TWO APPLICATIONS OF INFREQUENCY OF PURCHASE AND DOUBLE HURDLE MODELS TO THE STUDY OF TIME USE

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James M. Payne

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JAMES M. PAYNE

Approved:

Mark F. Owens

Dr. Mark F. Owens, Committee Chair

E. Anthon Eff

Dr. E. Anthon Eff, Committee Member

Steven Livingston

Dr. Steven G. Livingston, Committee Member

Charles L. Baum II

Dr. Charles L. Baum, Chair, Economics and Finance Department

Michael D. Allen

Dr. Michael D. Allen, Dean, College of Graduate Studies

TO MY MOTHER AND FATHER

who, unable to attend college, ensured that I did

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ABSTRACT

Using a household production framework, these articles examine two important components of people's time allocation. Data from the American Time Use Survey (ATUS) for 2003 – 2010 are analyzed with infrequency of purchase and double hurdle models to account for the idiosyncrasies of the time diaries.

The first article investigates parents' time allocation between direct and indirect child care for producing human capital in their children. Sources of the "time gap" between men and women are identified by decomposition. Endogeneity and selection bias are managed simultaneously with a multi-step estimation process. I use multiple imputation to handle missing data and an inverse hyperbolic sine transformation to correct for heteroskedasticity and nonormality of residuals.

I find that mothers increase indirect child care time relative to direct child care as hourly earnings rise, evincing a substitution effect. This effect is stronger for whites, college graduates, and single parents. Greater amounts of both types of care are associated with higher incomes for mothers and fathers. Parent-students of both sexes devote less time to both types of care. More schooling is associated with sizable increases in both types of care for women. Longer work hours reduce child care time for men far more than women, suggesting that women reduce leisure or household work to preserve child care time. Rising earnings attenuates the time gap, while schooling increases it. Also, I find evidence of negative selection in reporting earnings for men in the ATUS.

Article two finds that Californians responded to the H1N1 pandemic of 2009 – 2010 by reducing work time to avoid catching the disease, again using infrequency of purchase and double hurdle models. ATUS data are combined with official mortality reports and local newspaper article counts. Modeling separately by region, sex, and age, I find evidence that some workers responded to reports of the pandemic in the news media but not to actual changes in mortality, with the most consistent effects for younger females in southern California and the Bay Area. The relative performance of multiple imputation and inverse probability weight methods are examined, with MI showing some advantage in finding significant results.

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INTRODUCTION

As national time use surveys have grown in number and breadth, so has the body of time use research. The two additions to this literature which follow use the relatively new American Time Use Survey (ATUS), which began gathering data on a one-day diary basis in 2003. Of the large number of time use categories included, only a few are both of interest to economists and have enough nonzero values to make useful estimates. Two of these are child care time and work time, which are the subjects of this study.

We know from long observation, both anecdotal and systematic, that the amount of time parents spend with their children, and the activities they do with them, have a powerful influence on the adult those children will become. Much of what we do for our children as parents do is not readily measurable, at least not by telephone surveys; but much of what is, is not only important in its own right, but is likely correlated with the rest. How parents with different levels of earnings, and hence different money incomes and opportunity costs of time, allocate their time is important as the distribution of income changes over time. And how changes in the ever-more chaotic American family structure affect the interaction of parents and children is of paramount importance for our children's well-being today, and for our society in the future.

I test the hypothesis that parents respond to changes in earnings, schooling, and family structure less by changing the gross amount of time they spend with their children, but by changing the composition of that time. I show that they shift their time, relatively speaking, away from direct child care time and toward indirect care, which consists of arranging for and facilitating persons outside the household—from grandparents to piano teachers to camp counselors—to spend time with their children. I also find that earnings and schooling both positively affect the total amount of time parents spend with their children, and that changes in family structure have different effects for men and women.

For employed persons, time engaged in market work is the most common single use of time recorded in ATUS besides sleeping. It has been a common study subject, but no study has, to my knowledge, attempted to determine the effect of a large scale pandemic on it, probably because few pandemics last long enough to leave a trail in the data. The H1N1, or "swine flu," pandemic of 2009 – 2010 was an exception. I track its effect on worker's behavior in the state of California. Living at the point of entry of the new and unknown disease into the US, Californians in 2009 had no template, no guide, for their response to the burgeoning pandemic, and some of their early behavior reflects the panic that gripped the state. The California Department of Public Health also crafted a response that included close monitoring of H1N1 incidence and, unlike other jurisdictions, made the data freely available despite its budget troubles.

I hypothesize that workers reduced work time, or stayed home from work altogether, on at least some days to avoid contracting the flu, and that this response was driven not by actual mortality reports but by news media coverage of the pandemic. I find evidence that some groups, particularly younger women, did this.

Economists studying time use have debated the appropriateness of the Tobit model, with evidence mounting that other specifications are better suited to the task. I use two alternatives—infrequency of purchase and double hurdle models—in both articles. Missing data are a serious problem not with the time use data themselves but with the demographic variables that accompany them, particularly earnings, and other work related variables suffer as well. I employ the method of multiple imputation, which has seen wide use in medical and biological research, to accommodate this, and also test it against inverse probability weights in the second article. I also use the inverse hyperbolic sine transformation of the dependent variables in the first article as a feasible method of correcting for the heteroskedasticity and nonnormality that are ubiquitous in time use data.

COPING WITH PROSPERITY: THE RESPONSE OF PARENTS' CHILD CARE TIME USE TO RISING EARNINGS

I. INTRODUCTION AND MOTIVATION

The amount of time parents spend on child care has long been a subject of research in time use studies. Aside from its importance from a policy perspective, it is one of the few categories of importance to economists with an abundance of nonzero values in diary-day time use data.

Child care time use studies have typically focused on the distinction between primary and secondary child care, a dichotomy that follows the classification system used in the time use data. Definitions vary among countries. In the American Time Use Survey (ATUS), a primary activity is defined as the activity that fulfills the main purpose of the survey participant during some particular period, and a secondary activity is one "done at the same time as the primary activity." (BLS, 2011b) But the distinction is often unclear. Does 30 minutes of household work or leisure while young children are present indicate a busy parent making efficient use of time by multitasking, or a feckless one giving scant attention to children in need of closer supervision? Following Craig (2006), I consider only primary child care. I include in child care only those activities that are unambiguously directed toward caring for or nurturing household children. As a result, the time measurements may seem unreasonably small—specifically, how can so many parents spend no time on their children in a day?—but the alternative is to use a noisy definition of child care that leads to inconclusive results.

Parents seek to invest in human capital in their children, a normal good, for which they use market goods and services and their own time inputs. (Becker, 1981) As parents' hourly earnings rise, so does the opportunity cost of time, and by the substitution effect they will reduce their own time inputs in favor of now relatively cheaper market goods. But the increase in earnings raises their income, so they will seek to invest more in children's human capital, which they will accomplish by using more of both market goods and their own time. The sign on earnings is thus ambiguous. The parameter estimates will still be worth observing, but they cannot falsify a hypothesis.

However, the effect on the *composition* of own-time inputs should be clear. Using market inputs involves more than just buying physical goods at the store. Parents also obtain services from nonhousehold members, and making arrangements for this requires using time. This can involve anything from phoning grandparents to arrange a visit, to meeting with a teacher or ballet instructor, to making plans for summer camp, or visiting colleges. The primary hypothesis tested in this study follows: As the opportunity cost of time rises, the relative price of using market services falls relative to the implicit price of direct child care, and whether they decrease or increase the gross amount of time they allocate to their children, parents will try to "leverage" their time by using proportionately more of it to acquire market services for their children, or, what amounts to the same thing, will increase the likelihood of engaging in this activity, which I describe as *indirect child care*, relative to direct child care, on any given day.

The opportunity cost hypothesis for gross child care time can still be tested imperfectly by using a parent's enrollment as a student in training, college, or university as a proxy. Status as a student does not imply a tight constraint of a more-or-less fixed number of hours per day. Study time can be allocated with some freedom to avoid conflict with other valued time uses. Anecdotes abound of parents who study after the children have gone to bed.[1] But still, student-parents will likely substitute study and class time for some child care time, and the coefficient on this variable should be negative. Since being a student rarely results in a concurrent increase in income, although payment of tuition and fees could create a negative income effect. Other problems exist; aside from concealing heterogeneity in course loads and study time allocation among students, this variable surely has a selection bias, since parents who pursue a college degree differ both from parents who completed their studies prior to having children as well as those who never attend college at all. However, since only in a few sad cases do parents remain students on an almost permanent basis, there should be many persons in the sample who, having once been student-parents themselves, share the same underlying characteristics but no longer face the time constraint. This variable can provide a suggestive but far from definitive test of the hypothesis.

I test five secondary hypotheses:

1. Parents with higher educational attainment should allocate more time to both types of child care. Griliches (1997) surveys the literature on human capital formation, which suggests that underlying personal characteristics drive human capital accumulation both for parents and their children.

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[1] ATUS also contains information of this type, although few studies have exploited it. One is Stewart's (2010) analysis of the timing of mothers' work and child care.

2. Parents with longer usual hours of market work should, of course, devote less time to both forms of child care, with direct care affected the most. But an interesting hypothesis is that the work-time elasticity of child care time is relatively low for women (Craig, 2006). Assuming women have a stronger preference for engaging in child care than men, then an increase in usual work hours should bring a greater reduction in men's child care time than women's.

3. The Current Population Survey (CPS), on which the ATUS is based and is its source of household data, collects no information on household wealth. I use home ownership as a weak proxy variable. Assuming that a positive wealth effect increases the demand for children's human capital, I expect a positive sign on this coefficient, but like the student variable, it allows only a suggestive test.

4. Among others, Kalenkoski, Ribar, and Stratton (2005) and Lundberg, Pabilonia, and Ward-Batts (2007) have examined the effect of family structure on child care time. In single-parent households, reduced total parent time inputs should affect time use. As primary caregivers, women likely reduce direct child care time; compared to married men, however, I expect that single men will compensate for the lack of a partner by spending more time on child care, although total child care time should be less than for two-parent households. Indirect time use to obtain services from out-of-household persons to care for the children should be greater, in proportion, for both men and women.

5. Regarding missing data in CPS, Bollinger and Hirsch (2010) concluded that men, much less so women, become less likely to report their earnings as those

earnings rise, a phenomenon known as negative selection. ATUS data include updates to CPS earnings records and, by doing away with proxy respondents, should reduce, but not eliminate, this. I compare multiple imputation and listwise deletion results to determine if ATUS data are afflicted to a similar extent, and hypothesize that some level of negative selection persists in ATUS.

This paper extends the literature in two ways. First, it proposes and tests a simple model to detect the substitution effect on parents' child care time when faced with a change in hourly earnings. Second, it introduces into the time use literature techniques that have been applied in other fields, including multiple imputation to deal with missing values in the ATUS data, decomposition methods to analyze the difference in men's and women's time use, and an inverse hyperbolic sine transformation to reduce heteroskedasticity and nonnormality.

The remainder of the paper is organized as follows. Section II reviews the literature on ATUS data, missing data analysis and imputation issues, the application of consumer expenditure models to time use studies, child care time use studies, and the inverse hyperbolic sine transformation. Section III presents the theoretical model. Section IV describes the data, section V presents the empirical results, and section VI concludes.

II. LITERATURE REVIEW

A. ATUS Data and Limitations

Early time use surveys were conducted in the Soviet Union from the 1920s to the 1960s and by the United States Department of Agriculture in the 1920s. They have since become common in the developed world, and the American Time Use Survey was initiated in 2003 as an ongoing project of the BLS and the Census Bureau. (Frazis and Stewart, 2007)

ATUS households are selected as a stratified random sample of the civilian noninstitutionalized population from the approximately 7,500 households completing participation in the Current Population Survey (CPS) each month, to which ATUS data is linked. Each observation in the data covers only a single "diary day."[2] Weekends are sampled disproportionately to provide an adequate subsample size. Unlike CPS, only the respondent is allowed to give information in ATUS; there are no proxy respondents.[3]

Self-employed persons' earnings are not reported in either CPS or ATUS. They would not be compatible with salaried or hourly workers' earnings in any event, because they could include a return on capital as well as labor inputs. Studies that use listwise deletion remove them from the data, by definition. Heckman and Lafontaine (2006) and Foster and Kalenkoski (2010) delete them. Hirsch and Schumacher (2004) and Bollinger and Hirsch (2006) retain them and impute their earnings.

The earnings of unemployed persons in ATUS are censored, as their observed wage is zero but their actual earnings accrue from household production. Working with ATUS data, Donald and Hamermesh (2009) take an alternate approach to that of Heckman (1979). They use the presence of young household children to represent the

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[2] Some of the other national surveys cover two days or more. Two-day surveys may not add any important information, and longer survey periods produce lower response rates. (Frazis and Stewart, 2010)

[3] Along with the designated-day strategy and apparent survey fatigue on the part of respondents who have recently completed the CPS round, this seems to explain the low response rates for the ATUS—56 percent for the years 2003-2007, well below the 80 percent level recommended by the Office of Management and Budget for federal surveys and the 90 percent rates typical for the CPS. Because of this, there is concern about nonresponse bias in the ATUS. (Krantz-Kent, 2008)

wage rate in identifying labor-force participation, followed by score-matching to impute the earnings of nonemployed persons.

Frazis and Stewart (2010) of the BLS emphasize the research consequences of the single-day time frame of the data, which produces a mismatch with long-run estimates. Considering the mean, variance, and quantiles, they show that only the mean of long-term time use can be calculated from daily data on occasional, e.g., once-per-week, activities. Because each person is represented by only a single observation in the data, the between-persons variance cannot be separated from the within-person day to day variance. Distributional differences prohibit producing long-run quantile estimates from short-run data.

Like time use surveys, consumption expenditure surveys include many zeros. Aside from measurement error, there are three likely reasons for a zero value: 1) The household's preferences are such that it would not participate in the market for the good regardless of income level or market price, as with tobacco for nonsmokers. 2) The household is at a corner solution for the good, given its income and the prices it faces. 3) The period of the survey is shorter than the period of consumption of the good, and so no purchase will be recorded for many households. (Sanchis-Llopis, 2001) Each of these situations requires a different solution.

A common approach in time use research (e.g., Floro and Miles, 2001; Craig, 2006; Kalenkoski, et al., 2005, 2007, and 2009; Kalenkoski and Foster, 2008; Connolly, 2008) has been to estimate a Tobit model, assuming the zeros to represent censored values of a latent variable, the intent to engage in the activity, which also must be determined by the same variables that determine the level of time use, and the coefficients must have the same signs. But this does not fit situations 2) and 3) above, which are often combined in time use data.

Gould (1992) shows that Tobit is inappropriate for consumption diary data, as the time window for the diaries does not match that for the estimates. Daunfeldt and Hellström (2007) reject it in favor of the double hurdle. Stewart (2009) observes that the bias is due to the inseparable mixture of actual and error zeros. Extending the work of Keen (1986), he shows that the same applies to time use diaries. Frazis and Stewart (2010) show that linear estimation of coefficients by ordinary least squares will be unbiased, and that Tobit and other censored data methods produce biased results. Foster and Kalenkoski (2010), examining one-day and two-day diaries from the Australian TUS, defend the use of Tobit, but do find that Tobit results are very sensitive to the length of the recording period.

B. CPS Imputation of Earnings and Labor Force Variables

CPS earnings measures are plagued with a high level of missing values due to nonreporting. Greenlees, Zieschang, and Reece (1982) show that missingness is correlated with the value of the missing variable itself—missing not at random (MNAR), or nonignorable missingness. The nonmissing observations, i.e., the ones for which the values of variable are reported, are different in some unknown way from the missing observations. (Schafer and Graham, 2002) Men's CPS earnings are afflicted with negative selection—the probability of a variable being reported decreases as earnings rises. (Bollinger and Hirsch, 2010)

ATUS relies on earnings data obtained from the last round of the respondent's participation in the CPS, between two and five months previous. Respondents are asked to update earnings and other labor force data at the time of the ATUS survey, which also provides an opportunity to correct inaccurate estimates made by proxy respondents. (Krantz-Kent, 2008) The level of missing data for earnings in CPS increased from around 15 percent prior to the revision of the survey questionnaire in 1994 to one-third by 2003. (Heckman and LaFontaine, 2006).

Since 1979, the CPS has imputed—"allocated"—missing values for earnings and other labor force variables with a modified sequential "hot deck" imputation procedure. Missing values are filled in with the donor's values, in what is actually a simplified version of the random within classes (RC) method. (Kalton and Kasprzyk,1982) Hot deck imputation can lead to downward-biased estimates of variance. Jones, et al. (2003) show that this problem can be mitigated by the use of model-assisted or adjusted jackknife variance computations, although the conditions for their successful application are frequently absent in survey data. Hirsch and Schumacher (2004) and Bollinger and Hirsch (2006) show that hot deck imputation in the CPS produces what they call "match bias;" group differentials not accounted for by class variables are biased toward zero. They use an inverse probability weight (IPW) approach in which the observations are reweighted by the inverse probability of being observed

Single imputation methods such as these, which create only one imputed value for each missing value in the data, understate the amount of uncertainty about the imputed value; in fact, they imply perfect certainty. Multiple imputation, or MI, developed by

Rubin (1987), is designed to solve this problem. This method has become popular in medicine and biostatistics. For each variable to be imputed, an imputation model is estimated, often by an Expectation-Maximization (EM) process (Dempster, Laird, and Rubin, 1977) that generates a simulated distribution of values for the variable from which a sample is drawn with replacement to fill in the missing values. This process is repeated to create $m > 1$ complete sets composed of observed and simulated values. The purpose is neither to create good estimates of the missing values, nor to add any extra information to the data. MI just fills in the blanks with values that will not bias the results, that is, to let the existing information be observed accurately. The m data sets are then analyzed individually and then combined, using Rubin's Rule, to form a set of scalar parameter estimates.

Because of resource constraints, many studies have used a small number of imputations, fewer iterations, commonly three to five, claiming that this provides an acceptable level of efficiency. Schafer (1997) argues that as few as $m = 3$ imputations is sufficient, because the Monte Carlo error is proportionate to the level of missingness, not to the number of observations, and because Rubin's Rule explicitly accounts for the Monte Carlo error. But a small number of iterations can lead to a large loss of statistical power, whereas 20 iterations reduce power falloff to less than 1% with 10% missing values. (Graham, Olchowski, and Gilreath, 2007)

C. Consumption Expenditure Models

Two types of models that have had wide use in modeling consumption expenditures from survey data also are applicable to time use studies.

In many consumption decisions, the decision to purchase a good, in any quantity, is separate from the decision about the quantity to purchase once participation in the market has been settled upon. Examples abound: Whether to buy a motor home, and how often to travel with it; whether to begin smoking, and how many cigarettes to buy afterward. There are two dependent variables to model: one discrete, the other count or continuous. Further, these decisions may not be governed by the same process. Often they share many of the same covariates, as is likely the case with the motor home; in others, such as cigarette smoking, they may share few or none.

The Tobit (Tobin, 1958) model requires the same right-hand variables for modeling both these decisions, and that they have the same sign for both. Assuming a corner solution, Cragg (1971) presented a method for estimating both the decision to purchase and the quantity decision within a unified framework but allowing for different sets of covariates. Lin and Schmidt (1984) proposed a variation which relaxed Cragg's assumption of independence between the estimates, instead imposing conditional independence. Known as the double hurdle, or two-part, model, in this modified form it has been used to model consumption expenditures for goods such as cheese (Gould, 1992, and Yen and Jones, 1997), rice (Gao, Wailes, and Cramer, 1995), prepared meals (Newman, et al., 2001), food away from home (Mihalopoulos and Demoussis, 2001), and tobacco and alcoholic beverages (Madden, 2001).

The double hurdle is applicable to time use studies because it addresses the existence of zeros in the data and makes separate estimates for participation in the activity and the extent of that participation. Stewart (2009) shows this model to be relatively unbiased when the participation decision is affected indirectly by the covariates through the consumption variable (conditional independence), but it delivers biased results when the relationship between the covariates and the participation decision is direct.

The infrequency of purchase model (Deaton and Irish, 1984), was developed for consumption expenditures survey studies which include many instances of zero expenditures. Keen (1986) modified the model to derive Engel curves for a variety of goods. It has been extended and applied to other consumer expenditure categories: butter (Blisard and Blaylock, 1993), clothing (Sanchis-Llopis, 2001, and Mihalopoulos and Demoussis, 2002), and alcoholic beverages (Pierani and Tiezzi, 2011). Its applicability to time use data has been suggested by Stewart (2009), who also presented an adaptation of Keen's model for time use studies.

D. Child Care Time Use

As one of the larger and more consistently reported categories of time use in ATUS and other national time use data, child care has been the subject of several studies. A large body of literature, summarized in Craig (2006), shows that, for women at least, the marginal effect on child care time of an increase in market work is negative but far less than one; they respond to an increase in work hours by limiting fertility and leisure.

Kalenkoski, et al. published a set of three related studies (2005, 2007, 2009) on different issues involving child care time use, particularly family structure, using correlated Tobit models with separate models for men and women. Citing Becker (1965), they hypothesized that single parents' time use may be affected by reduced total parent time resources as well as more severe limits on exploiting economies of scale and specialization in household work. They concluded that single parents spend more time both on child care and market work than married or cohabiting parents, and found that higher wages are associated with more primary child care time.

Donald and Hamermesh (2009) estimated log-linear and probit models for a stochastic quadratic utility function dependent on consumption, household production, and leisure. They found that an hour of work time reduces time devoted to all other functions by a greater amount due to the fixed time costs of going to work. If child care time use is inelastic with respect to work time, then other forms of household production and leisure must be reduced disproportionately.

Gronau (1973) developed an early model for estimating the value and potential wage of nonworking women's time in the context of the husband's earnings. He extended this (1977) by developing a model of household work to distinguish it more clearly from leisure. He noted the difficulty of making the distinction in practice, particularly with regard to time spent with children. This was the starting point for Kimmel and Connolly (2006), who used ATUS data to estimate a four-equation model, one each for market work, household work, leisure, and child care, the first three of which were estimated as Tobit models. They reported that child care time responds to prices and incomes in much the same way as market work. Gronau and Hamermesh (2008) presented a model for the demand for variety in household production which explicitly incorporated wage rates to account for differences in prices among households.

Cherchye, De Rock, and Vermeulen (forthcoming) extended the collective labor supply model of Blundell, Chiappori and Meghir (2005) which they applied to a sample of Dutch parents, concluding that mothers do not spend more time caring for children than fathers. Stewart (2010) used ATUS data and concluded that working mothers shift child care to lower-opportunity cost times of the day and rely on out-of-household persons to provide care.

E. Inverse Hyperbolic Sine ($sinh^{-1}$) Transformation

The use of natural logarithmic transformations to reduce heteroskedasticity and nonnormality in errors is commonplace. But time use data cannot be log-transformed due to the presence of zero values. Burbidge, Magee, and Robb (1988) propose using an inverse hyperbolic sine ($sinh^{-1}$) transformation, which can be interpreted much like the log. But it is defined for negative and zero values, and is approximately linear for small values of y. (Pence, 2006)

Consumption expenditure data share time use's propensity for zero values. The $sinh^{-1}$ transformation has been used in studies of consumption of cheese (Yen and Jones, 1997) and food-away-from-home (Mihalopoulos and Michael, 2001) Other researchers in agricultural economics have applied it in studies of crop yields; see Moss and Shonkwiler (1993), Ramirez (1997), and Wang, et al. (1998). Woolley (2011) argues that, in analyzing household wealth data, $sinh^{-1}$ transformations should be more widely used.

III. THEORETICAL MODEL

A. A Model of Time Substitution

Like Hamermesh (2008), I assume a CES household production function for children's human capital, with the two inputs being parents' own time and market services, i.e., time of other nonhousehold persons. (I ignore physical goods for simplicity.) Parent's own time is the only input used for direct child care, but market services require two inputs: the purchases themselves (*P*) plus the time the parent uses to acquire and make arrangements for the services on behalf of the children. I define own time that enters directly into the production function as *FACETIME,* or direct child care time, and indirect child care time as *BEHALF.* The price of *FACETIME*, p_f, is w, the parent's hourly wage rate or equivalent. The price of market services is a composite of the price of purchases, p_p, and the implicit price of *BEHALF* time, $p_b = p_f = w$.[4] Letting γ and τ represent the shares of these two inputs in the production of market services *S*, with $\gamma + \tau = 1$, the price of market services is just the weighted mean of p_p and p_b:

$$p_s = \gamma p_p + \tau p_b \tag{3.1}$$

The effect of a change in the wage rate on the price of *FACETIME* $\left(\frac{\partial p_f}{\partial w}\right)$ is by definition equal to one. Assuming the price of purchased services to be independent of the parent's wage rate, the effect of a change in the wage rate on the price of market services *S* is

$$\frac{\partial p_s}{\partial w} = \frac{\partial(\gamma p_p + \tau p_b)}{\partial w} = \frac{\partial(\gamma p_p)}{\partial w} + \frac{\partial(\tau p_b)}{\partial w} = 0 + \frac{\partial(\tau p_f)}{\partial w} = \tau < 1 \tag{3.2}$$

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[4] I simplify by assuming that *FACETIME* and *BEHALF* are equally capable, or incapable, of being shifted to less costly times of the day or week, although the parents' timing of various kinds of work (see Stewart, 2010) suggests otherwise.

So an increase in the parent's wage rate will raise the price of *FACETIME* relative to that of *BEHALF* in the proportion $1/\tau$.

An increase in the wage rate will increase parent's income $M = W + N$, where W is wage income and N is nonwage income, or income from all other sources, so $\frac{\partial M}{\partial w} \geq 1$.

Given that the output variable—children's human capital—is unobservable in data gathered while it is still being produced (much like real life), we can only estimate demand functions for inputs, assuming a perfectly competitive market for purchased services and that the parents act as cost minimizers. Following Rutherford (2009), letting time inputs for *FACETIME* and market services be f and S, we have the unconstrained utility function

$$U(f,S) = (\alpha f^{\rho} + (1-\alpha)S^{\rho})^{1/\rho} \tag{3.3}$$

where ρ is the elasticity of substitution between the two goods. Introduction of prices p_f and p_s and an income constraint M leads to the Lagrangian

$$\mathcal{L} = U(f,S) - \lambda\big(M - p_f f - p_s S\big)\,. \tag{3.4}$$

Solving for first derivatives gives

$$\frac{\partial \mathcal{L}}{\partial f} = \frac{\partial U}{\partial f} - \lambda p_f = \frac{\partial U}{\partial f} - \lambda w \tag{3.5}$$

and substituting from (3.1)

$$\frac{\partial \mathcal{L}}{\partial S} = \frac{\partial U}{\partial S} - \lambda p_s = \frac{\partial U}{\partial S} - \lambda\big(\gamma p_p + \tau p_b\big) = \frac{\partial U}{\partial S} - \lambda \gamma p_p - \lambda \tau w \tag{3.6}$$

The input demand functions can be derived as

$$f\big(p_f, p_s, M\big) = \left(\frac{\alpha}{p_f}\right)^{\sigma} \frac{M}{\alpha^{\sigma} p_f^{1-\sigma} + (1-\alpha)^{\sigma} p_s^{1-\sigma}} \tag{3.7}$$

and

$$b(p_f, p_s, M) = \left(\frac{1-\alpha}{p_s}\right)^{\sigma} \frac{M}{\alpha^{\sigma} p_f^{1-\sigma} + (1-\alpha)^{\sigma} p_s^{1-\sigma}} \tag{3.8}$$

where $\sigma = \frac{1}{1-\rho}$ and $1 - \sigma = \frac{-\rho}{1-\rho}$. This results in the indirect utility function

$$V(p_f, p_s, M) = M\left(\alpha^{\sigma} p_f^{1-\sigma} + (1-\alpha)^{\sigma} p_s^{1-\sigma}\right)^{\frac{1}{\sigma-1}} \ . \tag{3.9}$$

Since U is homogeneous of degree one,

$$U(\lambda f, \lambda S) = \lambda U(f, S) \tag{3.10}$$

V is likewise linearly homogeneous in income:

$$V(p_f, p_s, \lambda M) = \lambda V(p_f, p_s, M) \tag{3.11}$$

and of degree -1 in prices:

$$V(\lambda p_f, \lambda p_s, M) = \lambda^{-1} V(p_f, p_s, M). \tag{3.12}$$

Because of the linear homogeneity of U, (3.9) can be converted to an exact price index

$$e(p_f, p_s) = \left(\alpha^{\sigma} p_f^{1-\sigma} + (1-\alpha)^{\sigma} p_s^{1-\sigma}\right)^{\frac{1}{\sigma-1}} \tag{3.13}$$

where e is the price of a unit of utility at the optimal bundle of f and S. Thus from 3.9, and substituting for p_s from (3.1), we can rewrite the indirect utility function as

$$V(p_f, p_p, p_b) = \frac{M}{e(p_f, p_p, p_b)}. \tag{3.14}$$

From 3.2 above, we have the result that an increase in the wage rate will reduce the price of market services relative to direct child care, and result in substitution of *BEHALF* for *FACETIME*. Assuming children's human capital to be a normal good, the income effect of the price change, $\frac{\partial V}{\partial M}$, will be in the same direction as the substitution effect.

The rise in the wage rate will increase the parent's income and have an effect separate from the substitution and income effects of the price change. Again assuming strict normality, an increase in wages will increase demand for children's human capital. Thus the change in *FACETIME* is indeterminate; if the effect of the change in income on demand is large enough, an increase in wages will offset the combined substitution and income effects of the price change and increase direct child care time. The positive price effect on market services will clearly be augmented by this, and *BEHALF* will unambiguously rise.

Assuming strict convexity and that the tangency condition holds, a parent will demand both direct child care inputs and purchased services, and hence will engage in both *FACETIME* and *BEHALF*. An increase in hourly earnings will both reduce the relative price of *BEHALF* and hence market services—in Figure 1, a rotation of the

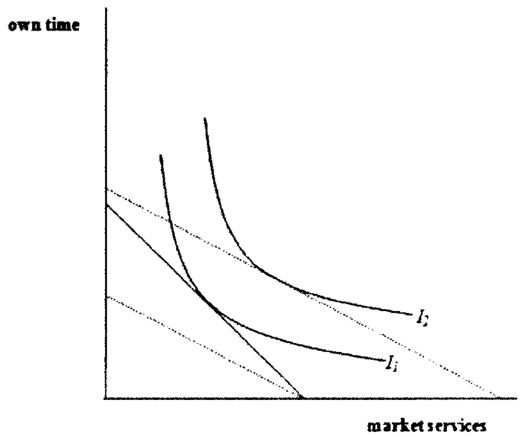

Fig. 1.—Infrequency of purchase model response to an increase in hourly earnings

budget line from *BB* to *B'B*—as well as increase income (shift from *B'B* to *BB''*). This figure represents the assumptions of the infrequency of purchase model introduced below, and incidentally illustrates the case of an increase in both types of time use.

All the above allows equations with time use as the dependent variable to be estimated as linear functions of the covariates. Separate models are estimated for time used in direct interaction with children and time used to obtain market goods and services for children. Market services are those provided by anyone other than the parents; even a day spent with grandma and grandpa would require time inputs by the parents for planning, communication, and transportation. A problem of the data is that the spouse's hourly wage rate equivalent is not observable and so I assume that, in a two-parent household, they face a joint input price.

Due to specialization within the household, I expect the covariates for men and women use to differ in magnitudes and perhaps in signs. Following Kalenkoski, et al. (2005, 2007, 2009), Connolly (2008), and Gronau and Hamermesh (2008), among others, I model their time use in separate regressions.

B. General Specifications

I estimate infrequency of purchase (IPM) and double hurdle models following the estimation of earnings using the modified sample selection model as described above. Robust standard errors are computed to accommodate heteroskedasticity.

The presence of zeros in the dependent variables requires an alternative to a logarithmic transformation for the reduction of heteroskedasticity and nonnormality. I use inverse hyperbolic sine *($sinh^{-1}$)* transformations (Burbidge, et al., 1988) of the dependent variables as

$$sinh^{-1} y = ln\left(y + \sqrt{y^2 + 1}\right) \tag{3.15}$$

To impute missing values for hourly earnings and other variables, I use multiple imputation (MI) with $m = 20$ imputed data sets. Rubin (1987) shows that relative efficiency of the MI process is

$$RE = \left(1 + \frac{\lambda}{m}\right)^{-1} \tag{3.16}$$

Where λ is the fraction of missing values and m is the number of imputations. For 20 imputations and the 15% missingness rate for hourly earnings in the data, relative efficiency is 99.26%.

All models are estimated using ATUS sample weights.

C. Specifications--Infrequency of Purchase Model (IPM)

The key characteristic of the IPM model (Deaton and Irish, 1984) is that all individuals are assumed to be doers of the activity at least some of the time, although not necessarily on the diary day. (Frazis and Stewart, 2010)

This model assumes strictly convex preferences as shown in Figure 1.

Following Stewart (2009) and Keen (1986), I define diary-day time use for purpose k of N possible uses by individual h as

$$e_{hk} = \frac{w_m\{\bar{c}_{hk} + u_{hk}\}}{p_{hk}}, k = 1, \ldots, N, \tag{3.17}$$

where e_{hk} is the observed diary-day time use, $\bar{c}_{hk}$ is long-term mean daily time use, and u_{hk} represents a random disturbance term, $E(u_{hk}) = 0$. The Bernoulli-distributed indicator

$w_{hk} = 1$ if the individual reported engaging in the activity on the diary day, 0 if not, and p_{hk} denotes the probability that the individual does the activity on a given day. u_{hk} is constrained to be $\geq -\bar{c}_{hk}$ and so e_{hk} is always nonnegative. We thus have terms for each of the two types of measurement errors in the data: w_{hk}, the censoring variable, and u_{hk}, which captures errors in variables. The model assumes them to be independently distributed.

Defining mean daily time use as a linear function of a set of characteristics $\boldsymbol{X}$ which influence time use in activity k gives

$$\bar{c}_{hk} = \boldsymbol{\beta}_0 + \boldsymbol{X\beta} \tag{3.18}$$

Combining equations (3.2) and (3.3) gives

$$e_{hk} = \beta_0 + \boldsymbol{X\beta} + \left\{\frac{(w_{hk} - p_{hk})\bar{c}_{hk} + w_{hk}u_{hk}}{p_{hk}}\right\} = \beta_0 + \boldsymbol{X\beta} + \eta_{hk} \tag{3.19}$$

Subtracting η_{hk} from both sides leaves us with

$$ipm\_y_{hk} = \{e_{hk} - \eta_{hk}\} = \beta_0 + \boldsymbol{X\beta} \tag{3.20}$$

Stewart (2009) shows this to be an unbiased estimator using OLS.

I constructed the η term as follows: a) w was set to 1 if the respondent engaged in the activity on the diary day, 0 if not. b) p was identified as the cumulative normal probability of engaging in the activity from a probit regression. c) The time use variable was regressed in OLS on a set of covariates using only the nonzero observations. The resulting equation was used to estimate $\bar{c}$ for all observations. Finally, d) u was generated as a random normal term with mean zero and a variance large enough to make $\{\bar{c}_{hk} + u_{hk}\}$ negative for at least some observations and then was constrained to meet the nonnegativity requirement. Once constructed, η was subtracted from actual observed time use to form new dependent variables which, following inverse hyperbolic sine transformation, were then used to generate parameter estimates in OLS.

The resulting dependent variable can take on negative as well as positive values, but, except trivially, not zero. It captures both the probability of participating in the activity on the diary day (p) and individual variation about the observed diary day value (u). It also resolves the piling-up-of-zeros problem that makes OLS a biased estimator for the raw data. In essence, it scales the dependent variable downward to accommodate random non-participation, using a different scaling parameter for each observation which is partly deterministic ($\bar{c}$) and partly stochastic (u).

That there is a difference between men's and women's activities with their children is obvious, but its magnitude and sources are not so clear. I use the counterfactual decomposition method of Blinder (1973) and Oaxaca (1973), hereafter B-O, to quantify this difference for linear models, and Fairlie's (2006) method for the first hurdle probit equations in the double hurdle model. Originally devised for, and still commonly applied to, the wage gap between men and women, these methods can be usefully applied to other situations in which group membership is not a matter of choice and hence selection is exogenous.

To my knowledge, these have not appeared in studies of time use.

As applied here, the B-O method begins by defining time use as

$$t_m = X_m \beta_m + u_m \tag{3.21}$$

with t being an n_m x 1 vector containing values for some time use category for all n_m males in the sample. t_f would give a similar equation for females. X is a matrix of observations on k explanatory variables, β a vector of parameters, and u an error vector. Estimating the regression line at the conditional means gives

$$\bar{t}_m = \bar{X}_m \hat{\beta}_m \tag{3.22}$$

The difference in time use between men and women is

$$\bar{t}_m - \bar{t}_f = \bar{X}_m \hat{\beta}_m - \bar{X}_f \hat{\beta}_f \tag{3.23}$$

Adding and subtracting $\bar{X}_m \hat{\beta}_f$ gives

$$\bar{t}_m - \bar{t}_f = \bar{X}_m(\hat{\beta}_m - \hat{\beta}_f) + (\bar{X}_m - \bar{X}_f)\hat{\beta}_f \tag{3.24}$$

The first right-hand term is the effect of otherwise unexplained gender differences on time use and the second term is the endowment effect. That is, $\bar{X}_m(\hat{\beta}_m - \hat{\beta}_f)$ is the variation in time use between the sexes that cannot be explained by differences in the other regressors, and $(\bar{X}_m - \bar{X}_f)\hat{\beta}_f$shows how female time use differs from that of males due to those differences. (Heinrichs and Kennedy, 2007)

In the typical use of the B-O decomposition in studies of wage gaps, the unexplained effect is usually interpreted as evidence of some form of discrimination, i.e., differences in wages not explained by observed characteristics are due to unobserved labor market conditions. But unless the model is correctly specified with no omitted variables, this runs the usual hazard associated with assuming that the error term represents some particular characteristic rather than what might be a large set of unobserved variables. (Jones, 1983) In a model of child care time use, in which mothers would be expected to play a different role than fathers, the unexplained component would combine the effects of biologically determined preferences as well as social norms. These cannot be separated using the ATUS data. As for the included regressors, unobserved endogeneity is a problem, as women who expect to spend much of their working years at home with children would invest less in human capital through schooling than men or women who intend to do otherwise, thus affecting their latent wage rate as estimated by the Heckman method. How to control for any of this using the ATUS data is not clear.

D. Specifications—The Double Hurdle Model

Unlike IPM, which assumes that all participants engage in the activity at least occasionally, the double hurdle models a corner solution in which, given current prices and incomes, the agent may choose not to engage in the activity at all. There are likely some parents who never engage in what ATUS defines as direct primary child care. Yet these must be rare, and I consider the corner solution argument less persuasive for *FACETIME.* (Frazis and Stewart, 2010) However, making arrangements for persons outside the household to spend time with the children might well be a specialized function in a two-parent household, with only one of the parents devoting more than negligible time to the task.[5] Figure 2 depicts these assumptions, assuming strict convexity and diminishing MRS but with |MRS| < $|\, p_f/p_s \,|$ and so not fulfilling the tangency condition.[6] About 80% of men did not engage in any *BEHALF* time on the diary day; possibly some never do. A double hurdle specification might be appropriate in

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[5] Reasons could include economies of scale and specialized skills. Also, *BEHALF* often involves making arrangements for activities that the parent will have to participate in to some extent, such as taking a child to baseball practice. Casual observation shows that the mother more often does this. Since she will have better information than the father about the day's activities, she may well prefer to keep the scheduling duties to herself. I suspect many fathers learn this the hard way.

[6] A similar outcome would arise from assuming concave preferences, but as this implies that the parent might, depending on prices, choose to engage in only one of direct child care or arrangement-making, but not both. It seems that this would be rare.

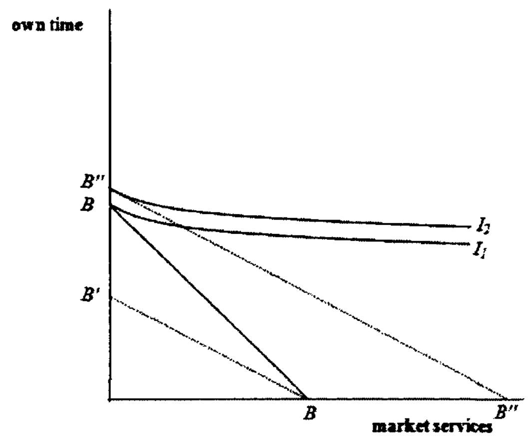

Fig. 2.—Double hurdle model response to an increase in hourly earnings, assuming specialization

this case. With special intention for *BEHALF,* I estimated double hurdle models for both dependent variables in $sinh^{-1}$ transformation of the original values.

This model, proposed by Cragg (1971), has been used in many household expenditure models. In that context it assumes a corner solution in which, given prices and incomes, many households choose never to consume the good, and is appropriate for goods such as tobacco and alcohol. It holds two distinct advantages in such studies over the Tobit model, which is nested in it; the two regressions need not include the same regressors, and the neither the signs nor the magnitudes of coefficients for variables that do appear in both need be the same.

Cragg pointed out that there are two hurdles to overcome before a positive result is observed, hence the name. First, the individual must have a desire to participate in the activity, and second, conditions must be favorable for the individual to realize participation. As originally specified, the model assumed independence between the two models. Omitting the time subscripts in the original, he proposed a first-tier function for the participation decision

$$f(y = 0|\boldsymbol{X}_1, \boldsymbol{X}_2) = C(-\boldsymbol{X}'_2\gamma/\sigma) + C(\boldsymbol{X}'_2\gamma/\sigma)C(-\boldsymbol{X}'_1\boldsymbol{\beta}) \tag{3.25}$$

which he suggested could be estimated by probit. Given a nonzero outcome, his corresponding density function for positive values of y is

$$f(y|\boldsymbol{X}_1, \boldsymbol{X}_2) = (2\pi)^{\frac{-1}{2}}\sigma^{-1}e^{-(y-X'_2\gamma)^2/2\sigma^2}C(\boldsymbol{X}'_1\boldsymbol{\beta}) \tag{3.26}$$

(Cragg, 1971)

Lin and Schmidt (1984) relaxed the independence assumption. With conditional independence, the model becomes, as restated by Wooldridge (2002),

$$f(y|\boldsymbol{X}, y > 0) = [\Phi(\boldsymbol{X\beta}/\sigma)]^{-1}\{\phi[y - \boldsymbol{X\beta}/\sigma]/\sigma\}, y > 0 \tag{3.27}$$

The cumulative density is equal to one due to the inclusion of the term $[\Phi(\boldsymbol{X\beta}/\sigma)]^{-1}$.

