did you eat/drink…" with the listed foods being milk and dairy, fruit, vegetables, grains, sweets, meat, and other protein (eggs, peanut butter, beans, and soy). The possible answers were the numbers of days from zero to seven.

A critical advantage of the PSID is that it also has information about several different types of government food assistance that the family may have received, including WIC, free and reduced-price school breakfasts and lunches, and SNAP. We measure receipt of the first three types of assistance using binary variables. In particular, we include a binary indicator for whether the family reported that at least one woman or child received WIC assistance in 2002. For each type of school meal, the CDS asks first whether the child ate the meals at school and second whether the meals were received for free or at a reduced price. We use these measures to create dummy variables that indicate whether the child received free or reduced-price breakfasts and lunches. The omitted categories would include children who did not eat school meals or who paid the regular price for those meals. To characterize benefits under the SNAP, we create two measures. First, we create a binary indicator of whether the child's family received SNAP in the year of the CDS child interview. Second, we create a continuous measure of the value of the SNAP benefits received that year expressed as a proportion of the family's size- and age-adjusted poverty standard.

Table 3.1 lists means of the food consumption measures for the entire study sample and for different groups conditional on their receipt of food assistance. The figures differ modestly from estimates reported in other surveys. For example, our data from the CDS-II indicate that 41.5 percent of 10 - 17 year olds "usually" had milk for breakfast, while 2001-2002 diary data from the National Health and Nutrition Examination Survey (NHANES) indicate that 53 percent of 12 - 19 year-olds reported having milk at breakfast (Beltsville Human Nutrition Research Center, 2011). Reports from the CDS-II for coffee, juice, cereal, toast, fruit, and eggs are higher than the corresponding values from the NHANES. Differences in the question (usual consumption versus a given day's consumption), the instrument (short recall questions versus a diary), and the identification of meals (the NHANES asks about eating episodes and then asks people to describe the type of meal) could account for the differences in values.

Comparisons of the conditional means reveal that children in WIC households report consuming more milk and snacks for breakfast than children in non-WIC households, but WIC children also report consuming less toast. Children who receive two school meals report consuming more juice, eggs, meat, and snacks for breakfast and less toast than children who do not receive school meals. Children who receive two school meals also report consuming milk, vegetables and grains on fewer days per week than children who do not receive school meals. Children in SNAP households report eating less toast for breakfast and consuming milk, vegetables, and grains on fewer days than children in non-SNAP households.

The differences in food consumption could be attributable to other characteristics of the children besides food assistance. To address this possibility, we conduct multivariate analyses that include many other measures that are likely to influence children's food consumption and are also likely to be associated with participation in food assistance programs. We control for family economic resources by including the ratio of family's income in 2002 (measured in the PSID as the sum of its earned income, unearned income and cash transfers) to its needs (measured by the Census Bureau estimate of the poverty level for a family of that size and age distribution). In addition to the continuous measure of the income-to-needs ratio, we include indicators for whether the ratio is below 1.3 and whether it is between 1.3 and 1.85, as these are standard food assistance eligibility thresholds.

We control for family composition through the use of four variables: the number of children in the family who are aged 0 - 5 years, the number of children who are aged 6 - 18 years, the number of adults who are 19 years or older, and an indicator for whether the family head is married. To account for time inputs and supervision from the parents, we also include indicators for the employment status of the head and of the spouse, if present. We also control for six education categories of the family head: did not attend high school, did not graduate from high school, graduated from high school or got a GED, attended but did not graduate from college, graduated from college, and received a graduate degree. There were 54 children with family heads for whom the education level was unknown; we include an indicator variable for this situation. We also include standard demographic and geographic controls, including measures of the child's gender and age, race and ethnicity, geographic region, and urban residence. Table 3.2 lists means of the independent variables for our analysis for the entire study sample and for groups of children conditional on their participation in food assistance programs.

Multivariate Analyses

To estimate how food assistance and our other independent variables are associated with the foods that children report usually eating for breakfast, we use linear probability (ordinary least squares, OLS) models. These multivariate models incorporate sample weights provided with the CDS, in order to be nationally representative. They include standard errors that are heteroskedasticity- robust and are clustered by family in the PSID, since two children from the same family may not have independent eating behaviors. Our multivariate analyses of weekly food consumption also use OLS with sample weights and robust and clustered standard errors.

One possible concern with the use of OLS for these analyses is that our outcomes are categorical—binary outcomes for breakfast consumption and counts from zero to seven for days of weekly consumption. OLS has the disadvantage of possibly predicting outside the range of the dependent variables and being inefficient. However, the coefficient estimates from the OLS model can be directly interpreted as marginal effects. OLS is also consistent and robust to alternative assumptions regarding the model errors. In sensitivity analyses (not shown but available upon request), we reestimated all of our OLS specifications using probit and ordered-probit models, with no substantive changes in the results.

Table 3.3 lists coefficient estimates from linear probability models of the determinants of children's consumption of different breakfast foods. The columns list results for models in which the dependent variables (from left to right) are the consumption of milk and other dairy products, coffee, juice, bread or toast, fruit, eggs, meat, snacks, or other foods. The rows list coefficients from our programmatic, economic, demographic, and geographic explanatory variables.

We begin by considering the results for the food assistance measures. Estimates from the first row indicate that children who received free or reduced-price school breakfasts reported having a statistically significant 14 percent higher probability of drinking juice with breakfast, a 10 percent higher probability of consuming fruit, and an eight percent higher probability of consuming snacks. SBP participation is estimated to be positively associated with the consumption of most other foods, but the estimates are not statistically different from zero.

Estimates from the regressions also indicate that participation in the school lunch program is associated with significantly higher reported levels of milk and dairy consumption (+13%) at breakfast. One interpretation of this result is that participation in the NSLP frees up household resources so that poor families can afford to provide their children with milk. The estimate could also reflect children being exposed to milk in their school lunches and consequently having more favorable attitudes about milk at other times.

Relative to the rest of the children in the full sample, children who were in a family that included one or more people who received WIC reported significantly higher probabilities of consuming dairy products (+22%), cereal (+16%), and snack foods (+18%) for breakfast but a lower probability of usually eating toast (−13%). The results for milk and cereal are consistent with substitution from WIC increasing the availability of these specific foods, which were available in the WIC package at the time of our study. The results are also consistent with children substituting cereal for bread in the morning.

