Economists and Time Use Data

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Disclaimer: The views expressed here are not necessarily those of the Bureau of Labor Statistics.

Outline

A Few Thoughts on Time Use Data

Estimation Issues

How Do Economists Use Time Use Data?

A Few Thoughts on Time Use Data

The distinctive feature of time-diary data, compared with other household survey data, is the short reference period of a single day or at most a few days

- More accurate data
- Relatively free from social desirability bias

But…

- Does not accurately measure long-term time use for any individual

Data from time-use surveys are <u>not</u> a sample of individuals

They are best thought of as sample of person-days

This has important consequences for analysis

A Few Thoughts on Time Use Data (continued)

Does the research question pertain to long-run or short-run time use?

- Long-run time use: Average time spent in an activity over a long period of time
- Short-run time use: Time spent in the activity on the diary day

Most policy-related questions require information on long-run time use

➔ Mismatch between period of interest (average time use over the course of a month or a year) and reference period of the data (diary day)

Estimation Issues – Summary of Two Papers

Frazis, Harley and Jay Stewart "How to Think About Time-Use Data: What Inferences Can We Make About Long- and Short-Run Time Use from Time Diaries?"*Annales d'Economie et Statistique* (*Annals of Economics and Statistics*) 105/106, January/June 2012, pp. 231-246.

Stewart, Jay "Tobit or Not Tobit?" *Journal of Economic and Social Measurement*. 38 (2013), pp. 263-290.

Our Main Questions

What measures of long-run time can (and can't) be estimated from single-day, single-person time diary data? (American Time Use Survey, for example)

What can we learn from time-use surveys that collect diaries for multiple days or from multiple individuals in a household that cannot be learned from single-day, single-person time-use surveys?

What are the implications for survey design?

Outline

Time use as a dependent variable

Time use as an independent variable

Time use on both sides of the equation

Time Use as a Dependent Variable

Let $\mathbf{t}_{ID}$ denote the universe of person days, so that $\mathbf{t}_{ID} = \bigcup_{i=1}^{I} \bigcup_{d}^{D} t_{id}$

(This is the sample frame of most time-use surveys)

i denotes an individual (*I* is the set of all individuals)

d denotes a day (*D* is the set of all days)

Let $\mathbf{t}_I = \{\bar{t}_1, \bar{t}_2, \cdots, \bar{t}_I\}$ denote the average time use of the *I* individuals in the population

(This is the long-run time use measure that we would like to estimate)

Time Use as a Dependent Variable (continued)

Let $g(\cdot)$ denote a statistic of interest

When does $g(\mathbf{t}_{ID}) = g(\mathbf{t}_I)$?

Artificial construct $\bar{\mathbf{t}}_{ID} = \{\bar{\mathbf{t}}_1, \bar{\mathbf{t}}_2, \cdots, \bar{\mathbf{t}}_I\}$, where $\bar{\mathbf{t}}_i = \{\bar{t}_i, \bar{t}_i, \cdots, \bar{t}_i\}$

(This is what $\mathbf{t}_{ID}$ would be if people did the same thing every day)

Clearly, $g(\bar{\mathbf{t}}_{ID}) = g(\mathbf{t}_I)$

This implies that $g(\mathbf{t}_{ID}) = g(\mathbf{t}_I)$ if $g(\mathbf{t}_{ID}) = g(\bar{\mathbf{t}}_{ID})$

That is, if the day-to-day variation in time use does not affect the value of the statistic

Examples

The mean satisfies this condition:

$$g(\mathbf{t}_{ID}) = \frac{1}{I \times D}\sum\nolimits_{i=1}^{I}\sum\nolimits_{d=1}^{D} t_{id} = \frac{1}{I}\sum\nolimits_{i=1}^{I}\left(\frac{1}{D}\sum\nolimits_{d=1}^{D} t_{id}\right) = \frac{1}{I}\sum\nolimits_{i=1}^{I}\bar{t}_i = g(\bar{\mathbf{t}}_{ID}).$$

➔ We can compute the average amount of time that individuals spend in an activity from a sample of person days

Examples (continued)

The variance does not:

We can write daily time use as:

$$t_{id} = m_i + e_{id},$$

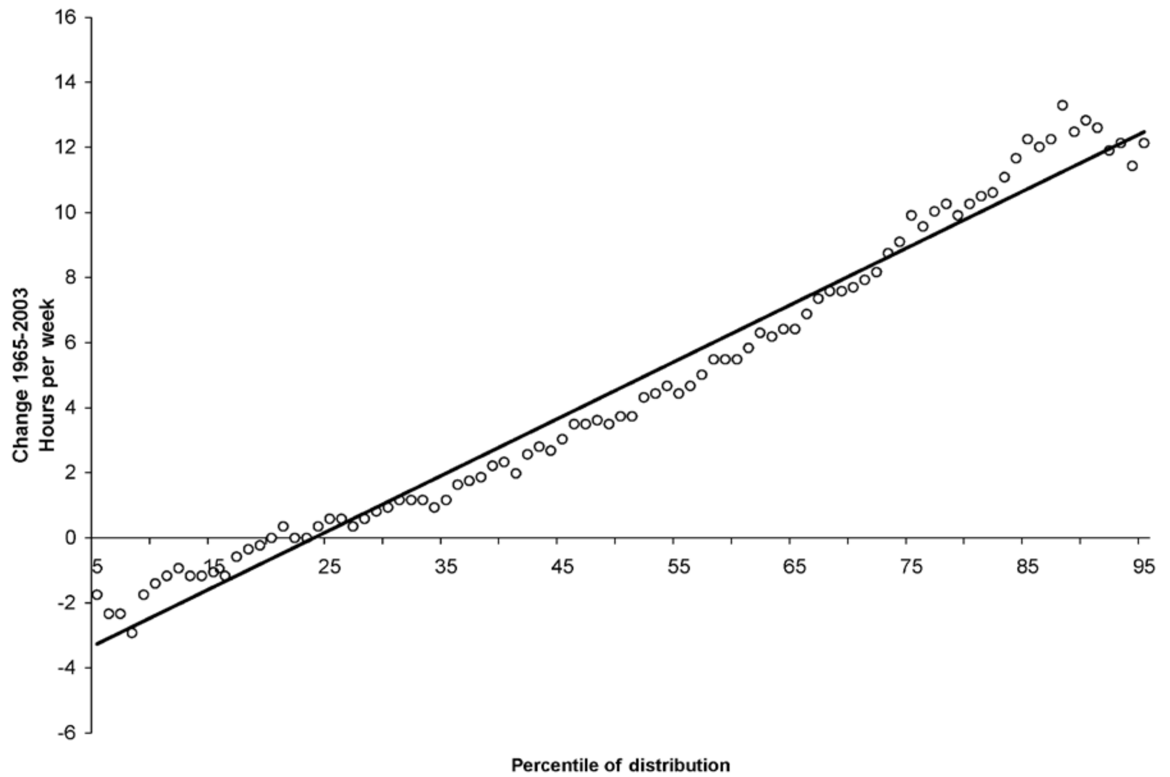
m_i = Long-run average time use

e_{id} = Deviation from long-run time use on day d (day-to-day variation)

$$g(\mathbf{t}_{ID}) = Var(m_i + e_{id}) = Var(m_i) + Var(e_{id}) \neq Var(m_i) = g(\bar{\mathbf{t}}_{ID})$$

The median is another statistic that does not satisfy the condition

Examples (continued)



Change by Percentile Point for Leisure, 1965–2003
This figure plots the change at each percentile point of the Leisure distribution (from Aguiar and Hurst 2007).

Examples (continued)

The data compare the endpoint years (1965 and 2003) from single-day surveys

The implicit interpretation in paper is that leisure grew more unequal across persons

But another interpretation is that distribution of time spent in leisure activities across days within persons grew more unequal with no change (aside from mean shift) in between-person distribution

We cannot distinguish the two from the data

Regressions – Tobit or Not Tobit?

