Youth Mental Health and Work Hours

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June 15, 2017

Abstract

Using the NLSY97 data, I apply the Generalized Method of Moments to identify the effects of mental health on youth labor supply. Improvements in mental health extend work hours. However, the effect is small and centralized in partnered men. A four percent increment in mental health adds at most seven minutes to men' average daily working time.

Introduction

Mental health disorder is a common health issue in the United States, affecting about 18 percent of American adults each year (NIH, 2015). The insidious effects of these ailments are in their ambiguous symptoms and the negative stigmas that prevent early intervention. The costs of mental health illnesses are realized through many channels, including increased personal expenditure on health-care service, increased public spending on disability support, income loss, and reduced productivity. Serious mental health illnesses alone cost the economy more than $300 billions each year (NIH, 2002).

This paper attempts to contribute to the discussion of mental health and work by answering the question, *What is the effect of mental health on young working adults?* For these workers, an onset of a mental health decease may yield long-lasting effects on their productivity and participation in the labor market. A good understanding of the spell of mental health and how it varies for different demographic groups is necessary for the design and evaluation of prevention programs. I find that mental health has a positive relationship with labor supply: better health expands the number of work hours. But the effects are modest. Most benefits are realized by men, especially partnered men. The effects on women are insignificant.

My second contribution to the literature is the application of the system Generalized Method of Moments (system GMM) to solve the issue of reverse causality between health and work. The GMM method frees the researcher from pursuing an exogenous instrumental variable –a quest that may eventually narrow the analysis to a limited set of specialized data set. The estimates from system GMM are in harmony with the literature, as discussed earlier. Further, I observe that by increasing the number of lag, the estimates gain strength. If the data set allows for longer observation period, the estimated effects can be larger.

In the following sections, I'll summarize key findings in the literature before proceeding with a brief discussion of the data. After that, I'll present the empirical framework and interpret the estimates obtained from fitting the proposed framework to data.

1 Literature Review

The technical issues in mental health literature are reverse causality, unobserved heterogeneity, and measurement errors. These problems arise from the endgeneity of health, and from the lack of ideal data sets with good measurements. The situation promotes variety in data choice and empirical approach. Ther are many novel instruments, such as 'death of a close friend' (Frijters et al., 2010), social support (Oeda et al., 2010), religiosity, counts of previous psychiatric illness (Chatterji et al., 2007), family history (Marcotte et al., 2000), stressful life event, and past health (Hamilton et al., 1997). Also, there has not been a consensus on choosing a measurement for mental health, even though most studies agree that it should be treated as an endogenous variable. The measurements vary from clinical standardized scores (Frijiet et al., 2010), to diagnosis (Ojeda et al., 2010; Chatterji et al., 2007), and illness symptoms (Marcotte et al., 2000). No measurement is perfect. Currie and Madrian (1999) argues that measurement errors in self-reported health is unlikely to be random because poor health status may be used as a claim to justify for withdrawal from the labor market. It is also unknown from most data sets that whether the individuals have received treatments. This, in turn, relates to other determinants of labor supply such as education, insurance, employment, and income.

In spite of the differences in approaches and data, there are consistent evidences for the positive relationship between mental health and labor market activities. Improvements in health lead to better labor market outcomes. The strength of this relationship varies for different population. Frijters et al. (2010) shows that a decrease in reported mental health leads to a reduction in labor force participation, with stronger effects on females and the elderly. Oeda et al. (2010) shows that mental illnesses reduce labor participation for male workers, but not on immigrants and females. Chatterji et al. (2007) shows that the effects vary greatly among among ethnics groups. Their conclusion from studying the influence of psychiatric disorders and mental distress on absenteeism reveals that only Latinos and White are affected by mental illnesses.

2 Data and Measurements

I use data from the *National Longitudinal Survey of Youth* , which is a comprehensive, on going, annual survey administered by the U.S Bureau of Labor Statistics. The survey follows a a group of people who were 12 to 18 in the first survey round. The selection of the initial cohort was conducted with sampling of households followed by sampling of eligible youth. The year-by-year attrition rate is five percent, and most youth in the initial cohorts still present in the survey pool. For each of these interviewees, a complete history of employment and health is available.