The associations between SNAP and foods consumed are more difficult to interpret, because our models control for both receiving SNAP and for the needs-adjusted value of the benefits received. Surprisingly, the estimates indicate that the receipt of SNAP is negatively associated with the consumption of toast and fruit. The estimates also indicate that higher levels of SNAP benefits, conditional on receipt, are associated with increased consumption of juice and fruit but decreased consumption of cereal. If we evaluated the coefficients for SNAP receipt and benefits at the average value of the needs-adjusted benefit level for participating households, the net associations of SNAP and foods consumed at breakfast are close to zero.

When we examine the coefficients for the other variables, we see that children in households with incomes below 130 percent of the poverty threshold are more likely to report drinking coffee and less likely to report eating fruit at breakfast than children living in households with incomes above 185 percent of the poverty threshold (the omitted category in our models). Conditional on income being within one of the categories that we set, additional income is positively associated with juice consumption and negatively associated with snack consumption at breakfast.

Among the household composition variables, the number of children under six years of age is positively associated with toast consumption, while the number of children aged six to 18 years is positively associated with milk and fruit consumption. The number of adults in the household is negatively associated with toast consumption.

Living in a household with an employed head is associated with less egg consumption, and living in a household with an employed wife is associated with less milk consumption. Children who live in households with the least educated heads report consuming less milk, toast, fruit, and snacks than children with heads who are high school graduates. Girls report consuming less milk, cereal, eggs, and meat than boys but more coffee and fruit. As children age they report consuming more coffee and less cereal and eggs. Black children report consuming less milk and coffee than white children but more eggs and meat.

Table 3.4 displays the coefficients and standard errors from OLS models of the number of days in the preceding week that the children reported eating foods from different food categories. From left to right, the columns list coefficients and standard errors for the weekly consumption of milk and dairy, fruit, vegetables, grains, sweets, meat, and other protein, such as peanut butter. The rows display the estimates associated with the same independent variables as Table 3.3.

In general, there are fewer statistically significant associations among the programmatic variables. Children who participated in the SBP reported eating sweets on 0.4 more days in the preceding week than other children who did not participate. Participation in the NSLP and household participation in WIC were not significantly associated with weekly reported food consumption. SNAP receipt was negatively associated with meat consumption, but the needs-adjusted benefit level was positively associated. Evaluated at the mean of the benefit value, the net effect of SNAP was close to zero.

Among the other variables in the model, the number of children aged six to 18 years is positively associated with milk, sweet, and meat consumption, while the number of adults is positively associated with fruit consumption. The results also indicate that children living with household heads who are more educated consume more foods than children living with less educated heads. The estimates also indicate that girls consume vegetables and grains on more days than boys but consume milk and other proteins on fewer days. Older children consume grains, sweets, and meat on more days than younger children. Black children consume milk and grains on fewer days than white children but consume sweets on more days. Hispanic children consume fewer vegetables but more other proteins.

The models in Tables 3.3 and 3.4 were estimated using the entire analysis sample of children from the CDS-II. Arguably, however, the food consumption patterns of children living in higher income households might not be comparable to those of children living in lower income households because of the differences in resources. Children in higher income households also would not be eligible for food assistance. We have re-estimated the models of breakfast consumption and weekly food consumption using a restricted sample of children who lived in households with incomes below 185 percent of the poverty threshold. These households would have been income eligible for reduced-price school meals and for WIC, and modest changes in income would have made them eligible for SNAP and free school meals. A drawback of this analysis is that it reduces our sample size by more than two-thirds. We report results for the programmatic and economic measures from these specifications in Tables 3.5 and 3.6.

Overall, the breakfast results for low-income children in Table 3.5 are similar to those for the sample as a whole. Free or reduced school breakfast is associated with significantly increased probabilities of juice (+18%), fruit (+19%), and snack food (+16%) consumption at breakfast, all three of which were also positive in the full sample. Children who received subsidized school lunches were 12 percentage points more likely to drink milk or eat dairy products for breakfast than other low-income children, although the estimate falls short of being statistically significant. Children in families that received WIC were significantly more likely to eat snacks and less likely to eat toast, results that accord with the full-sample estimates. However, estimates for the associations between WIC participation and milk and cereal consumption are smaller in the low-income sample and lose their statistical significance. In the low-income sample, SNAP participation is associated with less milk consumption and more cereal consumption, while the value of SNAP benefits is associated with less cereal and meat consumption.

For Table 3.6, weekly foods eaten by children in low-income families, results are again similar to those of the full sample. School breakfast subsidies are still associated with significantly greater weekly sweets consumption (+0.7 days) and with increased fruit consumption (+0.6 days). As with the full sample, low-income children who received school lunches still have no statistically significant differences in the number of days that foods are eaten in a week. However, children in families that participated in the WIC program ate meat (−1.0 days) and sweets (−0.8 days) less often than children in other families; this makes some sense, as these are not food types subsidized by the program. Finally, participation in SNAP has very similar results to those of the full sample, and only meat consumption has a statistically significant coefficient (−0.6 days for SNAP recipients).

Conclusions

In this article, we used 2002-2003 data from the second Child Development Supplement of the Panel Study of Income Dynamics to examine the association between households' participation in the SNAP, SBP, NLSP, and WIC and individual 10 - 17 year-old children's reports of breakfast and weekly food consumption. Our study contributes to the literature on the effectiveness of food assistance programs in two ways. First, it considers participation in all of the major food assistance programs. Despite the frequency of multiple program participation among low-income families with children (Newman, Todd, and VerPloeg, forthcoming), few studies have examined the direct effects of these programs together. Second, our study adds to our knowledge about the sharing of food assistance between family members who are and are not targeted for benefits. In particular, we examine how WIC assistance that is intended for pregnant women, mothers, infants, and very young children may benefit older children.

Results from our analyses provide some evidence that is consistent with sharing. Our estimates indicate that WIC participation by others in the household is associated with increased consumption of milk and cereal at breakfast by older children. WIC participation is also associated with increased consumption of snacks and decreased consumption of toast at breakfast.

Looking at programs that are targeted towards the children directly, we find that participation in the SBP is associated with increased consumption of juice, fruit, and snacks at breakfast and sweets during the week. Participation in the NSLP is associated with increased consumption of milk. The receipt of SNAP is estimated to reduce the consumption of toast and fruit at breakfast and the consumption of meat over the week. However, conditional on receiving SNAP, additional benefits are associated with increased consumption of juice at breakfast, decreased consumption of toast at breakfast, and increased consumption of meat through the week.