Time-diary data typically have a large number of “zeros”

There is a long tradition of treating these zeros as censored observations and using Tobit to estimate regression equations

But the zeros in time-diary data are typically <u>not</u> due to censoring because researchers are typically analyzing the amount of time spent in an activity by *people who do the activity*

Examples include:

- Time spent in childcare by parents
- Time spent working by the employed
- Time spent looking for work by the unemployed

Regressions (continued)

In these cases, the zeros are due to the short reference period combined with the large amount of day-to-day variation how people spend their time

Given the zeros in time-diary data are not due to censoring, it is not clear that Tobit is appropriate

Compare:

- Tobit
- A two-part model (probit on all observations and OLS on the positives) similar to Cragg (1971)
- OLS

Theory - The Infrequency of Purchase Model (IPM)

Time-diary data are similar to expenditure data ➔ IPM

Expenditures during reference period *t* can be written as:

$$(1) \qquad e_t = \frac{w_t\{\bar{c} + u_t\}}{p} \quad \Rightarrow \quad e_t = \begin{cases} 0 \\ \{\bar{c} + u_t\}/p \end{cases}$$

where

e_t = expenditures on the good

w_t = 1 if the good is purchased during reference period

$\bar{c}$ = consumption of the good

u_t = a random term (where $E(u_t) = 0$)

p = probability that the good is purchased during reference period

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Theory – Adapting the IPM to Time-Diary Data

All of the terms of the IPM have analogous interpretations in time-diary data

e_t = Expenditures ➔ Time spent on diary day

$\bar{c}$ = Consumption ➔ Long-run average time spent on activity

p = Prob(purchase good) ➔ Prob(do activity)

w_t = Purchases good ➔ Does activity

Theory – The Regression Equation

Ideally, we would like to estimate:

$$(2) \qquad \bar{c} = \alpha + \beta X$$

But we do not observe long-run time use

Combining equations (1) and (2) gives us:

$$\begin{aligned} e_t &= \alpha + \beta X + \{(w_t - p)\bar{c} + w_t u_t\} / p \\ &= \alpha + \beta X + \eta_t , \end{aligned}$$

which can be estimated using OLS

It can be shown that OLS estimates are unbiased (see paper)

Construction of Simulation Data

Simulated sample of 50,000 "individuals"

28 days of data for each individual in the sample

Tobit assumptions for long run time use

$$\bar{c} = 10 + 1.5x_1 - 3x_2 + 2x_3 + \theta \quad \text{where} \quad \theta \sim \mathrm{N}(0,1)$$

Day-to-day variation is added in a way that preserves the normality of θ (see paper for details)

Simulation Results

I varied the fraction of zeros in the data and compared estimated effects to the true parameter values

- OLS – Estimated coefficients
- Tobit and two-part model – Estimated marginal effects (evaluated at mean of covariates)

Bias is computed as a percentage of the true parameter value

- Bias > 0 ➔ Magnitude is overestimated
- Bias < 0 ➔ Magnitude is underestimated
- Bias < −1 ➔ Effect is wrong-signed

Figures graph bias against the fraction of zero observations

Alternative assumptions about relationship between the probability of a zero and the variables in the model

Fig. 1: (1−*p*) is Independent of All Variables in the Model

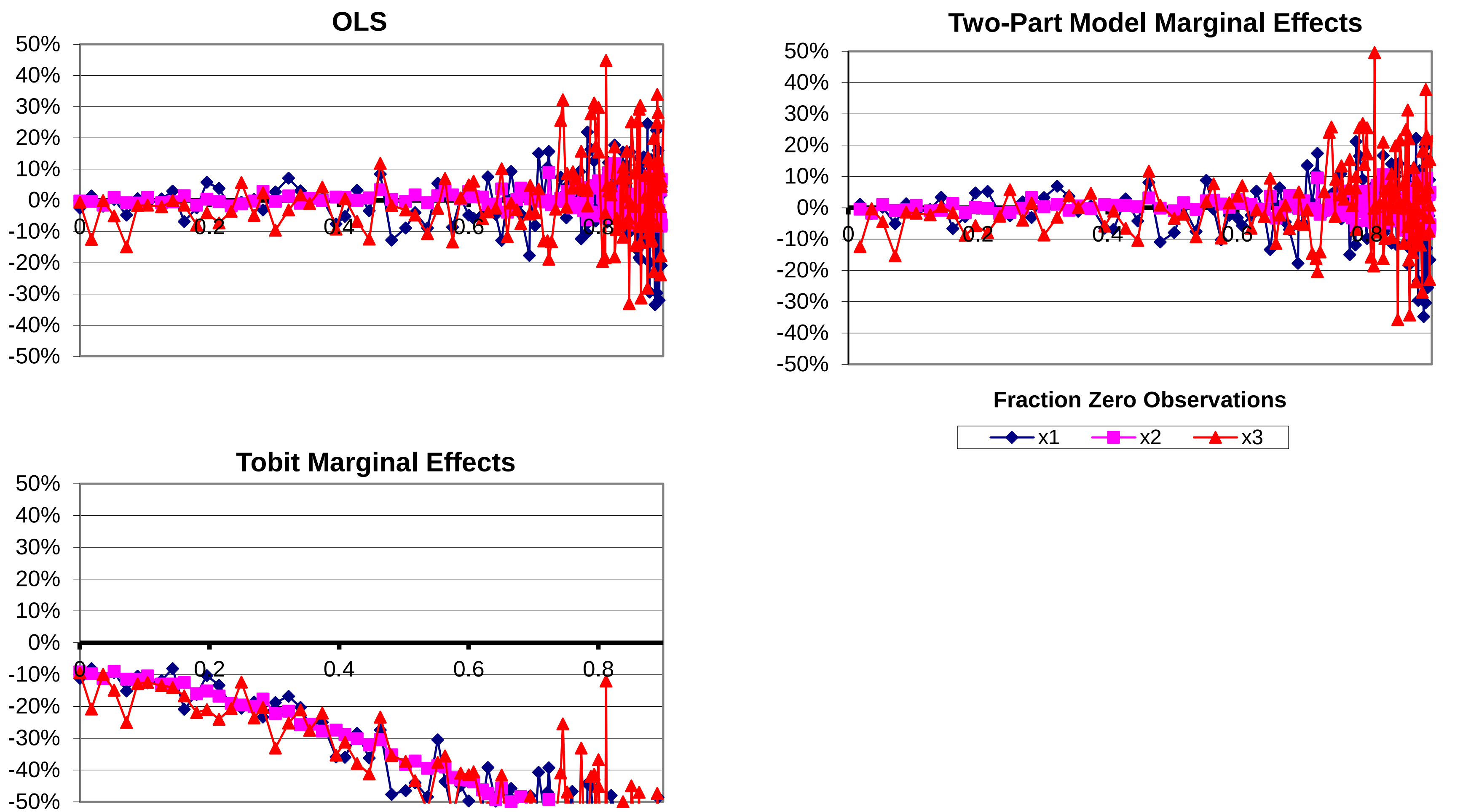

Fig. 2a: (1−p) is Negatively Related to $\bar{c}$

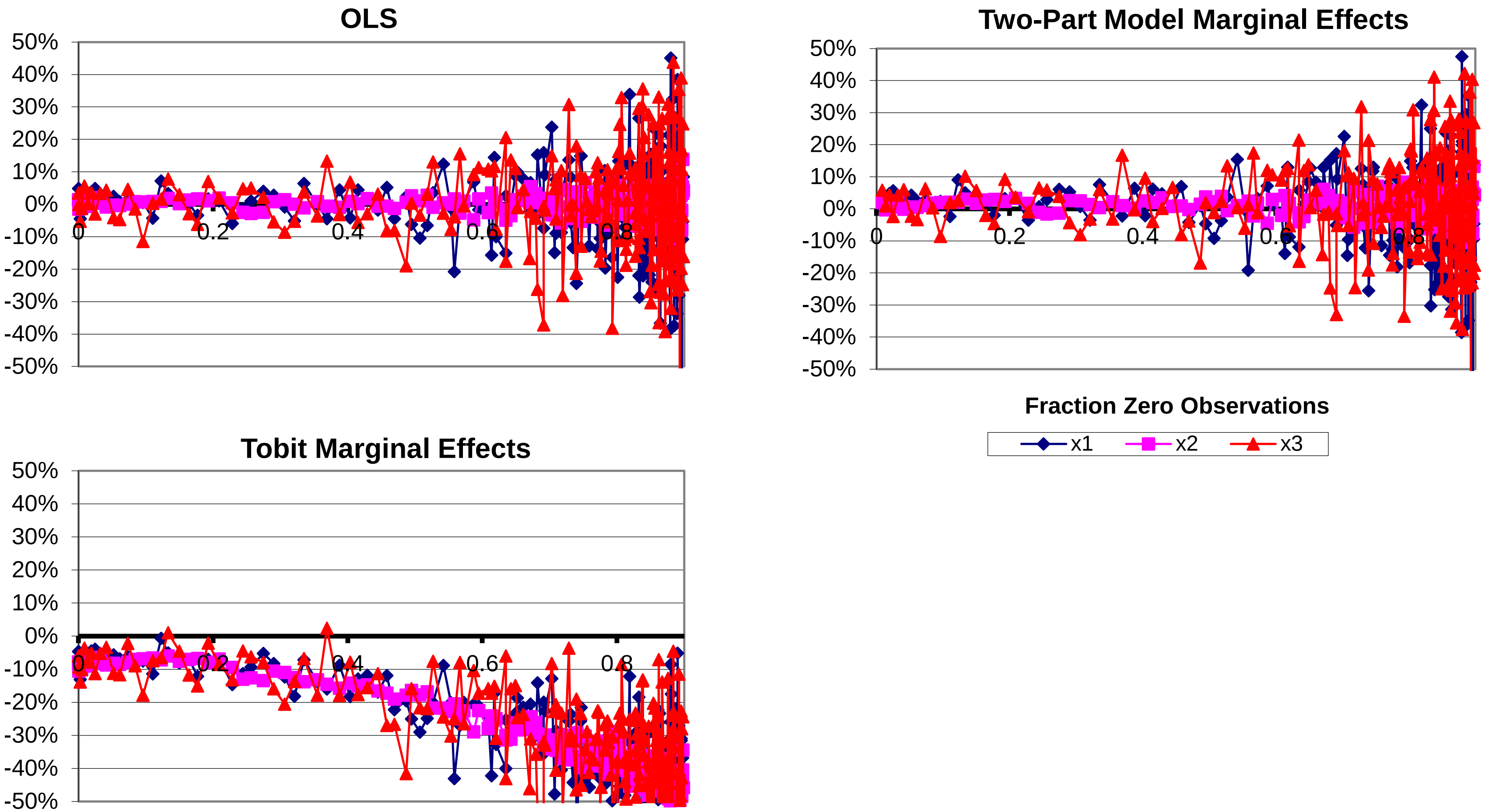

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Fig. 3: (1−*p*) is Negatively Related to x_1