The corresponding density function for positive values of y is

$$f(y|\boldsymbol{X};\boldsymbol{\theta}) = [1 - \Phi(X\gamma)]^{1[y=0]}\{\Phi(X\gamma)[\Phi(X\boldsymbol{\beta}/\sigma)]^{-1}[\phi(\{y - \boldsymbol{X\beta}\}/\sigma)/\sigma]\}^{1[y>0]} \tag{3.28}$$

The Tobit model is nested within this when $\gamma = \boldsymbol{\beta}/\sigma$. The second tier equation is estimated as a truncated normal model. I did this with least squares, owing to the relative ease of estimating this with multiple imputations. Preliminary results were identical to those obtained with maximum likelihood and are discussed in Appendix C.

I use the method of Fairlie (2006) for decomposition of the probit model results. The B-O method assumes a linear relationship among the variables and coefficients from binary models cannot be used with them directly. Fairlie uses a method which draws a sample from the larger group equal in size to the smaller group, and then matches each member of the smaller group with the best-match member of the other. This process is repeated several times; I used 100 repetitions for each model.

Using the same notation as above, the decomposition is expressed as

$$\bar{T}_m - \bar{T}_w = \left[\sum_{i=1}^{n_m} \frac{f(X_{mi}\hat{\beta}_m)}{n_m} - \sum_{i=1}^{n_w} \frac{f(X_{wi}\hat{\beta}_m)}{n_w}\right] + \left[\sum_{i=1}^{n_w} \frac{f(X_{wi}\hat{\beta}_m)}{n_w} - \sum_{i=1}^{n_w} \frac{f(X_{wi}\hat{\beta}_w)}{n_w}\right] \quad (3.29)$$

where T is a binary choice variable, $T = 1$ if the individual participates in the activity, 0 otherwise.

IV. DATA

I began with the ATUS data for the entire 2003-2010 period, which includes a total of 112,038 individuals. Removing all persons outside the ages of 20 through 64 reduced the sample to 84,892. After deleting 331 persons who were disabled or retired, 84,561 observations remained. Restricting the sample only to households with a resident child under age 18 removed 38,830 persons and reduced the sample to 45,725, and removing a further 9 who lived in group quarters produced a sample of 45,716. Due to nonimputed values for some regressors[7], the models were estimated with a sample of 45,649.[8]

All variables used in the models are defined in Table 1. Table 2 presents descriptive statistics of continuous and count variables and Table 3 summarizes categorical variables.

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[7] 55 of the 67 lost observations resulted from nonimputed missing values for BUSFARM, family ownership of a farm or business.

[8] Only time spent with own-household children is considered in this study. No distinction was made among the respondent's own children, stepchildren, children of an unmarried partner, or foster children. Time spent with one's own children who reside outside the household—say, living with a former spouse--is excluded. No information is provided on non-household children, nor is their existence indicated, except that they appear in the data if the respondent happened to spend time with them on the diary day.

Table 1
Definitions of Variables

Dependent variables (as $sinh^{-1}$)	Definition
FACETIME	time use involving direct interaction with household children on diary day, in minutes
BEHALF	time use for planning and arranging market-based activities, for household children on diary day, in minutes

Independent Variables	Definition	In selection model First stage	In selection model Second stage	In final model
rEARNHRhat	real hourly earnings, 2003 $ *(estimated in second stage)*			x
AGE	in years on diary day	x	x	x
FEMALE	= 1 for female	x	x	x
WHITE	= 1 if respondent self-identifies as white	x		x
& BLACK	= 1 if respondent self-identifies as black *(omitted category: other race)*		x	x
HISPANIC	= 1 for self-identified hispanic origin	x	x	x
CITIZEN	= 1 if a US citizen	x	x	x
MILITARY	= 1 if householder or partner is in the armed forces	x	x	x
METRO	= 1 if respondent resides in a metropolitan area		x	x
OWNHOME	= 1 if householder owns/mortages the family residence			x
HISCHOOL,	= 1 if high school diploma	x*	x*	x
SOMECOLL,	= 1 if some college but no bachelors' degree	x*	x*	x
*& COLLEGE***	= 1 if bachelors' degree or higher *(omitted category: less than high school diploma)*		x*	x
STUDENT	= 1 if respondent is currently enrolled in training, college, or university		x	x
CHILDAGE	age of youngest child under 18 residiing in the household		x	x
NUMKIDS	number of children under age 18 residing in the household	x		x
PARTNER	= 1 for a household with two non-married parents		x††	x
& SINGLEPT	= 1 for a single parent with no spouse or domestic partner *(omitted category: two married parents)*	x†		x
GOVEMP,	= 1 for state, local, and federal government employees			x
PRIVEMP,	= 1 for employees of privately-owned firms			x
SELFEMP,	= 1 for self-employed persons			
& VOLUNTR	= 1 for persons engaged in nonpaid work *(omitted category: self-employed and volunteer)*			
BUSFARM	= 1 if any member of the household owns a business or farm	x	x	x
WORKHOURS	respondents usual hours worked weekly at all jobs			x
SPOUSEHRS	spouse/partner's usual hours worked weekly at all jobs (= 0 for single parents)	x		x
HOLIDAY	= 1 if the diary day was a holiday‡			x
day of week	*omitted category: Saturday*			x
month	*omitted category: June*			x
year	*omitted category: 2010*	x‡‡	x‡‡	x

* First and second stage models included: less than high school, high school, some college, associates degree, bachelors degree (graduate degree omitted)

**In the sample selection and other preliminary models,the educational attainment variables were defined as: less than high school, high school diploma, some college, associates degree, bachelors degree, and graduate degree. In the main models with the full set of regressors, severe collinearity problems resulted and the variables were aggregated as they appear here.

† First stage model included: married, separated, divorced, widowed, single parent (never married omitted)

†† Second stage model included: married, separated, divorced, widowed (single parent and never married omitted)

‡ New Year's, Easter, Memorial Day, Fourth of July, Labor Day, Thanksgiving, and Christmas

‡‡ First stage model included 2005 & 2007; second stage, 2003

Table 2
Descriptive Statistics for Continuous Variables

Weighted by ATUS survey weights†

	Men (n = 18,712)					Women (n = 27,004)				
Variable	Mean	Standard error	Q_1	Median	Q_3	Mean	Standard error	Q_1	Median	Q_3
FACETIME‡										
all days	40.519	0.588	0	0	55	80.594	0.668	0	40	120
weekdays	39.070	0.797	0	0	55	85.744	0.963	0	45	125
weekends	44.152	0.920	0	0	55	67.685	0.896	0	20	95
BEHALF‡										
all days	6.417	0.206	0	0	0	13.764	0.220	0	0	10
weekdays	6.090	0.237	0	0	0	15.533	0.298	0	0	15
weekends	7.238	0.398	0	0	0	9.330	0.339	0	0	0
*rEARNHRhat**	18.342	0.041	14.031	17.318	22.235	15.576	0.032	11.570	14.652	19.068
AGE	38.524	0.071	31	39	45	36.970	0.058	30	37	44
CHILDAGE	7.057	0.039	2	6	12	6.878	0.032	2	6	11
NUMKIDS	1.903	0.007	1	2	2	1.913	0.006	1	2	2
WORKHRS	40.232	0.136	40	40	50	24.218	0.121	0	30	40
*SPOUSEHRS***	36.024	0.092	30	40	40	44.707	0.081	40	40	50

*Uses 20 multiple imputed data sets; effective sample sizes 374,240 (men) and 540,080 (women).

**Excludes single parents (n = 16,464 for men, 18,889 for women)

† Sample restricted to ages 20 - 64 only.

‡ 58.0% of men, and 34.3% of women, reported no time use for *FACETIME*, as did 79.3% and 60.7%, respectively, for *BEHALF*. For *FACETIME*, no time use was reported by 15.72%, 13.89%,a nd 11.29% of women with a child under ages 5, 3, and 1, respectively.

Two dependent variables are studied:

FACETIME = Time use for human-capital creating activities that involve direct interaction with household children,

BEHALF = Time use for human-capital creating activities that do not involve direct interaction with household children. See Appendix A for a list of the ATUS variables included in each.

Human capital can be created in children through both direct interaction, such as helping with homework, providing medical care, and playing sports, as well as planning and arranging their activities in the care of persons outside the household. I expect

Table 3
Frequency Distributions for Demographic Variables
Unweighted

	Men (n = 18,712)		*Women (n = 27,004)*	
Variable	*f*	%	*f*	%
Race:				
Black	1,361	7.3	3,220	11.9
White	16,141	86.3	22,094	81.8
Other	1,210	6.5	1,690	6.3
Hispanic ancestry	2,730	14.6	4,243	15.7
US citizen	16,663	89.1	24,076	89.2
Military	33	0.2	591	89.2
Metropolitan area	15,388	82.2	22,288	82.5
Education:				
Less than high school	1,888	10.1	2,754	10.2
High school diploma	4,896	26.2	6,895	25.5
Some college	5,008	26.8	8,374	31.0
Bachelors' degree or higher	6,920	37.0	8,981	33.3
Marital status:				
Married	15,759	84.2	17,965	66.5
Cohabiting	705	3.8	924	3.4
Single Parent	2,248	12.0	8,115	30.1
Homeowner*	15,029	80.4	19,281	71.5
Employment status:				
Government employee	2,286	12.2	3,634	13.5
Private sector employee	12,341	66.0	13,334	49.4
Self employed	2,243	12.0	1,645	6.1
Volunteer	5	0.0	32	0.1
Not employed	1,837	9.8	8,359	31.0
Owns a business or farm*	3,329	17.8	3,858	14.3

*Missing values: Homeowner, 26 men/41 women; metropolitan area, 2/5; Owns a business or farm, 25/30

parents with a higher opportunity cost of time to substitute services purchased in the market for some direct interaction. I model direct interaction *(FACETIME)* and indirect child care, or arranging activities involving nonfamily service providers *(BEHALF)*, separately to investigate this.[9]

Real hourly earnings, *rEARNHR,* was calculated from earnings estimates from ATUS and the Consumer Price Index. The method used to construct this variable is described in Appendix H.

I use multiple imputation to impute missing values for earnings. I accomplish this with a Markov Chain Monte Carlo (MCMC) process, iterated 20 times for each dependent variable, creating 20 sets of imputed data. The regression model results from each of the imputed data sets are then combined according to Rubin's Rule (Rubin, 1987).

The real earnings variable is encumbered with both an endogenous relationship with time use[10] as well as sample selection bias, since nonemployed persons report a wage rate of zero. Usual methods of dealing with these problems involve two step estimation processes, in which instrumental variables are used to make estimates of the endogeneous regressor prior to their inclusion in the appropriate second, main, equation or, for selection bias, to obtain the inverse Mills ratio for inclusion in the second equation to account for nonobservance. Correcting for both problems requires that these two processes be carried out simultaneously, to produce only a single instrumented value.

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[9] Note that this distinction differs from that described as *primary*, as opposed to *secondary*, child care in the time use literature. These terms refer to whether the activity served the main purpose of the individual during the time period measured (primary) or was carried out in concurrence with, but subordinate to, that activity (secondary). Following Craig (2006), I do not consider secondary child care.

[10] The correlation coefficient between the first and second regressions in the Heckman sample selection model was 0.14, p-value $<.0.001$.

I used the method of Millimet (2001), based on Amemiya (1985). First, using Heckman's (1979) method, I obtained the inverse Mills ratio from a probit model of the variable *WORKING* = 1 for all respondents whose response for the *TELFS* variable in ATUS indicated they were employed and not absent from work due to layoff or other reasons in the week prior to the diary day.[11] To ensure identification, I included *NUMKIDS,* the number of household children under age 18, in the first-step model but not the second. This variable is positively related to the probability of being employed but not a predictor of the wage rate.[12] Since the purpose of this regression was purely predictive, the regressors were selected by a forward stepwise process.[13] The second-step OLS regression estimated earnings as *rEARNHRhat,* using the inverse Mills ratio and an instrument for earnings, but excluding *NUMKIDS*—thus controlling for both endogeneity and selection bias. The instrument for earnings is *METRO,* which is correlated with *rEARNHR* but only weakly with *FACETIME* and *BEHALF.*[14]

WORKHRS is defined as the respondent's total usual hours worked weekly at all jobs and places an important constraint on child care activities. Actual work hours vary over time, and while the *TELFS* variable in ATUS provides information on current work

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[11] This variable was not included in the models estimated below. It was replaced with a set of employment category variables: *PRIVEMP, GOVEMP, SELFEMP, VOLUNTR,* and the omitted *NONEMP. WORKING* = 1 for all categories but *NONEMP.*
[12] The point biserial correlation coefficient for *NUMKIDS* and *WORKING* is 0.54; Pearson-*r* for *NUMKIDS* and *rEARNHR* is -0.06.
[13] They were *FEMALE, WHITE, CITIZEN, HISPANIC, MILITARY, AGE, LTHSCHL, HISCHOOL, SOMECOLL, ASSOCIATES, BACHELORS, STUDENT, CHILDAGE, NUMKIDS, MARRIED, SEPARATED, WIDOWED, DIVORCED, SINGLEPT, BUSFARM, SPOUSEHRS,* and year dummies for 2005and 2007.
[14] *FEMALE, BLACK, CITIZEN, HISPANIC, MILITARY, METRO, AGE, LTHSCHL, HISCHOOL, SOMECOLL, ASSOCIATES, BACHELORS, STUDENT, CHILDAGE, MARRIED, WIDOWED, SEPARATED, DIVORCED, BUSFARM,* and a year dummy for 2003. Point biserial correlation coefficients for *METRO* are 0.10 (*rEARNHR*) and 0.04 and 0.02 for *FACETIME* and *BEHALF. METRO* was strongly significant in the second step estimation of *rEARNHRhat,* with t = 19.67.

status, it does not indicate whether the respondent actually worked on the diary day, so it is not a perfect indicator of the time constraint. But for a study of long-term time use, usual hours worked is more appropriate than reported diary-day work hours, or time used for home production activities, both of which would anyway be correlated with the dependent variable. (Frazis and Stewart, 2010) Usual weekly work hours and single-day child care time use should be orthogonal.[15]

In the context of the household production function, each parent makes specialization choices dependent on the time inputs provided by the other. (Gronau, 1973) Thus, the number of hours worked by one's spouse (or unmarried partner)—*SPOUSEHRS*—reduces the quantity of the spouse's time inputs available for child care.[16] Spouse's usual work hours are available in ATUS and, like the respondent's usual work hours, should be orthogonal to actual diary day time use. For single parent households, spouse's work hours are set to zero. The binary variable *SINGLEPT* distinguishes such a household from one having two parents with only one employed.

If, as previous studies indicate, child care time is highly inelastic with respect to market work, then a one-hour increase in *spouse's* work hours should increase the spouse's child care time by only a few minutes. The (respondent) parent would need to increase child care time by the same amount to prevent total child care time provided by

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[15] One potential problem: Working parents whose work hours vary greatly from day to day are more likely to be contacted successfully for their interview—regarding their time use on the previous day—on "slow" days than busy ones. If the pattern of slow and busy days shows higher than first order autocorrelation—busy days come in bunches—then the diary day is more likely to be a slower than average day. Otherwise, the bias is likely to be minimal. The designated-day strategy (discussed above) is designed expressly to minimize this problem.

[16] I ignore the endogeneity of the work and child care time use decisions. For that matter, the choice between remaining single or marrying—or remaining married or divorcing—is endogenous to work, too. (Lundberg, et al., 2006)

the two parents from declining. Considering both substitution and income effects, spouse's work hours and the respondent's child care time should be directly related. An increase in spouse's work hours would induce an intrafamily substitution of respondent's time for spouse's time and so increase child care by the respondent, who would make a utility-maximizing choice at the margin to decrease time use for home production, leisure, or market work. Given a constant hourly wage, an increase in spouse's work hours increases household money income. Assuming children's human capital to be a normal good, the (probably small) income effect would also increase the respondent's child care time, assuming diminishing but positive marginal efficiency of child care time in producing human capital. I expect the coefficient on spouse's work hours for direct child care time to be positively signed but less than unity, likely much less; its effect on *BEHALF* is ambiguous. Also, since women in the sample on average spend more time on child care—80.594 minutes and 13.764 minutes for *FACETIME* and *BEHALF* daily, respectively, compared to men's 40.519 minutes and 6.417 minutes—their marginal effects may differ as well.

ATUS gathers no data on financial assets. But a household's wealth, and hence its investment earnings and ability to borrow on the market, could affect its response to income shocks or could be used to supplement income over time. As a proxy measure for household wealth, I define $OWNHOME = 1$ if the respondent owns the family residence, with or without a mortgage. This variable introduces noise into the estimates but adds otherwise unavailable information.

Schooling was measured with a set of four dummy variables: *LTHSCHL*, indicating less than a high school diploma, which was the omitted category; and *HISCHOOL, COLLSOME,* and *COLLEGE,* for high school diploma, some college but less than a bachelors degree, and a bachelors degree or higher.[17]

V. EMPIRICAL RESULTS

A. Infrequency of Purchase Models

Multiple imputation estimates for the dependent variables for men and women are displayed in Tables 4 through 17. The inverse hyperbolic sine coefficients can be interpreted as showing the percent response of the dependent variable to a change in the regressors. All effects described are significant at $\alpha = .05$ or less.

i. Direct Child Care Time—*FACETIME*

The men's and women's models explain 9% and 14% of the total variation in *FACETIME,* respectively, and both models show joint significance. (See Table 4.)

Real hourly earnings is positively related to child care time for both men and women. The relationship is stronger for men, $\hat{\beta}_m = 0.0517$, $\hat{\beta}_f = 0.0420$. At the means of *FACETIME* (40.519 minutes a day for men and 80.594 for women) and *rEARNHR* ($18.342 and $15.576), a one-dollar increase in hourly earnings (5.45% for men and 6.42% for women) would raise child care time for a man by approximately 5.17%, or 2.095 minutes a day, and 4.2%, or 3.385 minutes for a woman, with implied elasticities

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[17] The first- and second-stage estimation models used a different set of covariates. *COLLSOME* and *COLLEGE* were instead disaggregated into some college and associates degree, and bachelors degree and graduate degree, respectively. But these were highly collinear with the estimated earnings variable, perhaps in part due to their role in estimating it. The set presented here reduced collinearity to a manageable level.

Table 4

Infrequency of Purchase Model (IPM) Results

Dependent variable *sinh^{-1} FACETIME* for men and women

Combined multiple imputation estimates (*m* = 20)

Boldface effects are significant at $\alpha = .05$

	Men (n=18,686)			Women (n=26,963)		
Variable	Coefficient	SE	p-value	Coefficient	SE	p-value
rEARNHRhat	**0.0517**	0.0253	0.042	**0.0420**	0.0196	0.033
BLACK	-0.1471	0.2233	0.510	-0.2572	0.1596	0.108
WHITE	0.2354	0.1619	0.146	0.1777	0.1214	0.144
CITIZEN	-0.2563	0.1590	0.107	0.0634	0.1245	0.611
HISPANIC	**-0.3417**	0.1507	0.024	**-0.4835**	0.1112	< 0.001
MILITARY	-0.2486	0.8861	0.779	-0.1351	0.1798	0.453
METRO	0.0453	0.1246	0.716	0.0580	0.1055	0.583
AGE	**-0.0189**	0.0066	0.004	**-0.0230**	0.0050	0.000
OWNHOME	**0.2738**	0.1100	0.013	**0.2517**	0.0761	0.001
HISCHOOL	-0.2108	0.1661	0.205	**0.4718**	0.1335	< 0.001
COLLSOME	-0.2410	0.1915	0.209	**0.6108**	0.1491	< 0.001
COLLEGE	-0.1562	0.3171	0.622	**0.7594**	0.2246	0.001
STUDENT	**-0.3660**	0.1844	0.047	**-0.5759**	0.1129	< 0.001
CHILDAGE	**-0.1857**	0.0091	< 0.001	**-0.1758**	0.0072	< 0.001
NUMKIDS	**0.1097**	0.0450	0.015	**0.1157**	0.0311	< 0.001
PARTNER	-0.0876	0.2300	0.703	-0.2223	0.1633	0.174
SINGLEPT	**0.5069**	0.2132	0.018	**-0.3357**	0.1611	0.038
GOVEMP	0.3639	0.2304	0.115	-0.1722	0.1451	0.236
PRIVEMP	0.2039	0.2064	0.323	-0.1713	0.1205	0.156
SELFEMP	0.2526	0.2383	0.289	-0.0779	0.1551	0.616
VOLUNTR	1.1872	0.8989	0.187	0.5254	0.5512	0.341
BUSFARM	**0.3083**	0.1537	0.045	0.0900	0.1174	0.444
WORKHRS	**-0.0307**	0.0034	< 0.001	**-0.0177**	0.0028	< 0.001
SPOUSEHRS	0.0015	0.0040	0.718	-0.0035	0.0032	0.275
SUNDAY	0.0647	0.1010	0.522	**0.2293**	0.0793	0.004
MONDAY	**0.3563**	0.1267	0.005	**0.5282**	0.1011	< 0.001
TUESDAY	0.1093	0.1395	0.434	**0.5323**	0.1001	< 0.001
WEDNESDAY	0.1572	0.1347	0.243	**0.4777**	0.0955	< 0.001
THURSDAY	0.1051	0.1379	0.446	**0.4192**	0.1104	< 0.001
FRIDAY	-0.2445	0.1360	0.072	-0.0655	0.1018	0.520
HOLIDAY	-0.3865	0.2949	0.190	-0.1307	0.2075	0.529
JAN	0.1017	0.1909	0.594	**0.5098**	0.1388	< 0.001
FEB	0.2953	0.1940	0.128	**0.4318**	0.1472	0.004
MAR	**0.4630**	0.1964	0.019	**0.3174**	0.1405	0.024
APR	0.2517	0.1886	0.182	0.2164	0.1491	0.147
MAY	0.3561	0.2005	0.076	**0.3132**	0.1443	0.030
JUL	-0.0168	0.1980	0.932	0.1894	0.1489	0.204
AUG	0.1778	0.1910	0.352	-0.0211	0.1542	0.891
SEP	0.2650	0.2007	0.187	**0.5229**	0.1518	0.001
OCT	0.3810	0.1955	0.052	**0.5518**	0.1449	< 0.001
NOV	0.2747	0.2167	0.206	**0.3869**	0.1526	0.012
DEC	**0.4188**	0.1998	0.036	**0.3641**	0.1495	0.015
Constant	**3.4233**	0.4736	< 0.001	**3.8446**	0.3020	< 0.001
adj. R^2	0.09			0.14		
F	**116.80**		< 0.001	**423.24**		< 0.001
df (for MI)	50, 24434			50, 10102		

† These 4 days are not significantly different at α .05 in either model

‡ In both models, summer months are significantly different from non-summer months at $\alpha = .05$;

Year dummy variables were used; none were significant at $\alpha = .05$

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

of 0.948 for men and 0.654 for women. The lower elasticity for women confirms the result of Craig (2006).

An imprecise measure of substitution due to opportunity cost is found in the *STUDENT* variable. Both male and female parents who are in school show sharply lower child care time. For men the reduction is 33.6%, or about 15.981 minutes, and 57.6% for women, about 47.677 minutes.

Educational attainment has no effect on men's time use, but has a strong positive correlation for women, which continues through all schooling levels. Compared to women with less than a high school diploma, whose mean daily time is 71.679 minutes, high school graduates spend 47.18% more time on direct child care, those with some college 61.08% more, and college graduates fully 75.94% more. That the effect differs so between the sexes implies family specialization. A higher level of education should increase an individual's marginal productivity in market work, but also for home production of human capital in children. Men generally apply their education to maximizing money income; many women apparently respond to their increased productivity by devoting a greater share of their time to raising children.

The decline in traditional married, two-parent families poses questions about human capital formation in children that have been taken up previously. My models offer a clear view of these issues. The effect of single parenthood (variable *SINGLEPT)* is especially striking. Single men with children unsurprisingly devote 50.69% more minutes each day to child care than their married counterparts (whose mean is 44.541 minutes). But single female parents' direct primary child care time is reduced by 33.57%

compared to married women's mean of 88.331 minutes, which suggests that, controlling for other variables, single men actually spend more time with their children (67.119 minutes) than single women (58.878 minutes). Among cohabiting respondents, effects are negative but not significant due to relatively large standard errors, indicating that the *PARTNER* category conceals a good bit of heterogeneity among these households. Households of this type vary widely from long-term committed relationships to ephemeral and unstable arrangements, which affects the relationship of adults and children and the time spent in human capital formation. But then, given the prevailing rates of divorce and remarriage in the US, the same is true of married couples to some extent, so it is not surprising that the two show no significant difference.

WORKHRS shows the expected inverse relationship to child care time, although the difference between the sexes is notable. An extra weekly hour of work reduces men's child care time by 3.77%, while for women, the effect is only 1.77%. Considering differences in direct child care time use, the reduction measured in minutes per day is about the same—1.646 minutes for men, 1.465 minutes for women. Calculated at the group means of time use and the median of a 40 hour work week, the elasticity of child care time with respect to usual weekly work hours is -1.51 for men and -0.71 for women, which is consistent with Kalenkoski, et al. (2009). To some extent, women substitute away from other forms of household work and leisure to preserve child care time, which is not the case with men.

Problems with interpreting the *SPOUSEHRS* variable were noted in the introduction. It has no observable effect on child care time; the coefficients are exceedingly small, at 0.0015 for men and -0.0035 for women, and are not significantly different from zero.

Among the remaining covariates, neither the respondent's race nor citizenship status has an otherwise unidentified effect on time use. Households with at least one parent in the military do not differ from others, nor do metropolitan area households differ from nonmetropolitan ones.[18] Respondents who self-identify as hispanic allocate considerably less time to child care than others—a reduction of 34.17% for men and 48.35% for women. The type of employer (*GOVEMP, PRIVEMP,* etc.) has no effect for either men or women, although men whose family owns a business or farm spend about 30% more time on child care. Older parents spend less time than younger ones, due perhaps to greater efficiency or just plain fatigue. The age of the youngest child in the household (*CHILDAGE)* and the number of children in the household *(NUMKIDS)* strongly affect child care time, inversely for *CHILDAGE* and directly for *NUMKIDS.* Men spend more time with children on Mondays and in the months of March and December. Women get time off from the kids on holidays, as well as Fridays and Saturdays; the other days of the week are not significantly different from each other. Summer months (June – August) are vacation time for moms, too.

The Blinder-Oaxaca decomposition of these results by sex is displayed in Table 5. This found an excess of women's time over men's of 1.464 as $sinh^{-1}$, or about 9.0823 minutes. This decomposes as 0.3717, or 2.945 minutes, due to differences in

[18] For men in military households, the coefficient is relatively large (-0.2486) but is not significant due to the extremely large standard error (0.8861), which suggests unobserved heterogeneity.

Table 5

Blinder-Oaxaca Decomposition for IPM

Dependent variable *sinh⁻¹ FACETIME*

Combined multiple imputation estimates (*m* = 20)

Boldface effects are significant at α = .05

	Differential	SE	*p*-value
Female	**3.2775**	0.0323	< 0.001
Male	**2.1311**	0.0402	< 0.001
Difference	**1.1464**	0.0537	< 0.001

	Decomposition	SE	*p*-value
Endowments	**0.3717**	0.0790	< 0.001
Coefficients	**0.9725**	0.0768	< 0.001
Interaction	**-0.1978**	0.0947	0.037

Variable	Endowment	SE	*p*-value	Coefficients	SE	*p*-value	Interaction	SE	*p*-value
rEARNHRhat	**-0.1472**	0.0725	0.043	-0.1784	0.5801	0.759	0.0277	0.0899	0.759
BLACK	-0.0067	0.0047	0.154	-0.0055	0.0147	0.708	-0.0021	0.0055	0.974
WHITE	**-0.0078**	0.0033	0.020	-0.0015	0.0832	0.706	0.0001	0.0038	0.707
OTHRACE	< 0.0001	0.0001	0.973	0.0036	0.0097	0.986	< 0.0001	0.0002	0.986
CITIZEN	-0.0025	0.0020	0.210	0.2739	0.1741	0.116	0.0031	0.0025	0.219
HISPANIC	0.0027	0.0023	0.228	-0.0290	0.0391	0.459	0.0011	0.0018	0.525
MILITARY	-0.0030	0.0106	0.779	0.0001	0.0009	0.900	0.0014	0.0108	0.900
METRO	0.0001	0.0003	0.846	0.0105	0.1353	0.938	< 0.0001	0.0004	0.977
AGE	**0.0294**	0.0105	0.005	-0.1560	0.3166	0.623	0.0063	0.0128	0.623
OWNHOME	**-0.0149**	0.0062	0.016	-0.0169	0.1052	0.872	0.0012	0.0075	0.873
LTHSCHL	-0.0021	0.0023	0.356	**-0.0886**	0.0278	0.002	**0.0086**	0.0041	0.033
HISCHOOL	0.0011	0.0018	0.524	0.0217	0.0342	0.525	-0.0014	0.0022	0.534
COLLSOME	-0.0038	0.0030	0.209	**0.0596**	0.0219	0.007	**0.0103**	0.0040	0.010
COLLEGE	< 0.0001	0.0017	0.982	0.0897	0.0641	0.162	-0.0028	0.0026	0.273
STUDENT	-0.0126	0.0065	0.053	-0.0133	0.0137	0.331	-0.0072	0.0075	0.334
CHILDAGE	**0.0336**	0.0129	0.009	0.0697	0.0829	0.402	-0.0018	0.0023	0.430
NUMKIDS	0.0012	0.0015	0.454	0.0113	0.1033	0.913	0.0001	0.0006	0.921
MARRIEDPT	0.0173	0.0134	0.197	**0.2634**	0.1102	0.017	**-0.0402**	0.0169	0.018
PARTNER	0.0004	0.0007	0.536	0.0086	0.0091	0.348	-0.0004	0.0007	0.590
SINGLEPT	**0.0460**	0.0198	0.021	**-0.0758**	0.0302	0.013	**-0.0648**	0.0259	0.013
NONEMP	-0.0867	0.0513	0.091	0.0429	0.0314	0.173	0.0822	0.0602	0.173
GOVEMP	-0.0006	0.0033	0.856	-0.0167	0.0266	0.529	-0.0024	0.0039	0.535
PRIVEMP	0.0353	0.0344	0.304	0.0037	0.1495	0.980	-0.0010	0.0400	0.980
SELFEMP	0.0080	0.0112	0.475	0.0056	0.0277	0.841	-0.0027	0.0135	0.841
VOLUNTR	0.0008	0.0007	0.290	-0.0001	0.0002	0.739	-0.0003	0.0008	0.736
BUSFARM	-0.0062	0.0034	0.066	-0.0354	0.0308	0.251	0.0044	0.0039	0.265
WORKHRS	**0.4914**	0.0544	< 0.001	**0.5222**	0.1749	0.003	**-0.2078**	0.0696	0.003
SPOUSEHRS	0.0025	0.0069	0.719	-0.1528	0.1621	0.348	-0.0084	0.0091	0.355
Total	**0.3717**	0.0790	< 0.001	**0.9725**	0.0768	<0.001	**-0.1978**	0.0947	0.037

Day of week, month, and year dummies and constant term (coefficients only) are omitted for brevity. Significant effects at α = .05 were observed for *SATURDAY* (–) and *FEBRUARY* (+) for the coefficients only.

endowments, i.e., extra time spent by women explained by difference in the values of their covariates; 0.9725, or 7.705 minutes, explained by the coefficients, that is, by how women respond to their x variables compared to men's response; and -0.1978 due to the interaction between the two. Regarding endowments, as earnings rise, men's and women's time use patterns become more similar. Time use differs less for whites than for other races, and less for homeowners. Men's and women's child care activity become more different as both they and their youngest household child age. The higher percentage of single parents who are women adds to the difference, as do differences in usual weekly work hours. Differences in coefficients appear for educational attainment, where the effect of having less than a high school diploma is smaller, and the effect of a college degree larger, for women; for marital status, where being married increases the difference for a woman and being single reduces it; and for usual work hours, where a woman responds such that, given the same work schedule, she will spend more time on child care than a man.

ii. Indirect Child Care Time—*BEHALF*

Parents spend less time on *BEHALF* activities (for women, 13.764 minutes a day, compared to 80.594 for *FACETIME*, from Table 2) and are much less likely to do *BEHALF* activities on a given day. 42.03% of men, and 65.73% of women, engaged in direct child care on their diary days, but only 20.74% and 39.26% did anything counted as *BEHALF*. This suggests that either a) many parents never put forth *BEHALF* time use, and are at a corner solution, or b) even in the context of the infrequency of purchase model, *BEHALF* behavior is, for many, very infrequent indeed, and proffers the double hurdle model.

The results of the infrequency of purchase models suggest the same. I present these in Tables 6 and 7, but it is clear that these models are misspecified. They show joint covariate significance only because of obvious control variables,

Table 6

Infrequency of Purchase Model (IPM) Results

Dependent variable *BEHALF* for Men and Women

Combined multiple imputation estimates (m = 20)

Boldface effects are significant at $\alpha \leq .05$

	Men (n=18,686)			*Women (n=26,963)*		
Variable	Coefficient	SE	p-value	Coefficient	SE	p-value
rEARNHRhat	-0.0164	0.0239	0.492	-0.0038	0.0221	0.865
BLACK	0.0653	0.1894	0.731	0.0409	0.1627	0.802
WHITE	0.0418	0.1359	0.758	-0.0511	0.1299	0.694
CITIZEN	-0.0314	0.1283	0.807	-0.2016	0.1263	0.111
HISPANIC	0.0523	0.1227	0.670	0.0404	0.1148	0.725
MILITARY	-1.0801	1.0021	0.281	0.2736	0.2028	0.178
METRO	-0.0108	0.1063	0.919	-0.0537	0.1109	0.629
AGE	**-0.0159**	0.0058	0.006	-0.0030	0.0051	0.561
OWNHOME	0.1325	0.0938	0.158	**0.1871**	0.0819	0.023
HISCHOOL	-0.1219	0.1279	0.341	0.0599	0.1359	0.660
COLLSOME	-0.2206	0.1543	0.153	-0.0325	0.1608	0.840
COLLEGE	-0.2446	0.2817	0.385	0.0306	0.2685	0.909
STUDENT	0.2621	0.1512	0.084	-0.0368	0.1211	0.762
CHILDAGE	**0.0155**	0.0075	0.040	**0.0158**	0.0074	0.034
NUMKIDS	**-0.1212**	0.0403	0.003	-0.0189	0.0352	0.590
PARTNER	0.1551	0.1688	0.358	-0.1065	0.1920	0.580
SINGLEPT	-0.1817	0.1656	0.273	0.0994	0.1885	0.598
GOVEMP	-0.1599	0.1983	0.420	-0.0395	0.1553	0.800
PRIVEMP	-0.0735	0.1797	0.683	-0.1025	0.1364	0.453
SELFEMP	-0.1392	0.2162	0.520	-0.0049	0.1763	0.978
VOLUNTR	0.1917	1.2721	0.880	0.5926	0.6977	0.396
BUSFARM	-0.0641	0.1404	0.648	0.0384	0.1245	0.758
WORKHRS	0.0040	0.0031	0.191	**-0.0064**	0.0031	0.041
SPOUSEHRS	-0.0064	0.0033	0.051	0.0003	0.0037	0.937
SUNDAY	-0.0092	0.0766	0.904	0.0282	0.0749	0.707
MONDAY	**-1.0269**	0.1125	< 0.001	**-1.1321**	0.1041	< 0.001
TUESDAY	**-1.0512**	0.1180	< 0.001	**-1.2190**	0.1066	< 0.001
WEDNESDAY	**-1.1564**	0.1184	< 0.001	**-1.2233**	0.1092	< 0.001
THURSDAY	**-1.1608**	0.1137	< 0.001	**-1.1511**	0.1083	< 0.001
FRIDAY	**-1.0226**	0.1127	< 0.001	**-1.2158**	0.1134	< 0.001
HOLIDAY	**0.8756**	0.1705	< 0.001	**1.1115**	0.1808	< 0.001
JAN	**-0.5016**	0.1457	0.001	-0.1176	0.1524	0.441
FEB	**-0.3572**	0.1589	0.025	-0.1942	0.1494	0.194
MAR	-0.2254	0.1486	0.130	-0.1983	0.1529	0.195
APR	-0.2829	0.1549	0.068	-0.1738	0.1692	0.305
MAY	-0.2714	0.1538	0.078	-0.1896	0.1640	0.249
JUL	0.1944	0.1444	0.178	0.1840	0.1473	0.212
AUG	0.0708	0.1517	0.641	-0.0490	0.1528	0.749
SEP	**-0.4178**	0.1585	0.008	-0.3132	0.1687	0.065
OCT	**-0.3966**	0.1621	0.015	-0.2216	0.1631	0.176
NOV	**-0.5337**	0.1709	0.002	-0.2369	0.1658	0.155
DEC	-0.2119	0.1562	0.175	-0.1805	0.1676	0.282
Constant	4.7314	0.3995		**3.5267**	0.3371	< 0.001
adj. R^2	0.03			0.03		
F	169.56		< 0.001	134.46		< 0.001
df (for MI)	50, 16171			50, 9840.8		

† These 4 days are not significantly different at α .05 in either model

‡ In both models, summer months are significantly different from non-summer months at $\alpha \leq .05$; within each of those groups, months do not differ significantly from each other

Year dummy variables were used; none were significant at α = .05

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

Table 7

Blinder-Oaxaca Decomposition for IPM

Dependent variable $sinh^{-1}$ *BEHALF*

Combined multiple imputation estimates (m = 20)

Boldface effects are significant at $\alpha \leq .05$

	Differential	SE	p-value
Female	2.1397	0.0328	< 0.001
Male	2.5620	0.0336	< 0.001
Difference	-0.4224	0.0465	< 0.001

	Decomposition	SE	p-value
Endowments	-0.0264	0.0733	0.719
Coefficients	**-0.5588**	0.0800	< 0.001
Interaction	0.1629	0.1031	0.116

Variable	Endowment	SE	p-value	Coefficients	SE	p-value	Interaction	SE	p-value
rEARNHRhat	0.0467	0.0681	0.493	0.2320	0.6158	0.707	-0.0360	0.0956	0.707
BLACK	0.0011	0.0039	0.977	0.0015	0.0135	0.772	0.0006	0.0050	0.979
WHITE	-0.0002	0.0027	0.776	-0.0448	0.0779	0.911	0.0020	0.0036	0.911
OTHRACE	< 0.0001	0.0002	0.931	0.0025	0.0088	0.566	< 0.0001	0.0002	0.567
CITIZEN	-0.0003	0.0013	0.811	-0.1458	0.1590	0.360	-0.0016	0.0020	0.413
HISPANIC	-0.0004	0.0011	0.691	-0.0024	0.0352	0.945	0.0001	0.0014	0.947
MILITARY	-0.0129	0.0120	0.283	0.0014	0.0011	0.207	0.0162	0.0123	0.187
METRO	< 0.0001	0.0002	0.949	-0.0356	0.1294	0.783	< 0.0001	0.0004	0.919
AGE	**0.0247**	0.0092	0.008	0.4976	0.3005	0.099	-0.0201	0.0122	0.102
OWNHOME	-0.0072	0.0052	0.163	0.0418	0.0967	0.666	-0.0030	0.0069	0.666
LTHSCHL	-0.0021	0.0019	0.288	-0.0233	0.0270	0.389	0.0023	0.0028	0.415
HISCHOOL	-0.0005	0.0016	0.763	0.0064	0.0360	0.860	-0.0004	0.0023	0.862
COLLSOME	-0.0032	0.0026	0.224	0.0067	0.0216	0.757	0.0012	0.0037	0.758
COLLEGE	0.0009	0.0017	0.587	0.0337	0.0689	0.625	-0.0011	0.0023	0.645
STUDENT	0.0090	0.0053	0.090	-0.0190	0.0127	0.139	-0.0103	0.0070	0.143
CHILDAGE	-0.0028	0.0017	0.109	0.0019	0.0766	0.980	-0.0001	0.0020	0.980
NUMKIDS	-0.0013	0.0017	0.446	0.1947	0.1014	0.055	0.0011	0.0015	0.470
MARRIEDPT	-0.0011	0.0102	0.915	-0.0053	0.1025	0.959	0.0008	0.0157	0.959
PARTNER	-0.0003	0.0005	0.542	-0.0120	0.0082	0.145	0.0005	0.0008	0.535
SINGLEPT	-0.0217	0.0149	0.148	0.0403	0.0270	0.138	0.0344	0.0231	0.138
NONEMP	0.0078	0.0630	0.901	-0.0141	0.0386	0.715	-0.0271	0.0739	0.715
GOVEMP	-0.0019	0.0042	0.646	-0.0005	0.0336	0.988	-0.0001	0.0049	0.988
PRIVEMP	0.0067	0.0463	0.885	-0.1031	0.2009	0.608	0.0276	0.0537	0.608
SELFEMP	0.0055	0.0146	0.704	0.0010	0.0357	0.978	-0.0005	0.0173	0.978
VOLUNTR	0.0002	0.0010	0.821	0.0001	0.0003	0.812	0.0003	0.0011	0.811
BUSFARM	0.0013	0.0028	0.652	0.0166	0.0302	0.583	-0.0021	0.0038	0.587
WORKHRS	-0.0647	0.0493	0.192	**-0.4206**	0.1822	0.023	**0.1674**	0.0726	0.023
SPOUSEHRS	-0.0109	0.0058	0.063	0.2054	0.1551	0.188	0.0114	0.0088	0.198
Total	-0.0264	0.0733	0.719	-0.5588	0.0800	< 0.001	0.1629	0.1031	0.116

Day of week, month, and year dummies and constant term (coefficients only) are omitted for brevity. Significant effects at α = .05 were observed for *SATURDAY* (−) and *FEBRUARY* (+) for the coefficients only.

adjusted R^2s are only 0.03, and the decomposition results are not significant. I reject this model for *BEHALF* and analyze this variable with the double hurdle model.

