OCCUPATIONAL DIFFERENCES IN ESTIMATES OF TIME AT WORK

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ABSTRACT

Previous national time-diary studies have paid little attention to respondent occupation, mainly because minimal research effort has been expended to ask and code occupation questions. In the 2003-07 ATUS data collection, on the other hand, occupation is of central concern. Occupations are an important determinant of paid work time. Respondents classified as being in managerial and farm occupations estimated they spent most time at work (44+ hours), while those in food, maintenance and service jobs reported the least (under 36 hours). This article examines the important role of occupation in the ***accuracy*** *of predictions of hours at work.*

We start from the position that time diaries are likely to produce more accurate estimates of paid work hours than do questionnaire items. We find that disparities between diary- and questionnaire-based estimates are strongly and significantly related to occupation, and while these disparities are decreased, they remain significant after multivariate adjustment for age, income and other demographic predictors of hours at work. Middle-income, middle-aged and married respondents reported higher disparities, but education and gender differences were minimal. Disparities within more specific occupations are also identified, with police officers, school teachers and lawyers showing greater disparities. Overall, occupation differences seem as important as income in predicting work hours and far more important than educational level.

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1 INTRODUCTION

The American Time-Use Survey (ATUS), in which a cross-section sample of the US public gives a complete accounting of what they do on a particular day, represents a great step forward in social science understanding and in advancing availability of more sensitive measures for public policy making. Its strict sample criteria, large sample size, continuous monitoring, elaborate coding scheme, replicated field procedures and wide availability are but a few of its methodological strengths.

One as of yet unexploited ATUS features is its detailed and elaborate coding of respondent occupation. In previous US time-diary studies, little or no attention has been paid to reporting of a respondent's occupation, and almost no effort was expended to ensure that when occupation questions were asked, they were asked and coded in a comparable manner. In the ATUS, on the other hand, occupation is a central concern of its sponsor, the Bureau of Labor Statistics, which has reason to pay extremely close attention to this background variable and has decades of experience in ensuring its careful and detailed capture in the ATUS data files.

This also presents a new research opportunity to learn more about a central predictor of how much time is spent at work in time-diary analysis and for public policy concerns. Much attention has been paid to, and explanatory power received from, the other two measures of "status" variables asked in diary surveys—namely education and income. For example, in his depiction of "Veblen in reverse", Gershuny (2009) has found a widening gap between college- and less-educated workers in several countries. There is also an important connection with income, in that one obvious way to increase one's income is to work more hours. This has become extremely relevant as concerns about "*Overworked Americans*" (Schor 1991), "*Busy Bodies"* (Burns (1993), "*Fighting for Time*" (Epstein and Kalleberg 2004), "*Work to Live*" (Robinson 2003), "*Take Back Your Time*" (de Graff 2003) *"Busier Than Ever"* (Darrah et al. (2007) are expressed in these shorthand titles to reflect concerns over an increasing "time crunch" in society.

A distinct reason for interest in this topic is a suspicion of systematic overestimates of paid work time—particularly by workers who genuinely have relatively long standard hours—emerging from questionnaire items. These concerns emerged quite early in the development of diary survey analysis (eg Hoffman, 1981, Niemi, 1983, Robinson and Bostrom, 1994). They were initially countered by a somewhat unfocussed reference to "regression to the mean" phenomena (Jacobs, 1998, Jacobs and Gerson 2004)—puzzling in particular insofar as the questionnaire and diary estimates in this case are are virtually simultaneous—and now largely discounted (eg by Frazis and

Stewart, 2004). There remains the possibility that specific groups properly claiming long hours of paid work may nevertheless overestimate their work time. It is perhaps understandable that agencies which invest heavily in funding questionnaires for this purpose should defend it. But since exactly parallel issues of imperfect and biased recall and social desirability effects, occurring in fields such as nutrition and household expenditure, result in the selection of diaries as the method of choice, makes the relative neglect of diary evidence for this purpose appear more problematical.

We might in particular expect variations in *working arrangements* (particularly in the regularity of work starting and stopping times, and in the degree of employer supervision of these) as well as in the work-time arrangement for payment either by employers or customers is likely to have implications for respondents' knowledge of their own work-hours, and hence their ability to answer the questionnaire items accurately. These working-time arrangements—and also the honorific or stigmatizing connotations, or the straightforward social desirability, of longer or shorter work hours—are likely to vary systematically between different types of occupation.