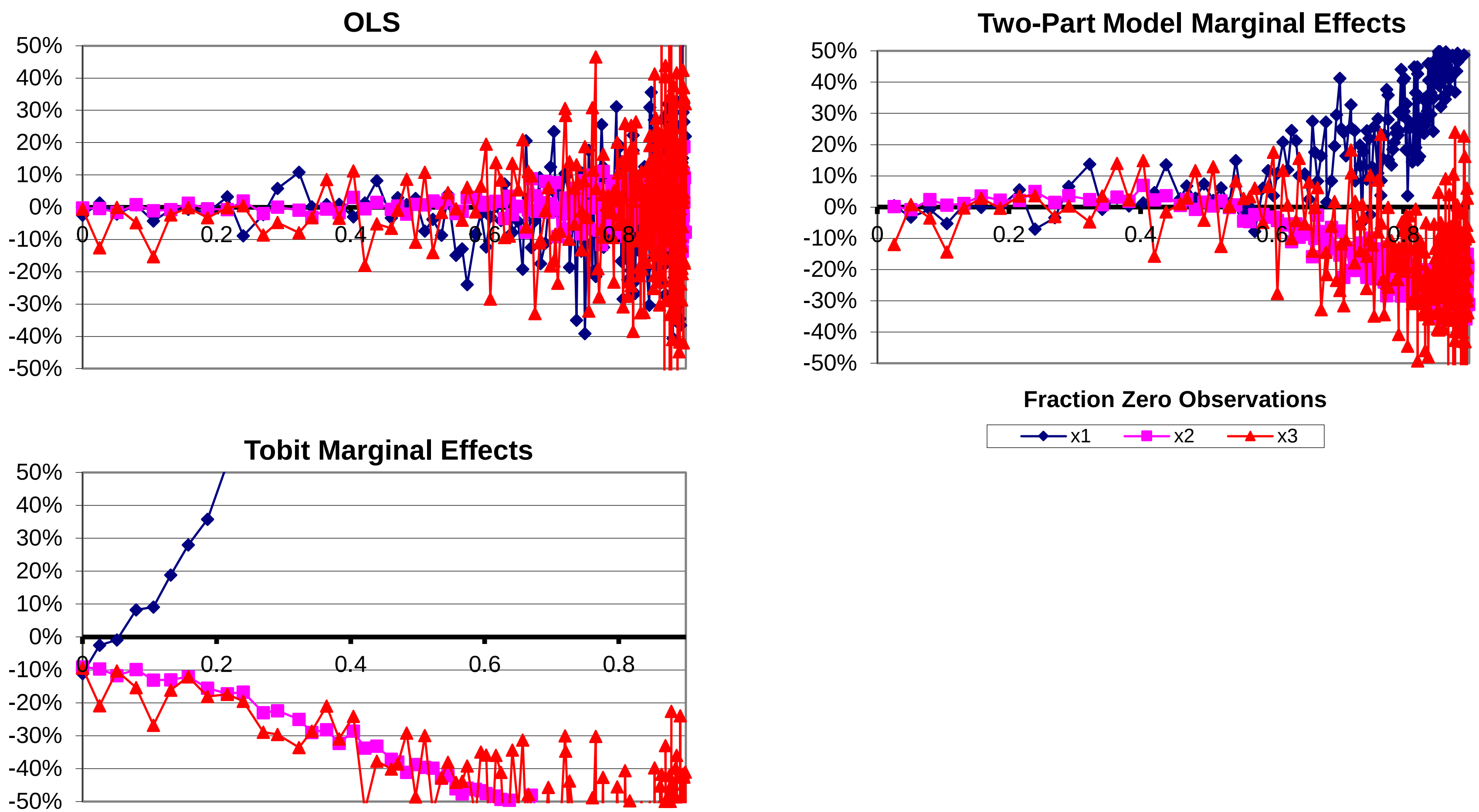


Fig. 4: (1−p) is Positively Related to x_2

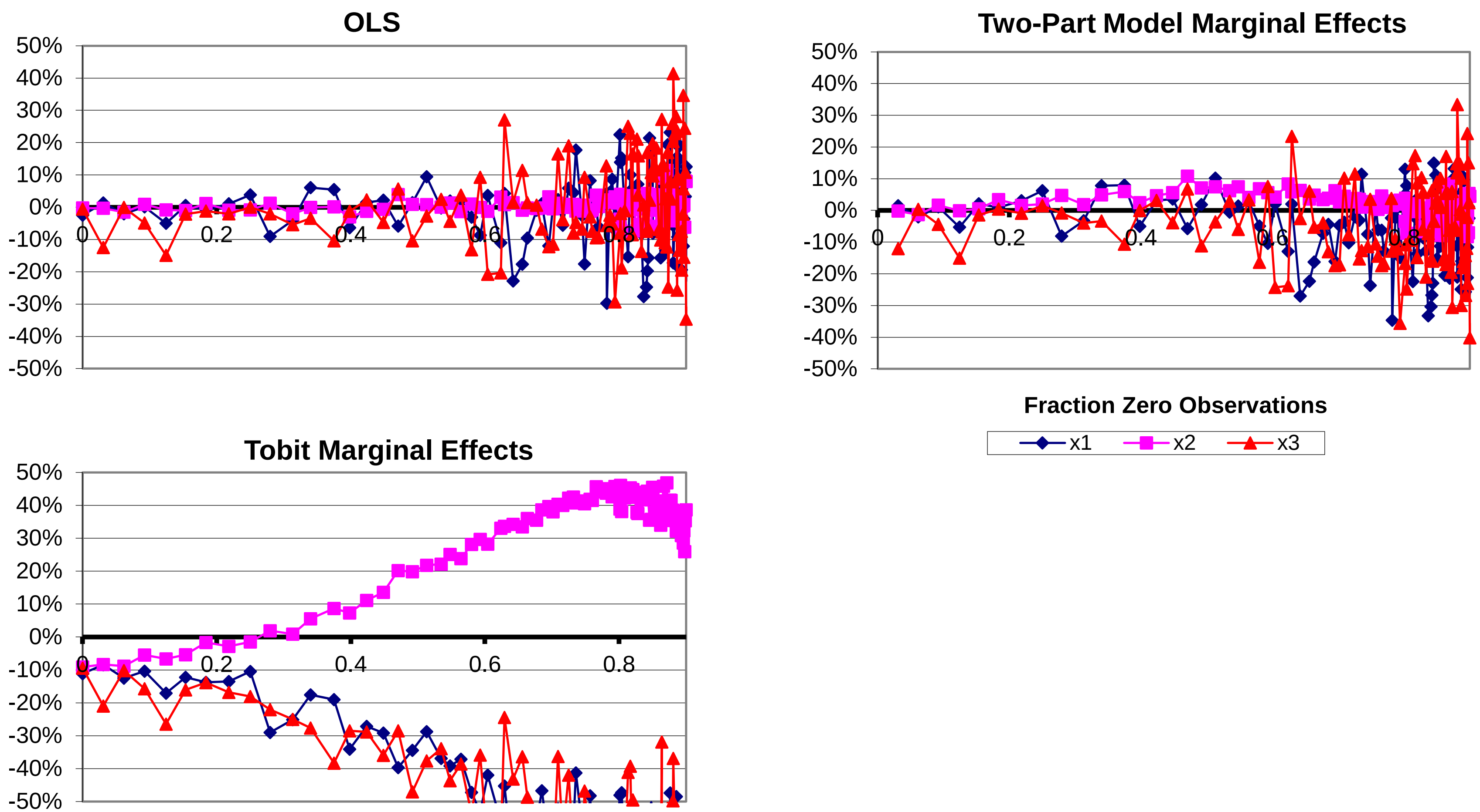
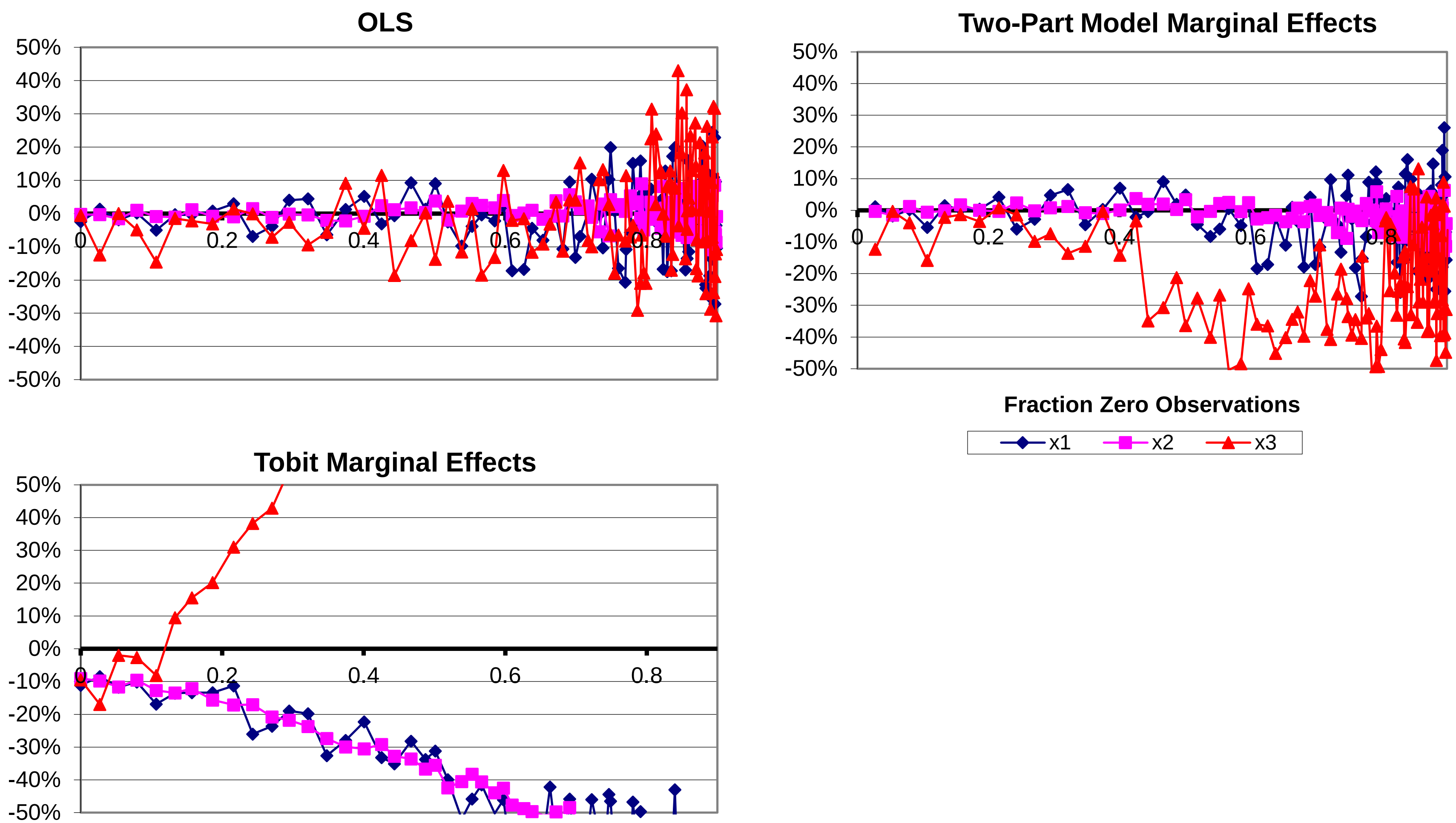
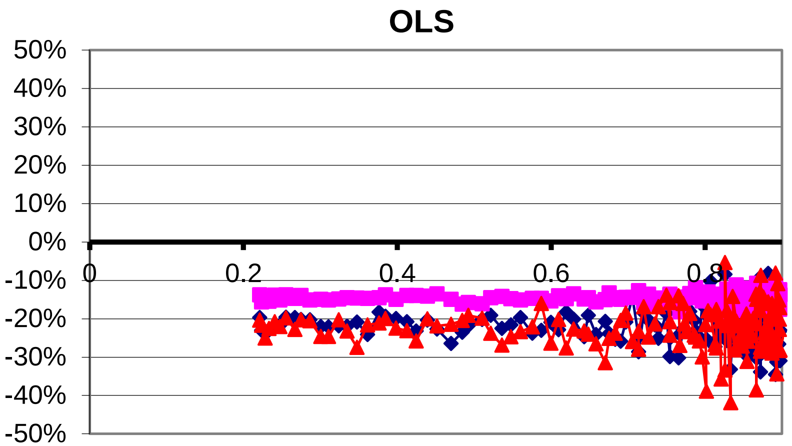