B. Double Hurdle Models

i. Direct Child Care Time—*FACETIME*

The double hurdle results are similar to those for the infrequency of purchase model. The first-tier probit regression estimates the probability of *FACETIME* taking on a positive value, i.e, of the parent actually engaging in some amount of *FACETIME* on the diary day. From Table 8, the effect for *rEARNHRhat* is positive and strongly significant, with marginal effects at the means of 0.0135 for men and 0.0083 for women, implying that a one-dollar increase in earnings increases the typical man's probability of doing direct child care by 1.35 percentage points, but only 0.83 points for a woman.[19] This is consistent with the finding in the decomposition of the IPM model, where the child care "time gap" shrinks with rising earnings. Child care time rises with schooling, but unlike the IPM result, the effect is more pronounced for men. Compared to men without a high school diploma, high school graduates are 9.56% more likely to provide child care on a particular day; some college or a college degree are indistinguishable at about 15% more. For women, all increments to schooling raise the probability; marginal effects are 6.15%, 9.73%, and 12.60%. Student status reduced the likelihood for 11% for both men and women. Longer weekly work hours reduce the likelihood only slightly (0.21% for men, 0.12% for women).

Unlike the IPM result, the probit model shows a significant positive effect for whites (5.82% for men, 7.85% for women), and contrarily, home ownership is associated with about a 5% reduction in the probability for both sexes. Single parents of both sexes

[19] The percent increases are additive, not multiplicative.

Table 8

Double Hurdle Model Results

Dependent variable *w_FACETIME* (= 1 for nonzero values of *FACETIME*), men and women

First hurdle probit model

Combined multiple imputation estimates (m = 20)

Boldface effects are significant at α = .05

	Men (n=18,686)				*Women (n 26,963)*			
Variable	Marginal effect††	Coefficient	SE	p-value	Marginal effect††	Coefficient	SE	p-value
rEARNHRhat	**0.0135**	**0.0350**	0.0086	< 0.001	**0.0083**	**0.0238**	0.0090	0.008
BLACK	-0.0159	-0.0414	0.0724	0.568	0.0093	0.0268	0.0639	0.675
WHITE	**0.0582**	**0.1533**	0.0521	0.003	**0.0785**	**0.2194**	0.0521	< 0.001
CITIZEN	**0.0526**	**0.1386**	0.0511	0.007	0.0333	0.0944	0.0484	0.051
HISPANIC	**-0.0895**	**-0.2378**	0.0490	< 0.001	**-0.0880**	**-0.2450**	0.0439	< 0.001
MILITARY	-0.1501	-0.4236	0.3105	0.172	-0.0316	-0.0889	0.0920	0.334
METRO	0.0013	0.0033	0.0431	0.939	-0.0060	-0.0172	0.0400	0.667
AGE	**-0.0020**	**-0.0051**	0.0022	0.019	**-0.0034**	**-0.0099**	0.0022	< 0.001
OWNHOME	**-0.0455**	**-0.1173**	0.0369	0.001	**-0.0529**	**-0.1553**	0.0321	< 0.001
HISCHOOL	**0.0956**	**0.2461**	0.0550	< 0.001	**0.0615**	**0.1809**	0.0505	< 0.001
COLLSOME	**0.1505**	**0.3850**	0.0628	< 0.001	**0.0973**	**0.2905**	0.0589	< 0.001
COLLEGE	**0.1511**	**0.3877**	0.1049	< 0.001	**0.1260**	**0.3813**	0.1038	< 0.001
STUDENT	**-0.1116**	**-0.3036**	0.0602	< 0.001	**-0.1101**	**-0.3007**	0.0426	< 0.001
CHILDAGE	**-0.0388**	**-0.1007**	0.0030	< 0.001	**-0.0406**	**-0.1170**	0.0032	< 0.001
NUMKIDS	**0.0280**	**0.0726**	0.0151	< 0.001	**0.0125**	**0.0361**	0.0154	0.019
PARTNER	-0.0229	-0.0599	0.0709	0.398	-0.0320	-0.0904	0.0661	0.171
SINGLEPT	**-0.1456**	**-0.3984**	0.0670	< 0.001	**-0.0476**	**-0.1349**	0.0654	0.039
GOVEMP	-0.0210	-0.0549	0.0759	0.469	-0.0026	-0.0073	0.0572	0.898
PRIVEMP	-0.0462	-0.1193	0.0694	0.086	-0.0231	-0.0665	0.0504	0.187
SELFEMP	-0.0368	-0.0965	0.0812	0.234	-0.0084	-0.0242	0.0624	0.699
VOLUNTR	**-0.3797**	**-1.8737**	0.6678	0.005	0.0295	0.0871	0.2443	0.721
BUSFARM	0.0323	0.0838	0.0514	0.103	0.0197	0.0567	0.0495	0.252
WORKHRS	**-0.0021**	**-0.0053**	0.0012	< 0.001	**-0.0028**	**-0.0082**	0.0011	< 0.001
SPOUSEHRS	-0.0004	-0.0011	0.0012	0.363	**0.0010**	**0.0030**	0.0013	0.020
SUNDAY	**0.0891**	**0.2275**	0.0315	< 0.001	**0.0820**	**0.2489**	0.0284	< 0.001
MONDAY†	**0.1441**	**0.3665**	0.0416	< 0.001	**0.2035**	**0.6961**	0.0407	< 0.001
TUESDAY†	**0.1219**	**0.3103**	0.0443	< 0.001	**0.1994**	**0.6767**	0.0408	< 0.001
WEDNESDAY†	**0.1161**	**0.2957**	0.0438	< 0.001	**0.1857**	**0.6195**	0.0407	< 0.001
THURSDAY†	**0.1272**	**0.3238**	0.0434	< 0.001	**0.1928**	**0.6481**	0.0415	< 0.001
FRIDAY	**0.0643**	**0.1649**	0.0428	< 0.001	**0.1069**	**0.3307**	0.0400	< 0.001
HOLIDAY	-0.0078	-0.0202	0.0834	0.808	**-0.1056**	**-0.2864**	0.0816	< 0.001
JANUARY	**0.0781**	**0.1993**	0.0595	0.001	**0.0890**	**0.2741**	0.0540	< 0.001
FEBRUARY	0.0480	0.1232	0.0643	0.055	**0.0858**	**0.2643**	0.0576	< 0.001
MARCH	**0.0514**	**0.1318**	0.0629	0.036	**0.0721**	**0.2191**	0.0566	< 0.001
APRIL	0.0451	0.1159	0.0616	0.060	**0.0630**	**0.1897**	0.0586	0.001
MAY	0.0398	0.1022	0.0636	0.108	**0.0966**	**0.3000**	0.0584	< 0.001
JULY‡	-0.0259	-0.0677	0.0625	0.279	-0.0350	-0.0986	0.0555	0.076
AUGUST‡	-0.0194	-0.0507	0.0615	0.410	0.0185	0.0540	0.0552	0.328
SEPTEMBER	**0.0875**	**0.2231**	0.0614	< 0.001	**0.0985**	**0.3067**	0.0601	< 0.001
OCTOBER	**0.0826**	**0.2107**	0.0618	0.001	**0.1056**	**0.3309**	0.0579	< 0.001
NOVEMBER	**0.0560**	**0.1435**	0.0656	0.029	**0.0948**	**0.2937**	0.0567	< 0.001
DECEMBER	0.0352	0.0906	0.0646	0.161	**0.0570**	**0.1710**	0.0577	0.003
Constant	- - -	**-0.4354**	0.1463	0.003	- - -	**0.4341**	0.1325	0.001
pseudo-R^2 ‡‡		0.18				0.24		
Wald χ^2		**2555.83**		< 0.001		**3980.14**		< 0.001
df		49				49		

Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator

†† Calculated at means of independent variables

† These 4 days are not significantly different at α .05 in either model

‡ In both models, summer months are significantly different from non-summer months at α = .05. December differs from the other non-summer months. July and August do not differ significantly from each other

Year dummy variables were used; 2008 significantly greater at α = .05 in both models

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

‡‡ McFadden's pseudo-R^2

have a lower likelihood than married parents, with a 4.76% reduction for women and 14.56% for men. While this is contrary to the IPM result, only 28.69% of single male parents reported positive child care time in ATUS, but 48.01% of other men did. Other variables broadly returned results similar to the IPM. As with the IPM, the probit models described the variation in women's behavior more fully, with a pseudo-R^2 of 0.24 to men's 0.18.

The Fairlie decomposition (Table 9) shows results similar to those of the IPM. Men's and women's probabilities converge with higher earnings and for whites, and diverge for older parents and those with older children, and for longer work hours. Unlike the IPM, convergence was observed for single parents, homeowners, high school graduates, and students, with diverging time use associated with having at least some college education or owning a home.

The second tier truncated normal model (Tables 10 and 11) produced little in the way of important results. For women, a college education was associated with a 16.52% increase in child care time, identical to the decrease for students. For men, aside from control variables, few showed significant effects. The lack of results here, including the decomposition, casts doubt on the applicability of the double hurdle model for this variable.

ii. Indirect Child Care Time—*BEHALF*

The men's results display the challenge of fitting a model to a dependent variable for which 80% of the values are zeros. The probit model (Table 12) produces a pseudo-R^2 of only 0.07. Earnings is not significant, but the three included schooling levels confer

Table 9

Fairlie Nonlinear Decomposition for Double Hurdle Model

Dependent variable *w_FACETIME* (= 1 for nonzero values of *FACETIME*)

First hurdle probit model

Combined multiple imputation estimates (*m* = 20)

Boldface effects are significant at α = .05

n = *45,649*

Variable	Contribution to gender difference†	SE	*p*-value
rEARNHRhat	**-0.0163**	0.0054	0.003
BLACK	0.0003	0.0007	0.678
WHITE	**-0.0021**	0.0006	< 0.001
CITIZEN	0.0007	0.0004	0.053
HISPANIC	**0.0025**	0.0004	0.000
MILITARY	-0.0002	0.0002	0.348
METRO	< 0.0001	0.0001	0.815
AGE	**0.0026**	0.0005	< 0.001
OWNHOME	**0.0020**	0.0005	< 0.001
HISCHOOL	**-0.0012**	0.0003	< 0.001
COLLSOME	**0.0042**	0.0011	< 0.001
COLLEGE	**0.0017**	0.0005	0.001
STUDENT	**-0.0029**	0.0004	< 0.001
CHILDAGE	**0.0083**	0.0004	< 0.001
NUMKIDS	**-0.0002**	0.0001	0.031
PARTNER	0.0001	0.0001	0.285
SINGLEPT	**-0.0049**	0.0023	0.037
GOVEMP	-0.0001	0.0004	0.900
PRIVEMP	0.0022	0.0017	0.194
SELFEMP	0.0003	0.0009	0.699
VOLUNTR	0.0000	0.0001	0.726
BUSFARM	-0.0004	0.0003	0.278
WORKHRS	**0.0310**	0.0041	< 0.001
SPOUSEHRS	**0.0008**	0.0003	0.020
SUNDAY	**0.0017**	0.0003	< 0.001
MONDAY	**0.0012**	0.0002	< 0.001
TUESDAY	-0.0002	0.0002	0.266
WEDNESDAY	**-0.0013**	0.0002	< 0.001
THURSDAY	**-0.0032**	0.0004	< 0.001
FRIDAY	**-0.0006**	0.0002	< 0.001
HOLIDAY	0.0001	0.0000	0.078
JANUARY	0.0002	0.0001	0.068
FEBRUARY	**0.0005**	0.0001	0.001
MARCH	-0.0001	0.0001	0.300
APRIL	0.0000	0.0001	0.506
MAY	**-0.0003**	0.0001	< 0.001
JULY	-0.0001	0.0001	0.135
AUGUST	0.0001	0.0001	0.365
SEPTEMBER	**-0.0006**	0.0002	< 0.001
OCTOBER	**-0.0009**	0.0002	< 0.001
NOVEMBER	-0.0001	0.0001	0.483
DECEMBER	**-0.0003**	0.0001	0.035

P(*w_FACETIME*=1 | *FEMALE* = 1)	0.6573
P(*w_FACETIME*=1 | *FEMALE* = 0)	0.4204
Difference	0.2369
Total explained	0.0248

†A negative coefficient reduces the difference. E.g., the negative coefficient on rEARNHRhat indicates that, as earnings rise, men's and women's probabilities of positive time use converge; i.e., at higher earnings, men's and women's time use become more alike.
A positive coefficient indicates that the probabilities diverge as the variable increases.

Table 10
Double Hurdle Model Results

Dependent variable *sinh* $^{-1}$ *FACETIME*, men and women

Second hurdle truncated normal model

Combined multiple imputation estimates (m = 20)

Boldface effects are significant at α = .05

	Men (n = 8,536)			Women (n = 17,761)		
Variable	Coefficient	SE	p-value	Coefficient	SE	p-value
rEARNHRhat	0.0130	0.0076	0.087	0.0083	0.0059	0.160
BLACK	**-0.1788**	0.0814	0.028	**-0.1102**	0.0527	0.037
WHITE	0.0277	0.0526	0.598	0.0085	0.0412	0.837
CITIZEN	**-0.1160**	0.0543	0.033	-0.0267	0.0363	0.462
HISPANIC	-0.0125	0.0511	0.807	**-0.1212**	0.0335	< 0.001
MILITARY	-0.6774	0.4819	0.160	**-0.1222**	0.0605	0.044
METRO	0.0736	0.0461	0.110	0.0280	0.0294	0.341
AGE	0.0001	0.0026	0.961	-0.0029	0.0018	0.102
OWNHOME	-0.0194	0.0410	0.636	0.0202	0.0247	0.413
HISCHOOL	-0.0809	0.0708	0.253	0.0640	0.0394	0.104
COLLSOME	-0.1250	0.0764	0.102	0.0802	0.0437	0.066
COLLEGE	-0.1348	0.1073	0.209	**0.1652**	0.0696	0.018
STUDENT	-0.0551	0.0676	0.415	**-0.1652**	0.0352	< 0.001
CHILDAGE	**-0.0804**	0.0044	< 0.001	**-0.0983**	0.0030	< 0.001
NUMKIDS	0.0078	0.0179	0.662	**0.0349**	0.0094	< 0.001
PARTNER	0.0535	0.0912	0.558	-0.0640	0.0533	0.230
SINGLEPT	0.0284	0.0854	0.739	0.0857	0.0509	0.092
GOVEMP	0.0085	0.0881	0.924	-0.1067	0.0460	0.020
PRIVEMP	-0.0716	0.0837	0.393	**-0.0972**	0.0393	0.013
SELFEMP	-0.0400	0.0940	0.670	-0.0502	0.0458	0.273
VOLUNTR	**0.4297**	0.1274	0.001	0.0785	0.1451	0.588
BUSFARM	**0.1027**	0.0511	0.044	0.0480	0.0345	0.165
WORKHRS	**-0.0064**	0.0015	< 0.001	**-0.0085**	0.0009	<0.001
SPOUSEHRS	0.0005	0.0014	0.752	0.0009	0.0010	0.383
SUNDAY	-0.0215	0.0385	0.576	**0.0524**	0.0256	0.041
MONDAY†	**-0.1311**	0.0467	0.005	**0.1845**	0.0315	< 0.001
TUESDAY†	**-0.2105**	0.0496	< 0.001	**0.1840**	0.0307	< 0.001
WEDNESDAY†	**-0.1865**	0.0496	< 0.001	**0.1828**	0.0288	< 0.001
THURSDAY†	**-0.1700**	0.0460	< 0.001	**0.1302**	0.0310	< 0.001
FRIDAY	**-0.2346**	0.0499	< 0.001	-0.0362	0.0326	0.267
HOLIDAY	0.0524	0.0973	0.590	-0.1306	0.0815	0.109
JANUARY	0.0630	0.0647	0.330	**0.1640**	0.0412	< 0.001
FEBRUARY	0.0264	0.0665	0.691	**0.1369**	0.0452	0.002
MARCH	0.0557	0.0725	0.442	**0.1480**	0.0430	0.001
APRIL	0.0566	0.0644	0.379	**0.1292**	0.0435	0.003
MAY	0.0370	0.0667	0.579	**0.1207**	0.0440	0.006
JULY‡	-0.0276	0.0735	0.707	0.0842	0.0467	0.071
AUGUST‡	0.0389	0.0721	0.590	0.0150	0.0462	0.746
SEPTEMBER	0.0375	0.0676	0.579	**0.1839**	0.0434	< 0.001
OCTOBER	0.0645	0.0680	0.343	**0.1782**	0.0424	< 0.001
NOVEMBER	0.0029	0.0722	0.967	**0.1289**	0.0440	0.003
DECEMBER	0.1170	0.0716	0.102	**0.1617**	0.0433	< 0.001
Constant	**5.3408**	0.1637	< 0.001	**5.3434**	0.0968	< 0.001
R^2	0.12			0.25		
F	**3803.00**		< 0.001	**10414.60**		< 0.001
df	50, 2.69E6			50, 2E7		

Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator.

Year dummy variables were used; at α = .05, 2009 was positive and significant for men only.

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

Table 11
Blinder-Oaxaca Decomposition for Double Hurdle Model
Dependent variable *sinh⁻¹ FACETIME*
Second hurdle truncated normal model
Combined multiple imputation estimates (m = 20)

Boldface effects are significant at $\alpha \leq .05$

	Differential	SE	*p*-value
Female	**5.0430**	0.0103	< 0.001
Male	**4.7812**	0.0149	< 0.001
Difference	**0.2618**	0.0181	< 0.001

	Decomposition	SE	*p*-value
Endowments	0.0294	0.0299	0.326
Coefficients	0.1709	0.0260	< 0.001
Interaction	0.0615	0.0355	0.084

Variable	Endowment	SE	*p*-value	Coefficients	SE	*p*-value	Interaction	SE	*p*-value
rEARNHRhat	-0.0491	0.0287	0.087	-0.0928	0.1883	0.622	0.0179	0.0363	0.622
BLACK	-0.0002	0.0003	0.454	-0.0011	0.0034	0.739	0.0001	0.0002	0.754
WHITE	**-0.0052**	0.0020	0.010	0.0044	0.0046	0.331	0.0021	0.0022	0.335
OTHRACE	**-0.0029**	0.0012	0.017	-0.0302	0.0296	0.306	0.0013	0.0013	0.315
CITIZEN	0.0022	0.0013	0.079	0.0791	0.0578	0.171	-0.0017	0.0014	0.212
HISPANIC	-0.0004	0.0016	0.807	-0.0166	0.0093	0.076	-0.0034	0.0020	0.100
MILITARY	-0.0098	0.0070	0.161	0.0004	0.0004	0.278	0.0080	0.0070	0.254
METRO	-0.0006	0.0006	0.290	-0.0385	0.0463	0.405	0.0004	0.0005	0.474
AGE	-0.0003	0.0055	0.961	-0.1145	0.1192	0.337	0.0063	0.0066	0.338
OWNHOME	0.0013	0.0026	0.636	0.0303	0.0366	0.408	-0.0026	0.0031	0.410
LTHSCHL	0.0021	0.0015	0.171	**-0.0150**	0.0063	0.018	**-0.0040**	0.0020	0.040
HISCHOOL	0.0000	0.0003	0.901	-0.0047	0.0108	0.663	-0.0001	0.0003	0.691
COLLSOME	-0.0013	0.0009	0.178	0.0107	0.0082	0.191	0.0014	0.0011	0.209
COLLEGE	0.0032	0.0037	0.388	**0.0535**	0.0271	0.048	-0.0088	0.0046	0.054
STUDENT	-0.0022	0.0027	0.417	-0.0052	0.0036	0.150	-0.0044	0.0031	0.153
CHILDAGE	**-0.0398**	0.0063	< 0.001	**-0.0834**	0.0248	0.001	**-0.0089**	0.0029	0.003
NUMKIDS	-0.0004	0.0009	0.667	0.0561	0.0419	0.181	-0.0013	0.0011	0.238
MARRIEDPT	0.0043	0.0069	0.532	0.0178	0.0451	0.693	-0.0032	0.0080	0.693
PARTNER	0.0001	0.0002	0.751	-0.0043	0.0033	0.190	-0.0002	0.0004	0.616
SINGLEPT	0.0002	0.0096	0.986	0.0054	0.0050	0.273	0.0120	0.0110	0.273
NONEMP	-0.0170	0.0170	0.316	0.0113	0.0085	0.186	0.0262	0.0198	0.186
GOVEMP	0.0001	0.0003	0.688	-0.0018	0.0072	0.806	0.0000	0.0002	0.836
PRIVEMP	**0.0282**	0.0080	< 0.001	0.0491	0.0339	0.147	-0.0154	0.0106	0.147
SELFEMP	**0.0057**	0.0026	0.028	0.0099	0.0068	0.146	-0.0049	0.0034	0.149
VOLUNTR	**0.0004**	0.0002	0.009	0.0000	0.0000	0.390	-0.0003	0.0002	0.128
BUSFARM	-0.0021	0.0012	0.081	-0.0088	0.0099	0.375	0.0011	0.0013	0.390
WORKHRS	**0.1170**	0.0276	< 0.001	-0.0853	0.0711	0.230	0.0387	0.0322	0.230
SPOUSEHRS	0.0007	0.0023	0.754	0.0136	0.0564	0.810	0.0007	0.0027	0.811
Total	0.0294	0.0299	0.325	**0.1709**	0.0260	<0.001	0.0615	0.0355	0.084

Day of week, month, and year dummies and constant term (coefficients only) are omitted for brevity. Significant effects at α = .05 were observed for *SATURDAY* (–) and *SUNDAY* (–) for both endowments and coefficients; *TUESDAY* (·), *WEDNESDAY* (·), and the constant (+) for coefficients; and *SATURDAY* ( ) and *SUNDAY* (·) for interaction.

probability increases of 4.24%, 6.06%, and 7.05% over a non-high school graduate. Students are about 4% less likely, and self-employed men about 5% more likely, to engage in *BEHALF* activities than others. In the second hurdle truncated normal model (Table 14) only 4 of the variables of interest are significant. Of those, one *(MILITARY)* has an improbably large coefficient of -1.2367, and two others, *SINGLEPT* and *STUDENT*, have negative and positive coefficients, respectively, which are difficult to explain in light of the other models.

BEHALF is generally done by women, and the results for them are clearer. In the first-hurdle probit model (Table 12), fit is only slightly better than for men, with adjusted $R^2 = 0.10$, but the individual coefficient results are more consistent with other findings. While the marginal effect of hourly earnings is small (0.0078), it is strongly significant. A one-hour increase in *WORKHRS* reduces the likelihood of engaging in indirect child care time by only 0.1%, compared with 0.85% for *FACETIME*. The likelihood for homeowners falls by 2.33%. There are statistically and practically significant positive effects for *WHITE* (7.05% more likely, compared to no effect on *FACETIME*) and *CITIZEN* (6.03%). All schooling levels have positive marginal effects but only *COLLSOME* (4.10%) is significant. Having one extra child in the household raises the probability by 5.33%. Employed women are more likely to use *BEHALF* time, with marginal effects positive for all employment categories: *GOVEMP* (9.29%), *PRIVEMP* (7.13%), and *SELFEMP* (5.81%). *SPOUSEHRS* has a small positive effect, with a one-hour increase in this variable raising *BEHALF* time by 0.17%, which provides some evidence for the hypothesis about this variable. The second hurdle model (Table 14)

Table 12
Double Hurdle Model Results
Dependent variable *w_BEHALF* (=1 for *BEHALF* > 0), for men and women
First hurdle probit model
Combined multiple imputation estimates (*m* = 20)

Boldface effects are significant at α ≤ .05

	Men (n = 18,686)				*Women (n = 26,963)*			
Variable	Marginal effects††	Coefficient	SE	*p*-value	Marginal effects††	Coefficient	SE	*p*-value
rEARNHRhat	0.0033	0.0123	0.0087	0.154	**0.0078**	**0.0207**	0.0076	0.006
BLACK	0.0020	0.0073	0.0772	0.925	0.0348	0.0909	0.0590	0.124
WHITE	0.0145	0.0547	0.0533	0.305	**0.0705**	**0.1899**	0.0477	< 0.001
CITIZEN	**0.0289**	**0.1109**	0.0565	0.049	**0.0603**	**0.1627**	0.0430	< 0.001
HISPANIC	-0.0110	-0.0411	0.0515	0.425	0.0011	0.0030	0.0400	0.940
MILITARY	0.1054	0.3416	0.3218	0.288	0.0106	0.0279	0.0705	0.693
METRO	0.0022	0.0083	0.0447	0.853	0.0159	0.0420	0.0361	0.244
AGE	**0.0024**	**0.0090**	0.0022	< 0.001	0.0005	0.0014	0.0019	0.473
OWNHOME	-0.0184	-0.0672	0.0400	0.093	**-0.0233**	**-0.0612**	0.0280	0.028
HISCHOOL	**0.0424**	**0.1532**	0.0586	0.009	0.0219	0.0576	0.0456	0.207
COLLSOME	**0.0606**	**0.2146**	0.0665	0.001	**0.0410**	**0.1074**	0.0527	0.042
COLLEGE	**0.0705**	**0.2505**	0.1088	0.021	0.0372	0.0975	0.0897	0.277
STUDENT	**-0.0415**	**-0.1642**	0.0680	0.016	-0.0247	-0.0657	0.0409	0.108
CHILDAGE	**-0.0017**	**-0.0064**	0.0031	0.039	**-0.0050**	**-0.0133**	0.0027	< 0.001
NUMKIDS	**0.0375**	**0.1392**	0.0151	< 0.001	**0.0533**	**0.1407**	0.0125	< 0.001
PARTNER	-0.0298	-0.1158	0.0788	0.142	-0.0021	-0.0056	0.0617	0.927
SINGLEPT	0.0246	0.0885	0.0748	0.237	0.0436	0.1142	0.0610	0.061
GOVEMP	0.0423	0.1492	0.0827	0.071	**0.0929**	**0.2395**	0.0528	< 0.001
PRIVEMP	0.0208	0.0782	0.0758	0.302	**0.0713**	**0.1882**	0.0453	< 0.001
SELFEMP	**0.0513**	**0.1792**	0.0904	0.047	**0.0581**	**0.1505**	0.0574	0.009
VOLUNTR	0.0778	0.2595	0.6184	0.675	-0.0795	-0.2188	0.3037	0.471
BUSFARM	0.0047	0.0174	0.0546	0.750	0.0303	0.0800	0.0430	0.063
WORKHRS	**-0.0012**	**-0.0046**	0.0013	0.001	**-0.0010**	**-0.0026**	0.0010	0.013
SPOUSEHRS	**0.0014**	**0.0052**	0.0015	0.001	**0.0017**	**0.0044**	0.0012	< 0.001
SUNDAY	**-0.0490**	**-0.1937**	0.0377	< 0.001	**-0.0660**	**-0.1782**	0.0291	< 0.001
MONDAY†	**0.1258**	**0.4153**	0.0431	< 0.001	**0.2981**	**0.7663**	0.0353	< 0.001
TUESDAY†	**0.1415**	**0.4617**	0.0438	< 0.001	**0.3193**	**0.8233**	0.0350	< 0.001
WEDNESDAY†	**0.1426**	**0.4647**	0.0448	< 0.001	**0.3168**	**0.8166**	0.0347	< 0.001
THURSDAY†	**0.1622**	**0.5218**	0.0444	< 0.001	**0.3262**	**0.8422**	0.0351	< 0.001
FRIDAY	**0.1329**	**0.4357**	0.0439	< 0.001	**0.3074**	**0.7913**	0.0353	< 0.001
HOLIDAY	**-0.1419**	**-0.7724**	0.1248	< 0.001	**-0.2963**	**-1.0685**	0.1040	< 0.001
JANUARY	**0.0879**	**0.2954**	0.0647	< 0.001	**0.0827**	**0.2133**	0.0502	< 0.001
FEBRUARY	**0.0558**	**0.1931**	0.0686	0.005	**0.0968**	**0.2490**	0.0533	< 0.001
MARCH	**0.0521**	**0.1813**	0.0653	0.005	**0.0830**	**0.2140**	0.0507	< 0.001
APRIL	**0.0611**	**0.2107**	0.0663	0.001	**0.0800**	**0.2066**	0.0521	< 0.001
MAY	**0.0650**	**0.2229**	0.0664	0.001	**0.1289**	**0.3301**	0.0523	< 0.001
JULY‡	**-0.0369**	**-0.1445**	0.0709	0.041	**-0.0636**	**-0.1724**	0.0534	0.001
AUGUST‡	-0.0103	-0.0386	0.0685	0.573	0.0075	0.0198	0.0524	0.706
SEPTEMBER	**0.0979**	**0.3256**	0.0666	< 0.001	**0.1450**	**0.3705**	0.0526	< 0.001
OCTOBER	**0.0909**	**0.3047**	0.0663	< 0.001	**0.1344**	**0.3440**	0.0515	< 0.001
NOVEMBER	**0.0867**	**0.2911**	0.0710	< 0.001	**0.1200**	**0.3076**	0.0524	< 0.001
DECEMBER	**0.0409**	**0.1440**	0.0686	0.036	**0.0687**	**0.1777**	0.0527	0.001
Constant	---	**-2.4418**	0.1595	< 0.001	---	**-2.2466**	0.1159	< 0.001
pseudo-R^2 ‡‡		0.07				0.10		
Wald χ^2		**975.29**		< 0.001		**2772.52**		< 0.001
df		49				49		

Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator
†† Calculated at means of independent variables
Year dummy variables were used, 2005 and 2008 were positive and significant at α = .05 for women only
Omitted categories Other race, less than high school, married parents, nonemployed, Saturday, June, 2010
‡‡ McFadden's pseudo-R^2

Table 13

Fairlie Nonlinear Decomposition for Double Hurdle Model

Dependent variable *w_BEHALF* (=1 for *BEHALF* > 0), for men and women

First hurdle probit model

Combined multiple imputation estimates (*m* = 20)

Boldface effects are significant at α = .05

n = 45,649

Variable	Contribution to gender difference	SE	*p*-value
rEARNHRhat	**-0.0210**	0.0079	0.008
BLACK	0.0012	0.0007	0.113
WHITE	**-0.0026**	0.0006	< 0.001
CITIZEN	0.0000	0.0001	0.630
HISPANIC	0.0000	0.0001	0.959
MILITARY	0.0001	0.0003	0.694
METRO	0.0000	0.0000	0.609
AGE	-0.0009	0.0012	0.474
OWNHOME	**0.0013**	0.0006	0.028
HISCHOOL	-0.0004	0.0003	0.269
COLLSOME	**0.0014**	0.0007	0.049
COLLEGE	-0.0007	0.0006	0.273
STUDENT	-0.0008	0.0005	0.106
CHILDAGE	**0.0006**	0.0001	< 0.001
NUMKIDS	**-0.0007**	0.0001	< 0.001
PARTNER	0.0000	0.0000	0.989
SINGLEPT	0.0052	0.0027	0.055
GOVEMP	**0.0009**	0.0002	< 0.001
PRIVEMP	**-0.0117**	0.0029	< 0.001
SELFEMP	**-0.0026**	0.0010	0.010
VOLUNTR	-0.0001	0.0001	0.477
BUSFARM	-0.0006	0.0003	0.064
WORKHRS	**0.0144**	0.0058	0.014
SPOUSEHRS	**0.0018**	0.0006	0.004
SUNDAY	**0.0004**	0.0001	< 0.001
MONDAY	**-0.0027**	0.0005	< 0.001
TUESDAY	0.0006	0.0004	0.103
WEDNESDAY	**0.0012**	0.0002	< 0.001
THURSDAY	0.0002	0.0004	0.598
FRIDAY	0.0005	0.0006	0.433
HOLIDAY	**0.0022**	0.0002	< 0.001
JANUARY	-0.0001	0.0001	0.107
FEBRUARY	**0.0003**	0.0001	< 0.001
MARCH	0.0000	0.0001	0.510
APRIL	-0.0001	0.0001	0.166
MAY	**0.0004**	0.0001	< 0.001
JULY	**0.0005**	0.0002	0.004
AUGUST	0.0000	0.0000	0.966
SEPTEMBER	-0.0001	0.0001	0.131
OCTOBER	-0.0001	0.0001	0.271
NOVEMBER	**0.0007**	0.0001	< 0.001
DECEMBER	-0.0001	0.0001	0.402

P(*w_BEHALF*=1 | *FEMALE* = 1) =	0.3926
P(*w_BEHALF*=1 | *FEMALE* = 0) =	0.2073
Difference =	0.1852
Total explained =	**-0.0115**

†A negative coefficient reduces the difference. E.g., the negative coefficient on rEARNHRhat indicates that, as earnings rise, men's and women's probabilities of positive time use converge; i.e., at higher earnings, men's and women's time use become more alike.
A positive coefficient indicates that the probabilities diverge as the variable increases.

Year dummy variables were used; none were significant at α = .05.

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

shows no effect of hourly earnings, suggesting a discrete effect only for this variable. Schooling levels are all positive, successively increasing, and significant; a college graduate spends about 33% more time on *BEHALF* than a non-high school graduate. *STUDENT* and *CHILDAGE* have the expected signs, but are much smaller than in the IPM model, although the 10.64% increase in time due to an extra child *(NUMKIDS)* is about the same. The negative effect of an increase in *WORKHRS* is small (-0.0073) but significant; for *SPOUSEHRS,* the effect is small (0.0052) but larger than in the IPM and is significant.

Decomposition of these effects is shown in Tables 13 and 15. Increases in hourly earnings narrow the probability gap between men and women for *BEHALF* but not the time gap for those with nonzero values. For both models, the gap narrows as the number of children rises, and widens with *CHILDAGE* and *SPOUSEHRS.*

C. Effect of Rising Earnings on *BEHALF* Relative to *FACETIME*

Discussed above, the primary purpose of this study is to determine whether, as earnings rise, parents substitute—proportionately—*BEHALF* time for *FACETIME.* The key insight of the model is expressed in equation (3.2), that the effect of an increase in hourly earnings raises the price of *FACETIME* relative to that of market services and hence leads parents to substitute markets services, and so *BEHALF*, for *FACETIME.* In the model the income effect is ambiguous, but we see here that it is large enough to increase both types of time use. Equation (3.2) indicates that *BEHALF* should increase in proportion to *FACETIME.* To conduct the test, some kind of ratio of the two variables, subject to a significance test, seems necessary. Ideally, we could test this relationship by

Table 14
Double Hurdle Model Results
Dependent variable $sinh^{-1}$ *BEHALF* for men and women
Second hurdle truncated normal model
Combined multiple imputation estimates (m = 20)

Boldface effects are significant at α = .05

	Men (n = 3,731)			Women (n = 9,570)		
Variable	Coefficient	SE	p-value	Coefficient	SE	p-value
rEARNHRhat	0.0119	0.0157	0.447	-0.0012	0.0102	0.906
BLACK	-0.0220	0.1369	0.873	0.0867	0.0847	0.306
WHITE	-0.0084	0.0939	0.929	**0.2311**	0.0694	0.001
CITIZEN	0.1003	0.0955	0.294	0.0712	0.0640	0.266
HISPANIC	-0.1247	0.0919	0.175	0.0338	0.0581	0.561
MILITARY	**-1.2367**	0.3275	< 0.001	**0.2410**	0.0968	0.013
METRO	-0.0198	0.0900	0.826	0.0306	0.0505	0.545
AGE	0.0021	0.0045	0.643	-0.0026	0.0031	0.412
OWNHOME	-0.0196	0.0716	0.784	0.0465	0.0432	0.282
HISCHOOL	0.1706	0.1085	0.116	**0.1633**	0.0740	0.027
COLLSOME	0.2306	0.1240	0.063	**0.1715**	0.0812	0.035
COLLEGE	0.1232	0.1955	0.529	**0.3336**	0.1277	0.009
STUDENT	**0.2220**	0.1033	0.032	**-0.1119**	0.0545	0.040
CHILDAGE	-0.0117	0.0070	0.094	**-0.0235**	0.0048	< 0.001
NUMKIDS	**0.0778**	0.0265	0.003	**0.1064**	0.0217	< 0.001
PARTNER	-0.2743	0.1551	0.077	-0.0628	0.0877	0.474
SINGLEPT	**-0.4058**	0.1260	0.001	0.1701	0.0892	0.057
GOVEMP	-0.2654	0.1444	0.066	0.0309	0.0759	0.684
PRIVEMP	-0.2458	0.1308	0.060	-0.0886	0.0690	0.199
SELFEMP	-0.0754	0.1477	0.610	-0.0916	0.0826	0.268
VOLUNTR	0.2049	1.7672	0.908	0.1161	0.6627	0.861
BUSFARM	-0.0843	0.0965	0.382	0.0495	0.0600	0.409
WORKHRS	-0.0034	0.0023	0.140	**-0.0073**	0.0016	< 0.001
SPOUSEHRS	-0.0007	0.0025	0.775	**0.0052**	0.0017	0.002
SUNDAY	**-0.4461**	0.1020	< 0.001	**-0.3309**	0.0634	< 0.001
MONDAY†	**-0.8875**	0.0926	< 0.001	**-0.2751**	0.0590	< 0.001
TUESDAY†	**-0.7128**	0.0916	< 0.001	**-0.3741**	0.0586	< 0.001
WEDNESDAY†	**-0.9420**	0.0893	< 0.001	**-0.4923**	0.0587	< 0.001
THURSDAY†	**-0.8469**	0.0935	< 0.001	**-0.3056**	0.0590	< 0.001
FRIDAY	**-0.9112**	0.0948	< 0.001	**-0.3561**	0.0610	< 0.001
HOLIDAY	-0.0185	0.2468	0.940	-0.0899	0.2560	0.725
JANUARY	-0.1359	0.1242	0.274	-0.0860	0.0751	0.252
FEBRUARY	-0.2142	0.1406	0.128	-0.1290	0.0801	0.108
MARCH	-0.0157	0.1324	0.906	-0.0914	0.0742	0.218
APRIL	0.0122	0.1346	0.928	-0.1333	0.0880	0.130
MAY	-0.1253	0.1301	0.336	-0.0105	0.0773	0.891
JULY‡	0.0773	0.1506	0.607	-0.0560	0.0841	0.506
AUGUST‡	-0.0809	0.1430	0.572	-0.0261	0.0817	0.749
SEPTEMBER	-0.0736	0.1295	0.570	-0.0694	0.0762	0.362
OCTOBER	0.0000	0.1266	> 0.999	-0.0205	0.0731	0.779
NOVEMBER	-0.1391	0.1252	0.267	**-0.1493**	0.0733	0.042
DECEMBER	-0.1093	0.1458	0.453	-0.1475	0.0778	0.058
Constant	**3.8397**	0.3006	< 0.001	**3.4595**	0.1837	< 0.001
R^2	0.08			0.12		
F	**467.40**		< 0.001	**1605.62**		< 0.001
df	50, 1.79E7			50, 2.07E7		

Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator

Year dummy variables were used; none were significant at α = .05

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

Table 15
Blinder-Oaxaca Decomposition for Double Hurdle Model
Dependent variable ***sinh⁻¹ BEHALF***
Second hurdle truncated normal model
Combined multiple imputation estimates (*m* = 20)

Boldface effects are significant at $\alpha = .05$.

	Differential	SE	*p*-value
Female	1.7538	0.0190	< 0.001
Male	1.0372	0.0227	< 0.001
Difference	0.7165	0.0296	< 0.001

	Decomposition	SE	*p*-value
Endowments	0.1329	0.0489	0.007
Coefficients	0.6773	0.0493	< 0.001
Interaction	-0.0937	0.0637	0.141

Variable	Endowment	SE	*p*-value	Coefficients	SE	*p*-value	Interaction	SE	*p*-value
rEARNHRhat	-0.0541	0.0517	0.295	0.1081	0.3602	0.764	-0.0208	0.0694	0.764
BLACK	-0.0003	0.0031	0.931	-0.0013	0.0077	0.864	-0.0006	0.0037	0.864
WHITE	0.0028	0.0019	0.141	**0.1911**	0.0512	< 0.001	**-0.0083**	0.0027	0.002
OTHRACE	-0.0003	0.0004	0.454	**-0.0143**	0.0058	0.013	0.0008	0.0009	0.383
CITIZEN	**-0.0051**	0.0023	0.028	-0.0006	0.0969	0.995	< 0.0001	0.0021	0.995
HISPANIC	0.0016	0.0026	0.525	0.0149	0.0166	0.370	0.0030	0.0034	0.380
MILITARY	-0.0007	0.0048	0.892	0.0001	0.0003	0.758	0.0016	0.0051	0.757
METRO	-0.0003	0.0007	0.706	0.0767	0.0810	0.344	-0.0008	0.0010	0.432
AGE	-0.0160	0.0085	0.059	-0.3340	0.2020	0.098	0.0185	0.0113	0.101
OWNHOME	0.0039	0.0043	0.368	0.0911	0.0623	0.144	-0.0077	0.0053	0.150
LTHSCHL	-0.0015	0.0022	0.484	-0.0069	0.0105	0.513	-0.0018	0.0028	0.519
HISCHOOL	0.0001	0.0004	0.776	-0.0035	0.0186	0.852	-0.0001	0.0005	0.855
COLLSOME	0.0019	0.0014	0.181	-0.0029	0.0135	0.830	-0.0004	0.0017	0.830
COLLEGE	0.0009	0.0062	0.890	0.0384	0.0503	0.445	-0.0063	0.0083	0.446
STUDENT	0.0083	0.0047	0.073	-0.0093	0.0064	0.145	-0.0078	0.0054	0.148
CHILDAGE	**0.0161**	0.0041	< 0.001	-0.0468	0.0407	0.250	-0.0050	0.0044	0.257
NUMKIDS	**-0.0076**	0.0033	0.020	**0.1705**	0.0674	0.011	-0.0039	0.0022	0.076
MARRIEDPT	**0.0279**	0.0097	0.004	0.0293	0.0703	0.677	-0.0052	0.0125	0.677
PARTNER	-0.0006	0.0010	0.592	0.0037	0.0049	0.447	0.0002	0.0004	0.662
SINGLEPT	**0.0671**	0.0138	< 0.001	-0.0082	0.0080	0.302	-0.0182	0.0177	0.302
NONEMP	-0.0363	0.0264	0.169	0.0249	0.0153	0.103	0.0578	0.0354	0.102
GOVEMP	0.0002	0.0006	0.682	**0.0637**	0.0145	< 0.001	-0.0011	0.0027	0.670
PRIVEMP	**0.0443**	0.0131	0.001	**0.3550**	0.0678	< 0.001	**-0.1113**	0.0217	< 0.001
SELFEMP	0.0012	0.0043	0.785	0.0221	0.0135	0.101	-0.0108	0.0066	0.104
VOLUNTR	**0.0006**	0.0002	0.013	-0.0001	0.0001	0.328	**-0.0018**	0.0006	0.005
BUSFARM	-0.0008	0.0018	0.667	0.0163	0.0184	0.376	-0.0021	0.0024	0.390
WORKHRS	0.0598	0.0426	0.161	-0.0527	0.1194	0.659	0.0239	0.0542	0.659
SPOUSEHRS	**0.0122**	0.0044	0.006	0.0495	0.0991	0.618	0.0024	0.0048	0.624
Total	0.1329	0.0489	0.007	**0.6773**	0.0493	< 0.001	-0.0937	0.0637	0.141

Day of week, month, and year dummies and constant term (coefficients only) are omitted for brevity. Significant effects at $\alpha = .05$ were observed for *SATURDAY (+)* and *SUNDAY (+)* for endowments; *SATURDAY (–)*, *SUNDAY (–)*, *MONDAY (+)*, *FRIDAY (+)* and *HOLIDAY (–)* for endowments; and *SATURDAY (+)* and *SUNDAY (+)* for interaction.

simply calculating the ratio of *BEHALF* to *FACETIME* and modeling that as a function of the covariates, but there are many zeros in both sets. The IPM transformation eliminates zeros, but introduces negative values for both variables in various combinations, still thwarting the calculation of a ratio. A ratio could thus not be formed *prior to* estimation of the models, but by finding a single model that fits both variables well and seems free of misspecification, parameter estimates can be generated and used in a postestimation test.