A strength of our analysis is the rich set of observed economic, demographic, and geographic controls that we are able to include from the PSID. Studies based on other food consumption surveys have generally had fewer controls. That said, our analyses do not include more sophisticated controls for the likely endogeneity of participation in the different food assistance programs. Thus, we are limited in our ability to make causal inferences.

Table 3.1. Means of Weekly and Breakfast Food Consumption

Usual Breakfast	(1) All Obs	(2) No WIC	(3) Received WIC	(4) 0 School Meals	(5) 1 School Meal	(6) 2 School Meals	(7) No SNAP	(8) Received SNAP
Milk	41.5%	40.7%	56.9%*	39.6%	43.5%	47.0%	41.8%	38.7%
Coffee	9.5%	9.2%	13.4%	8.2%	11.7%	12.2%	9.0%	13.7%
Juice	40.2%	39.8%	48.4%	39.1%	33.7%	49.7%**	39.9%	43.0%
Cereal	46.1%	45.8%	52.4%	45.7%	45.1%	48.4%	46.5%	42.8%
Toast	34.6%	35.4%	19.0%**	37.5%	29.4%*	28.0%**	36.1%	22.3%***
Fruit	19.9%	19.5%	28.8%	18.7%	18.9%	25.5%*	19.9%	20.5%
Eggs	23.5%	23.4%	25.5%	21.1%	22.1%	33.4%***	22.5%	31.4%
Meat	10.1%	10.0%	12.2%	8.3%	11.8%	15.4%**	9.7%	13.5%
Snacks	16.0%	15.1%	34.2%**	13.9%	17.9%	22.6%**	15.6%	19.4%
Other	16.2%	16.8%	5.8%***	19.0%	12.2%**	8.9%***	17.3%	7.3%***
Days/Week	All Obs	No WIC	Received WIC	0 School Meals	1 School Meal	2 School Meals	No SNAP	Received SNAP
Milk	5.4	5.4	5.2	5.5	5.0**	4.9***	5.4	4.8***
Fruit	4.9	4.9	4.9	4.9	4.8	5.0	4.9	5.0
Vegetables	4.1	4.1	3.9	4.3	4.0	3.7***	4.2	3.4***
Grains	5.8	5.8	5.3	6.0	5.6**	5.3***	5.9	5.3**
Sweets	4.7	4.7	4.1	4.7	4.3*	4.8	4.7	4.6
Meat	5.2	5.2	4.7	5.2	5.2	5.0	5.2	5.0
Protein	3.6	3.6	3.7	3.6	3.8	3.7	3.7	3.6

Note: Authors' calculations of the percentages of children aged 10-17 years in the 2002 CDS-II who reported usually consuming the listed food for breakfast (top panel) and means of the number of days those children ate the listed foods in the week preceding the interview. All of the statistics were calculated using sample weights provided with the PSID. Asterisks indicate whether the percentages or means are significantly different for children receiving food assistance relative to those who do not.
***Coefficient different from zero with $p < 0.01$; **Coefficient different from zero with $p < 0.05$; *Coefficient different from zero with $p < 0.1$.

Table 3.2. Means of Independent Variables

VARIABLES	(1) All Obs	(2) No WIC	(3) Rec. WIC	(4) 0 Sch. Meals	(5) 1 Sch. Meal	(6) 2 Sch. Meals	(7) No SNAP	(8) Rec. SNAP
Free/Reduced School Breakfast	0.191	0.168	0.634	0.000	0.072	1.000	0.139	0.624
Free/Reduced School Lunch	0.312	0.283	0.876	0.000	0.928	1.000	0.251	0.829
Received WIC	0.049	0.000	1.000	0.007	0.105	0.165	0.029	0.223
Received Food Stamps	0.106	0.086	0.479	0.023	0.191	0.351	0.000	1.000
Food Stamps Value/Needs	0.014	0.010	0.081	0.003	0.023	0.047	0.000	0.128
Ratio of Income/Needs	4.154	4.306	1.228	5.196	2.603	1.468	4.502	1.208
130%< Income/Needs <185%	0.097	0.085	0.338	0.034	0.272	0.197	0.096	0.111
Income/Needs <130%	0.172	0.155	0.490	0.052	0.287	0.529	0.112	0.677
# of Children Age <6	0.173	0.121	1.163	0.106	0.261	0.353	0.141	0.438
# of Children Age >5, <19	2.087	2.044	2.906	1.931	2.326	2.484	2.014	2.698
# of Adults Age >18	2.038	2.039	2.022	2.090	1.976	1.895	2.091	1.594
Family Head is Married	0.749	0.750	0.729	0.831	0.615	0.544	0.793	0.375
Head is Employed	0.855	0.861	0.729	0.907	0.805	0.698	0.892	0.540
Wife is Employed	0.554	0.568	0.280	0.671	0.438	0.206	0.608	0.099
Head had no High School	0.065	0.046	0.445	0.009	0.160	0.204	0.051	0.185
Head did not graduate H.S.	0.070	0.068	0.126	0.033	0.134	0.160	0.061	0.149
Head had some college	0.200	0.208	0.045	0.220	0.189	0.134	0.206	0.154
Head graduated from college	0.263	0.271	0.099	0.351	0.117	0.048	0.289	0.043
Head received graduate degree	0.067	0.071	0.000	0.099	0.000	0.001	0.074	0.012
No Data on Head’s Education	0.027	0.027	0.023	0.023	0.034	0.037	0.028	0.017
Female	0.500	0.492	0.671	0.488	0.472	0.570	0.492	0.573
Child’s Age at Interview	13.589	13.594	13.496	13.858	13.293	12.814	13.649	13.082
Child is Black	0.176	0.170	0.295	0.089	0.292	0.412	0.146	0.437
Child is Hispanic	0.131	0.108	0.576	0.049	0.276	0.322	0.111	0.294
Central Region	0.242	0.246	0.162	0.268	0.278	0.115	0.248	0.196
Southern Region	0.327	0.330	0.267	0.291	0.291	0.493	0.315	0.428
Western Region	0.253	0.244	0.439	0.241	0.237	0.313	0.251	0.277
Rural Area	0.280	0.281	0.252	0.281	0.212	0.327	0.275	0.317

Note: Authors’ calculations of the means of the listed characteristics for children aged 10 - 17 years in the 2002 CDS-II. Omitted categories are high school graduate, white, and North-East region. All of the statistics were calculated using sample weights provided with the PSID.