This article addresses many of these concerns by applying the detailed ATUS occupation codes to questions about hours at work. Its central measure of interest is the hours of paid work that ATUS respondents report in their retrospective diary accounts of what they did across the 24 hours of the previous day. These diaries are open-ended accounts of all of a worker's daily activities, and their beginning and ending times, in sequential order across the day. In that way, the diary preserves the important "zero-sum" feature of time, that is, if aggregate time on one activity (like TV) increases, time on some other activity (like work or sleep) must decrease.

The open-end diary accounts, consisting of about 20 activities reported across the day, are then coded into one of 450 categories of time use, which are the recoded into larger categories like paid work, child care, personal hygiene or TV viewing. As noted above, central interest in this article is on diary time reported and coded as paid work, although previous articles based on ATUS data have tended to focus on differences in details of family care (particularly child care), meal times and travel during the day. Further information on procedures for and availability of data in the ATUS can be found at *bls.gov* and in Abraham et al. (2006).

These time expenditures are usually analyzed as a function of the rich set of potential predictors of time available both from the ATUS interview itself, and from the 8-wave panel of Current Population (CPS) surveys that preceded it, usually focused on details of respondent employment and unemployment situations. Among them are two types of estimate questions that BLS regularly and historically has employed to measure hours at work, one asking about "usual" hours at work, the other about "actual" hours worked in the previous week. The usual hours question was then repeated in the

ATUS for respondents who had changed their work schedules since the final (eighth) CPS interview (usually conducted about 3 months prior to the ATUS interview). The CPS and ATUS also collect details about the respondents' personal background (like gender, age and income), family situation (like household size and presence of children) and location (like region, type of household dwelling). Adjustments for five of the more important of these predictor variables are included in the following analyses.

Outline of this article

The main focus and structure of this article is summarized by Tables 1 and 2. Table 1 (selecting, as throughout this paper, respondents aged 20-59) provides basic descriptive statistics for hours of work in each of 22 broad occupational categories. Columns 1-3 show average hours and standard errors of questionnaire-derived estimated paid work per week for each of the three estimate questions: ATUS "Usual" hours in column 1 (WK1), CPS "Usual" hours in column 2 (WK2), and CPS "Actual" hours in column 3 (WK3).

Column 4 shows estimates of average hours of *weekly* work for all people in that occupation plus standard errors, as extrapolated from the ATUS daily diaries (i.e. weighted so that each day of the week is equally represented and multiplied by 7). The result of this procedure is that the mean should be identical to a hypothetical equivalent calculated from a 7-day diary, but with a much higher variability, since there will be underestimated week equivalents from short-work or non-work days and overestimated week-equivalents from normal or long workdays. (It should be noted that these extrapolated estimates were verified by close matches with figures from the BLS annual press release tables on diary hours at work).

The first three panels of Table 2 show the occupation-specific mean disparities between estimate and diary hours, together with their standard errors. The differences between the estimates in columns 1 to 3 of Table 1 and the time reported in the diaries in column 4 (of these the CPS "actual" estimate in column 3, the most conservative, generally the lowest, seems the most appropriate comparator to the diary). Positive numbers mean that the estimated hours were higher and negative numbers mean that the diary hours were higher.

The final three panels show equivalent multivariate regression coefficients. The dependent variable in these three equations is in each case the difference between the questionnaire and the diary paid work time estimates whose means are in panels 1 to 3. We use standard OLS (SPSS vs. 16) OLS dummy variable (0/1) regression. Panels 4 to 6 give the coefficients associated with the 22 occupational categories, adjusted for the five non-occupational demographic predictors of work hours whose effects are shown in Table 3. Note that the occupational regression coefficients in these columns are all expressed relative to the reference or default occupational category “Sales and related”, selected because its CPS actual estimate has a mean unadjusted gap close to zero hours. As a result the regression coefficients in this latter group of three panels provide intuitively straightforward comparators for the simple mean occupational gaps, in the form of estimators of the gap *adjusted for the non-occupational predictors*.

The final table examines estimate-diary disparities by demographic factors *for more detailed occupation within* the 22 main BLS categories. The simple raw disparities are shown first, followed by the coefficients representing the occupation-specific disparities after regression adjustment as described in the previous paragraph, We again select the occupational group with the smallest absolute estimation gap between questionnaire and diary mean work time (sales representatives) as the reference category, to enable the same interpretation as above.

