How Does Time Use Affect the Likelihood of Becoming Obese?

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We undertake a careful examination of the role of time use in obesity using the Eating and Health module of the American Time Use Survey (ATUS). The ATUS provides a detailed look at how people spend their time over a 24-hour period. But body mass is affected by behavior over a longer period of months or years. Given the considerable day-to-day variation in time use, the time diaries can be viewed as measuring long-run time use with error. Furthermore, behavior and obesity might be jointly determined, or obesity might influence behavior.

The mismatch between the time period of interest and the time period observed in the data has been underappreciated in previous research. This mismatch introduces bias even if researchers are uninterested in causal effects[1]. For example, previous work has regressed BMI on time use variables in an attempt to estimate the association of time use on a typical day with BMI.[2] What they actually estimated was the association of time use yesterday with BMI today.

The good news is that both the endogeneity of time use and the measurement error due to the mismatch between time periods can be addressed using instrumental variables. The bad news is that finding valid instruments that predict long-run time use is extremely difficult.[3]

In the absence of traditional instruments that are neither weak nor dependent on questionable exclusion restrictions, we address these issues using an approach developed by Lewbel (2011). He shows that heteroskedasticity in an explanatory variable that is endogenous or measured with error can be used to construct instruments for that variable. Consider BMI and observed minutes in some activity, *M*, where

$$BMI = X\beta_1 + M\gamma + \varepsilon_1, \text{and} \tag{1}$$
$$M = X\beta_2 + \varepsilon_2. \tag{2}$$

[1] See Frazis and Stewart (2010) for a discussion of this problem, as well as others that arise from the use of time-diary data.
[2] E.g., Shields and Tremblay (2008), Dunton et al. (2009), and Kolodinsky and Goldstein (2011)
[3] We've tried numerous instruments based on prices, weather and other MSA-level variables. We also tried using variables that predicted time use on individual days, such as deviations of weather from the norm, and then summing those effects over time. We were uncomfortable with all of those results.

Lewbel's approach requires a vector of exogenous variables, *Z*, that satisfies the following assumptions

$$Cov(Z, \varepsilon_2^2) \neq 0, \text{and} \quad \text{(A1)}$$

$$Cov(Z, \varepsilon_1 \varepsilon_2) = 0. \quad \text{(A2)}$$

In our context, it is sufficient for *Z* to be correlated with heteroskedasticity in ε_2, but uncorrelated with both the short-run measurement error and any unobserved common factor. The equations can then be estimated using 2SLS with $(Z - \bar{Z})\varepsilon_2$ as instrumental variables.

Essentially, this estimator replaces traditional exclusion restrictions, which make assumptions about the coefficients in a system of equations, with assumptions about the covariance of certain variables with the error terms. This approach allows identification when traditional instruments are weak or the exclusion restrictions for available instruments are questionable.

Lewbel (2011) shows that both (A1) and (A2) are easily tested. (A1) is reflected in the F statistic for $(Z - \bar{Z})\varepsilon_2$ in the first stage, and can be tested directly using standard tests for heteroskedasticity. (A2) can be tested using Hansen or Sargan tests of overidentifying assumptions. We can even use difference-in-Hansen tests to examine the validity of subsets of the *Z* vector.

At this point, we have preliminary estimates (with the appropriate tests). Table 1 presents select results for men and women with various time use activities considered one at a time. Our results suggest that time spent exercising (defined as physically active leisure) reduces body mass and the probability of being obese for women, but not for men. On the other hand, time spent walking or biking that is not leisure (e.g., commuting or walking a dog) reduces the body mass of both men and women. Our guess is that gains in muscle mass from exercise explain the results for men. We also find evidence that time spent in market work increases the probability of being overweight for both genders, and time spent in "secondary eating" (grazing) results in lower body mass for women.

We have estimated some results that include two activities at the same time so that we can examine how the effects of various activities change when they are considered simultaneously with other activities. Time spent in one activity means time not spent in another. So far, the results for exercise and walking or biking appear very consistent regardless of which other activities included.

Table 1. Effects of Minutes in Activity on Body Mass

Each Activity Considered in Separate Regressions

	Women			Men		
VARIABLES	BMI	Overweight	Obese	BMI	Overweight	Obese
Exercise	-0.0343***	-0.0021**	-0.0027***	0.0101	-0.0006	0.0026*
	(0.0129)	(0.0011)	(0.0009)	(0.0155)	(0.0012)	(0.0015)
First-Stage F-Statistic	83.01	83.01	83.01	42.60	42.60	42.60
Overid. Test p-value	0.681	0.716	0.759	0.866	0.874	0.964
Walking or Biking, Not as Exercise	-0.0221***	-0.0002	-0.0012**	-0.0344***	-0.0035***	-0.0022***
	(0.0078)	(0.0007)	(0.0005)	(0.0102)	(0.0010)	(0.0007)
First-Stage F-Statistic	1309	1309	1309	607.6	607.6	607.6
Overid. Test p-value	0.630	0.713	0.862	0.592	0.579	0.740
Sleep	0.0205**	0.0004	0.0005	0.0055	0.0011	0.0007
	(0.0103)	(0.0005)	(0.0005)	(0.0110)	(0.0010)	(0.0008)
First-Stage F-Statistic	15.42	15.42	15.42	21.10	21.10	21.10
Overid. Test p-value	0.990	0.532	0.915	0.899	0.628	0.679
Time Eating, Primary	-0.0032	-0.0009	0.0004	0.0282	0.0014	0.0024
	(0.0141)	(0.0009)	(0.0008)	(0.0221)	(0.0018)	(0.0017)
First-Stage F-Statistic	50.86	50.86	50.86	37.16	37.16	37.16
Overid. Test p-value	0.977	0.977	0.989	0.876	0.623	0.469
Time Eating, Secondary	-0.0037***	-0.0003**	-0.0003***	-0.0039	-0.0001	0.0003
	(0.0011)	(0.0001)	(0.0001)	(0.0039)	(0.0003)	(0.0003)
First-Stage F-Statistic	719.5	719.5	719.5	240.5	240.5	240.5
Overid. Test p-value	0.890	0.790	0.303	0.798	0.487	0.955
Market Work, Total	0.0162	0.0015*	0.0002	0.0072	0.0009**	0.0000
	(0.0105)	(0.0008)	(0.0005)	(0.0050)	(0.0004)	(0.0004)
First-Stage F-Statistic	13.21	13.21	13.21	14.99	14.99	14.99
Overid. Test p-value	0.839	0.867	0.494	0.664	0.978	0.455
TV Watching, Total	-0.0064	0.0001	-0.0005	-0.0060	-0.0005	0.0000
	(0.0052)	(0.0003)	(0.0003)	(0.0045)	(0.0004)	(0.0003)
First-Stage F-Statistic	37.83	37.83	37.83	43.88	43.88	43.88
Overid. Test p-value	0.950	0.943	0.881	0.710	0.585	0.733
All Low-Intensity Time Other than Sleep	0.0051	0.0000	0.0003	0.0065	0.0005	0.0004
	(0.0071)	(0.0004)	(0.0005)	(0.0056)	(0.0004)	(0.0004)
First-Stage F-Statistic	12.41	12.41	12.41	18.25	18.25	18.25
Overid. Test p-value	0.560	0.571	0.694	0.857	0.686	0.795