Table 3.3. Linear Models of Breakfast Consumption

VARIABLES	(1) Milk	(2) Coffee	(3) Juice	(4) Cereal	(5) Toast	(6) Fruit	(7) Eggs	(8) Meat	(9) Snacks	(10) Other
School Breakfast	0.020	0.012	0.140**	0.089	0.001	0.098**	0.054	0.041	0.082*	-0.023
	(0.060)	(0.040)	(0.056)	(0.058)	(0.052)	(0.050)	(0.053)	(0.036)	(0.044)	(0.037)
School Lunch	0.125**	0.014	-0.046	0.001	0.032	-0.019	-0.004	0.006	-0.017	-0.025
	(0.058)	(0.035)	(0.050)	(0.050)	(0.052)	(0.042)	(0.046)	(0.031)	(0.042)	(0.034)
Received WIC	0.217**	0.019	0.083	0.159*	-0.132*	-0.007	-0.004	0.044	0.178**	-0.061
	(0.099)	(0.065)	(0.088)	(0.095)	(0.072)	(0.079)	(0.084)	(0.052)	(0.072)	(0.047)
Received Food	-0.159	-0.041	-0.128	0.110	-0.155*	-0.127**	0.018	0.032	0.022	-0.022
Stamps	(0.101)	(0.052)	(0.084)	(0.093)	(0.091)	(0.062)	(0.108)	(0.070)	(0.066)	(0.055)
Food Stamp	0.451	0.231	0.890*	-1.083**	0.396	0.875**	-0.030	-0.343	-0.322	0.114
Value/Needs	(0.614)	(0.390)	(0.512)	(0.512)	(0.533)	(0.442)	(0.740)	(0.521)	(0.377)	(0.333)
Income/Needs	-0.000	-0.001	0.006***	-0.002	-0.000	-0.001	-0.002	-0.000	-0.002*	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Income/Needs	-0.057	-0.001	0.037	-0.046	-0.066	0.006	-0.050	0.029	-0.015	0.085*
is >1.3 & <1.85	(0.062)	(0.038)	(0.057)	(0.059)	(0.057)	(0.043)	(0.049)	(0.032)	(0.047)	(0.045)
Income/Needs	-0.057	0.087**	-0.052	-0.047	-0.048	-0.074*	-0.042	0.013	-0.069	0.004
is <1.3	(0.057)	(0.043)	(0.058)	(0.062)	(0.062)	(0.040)	(0.052)	(0.037)	(0.046)	(0.045)
# of Children <6	-0.040	-0.023	-0.028	-0.030	0.066*	0.037	-0.029	-0.015	-0.009	0.016
	(0.035)	(0.017)	(0.036)	(0.036)	(0.037)	(0.031)	(0.032)	(0.020)	(0.025)	(0.026)
# of Child between	0.038**	0.000	0.024	0.028	0.013	0.046***	-0.003	0.004	0.002	-0.017
6 and 18	(0.016)	(0.011)	(0.017)	(0.018)	(0.018)	(0.013)	(0.015)	(0.011)	(0.012)	(0.012)
# of Adults >18	-0.009	-0.008	0.038	0.031	-0.051**	0.019	0.014	0.012	0.016	-0.004
	(0.027)	(0.016)	(0.028)	(0.027)	(0.025)	(0.022)	(0.025)	(0.021)	(0.020)	(0.019)
Head is Married	0.023	0.004	-0.052	-0.025	0.072	0.009	0.011	-0.027	-0.050	0.016
	(0.062)	(0.037)	(0.063)	(0.063)	(0.055)	(0.045)	(0.057)	(0.037)	(0.046)	(0.045)
Head is Employed	-0.025	-0.035	0.004	0.058	-0.061	0.020	-0.112**	-0.012	-0.015	0.083***
	(0.051)	(0.040)	(0.048)	(0.046)	(0.052)	(0.033)	(0.047)	(0.032)	(0.036)	(0.028)
Wife is Employed	-0.077*	-0.020	-0.033	0.014	-0.030	-0.008	0.000	-0.003	0.034	0.017
	(0.046)	(0.028)	(0.044)	(0.046)	(0.041)	(0.036)	(0.039)	(0.026)	(0.033)	(0.034)
Head did not attend	-0.205**	-0.014	-0.117	-0.040	-0.176**	-0.145**	-0.108	0.030	-0.116*	0.003
High School	(0.089)	(0.070)	(0.077)	(0.091)	(0.077)	(0.069)	(0.078)	(0.043)	(0.067)	(0.046)
Head did not grad.	0.008	0.012	-0.154**	-0.035	-0.099*	-0.027	-0.012	0.010	-0.033	0.030
High School	(0.066)	(0.045)	(0.065)	(0.065)	(0.055)	(0.047)	(0.061)	(0.043)	(0.048)	(0.048)