2. RESULTS

Estimated work hours

The three “estimate” columns in Table 1 are slightly different in their averages, with the ATUS usual hours being highest at 42.4 hours and the CPS actual hours being lowest at 40.0 hours. Nonetheless the three questions all agree that managers and executives and farm workers (as distinct from farm managers and owners in general who are under the manager category in this table) estimate the longest work hours at or approaching 45 hours per week, while food, maintenance and personal service workers are lowest at 36-37 hours per week.

Extrapolated weekly hours from the diary

As in their weekly estimates, longest diary hours are found for managers and farm workers, and lowest for food, maintenance and personal service workers, as shown in the next columns. However, the differences between the extreme groups are smaller in the diaries than in the questionnaire estimates. The diary work hours overall (39 hours) are slightly, but significantly, (by inspection of the standard errors) lower than for the lowest questionnaire estimates (CPS actual, at 40 hours).

Estimate minus diary differences

The largest differences between unadjusted questionnaire estimates and diary work hours (Table 2) are found for those employed in legal, education and protective (mainly police officers, security guards and firemen) jobs, whose estimates are at least four weekly hours higher than their average diary hours. The lowest discrepancies are found for food and sales workers. Differences of less than an hour per week are found for management, scientists, social/community workers, arts and entertainment, medical workers (mainly nurses and doctors), other health workers, personal service workers, maintenance, production and transport workers.

Adjusted differences after multivariate controls

We see that the mean occupational gaps (panels 4 to 6 in Table 2) are generally a little lower after adjustments for the five non-occupational predictors of work hours are taken into account. (Table 3 compares the partial regression coefficients for these variables before and after the occupational predictors are taken into account). It emerges that, although reducing the Table 1 estimation gaps, some significant occupational differences continue to be in evidence after adjusting for the non-occupational predictors.

Focusing on the key comparison of the CPS "actual" with the diary measure (panels 3 and 6), some estimates that were significantly different from zero in column 3 become insignificant in column 6 (management, business, engineers, construction and production workers). Computer, office occupations, legal and education workers' estimated gaps remain significant, though diminished; note, however, that in the last two cases the estimate overestimate as compared to the diary is still four hours per week. In the cases of personal care and protective services workers the overestimate remains unchanged (in the latter case at a remarkable 5.9 hours per week). And installation and transportation workers' estimated gaps actually increase once the other controls are included. In other words, many of the simple estimate-diary occupation disparities can be accounted for by workers in these occupations being different in their age, education, income and the like. Exactly *which* of these factors is involved is examined next in Table 3.

Non-occupational demographic predictors

Table 3 shows that, while many of the non-occupational categories have significant effects, few have a particularly strong association with the occupational disparities in estimated vs. diary work hours. More specifically, the average disparities across occupational categories seen in Table 2 are slightly higher for *women* than for men, as suggested by the reduction in the “woman” effect once occupational controls are introduced. The disparities for *age* are similar with and without controls. Figure 1, which instantiates the age and age-squared terms in Panel 2 of Table 3, shows an inverted-U relation with age; people in mid-age overestimating work hours by about 1 hour/week, where both the very youngest workers (less than 25 years) and the very old (57-60) underestimate to a somewhat smaller extent. There is a substantial difference for *education coefficients*, once occupation is added, indicating that much of the difference between panels 3 and 6 in Table 2 is to be explained by educational differences associated with occupations. But the *income* effect in Table 3 appears to be pretty much unchanged by the introduction of occupational categories, indicating that this not a major source of the changes between the simple mean occupational gaps and the regression estimates of occupational gaps in Table 2.

More detailed occupation grouping

The ATUS has a more detailed set of categories nested within the 22 categories in Table 1. Several of these have relatively large numbers of respondents (here over about 200 respondents) from which to make estimates for more fine-grained analyzes. Some 63 of these are listed in Table 4, along with their sample sizes, estimated work hours, diary work hours, differences between estimate and diary averages -- and these disparities remain after the five demographic predictors after regression adjustment for these factors – much as in the display and procedures employed in connection with Figure 1.