Table 1 summarized the descriptive statistics of the sample[1]. The counts of observations and unique individual shows that there is an active flow in survey participation and cohabitation status. The statistics reveals gender gaps in hours and wage. On average, men work more than women by seven to ten hours per week. Partnered men appear to work more than their single peers by two hours per week. Men earn more than women, and partnered individuals earn more than singles. The gap in wage between singles and partnered may have manifested through age effects: married individuals are older and therefore may have have longer tenure in the labor force.

To measure mental health, I compute the Mental Health Score using the five-question Mental Health Inventory Index (MHI5). The MHI5 questions are drawn from the set of 18 questions asked by medical professionals when evaluating a patient's depression. The questions and raw scores for the responses are as follows:

[1]The data comes from five survey rounds between 2002 and 2010, even years. Youth are defined as people who aged between 21 and 35 at the time of interview.

How much of the time during the last month have you [...]	All	Most	Some	None
[1] been a very nervous person?	1	2	4	6
[2] felt so down in the dumps that nothing could cheer you up?	1	2	4	6
[3] felt downhearted and blue?	1	2	4	6
[4] felt calm and peaceful?	6	5	3	1
[5] been a happy person?	6	5	3	1

A participant answering all question will have a total raw score between 5 and 30. This score then will be converted into a 0-100 scale index using the formula $MHI5 = 100 * \frac{r}{V}$, where r is the total raw score and V is the measurement range. Higher index implies better mental state.

In our sample, cohabitation and marriage appears to improve mental health for both gender by more than two standard deviations. Men appear to have better health report than women. The year to year assessment shows that our measurement is stable through five survey rounds. In another word, it is unlikely to come across someone whose health index changes by two out of one hundred. The gap in other factors of labor production tends to be stylized in the opposite direction. On average, men have shorted schooling duration, lower education level, and more labor market experience than women.

Table 1: Descriptive Statistics

	Full Sample	Male		Female	
		Single	Partnered	Single	Partnered
Observations	6550	836	2081	1445	2188
Unique individuals	3121	536	1101	831	1206
Variables					
Total Hours	1863.87	1830.00	1967.85	1785.03~	1813.50~
	7.16	18.71	9.00	14.51	13.70
Usual Hours	35.17	34.53*	37.13	33.68~*	34.22~
	0.14	0.35	0.17	0.27	0.26
Mental Health Score	72.84	71.25	77.70	66.31	71.94
	0.34	0.90	0.51	0.79	0.50
Two year change	0.91	1.71~	1.00~*	-0.02~	1.02~*
	0.18	0.68	0.31	0.50	0.33
log(Wage)	2.50	2.52	2.83	2.22	2.31
	0.02	0.04	0.02	0.03	0.02
General Health Score	68.18	67.59~	70.08~*	64.17	68.56*
	0.42	1.16	0.65	0.90	0.69
Age	26.13	25.88*	26.41	25.69*	26.16
	0.03	0.09	0.05	0.07	0.05
Black or Hispanic	0.35	0.46*	0.31*	0.51*	0.27*
	0.01	0.03	0.02	0.02	0.01
Number of Kids [0]	0.13	0.71	0.08	0.04	0.02
	0.01	0.02	0.01	0.01	0.00
[1 to 2]	0.76	0.28	0.83*	0.82~	0.83~*
	0.01	0.02	0.01	0.02	0.01
[3+]	0.11	0.01	0.09	0.13~	0.15~
	0.01	0.00	0.01	0.01	0.01
Years of Schooling	12.66	11.84	12.52	12.51	13.15
	0.05	0.12	0.09	0.10	0.09
Education [Less than High-school]	0.25	0.35	0.27	0.25~	0.21~
	0.01	0.03	0.02	0.02	0.01
[High-school]	0.55	0.57~	0.54~*	0.60	0.53*
	0.01	0.03	0.02	0.02	0.02
[College or more]	0.20	0.09	0.19	0.15	0.26
	0.01	0.02	0.01	0.01	0.02
Labor Market Experience	7.47	8.04~	7.90~	7.18~	7.01~
	0.05	0.13	0.09	0.11	0.09

Notes:
All estimates are significant at 95 percent confidence level across gender and cohabitation groups, unless indicated otherwise. (~): Not significant within gender group. (*): Not significant within cohabitation group.