Head attended Some College	0.003	-0.004	-0.019	-0.027	0.024	0.036	0.036	0.022	-0.029	-0.026
	(0.043)	(0.027)	(0.043)	(0.046)	(0.046)	(0.033)	(0.039)	(0.024)	(0.034)	(0.034)
Head is College Graduate	0.009	0.031	-0.028	0.000	0.031	0.044	-0.003	0.033	-0.036	-0.043
	(0.045)	(0.030)	(0.046)	(0.046)	(0.048)	(0.035)	(0.039)	(0.029)	(0.033)	(0.033)
Head has a Graduate Degree	0.183**	-0.005	-0.029	0.024	0.065	0.055	0.045	0.003	-0.033	-0.063
	(0.078)	(0.041)	(0.070)	(0.074)	(0.068)	(0.055)	(0.059)	(0.030)	(0.055)	(0.058)
No Education Data	-0.187*	0.059	-0.054	-0.084	-0.134	0.037	-0.111**	0.170*	0.018	0.057
	(0.106)	(0.081)	(0.103)	(0.108)	(0.085)	(0.084)	(0.054)	(0.094)	(0.092)	(0.088)
Child is Female	-0.165***	0.038**	0.021	-0.102***	0.010	0.068***	-0.092***	-0.051**	0.018	0.098***
	(0.030)	(0.018)	(0.032)	(0.032)	(0.032)	(0.023)	(0.028)	(0.021)	(0.024)	(0.023)
Child's Age	-0.002	0.011***	-0.005	-0.029***	0.002	-0.008	-0.017***	0.003	0.006	0.024***
	(0.007)	(0.004)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Child is Black	-0.168***	-0.058*	0.062	-0.072	-0.021	0.032	0.101**	0.073**	-0.007	-0.007
	(0.050)	(0.035)	(0.044)	(0.048)	(0.052)	(0.034)	(0.039)	(0.031)	(0.035)	(0.035)
Child is Hispanic	0.065	-0.012	0.060	-0.072	-0.011	0.117**	0.189***	-0.091***	0.145**	-0.136***
	(0.070)	(0.049)	(0.071)	(0.068)	(0.067)	(0.056)	(0.068)	(0.025)	(0.070)	(0.039)
Central Region	-0.073	-0.027	-0.014	-0.028	-0.104**	-0.018	-0.046	-0.019	0.055*	0.056
	(0.047)	(0.029)	(0.051)	(0.051)	(0.050)	(0.039)	(0.041)	(0.023)	(0.032)	(0.036)
Southern Region	0.014	-0.022	-0.007	-0.041	-0.097*	-0.014	0.012	0.061**	0.110***	0.027
	(0.049)	(0.029)	(0.051)	(0.050)	(0.051)	(0.038)	(0.042)	(0.027)	(0.034)	(0.036)
Western Region	0.099*	0.020	-0.077	0.038	-0.023	0.003	0.003	0.042	0.052	0.015
	(0.056)	(0.033)	(0.054)	(0.053)	(0.057)	(0.044)	(0.047)	(0.033)	(0.036)	(0.037)
Rural Area	0.036	0.030	0.006	-0.031	-0.064*	-0.035	0.030	0.005	-0.038	0.021
	(0.038)	(0.025)	(0.036)	(0.037)	(0.037)	(0.028)	(0.034)	(0.024)	(0.027)	(0.029)
Constant	0.497***	-0.025	0.394***	0.794***	0.512***	0.102	0.544***	0.029	0.024	-0.247***
	(0.124)	(0.086)	(0.123)	(0.125)	(0.123)	(0.097)	(0.101)	(0.068)	(0.100)	(0.083)
Observations	1,582	1,582	1,582	1,582	1,582	1,582	1,582	1,582	1,582	1,582
R-squared	0.094	0.045	0.037	0.056	0.048	0.053	0.063	0.068	0.053	0.086

Note: Authors' estimates from linear regressions estimated using data for children aged 10 - 17 years in the CDS-II; estimates incorporate sampling weights. Robust standard errors clustered by family are shown in parentheses.
***Coefficient different from zero with $p < 0.01$; **Coefficient different from zero with $p < 0.05$; *Coefficient different from zero with $p < 0.1$.

Table 3.4. Linear Models of Weekly Food Consumption

VARIABLES	(1) Milk	(2) Fruit	(3) Veg.	(4) Grains	(5) Sweet	(6) Meat	(7) Protein
School Breakfast	0.250	0.345	-0.052	-0.175	0.430*	0.047	0.047
	(0.204)	(0.219)	(0.252)	(0.178)	(0.229)	(0.204)	(0.219)
School Lunch	-0.174	-0.004	0.405	-0.097	-0.105	0.168	0.189
	(0.192)	(0.184)	(0.250)	(0.162)	(0.226)	(0.174)	(0.185)
Received WIC	0.460	-0.319	0.005	-0.255	-0.316	-0.379	-0.126
	(0.365)	(0.298)	(0.413)	(0.327)	(0.371)	(0.335)	(0.376)
Received Food	-0.409	0.190	-0.658	-0.227	0.105	-0.566*	-0.113
Stamps	(0.365)	(0.352)	(0.423)	(0.347)	(0.445)	(0.305)	(0.389)
Food Stamp	1.635	1.592	1.750	0.085	-1.513	3.660*	-0.073
Value/Needs	(1.985)	(1.806)	(2.598)	(1.858)	(2.587)	(1.911)	(2.360)
Income/Needs	-0.001	0.019**	-0.001	-0.022**	0.005	-0.005	-0.001
	(0.007)	(0.009)	(0.013)	(0.009)	(0.010)	(0.007)	(0.010)
Income/Needs	0.228	0.345	-0.183	0.122	-0.059	-0.393*	-0.083
is >1.3 & <1.85	(0.221)	(0.232)	(0.281)	(0.185)	(0.255)	(0.213)	(0.217)
Income/Needs	-0.054	-0.113	0.095	0.267	0.112	-0.319	-0.201
is <1.3	(0.231)	(0.239)	(0.291)	(0.185)	(0.263)	(0.259)	(0.234)
# of Children <6	-0.077	-0.030	0.254	-0.078	-0.025	-0.056	0.038
	(0.132)	(0.132)	(0.175)	(0.110)	(0.163)	(0.151)	(0.158)
# of Child between	0.114*	0.026	0.122	0.027	0.124*	0.117**	0.058
6 and 18	(0.058)	(0.069)	(0.084)	(0.047)	(0.069)	(0.056)	(0.066)
# of Adults >18	0.089	0.239**	-0.035	0.038	0.015	-0.171	0.027
	(0.090)	(0.100)	(0.132)	(0.096)	(0.138)	(0.112)	(0.103)
Head is Married	0.027	0.055	0.278	-0.159	-0.214	0.330	-0.170
	(0.216)	(0.241)	(0.274)	(0.210)	(0.258)	(0.241)	(0.242)
Head is Employed	0.147	0.346*	0.318	0.099	0.120	-0.069	-0.103
	(0.195)	(0.205)	(0.238)	(0.175)	(0.228)	(0.199)	(0.215)
Wife is Employed	-0.154	-0.028	0.016	0.109	0.257	-0.041	0.148
	(0.151)	(0.183)	(0.226)	(0.143)	(0.186)	(0.173)	(0.171)
Head did not attend	-0.790**	-0.035	0.158	0.210	-0.161	-0.496	-0.382
High School	(0.365)	(0.308)	(0.484)	(0.246)	(0.422)	(0.379)	(0.401)
Head did not grad.	-0.393*	-0.437	-0.559*	0.105	0.077	0.109	-0.347
High School	(0.228)	(0.332)	(0.304)	(0.193)	(0.277)	(0.260)	(0.273)
Head attended	0.122	0.349**	0.407**	0.193	-0.145	-0.068	0.151
Some College	(0.162)	(0.173)	(0.203)	(0.141)	(0.193)	(0.176)	(0.177)
Head is College	0.202	0.228	0.657***	0.420***	0.085	-0.054	-0.063
Graduate	(0.159)	(0.176)	(0.199)	(0.129)	(0.188)	(0.157)	(0.166)
Head has a	0.535***	-0.060	1.017***	0.915***	0.418	-0.024	0.505*
Graduate Degree	(0.196)	(0.315)	(0.332)	(0.163)	(0.297)	(0.259)	(0.297)
No Education Data	0.122	-0.307	-0.136	-0.050	0.068	0.476	-0.024
	(0.285)	(0.514)	(0.377)	(0.479)	(0.454)	(0.307)	(0.354)
Child is Female	-0.329***	0.120	0.247*	0.205**	-0.041	-0.044	-0.293**
	(0.109)	(0.127)	(0.141)	(0.095)	(0.129)	(0.119)	(0.129)
Child’s Age	0.036	-0.009	0.048	0.081***	0.063**	0.212***	0.021
	(0.024)	(0.026)	(0.031)	(0.019)	(0.027)	(0.026)	(0.029)
Child is Black	-0.821***	0.281	-0.330	-0.396**	0.189	0.335**	-0.242
	(0.193)	(0.199)	(0.228)	(0.165)	(0.183)	(0.168)	(0.193)
Child is Hispanic	-0.328	0.154	-0.859**	-0.091	-0.521	0.250	0.889***
	(0.259)	(0.292)	(0.341)	(0.174)	(0.333)	(0.262)	(0.272)