It will be remembered that the largest questionnaire/diary disparities in Table 2 were found for workers in the legal, education and protective occupations. In Table 4, it becomes possible, for example, to separate lawyers from paralegals and other support staff. Table 4 shows that, after adjustment for non-occupational determinants, the major disparity is found among lawyers themselves (7.2 hours) and not their supporting staff (-0.4 hours). In the case of workers in education, on the other hand, a notable disparity is found across virtually all groups of teachers, ranging from 8.1 hours for those teaching in elementary school vs. college teachers with their 2.0 hour discrepancy. In the case of protective workers, only police officers and security guards have sufficient samples to compare, and here it is the police who show the greater disparity (10.3 vs. 6.3 hours per week).

Some of the occupations with the largest disparities in Table 4 are found within the first category of managers in Table 1. For example, chief executives and medical managers are above average (at 3.3 and 5.4 hours) in their estimates vs. diary disparities, while managers at food and construction facilities actually report more work in their diaries than they estimated. Within the arts category, designers estimate 3 hours more than in their diaries. Within the lowest overall discrepancy category of food workers, waiters underestimate their work hours as *lower* than in their diaries, all groups of sales workers report below average disparities. Hairdressers are also above average in reporting 5-hour higher estimates than diary work hours (though when other non-occupational factors are accounted for third this becomes a similar-sized under-estimate).

While farm laborers (along with managers) report high unadjusted diary work hours, their disparities in estimates with the diary are negative once non-occupational variation is added to the regressions equation.

A note on the work hours of lawyers, doctors and other workaholics

No analysis of occupational work hours would be complete without some comments on the work hours of lawyers, doctors and other high-paid workers. A stereotype has been built of 80+ workweeks of lawyers in particular, with perhaps even longer work hours for doctors on 24-hour call. That may be what they boast to friends, neighbors or fellow party-goers, but that is not what they report to Census Bureau interviewers. Less than 2% of lawyers report they worked more than 80 hours the preceding week, and only about 15% reported 60 hours or more. On the other hand, more than 10% of doctors report more than 80 hours (topped only by farmers, not farm laborers, at 12%), another 28% of doctors said they put in more than 60 hours.

As noted the diary figure in Table 4, the doctors' claimed hours are the highest in the table – but still are only 1.3 hours above their diary records. By contrast, lawyers' claimed 44 work hours for the preceding week are more than 7 hours greater than their diary reports, hardly changed after adjustment for other determinants, are almost twice as high as the discrepancy for doctors. There are occupations with larger disparities (10 hours for police officers), but the lawyer mis-estimates are the largest in Table 4. The even higher questionnaire estimates for farmers are much more consistent with what they report in their diaries.

In brief, then, fewer lawyers match their estimated work hours with what they report in diaries than doctors or farmers. And their 37 diary hours of work remain about average. As one colleague suggested, perhaps the 80-hour figure would hold for junior law partners in the Washington-New York areas, but (perhaps fortunately) even the detailed occupation codes in the ATUS do not allow us to identify them.

3. SUMMARY AND CONCLUSIONS

Although few researchers have taken advantage of the detailed occupation codes in the ATUS, or of occupation as a predictor of time, there are significant occupation differences in both estimates of work hours and time at work reported in the ATUS time diaries. Managers and farm workers estimate up to 10 hours more work hours than those in food, maintenance and service occupations, and this holds in the work hours they report in their diaries. Moreover, these disparities generally still hold after other demographic predictors of work hours (like income and age) are taken into account.

There are also important occupation differences in the disparities between diary and work hours, with workers in legal, education and protective occupations reporting diary work hours that are up to 6 hours lower than in their workweek estimates. Examination of more detailed occupation distinctions within the broader 22-occupation BLS categories reveals that within the legal category, lawyers report higher disparities than reported by their legal support staff. Within the protective occupations, police officers report higher disparities than security guards. In contrast, teachers at all levels of education report higher disparities, with elementary school teachers giving workweek estimates that are 8 hours greater than those reported in the diaries.

There were notable differences in groups with lower disparities as well. Food workers actually reported slightly *lower* estimates than that reported in diaries, and this was particularly true for stock-clerks supervisors. That was true as well for managers in the food and construction vs. other fields. Within the arts, designers reported almost 4 hours more weekly work in their diaries than in their questionnaires.