The first-tier probit model fit both variables relatively well for women, with earnings strongly significant. To conduct the test, I fit a bivariate probit model to the $sinh^{-1}$ transformation of the two variables, as was done separately for the double hurdle. All covariates that were either significant in one or both of the individual probit regressions, or part of a set of dummy variables of which at least one was significant, were retained; the variables *MILITARY, METRO,* and *BUSFARM* were deleted.

The combined results for the 20 imputations appear in Table 16. The correlation of the residuals proved significant (r =0.41, t = 26.87, p-value < 0.001), with minimum χ^2 = 6325.20 (p-value < 0.001). From the probit coefficients the marginal effects were calculated for the earnings variable using 30 pairings of values of earnings and *CHILDAGE*, the age of the youngest household child.[20] (The estimates of the marginal effects were more sensitive to the value of this variable than other regressors.) 5 values of *CHILDAGE* (P_{10}, Q_1, median, Q_3, *and* P_{90}) were paired with 6 values of *rEARNHRhat*

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[20] The marginal effects were obtained by estimating the equation at the specified values, then applying the chain rule to obtain the first order partial derivative.

Table 16

Bivariate Probit Model Results

Dependent variables ***sinh***$^{-1}$ ***FACETIME*** **and** ***sinh***$^{-1}$ ***BEHALF,*** **women only**

Combined multiple imputation estimates (*m* = 20)

Boldface effects are significant at α = .05

n = 26,963

	sinh^{-1} *FACETIME*			*sinh*$^{-1}$ *BEHALF*		
Variable	Coefficient	SE	*p*-value	Coefficient	SE	*p*-value
rEARNHRhat	**0.0155**	0.0056	0.006	**0.0174**	0.0049	< 0.001
BLACK	0.0176	0.0611	0.773	0.0906	0.0577	0.116
WHITE	**0.2214**	0.0507	< 0.001	**0.1930**	0.0476	< 0.001
CITIZEN	**0.1044**	0.0471	0.027	**0.1623**	0.0422	< 0.001
HISPANIC	**-0.2552**	0.0402	< 0.001	0.0005	0.0371	0.990
AGE	**-0.0081**	0.0019	< 0.001	0.0020	0.0017	0.251
OWNHOME	**-0.1454**	0.0317	< 0.001	**-0.0568**	0.0279	0.042
HISCHOOL	**0.1934**	0.0494	< 0.001	0.0640	0.0445	0.150
COLLSOME	**0.3142**	0.0531	< 0.001	**0.1242**	0.0480	0.010
COLLEGE	**0.4552**	0.0775	< 0.001	**0.1447**	0.0688	0.036
STUDENT	**-0.3035**	0.0420	< 0.001	-0.0654	0.0405	0.106
CHILDAGE	**-0.1153**	0.0031	< 0.001	**-0.0137**	0.0027	< 0.001
NUMKIDS	**0.0423**	0.0149	0.005	**0.1413**	0.0125	< 0.001
PARTNER	-0.0975	0.0646	0.131	-0.0151	0.0608	0.804
SINGLEPT	**-0.1316**	0.0640	0.040	0.1079	0.0602	0.073
GOVEMP	-0.0074	0.0568	0.896	**0.2343**	0.0525	< 0.001
PRIVEMP	-0.0676	0.0497	0.174	**0.1870**	0.0451	< 0.001
SELFEMP	-0.0225	0.0594	0.705	**0.1884**	0.0550	0.001
VOLUNTR	0.0427	0.2335	0.855	-0.1627	0.2983	0.585
WORKHRS	**-0.0078**	0.0011	< 0.001	**-0.0024**	0.0010	0.020
SPOUSEHRS	**0.0031**	0.0012	0.015	**0.0045**	0.0012	< 0.001
SUNDAY	**0.2503**	0.0279	< 0.001	**-0.1801**	0.0288	< 0.001
MONDAY†	**0.6941**	0.0402	< 0.001	**0.7511**	0.0352	< 0.001
TUESDAY†	**0.6834**	0.0409	< 0.001	**0.8099**	0.0350	< 0.001
WEDNESDAY†	**0.6267**	0.0404	< 0.001	**0.8031**	0.0347	< 0.001
THURSDAY†	**0.6495**	0.0411	< 0.001	**0.8305**	0.0351	< 0.001
FRIDAY	**0.3285**	0.0396	< 0.001	**0.7788**	0.0352	< 0.001
HOLIDAY	**-0.2869**	0.0805	< 0.001	**-1.0466**	0.1021	< 0.001
JANUARY	**0.2681**	0.0531	< 0.001	**0.2103**	0.0499	< 0.001
FEBRUARY	**0.2653**	0.0567	< 0.001	**0.2433**	0.0531	< 0.001
MARCH	**0.2188**	0.0557	< 0.001	**0.2079**	0.0506	< 0.001
APRIL	**0.1913**	0.0582	0.001	**0.2058**	0.0518	< 0.001
MAY	**0.2997**	0.0580	< 0.001	**0.3247**	0.0521	< 0.001
JULY‡	-0.0984	0.0546	0.071	**-0.1692**	0.0530	0.001
AUGUST‡	0.0511	0.0543	0.346	0.0205	0.0519	0.693
SEPTEMBER	**0.3114**	0.0594	< 0.001	**0.3612**	0.0525	< 0.001
OCTOBER	**0.3389**	0.0572	< 0.001	**0.3376**	0.0513	< 0.001
NOVEMBER	**0.2971**	0.0562	< 0.001	**0.3006**	0.0523	< 0.001
DECEMBER	**0.1732**	0.0570	0.002	**0.1706**	0.0526	0.001
Constant	**0.4018**	0.1285	0.002	**-2.1857**	0.1144	< 0.001
ρ*	**0.41**	0.0161	< 0.001			
Wald χ^2**	**6325.20**		<0.001			
df	92					

Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator.

*Calculated as the hyperbolic tangent of Fisher's *z* transformation of the correlation coefficient.

**Lowest reported value of 20 imputation; largest was 6357.22

Year dummy variables were used; 2008 was positive and significant at α = .05.

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

(the same 5 plus P_{95}) to produce the set of 30. All estimates used women's medians for *WORKHRS* and *SPOUSEHRS,* means of *AGE* and *NUMKIDS*, with dummy variables selected for: white, college graduate, US citizen, married, homeowner, not a student, employed by a private firm, for a Monday in January, 2009.[21] These effects were calculated using the first imputed data set only.[22] A χ^2 test of the hypothesis of equality of the marginal effects for each pairing was done, and for those with significantly different effects, the ratio of the marginal effect of *BEHALF* to that of *FACETIME* was observed.

These appear in Table 17, which presents a sensitivity test. This shows that, as real hourly earnings rises, the marginal effect of earnings on the probability of engaging in *BEHALF* (ME_{BEHALF}) activities rises relative to that of *FACETIME* ($\mathrm{ME}_{FACETIME}$). Both marginal effects rise with earnings, but ME_{BEHALF} rises at a higher rate, causing the ratio to rise. Cell shading indicates the value of this ratio, darkening as it rises; this shows a clear fan-shaped movement from lower left (negative values) to the top center, to the lower right (highest positive values). At low hourly earnings, ME_{BEHALF} is less than 5% of that for $\mathrm{ME}_{FACETIME}$, implying that a 1% increase in earnings while earnings are low induces very little relative change in indirect child care time. At the 90[th] percentile

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[21] In preliminary testing, effects for blacks were similar but not as pronounced. Non-college graduates and unmarried women did not show significant effects, nor did Saturday.

[22] Asparouhov and Muthén (2010) point out that combining χ^2 statistics from multiple imputations cannot be done; they recommend the practice of reporting the distribution of χ^2 statistics. But a χ^2 test is used for each of the 30 pairings, which would make MI unwieldy at best in this case. An analysis of the χ^2 statistics for the first 7 imputations for the last (lower right) cell in Table 8A showed minimal variation, with no value of χ^2 being greater than 0.21. Likewise, the marginal effect for *FACETIME* showed a mean of 0.3234 with a range of 0.0077 and a coefficient of variation of less than 1%, with similar results for *BEHALF*. I judged that using a single imputation would not materially affect the results.

Table 17

Ratios of Marginal Effects of Real Hourly Earnings, as $ME_{BEHALF} / ME_{FACETIME}$

Women, white college graduates

Bivariate probit model

All effects are significant at α = .05. Shading of cells darkens as ratio exceeds 0, 0.05, 0.10, 0.15, 0.20, 0.30, and 0.40.
Each cell shows the marginal effect and accompanying statistics estimated at the values of *CHILDAGE* and *rEARNHRhat* indicated.
Wald χ^2 test is for H_0: $ME_{FACETIME} = ME_{BEHALF} = 0$

Cell contents:	
Wald χ^2 2df	p-value
$ME_{FACETIME}$	ME_{BEHALF}
$ME_{BEHALF}/ME_{FACETIME}$	

		rEARNHRhat (2003 $)					
		$9.44	*$11.57*	*$14.65*	*$19.07*	*$23.25*	*$26.04*
CHILDAGE (years)		P_{10}	Q_1	*Median*	Q_3	P_{90}	P_{95}
0	P_{10}	13.37 0.0013 1.7990 0.0624 **0.0347**	13.44 0.0012 1.8314 0.0988 **0.0539**	13.70 0.0011 1.8780 0.1515 **0.0807**	14.45 0.0007 1.9450 0.2271 **0.1168**	15.67 0.0004 2.0077 0.2986 **0.1487**	16.84 0.0002 2.0499 0.3465 **0.1690**
2	Q_1	13.72 0.0010 1.5687 0.0350 **0.0223**	13.77 0.0010 1.6010 0.0714 **0.0446**	14.00 0.0009 1.6470 0.1242 **0.0754**	14.70 0.0006 1.7140 0.1997 **0.1165**	15.85 0.0004 1.7770 0.2712 **0.1526**	16.16 0.0003 1.8193 0.3191 **0.1754**
6	*Median*	14.50 0.0007 1.1107 -0.0197 **-0.0177**	14.49 0.0007 1.1340 0.0167 **0.0147**	14.63 0.0007 1.1860 0.0694 **0.0585**	15.18 0.0005 1.2527 0.1450 **0.1157**	16.42 0.0003 1.3158 0.2165 **0.1645**	17.04 0.0002 1.3581 0.2644 **0.1947**
11	Q_3	15.64 0.0004 0.5309 -0.0881 **-0.1659**	15.51 0.0004 0.5630 -0.0518 **-0.0920**	15.46 0.0004 0.6095 0.0010 **0.0016**	15.70 0.0004 0.6762 0.0766 **0.1133**	16.28 0.0003 0.7393 0.1481 **0.2003**	16.88 0.0002 0.7815 0.1960 **0.2508**
15	P_{90}	16.71 0.0002 0.0697 -0.1429 **-2.0502**	16.42 0.0003 0.1018 -0.1065 **-1.0462**	16.15 0.0003 0.1483 -0.0537 **-0.3621**	16.05 0.0003 0.2150 0.0218 **0.1014**	16.28 0.0003 0.2780 0.0933 **0.3356**	[illegible]

Estimated for female, white, college graduate, US citizen, married, homeowner, not a student, employed by a private firm, for a Monday in January, 2009, with women's medians of weekly work hours and spouse's work hours, and other variables set to women's means.

of earnings, however, the proportion rises to about 15%. All this implies that at low earnings, an incremental increase in earnings is insufficient to induce parents to substitute the time of others for their own child care time, but as earnings rise, so does their tendency to leverage their time by using it to engage the services of others. This strongly supports the hypothesis that parents shift their time toward *BEHALF* as earnings rise.

Table 18

Ratios of Marginal Effects of Real Hourly Earnings, as $ME_{BEHALF} / ME_{FACETIME}$

Women, by race and schooling

Bivariate probit model

Evaluated at median of *CHILDAGE* (Age 6)

All effects are significant at $\alpha = .05$. Shading of cells darkens as ratio exceeds 0, 0.05, 0.10, and 0.15.

Each cell shows the marginal effect and accompanying statistics estimated at the values of *CHILDAGE* and *rEARNHRhat* indicated.

Wald χ^2 test is for H_0: $ME_{FACETIME} = ME_{BEHALF} = 0$

Cell contents:

Wald χ^2 2*df*	*p*-value
$ME_{FACETIME}$	ME_{BEHALF}
$ME_{BEHALF}/ME_{FACETIME}$	

	rEARNHRhat (2003 $)					
	$9.44 P_{10}	*$11.57* Q_1	*$14.65* *Median*	*$19.07* Q_3	*$23.25* P_{90}	*$26.04* P_{95}
Black, High School Diploma	16.06 0.0003 0.6388 -0.2041 **-0.3195**	16.10 0.0003 0.6709 -0.1677 **-0.2500**	16.33 0.0003 0.7174 -0.1150 **-0.1603**	17.03 0.0002 0.7841 -0.0394 **-0.0502**	18.57 0.0001 0.8471 0.0321 **0.0379**	19.25 0.0001 0.8894 0.0800 **0.0899**
White, High School Diploma	15.75 0.0001 0.8417 -0.1033 **-0.1227**	15.88 0.0004 0.8738 -0.0669 **-0.0766**	16.24 0.0003 0.9204 -0.0142 **-0.0154**	17.17 0.0002 0.9870 0.0614 **0.0622**	18.60 0.0001 1.0501 0.1329 **0.1266**	19.05 <0.0001 1.0929 0.1808 **0.1654**
Black, College Degree	15.32 0.0005 0.9044 -0.1206 **-0.1333**	15.23 0.0005 0.9366 -0.0842 **-0.0899**	15.28 0.0005 0.9831 -0.0314 **-0.0319**	15.68 0.0004 1.0500 0.0442 **0.0421**	16.47 0.0003 1.1130 0.1156 **0.1039**	17.27 0.0002 1.1550 0.1635 **0.1416**
White, College Degree	14.50 0.0007 1.1107 -0.0197 **-0.0177**	14.49 0.0007 1.1340 0.0167 **0.0147**	14.63 0.0007 1.1860 0.0694 **0.0585**	15.18 0.0005 1.2527 0.1450 **0.1157**	16.42 0.0003 1.3158 0.2165 **0.1645**	17.04 0.0002 1.3581 0.2644 **0.1947**

Estimated for female, US citizen, married, homeowner, not a student, employed by a private firm, for a Monday in January, 2009, with women's medians of weekly work hours and spouse's work hours, and other variables set to women's means.

The marginal effects vary by race, education level, and for single-parent households. Table 18 contrasts the results for whites and blacks and those with a high school diploma versus those with a bachelors degree or higher. These effects are estimated only at the median of *CHILDAGE* (6 years of age) and use the same values as above for all other variables. The trend is the same, with the $ME_{BEHALF}/ME_{FACETIME}$ ratio rising with earnings, but the magnitudes and signs differ. For blacks, an increase in earnings reduces the likelihood of *BEHALF* behavior through the third quartile of earnings for high school graduates and through the median for college graduates; for

Table 19

Ratios of Marginal Effects of Real Hourly Earnings, as $ME_{BEHALF} / ME_{FACETIME}$

Women, by race and type of household, high school diploma only

Bivariate probit model

Evaluated at median of *CHILDAGE* (Age 6)

Boldface effects are significant at α = .05. Shading of cells darkens as ratio exceeds 0, 0.05, 0.10, 0.15, and 0.20.

Each cell shows the marginal effect and accompanying statistics estimated at the values of *CHILDAGE* and *rEARNHRhat* indicated.

Wald χ^2 test is for H_0: $ME_{FACETIME} = ME_{BEHALF} = 0$

Cell contents:

Wald χ^2 2df	p-value
$ME_{FACETIME}$	ME_{BEHALF}
$ME_{BEHALF}/ME_{FACETIME}$	

	rEARNHRhat (2003 $)					
	$9.44	*$11.57*	*$14.65*	*$19.07*	*$23.25*	*$26.04*
	P_{10}	Q_1	*Median*	Q_3	P_{90}	P_{95}
Black, Two Parents	16.06 0.0003 0.6388 -0.2041 **-0.3195**	16.10 0.0003 0.6709 -0.1677 **-0.2500**	16.33 0.0003 0.7174 -0.1150 **-0.1603**	17.03 0.0002 0.7841 -0.0394 **-0.0502**	18.57 0.0001 0.8471 0.0321 **0.0379**	**19.25 0.0001** **0.8894 0.0800** **0.0899**
White, Two Parents	15.75 0.0001 0.8417 -0.1033 **-0.1227**	15.88 0.0004 0.8738 -0.0669 **-0.0766**	16.24 0.0003 0.9204 -0.0142 **-0.0154**	17.17 0.0002 0.9870 0.0614 **0.0622**	**18.60 0.0001** **1.0501 0.1329** **0.1266**	**19.05 <0.0001** **1.0929 0.1808** **0.1654**
Black, Single Parent	16.08 0.0003 0.4986 -0.1037 **-0.2080**	16.19 0.0003 0.5307 -0.0673 **-0.1268**	16.50 0.0003 0.5772 -0.0146 **-0.0253**	17.28 0.0002 0.6439 0.0610 **0.0947**	**18.47 0.0001** **0.7069 0.1325** **0.1874**	**19.57 0.0001** **[illegible] 0.1804** **0.2408**
White, Single Parent	- - - * 1.7990 0.0624 0.0347	16.00 0.0003 0.7336 0.0335 **0.0457**	**16.45 0.0003** **0.7802 0.0863** **0.1106**	**17.47 0.0002** **0.8469 0.1618** **0.1910**	**18.45 0.0001** **0.9099 0.2333** **0.2564**	**20.30 <0.0001** **0.9522 0.2812** **0.2953**

Estimated for female, US citizen, high school diploma, homeowner, not a student, employed by a private firm, for a Monday in January, 2009, with women's medians of weekly work hours and spouse's work hours, and other variables set to women's means.

* Postestimation test did not converge.

whites the effect turns positive at lower earnings for both education levels. For both races, ME_{BEHALF} turns positive at a lower earnings level for college graduates.

Considering high school diploma holders only, Table 19 compares two-parent and single parent families. Due to attenuation of $ME_{FACETIME}$ and, for higher earnings levels, larger marginal effects for *BEHALF*, the ratio shows the same progression but becomes larger at higher earnings, implying that as earnings rise, single-parent households substitute market services and *BEHALF* activities more strongly than two-parent households. This is consistent with the difference in time resources.

Also interesting is the interaction of the level of earnings and the age of the youngest child in the household. For those earning at or below the third quartile, the marginal- effects ratio declines slightly as the children become older, but at the 90^{th} percentile and above, the ratio rises for older children. Explaining this would go beyond the data, but clearly the behavior of parents bifurcates somewhere between the 75^{th} and 90^{th} percentiles of earnings. For very young children, *BEHALF* time would consist largely of arranging for other people engage in direct, one-on-one care—babysitting, doctor visits, and the like, demand for which is likely to be somewhat inelastic with respect to earnings. As children grow, demand for this type of care diminishes and choices multiply, with demand for these now more varied services becoming more elastic. On this reasoning, parents with low and high earnings alike would be unable to avoid at least some *BEHALF* activity for infants, but as the children grow, low income parents would not acquire as much outside services as those with higher earnings, which would show up as a reduction in the share of time devoted to indirect child care as the children age. High income parents would likely increase their use of outside services and hence devote relatively more time to the task of arranging them.

VI. CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

A. Determinants of Child Care Time Use

The analysis presented here brings a novel and important distinction into the literature. To my knowledge, no previous study has examined the how parents allocate their time among direct and indirect uses for the purpose of building their children's stock of human capital. The model shows that mothers, at least, budget their time between nurturing their children and obtaining out-of-household help with the task in ways that accord with straightforward utility maximization.

An increase in hourly earnings leads parents to substitute market services for child care they provide themselves, as evidenced in the relative shift of time toward indirect child care. This is true for both men and women, and cuts across races and education levels. The effect is stronger for single parent households.

I find that earnings positively affects both types of child care time use, indicating that, at least at the means of the covariates, the income effect on demand for children's human capital dominates the substitution effect arising from the rising opportunity cost of time. For direct child care, the effect falls on both the amount of time used as well as the probability on any given day, with the effects somewhat stronger for men. A higher level of hourly earnings increases the likelihood that a woman will spend some time on indirect child care on a given day, but it has no effect on the mean amount of time used. This activity appears to be a specialty of women, and no significant results for men were found. Increases in earnings attenuate the observed difference between men and women for both types of time use.

Students engage in less of both types of time use, with the amount of time, although not the probability, reduced more sharply for women. This admittedly flawed proxy for opportunity cost of time thus provides limited evidence for a substitution effect.

Schooling is associated with a dramatic increase in the amount of time women spend in direct child care, with college-educated women providing three-quarters again as much time as those lacking a high school diploma, confirming the effect of the latent preference for human capital. The effect is of a lower magnitude but still strong for the probability of engaging in direct care on any given day, and applies about equally to men as well. This implies that, while men provide much less direct child care overall, their preference for human capital still affects the consistency of their contact with their children. Education level contributes to the gender difference in the probability of direct care time but not the amount of time devoted, indicating that the strength of human capital preference on day-to-day consistency tends to be greater for women. Men were more likely to spend time on indirect child care on their diary day as their education level rose; evidence for women is weaker, although better-educated women clearly provide more of this time overall.

Work hours reduce both the likelihood and amount of both types of time use, although the effect is generally weaker for women, confirming earlier studies. But I find that a longer work week has a marginally stronger effect on the men's likelihood of indirect child care. That men and women respond differently to increasing work hours is seen in the decomposition results, which show some evidence that a longer work week increases the differences between men and women.

Home ownership, included as an indicator for household wealth, positively influences direct child care for both sexes and reduces the gap between them. It has the opposite effect on indirect care.

Single female parents spend considerably less time on direct child care, and males much more, than their married or cohabiting counterparts. I found no effect on time used for market services.

I confirm the conclusions of Bollinger and Hirsch (2010) that men, and much less so women, exhibit negative selection in reporting their earnings in the ATUS, resulting in nonignorable missingness in the data.

B. Infrequency of Purchase and Double Hurdle Models

The infrequency of purchase informally appears to be better suited to direct child care, consistent with the assumption of strongly convex preferences and fulfillment of the tangency condition. As expected, the double hurdle model performed better with indirect time use, at least for women.

C. Multiple Imputation

Multiple imputation entails a high cost in effort and, due to software constraints, places effective limits on model selection. It does offer the possibility of increased ability to reject null hypotheses, and more important, to reduce apparent selection bias. I recommend the multiple imputation method for general use with survey data, but caution that the results may not always justify the cost.

While a large number of imputations might be useful when working with small data sets, the minimal, often trivial, difference in estimates among imputations suggests that many fewer imputations would generate essentially identical results with less cost and complexity. However, drawing an unusual sample for one of the early imputations can result in coefficient estimates not converging on the long-run value for several imputations, as was the case in this paper; fewer than 10 imputations would have materially changed the estimate for *rEARNHRhat,* as detailed in Appendix D.

Combining any number of imputations is difficult for some test statistics and for many models. Researchers who consider using MI should determine in advance the feasibility of the models they intend to use, and investigate the use of different software packages. The devil is in the details, and models that are tedious in one package can be less so in another.

Summarizing the results detailed in Appendix D, the removal of some of the apparent missingness at random (MAR) from women's earnings was sufficient to reject the null hypothesis in the IPM model, which would not have been possible with ordinary listwise deletion. First-hurdle probit results tell a different story, and the record, and recommendations, for the use of MI are mixed.

D. Extensions of the Model

Time use data for all members of a household rather than individuals, such as the Dutch data used by Cherchye, et al. (forthcoming) would allow estimation of a multiple equation model to incorporate spouse's time resources more precisely.

Extending the infrequency of purchase model for direct child care time to a seemingly unrelated regression framework would allow other complete estimation of all major categories of time use simultaneously. This holds out hope of building a better model for men, whose infrequent indirect child care time was a problem in this study.

The effect of the age of the youngest child in the household on the estimates is very powerful. Further modeling using dummies and decomposition methods for this variable could uncover differences that estimation at the mean does not.

The influence of the covariates may differ for high- and low-child care time users. The infrequency of purchase model should allow the estimation of quantile regressions, which the raw data do not.

Finally, although the superiority of the infrequency of purchase model for direct child care, and the double hurdle for indirect care, seem evident, it would be desirable to conduct a rigorous specification test. If both methods are estimated by maximum likelihood methods, a Vuong (1989) test would suffice. Development of a method to combine all the necessary parameter estimates for this test from the multiple imputation results is a necessary task for this to be realized.

Many of the participants in the ATUS were excluded from the preceding study. Some are parents whose children have since grown and left home; some are parents-to-be; and some will never have children. A different subset of people is the subject of the next article, which examines the effect of the H1N1 pandemic of 2009 – 2010 in California on work time use. At root the two studies are similar: How do rational, utility-maximizing individuals respond to changes in their environment to minimize the loss, or maximize the gain, from the new circumstances? Many of the same econometric methods and tools are employed, but different conditions in the data, and different questions to be answered, lead to the use of other methods as well.

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APPENDICES

Appendix A

Definitions of Time Use Variables

The dependent variables *FACETIME* and *BEHALF* are the sums of two complementary subsets of the disaggregate child-related time use measures. *FACETIME* activities involve direct interaction with the child. *BEHALF* activities include all activities undertaken to provide or procure some benefits for the child that do not involve primary interaction with the child.

Table 20
Definition of Child Care Variables *FACETIME* and *BEHALF*

FACETIME	ATUS ID	Description
	t030101	Physical care for household children
	t030102	Reading to/with household children
	t030103	Playing with household children, not sports
	t030104	Arts and crafts with household children
	t030105	Playing sports with household children
	t030186	Talking with/listening to household children
	t030203	Home schooling of household children
	t030201	Homework (household children)
	t030301	Providing medical care to household children
	t030199	Caring for and helping household children, n.e.c.
	t030109	Looking after household children (as a primary activity)

BEHALF	ATUS ID	Description
	t030108	Organization and planning for household children
	t030110	Attending household children's events
	t030202	Meetings and school conferences (household children)
	t030111	Waiting for/with household children
	t030112	Picking up/dropping off household children
	t030204	Waiting associated with household children's education
	t030299	Activities related to household child's education, n.e.c.
	t030302	Obtaining medical care for household children
	t030303	Waiting associated with household children's health
	t030399	Activities related to household child's health, n.e.c.
	t080101	Using paid childcare services
	t080102	Waiting associated with purchasing childcare services
	t080199	Using paid childcare services, n.e.c.

Appendix B

Comparison of Estimation Methods for the Double Hurdle Truncated Normal Regression

Cragg's (1971) double hurdle model is estimated here as revised by Lin and Schmidt (1984), assuming conditional independence. The first hurdle, which determines participation in the activity, is a straightforward application of probit and is estimated using maximum likelihood. The second hurdle is a truncated normal regression in which those who have chosen to engage in the activity determine their level of participation, or indeed whether they will actually participate at a nonzero level. This is specified as

$$Prob(x > a) = 1 - \Phi\left(\frac{a - \mu}{\sigma}\right) \quad \text{(C.1)}$$

(Greene, 1993) Different approaches to estimating this model appear in the literature. I investigate three here. Each was estimated using the first imputed set of my data with $sinh^{-1}$*FACETIME* as the dependent variable and the full set of regressors. Each is estimated using all observations, male and female, with a dummy variable to account for the sex of the respondent. All regressions were run in Stata 9. Results are shown in Table 21.

Ordinary least squares assuming a (truncated) normal distribution with robust standard errors, and incorporating no information from the first-tier probit regression, produced the results shown in column 1. The method of Burke (2009), which he incorporates in his user-written Stata module **craggit,** was used to estimate the results shown in estimates the second equation as shown in Column 2. The purpose of his module is to estimate both models with one command and to combine the results in a single panel for ease of analysis. Since the probit equation must be estimated by maximum likelihood, he estimates the second equation using ML as well.[23]

Gould, Pitblado, and Sribney (2003), afterward GPS, present an OLS approximation by maximum likelihood. Estimates using their method are shown in column 3.

Greene (1993) notes that least squares estimates the truncated normal model as

$$\begin{aligned} y_i|y_i > a &= E[y_i|y_i > a] + u_i \\ &= \boldsymbol{\beta}'\boldsymbol{x}_i + \sigma\lambda + u_i \end{aligned} \tag{C.3}$$

where λ is the inverse Mills ratio and the error term, u_i, has zero mean but since its variance is

$$\sigma_{u_i}^2 = \sigma^2(1 - \lambda_i^2 + \lambda_i a_i) \tag{C.2}$$

it is heteroskedastic. Least squares coefficient estimates are generally proportional to maximum likelihood but are frequently attenuated.

Table 21 compares the results of the three models. The coefficients and standard errors of all three are practically identical. GPS succeeds in mimicking the OLS coefficients exactly, while Burke's differ only trivially. Standard errors for all differ by less than 0.1%. I report these in the table at more the usual number of decimal places because otherwise there are no observable differences. Owing to the much greater ease in combining the regression results of the multiple imputations using OLS, I use that method in estimating the second tier double hurdle equation.

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[23] A problem is that this module does not seem to work with the user-written **mim** command for combining the estimates for the imputations.

Table 21

Comparison of Maximum Likelihood and Ordinary Least Squares Results

Second hurdle truncated normal model for *FACETIME* > 0 only, Males and Females

Dependent variable $sinh^{-1}$ *FACETIME*

	1. Ordinary Least Squares				2. Maximum Likelihood (Burke)				3. Maximum Likelihood (GPS)			
	Coefficient	Standard Error	*t*	*p-value*	Coefficient	Standard Error	*z*	*p-value*	Coefficient	Standard Error	*z*	*p-value*
rEARNHRhat	0.009306	0.004483	2.08	0.038	0.009306	0.004479	2.08	0.038	0.009306	0.004479	2.08	0.038
FEMALE	0.176868	0.023480	7.53	< 0.001	0.176875	0.023458	7.54	< 0.001	0.176868	0.023457	7.54	< 0.001
BLACK	-0.126825	0.044485	-2.85	0.004	-0.126831	0.044444	-2.85	0.004	-0.126825	0.044443	-2.85	0.004
WHITE	0.016334	0.032792	0.50	0.618	0.016335	0.032761	0.50	0.618	0.016334	0.032760	0.50	0.618
CITIZEN	-0.058808	0.030362	-1.94	0.053	-0.058808	0.030334	-1.94	0.053	-0.058808	0.030333	-1.94	0.053
HISPANIC	-0.089218	0.028007	-3.19	0.001	-0.089222	0.027981	-3.19	0.001	-0.089218	0.027980	-3.19	0.001
MILITARY	-0.115981	0.060480	-1.92	0.055	-0.115987	0.060424	-1.92	0.055	-0.115981	0.060423	-1.92	0.055
METRO	0.046149	0.024611	1.88	0.061	0.046152	0.024589	1.88	0.061	0.046149	0.024588	1.88	0.061
AGE	-0.002232	0.001465	-1.52	0.128	-0.002232	0.001464	-1.52	0.127	-0.002232	0.001464	-1.52	0.127
OWNHOME	0.007508	0.021512	0.35	0.727	0.007509	0.021493	0.35	0.727	0.007508	0.021492	0.35	0.727
HISCHOOL	0.025504	0.035128	0.73	0.468	0.025504	0.035096	0.73	0.467	0.025504	0.035095	0.73	0.467
COLLSOME	0.022325	0.038341	0.58	0.560	0.022323	0.038306	0.58	0.560	0.022325	0.038304	0.58	0.560
COLLEGE	0.080151	0.057188	1.40	0.161	0.080150	0.057135	1.40	0.161	0.080151	0.057133	1.40	0.161
STUDENT	-0.140090	0.031353	-4.47	< 0.001	-0.140093	0.031324	-4.47	< 0.001	-0.140090	0.031323	-4.47	< 0.001
CHILDAGE	-0.092601	0.002477	-37.39	< 0.001	-0.092606	0.002475	-37.42	< 0.001	-0.092601	0.002474	-37.42	< 0.001
NUMKIDS	0.027446	0.008909	3.08	0.002	0.027449	0.008901	3.08	0.002	0.027446	0.008901	3.08	0.002
PARTNER	-0.025294	0.047203	-0.54	0.592	-0.025298	0.047160	-0.54	0.592	-0.025294	0.047158	-0.54	0.592
SINGLEPT	0.080864	0.041394	1.95	0.051	0.080867	0.041356	1.96	0.051	0.080864	0.041355	1.96	0.051
GOVEMP	-0.065748	0.038731	-1.70	0.090	-0.065735	0.038696	-1.70	0.089	-0.065748	0.038694	-1.70	0.089
PRIVEMP	-0.086044	0.033984	-2.53	0.011	-0.086033	0.033953	-2.53	0.011	-0.086044	0.033951	-2.53	0.011
SELFEMP	-0.040122	0.041244	-0.97	0.331	-0.040110	0.041207	-0.97	0.330	-0.040122	0.041205	-0.97	0.330
VOLUNTR	0.081190	0.143739	0.56	0.572	0.081204	0.143604	0.57	0.572	0.081190	0.143602	0.57	0.572
BUSFARM	0.068171	0.028473	2.39	0.017	0.068172	0.028447	2.40	0.017	0.068171	0.028446	2.40	0.017
TEHRUSLT	-0.008245	0.000776	-10.63	< 0.001	-0.008246	0.000775	-10.64	< 0.001	-0.008245	0.000775	-10.64	< 0.001
TESPUHRS	0.000910	0.000747	1.22	0.223	0.000910	0.000746	1.22	0.223	0.000910	0.000746	1.22	0.223
SUNDAY	0.023723	0.021602	1.10	0.272	0.023724	0.021582	1.10	0.272	0.023723	0.021581	1.10	0.272
MONDAY	0.063376	0.026478	2.39	0.017	0.063380	0.026454	2.40	0.017	0.063376	0.026453	2.40	0.017
TUESDAY	0.040371	0.026795	1.51	0.132	0.040375	0.026771	1.51	0.132	0.040371	0.026770	1.51	0.132
WEDNESDAY	0.049650	0.025608	1.94	0.053	0.049653	0.025584	1.94	0.052	0.049650	0.025583	1.94	0.052
THURSDAY	0.015933	0.026056	0.61	0.541	0.015935	0.026032	0.61	0.540	0.015933	0.026031	0.61	0.540
FRIDAY	-0.113288	0.027618	-4.10	< 0.001	-0.113295	0.027593	-4.11	< 0.001	-0.113288	0.027592	-4.11	< 0.001
HOLIDAY	-0.058821	0.062428	-0.94	0.346	-0.058823	0.062371	-0.94	0.346	-0.058821	0.062369	-0.94	0.346
JAN	0.123241	0.035541	3.47	0.001	0.123247	0.035509	3.47	0.001	0.123241	0.035507	3.47	0.001
FEB	0.098439	0.037558	2.62	0.009	0.098444	0.037524	2.62	0.009	0.098439	0.037522	2.62	0.009
MAR	0.119337	0.038374	3.11	0.002	0.119339	0.038339	3.11	0.002	0.119337	0.038337	3.11	0.002
APR	0.102570	0.036431	2.82	0.005	0.102577	0.036398	2.82	0.005	0.102570	0.036396	2.82	0.005
MAY	0.094480	0.037162	2.54	0.011	0.094486	0.037128	2.54	0.011	0.094480	0.037127	2.54	0.011
JUL	0.046850	0.039934	1.17	0.241	0.046850	0.039898	1.17	0.240	0.046850	0.039896	1.17	0.240
AUG	0.019524	0.039450	0.49	0.621	0.019523	0.039415	0.50	0.620	0.019524	0.039413	0.50	0.620
SEP	0.126778	0.037434	3.39	0.001	0.126784	0.037400	3.39	0.001	0.126778	0.037399	3.39	0.001
OCT	0.132147	0.036757	3.60	< 0.001	0.132152	0.036724	3.60	< 0.001	0.132147	0.036722	3.60	< 0.001
NOV	0.081362	0.038483	2.11	0.035	0.081366	0.038448	2.12	0.034	0.081362	0.038446	2.12	0.034
DEC	0.140871	0.038087	3.70	< 0.001	0.140877	0.038052	3.70	< 0.001	0.140871	0.038051	3.70	< 0.001
Y2003	0.063378	0.028771	2.20	0.028	0.063380	0.028745	2.20	0.027	0.063378	0.028744	2.20	0.027
Y2004	0.056601	0.033113	1.71	0.087	0.056604	0.033083	1.71	0.087	0.056601	0.033082	1.71	0.087
Y2005	0.007898	0.031679	0.25	0.803	0.007898	0.031651	0.25	0.803	0.007898	0.031649	0.25	0.803
Y2006	0.012939	0.031383	0.41	0.680	0.012939	0.031354	0.41	0.680	0.012939	0.031353	0.41	0.680
Y2007	0.040102	0.030833	1.30	0.193	0.040103	0.030805	1.30	0.193	0.040102	0.030803	1.30	0.193
Y2008	0.018924	0.032241	0.59	0.557	0.018925	0.032212	0.59	0.557	0.018924	0.032211	0.59	0.557
Y2009	0.027562	0.032113	0.86	0.391	0.027564	0.032084	0.86	0.390	0.027562	0.032082	0.86	0.390
Intercept	5.257804	0.086825	60.56	< 0.001	5.257794	0.086745	60.61	< 0.001	5.257804	0.086742	60.61	< 0.001

Appendix C

Considerations in Selecting *m* for Multiple Imputation

Figure 3 shows the effects of increasing the number of imputations on estimates for *rEARNHRhat* in the infrequency of purchase model for *FACETIME* for women. The first imputation generated an unusually low coefficient estimate of 0.01937, compared to the overall mean of 0.04197. The estimates "recovered" to the long-run value quickly, with the mean of the next 4 imputations equal to 0.04102. By the 10^{th} imputation, the MI average had reached 0.04018 and did not again dip below 0.04. This raises concern that the MCMC process had not stabilized by the first imputation, although the number of burn-in imputations used was the SAS default of 200. However, imputation number 17 produced a coefficient estimate nearly as low, at 0.02015, so the first imputation may just have been a representation of heterogeneity in the sample. Also with the 10^{th} imputation, the coefficient of variation of the individual coefficient estimates stabilized, and the *t*-statistic crossed the threshold of 2.00, below which it did not again fall. I am not suggesting 10 as the magic number, but in this case, the estimates would not have been notably different had the process stopped there.

This points up the need to do two things when using MI: First, use a sufficient number of imputations, and second, closely examine the estimates of the different imputations, and not just the overall means.

One other interesting result: The standard errors were essentially stationary over the 20 imputations, as expected, but they show positive third order autocorrelation (DW = 1.0986, p-value = 0.0321).

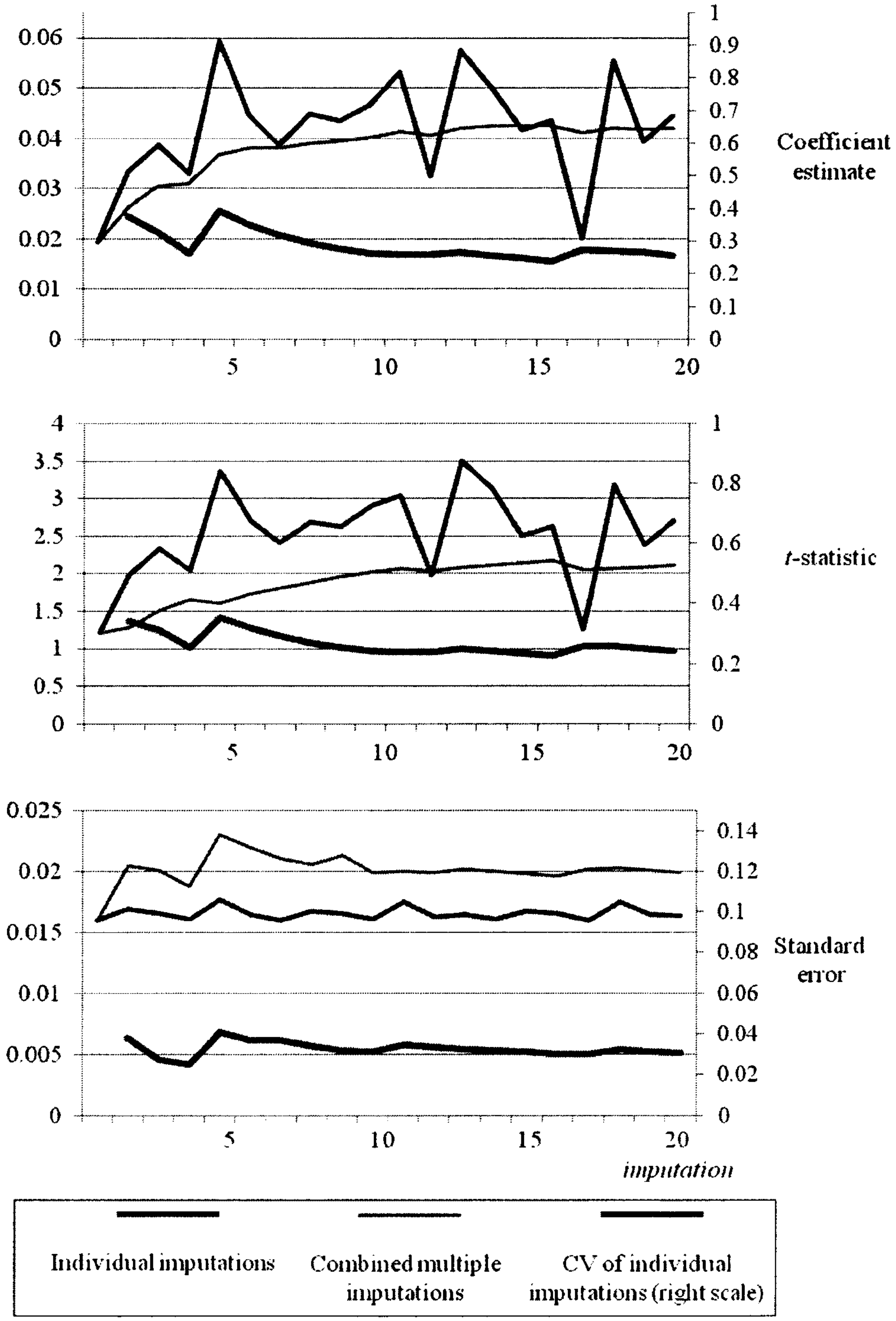

Fig. 3.—Effect of increasing the number of imputations on coefficient estimates, *t*-statistics, and standard errors for *rEARNHRhat* variable

Appendix D

Comparison of Multiple Imputation and Listwise Deletion Estimates

While the literature discusses missingness as being of three distinct types, for survey researchers it is more appropriate to think of it as having three *components*, each of which should be assumed present in the data. Imputation methods of any type can only control for MCAR and MAR missingness, leaving the more intractable MNAR problem unresolved. But a good imputation method can greatly improve results by minimizing the missingness that remains in the data. Survey data cannot be made *clean,* but they can be made cleaner. Good imputation can—but might not—make the difference between successful research and inconclusive results.