Central Region	0.021	-0.145	-0.375	-0.120	-0.028	-0.009	0.153
	(0.185)	(0.189)	(0.241)	(0.149)	(0.227)	(0.191)	(0.188)
Southern Region	-0.065	-0.503**	-0.186	-0.179	-0.030	-0.048	0.451**
	(0.183)	(0.200)	(0.246)	(0.149)	(0.208)	(0.198)	(0.190)
Western Region	0.113	-0.287	-0.172	-0.262	0.025	-0.278	0.217
	(0.190)	(0.211)	(0.258)	(0.162)	(0.236)	(0.223)	(0.209)
Rural Area	0.003	-0.052	-0.025	-0.019	-0.016	0.111	0.027
	(0.138)	(0.152)	(0.173)	(0.124)	(0.172)	(0.151)	(0.154)
Constant	4.689***	4.053***	2.650***	4.595***	3.441***	2.348***	3.136***
	(0.468)	(0.521)	(0.640)	(0.383)	(0.511)	(0.498)	(0.545)
Observations	1,564	1,573	1,571	1,576	1,573	1,572	1,563
R-squared	0.087	0.043	0.082	0.085	0.033	0.085	0.036

Note: Authors' estimates from linear regressions estimated using data for children aged 10 - 17 years in the CDS-II; estimates incorporate sampling weights. Robust standard errors clustered by family are shown in parentheses. ***Coefficient different from zero with $p < 0.01$; **Coefficient different from zero with $p < .05$; *Coefficient different from zero with $p < 0.1$

Table 3.5. Breakfast Consumption in Low Income Families

VARIABLES	(1) Milk	(2) Coffee	(3) Juice	(4) Cereal	(5) Toast	(6) Fruit	(7) Eggs	(8) Meat	(9) Snacks	(10) Other
School Breakfast	0.050	-0.000	0.182***	0.100	0.014	0.190***	0.033	0.037	0.165***	-0.037
	(0.078)	(0.059)	(0.065)	(0.073)	(0.063)	(0.059)	(0.064)	(0.046)	(0.054)	(0.046)
School Lunch	0.122	-0.034	-0.037	0.029	-0.034	-0.065	-0.005	0.050	-0.052	0.003
	(0.086)	(0.066)	(0.071)	(0.074)	(0.081)	(0.049)	(0.076)	(0.051)	(0.048)	(0.052)
Received WIC	0.141	0.036	0.143	0.012	-0.240***	-0.015	-0.071	0.099	0.218***	-0.049
	(0.102)	(0.072)	(0.095)	(0.105)	(0.077)	(0.080)	(0.087)	(0.065)	(0.081)	(0.055)
Received Food	-0.190*	-0.064	-0.065	0.175*	-0.142	-0.057	0.039	0.115	0.024	-0.070
Stamps	(0.114)	(0.064)	(0.092)	(0.090)	(0.107)	(0.080)	(0.109)	(0.072)	(0.089)	(0.043)
Food Stamp	0.586	0.332	-0.355	-1.275**	0.608	0.311	-0.724	-1.346***	-0.484	0.606*
Value/Needs	(0.738)	(0.517)	(0.586)	(0.544)	(0.641)	(0.476)	(0.669)	(0.396)	(0.530)	(0.342)
Income/Needs	-0.055	0.152*	-0.125	-0.056	-0.114	0.122*	0.142*	0.028	0.071	-0.166**
	(0.080)	(0.083)	(0.096)	(0.094)	(0.096)	(0.066)	(0.076)	(0.055)	(0.059)	(0.073)
Income/Needs	-0.058	0.221***	-0.181**	-0.039	-0.084	-0.045	0.121*	0.009	-0.001	-0.187***
is <1.3	(0.092)	(0.070)	(0.085)	(0.087)	(0.079)	(0.065)	(0.070)	(0.051)	(0.059)	(0.067)
# of Children <6	0.020	-0.026	-0.042	0.033	0.077	0.037	0.038	-0.041	-0.002	-0.018
	(0.053)	(0.034)	(0.053)	(0.050)	(0.056)	(0.046)	(0.052)	(0.034)	(0.047)	(0.028)
# of Child between	0.035	0.031	-0.001	0.022	-0.008	0.055***	0.010	0.001	0.022	-0.018
6 and 18	(0.023)	(0.020)	(0.023)	(0.028)	(0.022)	(0.017)	(0.021)	(0.015)	(0.017)	(0.013)
# of Adults >18	-0.048	-0.027	0.057	-0.045	0.001	0.033	0.027	0.006	0.070**	0.031
	(0.042)	(0.033)	(0.042)	(0.042)	(0.046)	(0.034)	(0.037)	(0.026)	(0.031)	(0.029)
Head is Married	0.158	-0.029	-0.182**	0.097	-0.138	-0.045	0.044	-0.008	-0.081	-0.003
	(0.096)	(0.070)	(0.089)	(0.085)	(0.085)	(0.074)	(0.086)	(0.055)	(0.065)	(0.058)
Head is Employed	-0.039	-0.039	-0.073	0.049	-0.003	-0.021	-0.180***	-0.046	-0.020	0.091**
	(0.060)	(0.045)	(0.056)	(0.060)	(0.064)	(0.048)	(0.063)	(0.043)	(0.052)	(0.046)
Wife is Employed	-0.232**	-0.069	-0.064	0.071	-0.001	0.007	-0.058	-0.010	0.009	0.059
	(0.097)	(0.067)	(0.078)	(0.091)	(0.072)	(0.074)	(0.073)	(0.042)	(0.061)	(0.064)
Head did not attend	-0.211**	-0.046	-0.088	0.102	-0.066	-0.125	-0.091	-0.021	-0.088	-0.025
High School	(0.106)	(0.087)	(0.097)	(0.102)	(0.084)	(0.086)	(0.095)	(0.059)	(0.069)	(0.056)
Head did not grad.	0.046	0.046	-0.176**	0.039	-0.055	-0.014	-0.077	-0.126***	-0.016	0.062
High School	(0.080)	(0.067)	(0.078)	(0.077)	(0.069)	(0.066)	(0.076)	(0.039)	(0.059)	(0.059)
Head attended	0.002	0.058	0.061	0.060	0.021	-0.005	0.061	0.049	-0.041	-0.002
Some College	(0.075)	(0.064)	(0.079)	(0.078)	(0.086)	(0.063)	(0.069)	(0.060)	(0.066)	(0.062)

