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The Effect of Mental Health on U.S. County Economic Growth*

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Abstract: Poor mental health creates significant economic costs, in addition to human suffering, and is a growing world-wide concern, especially with an aging population. To estimate the cost of this disease in the U.S., we adopt a conventional economic growth model and include the number of poor mental health days (PMHD) as a right-hand side variable. Controlling for various county-level variables associated with income growth, our results suggest that one additional PMHD is associated with a 1.84 percentage point lower per capita real income growth rate, or $53 billion less total annual income, across the U.S. between 2008 and 2014. This effect is in addition to the income losses associated with the Great Recession.

Keywords: mental health, per capita income growth

JEL Codes: R11, I15

1. INTRODUCTION

The global economic cost of mental illness is projected to exceed $16 trillion over the next 20 years (Bloom et al., 2011), an amount greater than that associated with any other non-communicable disease. Over half of these costs (55 percent) will be incurred in high-income countries, amounting to about $450 billion annually (*ibid.*). The economic cost or earnings losses associated with mental health disorders have been estimated for a number of countries, including France (Chevreul et al., 2013), Spain (Barbaglia et al., 2012), China (Lee et al., 2010), and the United States (Kessler et al., 2008), as well as for Europe as a whole (Wittchen et al., 2011). Cost estimates such as these include medical and opportunity costs, and they can be obtained through one of three approaches (Thomas, 2008): (1) direct and indirect cost of illness estimates; (2) value of lost output or lowered economic growth; and (3) value of a statistical life. In all cases, key assumptions about the future are needed, including how mental health affects the supply of labor and capital stocks, in the case of the second approach.

The direct costs of treating mental illness including costs of insurance are substantial and of significant public concern. At the same time, less attention has been paid to indirect costs such

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as employment and income losses, which are sizeable. These costs arise due to dis-employment effects as well as earnings losses, conditional on employment. Marcotte and Wilcox-Gok (2001) suggest that 5-6 million U.S. workers cannot find work due to mental health problems and among those employed, poor mental health may reduce annual income by as much as \$3,500-\$6,000 per worker, totaling approximately \$100-\$170 billion in annual losses. Anecdotal evidence from rural communities in the U.S. suggests that even when these areas are able to attract new employers, or benefit from new forms of energy exploration such as hydraulic fracturing, firms often are unable to find capable workers because of widespread drug abuse and related un-employability concerns.

Goetzel et al. (2000) show that mental health ranks among the top 10 costliest illnesses for U.S. employers, when accounting both for the direct medical expenditures and additional costs of employee absence and productivity losses. Aggregating these direct costs and those associated with workplace absence, short-term disability, and self-reported on-the-job productivity losses, Goetzel et al. (2004) estimate mental illness to be the third costliest disease in the U.S., averaging \$348 per employee annually, lagging behind only hypertension (\$392) and heart diseases (\$368).

In this paper, we seek to estimate *ex post* income losses in U.S. counties in recent years due to poor mental health, rather than predict the future cost of mental illness. We extend earlier research that compares earnings in the preceding 12 months of 5,000 individuals with and without mental illness, holding constant other determinants of income (Kessler et al., 2008). These authors estimate the contemporaneous annual cost of mental illness to be \$193.2 billion using 2001-2003 data. Our approach differs from previous work in that we use county-level data on inflation-adjusted income growth in a period (2008-2014) *after* the occurrence of the period in which the *average level* of mental health is measured (2002-2008 average value).

2. LITERATURE AND CONCEPTUAL FRAMEWORK

Poor mental health days can affect labor market success in several important ways. One obvious impact is the lack of motivation and energy, in addition to potentially adverse relationships with co-workers, which may lead to low job performance and productivity. Another is periodic absence from work due to sickness. The literature examining the relationship between employee well-being and work productivity dates back to the 1930s (see Hersey, 1932; Kornhause and Sharp, 1932). The so called "happy-productive worker" hypothesis postulates that happy workers are more efficient and productive and less likely to turn over than their unhappier counterparts. Despite the considerable interest in the subject, a great deal of inconsistency remains in uncovering the relationship between the two; some suggest a positive linkage while others indicate no relationship at all (see Wright and Cropanzano, 2007 for review). The inconsistencies appear to be largely due to differences in measuring "happiness." In particular, job satisfaction may not be the most effective proxy for happiness (Brief and Weiss, 2002; Wright, 2004). More recently, attention has shifted to understanding the relationship not only between job satisfaction and productivity, but rather the linkages between general psychological well-being (PWB), sometimes referred to as subjective well-being (SWB), which also includes emotional states of employees beyond the work place.