Among five demographic predictors of these hours and discrepancies, income was found to have an effect on work hours independently of occupations. Significant occupation differences in paid work time are maintained alongside the other two “status” work predictors, income and education.

The important role that occupation plays in explaining differences in work hours suggests that it may be as important in predicting other aspects of daily life covered in the ATUS. The ATUS data provide an opportunity to examine whether occupation predicts other aspects of time use, especially free time. How much activities at work “spill over” into free-time choices seems a particularly apt topic to explore with these data, as well as discriminating between occupations in all aspects of their lives after work. Do cooks spend more time preparing home-cooked meals, social workers more time helping others, health workers more time working out, mechanics fixing up their own cars and the like? The answers lie not far beneath the surface within the rich ATUS data files.

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Table 1

Disparities by 22 occupations between estimate and diary reports of work hours.

	Estimated weekly hours, different estimate questions							
	1) ATUS usual WK1		2) CPS usual WK2		3) CPS actual WK3		Diary	
	1		2		3		4	
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
Management	**48.0**	0.07	**45.5**	0.06	**45.2**	0.07	**44.4**	0.18
Business. financial	**43.4**	0.09	**42.2**	0.08	**41.4**	0.10	**40.1**	0.26
Computer, etc	**43.6**	0.10	**42.2**	0.08	**41.7**	0.12	**39.8**	0.35
Engineers, architects	**44.3**	0.11	**42.8**	0.1	**42.2**	0.12	**41.2**	0.39
Scientists	**41.8**	0.19	**40.0**	0.17	**39.7**	0.21	**39.0**	0.52
Community, social work	**43.1**	0.18	**41.4**	0.16	**40.3**	0.19	**40.6**	0.43
Legal	**44.2**	0.22	**42.3**	0.21	**41.7**	0.23	**36.9**	0.52
Education	**40.8**	0.11	**39.4**	0.1	**37.7**	0.11	**33**	0.24
Arts, entertainment	**40.2**	0.22	**39.5**	0.18	**38.2**	0.21	**38.5**	0.42
Medical	**40.3**	0.11	**39.1**	0.1	**38.4**	0.12	**38**	0.3
Health support	**37.1**	0.17	**36.9**	0.14	**35.6**	0.15	**34.9**	0.39
Protection	**46.6**	0.17	**43.5**	0.15	**44.5**	0.19	**38.6**	0.51
Food	**36.6**	0.14	**35.8**	0.13	**35.1**	0.14	**35.3**	0.30
Maintenance	**38.6**	0.14	**37.5**	0.12	**36.3**	0.13	**36.6**	0.30
Personal services	**37.0**	0.19	**36.9**	0.17	**35.9**	0.17	**33.4**	0.37
Sales and related	**42.4**	0.08	**40.8**	0.08	**39.9**	0.08	**39.9**	0.19
Office	**39.2**	0.05	**38.2**	0.05	**37.1**	0.06	**34.9**	0.15
Farm	**50.1**	0.37	**46.7**	0.35	**46.6**	0.37	**48,0**	0.78
Construction	**43.4**	0.09	**41.5**	0.07	**40.2**	0.09	**41.9**	0.24
Installers	**44.9**	0.11	**42.7**	0.08	**42.7**	0.11	**41.8**	0.31
Production	**42.9**	0.07	**41.1**	0.05	**40.8**	0.07	**40.1**	0.22
Transport	**45.3**	0.12	**42.2**	0.09	**41.7**	0.10	**41.5**	0.27

Table 2
Occupational disparities in estimate-diary gap* (Controls shown in Table 3)

Gaps significantly (>2 se) different from zero or default category in **larger bold type**