Consistent with the conclusion of Bollinger and Hirsch (2010), men in the sample are much less likely to report earnings in the CPS and ATUS; earnings is missing for 20.78% of men but only 12.31% of women ($\chi^2 = 597.3$, 1 *df*, *p*-value < 0.001). But the key issue is not the level of missingness, but whether it is nonignorable. Bollinger and Hirsch found that men become less likely to report their earnings as their earnings rise, creating nonignorable missingness.

They investigated the question by comparing two different sets of CPS data, the regular last month-in-sample files with the March Supplement. My approach is to compare the results of multiple imputation estimates with listwise deletion, or simple omission of observations with missing earnings. Refer to Tables 22 and 23, which show the results of the infrequency purchase model regressions for *FACETIME,* using multiple imputation and listwise deletion, respectively. I examine the coefficients for the earnings

Table 22

Infrequency of Purchase Model (IPM) Results

Listwise deletion

Dependent variable *sinh⁻¹ FACETIME* for Men and Women

Boldface effects are significant at $\alpha \leq .05$

	Men (n=14,804)			*Women (n=23,645)*		
Variable	Coefficient	SE	p-value	Coefficient	SE	p-value
rEARNHRhat	0.0488	0.0275	0.076	0.0043	0.0175	0.804
BLACK	-0.0717	0.2403	0.765	-0.1169	0.1550	0.451
WHITE	0.2531	0.1767	0.152	**0.2638**	0.1277	0.039
CITIZEN	**-0.4022**	0.1635	0.014	0.0860	0.1148	0.454
HISPANIC	**-0.3996**	0.1561	0.010	**-0.5333**	0.1020	< 0.001
MILITARY	-1.3845	1.0220	0.176	-0.1646	0.1632	0.313
METRO	0.0491	0.1343	0.714	**0.2084**	0.0900	0.021
AGE	**-0.0248**	0.0068	< 0.001	**-0.0184**	0.0046	< 0.001
OWNHOME	**0.3186**	0.1144	0.005	**0.2046**	0.0717	0.004
HISCHOOL	-0.2394	0.1666	0.151	**0.5233**	0.1234	< 0.001
COLLSOME	-0.2453	0.1937	0.206	**0.6759**	0.1398	< 0.001
COLLEGE	-0.2401	0.3311	0.468	**1.0707**	0.2113	< 0.001
STUDENT	**-0.4034**	0.1838	0.028	**-0.6164**	0.1070	< 0.001
CHILDAGE	**-0.1867**	0.0095	< 0.001	**-0.1819**	0.0068	< 0.001
NUMKIDS	**0.1124**	0.0473	0.018	**0.1264**	0.0313	< 0.001
PARTNER	-0.2106	0.2465	0.393	-0.2731	0.1561	0.080
SINGLEPT	**0.5238**	0.2114	0.013	**-0.3226**	0.1484	0.030
GOVEMP	0.2441	0.2497	0.328	-0.1696	0.1458	0.245
PRIVEMP	0.1942	0.2316	0.402	-0.1872	0.1296	0.149
SELFEMP‡	---	---	---	---	---	---
VOLUNTR‡	---	---	---	---	---	---
BUSFARM	0.3210	0.1733	0.064	0.0320	0.1109	0.773
WORKHRS	**-0.0300**	0.0042	< 0.001	**-0.0166**	0.0032	< 0.001
SPOUSEHRS	0.0005	0.0038	0.888	-0.0018	0.0029	0.534
SUNDAY	0.0412	0.1107	0.710	**0.2816**	0.0784	< 0.001
MONDAY	0.2627	0.1371	0.055	**0.5582**	0.0970	< 0.001
TUESDAY	0.0965	0.1448	0.505	**0.5334**	0.0968	< 0.001
WEDNESDAY	0.1578	0.1443	0.274	**0.4420**	0.0943	< 0.001
THURSDAY	0.0006	0.1435	0.997	**0.4321**	0.0979	< 0.001
FRIDAY	-0.1797	0.1413	0.204	-0.0791	0.1006	0.431
HOLIDAY	-0.3116	0.3190	0.329	-0.0985	0.1991	0.621
JAN	-0.0097	0.2036	0.962	**0.4212**	0.1317	0.001
FEB	0.2727	0.2033	0.180	**0.4017**	0.1421	0.005
MAR	**0.4428**	0.1929	0.022	0.2445	0.1380	0.076
APR	0.1644	0.1992	0.409	0.2436	0.1426	0.088
MAY	0.2650	0.2044	0.195	**0.3307**	0.1414	0.019
JUL	-0.1184	0.2092	0.571	0.1595	0.1418	0.260
AUG	0.0990	0.1999	0.620	0.0826	0.1411	0.558
SEP	0.1581	0.2033	0.437	**0.5692**	0.1355	< 0.001
OCT	0.3539	0.1980	0.074	**0.4978**	0.1337	< 0.001
NOV	0.2996	0.2112	0.156	**0.2807**	0.1425	0.049
DEC	0.2255	0.2109	0.285	**0.3190**	0.1426	0.025
Constant	**3.9324**	0.4802	< 0.001	**3.8320**	0.2950	< 0.001
adj. R^2	0.09			0.14		
F	**23.78**		< 0.001	**71.01**		< 0.001
df	47, 14756			47, 23597		

† These 4 days are not significantly different at α = .05 in either model

within each of those groups, months do not differ significantly from each other

Year dummy variables were used; none were significant at α = .05

Omitted categories: Other race, less than high school, married parents, nonemployed, Saturday, June, 2010

‡ No earnings were reported for these categories in CPS, so they were omitted from the model

Table 23

Blinder-Oaxaca Decomposition for IPM

Listwise deletion

Dependent variable *sinh*$^{-1}$ *FACETIME*

Boldface effects are significant at $\alpha \leq .05$

	Differential	SE	*p*-value		Decomposition	SE	*p*-value
Female	**3.3004**	0.0294	< 0.001	Endowments	**0.3805**	0.0823	< 0.001
Male	**2.1277**	0.0429	< 0.001	Coefficients	**0.8718**	0.0723	< 0.001
Difference	**1.1727**	0.0520	< 0.001	Interaction	**-0.0796**	0.0961	0.408

Variable	Endowment	SE	*p*-value	Coefficients	SE	*p*-value	Interaction	SE	*p*-value
rEARNHRhat	-0.1298	-1.7700	0.077	-0.8092	0.5936	0.173	0.1183	0.0868	0.173
BLACK	-0.0048	-1.0300	0.964	-0.0037	0.0161	0.941	-0.0012	0.0054	0.969
WHITE	-0.0069	-2.1100	0.304	0.0183	0.0846	0.820	-0.0008	0.0037	0.820
OTHRACE	**< 0.0001**	0.0500	0.035	0.0007	0.0101	0.829	< 0.0001	0.0000	0.829
CITIZEN	-0.0050	-1.6900	0.092	**0.4153**	0.1700	0.015	0.0060	0.0036	0.093
HISPANIC	0.0045	1.4900	0.137	-0.0288	0.0402	0.474	0.0015	0.0023	0.505
MILITARY	-0.0178	-1.3500	0.177	0.0011	0.0010	0.257	0.0157	0.0133	0.240
METRO	0.0001	0.2500	0.805	0.1321	0.1341	0.325	0.0003	0.0008	0.752
AGE	**0.0310**	3.3700	0.001	0.2420	0.3117	0.438	-0.0080	0.0103	0.439
OWNHOME	**-0.0160**	-2.6300	0.009	-0.0855	0.1013	0.399	0.0057	0.0068	0.401
LTHSCHL	-0.0026	-1.0600	0.291	**-0.1136**	0.0292	0.000	**0.0109**	0.0049	0.028
HISCHOOL	0.0017	0.6000	0.546	0.0046	0.0371	0.902	-0.0004	0.0033	0.902
COLLSOME	-0.0021	-0.8700	0.383	0.0447	0.0230	0.052	0.0056	0.0031	0.067
COLLEGE	-0.0006	-0.3000	0.762	**0.1495**	0.0599	0.013	0.0060	0.0039	0.125
STUDENT	**-0.0117**	-2.0900	0.036	-0.0153	0.0153	0.317	-0.0062	0.0062	0.322
CHILDAGE	**0.0467**	3.2300	0.001	0.0332	0.0818	0.685	-0.0012	0.0029	0.687
NUMKIDS	0.0030	1.4400	0.150	0.0265	0.1072	0.805	0.0004	0.0015	0.807
MARRIEDPT	0.0123	0.9300	0.354	**0.2405**	0.1086	0.027	**-0.0358**	0.0163	0.028
PARTNER	0.0007	0.6600	0.508	0.0115	0.0097	0.239	-0.0005	0.0009	0.542
SINGLEPT	**0.0505**	2.6400	0.008	**-0.0861**	0.0299	0.004	**-0.0654**	0.0229	0.004
NONEMP	-0.0341	-0.9400	0.349	0.0371	0.0250	0.139	0.0619	0.0418	0.139
GOVEMP	0.0005	0.7200	0.472	-0.0184	0.0153	0.229	-0.0007	0.0008	0.414
PRIVEMP	-0.0115	-0.5400	0.590	-0.0857	0.0768	0.265	0.0277	0.0249	0.265
BUSFARM	0.0069	1.7600	0.078	-0.0235	0.0167	0.161	-0.0062	0.0045	0.172
WORKHRS	**0.4689**	7.1300	< 0.001	**0.5158**	0.2021	0.011	**-0.2089**	0.0819	0.011
SPOUSEHRS	0.0009	0.1400	0.888	-0.0708	0.1459	0.628	-0.0037	0.0076	0.629
Total	**0.3805**	0.0823	< 0.001	**0.8718**	0.0723	< 0.001	-0.0796	0.0961	0.408

Day of week, month, and year dummies and constant term (coefficients only) are omitted for brevity. Significant effects at $\alpha = .05$ were observed for *SATURDAY (–)*, *JANUARY (–)*, and *MARCH (–)* for coefficients.

variable, *rEARNHRhat*, which is both the key regressor in the models and the variable with the highest rate of missingness. The multiple imputation process constructs the imputed values from a distribution estimated from the actual values of the covariates, and so accounts for missingness that is correlated with one or more of the covariates, i.e., missing at random, MAR. If the coefficient estimates and standard errors differ greatly between MI and listwise deletion, MAR is suggested. But if there is little difference between the estimates, it implies that MI had little effect, and the missingness was either truly random (unlikely for these data) or was correlated with the missing variable itself, that is, nonignorable missingness.

For men, the multiple imputation coefficient is 0.0517 and the standard error 0.0253, giving a t of 2.04 and p-value of 0.042. With listwise deletion the coefficient is attenuated somewhat, to 0.0488, and the standard error at bit larger at 0.0275. The consequence is that, with t = 1.77 and p-value = 0.076, the result is no longer significant, although it is still roughly of the same character. For women the effect is more dramatic. With MI, the result is strongly significant with $\hat{\beta}$ = .0420, SE = .0196, t = 2.15, and p-value = 0.033; with listwise deletion, the standard error actually improves a bit to .0175, but the coefficient estimate nearly vanishes to .0043, resulting in a t of 0.25.

A different tale comes from Table 24, which compares the results for the first hurdle probit model for women. The MI and listwise deletion estimates are very similar, with the marginal effects being attenuated by 13% for *FACETIME* and 9% for *BEHALF*. The standard errors show no pattern. Generalizing from just two data points, it seems likely that the $ME_{FACETIME}/ME_{BEHALF}$ ratios which address the primary hypothesis would have differed little.[24]

Table 24

Comparison of Multiple Imputation and Listwise Deletion Estimates

First hurdle probit model for x = *rEARNHRhat*

	Marginal effect at means	Probit coefficient	Standard error	*p*- value
FACETIME				
MI	0.0083	0.0208	0.0062	0.001
Listwise deletion	0.0072	0.0288	0.0095	0.002
BEHALF				
MI	0.0078	0.0207	0.0076	0.006
Listwise deletion	0.0071	0.0187	0.0054	0.001

All this suggests three things. First, for the change in women's IPM estimate to be so great, MI must have removed much of the bias produced by missingness, implying that for them missingness is strongly correlated with the covariates—i.e., missing at random, or MAR. MI's smaller, though important, effect on men's estimate indicates that there was much less MAR to be removed, implying that their missingness is correlated not so much with the covariates as with the level of earnings itself—missing not at random. This does not allow a test of the sign of the selection bias, but it does strongly suggest that bias exists. Second, the small difference in the probit estimates suggests that the effect of missing value bias varies with model specification, as does the

[24] These models use a slightly different set of variables than the IPM estimates (3 insignificant dummy variables were omitted) but rerunning the models with those variables had negligible effects.

value of removing that bias by imputation. Researchers who use MI should realize that the considerable effort required does not promise a sure improvement in results.

The third, broad, conclusion is that, when we take the usual approach of listwise deletion, we can, at least some of the time, fail to extract the *information* from the *data* which, after all, is the point of empirical research. MI, at worst, does no harm, and improvements in software to make it less cumbersome are welcome.

THE CALIFORNIA H1N1 PANDEMIC AND WORK TIME USE

I. INTRODUCTION AND MOTIVATION

The availability of micro-level time use data from the American Time Use Survey (ATUS) has inspired a number of studies on the determinants of household time use in recent years. Few researchers have explicitly investigated how people shift an activity over a period of time in response to exogenous shocks. Reasons for this might include the brevity of many such shocks, which generate insufficient amounts of data, and the difficulty in matching data those shocks with the time use diaries.

The primary purpose of this paper is to determine, first, whether employed Californians adjusted the amount of time they spent working as a consequence of the H1N1 pandemic of 2009-2010. I hypothesize that work time fell in response to increases in measured H1N1 prevalence as people stayed home to avoid contact with the public and reduce the risk of infection. And since people operate on their perceptions of risk, rather than actual conditions, I expect a stronger response to increases in news coverage of the pandemic than to increases in reported deaths, assuming risk aversion. Also, I expect the adjustment to consist of both an intertemporal substitution, i.e., staying home and shifting work effort away from times of perceived high risk to safer periods, as well as a straightforward substitution of leisure and home production for labor. Assuming that an exogenous shock such as the pandemic would not alter people's preferences for work and leisure, and hence leave the utility function unchanged, I expect to see evidence of shifting. I test this by comparing the results of infrequency of purchase and double hurdle models. I account for the many missing values of hourly earnings with inverse probability weighting and multiple imputation methods.

My paper complements the literature in two ways. 1) It is the first paper, to my knowledge, to estimate the influence of a pandemic on time use. 2) It compares the effects of inverse probability weighting and multiple imputation on time use estimates.

The paper proceeds according to this plan: The introduction and description of the H1N1 pandemic is followed by a review of the literature in Section 2 that focuses on a) time use studies that involve exogenous shocks, and b) a comparison of different models used to estimate time use regressions. A discussion of the theoretical economic, estimation, and imputation models follows in Section 3. Section 4 describes the ATUS and H1N1 incidence data. Section 5 presents empirical models and results, and section 6 concludes and shows a path for future research.

The H1N1 Pandemic

Popularly called the "swine flu," the novel strain known as influenza A virus subtype H1N1is one of a long line of swine-origin influenza strains that can be transmitted from pigs to people. Most cannot be passed from person to person and are usually harmless, but some, such as H1N1, are contagious among humans and can have devastating effects. Such zoonotic swine flus break out in human populations from time to time, driven by the ongoing evolution of the virus.

The H1N1 virus is suspected of having first spread to humans in the village of La Gloria, Veracruz state, Mexico, sometime in 2008, but was not positively identified until April, 2009. The town is home to a large hog confinement farm. Many of its residents make a weekly commute to work in Mexico City 160 miles away, which may have helped speed the spread of the virus into the human population.

In California, media interest in the nascent H1N1 pandemic was scant while the disease remained confined to Mexico but grew rapidly once the first cases in California were reported on April 15 and 17. Lurid reports of the progress of the disease in Mexico plus fear of an imminent invasion by the previously unknown microbe provided the perfect setting for selling newspapers using alarmist and omnipresent coverage.[25] The concern might have been overstated but was not misplaced; people over the age of 60 usually bear a disproportionate incidence of a flu outbreak, but H1N1 tended to strike young adults and children, and induced pneumonia even in some previously healthy persons. As a flu panic roared across the state, schools closed early for the summer as a preventive measure, and anecdotes of people avoiding contact with the public became common. The number of persons seeking treatment for flu-like symptoms spiked in late April and early May, overburdening the state's medical care system. Few of the early cases—only 5 to 7%—tested positive for H1N1, and even some of the media wondered whether they had cried wolf. Following the initial panic—and drop in media coverage—reported incidence plunged, and as a result the rate of positive tests rose to 49% by mid-June. (Baxter, 2010) Confirmed cases in the state rose rapidly through late June and then declined through July, although hospitalizations continued to rise throughout the summer.

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[25] The death rate reported in Mexico early in the pandemic seems to have been overstated. The simple case fatality ratio is calculated as the number of deaths from a disease divided by the total number of cases. Since deaths are generally reported with some accuracy, if the number of total cases is severely underreported, which commonly happens in poor countries with limited medical care facilities, the death rate can appear to be quite high. The reported Mexican case fatality ratio through July 19, 2009 was 1.23%, compared with 0.68% for the US over the same period. (Garske, et al., 2009)

The number of deaths rose sharply in late June and reached a first-wave peak of 24 in the first week of August, declining to fewer than 10 weekly in mid-September. The number of hospitalizations stabilized at around 175 weekly though late summer.

However, as California children returned to school in mid-August, the second wave of the pandemic began. Hospitalizations rose in mid-September, with a rapid escalation in October, and reached a weekly peak of 773 in the last week of October. (CISP Weekly Report, Week 43, 2009) Deaths peaked in the week ending November 14 at 49. (CDPH, 2010) Media coverage, however, did not respond as it had in the spring. There was an observed increase in coverage, but this neither rose as sharply as the actual incidence of the disease nor approached the level seen in April and May. Despite the perceived severity of the pandemic, the actual number of deaths was small relative to historical flu outbreaks. The 596 deaths reported statewide over the pandemic come to about one death per every 62,000 Californians; using low-end estimates, one in every 212 Americans perished in the Spanish flu outbreak of 1918. Also, 2,127 traffic fatalities were recorded statewide for the period April – December 2009 alone. (California Highway Patrol, 2011)

National records on H1N1 incidence are not readily available for general researchers from Centers for Disease Control, and most state health agencies do not provide data. It is extremely fortunate that CDPH has maintained a freely-available set of incidence data online since the early days of the pandemic. The availability of these data, along with California's large population and its status as the first-wave US state in the H1N1 pandemic, made it an ideal subject for this study.

Searchable online newspaper archives were the source of data on H1N1 coverage in the media.

II. LITERATURE REVIEW

A. Time Use Studies

Casual observation indicates that people alter their usual schedules in response to potentially dangerous localized or broadly regional events of any kind, such as storms and earthquakes. But most of these are of relatively short duration—days or even hours—and so their effects cannot be measured by time use diaries. Even some severe pandemics, such as the SARS outbreak of 2003, pass too quickly to make an observable effect. The H1N1 pandemic lasted nearly a year, and came in two separate waves, which generated a relatively large number of observations in the ATUS diaries.

Few time use studies have combined ATUS data directly with data from external sources. Kalenkoski, Ribar, and. Stratton (2005) used local area unemployment rates as a control variable in a study of the effects of marital status on parental child care. This variable did not significantly affect child care time use. Connolly (2008) modeled the effect of weather on work effort using a Tobit specification. She combined ATUS data with daily weather data finding limited evidence of shifting of work from sunny days to rainy ones. Christian (2009) controlled for exogenous weather effects using Connolly's data, and used metropolitan area traffic accidents as an instrument in a study of the length of the daily commute and health-producing activity time. Hamermesh, Myers, and Pocock (2008) incorporated television schedules and time zone definitions in a study of the timing of market work and sleep. Going further, Bertrand and Schanzenbach (2009) conducted their own survey, modeled after ATUS, to gather more information about food intake in a study of the effect of eating, as a secondary activity, on obesity.

The Tobit model (Tobin, 1958) has appeared in several time use studies. (See among others Floro and Miles, 2001; Craig, 2006; Kalenkoski, et al., 2005, 2007, and 2009; Kalenkoski and Foster, 2008; Connolly, 2008; Christian, 2009.) Its familiarity, and the availability of software to estimate it, have made it widely used, perhaps more than is warranted. Stewart (2009) showed that Tobit will generate biased results under situations typically present in time use data and that a double hurdle or infrequency of purchase model will perform better in most situations. Where the dependent variables rarely take on zero values, as in Gronau and Hamermesh's (2008) study of the demand for variety in time use, OLS is capable of generating unbiased estimates.

A fundamental problem with using Tobit is that it assumes that some limiting value, in this case a zero, it s not the true value but obscures a latent value below (or above) that. In Tobin's archetypal case, some households moved between the two rounds of an expenditure survey and were not sampled in the reinterview, so their second-round spending is censored. In this case zeros in the data do not represent true zeros, but instead some unobserved value. (Tobin, 1958)

Time use data are replete with zeros, but for a different reason. The one-day diary period is much shorter than the period of analysis of interest to any researcher. A zero time use for any given day might indicate a person in a corner solution who never does the activity, or it could result from the obvious fact that people do not do every activity they ever engage in, every single day. Frazis and Stewart (2010) show that the nonzero day-to-day variation in time use results in data that, analyzed from a longer-term perspective, show truncation at zero, but not censoring. For time use data, the question is not what value the zeros really represent; they represent zeros. The question is *why* they are zero.

The sample selection model developed by Heckman (1979) has also been considered for time use analysis, but like the Tobit model, it does not suit the data. Heckman's model assumes that the dependent variable is unobserved for some nonrandom subsample of the data, but this does not describe zero time use values.

The infrequency of purchase model, or IPM (Deaton and Irish, 1984) has been widely applied in modeling consumer expenditures from survey data (Sanchis-Llopis, 2001; Mihalopoulos and Demoussis, 2002; Pierani and Tiezzi, 2011). Hamermesh and Trejo (2010) compared it to the double hurdle in their study of immigrants' time use. It can be estimated by OLS after the dependent variable has been transformed to accommodate uncertainty about long-term time use.

A seminal paper by Cragg (1971) presented a method for estimating the decision to purchase and the quantity decision within a unified framework but allowing for different sets of covariates. Known as the double hurdle, or two-part, model, it has been used in various forms to model consumption expenditures for goods such as cheese (Gould, 1992), rice (Gao, Wailes, and Cramer, 1995), prepared meals (Newman, Henchion, and Matthews, 2001), and tobacco and alcoholic beverages (Madden, 2001). Bettin, Lucchetti, and Zazzaro (2009) incorporate endogenous regressors into the model to estimate workers' remittances using LIML. They use a reduced form model and assume that endogeneity exists only for the second hurdle and not for the probability of making remittances.

The double hurdle is potentially applicable for time use studies because it addresses the existence of zeros in the data and allows participation in the activity and the extent of that participation to be estimated separately. Stewart (2009) found this model to produce relatively unbiased results when the participation decision is affected indirectly by the covariates through the consumption variable, but it delivered biased results when the relationship was direct.

Recent studies (Daunfeldt and Hellström, 2007, Wodjao, 2007, and Vaaraa and Materoa, 2011) have found the double hurdle preferable to the Tobit model for time use estimation. Foster and Kalenkoski (2010) concluded that estimation by Tobit is more susceptible to changes in time-diary window length than OLS. Wooldridge (2011) notes the superiority of the double hurdle model to the sample selection model in estimating hours worked.

The original Cragg model is not simple to fit, since both parts of the likelihood function must be maximized simultaneously; "two-part model" does not imply "two-step estimation." (Fennenma and Sinning, 2007) Lin and Schmidt (1984) observed that the popularity of Tobit over the Cragg model was likely due to greater familiarity with, and better availability of software to perform, the former, and generalized the model to a conditional independence assumption.[26] Recent applications of the double hurdle (Burke, 2009; Hamermesh and Trejo, 2010) simplify matters by estimating the models with fully

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[26] Sadly, this situation persists nearly 30 years later. Popular software packages still have limited and temperamental double hurdle capabilities. As a result the full independence specification prevails.

independent errors, accomplished by estimating the probit for all observations and the second, truncated normal, model, for nonzero observations only, with no simultaneity.

B. H1N1 Pandemic Risk Perception Studies

Ibuka, et al. (2010) designed and conducted a scientific survey of 1,290 Americans on H1N1 risk perception in late April and May 2009, shortly after the disease had entered the country. They measured media attention by counting the nationwide frequency of newspaper articles and television and radio broadcast transcripts on the subject of "flu" using *LexisNexis® Academic.* They found a significant correlation (r = 0.91) between newspaper and television coverage of the subject, and following Hochman, et al. (2008), relied on newspaper articles alone. They found that women had higher perceptions of risk of contracting H1N1, a greater interest in taking both preventive and curative medicine to combat the disease, and were far more likely to gather information about the pandemic. They found a small but significant relationship between the number of reported cases of H1N1 and people quarantining themselves in some way, but no relationship between the number of deaths and quarantine efforts. (Note that very few H1N1 deaths had actually been reported in the US by the end of the survey on May 26, including precisely 1 in the state of California, where the disease entered the country.) 2.1% of the respondents overall said they had stayed home from work due to the outbreak.

Regarding specific time-use aspects of H1N1, Jones and Salathé (2009) found that avoidance of contact with persons outside the household—"social distancing"— took many forms during the pandemic. In a nonprobability internet-based sample of 6,249, 69% of whom were Americans, initiated at Stanford University shortly after the first reported case in California, and spread through online social networks, they found that avoiding work ranked among the least common responses to the pandemic. But considering that the most popular responses were "wash hands more frequently," "avoid travel to affected foreign countries or states," primarily Mexico, the source of the virus, and "avoid people sneezing or coughing," even infrequent avoidance of work would account for a greater reallocation of time than other flu-avoidance strategies.

III. THEORETICAL MODEL

A. Economic Model

The model seeks solely to express the effect of a reduction, or shift, in work time to avoid contracting H1N1.[27] An individual's work time and consequent money income would be orthogonal to many factors affecting utility maximization, such as goods prices, behaviors that have long-term effects on health, and the actual underlying risk of contracting the disease, which would be determined by the prevalence of the virus in the population. I consider an individual *i* with a twice-differentiable utility function

$$U_i = U(X_i, N_i, h_i) \tag{3.1}$$

where *X* and *N* are vectors of market and nonmarket goods, respectively. Market goods must be purchased with money income *M* and are subject to prices p_x, but prices are exogenous to the change in the individual's work time. Nonmarket goods include both leisure and home-produced goods; in this context the distinction is irrelevant. Both require own-time inputs *T* which face a daily allocation of a weekly average constraint of

[27] Assuming altruism, people would also reduce work time when ill to avoid spreading the disease, but that would not affect the model.

$\bar{T} = 168 - WORKHRS$, defined as usual weekly work hours. h is the individual's current health stock, modeled as a form of human capital following Grossman (1972). Health would depend on market goods related to health *(G)*, such as medical care; long-term behaviors that invest in health *(I)*, which could be positive, such as following a healthy diet, or negative, such as smoking or drag racing; and the individual's endowment of health-related characteristics *(E)*. For the short-run model I employ, these can all considered fixed, and the health stock production function simplifies to merely

$$h_i = H(s_i; \bar{G}_i, \bar{I}_i, \bar{E}_i) \tag{3.2}$$

where s represents exogenous shocks to health. Some shocks might be beneficial but contracting H1N1 can be assumed to be strictly negative $\left(\frac{\partial h}{\partial s} < 0\right)$. Flu of any type can be transmitted and contracted during ordinary everyday activities and without direct physical contact, so I assume these shocks to be unaffected by health investment activities (*I*) and treat them as random. I describe them as

$$s_i = S(\mu_i, B_i) \tag{3.3}$$

where μ consists of stochastic shocks to health, which I limit to contracting H1N1, while B involves short term behavioral responses, which can ameliorate or avoid these shocks. I assume that people are risk averse to these shocks and will respond to elevated risk by incurring avoidance higher costs. I define B to consist solely of time taken off from work to avoid potential exposure to the H1N1 virus, so missing work would be expressed as an increase in B. Staying home from work might prevent catching the flu and should at worst be harmless, so $\frac{\partial s}{\partial B} \leq 0$.

The income *(M)* and time *(T)* constraints are of in the usual form, with $\frac{\partial M}{\partial B} \leq 0$ and $\frac{\partial T}{\partial B} = 1 > 0$, since taking time off from work would reduce money income, at least for non-salaried workers,[28] but would in equal measure increase time inputs available for leisure and household production.[29] Hence, the marginal effect of a temporary reduction in work time—and thus an increase in *B*—on utility is

$$\frac{\partial U}{\partial B} = \frac{\partial X}{\partial M}\frac{\partial M}{\partial B} + \frac{\partial N}{\partial T}\frac{\partial T}{\partial B} + \frac{\partial h}{\partial s}\frac{\partial s}{\partial B}. \tag{3.4}$$

For $\partial B > 0$, the first right-hand term in (3.4) will be negative. Since $\frac{\partial T}{\partial B} = 1$, the second term would become $\frac{\partial N}{\partial B} > 0$. The third term is nonnegative, but its magnitude would be impossible to evaluate definitely for an individual due to the partly random nature of *s*.

Utility maximization would require an individual to set the potential positive effect on the health stock *h*, as well as the gain in leisure time and home production *N*, against the reduction in money income *M* and hence consumption of market goods *X*. Setting $\frac{\partial U}{\partial B} = 0$ as a first-order condition, the individual would choose *B* such that

$$-\frac{\partial X}{\partial M}\frac{\partial M}{\partial B} = \frac{\partial N}{\partial B} + \frac{\partial h}{\partial s}\frac{\partial s}{\partial B}. \tag{3.5}$$

This choice would depend crucially on the individual's perceptions of the risk of contracting the flu, of serious health problems if infected, and of the efficacy of avoiding contact with the public, all of which would affect the magnitude of $\frac{\partial s}{\partial B}$ and so the last

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[28] If people shift work time from perceived high-risk times to safer ones, they also shift, rather than reduce, income as well. Even so, income would be less optimally timed, compared to a no-flu scenario. This would reduce the magnitude, but not change the sign, of the first right-hand term in (3.4).

[29] Using ATUS data, Donald and Hamermesh (2009) found that even a small amount of work time on a diary day led to a reduction in both leisure and household production time.

term.[30] If missing a day's work can prevent catching the flu and avoid a serious illness or even death, it could be overwhelmingly large. Of course, it could, and most often would be, zero, but in any event it would be unobserved and so unknown to the individual. In the highly urbanized environment of the California counties represented in the sample, local news media reports would be a major, perhaps the most important, influence on risk perception. Demographic groups likely vary in risk preference. Income constraints differ quantitatively, but also in terms of diversification, as between single- and multiple-income households, and those with and without nonlabor income. Some individuals would thus have a predisposition to respond to the pandemic more strongly than others.

B. Model Specifications

I estimate both infrequency of purchase and double hurdle models due to the accumulation of evidence that they are more appropriate for time use data than the Tobit model used in earlier studies.

i. Infrequency of Purchase Model (IPM)

The key characteristic of the IPM model (Deaton and Irish, 1984) is that all individuals are assumed to be doers of the activity at least some of the time, although not necessarily on the diary day. This seems appropriate for work time use when the sample is restricted to employed persons only. Following Stewart (2009) and Keen (1986), I define diary-day time use for purpose k of N possible uses by individual h as

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[30] During severe periods of the pandemic, the magnitude of $\partial N/\partial B$ would likely be reduced because closures of businesses and public attractions would reduce opportunities for leisure. Staying home from work would really mean staying home.

$$e_{hk} = \frac{w_m\{\bar{c}_{hk} + u_{hk}\}}{p_{hk}}, k = 1,. . ., N, \tag{3.2}$$

where e_{hk} is the observed diary-day time use, $\bar{c}_{hk}$ is long-term mean daily time use, and u_{hk} represents a random disturbance term, $E(u_{hk}) = 0$. The Bernoulli-distributed indicator $w_{hk} = 1$ if the individual reported engaging in the activity on the diary day, 0 if not, and p_{hk} denotes the probability that the individual does the activity on a given day. u_{hk} is constrained to be $\geq -\bar{c}_{hk}$ and so e_{hk} is always nonnegative. We thus have terms for each of the two types of measurement errors in the data: w_{hk}, the censoring variable, and u_{hk}, which captures errors in variables. The model assumes w_{hk} and u_{hk} to be independently distributed.

Defining mean daily time use as a linear function of a set of characteristics $\boldsymbol{X}$ which influence time use in activity k gives

$$\bar{c}_{hk} = \boldsymbol{\beta}_0 + \boldsymbol{X\beta} \tag{3.3}$$

Combining equations (3.2) and (3.3) gives

$$e_{hk} = \beta_0 + \boldsymbol{X\beta} + \left\{\frac{(w_{hk} - p_{hk})\bar{c}_{hk} + w_{hk}u_{hk}}{p_{hk}}\right\} = \beta_0 + \boldsymbol{X\beta} + \eta_{hk} \tag{3.4}$$

Subtracting η_{hk} from both sides defines the transformed dependent variable

$$y_{ipm} = \{e_{hk} - \eta_{hk}\} = \beta_0 + \boldsymbol{X\beta} \tag{3.5}$$

Stewart (2009) shows this to be an unbiased estimator using OLS.

I constructed the η term as follows: a) w is set to 1 if the respondent engaged in the activity on the diary day, 0 if not. b) p is identified as the cumulative normal probability of engaging in the activity from a probit regression on a selection of the covariates. c) $\bar{c}$ is estimated by an OLS regression of the time use variable on another selection of covariates, using only those respondents who reported nonzero time use. Finally, d) u is generated as a random normal term with mean zero, constrained so that $\{\bar{c}_{hk} + u_{hk}\}$ meets the nonnegativity requirement. Once constructed, η is subtracted from actual observed time use to form a new dependent variable y_{ipm}, for the OLS estimation.

The resulting dependent variable can take on negative as well as positive values, but not, except trivially, zero. It captures both the probability of participating in the activity on the diary day (p) and individual variation about the observed diary day value (u). It also resolves the piling-up-of-zeros problem that makes OLS a biased estimator for the raw data. Essentially, it scales the dependent variable downward to accommodate random non-participation, using a different scaling parameter for each observation which is partly deterministic ($\bar{c}$) and partly stochastic (u).

ii. Double Hurdle Model

This model, proposed by Cragg (1971), has been used in many household expenditure models. It assumes a corner solution in which, given prices and incomes, many households choose never to consume the good, and is appropriate for goods such as tobacco and alcohol. It holds two distinct advantages in such studies over the Tobit model, which is nested in it; the two regressions need not include the same regressors, and the neither the signs nor the magnitudes of coefficients for variables that do appear in both need be the same.

Cragg pointed out that there are two hurdles to overcome before a positive result is observed, hence the name. First, the individual must have a desire to participate in the activity, and second, conditions must be favorable for the individual to realize participation. As originally specified by Cragg, the model assumed independence between the two models. Omitting the time subscripts in the original, he proposed a first-tier function for the participation decision

$$f(y = 0|\boldsymbol{X}_1, \boldsymbol{X}_2) = C(-\boldsymbol{X}'_2\gamma/\sigma) + C(\boldsymbol{X}'_2\gamma/\sigma)C(-\boldsymbol{X}'_1\boldsymbol{\beta}) \tag{3.6}$$

which he suggested could be estimated by probit. Given a nonzero outcome, his corresponding density function for positive values of y is

$$f(y|\boldsymbol{X}_1, \boldsymbol{X}_2) = (2\pi)^{\frac{-1}{2}}\sigma^{-1}e^{-(y-X'_2\gamma)^2/2\sigma^2}C(\boldsymbol{X}'_1\boldsymbol{\beta}) \tag{3.7}$$

(Cragg, 1971)

Lin and Schmidt (1984) relaxed the independence assumption. As restated by Wooldridge (2002), the model becomes

$$f(y|\boldsymbol{X}, y > 0) = [\Phi(\boldsymbol{X\beta}/\sigma)]^{-1}\,\{\phi[\mathrm{y} - \boldsymbol{X\beta}/\sigma]/\sigma\}, y > 0 \tag{3.8}$$

The cumulative density is equal to one due to the inclusion of the term $[\Phi(\boldsymbol{X\beta}/\sigma)]^{-1}$. The corresponding density function for positive values of y is

$$f(y|\boldsymbol{X};\boldsymbol{\theta}) = [1 - \Phi(X\gamma)]^{1[y=0]}\{\Phi(X\gamma)[\Phi(\boldsymbol{X\beta}/\sigma)]^{-1}[\phi(\{\mathrm{y} - \boldsymbol{X\beta}\}/\sigma)/\sigma]\}^{1[y>0]} \tag{3.7}$$

The Tobit model is nested within this when $= \boldsymbol{\beta}/\sigma$, although, as Greene (1993) observes, this requires the coefficients to be the same in both regressions. The second tier equation is estimated as a truncated normal model.

The corner-solution nature of this model that might seem to disqualify it for a study of work time use. By definition, every employed person goes to work at least some days. The IPM model, which assumes that everyone in the population is a doer of the activity but does not engage in it every day, probably is a better fit for work time use models generally. But if the contagious H1N1 pandemic discouraged people from going to work to avoid exposure to the disease, it would show up as a discrete effect—at least some people would have stayed home from work some days during the pandemic. People who went to work anyway might have worked the same amount of time as in the absence of H1N1, although crowd-avoidance tactics, such as arriving or leaving work at irregular times, could have reduced it. Also, workers in retail trades or similar occupations would have faced reduced demand for their services, resulting in temporarily shorter work hours. The double hurdle allows both hypotheses to be examined. The probability of an individual clearing the first hurdle—whether or not to go to work—is modeled by a probit regression. The second hurdle, how much time to spend at a work, given that the first hurdle is cleared, is estimated as a truncated normal regression. Unlike the Tobit, the second equation may have different regressors from the first, and variables that are repeated are allowed to have different signs. So, the two decisions—going to work, and how long to stay at work, exhibit conditional independence, which is the key feature of the model.

iii. Missing Data and Multiple Imputation (MI) Methods

Missing data values plague survey data, and the type of missingness affects the strategy for dealing with it. A brief discussion focusing on estimation strategies follows.

Let the probability of a variable y being observed for individual i be $P(y_i = y_i^*)$, and let X represent a vector of other related variables. If values are missing completely at random (MCAR), then $P(y_i = y_i^*) \mid (y_i, X_i)$ is a constant. That is, missingness is a truly random phenomenon and cannot be explained by either the missing variable itself or any other variables. In such cases, listwise deletion—simply deleting observations with missing values—is a sufficient solution. The only cost is a reduction in degrees of freedom and a consequent loss of power, but no bias is introduced, because the observations with missing values are not different, on average, from those with reported values. Deleting the observations reduces the amount of *data,* but not the amount of *information.* Unfortunately, we rarely see MCAR in economic data.

A variable is said to be missing at random (MAR) if $P(y_i = y_i^*)=f(X_i)$, i.e., if missingness can be explained by other variables in the data. In this case, missingness can be modeled because the other variables contain information on missingness. In practice, omitted variables often produce a poor-fitting model and noisy imputations, particularly with survey data. The choice of imputation model and variables is crucial.

If $P(y_i = y_i^*)=f(y_i)$, the data are said to be missing not at random, or MNAR. This case, which appears often in economic data, is most troubling. It is difficult to model missingness because the information needed to make imputations is contained in the missing values themselves; the messenger is lost, and with him, the message. Greenlees, Reece, and Zieschang (1982), using a stochastic censoring model with auxiliary data, showed the existence of MNAR in CPS earnings data.

Several strategies exist for imputing missing values in typical survey data. The usual approaches in the literature range from listwise deletion—which is simple but usually biased—to single imputation. Single imputation methods impute each missing value once, that is, they complete the data set by filling in the missing values. A related approach is inverse probability weighting, or IPW. Strictly speaking, this is not an imputation method, as it does not replace missing values, but weights the nonmissing values by the inverse of their probability of being observed.

Single imputation results in understating the amount of uncertainty about the imputed value; in fact, it implies perfect certainty that the imputed value is the correct one. Multiple imputation, or MI, based on the method of Rubin (1987), is designed to solve this problem. Impractical until recent years, this method has become popular in some fields, particularly medical research, with the arrival of cheap computing power and software designed to simplify the process of combining the estimates, although it has not yet become common in economics. It typically uses estimates of missing values generated by an Expectations-Maximization (EM) process.