For example, a longitudinal study by Bolger and Schilling (1991) suggests that people who are predisposed to negative emotions are more likely to engage in arguments and negative relationships with co-workers. Cropanzano and Wright (2001) also argue that unhappy people are more defensive with co-workers, generally exhibit pessimism and low self-esteem, and are more sensitive to threats. Furthermore, those who are depressed may exhibit little to no motivation and energy, and thus have poor work performance. On the contrary, positive emotions boost productivity because positive people are more cooperative and helpful (Isen and Baron, 1991), more efficient and can creatively deal with complex tasks, and accumulate resources (e.g., social capital) for better future performance (Estrada et al., 1997; Madjar et al., 2002; Madjar, 2008; Fredrickson, 2003).

Another channel through which poor emotional health could lead to labor market failures is because mental illness may reduce individuals' investment in human capital and hinder their innate ability, which in turn limits their productivity (see Bartel and Taubman, 1979). This happens because individuals are forced to limit their labor time due to illness and are able to enter into only a restricted set of market activities. Specific to mental health, evidence suggests a prevalence of mental illness during late adolescent age and early childhood (Mental Health Commission, 1999). These are periods when individuals are actively engaged in education and training (Harnois and Gabriel, 2002), interruption of which in turn reduces skills and qualifications and may affect future employment opportunities and reduce productivity and income. Berndt et al. (2000) report empirical evidence that early onset chronic depressions lead to a significant human capital loss (e.g., educational attainment) for women in the U.S. (see also Fletcher, 2008). Estimates of employment losses due to mental illness vary in the literature by type of mental disorder and the sample studied. For example, employing the national comorbidity survey, Ettner et al. (1997) find that psychiatric disorder reduces employment by 11 percent among both men and women in the U.S., negatively affecting work hours and wage earnings. Frijters et al. (2010) also suggest that the probability of labor force participation declines by 17 percent as a result of increased mental disorders in Australia and that it is larger for females and older individuals (see also Zhang et al., 2009). Chatterji et al. (2007) show that employment effects of psychiatric disorders and mental stress are higher among Latinos and the white American born population, while the effect is mixed among Asians descendants in the U.S. (see also Ojada et al., 2009) for variations by gender and immigration status).[1]

Instead of making explicit assumptions about the effect of current or future mental health on the supply of labor or capital, and then forecasting the effect as is done in most previous studies, we introduce a measure of poor emotional well-being (referred to as (poor) mental health days throughout) into a county-level economic growth model. We underscore that the measure of mental health employed in our study does not refer to medically diagnosed mental illness. According to the Behavioral Risk Factor Surveillance System (BRFSS), which is the source of our data, the mental health days refer to the perceived emotional well-being of respondents and is a response to the specific question, "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" We are thus able to test statistically whether the poor mental health state measure affects economic growth and, if so, by how much.

[1] An alternative proposed in the literature to measure the productivity loss associated with poor health is the friction cost approach. The premise underlying this approach is that the costs of illness are equivalent to the costs of finding replacements for the ill workers (Koopmancschap and van Inevald, 1992). These replacement costs are a function of the length and expense to restore productivity to its pre-morbidity level as well as the number of unemployed workers who can rapidly substitute into the production process.

3. EMPIRICAL MODEL

We start with a simple economic growth model (e.g., Barro, 1991). Let $\Delta y_{i\Delta t}$ denote per capita income growth in county *i* over period Δt that starts at t_0. Further, let X_{it_0} denote a vector of determinants of economic growth, including initial per capita income at t_0 and a set of control variables familiar from the literature (e.g., Goetz et al., 2011). We add to this model our measure of emotional well-being, the number of poor mental health days ($pmhd_i$) reported by respondents in the *i*th-county, also measured at t_0. This provides the following estimating equation, with β and γ representing parameters to be estimated and ε_i denoting a well-behaved error term:

$$\Delta y_{i\Delta t} = \beta X_{it_0} + \gamma\, pmhd_{it_0} + \varepsilon_i \tag{1}$$

This set-up tends to mitigate any potential endogeneity bias (Levinson et al., 2010; Sareen et al., 2011) because the ensuing per capita income growth rate measured over Δt cannot affect the beginning period (t_0) variables in $\boldsymbol{X}$.[2] The hypothesis tested is that poor mental health is not associated with income growth rates at the county-level, i.e., H_0: γ=0, versus the alternative, that it is associated with lower growth: H_A: γ<0, which would be consistent with findings in the literature.