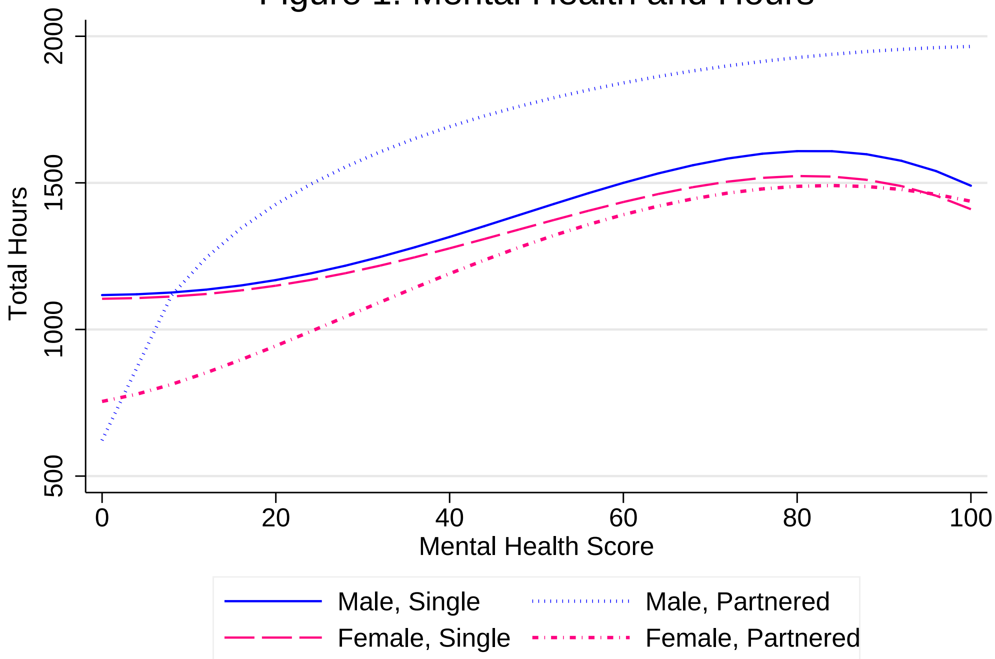

Figure 1: Mental Health and Hours

The unconditional relationship between mental health and hours is illustrated in Figure 1. People with better health appear to work more while those with grave conditions work less. However, the effect is not equal across gender and cohabitation status. Men appear to work more hours at every level of health. The gap is more obvious for partnered people: cohabitation adds hours for men while compressing hours for women. As a result, the gap between single and partnered men are consistent for almost all health levels. For women, however, the gap diminish as health increases; from the index of 60 and up, there is hardly any difference in between single and partnered women.

The depiction seen in Figure 1 resonates with findings in the literature about the positive relationship between mental health and labor supply. However, this conjecture needs to be re-assessed with the control for other determinants such as years of schooling, education level, wage, and labor market experience. The following section presents the theoretical framework and empirical approach to solve the issues.

3 Estimation Framework

The data generation process for N individuals over T periods is assumed to have the form:

$$Y_{it} = \alpha Y_{i(t-1)} + \beta X_{it} + \theta O_{it} + \eta_i + v_{it}$$

where the disturbance terms are assumed to have standard properties:

$$E(\eta_i) = 0, E(v_{it}) = 0, E(\eta_i v_{it}) = 0, E(v_{it} v_{is}) = 0, \forall t \neq s$$

In this environment, Y_{it} is participation in labor market measured by hours at time t of individual i, X_{it} is mental health measurement, and O_{it} is the matrix of other variables. The parameter matrix β is of interest; it represents how many hour will be supplied for a level of mental health.