Head is College Graduate	0.106	0.090	0.087	0.285**	0.157	-0.084	0.067	-0.063	-0.145**	-0.046
	(0.126)	(0.093)	(0.120)	(0.111)	(0.112)	(0.075)	(0.106)	(0.066)	(0.071)	(0.076)
Head has a Graduate Degree	0.498**	-0.218**	-0.286**	0.125	-0.180	0.026	-0.190*	-0.095	0.139	-0.208**
	(0.202)	(0.098)	(0.124)	(0.294)	(0.230)	(0.084)	(0.097)	(0.069)	(0.187)	(0.093)
No Education Data	-0.255**	0.182	-0.246*	-0.153	-0.149	-0.073	-0.089	0.038	-0.236***	0.146
	(0.106)	(0.160)	(0.141)	(0.148)	(0.096)	(0.126)	(0.107)	(0.112)	(0.069)	(0.131)
Child is Female	-0.142***	0.062	0.132**	0.002	-0.021	0.072*	-0.114**	-0.017	0.015	0.028
	(0.055)	(0.038)	(0.058)	(0.059)	(0.058)	(0.040)	(0.054)	(0.042)	(0.040)	(0.029)
Child’s Age	0.004	0.015	-0.008	-0.015	-0.005	0.018*	-0.006	0.016**	0.015	0.015**
	(0.012)	(0.009)	(0.012)	(0.014)	(0.013)	(0.010)	(0.010)	(0.008)	(0.010)	(0.008)
Child is Black	-0.115	-0.138**	0.056	-0.045	0.041	-0.088*	0.155**	0.130**	-0.137***	-0.055
	(0.082)	(0.058)	(0.068)	(0.077)	(0.081)	(0.051)	(0.064)	(0.052)	(0.053)	(0.051)
Child is Hispanic	0.053	-0.046	0.180*	-0.158	0.161	0.192**	0.276***	-0.032	-0.051	-0.105
	(0.106)	(0.112)	(0.105)	(0.103)	(0.111)	(0.095)	(0.099)	(0.049)	(0.068)	(0.073)
Central Region	-0.244**	-0.075	-0.085	-0.064	-0.191**	-0.018	-0.088	-0.012	0.106*	0.056
	(0.099)	(0.074)	(0.100)	(0.109)	(0.088)	(0.073)	(0.087)	(0.062)	(0.064)	(0.072)
Southern Region	-0.141	-0.039	0.061	-0.106	-0.160*	0.042	-0.039	0.059	0.170***	-0.050
	(0.093)	(0.062)	(0.094)	(0.100)	(0.091)	(0.078)	(0.083)	(0.050)	(0.058)	(0.068)
Western Region	0.038	0.118	-0.130	-0.053	-0.169	-0.205*	-0.176*	0.003	0.047	-0.052
	(0.113)	(0.094)	(0.112)	(0.125)	(0.106)	(0.111)	(0.097)	(0.055)	(0.064)	(0.076)
Rural Area	-0.011	0.123**	-0.014	-0.135**	0.011	-0.060	0.080	-0.032	-0.032	0.013
	(0.069)	(0.056)	(0.059)	(0.064)	(0.063)	(0.050)	(0.067)	(0.037)	(0.054)	(0.052)
Constant	0.564**	-0.323	0.702***	0.682**	0.745***	-0.319	0.163	-0.144	-0.276	0.216
	(0.249)	(0.208)	(0.255)	(0.276)	(0.278)	(0.197)	(0.207)	(0.153)	(0.206)	(0.171)
Observations	494	494	494	494	494	494	494	494	494	494
R-squared	0.197	0.165	0.179	0.113	0.099	0.151	0.131	0.148	0.130	0.160

Note: Authors’ estimates from linear regressions estimated using data for children aged 10 - 17 years living in households with incomes below 185 percent of the poverty line in the CDS-II. The models also include controls for family structure, parents’ employment status, the family head’s education, the child’s gender, age, and race/ethnicity, the region of residence, and urban residence. The estimates incorporate sampling weights. Robust standard errors clustered by family are shown in parentheses.

***Coefficient different from zero with $p < 0.01$; **Coefficient different from zero with $p < 0.05$; *Coefficient different from zero with $p < 0.1$.