In addition to starting year or initial per capita income (measured in 2008, which also coincides with the depth of the Great Recession nationally) our control variables include: educational attainment, social capital, which has been used in similar studies previously and was used recently to study economic mobility (Chetty et al., 2014), population density, and the county's natural amenities. We also control for urban-rural status of a county. As a robustness check, we sequentially add additional controls including industry structure, physical (in)activity of county residents, regional fixed effects, and median age in a county.

4. DATA SOURCES AND DESCRIPTIVE STATISTICS

We retrieve county-level data from various public sources, including the Bureau of Economic Analysis[3] for per capita income, the U.S. Census for population and educational attainment, and the Northeast Regional Center for Rural Development (NERCRD)[4] for social capital for the 3,113 counties (Rupasingha et al., 2006, with updates). The latter variable is an index constructed using variables measuring density of civic, religious, sports, political, and business associations, along with voter turn-out, non-profit organizations, and county response rates to the Census Bureau Decennial census (for details, see Rupasingha et al., 2006). Social capital measures the level of civic engagement in a community that, like human and physical capital, has in previous studies been found to be associated with income growth (e.g., Rupasingha et al., 2007). The *pmhd* variable is available from the County Health Rankings[5] and is derived from the Behavioral Risk Factor Surveillance System (BRFSS). This variable is reported only for counties with *n*>50 respondents, i.e., for 2,906 counties in 2010, and it represents an average of

[2] We also acknowledge that this approach may not fully eliminate endogeneity because of strong path dependency between the two variables. For example, Goetz et al. (2015) find that income significantly affects county-level mental health. However, obtaining instruments is a great challenge. Dropping *pmhd* in a robustness test, we find that the remaining parameter estimates do not change substantially.

[3] Available at http://www.bea.gov/regional/index.htm

[4] Available at http://aese.psu.edu/nercrd

[5] The specific question asked of respondents is, "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how may days during the past 30 days was your mental health not good?" Data are available at http://www.countyhealthrankings.org

data collected from 2002 to 2008. Since this is the earliest period for which the variable is available, we are limited in the choice of our time lag to six years (2008-2014): per capita income data are only available for 2014 as of this writing. The sample average *pmhd* is approximately 3.5 days, the minimum value being as low as a half-day (0.44) and the maximum exceeding 8 days.

To control for other health indicators that may also be associated with income growth as well as mental health, we calculate the percent obese population in a county based on county Health Rankings & Maps data.[6] Industry structure for a county is captured in the shares of employment in the following economic sectors based on the employment series published in the U.S. Census County Business Patterns (CBP): (i) Agricultural, Forestry, and Fishing; (ii) Construction; (iii) Manufacturing; and (iv) Transportation and Warehousing sectors. We hypothesize that the effects are largely negative because blue-collar occupations, and manufacturing in particular, are increasingly under pressure due to automation and globalization. Pierce and Schott (2016) suggest that the rising mortality rates of middle-aged males identified in Case and Deaton (2015) coincide with the opioid epidemic that started with China's ascension to the WTO, and rising import competition in the U.S. for manufactured goods.

The county natural amenity score was obtained from the USDA. The score is constructed using a county's topography, water area, and six measures of climate including various measures of sun light, temperature, and humidity. Higher values of this scale indicate a higher amenity rate.[7] Table 1 presents summary statistics for the dependent and explanatory variables, along with