If the error term satisfies the regularity conditions, we will obtain an unbiased and consistent estimate of β from this framework. However, there are two issues. First, the relationship between Y_{it} and X_{it} can be in either direction: a worker may adjust labor supply according to her mental well-being, or working longer hours keeps her mentally satisfied, or people who work longer hours can afford better remedies to relinquish their health stocks. The explanatory variable therefore may be correlated with the error terms. The other issue is the existence of time-invariant unobserved heterogeneity. There can be demographic and work-related factors that nurture a person's mental health and her decision on work but are not observed in the data. Some examples of these are depression coping skills, family support, medical intervention, and working environment. To illustrate this point, consider the case where X_{it} follows an auto-regressive process:

$$X_{it} = \sigma X_{i,t-1} + \tau \eta_i + \theta v_{it} + e_{it}$$

The source of bias comes from the effect of η_i and v_{it} on both X_{it} and Y_{it}.

To address the complication with endogeneity in X_{it}, we can employ instrumental variables to collect variations in this variable that genuinely come from random component in health. However, this approach requires the existence of good instruments, which is not always guaranteed in practice. Particularly for NLSY97, the pool of information that can be used to instrument for mental health is limited after filtering out observations without health data. The alternative approach is to exploit the linear moment restriction and the presence of lagged variable to get an appropriate internal instruments. Consider the first difference transformation:

$$\Delta Y_{it} = \alpha \Delta Y_{i(t-1)} + \beta \Delta X_{it} + \theta \Delta O_{it} + \Delta v_{it}$$

Arellano and Bond (Arelano and Bond 1991) and Holtz-Eakin et. al (Holtz-Eakin et. al 1988) gives us the relief that the first difference can be instrumented by the lagged level, i.e. ΔX_{it} can be instrumented by $X_{i,t-1}$. This method requires two moment conditions:

$$E(Y_{i,t-s} \Delta v_{it}) = 0$$

$$E(X_{i,t-s} \Delta v_{it}) = 0$$

The method is not efficient in two situations: when α is closer to unity and when the variance of fixed effect η_i increases relative to the variance of v_{it}, as pointed out in Blundell and Bond (1998). Both are relevant to our case. To solve the issue, Blundell and Bond (1998) suggests using the lagged differences to instrument for levels, i.e. $X_{i,t-1}$ is instrumented by ΔX_{it}. This requires two additional moment conditions:

$$E((\eta_i + v_{it}) \Delta Y_{i,t-s}) = 0$$

$$E((\eta_i + v_{it})\Delta X_{i,t-s}) = 0$$

This approach is also known as the system GMM approach. In this paper, I will restrict analysis to only system GMM for the reasons pointed out in Blundell and Bond (1998).

4 Estimation Results

Recall the data generation process:

$$Y_{it} = \alpha Y_{i(t-1)} + \beta X_{it} + \theta O_{it} + \eta_i + v_{it}$$

The left-hand side variable Y_{it} is the total hours worked in year[2] t by individual i[3].

On the right-hand side, $X_{i,t}$ is the mental health score computed according to the MHI5. O_{it} includes reported physical health, age, race, number of kids (categorical variable for zero, one to two, three and more), years of education, education level (less than high-school, high-school, college or more), labor market experience and wage. Wage is treated as either endogenous or exogenous. The multiple specifications on wage is to observe the change in effects of mental health relatively to wage because they are both important determinants of labor supply.

I consider 6 estimation procedures spanned by the inclusion of wage as an endogenous/exogenous right-hand side variable and whether the sample include unemployed individuals. The unemployed are defined as people whose status is 'unemployed' or worked less than five hours per week during the survey year. The assignment of full sample and the sample of working individuals (working sample) is in place to assess

[2]The annual hours are top-coded at 99 percentile.