	Mean gap by occupation						Regression coefficient after controls*					
	1		2		3		4		5		6	
	ATUS "usual" minus diary		CPS "usual" minus diary		CPS "actual" minus diary		ATUS "usual" minus diary		CPS "usual" minus diary		CPS "actual" minus diary	
Multiple R							0.06		0.07		0.07	
	Mean	se	Mean	se	Mean	se	b	se	b	se	b	se
All	**3.4**	0.06	**1.8**	0.06	**1.1**	0.06						
Management	**3.6**	0.18	**1.1**	0.19	**0.7**	0.18	0.3	0.25	**-0.7**	0.27	0.0	0.26
Business and finance	**3.4**	0.26	**2.1**	0.27	**1.3**	0.27	0.4	0.32	0.3	0.34	0.6	0.34
Computer and maths	**4.0**	0.34	**2.6**	0.35	**1.9**	0.35	**1.0**	0.38	0.8	0.41	**1.4**	0.41
Engineers	**2.9**	0.38	**1.7**	0.39	**1.0**	0.39	-0.8	0.41	0.2	0.44	0.5	0.44
Scientists	**2.8**	0.51	0.7	0.53	0.6	0.53	-0.4	0.53	-0.9	0.57	0.2	0.58
Community& social care	**2.9**	0.41	**1.1**	0.44	-0.4	0.43	0.2	0.47	-0.7	0.50	-0.9	0.50
Legal occupations	**6.9**	0.53	**5.0**	0.55	**4.8**	0.52	**3.0**	0.57	**2.6**	0.62	**4.0**	0.61
Education, training	**8.0**	0.23	**6.5**	0.24	**4.7**	0.24	**4.6**	0.30	**4.1**	0.33	**4.0**	0.33
Arts, entertainment	**1.4**	0.43	**1.0**	0.45	-0.3	0.43	**-1.2**	0.44	-0.5	0.49	-0.5	0.48
Healthcare professional	**2.5**	0.29	**1.6**	0.30	0.4	0.30	-0.4	0.31	-0.5	0.34	-0.6	0.34
Healthcare support	**2.2**	0.40	**1.5**	0.41	0.7	0.39	**1.0**	0.42	0.5	0.46	0.8	0.46
Protective service	**8.1**	0.52	**5.5**	0.53	**5.9**	0.51	**4.8**	0.44	**4.6**	0.47	**5.9**	0.47
Food preparation	**1.3**	0.29	-0.3	0.31	-0.2	0.30	-0.5	0.34	**-0.9**	0.37	0.7	0.37
Building and grounds	**1.6**	0.29	**0.8**	0.31	-0.3	0.30	0.2	0.35	0.4	0.39	0.5	0.39
Personal care	**3.5**	0.34	**2.9**	0.38	**2.6**	0.36	**1.2**	0.37	**1.5**	0.42	**2.6**	0.41
Sales and related	**2.3**	0.18	**1.0**	0.19	0.1	0.18	(ref)		(ref)		(ref)	
Office and admin	**4.3**	0.15	**3.1**	0.16	**2.3**	0.16	**1.6**	0.24	**1.6**	0.25	**2.0**	0.25
Farming etc	**2.1**	0.75	**-1.7**	0.81	-1.4	0.75	**1.5**	0.67	**-1.4**	0.74	-0.2	0.73
Construction etc	**1.5**	0.24	-0.3	0.25	**-1.7**	0.25	0.2	0.30	0.1	0.33	-0.7	0.32
Installation etc	**3.4**	0.30	**1.2**	0.31	**1.0**	0.31	0.6	0.34	0.6	0.36	**1.3**	0.36
Production	**2.6**	0.22	**0.7**	0.22	**-1.7**	0.22	0.5	0.28	0.2	0.30	-0.7	0.32
Transportation	**3.7**	0.26	**0.7**	0.28	**1.0**	0.27	**1.9**	0.30	**0.9**	0.33	**1.3**	0.36

***** Occupational effects on questionnaire minus diary estimates, controlling for age, age squared, sex, income, education and marital status

Table 3
Other demographic predictor effects of estimate-diary gap,
(With and without occupation controls)*

Gaps significantly (>2 se) different from default category in **large bold type**

		1		2	
		No occupation controls		With occupation controls	
Multiple R		0.06		0.07	
		b	se	b	se
Sex					
	Men	(ref)		(ref)	
	Women	**1.4**	0.12	**1.0**	0.14
	Age	**0.4**	0.05	**0.4**	0.05
	Age squared/1000	**-4.7**	0.56	**-4.6**	0.57
Income					
	Bottom quartile	(ref)		(ref)	
	Second quartile	**1.2**	0.18	**1.1**	0.18
	Third quartile	**1.4**	0.19	**1.4**	0.19
	High income	**1.9**	0.25	**2.1**	0.25
	Top 5%	**2.9**	0.31	**3.3**	0.31
	No information	-0.2	0.22	-0.2	0.22
Education					
	Some high school	**-1.3**	0.26	**-0.6**	0.29
	High school grad	-0.6	0.19	-0.2	0.22
	Some college	0.2	0.20	**0.5**	0.22
	College grad	0.1	0.21	**0.6**	0.21
	Post-grad	(ref)		(ref)	
marital status					
	Married	**0.8**	0.17	**0.8**	0.17
	Previously married	**0.6**	0.23	**0.6**	0.23
	Never married	(ref)		(ref)	
(Constant)		**-8.0**	0.87	**-9.2**	0.33