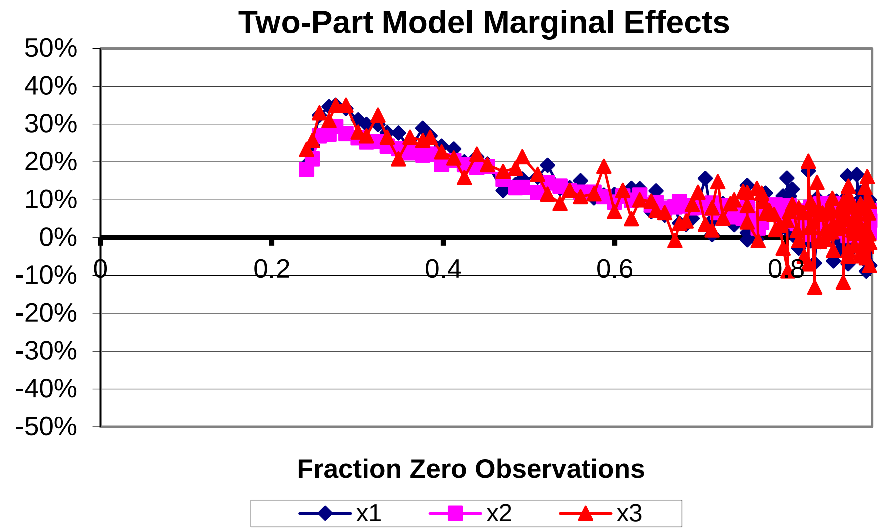


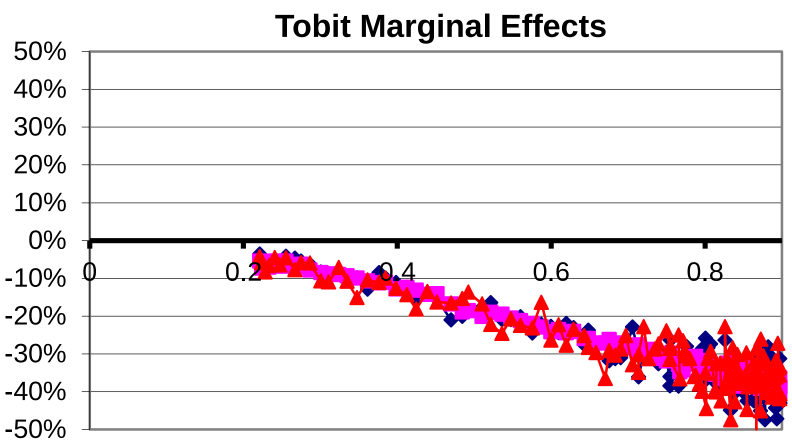
Fig. 5: $(1-p)$ is Negatively Related to x_3



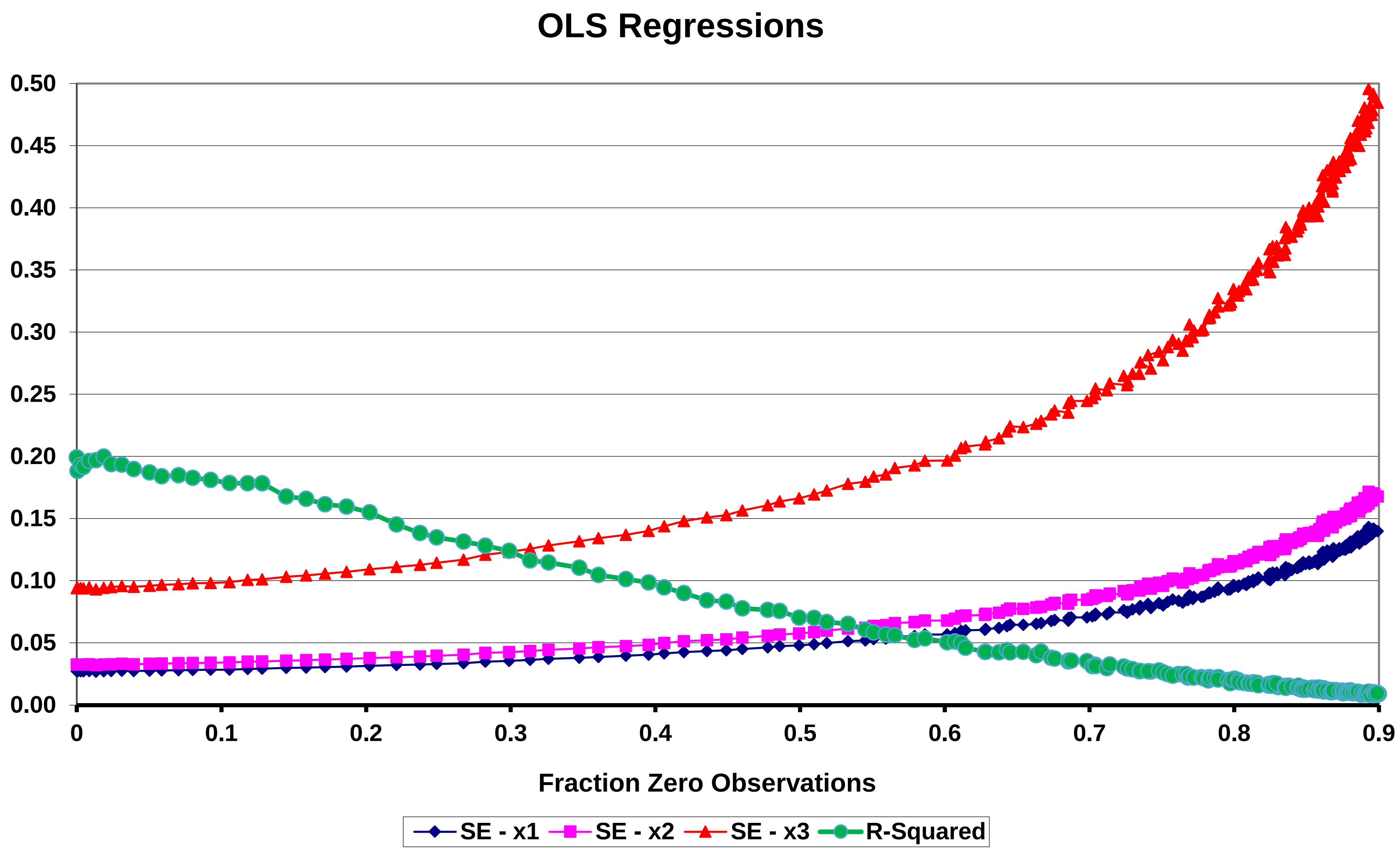
What If “Doers” Cannot Be Identified?