[3]The total hours is useful for analysis when the effects are marginal. Consider a worker who took a week off work to see a psychiatrist. Her usual weekly hours may not capture this event, but her summations of hours for the year would change.

the spell of selection into working[4]. The effects of health can be underestimated in the working sample because the sample does not include people who are discouraged from work because of poor health.

Table 2 displays the system GMM estimates obtained with instruments being the one-period lag difference. The full-sample estimates for mental health are greater than those in the working sample. This indicates some level of selection bias into employment as mentioned before. However, the bias is alleviated with the inclusion of wage, regardless of whether wage is specified as endogenous or exogenous. Column 3 shows that for each increment in mental health, total hours increase by 4.3. An increment of 4 points in mental health score (1 point out of 25 according to MHI5) will add 17.2 hours to the yearly total, or 3.9 minutes to each day of work[5]. The effects of mental health is smaller compared to the other variables such as age, number of kids, education level, and labor market experience. Regarding the number of kids, the estimates show that individuals who have one to two children work more than those who do not have children by 125 hours, and more than those who have 3 children by 223 hours. This means that the effect of an additional child is non-linear, and the parents are more likely to forsake hours when the family size grows.

Table 3 shows the estimates obtained when there is no restriction on instruments[6]. All the possible lags are employed while the number of groups and observations remain unchanged. Compared to results in Table 2, the estimates of mental health are greater here. Meanwhile, the gaps between the full-sample estimates and working-sample estimates are smaller. In column 10, the effect of one unit increment in mental health is now 7.4 hours. An increment of 4 points in mental health score will add 29.6 hours to yearly total, or 6.7 minutes to each day of work. The sign of estimates for the other variables remain

[4] There are other formal ways to control for selection to work, but they are not discussed here.

[5] I define a year to be 53 weeks of five working days.

[6] The lags are allow to be chosen from one-period difference to four-period difference.

unchanged, but the magnitude of effects is reduced slightly. The increments in estimates of mental health implies that in an ideal setting when the historical data on mental health are richer (larger T), we may have larger estimates.

To access how the influence of mental health varies with gender and cohabitation status, I re-estimate the system GMM with endogenous wage and no instrument restriction (column 10) on the four samples generated by gender and status. The effects of mental health tend to be disparate between cohabitation status. Only the estimates for partnered individuals are significant (Column 15, 17, 20), and men benefit from health improvement more than women by 1.3 to 7.1 hours. The estimates for partnered men are 7.7 and 7.0 hours per score for the full sample and working sample, respectively. For women, only the full sample estimate for the partnered ones is significant, with a coefficient of 5.5 hours.

All specifications are tested significant against the Arellano-Bond test for auto-regression, the Sargan test of over identification restrictions, and the Hansen test of over identification restrictions. The estimates of mental health scores are in harmony with the literature, that an increment in mental health leads to more hours of work. However, the effect is rather small, in size of minutes per working day. Most gains in hours are realized in partnered individuals, especially partnered men. Other groups such as single men, single women, and partnered women in the full sample do not receive benefits from better health.