* Effects on(CPS actual - diary estimates), controlling for occupational status as in Table 2

Table 4: WORKHOUR DIFFERENCES BY DETAILED OCCUPATION **(Same regression controls as in Table 2; * p=.05 ** p=.005 *** p=.0005)**

	Cases (n=)	wk3	diary	wk3 - diary	reg	
CHIEF EXECUTIVE	664	48.5	43.8	**4.1**	**3.4**	***
OPERATION MGR.	366	45.6	43.1	**1.5**	**1.0**	
MARKET MGR	395	45.6	39.9	**4.4**	**3.7**	***
FINANCE MGR	463	42.0	44.2	**-1.9**	**-2.5**	**
FARMER	378	51.8	49.3	**-2.5**	**-2.4**	*
CONSTRUCT MGR	323	45.2	48.8	**-4.5**	**-4.6**	***
EDUCATION ADMIN	389	42.8	42.7	**-0.3**	**-0.6**	
FOOD MGR	283	49.4	50.1	**-0.6**	**-0.3**	
MEDICAL MGR	242	43.0	37.2	**6.1**	**5.4**	***
HUMAN RESOURCE	319	40.7	38.6	**1.7**	**1.2**	
MGMT ANALYST	273	42.6	39.3	**2.4**	**2.1**	
ACCOUNTANT	777	41.3	39.9	**1.2**	**0.8**	
COMPUTER-SCIENTIST	326	42.8	40.3	**2.1**	**1.9**	*
SOFTWARE	419	41.9	39.1	**2.7**	**2.5**	***
ELECTRICAL ENGINEER	633	44.1	43.0	**1.7**	**1.7**	
COUNSELOR	259	40.4	38.1	**2.2**	**2.1**	
SOCIAL WORKER	341	38.6	37.6	**0.7**	**0.3**	
CLERGY	199	46.1	45.3	**-0.9**	**-0.4**	
LAWYER	474	44.4	37.4	**7.4**	**7.2**	***
LEGAL SUPPORT	238	36.9	36.2	**0.1**	**-0.4**	
PROFESSOR	599	37.4	35.2	**1.7**	**2.0**	*
PRESCHOOL	366	35.9	32.6	**2.3**	**1.9**	
ELEMENTARY	1268	40.0	33.6	**6.0**	**5.6**	***
SECONDARY	550	41.5	38.7	**2.7**	**2.6**	**
OTHER TEACHER	419	33.0	24.2	**8.5**	**8.1**	***
DESIGNER	341	38.2	40.4	**-3.5**	**-3.7**	***
MD	341	52.4	50.3	**1.6**	**1.3**	
NURSE	1180	36.7	35.0	**0.9**	**0.0**	
POLICE	253	45.0	37.1	**10.2**	**10.2**	***
SECURITY GUARD	267	41.6	35.3	**5.5**	**6.3**	***
FOOD SUPER	217	39.8	38.1	**1.7**	**2.2**	*
COOK	608	37.4	37.9	**-0.9**	**0.2**	
WAITER	472	30.4	33.0	**-2.5**	**-1.8**	*
DINING ATTENDANT	200	31.4	29.5	**4.5**	**5.4**	**
JANITOR	793	36.6	35.8	**-0.1**	**0.9**	
MAID	587	31.3	28.3	**1.5**	**1.9**	*
GROUNDSKEEPER	421	38.5	38.4	**-2.8**	**-1.5**	
HAIRDRESSER	227	34.4	29.4	**4.6**	**4.6**	**
CHILD CARE	707	37.0	34.5	**0.7**	**0.7**	
RETAIL SUPER	1206	44.2	45.1	**-1.4**	**-1.3**	
NONRETAIL SUPER	525	44.7	44.0	**0.2**	**0.0**	
CASHIER	989	32.2	31.6	**-0.1**	**0.5**	
RETAIL SALES	1012	35.3	32.5	**1.0**	**1.4**	*
SALES REP	554	43.9	42.5	**0.0**	**(ref)**	
REAL ESTATE	370	42.7	38.3	**2.9**	**2.6**	*
OFFICE MGR	617	40.4	38.9	**1.6**	**1.0**	
BOOKKEEPER	660	35.0	30.4	**2.9**	**2.3**	*
CUSTOMER SERVICE	695	37.7	36.8	**0.7**	**0.9**	
RECEPTION	523	33.5	32.9	**0.2**	**0.3**	
STOCK CLERK	460	36.5	40.0	**-3.8**	**-3.2**	***
SECRETARY	1452	36.2	31.8	**3.6**	**3.0**	***
OFFICE CLERK	350	33.7	29.8	**2.4**	**2.2**	*
FARM HELP	299	46.8	48.3	**-3.4**	**-2.0**	*
CONSTRUCT SUPER	317	43.1	43.6	**-1.7**	**-1.3**	
CARPENTER	518	38.2	40.1	**-3.5**	**-2.5**	**
LABORER	334	38.1	38.8	**-4.3**	**-2.9**	**
ELECTRICIAN	302	42.1	41.2	**-0.2**	**0.4**	*
PAINTER	197	40.3	36.7	**1.7**	**2.8**	*