R^2 and Standard Errors



Time-use as an Independent Variable

Suppose we would like to estimate the following equation:

$$Y_i = X_i\beta + t_{id}\gamma + u,$$

where Y is a long-term outcome such as obesity or wages

A single day's time use virtually no effect on Y

In this case t_{id} a proxy for long-run time use, m_i

We can view this as a case of classical measurement error:

$(t_{id} – m_i) = e_{id}$, which is uncorrelated with m_i

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Time-use as an Independent Variable (continued)

The coefficient on t_{id} is biased downward in magnitude if only one time-use variable is included as a RHS variable

If more than one time-use variable is included, then the sign of the bias cannot be determined (*i.e.*, sign reversal is possible)

Solutions:

- Instrumental variables (Pinkston and Stewart 2009)
- Aggregation (Faberman 2010)

Note that with IV estimation, it is not necessary for the data on outcomes to be from the same dataset that has information on time use

Time Use on Both Sides of the Regression Equation

Suppose we would like to estimate the following equation:

$$t_{id}^{A} = \alpha + \beta t_{id}^{B} + u_{id}$$

Time spent in activity *A* is a function of the time spent in activity *B.*

What does OLS estimate?

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Time Use on Both Sides of the Regression Equation (cont.)

The OLS coefficient can be expressed as:

$$\beta = \frac{Var(m_i^B)\beta_m + Var(e_{id}^B)\beta_e}{Var(m_i^B) + Var(e_{id}^B)}$$

where:

β_m coefficient from regression $m_i^A = \alpha_m + \beta_m m_i^B + u_m$ (LT)

β_e coefficient from regression $e_{id}^A = \alpha_e + \beta_e e_{id}^B + u_e$ (ST)

➔ The OLS estimate is a weighted average of these two effects, where the weights are not known

Time Use on Both Sides of the Regression Equation (cont.)

Interpretation of the coefficients:

- Across person (β_m): do people who spend a lot time in activity A also spend a lot of time in activity B?
- Within day (β_e): do people tend to do activities A and B on the same day?

OLS estimates are a weighted average of these two effects (where the weights are unknown)

Either question might be of interest, but it is hard to imagine what question a mixture of the two effects might answer

Time Use on Both Sides of the Regression Equation (cont.)

Instrumental variables can be used to estimate either β_m or β_e

Example: Christian (2009) used traffic accidents on the diary day as instrument, which implies that he is identifying β_e and that it is short-run time use (e_{id}^{B}) that is of interest

An alternative would be to use a long-run measure of traffic patterns, such as average commute time (by metropolitan area) to instrument for m_i

Another alternative to identifying the effect on long-run time use would be to use traffic accidents on the diary day, but aggregate over the entire year

Conclusions

The short reference period of time diaries has important implications the analysis of time-use data

In particular, time spent in an activity on the diary day is a noisy measure of long-term time use

Time diary data are best thought of as a sample of person-days—they are not a sample of individuals

Conclusions (continued)

Implications

- Estimated means from time-diary data accurately reflect the long-run means of individuals
- Other statistics such as medians, variances do not accurately reflect long-run counterparts for individuals
- Day-to-day variation in time-use variables needs to be accounted for when they are used as explanatory variables
- Association between different time-use variables is a mixture of the long-term and short-term relationships. Simple least-squares estimates of the association are uninterpretable.

Conclusions (continued)

Tobit is not appropriate for time-diary data when the researcher is interested in long-run time use

The marginal effects using Tobit are biased and the bias increases with the fraction of zero observations in the data

> ➔ It is not valid to compare the coefficients from two groups if the fraction of zero observations differs substantially between the two groups

The two-part model generates unbiased marginal effects as long as the probability of doing the activity on the diary day is not a function of one of the covariates

Conclusions (continued)

OLS generates unbiased estimates

This result holds regardless of the fraction of zeros in the data and whether the probability of doing the activity on the diary data is a function of one of the variables in the model

All three procedures perform poorly when it is impossible to identify “doers’

However OLS estimates can be corrected (Green, 1981)

➔ It is difficult to justify using either Tobit or the two-part model with time-diary data

What Questions Have Economists Examined?

- Trends in leisure
- Accuracy of hours data in household surveys
- Inequality
- Job search and behavior of the unemployed
- Time use and health/obesity
- Wages and childcare
- Household production
- Timing of activities
- Sleep

How Does Nonmarket Production Affect Measured Earnings Inequality?

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Measuring Inequality

The standard approach is to use the hourly wage, weekly earnings, or annual earnings or income.

Several fairly recent studies have taken alternative approaches:

- Consumption Inequality - Johnson and Shipp (1997)
  Krueger and Perri (2002)
- Compensation - Pierce (2001)
- Well Being - Wolff, Zacharias, and Caner (2004)
- Income plus HH Production - Gottschalk and Mayer (1999)

Our approach is to examine inequality of extended income:

- Extended income = Earnings plus value of HH production

Why Look at Extended Income?

Household production is equivalent to generating income

Theory predicts that high-wage individuals/families are more likely to purchase goods and services compared with low-wage individuals/families

Hire maids vs. doing housework

Prepare meals vs. eating at a restaurant

Standard measures of earnings inequality do not account for this substitution of market goods for nonmarket goods by high-wage individuals/families.

➔ Theory predicts that incorporating nonmarket production will reduce measured inequality

Data

ATUS data matched to March CPS data

Separate sub-samples for married and single individuals

Sample restrictions based on:

- Age (25-64)
- Number of hours worked (minimum number required)
- Wages (not too low)
- Multiple jobholding (no multiple jobholders)

Valuing Nonmarket Production

Third-person criterion to classify activities as nonmarket work

We only include activities that directly contribute to the well-being of household members

- Include housework and care of household members
- Exclude volunteer work and care of non-household members

Two definitions - with and without secondary child care

Two valuation approaches - generalist wage and specialist wage

Estimating the Value of Household Production

Ideally, would like long-run time use for each spouse

But ATUS only collects one diary day from each household

➔ We must impute the value of household production

Estimating the Value of Household Production (continued)

First step is to regress the value of household production on a function of income and other covariates

$$P_i^d = f_d(Z_i, X_i) + u_i^d$$

d = D (weekday) or E (weekend day)

Z_i = Log of family income for person *i*

X_i = Vector of demographic covariates for person *i*

u_i^d = Error term

Separate equations for each sex × marital status × day-of-week cell (8 regressions total)

Estimating the Value of Household Production (continued)

For our imputation, it is important that we capture the relationship between income and household production

➔ We used a flexible functional form for $f(Z,X)$

Fourier series regression:

$$f(Z,X) = a + Zb + cZ^2 + \sum_{j=1}^{J} (\beta_{1j} \cos(jZ) + \beta_{2j} \sin(jZ)) + X\beta$$

The income variable Z has been transformed so its value falls between 0 and 2π

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Estimating the Value of Household Production (continued)

Next, use estimated regression coefficients to compute predicted value of household production for each person *i*:

$$\hat{P}_i = 5\hat{f}_D(Z_i, X_i) + 2\hat{f}_E(Z_i, X_i)$$

For married-couple households, the value of household production is:

$$\hat{P} = \hat{P}_W + \hat{P}_H$$

Variation Due to Unobserved Factors

However, predicted values do not include important variation that is due to unobservable factors