Table 2: Effects on Hours, One Lag instruments

Wage Specification	No Wage		Endogenous Wage		Exogenous Wage	
Sample	Full (1)	Working (2)	Full (3)	Working (4)	Full (5)	Working (6)
Estimates						
Lagged Hours	0.409***	0.136***	0.328***	0.299***	0.229***	0.179***
	-0.0149	-0.0159	-0.0229	-0.023	-0.0177	-0.0173
Mental Health Score	11.54***	5.585***	6.615***	4.330**	8.938***	6.141***
	-1.373	-1.228	-1.699	-1.611	-1.369	-1.309
Physical Health Score	0.553	1.523*	3.808***	4.025***	1.869**	1.922**
	-0.642	-0.613	-0.801	-0.785	-0.686	-0.671
Age	0.998	36.18***	60.83***	111.9***	32.98***	47.60***
	-8.152	-7.165	-10.38	-15.92	-7.963	-11.63
Number of Kids [1-2]	117.8**	65.62	120.7*	125.0*	82.38	46.17
	-41.57	-39.79	-54.41	-52.99	-45.17	-44.18
[3]	-20.17	-35.71	-100.8	-93.16	-45.39	-57.93
	-50.29	-51.07	-73.78	-72.38	-60.7	-59.12
Years of Education	18.41*	3.302	47.63***		12.69	
	-9.382	-8.65	-12.4		-9.47	
Education Level [High school]	20.57	49.96	117.8*	119.4*	56.43	49.95
	-36.39	-35.5	-52.3	-52.15	-39.69	-39.02
[College and More]	80.76	89.31	227.3**	220.4*	124.5	87.58
	-75.7	-63.7	-87.31	-87.98	-68.69	-67.27
Log(Wage)			-1089.3***	-1109.3***	-325.3***	-255.1***
			-63.87	-72.76	-25.91	-27.22
Experience				-48.67***		-12.34
				-12.53		-9.277
Observations	7551	5768	4766	4603	4766	4603
Groups	4045	3371	2952	2873	2952	2873
Instruments	19	19	24	24	20	20
Obs. per group Min/Mean/Max	1/1.87/3	1/1.71/3	1/1.61/3	1/1.60/3	1/1.61/3	1/1.60/3

Standard errors in the second line $*p < 0.05, **p < 0.01, ***p < 0.001$.

Table 3: Effects on Hours, All Lag instruments

Wage Specification	No Wage		Endogenous Wage		Exogenous Wage	
Sample	Full (7)	Working (8)	Full (9)	Working (10)	Full (11)	Working (12)
Estimates						
Lagged Hours	0.517***	0.335***	0.486***	0.464***	0.395***	0.361***
	-0.0132	-0.0142	-0.0227	-0.0216	-0.0158	-0.0156
Mental Health Score	12.56***	9.408***	9.219***	7.351***	11.22***	8.817***
	-1.372	-1.263	-1.694	-1.567	-1.408	-1.351
Physical Health Score	0.226	0.833	2.995***	2.973***	1.21	1.199
	-0.659	-0.651	-0.809	-0.778	-0.711	-0.702
Age	-6.134	18.88**	45.91***	91.17***	15.92*	32.35**
	-8.249	-7.062	-10.15	-15.01	-7.834	-11.39
Number of Kids [1-2]	110.5**	47.8	109.0*	102.1*	73.54	35.09
	-42.39	-41.06	-54.26	-51.88	-46.24	-45.12
[3]	-16.79	-38.5	-92.15	-86.9	-40.7	-55.25
	-50.76	-52	-71.67	-68.66	-60.76	-59.27
Years of Education	16.33	2.312	47.81***		15.33	
	-9.265	-8.512	-11.95		-9.271	
Education Level [High school]	2.814	23.73	95.1	89.23	36.75	29.28
	-35.03	-33.27	-48.84	-46.76	-37.16	-36.16
[College and More]	62.37	74.36	194.9*	176.6*	96.95	62.87
	-75.1	-62.76	-83.65	-81.7	-66.74	-64.94
Log(Wage)			-1044.1***	-995.7***	-324.5***	-258.5***
			-61.78	-69.3	-26.5	-28.11
Experience				-46.46***		-15.25
				-11.71		-9.005
Observations	7551	5768	4766	4603	4766	4603
Groups	4045	3371	2952	2873	2952	2873
Instruments	25	25	33	33	26	26
Obs. per group Min/Mean/Max	1/1.87/3	1/1.71/3	1/1.61/3	1/1.60/3	1/1.61/3	1/1.60/3

Standard errors in the second line $*p < 0.05, **p < 0.01, ***p < 0.001$.