Table 3.6. Weekly Food Consumption in Low Income Families

VARIABLES	(1) Milk	(2) Fruit	(3) Veg.	(4) Grains	(5) Sweet	(6) Meat	(7) Protein
School Breakfast	0.171	0.617**	0.159	-0.111	0.660**	0.100	0.263
	(0.224)	(0.283)	(0.325)	(0.194)	(0.260)	(0.266)	(0.287)
School Lunch	-0.295	-0.273	-0.023	-0.151	0.002	0.119	-0.352
	(0.234)	(0.275)	(0.415)	(0.210)	(0.317)	(0.245)	(0.294)
Received WIC	-0.107	-0.217	-0.515	-0.288	-0.985**	-0.764**	-0.086
	(0.411)	(0.343)	(0.458)	(0.387)	(0.400)	(0.368)	(0.471)
Received Food	-0.396	-0.053	-0.715	-0.311	0.239	-0.609*	0.072
Stamps	(0.340)	(0.458)	(0.502)	(0.329)	(0.384)	(0.355)	(0.490)
Food Stamp	1.275	1.440	0.490	0.409	0.331	2.531	-3.605
Value/Needs	(2.511)	(2.551)	(3.556)	(2.179)	(2.792)	(2.223)	(2.873)
Income/Needs	-0.992***	-0.239	-0.280	-0.118	-0.375	0.047	-0.115
	(0.316)	(0.381)	(0.454)	(0.260)	(0.391)	(0.318)	(0.391)
Income/Needs	-1.051***	-0.563	0.018	-0.102	-0.330	-0.122	-0.232
is <1.3	(0.299)	(0.365)	(0.425)	(0.282)	(0.374)	(0.325)	(0.358)
# of Children <6	0.075	-0.085	0.230	-0.157	-0.062	0.227	-0.056
	(0.178)	(0.185)	(0.204)	(0.186)	(0.232)	(0.195)	(0.235)
# of Child between	-0.001	0.042	0.090	-0.013	0.004	0.070	0.040
6 and 18	(0.090)	(0.094)	(0.115)	(0.071)	(0.090)	(0.085)	(0.097)
# of Adults >18	0.221	0.404***	0.050	0.081	0.266	-0.107	0.106
	(0.165)	(0.154)	(0.237)	(0.166)	(0.212)	(0.181)	(0.184)
Head is Married	-0.294	0.208	0.055	-0.172	-0.492	-0.118	-0.227
	(0.345)	(0.390)	(0.498)	(0.317)	(0.416)	(0.389)	(0.391)
Head is Employed	0.176	0.063	-0.141	-0.254	0.043	-0.413	-0.441
	(0.286)	(0.269)	(0.320)	(0.256)	(0.334)	(0.280)	(0.338)
Wife is Employed	0.121	0.090	0.363	0.374	0.263	0.288	0.423
	(0.316)	(0.298)	(0.375)	(0.266)	(0.305)	(0.332)	(0.340)
Head did not attend	-0.202	0.093	0.835	0.595**	0.393	0.217	0.072
High School	(0.337)	(0.411)	(0.525)	(0.276)	(0.426)	(0.391)	(0.464)
Head did not grad.	-0.077	-0.061	0.021	0.405*	0.489	0.305	-0.004
High School	(0.268)	(0.408)	(0.406)	(0.237)	(0.339)	(0.311)	(0.345)
Head attended	0.154	0.687*	0.727*	0.352	-0.271	-0.001	0.410
Some College	(0.313)	(0.352)	(0.379)	(0.296)	(0.402)	(0.334)	(0.342)
Head is College	0.745*	0.590	1.329***	0.623	0.678*	-0.168	-0.057
Graduate	(0.418)	(0.466)	(0.506)	(0.397)	(0.403)	(0.400)	(0.326)
Head has a	-0.236	0.013	0.337	1.206***	1.052	0.380	1.167*
Graduate Degree	(1.395)	(0.982)	(1.273)	(0.364)	(1.021)	(0.812)	(0.665)
No Education Data	0.395	-0.141	-0.372	0.470	0.481	0.836	0.137
	(0.518)	(0.891)	(0.770)	(0.594)	(0.489)	(0.845)	(0.587)
Child is Female	-0.426*	-0.351	-0.187	0.261	-0.354*	0.054	-0.614***
	(0.219)	(0.245)	(0.273)	(0.165)	(0.210)	(0.206)	(0.233)
Child’s Age	-0.011	-0.020	-0.043	0.028	0.049	0.226***	0.028
	(0.047)	(0.044)	(0.059)	(0.035)	(0.048)	(0.049)	(0.050)
Child is Black	-0.158	0.511	-0.148	0.017	0.793**	0.551*	-0.043
	(0.288)	(0.370)	(0.392)	(0.243)	(0.327)	(0.299)	(0.355)
Child is Hispanic	0.273	-0.146	-0.544	0.109	-0.342	0.409	0.938**
	(0.353)	(0.470)	(0.553)	(0.293)	(0.469)	(0.439)	(0.391)
Central Region	-0.496	0.333	0.122	-0.494	-0.220	-0.558	0.370
	(0.332)	(0.457)	(0.543)	(0.343)	(0.393)	(0.412)	(0.404)

Southern Region	-1.034***	0.273	0.315	-0.445	-0.292	-0.555	0.229
	(0.319)	(0.421)	(0.507)	(0.318)	(0.316)	(0.418)	(0.371)
Western Region	-0.786**	0.257	-0.009	-0.710*	-0.023	-1.229**	-0.002
	(0.376)	(0.536)	(0.635)	(0.375)	(0.441)	(0.562)	(0.467)
Rural Area	0.216	-0.053	-0.271	-0.216	-0.477	0.176	-0.021
	(0.305)	(0.264)	(0.313)	(0.295)	(0.348)	(0.292)	(0.329)
Constant	7.474***	4.346***	4.280***	5.872***	4.062***	2.422**	3.674***
	(0.884)	(0.990)	(1.252)	(0.785)	(0.942)	(0.947)	(1.093)
Observations	486	490	488	493	491	491	489
R-squared	0.122	0.106	0.098	0.100	0.163	0.153	0.093

Note: Authors' estimates from linear regressions estimated using data for children aged 10 - 17 years living in households with incomes below 185 percent of the poverty line in the CDS-II. The models also include controls for family structure, parents' employment status, the family head's education, the child's gender, age, and race/ethnicity, the region of residence, and urban residence. The estimates incorporate sampling weights. Robust standard errors clustered by family are shown in parentheses.
***Coefficient different from zero with $p < 0.01$; **Coefficient different from zero with $p < 0.05$; *Coefficient different from zero with $p < 0.1$.

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