- Person-specific (long-run) variation
- Day-to-day (short-run) variation

Decomposing the error term, we have:

$$P_i^d = f_d(Z_i, X_i) + (m_i^d + e_i^d)$$

m_i^d = Person-specific variation

e_i^d = Within-person day-to-day variation

Variation Due to Unobserved Factors (continued)

If $Var(m_i^d) = 0$, the error term represents day-to-day variation

If $Var(e_i^d) = 0$, the error term represents person-specific variation

If $Var(m_i^d) > 0$, then $\hat{P}$ understates the variability of household production

To capture unobserved person-specific variability, we would like to add a random term to the predicted values of household production

Variation Due to Unobserved Factors (continued)

Adding a random term to the predicted values yields:

$$\hat{P}_i = 5\hat{f}_D(Z_i, X_i) + 2\hat{f}_E(Z_i, X_i) + ks_i,$$

where:

$s_i \sim N(0, M)$

$M = (5\sigma_D + 2\sigma_E)^2$ = Maximum value of $Var(m_i^d)$ (assuming no day-to-day variation)

$0 < k \leq 1$

$k = 0$ ➔ All variation is day-to-day

$k = 1$ ➔ All variation is person specific

Table 3: Inequality Measures – Coefficient of Variation

Generalist Wage Secondary Childcare Included OECD Equivalence	Coefficient of Variation	Gini Coefficient
(1) Family income (Y)	0.942**	0.409**
(2) = Y + $\hat{P}$	0.741	0.301**
(3) = Y + $\overline{P}$	0.738	0.293
(4) = Y + $\hat{P}$ + .25 × s_i	0.742	0.302**
(5) = Y + $\hat{P}$ + .5 × s_i	0.745	0.306**
(6) = Y + $\hat{P}$ + s_i	0.756**	0.318**

*,** Significantly different from Row (3) at 5 percent level,1 percent level.

Observations and Conclusions

Extended income is more evenly distributed than money income

Adding a random term to the predicted value of household production increases inequality, but not by very much

Adding the mean value of household production reduces measured inequality by almost as much as does adding the predicted value of household production

➔ The more-equal distribution of extended income is not due to the negative correlation between money income and household production

Rather, it is due to the addition of a large constant—the average value of household production—to money income

The Timing of Maternal Work and Time With Children

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Outline of the Presentation

Introduction

Theoretical Model

Empirical Results

How Does Employment Affect Time With Children?

Large body of research on how parental employment affects their children's development

Evidence is mixed

- Negative effects – Baum (2003), Ruhm (2004)
- Positive effects – James-Burdumy (2005)

None of these papers investigates the mechanism by which employment might affect child development

Parental time spent on educational activities with their children – Cawley and Liu (2007)

No research on when these activities take place

Why Do We Care When Parents Spend Time With Children?

Research on circadian rhythms has shown that:

- People have preferences for different time of day
- Cognitive performance is better at preferred times of day
- Preferences vary with age

Children, especially young children, prefer mornings

Teens and young adults prefer afternoons and evenings

The crossover point is at about age 12 or 13

➔ Parent-child interactions will be more beneficial for children if they occur earlier in the day

A Simple Model of Timing

Two-stage maximization model

1. Mothers decide how much time to spend on each activity—including childcare
2. Mothers decide how to allocate that time across days and times of day

In the second stage, mothers will allocate activities to times when the activity is most productive

Examples:

- Indoor housework can be done any time
- Yard work is easier to do during the day
- Quality time with children is more valuable and enjoyable at times when children are more awake (early in the day)

Implications of the Model

Parents prefer to spend more time in enriching childcare activities at times when those activities are more "productive"

- Time of day (mornings vs. afternoons and evenings)
- Day of week (workdays vs. nonwork days)

Data

ATUS data from 2003-2005

Women age 18+ -- four subsamples

- Mothers of children age 0-4
- Mothers of children age 5-9
- Mothers of children age 10-17
- Women without children

No children in other age groups

To be counted as childcare, there must be a child under 5 present during the episode

Empirical strategy:

Compare timing of enriching childcare on the work and nonwork days of employed mothers

Compare work schedules of mothers and women who are not parents

Table 1: Time Spent in Childcare (hours per day)

	Employed full time			Employed part time			
	Workdays	Nonwork Days*	All Days	Workdays	Nonwork Days*	All Days	Not employed
Mothers of 0-4 Year-Old Children							
Childcare (with child < 5)							
Routine childcare	0.9	1.9	1.3	1.3	1.9	1.7	1.9
Enriching childcare	0.7	1.4	1.0	1.0	1.9	1.5	1.9
Mothers of 5-9 Year-Old Children							
Childcare (with child 5-9)							
Routine childcare	0.5	0.6	0.5	0.6	0.8	0.7	0.7
Enriching childcare	0.7	1.4	0.9	0.7	1.5	1.1	1.6
Mothers of 10-17 Year-Old Children							
Childcare (with child 10-17)							
Routine childcare	0.1	0.1	0.1	0.2	0.2	0.2	0.3
Enriching childcare	0.4	0.9	0.6	0.5	0.8	0.7	1.0

Figure 1: Distribution of Time Spent in Enriching Childcare by Mothers of 0-4 Year-Old Children

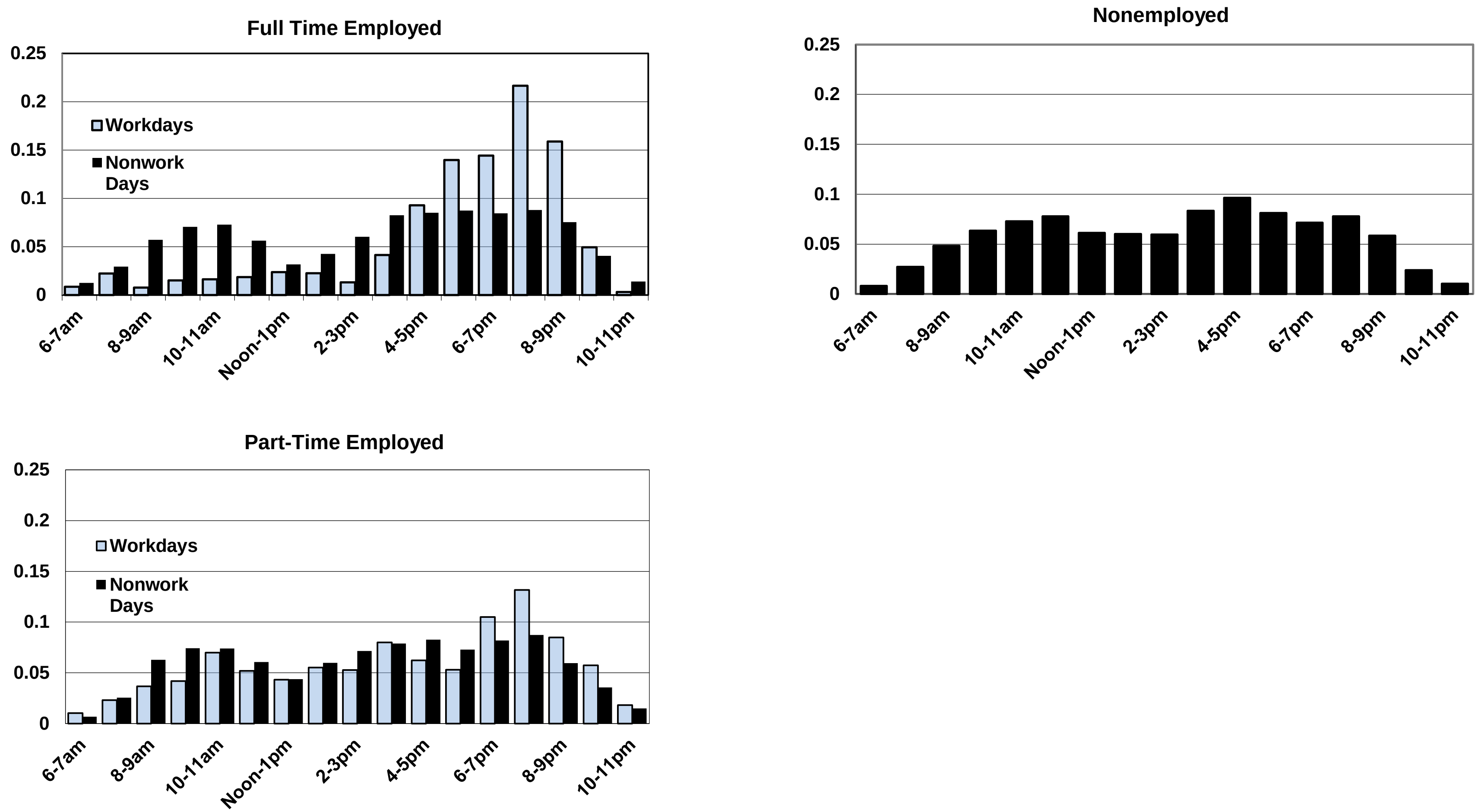
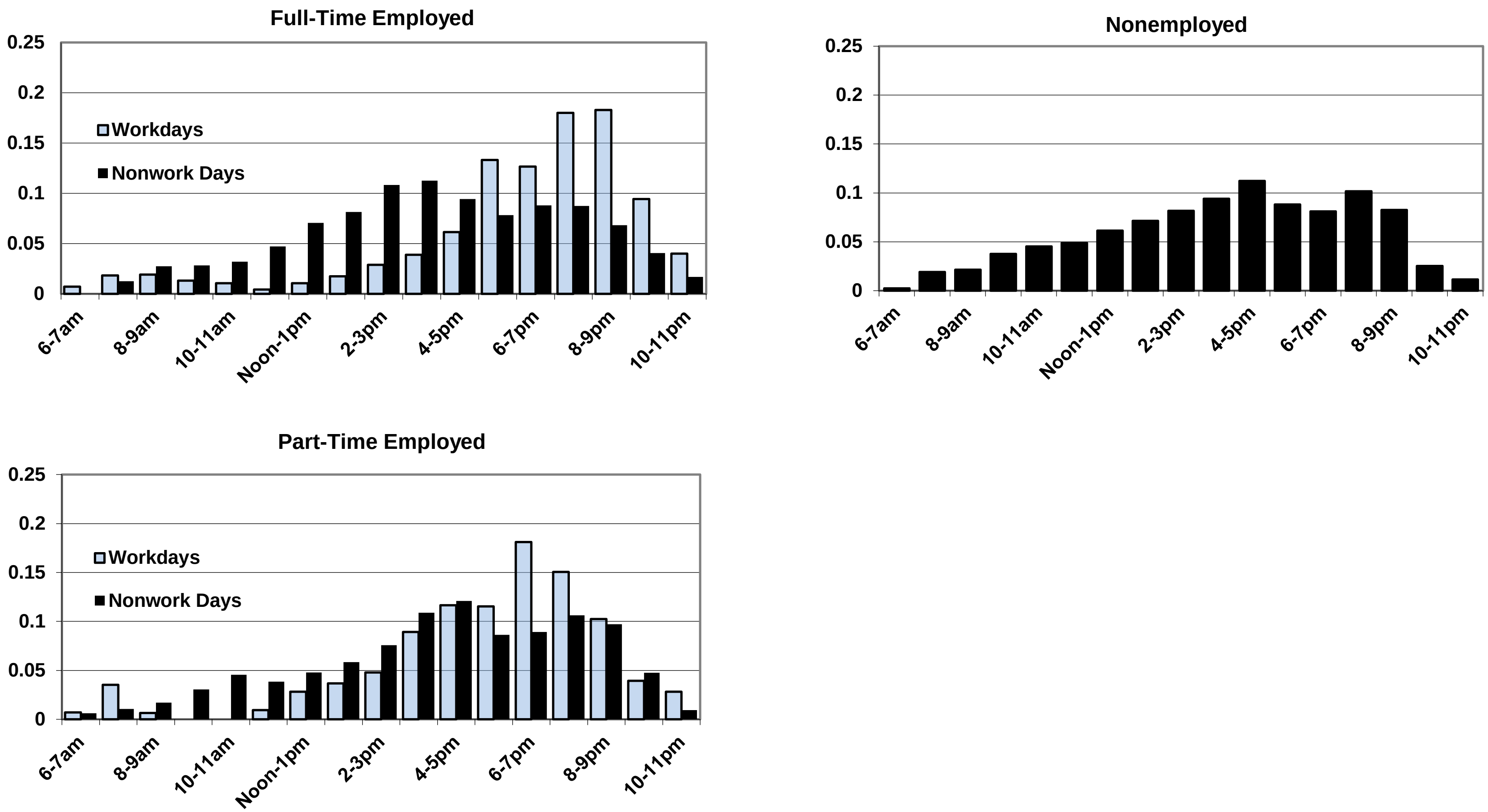