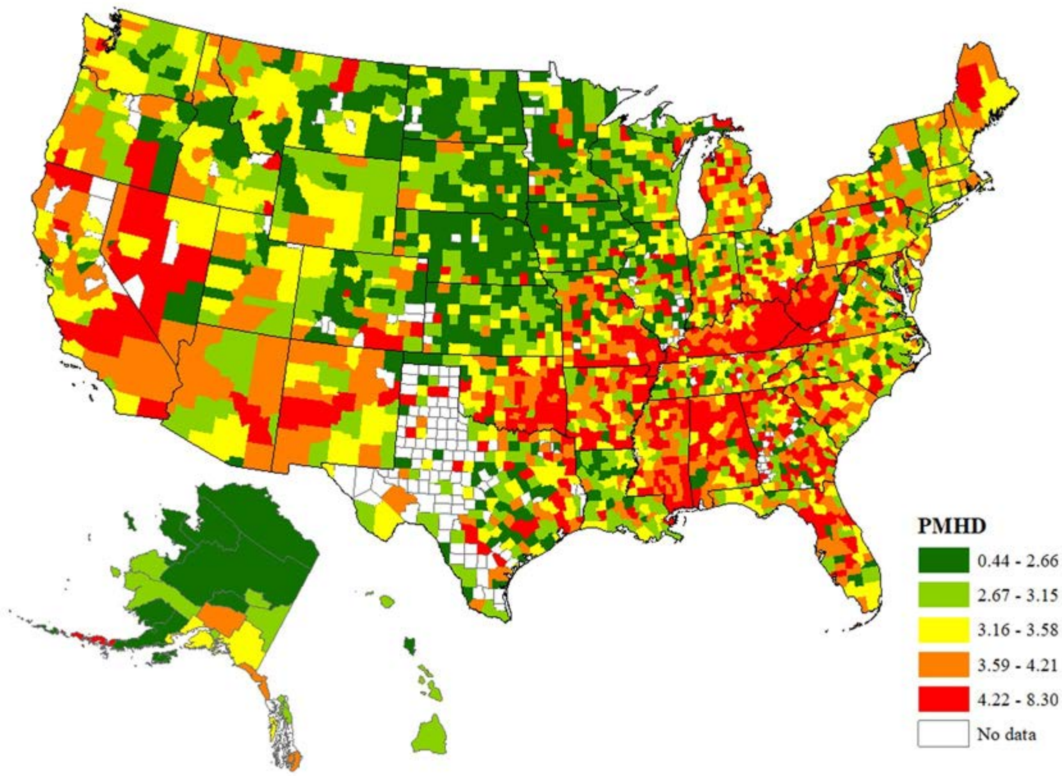
Table 1: Summary Statistics and Hypothesized Directions of Effects

Variable	Definition	Source	Effect	Mean	Std. Dev.	Min	Max
change_income	(income 2014−income 2008)/income 2008 x 100	BEA	NA	7.7	15.59	-49.40	401.0
Initial income	Per capita personal income ($x10^3$), 2008	BEA	−	36.3	9.15	15.80	119.30
edu_bachelor+	% with a bachelor's degree or higher 2000	Census	+	16.7	7.83	4.90	60.50
social capital	Social capital index, 2005	NERCRD	+	-0.03	1.59	-3.80	15.20
pmhd	Average reported number of poor mental health days per month, 2002-2008	County Health Ranking	−	3.50	1.03	0.40	8.30
% obese	% obese population, 2002-2008	County Health Ranking	−	28.40	3.66	12.50	43.50
Manufacturing	% employed in manufacturing sector, 2002-2008	U.S. Census CBP	−	17.0	12.02	0.00	69.90
Construction	% employed in construction sector, 2002-2008	U.S. Census CBP	−	6.60	3.78	0.00	47.10
AgForestFishing	% employed in agriculture, fishing and forestry sectors, 2002-2008	U.S. Census CBP	−	0.80	1.71	0.00	35.70
TransportWarehouse	% employed in transportation & warehousing sectors, 2002-2008	U.S. Census CBP	−	3.60	3.11	0.00	42.20
Amenity Scale	Natural Amenity Scale, 2000	USDA	+	0.00	2.28	-5.40	11.20
Median Age	Median resident age in the county	Census	+	37.30	3.89	20.70	54.30
RUCC	Rural-urban Continuum code (1-9), 2003	USDA, ERS	?	5.0	2.65	1	9

[6] Data available at http://www.countyhealthrankings.org/

[7] More information about the natural amenity scale can be found at http://www.ers.usda.gov/data-products/natural-amenities-scale.aspx

Figure 1 Average Number of Reported Poor Mental Health Days, 2002-2008



Note: Data are not available for counties with n<50 observations

definitions, sources and the expected direction of the effect. Figure 1 shows the distribution in quintiles of the dependent variable across the U.S., for counties with valid observations.