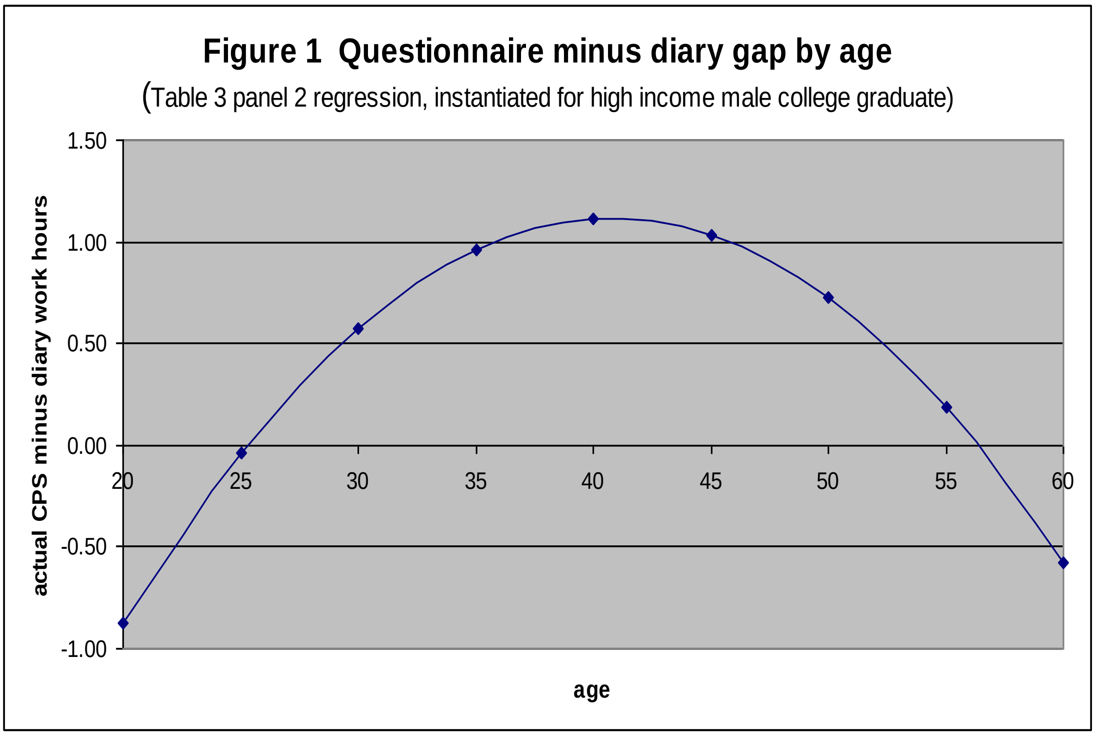

Figure 1 Questionnaire minus diary gap by age
(Table 3 panel 2 regression, instantiated for high income male college graduate)
1.50
1.00
0.50
0.00
-0.50
-1.00
20
25
30
35
40
45
50
55
60
actual CPS minus diary work hours
age