Because of resource constraints, many studies have used fewer iterations, commonly three to five, claiming that this provides an acceptable level of efficiency. Schafer (1997) argues that as few as $m = 3$ imputations is sufficient, because the Monte Carlo error is proportionate to the level of missingness, not to the number of observations, and because Rubin's Rule explicitly accounts for the Monte Carlo error. But Graham, Olchowski, and Gilreath (2007), working from constructed data, show that a using a smaller number of iterations can lead to a large loss of statistical power. They show that 20 iterations reduced the power falloff to less than 1% with 10% missing data, a point also made by Yuan (2000). They also argue that a small number of imputations does not even permit efficiency to be estimated accurately. In my study of child care time use in the first section of this paper, involving much larger data sets, I used 20 imputations. I found that the combined coefficient estimates tended to converge to a stable value in 7 to 10 imputations, although the data need close watching, because the draw of a single extreme imputation can impede convergence.

iv. Work Reduction vs. Work Shifting

Assuming that work time was affected by the pandemic, the question becomes, how much did Californians simply reduce market work effort in favor of leisure and home production, and how much did they shift market work from more to less risky time periods? I incorporate the use of a lag value of the independent variable to capture this. Work time use would be reduced by a high level of current, or at least recent, H1N1 incidence. A high 1- or 2-week lag value might be associated with an increase in current

Table 25
First- and Second-Order Autocorrelations of *M_DMA*, by DMA
All observations

Boldface effects indicate significant autocorrelation at $\alpha = .05$

	First Order Autocorrelation			Second Order Autocorrelation		
		p-value			*p*-value	
AC Nielsen DMA	DW	< DW	> DW	DW	< DW	> DW
Bakersfield	**1.068**	< 0.001	0.999	**1.128**	<0.001	0.999
Chico/Redding	**1.343**	0.004	0.996	**1.497**	0.029	0.972
Fresno/Visalia	2.016	0.468	0.533	2.017	0.525	0.475
Los Angeles & Palm Springs	**1.289**	0.002	0.998	**1.556**	0.047	0.953
Monterey/Salinas	**1.242**	0.001	0.999	2.108	0.656	0.344
Sacramento/Stockton/Modesto	**1.081**	< 0.001	0.999	**1.323**	0.005	0.995
San Diego	**1.193**	0.001	0.999	1.808	0.237	0.763
San Francisco/Oakland/San Jose	**1.345**	0.004	0.996	1.851	0.289	0.711
Sta. Barbara/Sta. Maria/S. Luis Obispo	**1.366**	0.005	0.995	**1.369**	0.008	0.992
Yuma, AZ/El Centro, CA	1.621	0.058	0.942	1.994	0.491	0.509

work effort as people work extra hours to avoid a net reduction in money income.[31]

Incorporating lag values introduces a time-series element into the data and raises the issue of autocorrelation. Table 25 shows the results of Durbin-Watson tests on the relative frequency of newspaper articles published on the H1N1 pandemic, which is the basis for *M_DMA*, main incidence variable in the model. These were conducted for the largest newspaper in each of the 10 ACNielsen Designated Marketing Areas, or DMAs, in the data. For all but two of the newspapers, the *Fresno Bee* and the *Yuma Sun,* there is strong evidence of positive first-order autocorrelation. Less obvious is second-order autocorrelation; two of the three largest metropolitan dailies, the *San Francisco Chronicle* and the *San Diego Union-Tribune*, show none, and it is present but much weaker in the largest, the *Los Angeles Times*. It persists strongly in the *Sacramento Bee,* but is generally weaker in all cases. The implication is that spikes in H1N1, real or perceived, generated waves of news coverage that lasted at least a week but weakened within two weeks. Thus, while this presents a problem for observations in the Sacramento area and some smaller DMAs, I use the two-week lag value for H1N1 incidence.[32]

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[31] This would differ from what could be called "swine flu fatigue"—at some point in the pandemic, people's new behaviors begin to fade as they return to pre-pandemic habits even though the actual risk—and even the perceived risk—have not fallen. Ibuka, et al. (2010) found evidence of this. This would be a long-term effect, as opposed to one that would occur over a fortnight as measured by the lag value of the regressor.

[32] The autocorrelation could have been dealt with by taking differences. I chose not to, for two reasons: 1) While this would have made the series stationary, it would also have complicated the interpretation of the primary variable of interest. 2) Ideally, I would measure *M_DMA* not over the artificial and arbitrary period of a fixed seven-day week; instead, I would record it over a *news cycle*; once the news moves on to a new topic, and the old one fades from public view, a new measurement period would begin. This is one instance of the effects of the unavoidable practice of measuring time in fixed units rather than by the passage of events. Since even when news reports on a topic are high, news article frequency will fluctuate somewhat during a news cycle, and so the variable would show a nonzero *within-cycle* variance, which is

IV. DATA

A. ATUS and CPS data

The initial sample consisted of all 112,038 participants in the American Time Use Survey (ATUS) from its inception in 2003 through 2010. Geographic location variables were obtained from the linked Current Population Survey (CPS) using the method described in Appendix C. Omitting individuals under the age of 20 and over 64 left a working-age adult sample of 84,892, and omitting retired and disabled persons reduced the sample to 84,561. Due to the redefinition of metropolitan areas with the introduction of the Census 2000 system, only those ATUS participants who completed the CPS May 2004 or later were retained, reducing the sample to 62,542. Omitting all but California residents left 6,237 observations. Participants with censored CPS geographic data could not be matched with flu incidence measures at the DMA level and were omitted from the sample, leaving a sample of 5,799. Omitting nonemployed persons[33] reduced the sample

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essentially noise in this context. But it is the *between-cycle* variance that we wish to account for in the model. If the news cycle lasts more than one week, as implied by first-order autocorrelation, then the first difference will, for some weeks, merely represent the level of within-cycle variance, which should be uncorrelated with the between-cycle variance, and like the within-cycle variance itself, this difference will just be noise. It clearly would not represent between-cycle variation. The pattern of autocorrelation here implies that the news cycle lasts more than one week but, for at least some areas, less than two. Keeping the two-week lag value in the model is the best available approximation of measuring time as "current news cycle" and "previous news cycle."

The one-week lag value clearly does not belong in the model. In this case, the strong first-order autocorrelation means the one-week lag is simply measuring the latter part of the same news cycle as the current-week value; it only appears to be a separate variable because of the way we define the measurement unit.

[33] My purpose is to estimate the effect of perceived H1N1 risk on work time, that is, to see if people missed work to avoid catching the flu, not because they were already sick from it. However, I left those persons who said they missed work due to illness in the *previous* week (ATUS variable *TEABSRSN* = 5) in the sample. They were 27 observations overall, including 6 in the pandemic period. Of these 6, 2 recorded their diaries in the first week of May, 2009, when the flu panic was at its peak, but few people had actually contracted the disease; 2 on July 6, 2009, during the pandemic's summer lull, and 2 in early spring 2010, when the pandemic was all but over. 3 of the 27, including 1 in the pandemic period, actually reported

to 4,626, and removing 6 outliers and 5 high-influence observations left the sample at 4,615.[34] Of these, 772, or 16.7%, recorded their diaries during the April 15, 2009 - May 1, 2010 pandemic period.

The time use variable *WORKTIME* was constructed from the ATUS diary data. It represents work time use at the individual's main job or other jobs, or miscellaneous market work, in minutes on the diary day. Appendix A provides details of these variables. The infrequency of purchase models used *ipm_WORKTIME,* constructed as described in section 3.b.i above.

Real hourly earnings, *rEARNHR,* was calculated from earnings estimates from the ATUS data and the Consumer Price Index. The method used to construct this variable from ATUS is described in Appendix B.

Earnings is generally endogenous with long-term average work hours, but not necessarily daily work time, which shows day-to-day as well as person-to-person variation. To test for this, I used two methods. First, for the infrequency of purchase models and the second tier linear estimates of the double hurdle models, I conducted a

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work time on their diary day. In any event, leaving these 27 people in the data did not affect the estimates. For the IPM model for Bay Area women age 40 and under, for example, omitting them changed the coefficient on *M_DMA* from -48.3328 to -47.9175. By comparison, deleting 27 observations at random changed the coefficient to -47.8859. There is no variable in ATUS to indicate whether the respondent was sick on the diary day. Another concern would be that people missed work to stay home to care for a child sick with H1N1. *TEABSRSN* also includes a category for work missed due to "child care problems," but only 3 of the 4,615 persons sampled, 1 in the pandemic period, gave this as a reason. No other response for this variable relates to illness or family issues. Grasping at straws, 16 respondents—with 2 in the pandemic period—said they had missed work for some miscellaneous reason. I concluded that leaving the 27 observations in the data was the best course.

[34] If a surge in the pandemic actually did induce people to reduce or shift work effort, then the effect at the margin could be enough for some people to quit their jobs altogether, even if only temporarily. In that case, employment status would be conditional on H1N1 incidence, which would create a sample selection problem. Surely at least some people in the state of California behaved this way, but I assume the number is negligible and ignore this in the models.

Hausman test on the null hypothesis of exogeneity using a single imputed data set. Based on the correlations with earnings and the *WORKTIME* variable, I selected instruments for citizenship status, current real minimum wage, number of persons living in the household, home ownership, hourly vs. salary or other pay arrangement, and spouse's usual weekly work hours. Coefficients for the residual were insignificant both for men (t = -0.58, df = 2,290, p-value = 0.5648) and women (t = 0.95, df = 2,236, p-value = 0.3445), indicating exogeneity and that consistent estimates could be obtained by OLS. For the double hurdle models, whether to go to work on a given day and how much time to spend at work are separate choices, and endogeneity between earnings and work time is possible in one case but not the other. I used Smith and Blundell's (1986) test for endogeneity for the first-hurdle probit models. I instrumented with spouse's usual weekly work hours for men and with citizenship status and home ownership for women. The null hypothesis of exogeneity was rejected in neither case (χ^2 = 0.020, 1 df, p-value = 0.888 for men; for women, χ^2 = 1.496, 1 df, p-value = 0.2213).

Demographic controls and day-specific dummies were obtained from ATUS. Year and month dummies were used as well. Table 26 describes all regressors obtained from ATUS that were used in the regressions.

B. Multiple Imputation of Missing Values

For the multiple imputation (MI) models, I imputed missing values for all variables except geographic locations using a Markov Chain Monte Carlo (MCMC) process. An Expectations-Maximization (EM) process is used to create the initial estimates for the draws. Regression models are then estimated separately for each

Table 26
Definitions of Variables

Dependent variable	Definition
WORKTIME	respondent's work time use on diary day, in minutes

Independent Variable	Definition
AGE	in years on diary day
WHITE	omitted category: Other race
BLACK	
HISPANIC	= 1 for self-identified hispanic origin
HISCHOOL	
SOMECOLL	
ASSOCIATES	omitted category: less than high school diploma
BACHELORS	
GRADUATE	
CHILD_0_2	
CHILD_3_5	age of youngest household child
CHILD_6_12	omitted category: no children
CHILD_13_17	
MARRIED	
SEPARATED	omitted category: never married
DIVORCED	
WIDOWED	
rEARNHR	real hourly earnings, 2003 $
WORKHOURS	usual hours worked weekly at all jobs
HOURLY	= 1 if paid an hourly wage
MULTJOB	= 1 if works at two or more jobs
STUDENT	= 1 if enrolled in college or university
SPOUSEHRS	usual hours worked weekly at all jobs by spouse or partner (0 if single)
FIREFIGHTER	
HEALTHWKR	
POLICE	omitted category: other occupation class
SCHOOLWKR	
PUBLICWKR	
TRANSPORT	
BUSFARM	= 1 if a household member owns a business or farm
day of week (6 vars.)	omitted category: Sunday
month (11 vars.)	omitted category: August
year (6 vars.)	omitted category: 2010
M_DMA *M_DMAL2*	Percent of total nontrivial H1N1-related stories published in the largest-circulation newspaper in the DMA of residence, appearing in the week which included the diary day, and a two-week lag
DdumCOL1 *DdumCOL3*	= 1 if an H1N1 death occurred in the county of residence in the week *preceding* the diary day *(DdumCOL1)*, with a two-week lag

† Each set appears as regressors in separate models

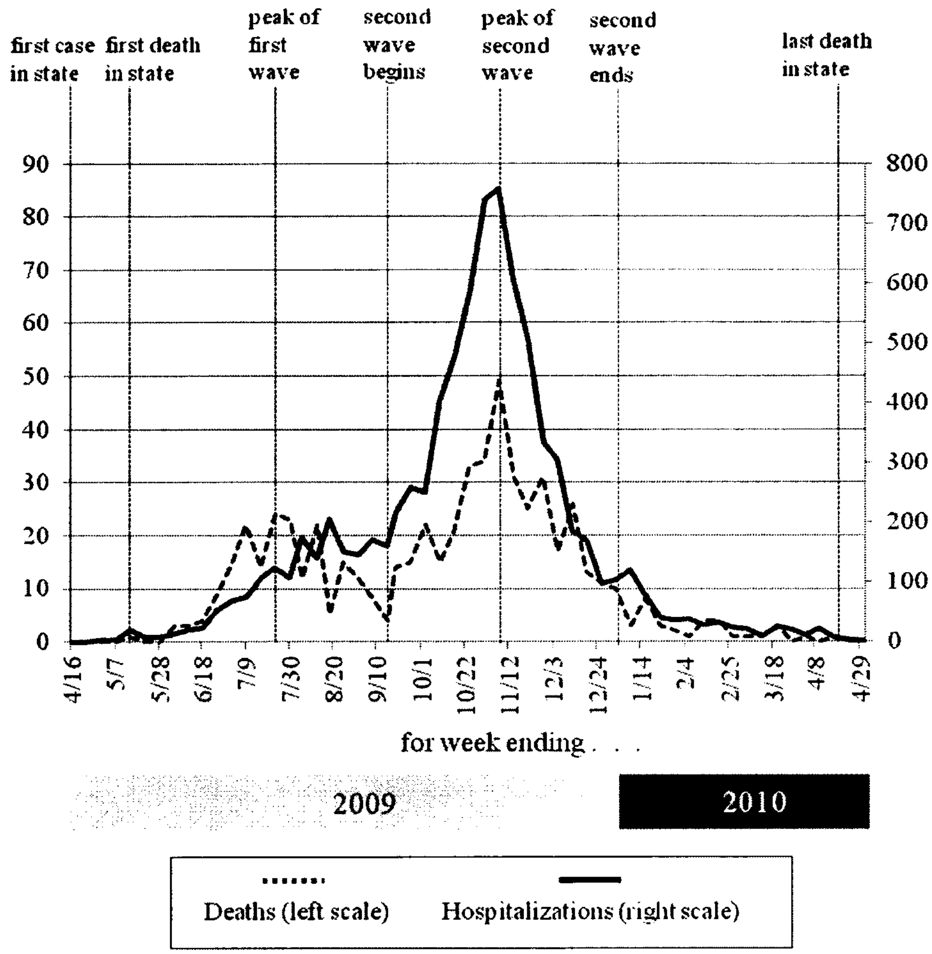


Fig. 4.—Statewide H1N1 deaths and hospitalizations, weekly, April 15, 2009 – May 1, 2010

imputation and the results combined, with software commands where possible and manually where not, following Rubin's Rule. For this study, I use 7 imputations, which, for 15% missing values, provides a relative efficiency of 95.23%.

C. California H1N1 Data from CDPH

Weekly county-level H1N1 mortality data were obtained from the California Department of Public Health (CDPH) as described in Appendix E. Each ATUS participant was matched with the H1N1 mortality rate per 10 million population for his county of residence for the week during which his diary day fell, as well as the two previous weeks. Similar assignments were made on the basis of CBSAs and DMAs. Figure 4 shows statewide hospitalizations and deaths due to H1N1 for the pandemic period.

D. California H1N1 Newspaper Article Data

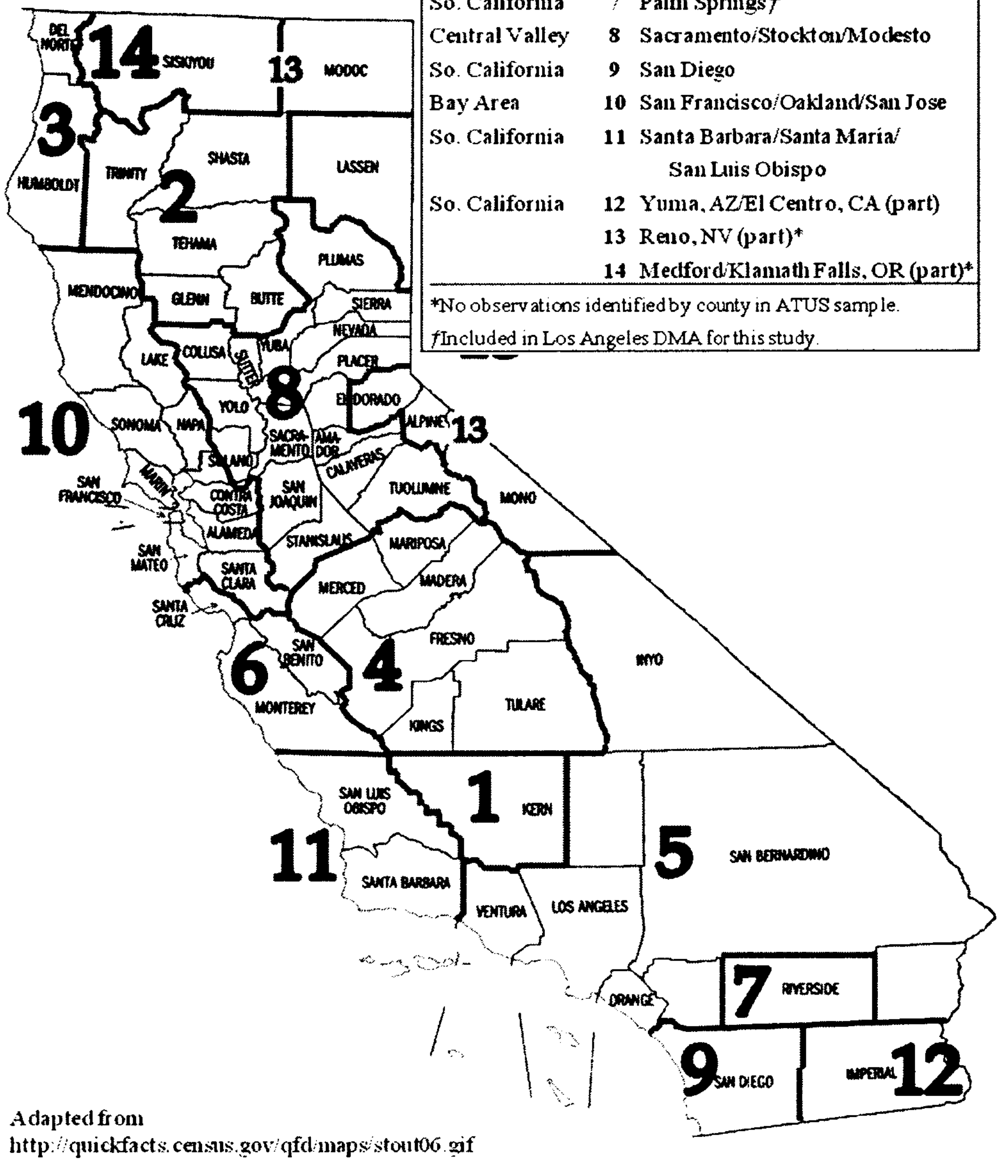
While newspaper circulation in California, as elsewhere, has fallen in competition with television and the internet, newspaper coverage of an issue remains a good indicator of overall media exposure. Readily accessible online archives make historical levels of newspaper coverage much easier to measure than other news sources. Also, newspaper articles can be counted easily because they are discrete; a given article is published only once per edition, unlike TV and radio news spots, which can air any number of times with varying audience sizes. Following Ibuka, et al. (2010), I measured H1N1 media exposure by frequency of newspaper articles.

The ACNielsen television marketing research firm assigns all locations in the country into various Designated Marketing Areas, or DMAs. Each DMA represents a "television market" of households having access to a common set of local TV stations. DMA boundaries, which are redrawn each year, generally follow county boundaries, often amalgamating two or more counties into a single DMA, although frequently a county will be apportioned between two different DMAs. DMAs often straddle state boundaries, particularly in rural areas. Figure 5 shows the 2009 DMA map of California.

For this study, the newspaper coverage of H1N1 was measured in those 10 of the 14 California DMAs which contained ATUS households with the county of residence

Study Region	#	ACNielsen DMA
Central Valley	1	Bakersfield
Central Valley	2	Chico/Redding
	3	Eureka*
Central Valley	4	Fresno/Visalia
So. California	5	Los Angeles
Bay Area	6	Monterey/Salinas
So. California	7	Palm Springs ƒ
Central Valley	8	Sacramento/Stockton/Modesto
So. California	9	San Diego
Bay Area	10	San Francisco/Oakland/San Jose
So. California	11	Santa Barbara/Santa Maria/ San Luis Obispo
So. California	12	Yuma, AZ/El Centro, CA (part)
	13	Reno, NV (part)*
	14	Medford/Klamath Falls, OR (part)*

*No observations identified by county in ATUS sample.
ƒIncluded in Los Angeles DMA for this study.



Adapted from
http://quickfacts.census.gov/qfd/maps/stout06.gif

Fig. 5.—2009 California AC Nielsen Designated Market Area (DMA) Map

identified. DMA definitions for calendar year 2009 were used. ATUS data cannot be disaggregated below the county level, so counties split between DMAs were assigned to the DMA containing the majority of the county population. The Palm Springs DMA consists solely of the Coachella Valley portion of Riverside County, the rest of which which is in the Los Angeles DMA. Those two DMAs were combined for this analysis.

While Ibuka, et al. (2010) conducted a nationwide study and so used nationwide news reports, I identified the newspaper with the largest self-reported print circulation in each of the 10 DMAs and conducted a search of each of these newspapers using either the newspaper's own online archives or, for the four major dailies,[35] ProQuest® Newsstand (ProQuest LLC, 2011).[36] The number of articles that appeared in each newspaper on the subject of the H1N1 pandemic was tallied on a weekly basis, running Friday through Thursday to correspond to the CDPH data, for the entire pandemic period. Only *published, individually titled,* articles—those appearing in the print edition and having a bespoke headline—were counted. Letters to the editor and advertisements were excluded. Table 27 lists the 10 DMAs with the primary newspaper and weekly frequencies of H1N1 articles for each. Relative frequencies—the weekly fraction of all articles published in a given newspaper on the subject of H1N1 during the April 15, 2009 – May 1, 2010 pandemic period—were recorded as well. Figure 6 shows the weekly

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[35] The *Los Angeles Times*, *Sacramento Bee*, *San Francisco Chronicle*, and *San Diego Union-Tribune*

[36] Print editions of newspapers, at least in 2009-2010, remained a better measure of strictly local news coverage than digital editions. Thus the *San Francisco Chronicle* is used for the San Francisco/ Oakland/San Jose DMA rather than the *San Jose Mercury-News* which, by virtue of its popular digital editions, counts among the nation's largest circulation dailies. A decade from now, measuring media coverage this way might seem a period piece.

Table 27
ACNielsen Designated Market Area (DMA) Media Coverage
Frequency of H1N1 articles* published in primary DMA newspaper

week ending . . .

ACNielsen DMA† and Newspaper	*4/23*	*4/30*	*5/7*	*5/14*	*5/21*	*5/28*	*6/4*	*6/11*	*6/18*	*6/25*	*7/2*	*7/9*	*7/16*	*7/23*	*7/30*	*8/5*	*8/12*	*8/18*	*8/25*	*9/1*	*9/8*	*9/15*	*9/19*	*9/26*	*10/3*	*10/10*	*10/17*	*10/24*	*10/31*	*11/7*	*11/14*	*11/21*	*11/28*	*12/5*	*12/12*	*12/19*	*12/26*	*1/2*	*1/9*	*1/16*	*1/23*	*1/30*	*2/6*	*2/13*	*2/20*	*2/27*	*3/6*	*3/13*	*3/20*	*3/27*	*4/3*	*4/10*	*4/17*	*4/24*	*5/1*	***TOTAL***
Bakersfield *Bakersfield Californian*	0	4	6	3	1	1	0	0	0	1	0	0	0	0	1	1	1	0	1	0	1	1	1	3	0	3	2	4	2	4	2	2	1	3	3	1	2	1	1	0	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0	**60**
Chico/Redding *Chico Enterprise-Record*	0	1	2	0	3	0	0	1	0	0	1	2	0	2	0	0	0	0	0	0	0	1	1	0	2	3	0	1	0	6	5	8	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	**44**
Fresno/Visalia *Fresno Bee*	0	0	5	1	0	0	0	0	1	0	1	0	0	0	0	1	1	1	0	1	0	4	0	0	0	2	0	1	2	4	0	1	0	2	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**30**
Los Angeles and Palm Springs** *Los Angeles Times*	1	32	31	6	8	2	2	3	3	3	1	4	1	2	8	2	2	2	6	5	2	14	3	5	3	5	8	11	13	8	10	5	2	7	3	2	6	0	2	1	2	0	2	3	0	1	1	1	1	0	2	0	0	0	0	**247**
Monterey *Salinas Californian*	0	11	17	3	0	1	3	1	0	0	1	3	1	0	0	0	1	0	0	1	1	0	1	0	3	1	0	2	2	2	1	0	0	3	0	1	0	1	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**66**
Sacramento/Stockton/Modesto *Sacramento Bee*	0	16	11	7	3	0	0	1	2	2	0	2	1	3	0	1	6	5	4	2	2	3	1	2	5	6	2	2	4	7	7	7	3	4	3	4	3	2	3	4	2	0	1	0	0	2	1	0	0	0	0	0	0	0	2	**148**
San Diego *San Diego Union-Tribune*	1	27	27	4	1	2	1	0	4	5	2	2	3	0	4	3	2	3	1	0	1	1	2	2	1	3	5	4	5	4	5	3	3	0	0	2	1	0	4	2	0	3	1	0	0	1	0	1	0	0	0	0	0	0	0	**146**
San Francisco/Oakland/San Jose *San Francisco Chronicle*	0	16	14	1	1	0	1	2	1	1	0	3	1	2	2	0	0	0	2	3	1	1	0	1	1	2	2	3	4	0	0	1	1	1	0	2	3	0	0	0	0	2	1	1	1	0	0	0	0	0	1	0	0	0	0	**79**
Sta. Barbara/Sta. Maria/S. Luis Obispo *Santa Barbara News-Press*	0	10	6	2	1	2	0	0	1	0	0	0	0	1	0	2	0	0	0	2	0	1	3	0	0	5	4	4	6	1	1	1	0	0	3	0	2	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**62**
Yuma, AZ/El Centro, CA *Yuma Sun*	0	2	6	2	0	1	0	0	2	0	0	0	1	0	0	1	1	0	0	1	2	0	0	2	0	2	2	2	3	1	0	1	0	2	1	3	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	**41**

*Excludes letters to the editor, advertisements, short, untitled articles, and articles which mention H1N1 only in passing.

†Due to the CPS censoring for counties of less than 100,000 population, no observations in the ATUS data can be identified for California counties in the Eureka, Reno, NV, and Medford/Klamath Falls, OR, DMAs.

**The Palm Springs DMA consists of the central portion of Riverside County. Since CDPH and ATUS data cannot be disaggregated below the county level, this DMA was included with the rest of Riverside County in the Los Angeles DMA.

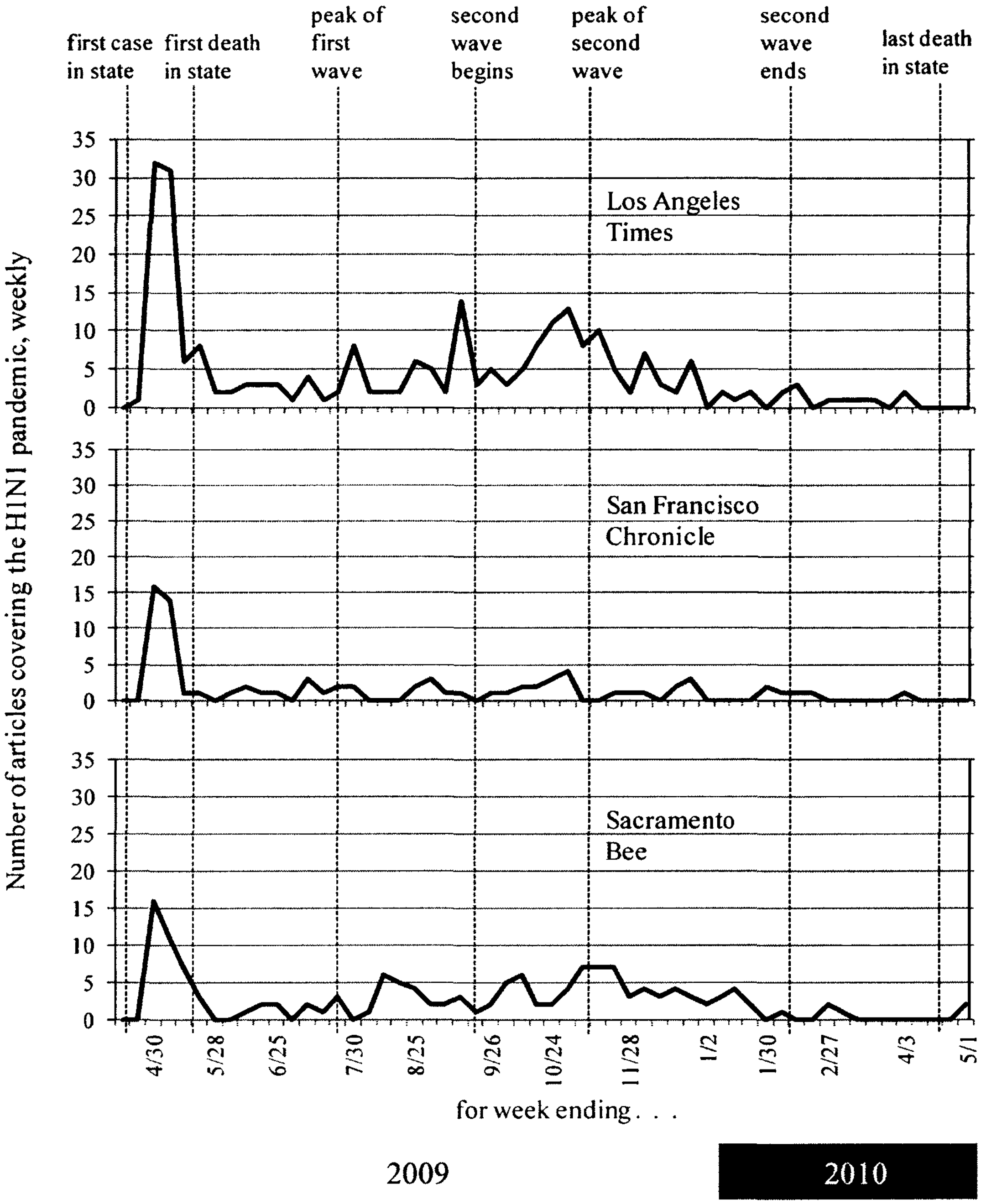

Fig. 6.—Newspaper articles on the H1N1 pandemic, April 15, 2009 – May 1, 2010

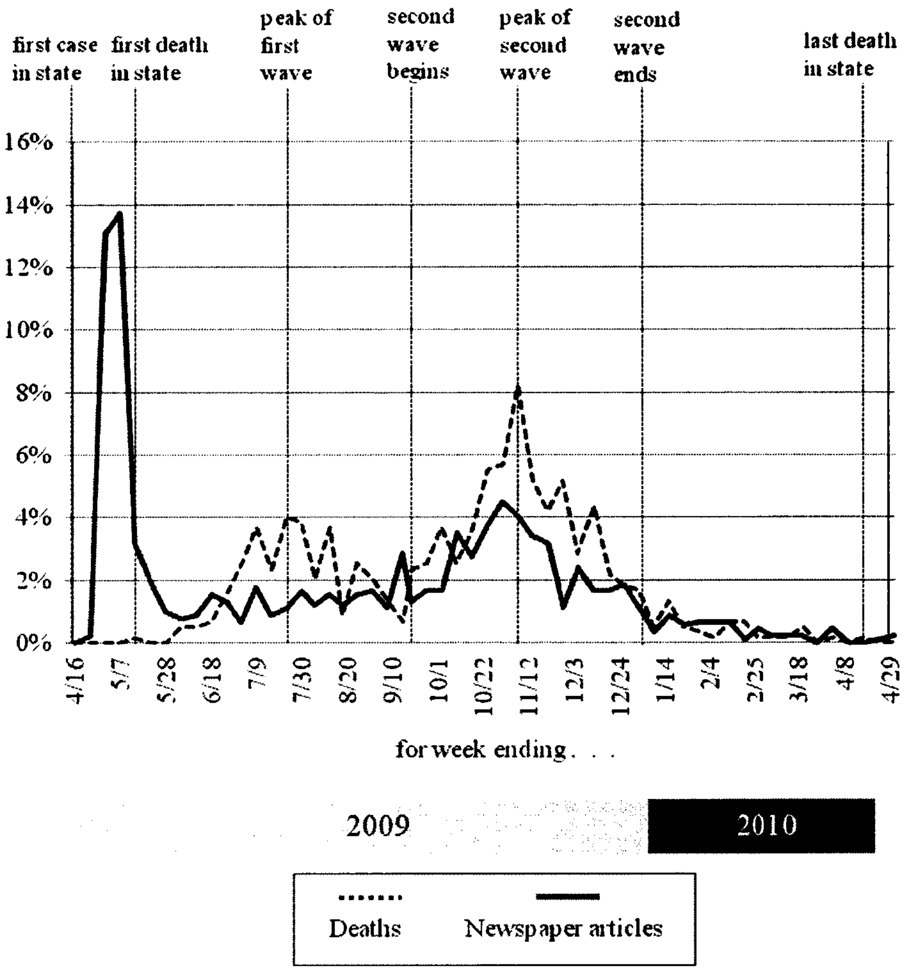

Fig. 7.—Statewide H1N1 deaths and newspaper articles, as % of pandemic total, weekly, April 15, 2009 – May 1, 2010

relative frequencies of articles for the largest daily newspapers in each of the three regions defined in this analysis.

Figure 7 compares the relative frequencies, over the pandemic period, of statewide deaths and newspaper articles. Articles were most abundant in the early weeks of the pandemic, before any deaths had occurred and while hospitalizations were still few. Newspaper articles did again become somewhat more common during the second wave of the pandemic, although the frequency never approached the early level. Overall, weekly newspaper article frequency showed no significant correlation with either deaths ($r = 0.15$, p-value = 0.260) or hospitalizations ($r = 0.24$, p-value = 0.080). Deaths and hospitalizations were positively correlated ($r = 0.86$, p-value < 0.001). The results are much the same even if the initial panic period (April – May 2009) is ignored. Considering only the second wave of the pandemic, September – December 2009, however, newspaper articles were correlated with both deaths ($r = .57$, p-value = 0.014) and hospitalizations ($r = 0.85$, p-value < 0.001), while the correlation of deaths and hospitalizations changed little (0.84).

I used two categories of H1N1 incidence measures:

1. *D_CO,* weekly deaths recorded in the county of residence, as deaths per 10 million population[37] and *DdumCO,* a dummy variable which = 1 if at least one death occurred in a given week in the county of residence. For both, since the official death totals would not be made public until after the diary day had passed, current-week values are not used in the models. Instead I use one- and three-week lags.

2. *M_DMA,* The relative frequency (measured over the entire pandemic) of all H1N1-related articles published in the week including the diary day in the largest-circulation daily newspaper in the DMA of residence. It is measured as a relative frequency because the total number of articles varied widely among the different local newspapers; the *Fresno Bee* published a mere 30 while the *Los Angeles Times* unleashed 247. Unlike the CDPH death reports, news articles are observed in real time, and so the

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[37] The scaling factor is used due to the small number of deaths overall, affecting only the magnitude of the coefficients estimates.

current week variable is included, along with a two week lag. The distribution of *M_DMA* overall was highly nonnormal (skewness = 9.450 and kurtosis = 117.2424; Jarque-Bera statistic = 2,677,811.53, significant at $\alpha = .05$), largely due to the preponderance of zeros.[38]

Neither of the two death incidence variables had any explanatory power in the models, which coincides with the results in Ibuka, et al. (2010). I report the *D_CO* results for the infrequency of purchase models only.

E. Descriptive Statistics

California is the most populous state (37,253,956 in the 2010 Census) and contains areas with distinct characteristics. I divided the state into its three major regions, each consisting of DMA clusters:

1. The Bay Area, comprised of the San Francisco/Oakland/San Jose and Monterey/Salinas DMAs. While this actually includes all counties between the ocean and the Central Valley from Mendocino County in the north to Monterey County in the south, 89.5% of the 867 participants—all but 91 residents of the Monterey/Salinas DMA, which consists of Santa Cruz and Monterey Counties—reside in a county that faces the Bay, and demographically those 91 are similar to the others.

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[38] Because of the high kurtosis, in particular, I also considered a dummy variable, *MdumDMA* = 1 if at least one H1N1 article was published in the local newspaper in the week preceding the diary day, as a substitute. I rejected it because it was unsuitable for the southern California region, particularly the Los Angeles DMA, home to 47.2% of the respondents. While the total number of articles rose and fell in line with other newspapers, because of the sheer size and breadth of coverage of an issue of the *Los Angeles Times*, at least one article was published each week from the beginning of the pandemic through the end of the second wave, at the end of 2009, giving each Los Angeles DMA resident participating during that time a value of 1 for the dummy variable. (See Table 2 and Figure 2.) In effect, the variable would have served merely as a pandemic period indicator.

2. The Central Valley, which consists of the Chico/Redding, Sacramento/Stockton/Modesto, Fresno/Visalia, and Bakersfield DMAs. It contains California's agricultural heartland, although 37.5% of the 744 participants live in metropolitan Sacramento.

3. Most populous of the three by far is Southern California, which consists of the remaining southern DMAs, those of Los Angeles, Palm Springs, and San Diego, plus Imperial County, which is part of the Yuma, AZ/El Centro, CA DMA. Highly urbanized, 78.1% of this region's 2,669 ATUS participants live in metropolitan Los Angeles (Los Angeles-Long Beach-Santa Ana or Riverside-San Bernardino-Ontario MSAs) with another 14.61% in metropolitan San Diego.

Due to CPS censoring of geographic variables, no participants could be identified as residing in any of the northernmost counties or the thinly populated areas along the Nevada border.

Table 28 shows summary descriptive statistics for the continuous variables; Table 29, frequencies for the demographic dummy variables; and Table 30, frequencies for the diary-day dummy variables. Each (except Table 30) is disaggregated by sex and region. Considering only significant differences ($\alpha = .05$), the Bay Area participants are notably different from the others, particularly the women. Most striking is the difference in family formation and family size. The mean number of children under age 18 living in the household for Bay Area women is 0.657, compared to 0.976 and 0.948 for Southern California and the Central Valley, respectively. Earnings for both sexes are higher in the Bay Area; women's are about 25% higher than elsewhere. Women in the Bay have more

Table 28

Descriptive Statistics for Continuous Variables, by Sex and Region

Weighted by ATUS survey weights

	Bay Area (n = 867)						*Southern California (n = 2669)*						*Central Valley (n = 744)*					
	n						*n*						*n*					
Variable	all	> 0*	Q_1	Mean	Q_3	SE	all	> 0*	Q_1	Mean	Q_3	SE	all	> 0*	Q_1	Mean	Q_3	SE
WORKTIME																		
Men	426	279	0	305.76	495	12.288	1361	831	0	335.06	524	7.077	387	238	0	354.66	550	13.761
Women	441	245	0	287.29	490	12.107	1308	726	0	288.76	490	6.823	357	198	0	286.50	480	12.780
AGE																		
Men	426		30	39.11	48	0.557	1361		29	39.02	48	0.315	387		30	39.45	48	0.629
Women	441		32	41.99	53	0.579	1308		30	39.72	49	0.327	357		31	41.82	50	0.630
NUMKIDS																		
Men	426	233	0	1.002	2	0.067	1361	742	0	0.963	2	0.033	387	238	0	1.182	2	0.065
Women	441	218	0	0.657	1	0.047	1308	716	0	0.976	2	0.036	357	219	0	0.948	2	0.061
*rEARNHR***																		
Men	426		12.10	23.85	32.67	0.747	1361		10.45	20.06	27.13	0.325	387		9.32	17.83	24.75	0.501
Women	441		13.81	22.31	29.48	0.581	1308		9.04	17.82	23.20	0.295	357		8.83	17.25	22.89	0.543
*WORKHRS***																		
Men	426		40	43.06	47.52	0.507	1361		40	43.05	49.43	0.318	387		40	43.84	50.00	0.657
Women	441		32	37.63	42	0.597	1308		30	37.08	40	0.345	357		31	36.84	40	0.661
SPOUSEHRS																		
Men	426	274	0	22.35	40	0.952	1361	864	0	23.73	40	0.567	387	274	0	26.75	40	0.929
Women	441	273	0	29.41	45	1.027	1308	685	0	24.15	40	0.627	357	215	0	29.27	42	1.231
M_DMA†																		
Men	67	33	0	1.48	1	0.448	228	177	0	1.66	2	0.158	53	30	0	1.54	2	0.344
Women	82	45	0	1.57	3	0.336	228	183	0	2.36	2	0.239	56	32	0	2.56	3	0.497

335 observations which could not be identified by region are omitted.

* Not weighted. Since half the ATUS diary days are weekends, this understates the true share of working days.

**Since all participants are employed, all show nonzero earnings and usual work hours.

† Descriptive statistics for *M_DMA* are for pandemic period observations only.