The rural-urban continuum codes for counties are compiled by the Economic Research Service of the U.S. Department of Agriculture (ERS/USDA) and are described in Table 2. Rural-Urban Continuum Codes are a classification scheme that differentiates counties by the population size as well as degree of urbanization and adjacency to a metro area. There are a total of nine codes, in an increasing order, with one indicating highly metropolitan area, while nine classifies a fully rural county type. Approximately 48 percent of the sample counties have a Rural-Urban Continuum Code of 5 or less, while 52 percent comprise relatively less urbanized and rural counties.

In addition, our model includes regional dummy variables that identify states within eight divisions of the Bureau of Economic Analysis, as reported in Table 3. As a robustness check we also account for the median age in a county using U.S. Census, 2000 Population Estimates.

5. RESULTS

Columns 1-6 of Table 4 report results from an OLS model, in which we sequentially add variables as a way to assess the endogeneity bias between poor mental health days and income growth that may be due to omitted variables. All model specifications include RUCC codes and

Table 2: Description of 2003 Rural-Urban Continuum Codes, Including Number of Counties and Distribution of Sample Counties Across RUCC

RUCC	Description	Obs.	Percent
Metro -			
1	Counties in metro areas of 1 million population or more	398	13.86
2	Counties in metro areas of 250,000 to 1 million population	319	11.11
3	Counties in metro areas of fewer than 250,000 population	340	11.84
Non-metro-			
4	Urban population of 20,000 or more, adjacent to a metro area	218	7.59
5	Urban population of 20,000 or more, not adjacent to a metro area	101	3.52
6	Urban population of 2,500 to 19,999, adjacent to a metro area	566	19.71
7	Urban population of 2,500 to 19,999, not adjacent to a metro area	409	14.24
8	Completely rural or less than 2,500 urban population, adjacent to a metro area	179	6.23
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area	342	11.91

Notes: Source is USDA ERS

Columns (4) – (6) also control for regional variations in income growth in the form of U.S. Census Bureau's division dummies. Regression coefficients for all variables are mostly consistent across the models, except for the number of poor mental health days, the magnitude of which declines as we add important variables, the omission of which resulted in upward-biased coefficient estimates.[8] We find that income convergence and social capital have the hypothesized positive effect on growth, the effect of the latter becoming insignificant in models with regional dummies. Educational attainment positively affects income growth across all model specifications. Also, all

Table 3: Description of BEA Regions, Including Number of Counties and Distribution of Sample Counties across Eight BEA Regions

BEA	Description	Freq.	Percent
1	New England Region (CT, ME, MA, NH, RI, VT)	67	2.33
2	Mideast Region (DE, DC, MD, NJ, NY, PA)	174	6.06
3	Great Lakes Region (IL, IN, MI, OH, WI)	410	14.28
4	Plains Region (IA, KS, MN, MO, NE, ND, SD)	599	20.86
5	Southeast Region (AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV)	1,014	35.31
6	Southwest Region (AZ, NM, OK, TX)	272	9.47
7	Rocky Mountain Region (CO, ID, MT, UT, WY)	199	6.93
8	Far West Region (AK, CA, HI, NV, OR, WA)	137	4.77

Source: Bureau of Economic Analysis, available online at http://www.bea.gov/regional/docs/regions.cfm

[8] As a robustness check, we estimated a fully specified model that also includes median age in a county. The estimated effect of the poor mental health days on income growth is similar to the effect reported in column (6) of Table 4. These results are available from the authors upon request