Figure 2: Distribution of Time Spent in Enriching Childcare by Mothers of 5-9 Year-Old Children



Dissimilarity Index

Weighted Absolute Deviation Index: Measures differences in the distribution of time spent in childcare

$$DI = \sum_{h=1}^{24}\left(\frac{\left|t_h^i - t_h^j\right|}{\left(t_h^i + t_h^j\right)} \times \frac{\left(t_h^i + t_h^j\right)}{\left(\sum_{h=1}^{24} t_h^i + \sum_{h=1}^{24} t_h^j\right)}\right) = \sum_{h=1}^{24}\left(\frac{\left|t_h^i - t_h^j\right|}{2}\right)$$

t_h^i = Fraction of time spent in childcare by group *i* during hour *h*

DI = 0 ➔ Distribution of childcare time is identical

DI = 1 ➔ No overlap

Interpretation: Percentage of time that must be reallocated to make the two groups the same

Dissimilarity Index Comparisons of the Distribution of Childcare on Workdays and Nonwork Days – Mothers of 0-4 Year-old Children

	Full-Time Employed		Part-Time Employed		
	Workday	Nonwork Day	Workday	Nonwork Day	Nonemployed
Full-Time Employed					
Workday	---	0.342	0.317	0.387	0.399
Nonwork Day	---	---	0.135	0.059	0.093
Part-Time Employed					
Workday	---	---	---	0.142	0.176
Nonwork Day	---	---	---	---	0.077

Time-of-Day Regressions

Estimated separate regressions for about 204 different times of day between 6:00am and 11:00 (5 minutes between times)

Dependent variable is 1 if respondent was working at that time

Each regression includes a set of covariates

Coefficient of interest is whether the respondent is the mother of a child age 0-4

Several possible control groups

- Mothers of children age 5-9
- Mothers of children age 10-17
- Women without children

Best control group is women without children

Figure 3: Difference in Percent of Full-Time Employed Mothers Working by Time of Day

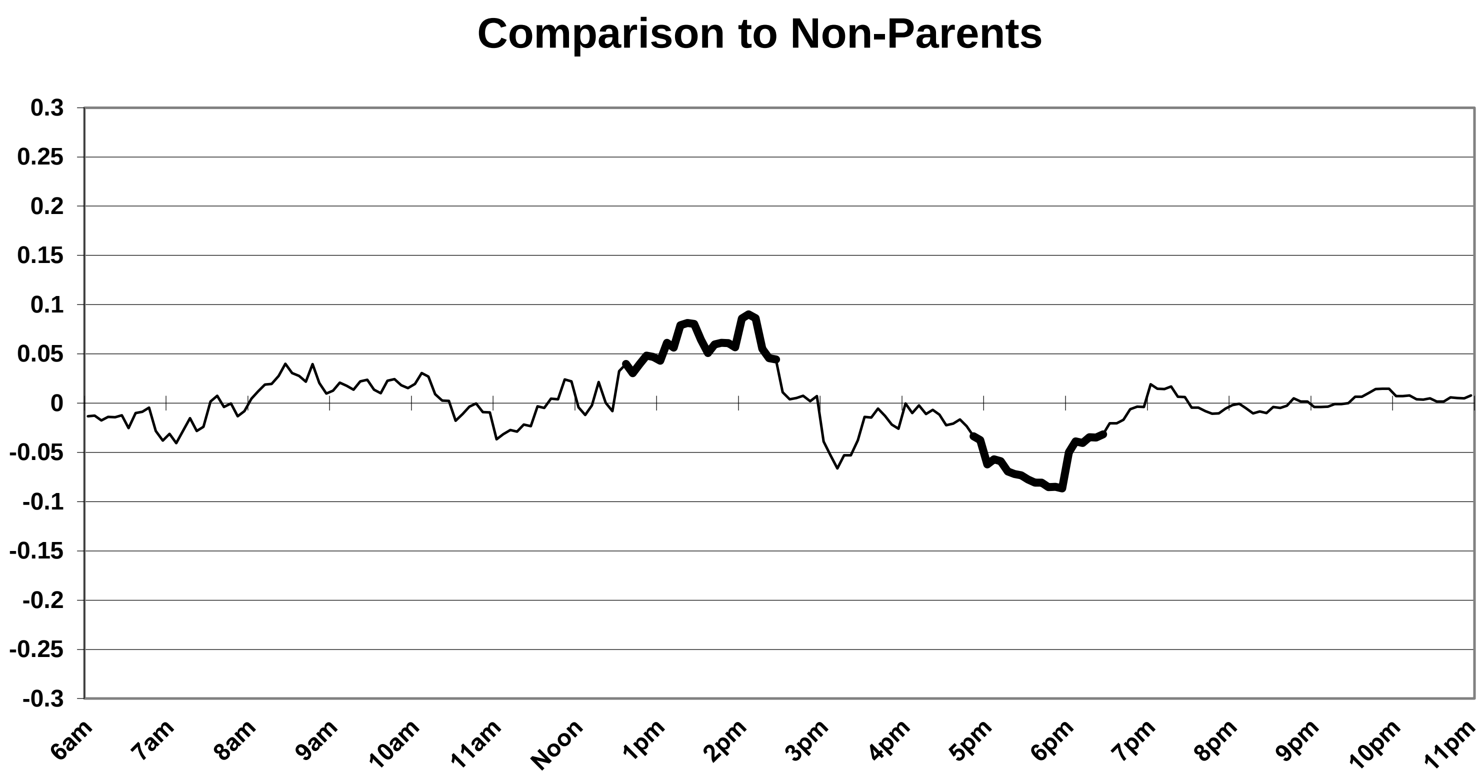


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Figure 4: Difference in Percent of <u>Part-Time</u> Employed Mothers Working by Time of Day