Table 29
Frequency Distributions for Categorical Variables

Unweighted

	Bay Area (n = 867)				*Southern California (n = 2669)*				*Central Valley (n = 744)*			
	Men (n = 426)		*Women (n = 441)*		*Men (n = 1361)*		*Women (n = 1308)*		*Men (n = 387)*		*Women (n = 357)*	
Variable	*f*	*%*	*f*	*%*	*f*	*%*	*f*	*%*	*f*	*%*	*f*	*%*
Race												
BLACK	22	*5.2*	27	*6.1*	86	*6.3*	117	*8.9*	17	*4.4*	12	*3.4*
WHITE	328	*77.0*	325	*73.7*	1124	*82.6*	1020	*78.0*	337	*87.1*	306	*85.7*
OTHRACE	76	*17.8*	89	*20.2*	151	*11.1*	171	*13.1*	33	*8.5*	39	*10.9*
HISPANIC	100	*23.5*	96	*21.8*	569	*41.8*	523	*40.0*	154	*39.8*	99	*27.7*
Education												
LTHSCHL	38	*8.9*	23	*5.2*	238	*17.5*	182	*13.9*	63	*16.3*	38	*10.6*
HISCHOOL	63	*14.8*	48	*10.9*	239	*17.6*	193	*14.8*	85	*22.0*	65	*18.2*
SOMECOLL	68	*16.0*	74	*16.8*	273	*20.1*	285	*21.8*	84	*21.7*	94	*26.3*
ASSOCIATES	28	*6.6*	54	*12.2*	115	*8.5*	161	*12.3*	39	*10.1*	48	*13.5*
BACHELORS	122	*28.6*	143	*32.4*	314	*23.1*	322	*24.6*	82	*21.2*	74	*20.7*
GRADUATE	107	*25.1*	99	*22.5*	182	*13.4*	165	*12.6*	34	*8.8*	38	*10.6*
Age of youngest child												
CHILD0_2	74	*17.4*	55	*12.5*	234	*17.2*	155	*11.9*	72	*18.6*	49	*13.7*
CHILD3_5	50	*11.7*	44	*10.0*	124	*9.1*	136	*10.4*	45	*11.6*	51	*14.3*
CHILD6_12	78	*18.3*	72	*16.3*	282	*20.7*	280	*21.4*	85	*22.0*	77	*21.6*
CHILD13_17	31	*7.3*	47	*10.7*	102	*7.5*	145	*11.1*	36	*9.3*	42	*11.8*
No children < 18	193	*45.3*	223	*50.6*	619	*45.5*	592	*45.3*	149	*38.5*	138	*38.7*
Marital status												
MARRIED	249	*58.5*	253	*57.4*	785	*57.7*	638	*48.8*	258	*66.7*	184	*51.5*
SEPARATD	13	*3.1*	22	*5.0*	68	*5.0*	80	*6.1*	13	*3.4*	19	*5.3*
DIVORCED	39	*9.2*	60	*13.6*	128	*9.4*	183	*14.0*	36	*9.3*	64	*17.9*
WIDOWED	1	*0.2*	10	*2.3*	10	*0.7*	44	*3.4*	1	*0.3*	12	*3.4*
NEVMARRD	124	*29.1*	96	*21.8*	370	*27.2*	363	*27.8*	79	*20.4*	78	*21.9*
Occupation category												
FIREFGHTR	2	*0.5*			5	*0.4*			6	*1.6*		
HEALTHWKR	2	*0.5*			3	*0.2*	4	*0.3*	1	*0.3*	2	*0.6*
POLICE	9	*2.1*	4	*0.9*	21	*1.5*	3	*0.2*	18	*4.7*		
PUBLICWKR	46	*10.8*	66	*15.0*	135	*9.9*	234	*17.9*	27	*7.0*	78	*21.9*
SCHOOLWKR	7	*1.6*	42	*9.5*	24	*1.8*	113	*8.6*	11	*2.8*	51	*14.3*
TRANSPORT	12	*2.8*			48	*3.5*	3	*0.2*	18	*4.7*		
OTHER	348	*81.7*	329	*74.6*	1125	*82.7*	951	*72.7*	306	*79.1*	226	*63.3*
MULTJOB	37	*8.7*	40	*9.1*	111	*8.2*	109	*8.3*	33	*8.5*	37	*10.4*
BUSFARM	79	*18.5*	80	*18.1*	246	*18.1*	229	*17.5*	63	*16.3*	62	*17.4*
STUDENT	22	*5.2*	32	*7.3*	66	*4.9*	114	*8.7*	18	*4.7*	31	*8.7*
MdumDMA	33	*7.8*	45	*10.2*	177	*13.0*	183	*14.0*	30	*7.8*	32	*9.0*

335 observations which could not be identified by region are omitted.

Table 30
Frequency Distributions for Diary Day Variables
Unweighted, all regions

Variable	*f*	%
Pandemic period*	769	*16.7*
Diary day:		
Sunday	1,176	*25.5*
Monday	448	*9.7*
Tuesday	461	*10.0*
Wednesday	458	*9.9*
Thursday	424	*9.2*
Friday	437	*9.5*
Saturday	1,211	*26.2*
*HOLIDAY***	72	*1.6*
Month:		
January	449	*9.7*
February	349	*7.6*
March	386	*8.4*
April	379	*8.2*
May	350	*7.6*
June	330	*7.2*
July	341	*7.4*
August	385	*8.3*
September	409	*8.9*
October	446	*9.7*
November	404	*8.8*
December	387	*8.4*
Year		
2004†	325	*7.0*
2005	671	*14.5*
2006	747	*16.2*
2007	699	*15.2*
2008	720	*15.6*
2009	720	*15.6*
2010	733	*15.9*

* April 15, 2009 - May 1, 2010
**New Year's, Easter, Memorial Day, 4th of July, Labor Day, Thanksgiving, Christmas. These observations were omitted from this analysis.
† May - December only

hours of work provided by a spouse or partner than those in Southern California, but about the same as for the Valley; this probably reflects the much higher rate of marriage in the Bay Area. Bay Area residents are more likely to be of a race other than black or white, more so for women, and much less likely to be hispanic. They have a higher level of schooling—a quarter of men and a third of women hold a bachelors degree; another quarter of men and a fifth of women have a graduate degree, far more than either of the other regions.

Considering only women age 40 and younger, differences among the three regions are even more striking. In the Bay Area, 36.8% hold a bachelors degree and a further 23.6% have graduate degrees; shares are 21.5% and 13.8%, and 10.0% and 12.4% for Southern California and the Central Valley. Despite the high rate of marriage, over half of Bay Area women—51.4%—have no children, and only 7.9% have more than two. In Southern California, these shares are 43.6% and 17.74%. Fertility is much higher in the Valley, with these shares being 23.4% and 23.7%. As is true for older females, 40-and-unders are more likely (56.6%) to be married in the Bay Area, compared to 43.7% and 48.4% for the other regions. The mean number of spouse's weekly work hours provided is consequently higher, at 27.7 for the Bay Area (22.0 and 24.2 for the other two regions; only the difference with Southern California is significant). The difference comes entirely from the higher rate of marriage; considering only married women, spouse's work hours are not significantly higher, at 44.2, compared to 42.7 and 43.9 for the other regions.

V. EMPIRICAL METHODS AND RESULTS

In preliminary models I found that work time use differs so much among the demographic groups and regions that simple intercept adjustments are not sufficient. Using *M_DMA* as the H1N1 incidence variable, I estimated twelve models for each of the infrequency of purchase and double hurdle models: for men and women; for those younger and older than 40; and for the three regions. The county-level death variable had no explanatory power in any of the models, as expected; I report results for the infrequency of purchase models only, for comparison. All models were estimated using both inverse probability weighting and multiple imputation. Models with significant effects for H1N1 incidence are reported below.

This level of disaggregation reduces the degrees of freedom and increases the risk of outlier interference. I systematically tested the results for the effects of high influence observations and made adjustments where necessary as follows: If any of the H1N1 incidence variables showed a significant result, I reran the model omitting all observations having a Cook's D exceeding the threshold of 4/n. (For the first hurdle probit models, I performed similar tests using logistic regression and Pregibon's (1981) *DFBETA* and *C* statistics.) If the results were materially unchanged—particularly, if the H1N1 coefficients' signs and significance did not change and the magnitude was stable—I concluded that the effects were broadly consistent throughout the subsample and report the original results. In two cases, the coefficient on *M_DMA* fell well below the level of significance and the models were discarded. Where relevant, I discuss the results of these tests below.

I test the following hypotheses:

i. H_A: Work time use fell in response to increases in reported H1N1 deaths

ii. H_A: Work time use fell in response to increases in news coverage of the H1N1 pandemic

ii. H_A: Workers shifted work time from riskier to safer time periods, that is, they made intertemporal substitutions

A potential problem for all three hypotheses involves workers' motivations. Workers who reduced work time might have done so willingly, for fear of catching the disease. But people who were surveyed during the panic period of late April, 2009, might have had little choice in the matter, given the number of school and business closings at that time. The problem would affect only a very small share of the sample, even in the pandemic period, but these could be high-influence observations. The incidence variable alone could not indicate if a reduction in work time reflected voluntary utility-maximizing behavior or just a mechanical response to a severe but temporary labor market demand constraint. Particularly for teachers, both the motivation to make up lost work time (because of fixed salaries) and the ability to do so (given fixed school calendars) would be lacking, and no substitution would take place.

I include a set of dummy variables for occupation type specifically to control for this. *SCHOOLWKR* = 1 for all school employees, who might have been unable to work during late April 2009, when school closings were common. *FIREFIGHTR, POLICE, TRANSPORT*, and *HEALTHWKR* control for people whose occupations might have placed greater demands on their time at various points during the pandemic.

PUBLICWKR =1 for other occupation categories that would involve regular and close contact with the general public, who might react more strongly to the pandemic than office workers or workers with limited contact with the public. All other occupations form the omitted category. Occupation categories were constructed from the Census Bureaus's 2002 Occupation Codes, (Census, 2002) which were current for the entire period of analysis.

Standard errors are corrected for heteroskedasticity using the Huber-White sandwich estimator (Huber, 1967; White, 1980) for the first-hurdle probit models and the degrees-of-freedom corrected HC1 estimator suggested by Hinkley (1977) and described by MacKinnon and White (1985) for all others.

ATUS survey weights are used for all regressions. For the inverse probability weight models, the IPW is multiplied by the survey weight.

A. Infrequency of Purchase Models

The dependent variable, *ipm_WORKTIME,* was constructed as described in section 3.B.i, above. It is thus the IPM-transformed value of the total time use for work on the diary day.

The model is estimated by OLS as

$$ipm\_WORKTIME = \beta_0 + \beta_1 e + \boldsymbol{D\varphi} + \boldsymbol{C\gamma} + \theta_1 H_t + \theta_2 H_{t-2} \tag{5.1}$$

where e = *rEARNHR,* real hourly earnings, $\boldsymbol{D}$ is the vector of demographic and work-related variables, $\boldsymbol{C}$ the vector consisting of controls for diary-day-specific effects plus year and month dummies. H_t and H_{t-2} are the current-week and two-week lag values of the H1N1 incidence measure.

Infrequency of purchase model results showed significant results for H1N1 incidence for two groups: women age 40 and under, in both Southern California and the Bay Area. Since women were more likely to perceive H1N1 as a health threat (Ibuka, et al., 2010), it is not surprising that both are for women. For each, results are reported for the *M_DMA* variables, which are significant, as well as *D_CO*, which are not. *M_DMA* results for both were robust to the deletion of high-influence observations, with the coefficient and *t*-statistic for *M_DMA* changing little in either case. I report the full data models here.

In interpreting the coefficients on *M_DMA,* recall that it represents the percent of total pandemic period H1N1 news articles appearing in the newspaper during the week including the diary day. A one-point increase in *M_DMA* would imply a rise in the overall share of articles from, say, 1% to 2% of the pandemic-long total. As for typical values of this variable, by construction (54 weeks and 100 percentage points) weekly means would be in the neighborhood of 2%. Actual sample means and standard errors are 1.532% and 0.272% for the Bay Area, 2.003% and 0.144% for Southern California,[39] and 1.926% and 0.292% for the Central Valley. The frequency of articles was volatile during the pandemic; for example, in the *San Francisco Chronicle,* weekly changes in *M_DMA* of at least one point occurred 30 times. (For raw frequencies see Table 27.)

The current-week value of *M_DMA* was one of the few variables with any explanatory power in the inverse probability weight model for Southern California women ages 40 and under (Table 31). It was strongly significant ($\hat{\beta}$ = -19.9895, t =

[39] The much lower standard error for southern California reflects the torrent of H1N1 articles in the *Los Angeles Times.*

-4.48, p-value < 0.001) and indicated that a one-point increase in *M_DMA* would decrease work time use by about 20 minutes on a given work day. The two-week lag of *M_DMA* was positive but not significant ($\hat{\beta}$ = 15.4644, t = 1.85, p-value = 0.066); as significant result would have provided evidence of work shifting. Other significant variables included those for the age of the youngest household child. Those with a child age 12 and younger spent many fewer minutes at work than those with an older child or no children. The negative coefficients on the three variables *CHILD_0_2, CHILD_3_5,* and *CHILD_6_12* were not significantly different from each other (χ^2 = 2.87, 2 *df*, p-value =0.2381). Hourly workers worked about 38 minutes more. Included as a control for H1N1-related labor market demand constraints, school employees (*SCHOOLWKR* = 1) showed work time use of about 58 minutes less than other workers. The model using county-level deaths showed similar coefficients for the control variables but the *D_CO* variables were not significant.

For Bay Area women (Table 32), the effect was more pronounced. A one-point increase in *M_DMA* reduced work time by about 48 minutes (t = -1.99, p-value = 0.048), with the two-week lag again positive but insignificant. Similar but larger effects were seen for the child age variables, although no effects were seen for hourly workers or school employees. Like their Southern California counterparts, women on the Bay did not change their work behavior in response to the actual level of deaths.

B. Double Hurdle Models

The first-hurdle equation is estimated by probit as

$$P(w\_WORKTIME = 1 \mid \hat{e}, \boldsymbol{D}, \boldsymbol{C}, \boldsymbol{H}) = \phi_0 + \phi_1 \hat{e} + \boldsymbol{D\varphi} + \boldsymbol{C\gamma} + \theta_1 H_t + \theta_2 H_{t-2} \quad (5.2)$$

Table 31

Infrequency of Purchase Model (IPM) Results for *WORKTIME*

Southern California women, age 40 and under

Inverse probability weight (IPW) models

Boldface effects are significant at α = .05

	H1N1 incidence indicators					
	1. News article frequencies			*2. Deaths*		
Variable	Coefficient	SE	*p*-value	Coefficient	SE	*p*-value
AGE	0.4498	1.7514	0.798	0.9569	1.7539	0.586
BLACK	-25.8190	37.6900	0.494	-32.1626	39.2962	0.414
WHITE	-21.6080	22.5223	0.338	-19.5892	22.4496	0.384
HISPANIC	-24.4724	19.5172	0.211	-28.9163	19.9634	0.148
HISCHOOL	4.1091	41.4076	0.921	3.9889	41.0342	0.923
SOMECOLL	13.0845	35.3700	0.712	1.1365	35.3309	0.974
ASSOCIATES	28.0707	38.5361	0.467	21.5116	38.9873	0.582
BACHELORS	23.9319	40.0201	0.550	17.7166	39.8179	0.657
GRADUATE	12.5391	45.1404	0.781	1.3065	45.4643	0.977
CHILD_0_2	**-56.9751**	24.2667	0.020	**-56.2757**	24.2142	0.021
CHILD_3_5	**-67.7337**	29.7162	0.023	**-70.2095**	30.3031	0.021
CHILD_6_12	**-100.1340**	23.5213	< 0.001	**-98.6261**	23.6963	< 0.001
CHILD_13_17	-67.3522	38.7164	0.083	-58.9700	40.0510	0.142
MARRIED	-39.2504	31.1336	0.208	-46.5121	31.4577	0.140
SEPARATED	68.3340	34.9280	0.051	63.3280	34.3809	0.066
DIVORCED	16.5114	38.6547	0.670	15.7095	39.3687	0.690
rEARNHR	0.2300	1.0869	0.833	0.3658	1.0842	0.736
WORKHRS	0.3589	1.0175	0.725	0.4034	1.0384	0.698
HOURLY	**37.8847**	18.9474	0.046	**42.7007**	18.8752	0.024
MULTJOB	-56.8720	35.8166	0.113	-53.7129	35.5060	0.131
STUDENT	-34.4793	23.5353	0.144	-27.4113	23.8300	0.251
SPOUSHRS	0.5016	0.6480	0.439	0.6265	0.6613	0.344
PUBLICWKR	33.5169	23.0024	0.146	37.7936	22.8881	0.100
SCHOOLWKR	**-58.2364**	28.4297	0.041	**-56.2847**	28.2286	0.047
BUSFARM	-19.0724	42.8887	0.657	-19.5420	43.3771	0.653
MONDAY	40.3209	28.7158	0.161	33.2418	29.5843	0.262
TUESDAY	44.5588	32.4331	0.170	42.9656	33.3881	0.199
WEDNESDAY	12.9542	37.8091	0.732	3.2558	37.9892	0.932
THURSDAY	25.8247	26.4090	0.329	17.2373	26.7667	0.520
FRIDAY	49.6563	29.2471	0.091	30.9179	29.6841	0.298
SATURDAY	4.2781	21.4377	0.842	-4.8440	22.4779	0.830
JAN	60.4324	44.6380	0.177	52.1912	44.6582	0.243
FEB	49.2098	41.5650	0.237	44.0671	41.0741	0.284
MAR	14.4209	45.2737	0.750	15.2169	44.4326	0.732
APR	43.7541	43.3838	0.314	44.2077	42.7475	0.302
MAY	55.5181	44.6276	0.214	20.5109	49.7923	0.681
JUN	23.0793	44.1041	0.601	14.7382	44.4310	0.740
JUL	-90.7807	59.4576	0.128	-94.3733	59.2462	0.112
SEP	33.3275	39.9592	0.405	27.4155	40.2528	0.496
OCT	-9.7364	40.7007	0.811	-15.5721	40.5564	0.701
NOV	7.1029	43.2389	0.870	-2.8415	43.1666	0.948
DEC	-0.3878	42.8571	0.993	-0.7220	43.0640	0.987
M_DMA4	**-19.9895**	4.4597	< 0.001			
M_DMAL2	15.4644	8.3793	0.066			
D_COL1				2.8185	11.2161	0.802
D_COL3				-4.48E-06	< 0.0001	0.409
Constant	**267.5744**	87.5062	0.002	**267.3455**	88.1547	0.003
adj. R^2	0.17			0.14		
F	**2.59**		< 0.001	**2.31**		< 0.001
df	50, 340			50, 340		
n	391			391		

Year dummies were included, but none were significant at α = .05.

Omitted categories: Other race, less than high school diploma, no children, never married, other worker category, Sunday, August, year 2010.

Table 32

Infrequency of Purchase Model (IPM) Results for *WORKTIME*

Bay Area women, age 40 and under

Multiple imputation (MI) models (m = 7 imputations)

Boldface effects are significant at α = .05

	H1N1 incidence indicators					
	1. News article frequencies			*2. Deaths*		
Variable	Coefficient	SE	p-value	Coefficient	SE	p-value
AGE	-3.9404	4.0231	0.329	-2.5564	4.2162	0.545
BLACK	-26.9008	73.9128	0.716	-30.4130	77.1199	0.694
WHITE	-62.4056	44.4484	0.162	-61.6984	44.6814	0.169
HISPANIC	65.7817	35.0936	0.062	56.8176	37.5738	0.132
HISCHOOL	21.8808	120.7174	0.856	30.8120	123.2173	0.803
SOMECOLL	5.6220	119.3075	0.962	13.8378	123.8103	0.911
ASSOCIATES	76.3480	112.8290	0.499	89.0127	115.6949	0.443
BACHELORS	95.7665	114.1764	0.403	107.5792	117.2849	0.360
GRADUATE	126.2810	128.2445	0.326	128.9703	128.8977	0.318
CHILD_0_2	**-98.3970**	49.1012	0.047	-86.3000	50.4704	0.089
CHILD_3_5	**-117.9673**	47.5480	0.014	**-128.4951**	50.7136	0.012
CHILD_6_12	**-152.6963**	61.2240	0.014	**-150.9210**	62.6773	0.017
CHILD_13_17	32.6262	71.5693	0.649	52.9485	70.5811	0.454
MARRIED	69.4305	64.8632	0.286	61.6808	63.8916	0.336
SEPARATED	-4.9137	72.8670	0.946	-15.5668	71.0076	0.827
DIVORCED	79.1817	83.9617	0.347	67.1408	82.6869	0.418
rEARNHR	-0.2361	1.5532	0.879	-0.2942	1.5103	0.846
WORKHRS	**7.6568**	1.4465	< 0.001	**7.6651**	1.5811	< 0.001
HOURLY	27.6071	41.9481	0.511	25.8345	44.6872	0.564
MULTJOB	-50.9377	68.0384	0.455	-62.9672	68.7865	0.361
STUDENT	-58.9891	40.1441	0.143	-59.7213	41.2235	0.149
SPOUSEHRS	0.7894	1.5481	0.611	0.7620	1.5492	0.623
PUBLICWKR	41.7446	44.1089	0.345	47.5554	47.8827	0.322
SCHOOLWKR	54.5022	59.8420	0.364	70.4013	61.9150	0.257
BUSFARM	-4.0762	46.6032	0.930	6.4553	48.0161	0.893
MONDAY	63.3119	55.7079	0.257	70.2915	62.6875	0.264
TUESDAY	**116.0040**	56.0595	0.040	**130.6239**	53.5481	0.016
WEDNESDAY	**139.9886**	55.5389	0.013	**139.8679**	61.0556	0.023
THURSDAY	**169.4570**	58.3600	0.004	**182.3542**	59.1607	0.002
FRIDAY	84.7957	52.4058	0.107	92.1078	53.6234	0.088
SATURDAY	76.7243	48.3692	0.114	90.6653	50.0659	0.072
JAN	-36.9934	75.6572	0.625	-22.1217	78.6001	0.779
FEB	**-179.8792**	87.2342	0.041	-149.4174	89.9965	0.099
MAR	58.2149	70.7150	0.411	55.4551	73.9208	0.454
APR	-56.6825	83.1387	0.496	-45.0378	85.6123	0.599
MAY	-64.0184	82.1461	0.437	-54.7167	85.1517	0.521
JUN	-45.7071	94.6046	0.630	-55.4652	98.3433	0.573
JUL	-112.5336	75.9247	0.140	-94.0669	83.5068	0.261
SEP	-138.2020	81.7802	0.093	-120.3268	86.5279	0.166
OCT	-117.4078	69.7270	0.094	-105.6900	73.2372	0.151
NOV	-23.9642	65.5110	0.715	1.3284	68.4904	0.985
DEC	-155.9282	87.4877	0.076	-156.6547	91.8753	0.090
M_DMA	**-48.3328**	24.2511	0.048			
M_DMAL2	10.8568	22.4936	0.630			
D_COL1				-0.4361	7.5712	0.954
D_COL3				1.747E-05	0.0001	0.748
Constant	-39.3944	176.3699	0.8235	-105.2421	180.7163	0.561
adj. R^2	0.37			0.36		
F	**11.66**		< 0.001	**11.29**		< 0.001
df	51, 18065			51, 20613		
n	188			182		

Year dummies were included, but none were significant at α = .05.

Omitted categories: Other race, less than high school diploma, no children, never married, other worker category, Sunday, August, year 2010.

where *w_WORKTIME* =1 if work time use on the diary day was nonzero. The second-tier model is

$$WORKTIME \ = \beta_0 + \beta_1\hat{e} + \boldsymbol{D\varphi} + \boldsymbol{C\gamma} + \theta_1 H_t + \theta_2 H_{t-2} \tag{5.3}$$

which is estimated as truncated normal using only observations with nonzero values of *WORKTIME*. *WORKTIME* is the actual number of minutes used for work on the diary day. The other variables are the same as for the IPM model above. The double hurdle allows different sets of regressors in the two equations, but lacking any theoretical justification for excluding any variables from one or the other, my models use the same for both tiers. The double hurdle is nonetheless a useful tool in this case since it allows the variables to take on different signs in the two equations.

Double hurdle model results are shown in Tables 33 through 36. Two inverse probability weight models were significant, for both female and male Southern California residents age 40 and under. Multiple imputation results were significant for two groups of over-40 year olds, Southern California women and Central Valley men. The inverse probability weight model for Bay Area men, and the multiple imputation model for Central Valley men, both age 40 and under, were rejected due to the effects of high-influence observations. Both showed significant positive coefficients on *M_DMA* in the first hurdle probit model, but removing those observations with the highest measured influence resulted in coefficients not significantly different from zero, and the models were dropped from consideration.

These models test variations of the hypotheses discussed above. Making the assumption that workers are at a corner solution, they allow me to investigate whether a spike in H1N1 incidence led workers to reduce work time by staying home from work on the diary day, as opposed to working for a shorter time.

As in the IPM regressions, county level death variables were statistically insignificant.[40] These results are not reported.

Table 33 and 34 show the inverse probability weight models. For Southern California women age 40 and under (Table 33), the probability of going to work was unaffected by the level of media coverage, as shown in the first hurdle probit model, but for those who did go to work, the second hurdle truncated normal model shows that a one-point increase in *M_DMA* led to a 12 minute reduction in work time ($\hat{\beta}$ = -11.9274, t = -2.15, p-value = 0.033). This is about half the magnitude of the IPM result ($\hat{\beta}$ = -19.9895). Making further comparisons to the IPM, the second-week lag of *M_DMA* is again positive but insignificant; among the controls, child age is significant only for children age 2 and under, and the coefficient, at -69.7537, is about 22% larger; for school employees the effect is nearly the same, as they worked about 60 minutes less than others on the diary day. Hourly worker status shows no effect, but usual weekly work hours exerts a positive effect of about 4 minutes for every extra hour of usual work. Blacks worked about 135 minutes less than women of races other than black or white, and the two policewomen in the subsample worked an average of 162 minutes more than others. Several diary-day controls were significant as well. With adjusted R^2 = 0.37, the second hurdle provided a much better fit than the IPM's 0.17.

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[40] In one model, the first hurdle probit for Southern California women age 40 and under, the three-week lag of *D_CO* was positive and statistically significant, but with a marginal effect of 0.0000000513 given an increase of one death per 10 million population, its practical significance is nil.

Table 33

Double Hurdle Model Results

Southern California women, age 40 and under

First hurdle probit and second hurdle truncated normal models, inverse probability weights

Boldface effects are significant at α = .05

Variable	*First hurdle* Marginal effect††	Coefficient	SE†	*p*-value	*Second hurdle* Coefficient	SE†	*p*-value
AGE	-0.0125	-0.0352	0.0190	0.064	-3.0982	1.6743	0.066
BLACK	0.0100	0.0285	0.3833	0.941	**-135.7024**	31.9085	< 0.001
WHITE	0.0363	0.1013	0.2442	0.678	-20.2572	21.1799	0.340
HISPANIC	0.0379	0.1071	0.2133	0.616	-11.8544	20.6773	0.567
HSCHOOL	-0.1184	-0.3206	0.3297	0.331	-28.2548	33.0326	0.394
SOMECOLL	-0.0820	-0.2264	0.3152	0.473	-38.4305	30.4238	0.208
ASSOCIATES	-0.0842	-0.2287	0.3723	0.539	4.2240	33.3440	0.899
BACHELORS	0.0118	0.0336	0.3457	0.923	-22.2903	34.4824	0.519
GRADUATE	0.1905	0.6305	0.4266	0.139	-61.8004	44.8919	0.170
CHILD_0_2	0.1289	0.3885	0.2466	0.115	**-69.7537**	21.2429	0.001
CHILD_3_5	0.0619	0.1809	0.3095	0.559	-21.4056	29.9730	0.476
CHILD_6_12	0.1541	0.4821	0.2800	0.085	-40.0660	26.4204	0.131
CHILD_13_17	0.0789	0.2357	0.4139	0.569	-48.0941	39.9932	0.231
MARRIED	0.1566	0.4554	0.3386	0.179	0.6271	29.7154	0.983
SEPARATD	-0.0701	-0.1909	0.3622	0.598	12.9949	38.1493	0.734
DIVORCED	0.1921	0.6683	0.3675	0.069	30.5436	44.5517	0.494
rEARNHR	-0.0051	-0.0143	0.0119	0.231	1.5101	1.5382	0.328
WORKHRS	**0.0136**	**0.0384**	0.0087	< 0.001	**3.8260**	0.9086	< 0.001
HOURLY	-0.1187	-0.3467	0.2173	0.111	6.8576	21.9289	0.755
MULTJOB	-0.1444	-0.3833	0.3219	0.234	**-66.5398**	33.0041	0.045
STUDENT	0.1565	0.4808	0.2474	0.052	-23.2539	22.5911	0.305
SPOUSEHRS	**-0.0050**	**-0.0140**	0.0071	0.048	-0.8105	0.6473	0.212
*POLICE***	---	---	---	---	**141.2009**	48.2252	0.004
PUBLICWKR	-0.1708	-0.4559	0.2684	0.089	46.4029	26.4727	0.081
SCHOOLWKR	-0.1646	-0.4365	0.2685	0.104	**-59.6189**	25.3472	0.020
BUSFARM	-0.1422	-0.3774	0.3548	0.287	-65.6641	61.3982	0.286
*MONDAY**	**0.3405**	**1.4017**	0.3121	< 0.001	**137.6254**	43.0561	0.002
*TUESDAY**	**0.3357**	**1.3415**	0.2995	< 0.001	**142.2748**	43.9728	0.002
*WEDNESDAY**	**0.3180**	**1.2832**	0.3094	< 0.001	79.3790	52.9472	0.136
*THURSDAY**	**0.3998**	**1.7052**	0.3036	< 0.001	**135.3397**	42.1899	0.002
*FRIDAY**	**0.3598**	**1.5111**	0.3359	< 0.001	**104.9453**	43.6684	0.017
SATURDAY	**-0.2030**	**-0.5360**	0.2621	0.041	-19.3328	62.4903	0.757
JANUARY	-0.0515	-0.1414	0.4422	0.749	43.2989	41.4998	0.298
FEBRUARY	0.0766	0.2277	0.4070	0.576	-26.5355	43.1360	0.539
MARCH	0.0286	0.0822	0.4433	0.853	-16.9841	39.0640	0.664
APRIL	0.0758	0.2243	0.4085	0.583	-47.7788	32.7583	0.147
MAY	0.1109	0.3412	0.4610	0.459	-7.2012	43.2865	0.868
JUNE	0.0994	0.3030	0.4755	0.524	9.1376	38.3808	0.812
JULY	0.1440	0.4610	0.4732	0.330	-77.5251	52.3054	0.140
SEPTEMBER	0.0006	0.0017	0.4190	0.997	-6.5427	34.6816	0.851
OCTOBER	0.1204	0.3711	0.4033	0.357	-46.9672	34.5382	0.176
NOVEMBER	-0.1020	-0.2752	0.3975	0.489	-65.1240	39.7855	0.104
DECEMBER	-0.0885	-0.2400	0.4402	0.586	45.1615	38.2980	0.240
M_DMA	0.0513	0.1448	0.1311	0.269	**-11.9274**	5.5407	0.033
M_DMAL2	-0.0108	-0.0305	0.1026	0.766	8.3594	9.1922	0.364
Constant	---	-0.5914	0.8191	0.470	**385.2716**	86.5740	< 0.001
R^2 ‡‡	0.33				0.37		
χ^2	**156.60**			< 0.001			
F					**3.61**		< 0.001
df	50				51, 175		
n	437				227		

† Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator (first hurdle) and HC1 (second hurdle). First-hurdle standard errors are for coefficients

†† Calculated at means of independent variables

*Monday - Friday are not significantly different for the first hurdle, χ^2 = 1.32, 4 *df*, *p*-value=0.8585

**Showed excessive collinearity in probit model

Year dummy variables were used, none were significant at α = .05 for either model

Omitted categories: Other race, less than high school, no children, never married, other worker type, Sunday, August, 2010

‡‡ First hurdle uses McFadden's pseudo-R^2

Table 34
Double Hurdle Model Results
Southern California men, age 40 and under
First hurdle probit and second hurdle truncated normal models, inverse probability weights
Boldface effects are significant at α = .05

	First hurdle				*Second hurdle*		
Variable	Marginal effect††	Coefficient	SE†	*p*-value	Coefficient	SE†	*p*-value
AGE	-0.0052	-0.0237	0.0212	0.263	2.5104	2.7746	0.367
BLACK	-0.2538	-0.8434	0.4436	0.057	-37.8262	66.2740	0.569
WHITE	0.0722	0.2975	0.2724	0.275	-21.3795	40.4589	0.598
HISPANIC	-0.0660	-0.2957	0.2562	0.249	30.8579	25.1922	0.222
HISCHOOL	**-0.2730**	**-0.9674**	0.2979	0.001	-12.7128	43.9830	0.773
SOMECOLL	0.0585	0.2875	0.3184	0.367	-49.1968	43.3399	0.258
ASSOCIATES	0.0034	0.0153	0.4520	0.973	39.2170	47.5508	0.411
BACHELORS	**-0.2263**	**-0.8119**	0.3619	0.025	-9.4520	47.4503	0.842
GRADUATE	0.0134	0.0623	0.4461	0.889	-47.3678	57.8052	0.414
CHILD_0_2	-0.1227	-0.4724	0.2801	0.092	-54.5760	35.4202	0.125
CHILD_3_5	0.0577	0.3034	0.3917	0.439	-22.0629	51.9611	0.672
CHILD_6_12	-0.1358	-0.5105	0.3438	0.138	-8.1243	35.3837	0.819
CHILD_13_17	**-0.4112**	**-1.2383**	0.4118	0.003	-112.5537	61.9147	0.071
MARRIED	0.0778	0.3797	0.2746	0.167	35.8317	37.1512	0.336
SEPARATD	0.0321	0.1578	0.4116	0.701	72.5766	73.7799	0.327
DIVORCED	0.0666	0.3647	0.4006	0.363	47.5571	47.3662	0.317
rEARNHR	0.0024	0.0107	0.0125	0.390	-2.7661	1.6911	0.104
WORKHRS	**0.0097**	**0.0440**	0.0138	0.001	3.3338	1.8509	0.074
HOURLY	0.0210	0.0936	0.2195	0.670	-50.6288	31.7311	0.113
MULTJOB	-0.0702	-0.2822	0.4316	0.513	-4.1256	45.1737	0.927
STUDENT	-0.0374	-0.1595	0.3266	0.625	9.0374	38.5119	0.815
SPOUSEHRS	-0.0019	-0.0087	0.0064	0.173	-0.1661	0.9286	0.858
POLICE	-0.1800	-0.6196	0.5941	0.297	**161.9526**	73.2827	0.029
PUBLICWKR	0.0875	0.4820	0.3437	0.161	21.6869	34.1300	0.526
SCHOOLWKR	**-0.5500**	**-1.5967**	0.7028	0.023	45.8302	72.3219	0.527
TRANSPORT	0.0466	0.2397	0.4148	0.563	-50.7276	64.2409	0.431
BUSFARM	**0.1182**	**0.8385**	0.4235	0.048	-4.8511	56.9413	0.932
MONDAY	**0.1784**	2.1210	0.4767	< 0.001	99.7848	65.9636	0.132
TUESDAY	**0.1964**	2.0239	0.3844	< 0.001	75.7526	60.5478	0.213
WEDNESDAY	**0.2753**	2.7710	0.3662	< 0.001	104.8268	57.4900	0.070
THURSDAY	**0.2726**	2.5302	0.3396	< 0.001	111.1441	57.5792	0.055
FRIDAY	**0.2119**	2.4822	0.4193	< 0.001	77.7965	54.7778	0.158
SATURDAY	0.0306	0.1467	0.2586	0.571	-2.3849	67.0712	0.972
JANUARY	-0.0191	-0.0835	0.4849	0.863	-98.4716	55.1677	0.076
FEBRUARY	-0.1619	-0.5808	0.4843	0.230	-64.4582	53.0430	0.226
MARCH	**-0.4818**	-1.4263	0.4884	0.003	-23.3382	52.6905	0.658
APRIL	-0.0205	-0.0892	0.5425	0.869	-74.8630	47.2831	0.115
MAY	**-0.2585**	-0.8667	0.4306	0.044	-14.4064	42.9356	0.738
JUNE	**-0.4163**	-1.2818	0.4787	0.007	-33.7912	54.2022	0.534
JULY	-0.1200	-0.4496	0.5332	0.399	-61.5333	60.3967	0.310
SEPTEMBER	**-0.3092**	-0.9972	0.4418	0.024	-3.9623	50.9441	0.938
OCTOBER	-0.0722	-0.2918	0.4173	0.484	-66.7807	51.3861	0.196
NOVEMBER	**-0.2787**	-0.9131	0.4637	0.049	-123.4163	71.2237	0.085
DECEMBER	-0.2352	-0.7953	0.4441	0.073	-49.6129	47.1368	0.294
M_DMA	0.0317	0.1437	0.1131	0.204	**52.4982**	21.3381	0.015
M_DMAL2	-0.0117	-0.0532	0.0694	0.444	**-38.6661**	14.7431	0.010
Constant	---	-1.4034	1.0485	0.181	**298.4099**	149.7150	0.048
R^2 ‡‡	0.46				0.19		
χ^2	**187.60**			< 0.001			
F					**1.93**		< 0.001
df	52				52, 161		
n	373				214		

† Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator (first hurdle) and HC1 (second hurdle). First-hurdle standard errors are for coefficients.
†† Calculated at means of independent variables.
Year dummy variables were used, year 2007 was significantly greater than year 2010 for the second hurdle.
Omitted categories: Other race, less than high school, no children, never married, other worker type, Sunday, August, 2010.
‡‡ First hurdle uses McFadden's pseudo-R^2

Men age 40 and under in Southern California generated an anomalous result. Table 34 shows a positive coefficient on the current week *M_DMA* variable and a negative coefficient for the two-week lag, the opposite of the expected, and this result was substantially the same even when high-influence observations were removed. I have no explanation for this, but note that there were no other results like it in 48 models tested,[41] and that the only other significant effect was for *POLICE* workers, who accounted for 13 of the 214 observations.

Multiple imputation results for Southern California women over age 40 are in Table 35. The probit shows a significant effect of high perceived H1N1 risk; a one-point increase in *M_DMA* reduced the likelihood of going to work by about 3%, measured as the marginal effect at the means of the regressors. The estimated effect for the two-week lag was much smaller and insignificant. Among demographic controls, hispanics were about 17% less likely to work; all levels of schooling showed a lower likelihood in relation to those without a high school diploma, although the effects were insignificant for those with a bachelors or graduate degree; likewise the presence of a child reduced the probability, with significant effects for children between ages 3 and 5 and 13 and over. Longer usual work hours made for a small increase. Students were about 17% more likely to work on the diary day, a result that does not coincide with any of the other models. As in all other models estimated, there is no effect of hourly earnings on one-day work time. The second hurdle shows effects only for work hours and occupation type, and diary day controls.

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[41]Involving 2 sexes, 2 age groups, 3 regions, 2 imputation methods, and 2 model specifications

Table 35

Double Hurdle Model Results

Southern California women over age 40

First hurdle probit and second hurdle truncated normal models, multiple imputation

Boldface effects are significant at $\alpha = .05$

Variable	First hurdle: Marginal effect††	First hurdle: Coefficient	First hurdle: SE†	First hurdle: p-value	Second hurdle: Coefficient	Second hurdle: SE†	Second hurdle: p-value
AGE	-0.0009	-0.0025	0.0127	0.845	-0.0993	1.5275	0.948
BLACK	-0.0247	-0.1000	0.2645	0.705	-10.3682	37.6817	0.783
WHITE	-0.0641	-0.2264	0.1832	0.217	-31.5753	25.3948	0.214
HISPANIC	**-0.1738**	**-0.4946**	0.1733	0.004	15.9961	25.5567	0.532
HISCHOOL	**-0.1909**	**-0.5048**	0.2567	0.050	1.4638	33.0759	0.965
SOMECOLL	**-0.3286**	**-0.8861**	0.2665	0.001	-12.1188	32.1054	0.706
ASSOCIATES	**-0.2831**	**-0.7871**	0.3308	0.018	-10.6103	36.9037	0.774
BACHELORS	-0.0952	-0.3338	0.2919	0.257	-12.1516	35.9363	0.735
GRADUATE	-0.0856	-0.3538	0.3811	0.359	-9.5931	44.5553	0.830
CHILD_0_2	-0.0020	0.0483	0.3313	0.884	32.9479	37.0239	0.374
CHILD_3_5	**-0.4418**	**-1.1594**	0.3319	< 0.001	30.9157	32.2777	0.339
CHILD_6_12	-0.1145	-0.3323	0.1949	0.088	-12.3952	24.6349	0.615
CHILD_13_17	**-0.1963**	**-0.5242**	0.1927	0.007	20.8662	27.6771	0.451
MARRIED	0.0500	0.0733	0.3251	0.822	22.1711	40.5447	0.585
SEPARATD	0.0879	0.2589	0.3263	0.428	13.1531	38.3992	0.732
DIVORCED	0.0279	0.0691	0.2098	0.742	0.5591	23.2127	0.981
*WIDOWED***	---	---	---	---	-7.5351	37.3594	0.840
rEARNHR	-0.0024	-0.0003	0.0099	0.979	0.3591	1.0733	0.738
WORKHRS	**0.0082**	**0.0208**	0.0063	0.003	**7.6663**	0.9057	< 0.001
HOURLY	0.0228	0.0546	0.1626	0.740	19.5737	22.3417	0.381
MULTJOB	0.0838	0.3344	0.2481	0.178	36.1495	31.9391	0.258
STUDENT	**0.1720**	**0.7068**	0.3564	0.047	-99.4919	72.7659	0.172
SPOUSEHRS	-0.0004	-0.0002	0.0069	0.981	-0.3077	0.9490	0.746
PUBLICWKR	0.0867	0.2734	0.1709	0.110	-37.3592	25.0363	0.136
SCHOOLWKR	-0.0607	-0.1970	0.2644	0.456	**-111.8967**	36.7167	0.002
TRANSPORT	-0.6135	-1.2653	1.0236	0.218	**129.5378**	56.6810	0.023
BUSFARM	0.1059	0.3377	0.1797	0.060	2.7031	25.6862	0.916
*MONDAY**	**0.3283**	**1.8687**	0.2320	< 0.001	**223.9959**	37.9640	< 0.001
*TUESDAY**	**0.3695**	**2.0987**	0.2310	< 0.001	**251.3760**	35.8170	< 0.001
*WEDNESDAY**	**0.3480**	**2.0095**	0.2343	< 0.001	**280.0239**	36.8421	< 0.001
*THURSDAY**	**0.3181**	**1.5237**	0.2361	< 0.001	**283.9738**	42.3588	< 0.001
*FRIDAY**	**0.3289**	**1.9430**	0.2410	< 0.001	**208.5804**	40.5913	< 0.001
SATURDAY	0.0764	0.2307	0.1753	0.188	**124.0490**	47.1149	0.009
JANUARY	0.0687	0.2925	0.3785	0.440	-79.2817	49.5805	0.111
FEBRUARY	0.0094	0.0944	0.3960	0.812	-25.8755	49.6513	0.603
MARCH	**0.1652**	**0.6757**	0.3441	0.050	**-115.6584**	54.9914	0.036
APRIL	0.0649	0.2453	0.3627	0.499	-67.3158	50.4674	0.183
MAY	**0.1666**	**0.7364**	0.3740	0.049	**-105.0744**	53.0708	0.048
JUNE	0.1371	0.5398	0.3755	0.151	-88.2060	55.7385	0.114
JULY	0.0560	0.2228	0.3512	0.526	5.3927	48.3906	0.911
SEPTEMBER	-0.0229	-0.0154	0.3463	0.965	**-105.5802**	50.9386	0.039
OCTOBER	**0.1625**	**0.6684**	0.3327	0.045	-54.4465	50.1675	0.278
NOVEMBER	0.1511	0.5769	0.3587	0.108	-94.2749	53.4100	0.078
DECEMBER	0.0349	0.1622	0.3444	0.638	-74.7125	47.6337	0.118
M_DMA	**-0.0312**	**-0.0909**	0.0438	0.038	-0.4641	4.1278	0.911
M_DMAL2	-0.0142	-0.0420	0.0599	0.483	7.5051	6.3503	0.238
Constant	---	-0.8611	0.9183	0.349	17.5288	118.7644	0.883
R^2‡‡	0.34				0.40		
χ^2‡	**285.38**			< 0.001			
F					**72.760**		< 0.001
df	51				53, 59051		
n	716				410		

† Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator (first hurdle) and HC1 (second hurdle). First-hurdle standard errors are for coefficients

†† Calculated at means of independent variables.