Table 4: Determinants of Economic Growth, 2008-2014

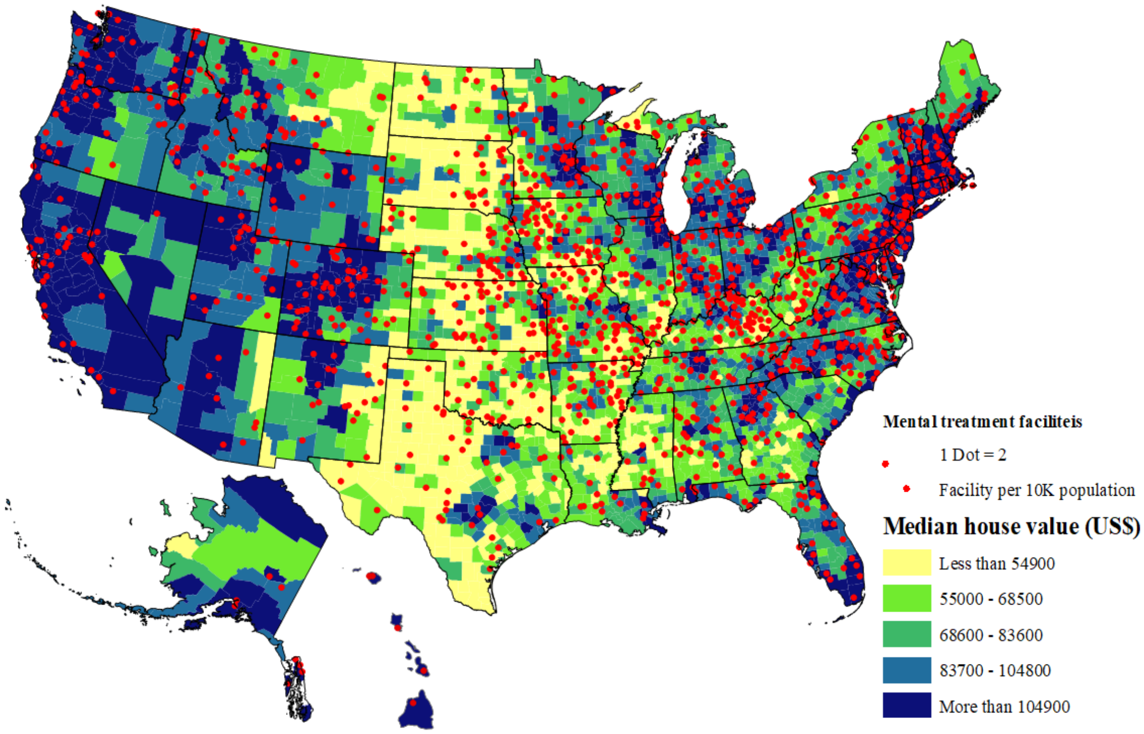
	(1)	(2)	(3)	(4)	(5)	(6)
pmhd0208	-2.158***	-2.158***	-2.125***	-1.875***	-1.855***	-1.844***
	(0.419)	(0.417)	(0.418)	(0.378)	(0.379)	(0.378)
Initialincome	-0.425***	-0.440***	-0.445***	-0.468***	-0.483***	-0.486***
	(0.122)	(0.124)	(0.123)	(0.128)	(0.131)	(0.131)
edu_bachelor	0.150*	0.150**	0.132*	0.172**	0.187**	0.180**
	(0.078)	(0.073)	(0.076)	(0.081)	(0.078)	(0.079)
pop_density	0.368*	0.362	0.354	0.366	0.379	0.376
	(0.213)	(0.233)	(0.235)	(0.233)	(0.246)	(0.247)
NaturalamenityScale	-0.197	-0.164	-0.228	-0.175	-0.160	-0.188
	(0.123)	(0.134)	(0.155)	(0.168)	(0.168)	(0.186)
socialcapital	0.954**	0.938**	0.894**	0.604	0.679	0.669
	(0.392)	(0.398)	(0.417)	(0.465)	(0.472)	(0.479)
RUCC_1	-10.213***	-10.452***	-10.416***	-10.172***	-10.475***	-10.453***
	(2.133)	(2.098)	(2.093)	(2.049)	(2.024)	(2.017)
RUCC_2	-11.760***	-11.726***	-11.697***	-11.369***	-11.429***	-11.412***
	(2.120)	(2.037)	(2.034)	(2.004)	(1.942)	(1.938)
RUCC_3	-11.598***	-11.461***	-11.437***	-11.415***	-11.361***	-11.344***
	(2.115)	(2.036)	(2.034)	(2.016)	(1.953)	(1.949)
RUCC_4	-11.223***	-11.179***	-11.188***	-11.243***	-11.197***	-11.182***
	(2.068)	(1.991)	(1.991)	(1.955)	(1.881)	(1.878)
RUCC_5	-11.387***	-11.567***	-11.515***	-11.978***	-12.004***	-11.963***
	(2.200)	(2.176)	(2.172)	(2.192)	(2.152)	(2.141)
RUCC_6	-8.076***	-7.650***	-7.696***	-8.021***	-7.709***	-7.717***
	(2.026)	(1.885)	(1.887)	(1.912)	(1.780)	(1.782)
RUCC_7	-7.417***	-7.322***	-7.366***	-7.281***	-7.179***	-7.182***
	(2.026)	(1.961)	(1.963)	(1.943)	(1.876)	(1.877)
RUCC_8	-6.764***	-6.079***	-6.113***	-6.283***	-5.864***	-5.874***
	(2.111)	(1.979)	(1.980)	(2.013)	(1.914)	(1.916)
AgForestryFishing		-0.538***	-0.518***		-0.374***	-0.367**
		(0.159)	(0.159)		(0.144)	(0.144)
Construction		0.005	-0.008		0.073	0.067
		(0.089)	(0.093)		(0.092)	(0.096)
Manufacturing		-0.029	-0.030		-0.001	-0.001
		(0.029)	(0.029)		(0.029)	(0.029)
TransportWarehouse		0.351***	0.355***		0.370***	0.373***
		(0.111)	(0.111)		(0.110)	(0.111)
Obese			-0.110			-0.056
			(0.089)			(0.092)
BEA FE	N	N	N	Y	Y	Y
R^2	0.12	0.13	0.13	0.14	0.14	0.14
N	2,830	2,830	2,830	2,830	2,830	2,830