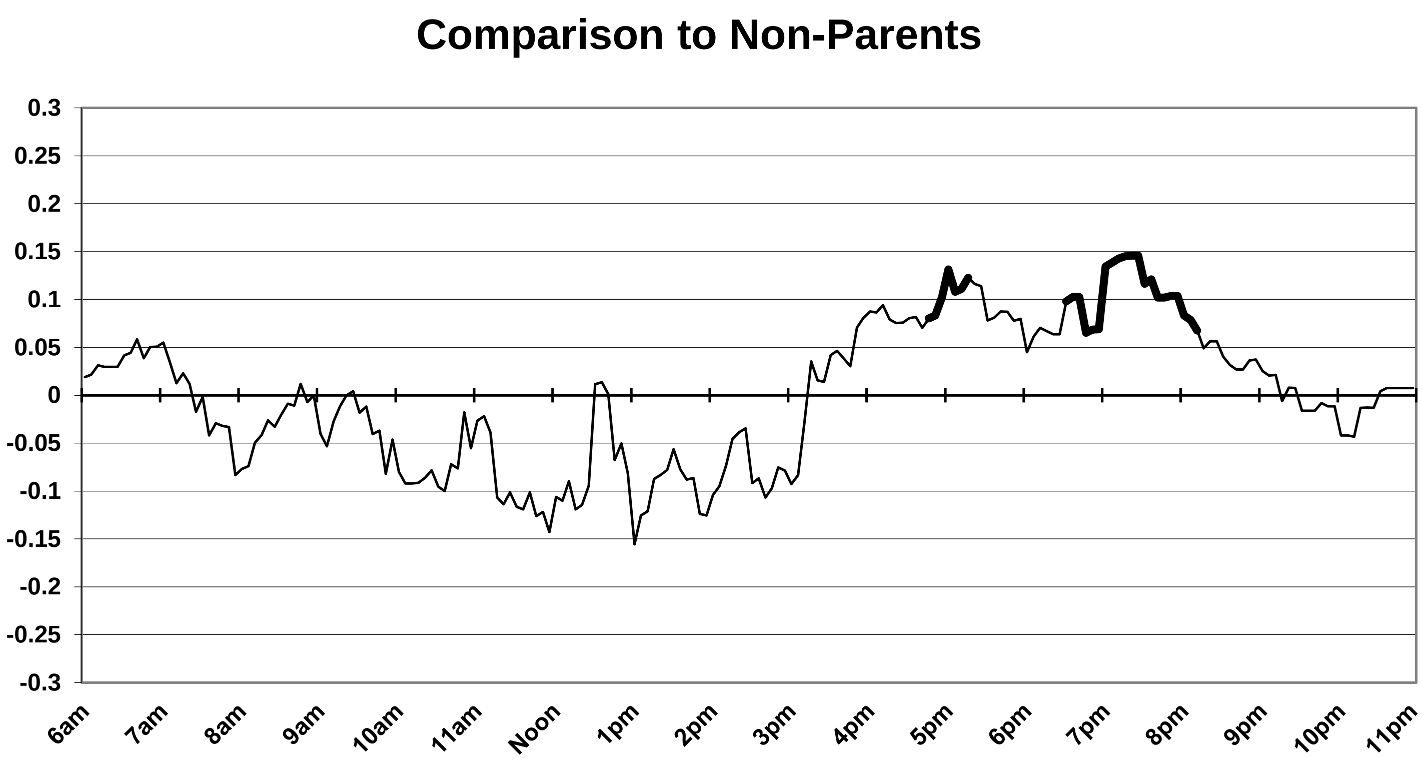

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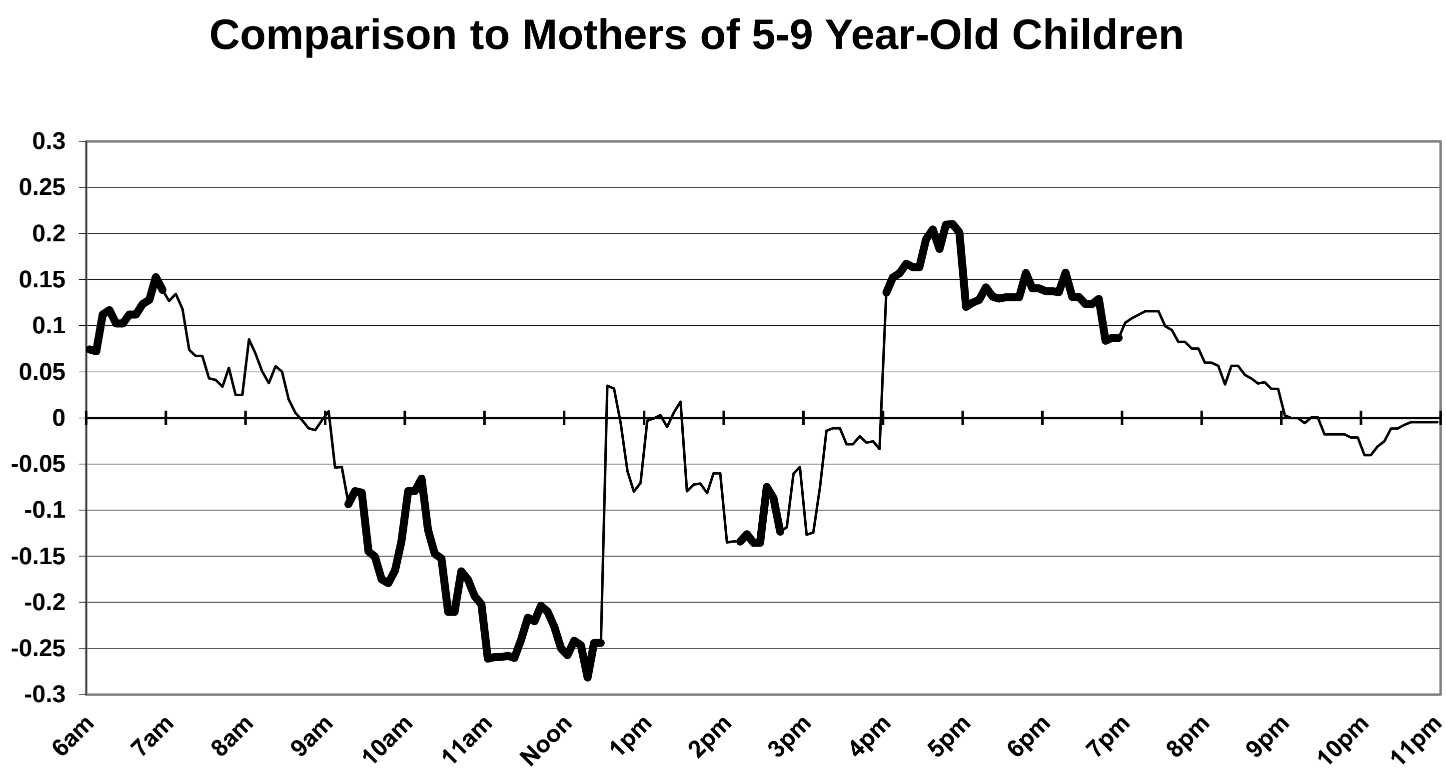
Figure 4: Difference in Percent of Part-Time Employed Mothers Working by Time of Day



Conclusions

Full-time employment places constraints on when mothers can spend time with their children.

- ➔ Mothers shift enriching care time from daytime hours to evening hours
- ➔ Looking only at the amount of time spent in childcare understates the effect of employment on parents time with children

Part-time employment places fewer constraints on when mothers spend time with their children

- ➔ Less shifting of childcare compared to full-time employed mothers
- ➔ Part-time employed mothers appear to adjust work schedules

Other Examples – Child Sleep Time

Question: How do school and maternal employment affect the amount of sleep children get?

Questions on when children under 13 woke up and went to sleep ➔ restrict sample to households with one child under 13

Weekend vs. weekday ➔ Look at wake-up and bed times separately

What is the appropriate control group?

Children on weekend?

Children in summer?

Other Examples – Child Sleep Time (continued)

Children go to bed about 34 minutes earlier on school nights, but wake up 78 minutes earlier on school days ➔ Net sleep loss of 34 minutes/day

Effect of sleep loss is cumulative ➔ By end of week, children are down more than 2.5 hours of sleep (20% of school time)

Other Examples – Assessing the Accuracy of Hours in the CPS

Compare average weekly hours in ATUS with average weekly hours in CPS

Average daily hours × 7

Matched vs. unmatched sample

Account for:

- Difference in response rates in CPS and ATUS
- Rotation group effects
- Actual changes in hours

Other Examples – Assessing the Accuracy of Hours in the CPS (continued)

Findings:

- CPS respondents report hours worked correctly on average
- Some groups over-report hours, while others under-report
- People work longer during the CPS reference week (the week that includes the 12th of the month) ➔ CPS hours are not representative of the entire month

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