**Showed excessive collinearity in probit model

*Monday - Friday are not signficantly different for the first hurdle; $\chi^2 = 4.92$, 4 *df*, p-value = 0.2957

Year dummy variables were used; none were significant at $\alpha = .05$ for either model.

Omitted categories: Other race, less than high school, no children, never married, other worker type, Sunday, August, 2010

‡‡ First hurdle uses McFadden's pseudo-R^2.

‡ Lowest value of the 7 imputations

The final set of estimates is the only model with significant effects for the Central Valley region, for men over age 40, shown in Table 36. A one-point increase in *M_DMA* led to about a 9% reduction in the probability of working on the diary day. As in the other models, the two-week lag of *M_DMA* was not significant.

C. Comparison of Missing Data Methods

To compare the two missing data methods I estimated a set of models using each of IPW and MI, along with listwise deletion.

Double hurdle results for Southern California women age 40 and under are in Tables 37 and 38. The inverse probability weight estimates replicate those in Table 33. The IPW and listwise deletion results are nearly the same. Considering only the coefficients significant in at least one of these two regressions, none differ by more than 8% (*MULTJOB* in the second hurdle), and the mean absolute percent difference is 2.9%. The coefficients for *M_DMA,* both insignificant, are nearly identical, and standard errors are likewise similar. This points out a weakness of the using the IPW method with survey data: since it is dependent upon a single regression for estimates of the probabilities of nonzero values, a poorly-fitting model will generate noisy estimates for weights with a large random component. Random weights are equivalent to no weights, and using no weights leaves us with listwise deletion. The probit model that generated the weights had a pseudo-R^2 of only 0.06. The regressors were essentially the same as used for the analysis models with the exception of the diary day controls, H1N1 indicators. The implication is that missingness of the earnings variable is relatively uncorrelated with the covariates, and so the data are either missing completely at

Table 36
Double Hurdle Model Results
Central Valley men over age 40
First hurdle probit and second hurdle truncated normal models, multiple imputation
Boldface effects are significant at $\alpha \leq .05$

	First hurdle				*Second hurdle*		
Variable	Marginal effect††	Coefficient	SE‡	p-value	Coefficient	SE‡	p-value
AGE	0.0084	0.0414	0.0265	0.120	**-5.8985**	2.7869	0.036
BLACK	**-0.8300**	**-2.7411**	0.8702	0.002	145.4348	147.4710	0.326
WHITE	**-0.1546**	**-1.4076**	0.6042	0.020	-22.5208	61.1343	0.713
HISPANIC	-0.1613	-0.7121	0.4055	0.081	28.4919	66.6225	0.670
HISCHOOL	-0.0184	-0.1086	0.5690	0.849	48.2641	57.7510	0.405
SOMECOLL	-0.0667	-0.3514	0.5990	0.561	**154.7511**	73.2147	0.037
ASSOCIATES	-0.1220	-0.5881	0.6450	0.363	**173.0466**	58.1678	0.004
BACHELORS	-0.2258	-0.9440	0.6117	0.127	92.9811	62.0983	0.137
GRADUATE	-0.0610	-0.3539	0.7354	0.632	-2.6471	91.2905	0.977
CHILD_0_2	0.1313	1.3901	0.7119	0.051	-97.7876	71.1699	0.172
CHILD_3_5	-0.4026	-1.2548	0.7064	0.077	2.3452	56.6268	0.967
CHILD_6_12	-0.1506	-0.6490	0.4070	0.112	45.9463	48.2642	0.343
CHILD_13_17	-0.1439	-0.6431	0.4988	0.197	83.3594	74.7426	0.267
MARRIED	0.1497	0.8114	0.7901	0.325	-86.0932	57.8701	0.140
SEPARATD	0.1058	0.8532	1.1682	0.468	-78.3861	152.2957	0.608
DIVORCED	0.0766	0.4606	0.5909	0.436	-7.4173	71.9294	0.918
rEARNHR	-0.0042	-0.0225	0.0212	0.308	-0.3890	2.3474	0.869
WORKHRS	**0.0124**	**0.0635**	0.0170	< 0.001	**11.2601**	1.7475	< 0.001
HOURLY	-0.1312	-0.7092	0.4733	0.167	**87.1479**	42.3585	0.042
MULTJOB	0.1210	0.9592	0.5632	0.090	**-134.0372**	59.5823	0.026
STUDENT	0.1171	1.2792	0.9261	0.171	8.6301	83.5272	0.918
SPOUSEHRS	0.0009	-0.0007	0.0180	0.970	1.7549	1.5718	0.267
FIREFGHTR	-0.1573	-0.5885	1.1877	0.621	**345.9836**	93.2025	< 0.001
*HEALTHWKR***	---	---	---	---	31.4727	112.6434	0.780
POLICE	**0.1225**	**2.3509**	1.0735	0.029	-170.0511	145.9733	0.246
PUBLICWKR	0.0610	0.3641	0.5946	0.542	86.1018	68.2728	0.210
SCHOOLWKR	**0.1253**	**1.5115**	0.7292	0.038	-3.8344	94.5956	0.968
TRANSPORT	-0.2404	-0.9009	0.7886	0.254	-29.2032	119.5382	0.807
BUSFARM	-0.2225	-0.7272	0.4343	0.095	-23.5550	44.9091	0.601
MONDAY	**0.1952**	**2.3058**	0.5539	< 0.001	131.7770	69.0302	0.059
TUESDAY	**0.2409**	**2.8754**	0.5995	< 0.001	110.3423	75.0339	0.144
WEDNESDAY	**0.2063**	**3.6372**	0.7443	< 0.001	77.0798	87.1485	0.378
THURSDAY	**0.2258**	**3.5208**	0.6570	< 0.001	**179.6299**	76.1728	0.020
FRIDAY	**0.2277**	**2.7028**	0.6001	< 0.001	81.7416	68.0143	0.232
SATURDAY	0.0723	0.4916	0.4297	0.254	-44.5474	90.0835	0.622
JANUARY	-0.0050	-0.1173	0.7174	0.870	78.3889	99.4484	0.432
FEBRUARY	-0.0169	-0.1256	0.7561	0.868	58.1531	103.2775	0.574
MARCH	-0.3752	-1.2362	0.9758	0.205	12.3502	144.5688	0.932
APRIL	-0.0347	-0.0580	0.8329	0.945	96.3977	90.4253	0.289
MAY	0.1075	0.8134	0.8023	0.311	203.8955	114.9822	0.079
JUNE	-0.0386	-0.3054	0.7797	0.696	**204.0222**	97.6696	0.039
JULY	-0.0971	-0.4682	0.6962	0.501	145.9726	86.9010	0.096
SEPTEMBER	0.1312	1.1100	0.7013	0.114	-50.2877	84.9620	0.555
OCTOBER	-0.0682	-0.2869	0.7215	0.691	152.8444	101.7473	0.136
NOVEMBER	-0.0455	-0.0951	0.7516	0.899	94.1682	106.9116	0.380
DECEMBER	0.1124	0.8902	0.7527	0.237	145.5681	99.5016	0.146
M_DMA	**-0.0878**	**-0.4414**	0.2049	0.032	45.3319	127.7678	0.723
M_DMAL2	0.0710	0.2949	0.2389	0.232	7.6774	64.4379	0.905
Constant	---	**-4.7313**	2.1930	0.038	97.9197	214.1256	0.648
R^2 ‡‡	0.55				0.67		
χ^2	**115.33**			< 0.001			
F					**36.33**		< 0.001
df	53				55, 17130		
n	193				117		

† Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator (first hurdle) and HC1 (second hurdle). First-hurdle standard errors are for coefficients
†† Calculated at means of independent variables.
**Showed excessive collinearity in probit model
*Monday - Friday are not significantly different for the first hurdle: $\chi^2 = 7.93$, 4 df, p-value = 0.0943
Year dummy variables were used; all years except 2004 were significantly greater than year 2010 for the first hurdle
Omitted categories: Other race, less than high school, no children, never married, other worker type, Sunday, August, 2010
‡‡ First hurdle uses McFadden's pseudo-R^2
‡ Lowest value of the 7 imputations

Table 37

Double Hurdle Model Results

Comparison of listwise deletion, inverse probability weight, and multiple imputation models

Southern California women, age 40 and under

First hurdle probit model

Boldface effects are significant at α = .05

	Listwise deletion			*Inverse probability weight*			*Multiple imputation*		
Variable	Coefficient	SE†	*p*-value	Coefficient	SE†	*p*-value	Coefficient	SE†	*p*-value
AGE	-0.0350	0.0191	0.067	-0.0352	0.0190	0.064	-0.0108	0.0161	0.505
BLACK	-0.0153	0.3850	0.968	0.0285	0.3833	0.941	0.0200	0.3406	0.953
WHITE	0.0795	0.2454	0.746	0.1013	0.2442	0.678	0.0971	0.2128	0.648
HISPANIC	0.1159	0.2156	0.591	0.1071	0.2133	0.616	0.0561	0.1823	0.758
HISCHOOL	-0.3539	0.3308	0.285	-0.3206	0.3297	0.331	-0.3927	0.2792	0.160
SOMECOLL	-0.2361	0.3137	0.452	-0.2264	0.3152	0.473	-0.4059	0.2582	0.117
ASSOCIATES	-0.2707	0.3712	0.466	-0.2287	0.3723	0.539	-0.3892	0.3194	0.224
BACHELORS	0.0185	0.3449	0.957	0.0336	0.3457	0.923	-0.2371	0.3126	0.452
GRADUATE	0.5917	0.4249	0.164	0.6305	0.4266	0.139	0.0295	0.4048	0.943
CHILD_0_2	0.3884	0.2466	0.115	0.3885	0.2466	0.115	0.2024	0.2078	0.330
CHILD_3_5	0.1906	0.3137	0.544	0.1809	0.3095	0.559	0.1603	0.2506	0.523
CHILD_6_12	0.5001	0.2810	0.075	0.4821	0.2800	0.085	0.1409	0.2363	0.551
CHILD_13_17	0.2306	0.4128	0.576	0.2357	0.4139	0.569	0.2922	0.3593	0.416
MARRIED	0.4745	0.3386	0.161	0.4554	0.3386	0.179	0.3050	0.2948	0.301
SEPARATED	-0.1675	0.3589	0.641	-0.1909	0.3622	0.598	-0.2793	0.3522	0.428
DIVORCED	0.6889	0.3719	0.064	0.6683	0.3675	0.069	0.5612	0.3115	0.072
rEARNHR	-0.0129	0.0120	0.284	-0.0143	0.0119	0.231	-0.0126	0.0138	0.387
WORKHRS	**0.0379**	0.0087	< 0.001	**0.0384**	0.0087	< 0.001	**0.0323**	0.0075	< 0.001
HOURLY	-0.3446	0.2180	0.114	-0.3467	0.2173	0.111	-0.2308	0.1727	0.182
MULTJOB	-0.4038	0.3254	0.215	-0.3833	0.3219	0.234	-0.0653	0.2965	0.826
STUDENT	**0.5132**	0.2481	0.039	0.4808	0.2474	0.052	0.3424	0.2162	0.113
SPOUSHRS	**-0.0146**	0.0071	0.040	**-0.0140**	0.0071	0.048	-0.0067	0.0065	0.300
PUBLICWKR	-0.4493	0.2732	0.100	-0.4559	0.2684	0.089	-0.1530	0.2136	0.474
SCHOOLWKR	-0.4584	0.2654	0.084	-0.4365	0.2685	0.104	-0.0825	0.2609	0.752
BUSFARM	-0.4443	0.3568	0.213	-0.3774	0.3548	0.287	-0.0669	0.2338	0.775
MONDAY	**1.4010**	0.3161	< 0.001	**1.4017**	0.3121	< 0.001	**1.6001**	0.2590	< 0.001
TUESDAY	**1.3568**	0.3020	< 0.001	**1.3415**	0.2995	< 0.001	**1.1974**	0.2466	< 0.001
WEDNESDAY	**1.2998**	0.3098	< 0.001	**1.2832**	0.3094	< 0.001	**1.4075**	0.2626	< 0.001
THURSDAY	**1.7219**	0.3036	< 0.001	**1.7052**	0.3036	< 0.001	**1.6086**	0.2572	< 0.001
FRIDAY	**1.5305**	0.3388	< 0.001	**1.5111**	0.3359	< 0.001	**1.4126**	0.2837	< 0.001
SATURDAY	-0.5077	0.2639	0.054	**-0.5360**	0.2621	0.041	-0.1305	0.2120	0.538
JAN	-0.1750	0.4456	0.694	-0.1414	0.4422	0.749	-0.2838	0.3569	0.426
FEB	0.2147	0.4078	0.598	0.2277	0.4070	0.576	0.1174	0.3419	0.731
MAR	0.0458	0.4462	0.918	0.0822	0.4433	0.853	-0.0080	0.3678	0.983
APR	0.1973	0.4107	0.631	0.2243	0.4085	0.583	0.0904	0.3299	0.784
MAY	0.2959	0.4609	0.521	0.3412	0.4610	0.459	0.3017	0.4012	0.452
JUN	0.3030	0.4821	0.530	0.3030	0.4755	0.524	-0.2038	0.3518	0.562
JUL	0.4174	0.4775	0.382	0.4610	0.4732	0.330	-0.1860	0.3903	0.634
SEP	-0.0080	0.4182	0.985	0.0017	0.4190	0.997	-0.1495	0.3461	0.666
OCT	0.3574	0.4057	0.378	0.3711	0.4033	0.357	0.1902	0.3305	0.565
NOV	-0.2711	0.3982	0.496	-0.2752	0.3975	0.489	-0.2011	0.3516	0.567
DEC	-0.2889	0.4411	0.512	-0.2400	0.4402	0.586	-0.1679	0.3548	0.636
M_DMA	0.1447	0.131	0.269	0.1448	0.1311	0.269	0.0363	0.0583	0.533
M_DMA2	-0.0325	0.102	0.751	-0.0305	0.1026	0.766	0.0074	0.0536	0.890
Constant	-0.5479	0.8238	0.506	-0.5914	0.8191	0.470	-0.8824	0.7442	0.236
R^2 ‡‡	0.33			0.33			0.27		
χ^2 ‡	**156.34**		< 0.001	**156.60**		< 0.001	**157.48**		< 0.001
df	50			50			50		
n	437			437			592		

† Reported standard errors are corrected for heteroskedasticity with the Huber-White sandwich estimator

Year dummy variables were used, none were significant at α = .05 for any model

Omitted categories: Other race, less than high school, no children, never married, other worker type, Sunday, August, 2010

‡‡ McFadden's pseudo-R^2

‡ For MI, lowest value of the 7 imputations

Table 38
Double Hurdle Model Results
Comparison of listwise deletion, inverse probability weight, and multiple imputation models
Southern California women, age 40 and under
Second hurdle truncated normal model

Boldface effects are significant at $\alpha \leq .05$

	Listwise deletion			*Inverse probability weight*			*Multiple imputation*		
Variable	Coefficient	SE†	*p*-value	Coefficient	SE†	*p*-value	Coefficient	SE†	*p*-value
AGE	-3.0693	1.6832	0.070	-3.0982	1.6743	0.066	**-5.9726**	1.7534	0.001
BLACK	**-137.0106**	32.0751	< 0.001	**-135.7024**	31.9085	< 0.001	**-83.0207**	35.4160	0.020
WHITE	-20.1283	21.4877	0.350	-20.2572	21.1799	0.340	-19.4924	23.0772	0.399
HISPANIC	-9.9070	20.5250	0.630	-11.8544	20.6773	0.567	1.6707	22.3825	0.941
HISCHOOL	-25.6809	32.7578	0.434	-28.2548	33.0326	0.394	-54.2733	29.6896	0.068
SOMECOLL	-37.7089	30.4622	0.217	-38.4305	30.4238	0.208	**-65.0040**	25.4164	0.011
ASSOCIATES	6.7624	33.2500	0.839	4.2240	33.3440	0.899	-61.2487	32.1385	0.058
BACHELORS	-21.7199	34.6668	0.532	-22.2903	34.4824	0.519	-42.9402	31.1917	0.170
GRADUATE	-61.3746	44.9103	0.174	-61.8004	44.8919	0.170	**-92.3011**	40.3212	0.023
CHILD_0_2	**-70.0329**	21.4360	0.001	**-69.7537**	21.2429	0.001	-30.8743	20.8341	0.139
CHILD_3_5	-21.4569	29.9325	0.474	-21.4056	29.9730	0.476	22.8763	29.1816	0.434
CHILD_6_12	-40.1247	26.5589	0.133	-40.0660	26.4204	0.131	18.8167	22.9454	0.413
CHILD_13_17	-49.6962	39.7066	0.212	-48.0941	39.9932	0.231	19.4875	40.0594	0.627
MARRIED	-2.8494	30.2998	0.925	0.6271	29.7154	0.983	-22.4051	23.7057	0.345
SEPARATED	10.2250	37.1728	0.784	12.9949	38.1493	0.734	11.9161	33.0097	0.718
DIVORCED	31.0336	45.1957	0.493	30.5436	44.5517	0.494	-11.0167	37.7913	0.771
rEARNHR	1.5938	1.5459	0.304	1.5101	1.5382	0.328	1.7700	1.7106	0.302
WORKHRS	**3.8363**	0.9053	< 0.001	**3.8260**	0.9086	< 0.001	**6.0013**	1.0299	< 0.001
HOURLY	9.0753	21.9191	0.679	6.8576	21.9289	0.755	-9.0235	23.8268	0.705
MULTJOB	**-72.0521**	32.6582	0.029	**-66.5398**	33.0041	0.045	**-85.9517**	31.8998	0.007
STUDENT	-24.3699	22.6558	0.284	-23.2539	22.5911	0.305	-12.2277	20.5307	0.552
SPOUSHRS	-0.7389	0.6574	0.263	-0.8105	0.6473	0.212	0.1605	0.5642	0.776
POLICE	**136.0157**	50.0724	0.007	**141.2009**	48.2252	0.004	**194.4185**	70.4309	0.006
PUBLICWKR	46.6845	26.4138	0.079	46.4029	26.4727	0.081	**61.8075**	30.7466	0.045
SCHOOLWKR	**-56.7783**	25.2014	0.026	**-59.6189**	25.3472	0.020	**-101.0807**	28.2075	< 0.001
BUSFARM	-63.2659	63.4027	0.320	-65.6641	61.3982	0.286	-17.9846	31.3653	0.567
MONDAY	**130.8247**	43.2950	0.003	**137.6254**	43.0561	0.002	**158.6526**	38.3340	< 0.001
TUESDAY	**138.4940**	44.3620	0.002	**142.2748**	43.9728	0.002	**135.3128**	40.3145	0.001
WEDNESDAY	74.1167	52.7305	0.162	79.3790	52.9472	0.136	**128.1351**	46.5769	0.006
THURSDAY	**128.6031**	42.5312	0.003	**135.3397**	42.1899	0.002	**161.3635**	38.0506	< 0.001
FRIDAY	**99.8983**	43.8496	0.024	**104.9453**	43.6684	0.017	**129.3292**	39.9037	< 0.001
SATURDAY	-21.9896	62.4644	0.725	-19.3328	62.4903	0.757	**104.3384**	52.6665	0.048
JAN	43.4722	41.6249	0.298	43.2989	41.4998	0.298	14.2519	44.5464	0.749
FEB	-28.1551	43.2350	0.516	-26.5355	43.1360	0.539	**-108.1928**	45.3483	0.018
MAR	-19.7207	39.0069	0.614	-16.9841	39.0640	0.664	-42.9441	34.0297	0.208
APR	-49.7081	32.1605	0.124	-47.7788	32.7583	0.147	**-73.6621**	31.8424	0.021
MAY	-9.3270	43.1345	0.829	-7.2012	43.2865	0.868	-32.3339	47.6461	0.498
JUN	8.0076	38.5716	0.836	9.1376	38.3808	0.812	21.4800	38.3833	0.576
JUL	-80.0930	52.1566	0.126	-77.5251	52.3054	0.140	-75.2977	58.3200	0.198
SEP	-6.9432	34.6898	0.842	-6.5427	34.6816	0.851	-25.3417	37.1080	0.495
OCT	-47.5214	34.5977	0.171	-46.9672	34.5382	0.176	**-74.5953**	32.1674	0.021
NOV	-62.1016	39.9881	0.122	-65.1240	39.7855	0.104	**-73.4207**	34.1578	0.032
DEC	42.8152	38.5987	0.269	45.1615	38.2980	0.240	-11.3214	**39.0432**	0.772
M_DMA	**-12.2312**	5.5359	0.028	**-11.9274**	5.5407	0.033	-8.9441	6.0440	0.140
M_DMAL2	7.0168	9.1490	0.444	8.3594	9.1922	0.364	5.8333	5.0015	0.244
Constant	**388.6093**	86.8309	< 0.001	**385.2716**	86.5740	< 0.001	**365.3839**	85.1775	< 0.001
adj. R^2	0.37			0.37			0.32		
F	**3.55**		< 0.001	**3.61**		< 0.001	**24.15**		< 0.001
df	51, 175			51, 175			46, 85967		
n	227			227			314		

† Reported standard errors are corrected for heteroskedasticity with the HC1 estimator

Year dummy variables were used, none were significant at $\alpha = .05$ for any model

Omitted categories: Other race, less than high school, no children, never married, other worker type, Sunday, August, 2010 random—unlikely, based on what is known about CPS earnings data—or is missing not at random, which IPW is not capable of correcting.

Multiple imputation estimates differ starkly. The probit results are similar, with most of the significant coefficients differing by 10% or less, but neither method explains this model well. For the second hurdle model, most coefficients that are significant in both models are of larger magnitude in MI (32% larger on average, even though the MI coefficient for *BLACK* is only 61% as large as the IPW value). Although standard errors are 4.5% larger, the resulting ratios give the MI method more power to reject null hypotheses, and it produces a larger number of significant coefficients (19) than IPW (11)—but, unfortunately, not the coefficient for *M_DMA*.

VI. CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

Regarding hypothesis i, I find no significant effects of deaths on work time use—the coefficients on the *D_CO* variables are all indistinguishable from zero. This conforms with expectations, if people form their perceptions of pandemic risk primarily based on news reports.

Considering hypotheses ii and iii together, support for a reduction, or reallocation, of work time comes from five of the six models reported above. Reductions in diary day work time use in response to a one-point increase in *M_DMA* ranged from 11minutes for Southern California women age 40 and under to 48 minutes for similar women in the Bay Area. Probit estimates showed that *M_DMA* increases reduced the likelihood of going to work by 3% and 9% for Southern California women and Central Valley men over 40, respectively. As noted above, ATUS does not record the health status of the person or household members on the diary day, so it is impossible to tell if someone missed work to care for someone with the flu or to stay in bed and get over the flu. Evidence of work shifting, as opposed to net work time reduction, is weak. Among the five models that show a negative effect on work effort, the two-week lag value of *M_DMA* is positive (15.4644) and near significance (*p*-value = 0.066) for Southern California women age 40 and under (IPM model); for the others is it inarguably zero. The best that can be said is that whatever effect news reports had on perceived risk and thereby time use, it faded within two weeks. This could be due to intertemporal shifting of work and leisure, if people waited out perceived dangerous times and then caught up on work and income, but it could be due to any number of other factors. The simplest explanation is that people changed their expectations rapidly in a fast-changing environment, and that new information supplanted old in the public mind as soon as it became available.

In the one case where infrequency of purchase and double hurdle results could be compared—for Southern California women age 40 and under, both using inverse probability weights—the double hurdle results seem more convincing. The first-tier probit regression showed no effect on the likelihood of going to work. For those who did, the second tier showed not only a significant effect for news article frequencies but, compared to the IPM result, rejected the null hypothesis for more controls, with signs and magnitudes that seem reasonable. The IPM found no effect of usual work hours, which seems odd, while the double hurdle produced a strongly significant coefficient of about 4 minutes of extra work for each additional hour of usual weekly work hours. The fit of the second tier, with adjusted R^2 of 0.37, was much better than the 0.17 of the IPM. The double hurdle's *M_DMA* coefficient was about half that of IPM, but both are reasonable.

I find limited support for use of MI over other methods for handling missing values. Now 25 years old, MI has come into use in medicine and biostatistics, but has been little noticed by economists. The computational demands and data set size imposed by MI presented no problem in this study; computer hardware has developed to the point where MI is feasible. MI produced generally stronger coefficient estimates than IPW or listwise deletion and of course resulted in larger data sets, so despite a small efficiency loss it had more power and so generated, over all variables, more significant results. The main obstacle to more widespread use of MI is the time and effort required. As a recent addition to statistical software packages, it is not yet well integrated, and dealing with any but the simplest regressions can be extremely cumbersome. Hopefully, software revisions will improve this situation and researchers will make wider use of it. I caution against using a smaller number of imputations, as one unusual imputation can wreak havoc with coefficient estimates and significance tests. The coefficient estimates were more variable among imputations than in my previous study on child care time use, which used data with many more observations. MI has good large sample properties, but with small data sets it should be used with care.

To extend this work, I plan to identify and incorporate labor market demand measures to account for employment constraints during the pandemic period. I also intend to investigate the effect of transactions costs of going to work on work time use during the pandemic. Time input estimates can be obtained from ATUS, particularly travel and grooming time, and external data sets can be accessed to model local-area costs.

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APPENDICES

Appendix E

Definition of Work Time Use Variable

The dependent variable in this study is constructed from the work-related time use variables in ATUS. In preliminary estimates I used a broad measure which comprised all work-related activities, including job search and general income-generating activities. This measure was relatively noisy and generated no significant results, and anyway many of these activities might not involve direct contact with the public. Instead I use a narrower variable, *WORKTIME,* which consists solely of time spent working at a job.

Table 39 below shows the ATUS time use categories included in this measure.

Table 39
Definition of *WORKTIME*

WORKTIME	ATUS ID	Description
	t050101	Work, main job
	t050102	Work, other job(s)
	t050189	Working, not elsewhere classified

Appendix F

Matching ATUS and CPS data

As noted by Connolly (2008), matching ATUS respondents with local area data cannot be done directly from ATUS. None of the geographic location variables collected as part of the CPS are carried over into ATUS, so it is necessary to match each ATUS respondent with his household record in the CPS, which presents several challenges. The CPS household scrambled identification variable, *HRHHID*, is constructed using information on geographical location and a random number. (Urban Institute, no date) It is unique for each CPS household in any given month, but not necessarily beyond that, and many duplicates exist. And since each resident of a CPS household is represented by a separate record, multiple instances of most values of *HRHHID* exist for any single month.

The *ATUS User's Guide* (BLS, 2011b) offers instructions for making the matches. Madrian and Lefgren (1999), and the Urban Institute (no date) describe methods for making longitudinal matches using Stata and SAS, respectively. I needed only to identify the CPS interview record for the eighth, and last, month-in-sample, or MIS-8, for each respondent, and so I used a simplified version of their method, as follows:

1. I referred to the CPS Basic file for each month September 2002 –October 2010. Since ATUS households are selected from the last month-in-sample, i.e., exiting, CPS households, and are interviewed between 2 and 5 months after exiting, The households in the ATUS data actually exited the CPS from September 2002 through October 2010. Geographic variables for individuals who exited the CPS prior to May

2004 were based on the 1990 Census definitions, which are incompatible with the 2000 Census definitions used afterward. These observations were purged from the data.

2. Each month's CPS file was read and two sets of variables were retained: 1) the match variables (household identifier, CPS survey year, CPS survey month) and 2) the geographic variables. All but the last month-in-sample households were deleted. A new identifier, *NEWID,* was concatenated in the form *YYYYMMNNNNNNNNNNNNNNN,* where *YYYY* is the survey year, *MM* is the month, and the *N*s are the 15 character *HRHHID* variable, which may include leading zeros.[42] Since each instance of *NEWID* specifies the identifier, month, and year, each instance represents a unique household. Only one person-record was kept per household to eliminate duplicates. (Since the ATUS respondents are drawn at random from the members of a selected household, the CPS record selected by this method is not necessarily the matching one for the ATUS respondent. However, it is always from the same household, which is sufficient to obtain the geographic location variables that are uniform for all household members.)

3. The 80 monthly data files (May 2004 – December 2010) were concatenated and sorted by *NEWID.*

4. The *NEWID* variable was replicated in a file drawn from the ATUS data consisting of identification variables. The CPS and ATUS files were merged and households not in the ATUS were deleted. Sorting on the ATUS identifier, *TUCASEID*, resulted in a master file linking each ATUS participant to the geographic location

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[42] *HRHHID* is stored in the ATUS data without the leading zeros. I padded the ATUS values with zeros to make the two consistent.

variables from the CPS, which could then be used to gather state-, county-, and metropolitan area-level data from external sources.

Appendix G

California Department of Public Health (CDPH) H1N1 Incidence Data

The H1N1virus was first documented in Mexico in March 2009 and spread rapidly. The first confirmed case of H1N1 in California—and the United States—was of a young boy in San Diego County, reported April 15, 2009. California's response to the burgeoning disease was crafted on an ad hoc basis. Early in the pandemic, the California Department of Public Health (CDPH) created a new unit within the Division of Communicable Disease Control, the Communicable Disease Emergency Response Branch (CDER), especially for the purpose of tracking the progress of the pandemic across the state. The first H1N1 incidence report made by CDPH covered the beginning of the pandemic through May 28, with the first death reported for the week ending June 4. It afterward made weekly reports, the purpose being to "show the geographic spread of the pandemic." By late September, it had become clear that "H1N1 was all over [California]," and the cash-strapped CDER moved to a monthly reporting basis. (Louie and Acosta, 2011)[43] Monthly reports continued through the official end of the pandemic on August 28, 2010, although the last of the 596 H1N1 fatalities was reported for the week ending April 17, 2010, a year after the appearance of the disease in the state.

Early reports (May 28 – July 16) reported five categories of H1N1 incidence: confirmed probable cases, confirmed cases, total cases, hospitalizations, and deaths. Many of those hospitalized in the hysteria of the early weeks of the outbreak were later

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[43] The author attempted to obtain from CDER either weekly data for the October 2009 –April 2010 period, or uncompiled reports from which weekly reports could be constructed. California's state budget troubles prevented the agency from providing these. (Louie and Acosta, 2011)

determined not to have had H1N1. (Baxter, 2010) Beginning with the July 23 report, continuing weekly through September 29, categories reported were total hospitalizations, incidence of hospitalizations per 100,000 population, and deaths. The first such monthly report, for the period ending October 24, reported three categories: severe cases, ICU cases, and deaths. Thus, only mortality was reported consistently throughout.

For this study I define the pandemic period as beginning with the first confirmed reported case on April 15, 2009, and ending May 1, 2010, the date of the last monthly county-level report in which a death was reported. My H1N1 incidence data are organized on a weekly basis beginning with the week Friday, April 9 – Thursday, April 15. The first reports on the pandemic in the news media appeared that week as well.

he CDPH's switch to monthly reporting ended the unbroken line of weekly reports and required me to impute weekly local-level mortality values. Weekly statewide mortality (and hospitalization) data are available from CDPH for the entire pandemic, and like the Provisional reports, were usually made on a Friday – Thursday basis. These were prepared on a different basis than the Provisional county reports, and unlike those, were revised on a weekly basis throughout the pandemic. As a result, the final statewide weekly totals generally do not match the numbers obtained by totaling the 58 county reports. With the pandemic over and the State of California deeply in debt, the tallies will never be reconciled.

I created imputed weekly mortality reports for the September 30, 2009 – May 1, 2010 period as follows: 1) I made two assumptions: a) the time trend for the statewide death data is the same as for the county data, although the reported totals differ, and b) the weekly distribution of deaths for each county over any given month matched that of the state as a whole. 2) For a particular month, say the period ending October 24, the statewide totals for the weeks of that same month were summed and the weekly proportions of the monthly total were calculated for each of the four (or five) weeks in that month. 3) For each county, the monthly Provisional total was allocated across the weeks of the month in proportion to the statewide weekly proportions obtained in the previous step. These estimates were appended to the weekly data.

CONCLUSION

"People optimize. Markets clear." (Trescott, 1989) That is how a professor many years ago summarized economic theory, which he stated not as a conjecture but an established fact. The passing years have given me no reason to doubt him. Subject to the usual disclaimer about distributional dispersion, parents generally want to provide material subsistence, and more, for their children, and they want to do things for, and with, their children. And workers who fear catching a mysterious disease balance the desire to earn an income against the goal of staying alive. Everybody *wants.* Demand arises when want faces a price. Armed with far-from-complete and often comically imperfect information, people generally make the best choices they can.

In the first article, I confirm earlier studies in finding that parents respond to a rise in hourly earnings by spending more time with their children, indicating a powerful effect of increasing income on child care time. Yet using a novel approach I also find clear evidence of a substitution effect, as parents shift their time toward indirect, arranging-and-facilitating behavior, an effect which, for women, appears to varying extents across races, education levels, and family structures. I find that women tend to reduce child care time when work hours increase, but not as much as men, indicating that they are more likely to give up leisure or other home production to preserve time with their children. I find that higher levels of schooling are associated with more time spent with children, especially for women, and that single women spend less time with their children that those with a married or unmarried partner, but that single men make up for some of the missing partner's time by supplying more than married men.

The second article finds evidence that at least some groups of people living through the ill-controlled natural experiment of the H1N1 pandemic in California responded to news reports of the pandemic by curtailing work time to avoid catching the flu. I find no evidence that they conditioned their behavior on actual reported H1N1 death reports from the CDPH. I find suggestive but far from definitive evidence that some intertemporal substitution of work from low-risk to high-risk periods occurred; the less heroic conclusion is that people reduced work time, and engaged in home production or leisure to maintain utility as best they could.

Both articles contribute to the time use literature by introducing multiple imputation methods for dealing with missing data, and the first article shows that the inverse hyperbolic sine can be an acceptable substitute when zero or negative values preclude using a logarithmic transformation.

REFERENCES

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APPENDIX

Appendix H

Definition of Real Hourly Earnings

Hourly earnings are used to approximate the opportunity cost of time for members of the sample for both articles. Estimating these from CPS data is a multi-step process.

Reported earnings are collected from CPS participants in two ways:

1. If the respondent reports that an hourly wage is received, he is asked to report the hourly wage rate, *TRERNHLY*.[44] If this exceeds $99.99, it is recorded at that value and a topcode variable *(TTHR)* is used to identify this. In some, but not all, cases, if the respondent refuses to provide the wage rate, it is allocated (imputed) using the sequential hot deck procedure; this is denoted by an allocation flag variable, *TRHERNAL*.
2. All employed respondents, including those who report an hourly wage, are asked to report their usual weekly earnings *(TRERNWA)*. If earnings exceed $2,885 weekly, they are set to that amount, indicated by a topcode flag, *TTWK*. Some, but not all, missing earnings are imputed, indicated by the allocation flag *TRWERNAL*.

Each respondent is also asked to report usual hours worked at his main job, other jobs, if any, and a total, *TEHRUSLT*. Missing values are not allocated.

Problems are present in the data, aside from allocation, missing values, and topcoding. Several report wages below the federal minimum applicable at the time of the survey.[45] Many of these report an hourly wage of $2.13, the federal minimum for tipped employees, which understates actual earnings. Occasional observations show weekly

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[44] I use the names assigned in ATUS. CPS ORG files use the same names with the first letter being a P instead of T.

[45] State and local minimum wages were ignored for this study.

earnings that, on an hourly basis, are improbably high, suggesting measurement error either in earnings or work hours.

I estimated real hourly earnings by the following procedure which follows Bollinger and Hirsch (2010). I began with the full age-20-through-64, nondisabled, nonretired sample of 84,561.

1. For the 19,764 participants who are not employed (23.37% of the sample), earnings were set to zero to distinguish them from true missing values. The censored wage offer for these people was estimated later by a sample selection model. For all others:

2. I used the ATUS earnings estimates, rather than those carried over from the CPS Outgoing Rotation Group (ORG) data. There are two reasons to prefer these:

a. ATUS participants are interviewed between 2 and 5 months after exiting CPS. They are asked to provide updates to earnings measures at that time, so the data are fresher.

b. In CPS only one respondent answers questions for the entire household, and this person may or may not be the one chosen to participate in ATUS. Bollinger and Hirsch (2006, 2010) point out the lower response rate and higher rate of revision for income measures reported by proxy. In ATUS the participant provides his or her own earnings estimate and the frequency of missing values is consequently lower.

3. For persons with a valid hourly wage rate—one that is neither missing, nor allocated, nor topcoded, nor below the federal minimum wage—the reported hourly wage was assigned as nominal hourly earnings. Workers reporting an hourly wage below the

minimum had their earnings reported from weekly earnings data in the next step. Many of these, apparently tipped employees, reported an hourly wage of $2.13, which does not represent their actual hourly earnings.

4. For all others:

a. Weekly earnings are topcoded, i.e., right-censored, for 1,219 observations (1.44 percent) of the final sample, which includes the 24 observations with a topcoded hourly wage. For these, I followed the method of Hirsch and Schumacher (2004) and Bollinger and Hirsch (2006) and assigned these workers the mean earnings for those above the cap for their survey year, assuming a Pareto distribution for the upper tail of the weekly earnings distribution, with these values drawn from calculations of Hirsch and Macpherson (2011).

b. If the weekly earnings and usual work hours variables are neither missing nor zero, nominal hourly earnings were estimated as *(weekly earnings) ÷ (usual work hours)* constrained to be no less than the federal minimum wage.

c. Zero weekly earnings resulted in nominal hourly earnings of zero; zero work hours, missing hourly earnings.

d. For missing weekly earnings or work hours, hourly earnings were set to missing.

Valid hourly earnings could be estimated from the reported hourly wage rate for 27,916 respondents, or 33.01% of the sample. Persons who reported a subminimum hourly wage were assigned the hourly earnings calculated from weekly earnings as in step 3b above. If this was also below the minimum wage, I considered their hourly earnings invalid and set them to missing. This affected 1,832 observations, or 2.17%.

Real hourly earnings, *rEARNHR,* was calculated by adjusting nominal earnings to constant January 2003 dollars using the CPI-U-SL.

Missing values accounted for 13,201, or 15.61%, of the observations. This is considerably lower than the 30 percent reported from original CPS data in Bollinger and Hirsch (2010), although the two are not directly comparable, as their sample included non-parents.[46] 11 observations showed values of nominal hourly earnings in excess of $250 with suspiciously few hours worked; I considered these spurious and set their earnings to missing. 68 other observations show hourly earnings of at least $100, many with relatively few hours worked (mean hours -9.70, SE = 0.71). Of these, 35 (51.47%) hold graduate degrees, 45 (66.18%) are females, and 31, fully 45.59%, are married or cohabiting females, and another 14, or 20.59%, are female single parents. All of this suggests the expected negative income effect on labor supply as well as time-use optimization by mothers. These observations were left as they were.

The final parent sample of 45,716 showed the same rate of missingness as the larger sample, with 7,213 missing earnings values, or 15.78%. Missingness was significantly more prevalent among men (20.78%) than women (12.31%),with $\chi^2 = 597.3$, 1 *df*, *p*-value < 0.001.

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[46] The ATUS-updated earnings also differ from the original CPS values for my sample. The updated values used here show much reduced (unweighted) skewness and kurtosis-3— 2.05 and 13.010, respectively, for the ATUS-updated *rEARNHR* versus 14.307 and 1020.91 for the CPS-derived value. The mean estimated using the ATUS updates was $12.323; for the CPS data, $12.360. (Ignoring the obvious nonnormality, t = -1.98, *p*-value = 0.0481). The ATUS-based estimates are considerably more efficient, (SE = 0.045, compared to 0.078), in part due to the larger number of observed values. The two are, however, highly correlated, with Pearson r = .99. Nonparametric tests could not be conducted due to the use of survey weights.

The sample used in the second article was obtained by selecting only California residents who indicated that they were employed.[47] The final sample of 4,615, consisting of nondisabled, employed (for pay) Californians age 20 through 64, not residing in group quarters, and who participated in the ATUS from May 2004 through December 2010, included 1,093 missing values, or 23.68% of the sample. Missingness was slightly though significantly more prevalent among men (25.80%) than women (21.49%); with sample weights, 22.84% to 20.19% ($\chi^2 = 34{,}494{,}652$, 1 *df*, p-value < 0.001). To make a direct comparison to the national sample I used in the first article, I excluded persons without children and, from the national sample, excluded nonworkers and all persons whose diary day fell before May 2004. This comparison showed a missingness rate of 24.22% for the 2,520 Californians and 20.51% for the remaining 26,552 overall; using the sample weights, the proportions were 22.26% and 20.21% ($\chi^2 = 37{,}344{,}923$, 1 *df*, p-value < 0.001). Bollinger and Hirsch (2010) note that missingness is more common in metropolitan areas, which predominate in the California sample.

Real hourly earnings, *rEARNHR,* was calculated by adjusting nominal earnings to constant January 2003 dollars using the CPI-U-SL. Descriptive statistics for *rEARNHR* are shown in Table 28.

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[47] CPS variable *TELFS*=1 (Employed – at work) or 2 (Employed – absent) only.