Dependent variable = ((income 2014 - income 2008) / income 2008) x 100; Robust Standard Errors clustered at the county level are reported in parenthesis.

RUCC_9 is an omitted rural-urban continuum code; BEA_8 is an omitted BEA region.. Significance levels for * $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$

else equal, the most rural areas (RUCC 9 or non-adjacent and with very small populations)had a statistically higher per capita income growth rate than all other rural and urban areas over the four-year period 2008-2014. The obesity rate has a negative albeit insignificant effect on income growth.

Figure 2: Mental Treatment Facilities & Median House Prices



As expected, the coefficient estimate on mental health is negative and statistically different from zero at the 1 percent level. This result is robust across the different specifications used in the sensitivity analysis. Based on these results, one additional reported average day of poor mental health in a county is associated with approximately a 1.84-2.16 percentage point reduction in the national per capita income growth rate, from 16.3 percent to 13.14-13.46 percent, depending on the model specification. In terms of total income, this works out to $53.03-$62.3 billion annually for each PMHD, or $183.5-215.6 billion at the average number of PHMD (which is 3.46 days/month). This number is of the same order of magnitude as those estimated in earlier work using different methods for the globe (Bloom et al., 2011) or the U.S. (Kessler, 2008).

People with mental health problems may be moving to low growth areas.[9] It is also possible that low- and high-income areas have heterogeneous effects on mental health. The effect of poor mental health days thus may differ between poor and wealthy counties. In addition, wealthier communities likely have more resources to address mental health problems, resulting in lower mental health days. In figure 2 we depict the total number of mental health facilities per 10,000 population in a county along with the distribution of median house value across U.S. counties. As expected, the wealthiest counties have the largest number of treatment facilities, with fewer treatment centers in relatively poorer counties. To understand how this sorting may affect the relationship between mental health days and income growth, we separated counties into poor and wealthy samples.

[9] This was suggested to us by a reviewer.

Table 5: Determinants of Economic Growth in Poor vs. Wealthy Counties

	Poor	Wealthy
pmhd0208	-2.299***	-0.869***
	(0.519)	(0.288)
Initialincome	-1.041***	-0.083
	(0.260)	(0.086)
edu_bachelor	0.658**	0.017
	(0.270)	(0.049)
pop_density	0.172	0.139
	(0.508)	(0.158)
Natural amenity Scale	-0.373	-0.326**
	(0.409)	(0.139)
Social capital	1.105	0.091
	(0.819)	(0.294)
Obese	-0.206	-0.106
	(0.171)	(0.087)
Agric., Forestry, Fishing, etc.	-0.603**	-0.038
	(0.260)	(0.112)
Construction	0.372*	0.073
	(0.214)	(0.074)
Manufacturing	-0.051	0.101***
	(0.043)	(0.023)
Transportation & Warehousing	0.498***	0.126
	(0.150)	(0.113)
RUCC dummies	Y	Y
Regional Dummies	Y	Y
R^2	0.17	0.12
N	1,378	1,452