Table 4: Effects on Hours, All Lag instruments, Endogenous Wage

Gender	Full Sample					Working Sampe				
Sample	All	MS	MP	FS	FP	All	MS	MP	FS	FP
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Estimates										
Lagged Hours	0.486***	0.515***	0.372***	0.347***	0.407***	0.464***	0.560***	0.385***	0.310***	0.366***
	-0.0227	-0.0736	-0.0328	-0.0462	-0.0373	-0.0216	-0.0891	-0.0308	-0.0418	-0.0344
Mental Health Score	9.219***	0.533	7.760*	0.18	5.485*	7.351***	-5.544	7.095*	-2.809	2.43
	-1.694	-5.149	-3.086	-3.471	-2.524	-1.567	-6.1	-3.236	-3.088	-2.352
Physical Health Score	2.995***	2.245	6.158***	6.892***	-1.454	2.973***	4.782	5.438***	5.862***	-0.607
	-0.809	-2.532	-1.262	-1.443	-1.374	-0.778	-2.91	-1.305	-1.362	-1.264
Age	45.91***	96.97***	46.46**	54.51**	26.22	91.17***	89.44**	43.99**	58.08**	26.76*
	-10.15	-28.91	-16.68	-20.75	-14.77	-15.01	-32.78	-16.91	-18.93	-13.63
Number of Kids [1-2]	109.0*	210	463.2***	163.1	165.4	102.1*	257.9*	459.0***	228.6	172.3
	-54.26	-108.1	-99.45	-180.8	-209.8	-51.88	-120.5	-103.5	-140.8	-192.3
[3]	-92.15	204.6	591.7***	-277.3	-7.972	-86.9	-72.73	561.0***	-181	38.16
	-71.67	-299.3	-125.2	-198.3	-213.5	-68.66	-351.5	-125.8	-170.3	-195.9
Years of Education	47.81***	68.09	64.97***	53.57	68.63***		94.31*	71.01***	49.54	60.02***
	-11.95	-38.88	-19.28	-30.81	-17.81		-47.54	-19.67	-28.13	-17.1
Education Level [High school]	95.1	-14.75	264.7***	305.9**	-99.28	89.23	-104.7	251.3**	251.0*	-37.56
	-48.84	-152.5	-77.86	-113	-78.22	-46.76	-170.4	-79.92	-105.4	-72.67
[College and More]	194.9*	149.8	223	662.1***	-7.49	176.6*	65.67	200.8	569.2**	31.8
	-83.65	-239.4	-136.6	-190.6	-129.6	-81.7	-274.9	-140.6	-182.1	-123.1
Log(Wage)	-1044.1***	-1314.7***	-1183.5***	-1181.0***	-843.7***	-995.7***	-1702.0***	-1232.1***	-1048.4***	-739.9***
	-61.78	-153.4	-109.4	-129	-90.51	-69.3	-184.3	-128.3	-133.1	-95.61
Experience						-46.46***				
						-11.71				
Observations	4766	582	1612	985	1578	4603	550	1592	944	1509
Groups	2952	441	1031	698	1072	2873	442	1025	674	1025
Instruments	33	33	33	33	33	33	33	33	33	33
Min/Mean/Max	1/1.61/3	1/1.32/3	1/1.56/3	1/1.41/3	1/1.47/3	1/1.60/3	1/1.30/3	1/1.55/3	1/1.40/3	1/1.47/3

Standard errors in the second line $*p < 0.05, **p < 0.01, ***p < 0.001$.
Sub-sample notations: M–Males, F–Females, S–Single, P–Partnered.

5 Conclusion

This paper has shown that mental health positively increases work hours at a minimal scale. Partnered men are the main beneficiaries of health improvement. These findings are not without bold abstractions. The analysis does not capture the situation where illnesses affect work through reduced productivity rather than absenteeism or hours. Another form of the effect is job change. The workers, in dealing with stress, may decide to switch to a more accommodating profession to maintain the same level of labor supply. The issue of self selection is shown to be affecting the estimates, even though the magnitude of bias does not appear to be worrying after controlling for gender and cohabitation status.

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