Dependent variable = ((income 2014 - income 2008) / income 2008) x 100; Robust Standard Errors clustered at the county level are reported in parenthesis; RUCC_9 is an omitted rural-urban continuum code; BEA_8 is an omitted BEA region. Significance levels for * $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$

We use the sample median housing value to differentiate wealthy and poor counties. A county is defined as wealthy if the median house value equals or is greater than $76,450 and is poor otherwise. This definition results in approximately 1,378 poor counties, making up 48.7 percent of the sample and 51.31 percent (total of 1,452 counties) relatively wealthy ones. Mean PMHD is approximately 3.36 and 3.55 days in the wealthy and poor sample, respectively. The two-sample comparison of these averages indicates that the average number of poor mental health days is statistically higher in less wealthy counties.[10]

In Columns (1) and (2) of Table 5 we report coefficients corresponding to the model specification in Column (6) of Table 4 for poor and wealthy counties, respectively. Poor mental health is associated with reduced income growth in both samples. The PMHD coefficient estimate is almost three times larger in poor than in wealthy counties. The results suggest that every

[10] The t-statistic associated with the two-sample comparison test was -4.71 (df=2,828)

additional poor mental health day is associated with an income growth reduction of about 2.3 percent in poor counties and 0.87 percent in wealthy counties.

These results have several important implications. Our results suggest that poor mental health, which tends to be more prevalent among low-income earners (Schille et al. 2012), creates an implicit toll on this segment of the population in terms of reduced income growth. Moreover, emotional and mental problems likely lead to fewer job opportunities for those who already face limited job market opportunities in poorer communities due to lack of education and specialized skills. This segment of population is also less likely to have health insurance from employers (due to the low-paying nature of the jobs). Only a comprehensive public strategy involving intervention both in terms of health insurance as well as care provision would likely address this growing health concern.

An important caveat of the estimation strategy employed in this study is that the OLS regression, even with the lagged explanatory variables, does not fully eliminate endogeneity bias between poor mental health days and income growth if there are unobservable factors that are correlated with both the endogenous variable and the error term in the model. Whether the bias in estimated coefficients is upward or downward requires knowledge about how these omitted unobservables affect both the endogenous variable and the dependent variable in the model (Wooldridge, 2016). The direction of the bias can be determined if we are able to assess how the omitted factors correlate with the endogenous variable and the dependent variable in the model. Generally, biases are downward (i.e., the true effect is larger than that shown by estimated coefficients) if the correlation between the omitted factors and endogenous variable (i.e., poor mental health days), and the correlation between the omitted factors and dependent variable (i.e., income growth), run in opposite directions. For example, other poor physical health conditions such as cancer or terminal illness are potentially omitted factors in our model. It is generally known that poor physical health is positively correlated with poor mental health, and negatively correlated with income growth. Thus, omitting such factors would generate a downward bias in our model. On the other hand, unobservable variables such as social support environment or greater access to mental health facilities may reduce mental health problems (i.e., the correlation is negative). These omitted factors, however, tend in turn to be positively correlated with income growth. Because of the opposite directions in the two correlations, the OLS coefficient estimates will again be downward biased. Thus, on balance we expect the estimated coefficients associated with the mental health problems in our model to be smaller than the true relationship, and they represent only the lower bound of adverse effect of mental health on income growth.

6. DISCUSSION AND CONCLUSION

We present an alternative method for measuring the economic cost of poor mental health, and our results suggest a sizeable negative effect. The annual cost of $53.03-$62.3 billion is of the same order of magnitude as estimated productivity losses due to failing transport infrastructure in the U.S. Our results are subject to the caveat that the period 2008-2014 may be unusual in American economic history, if only because it follows closely the 2007-2008 Great Recession. Our work also demonstrates the feasibility of estimating the ex post association between PMHD and economic growth at the county level, in conjunction with other explanatory factors. Rather than assuming how mental health affects economic outcomes using one of the three approaches listed in the introduction,[11] which are based on key assumptions, our ex post approach instead estimates the actual association with economic performance, holding constant other pertinent determinants of income growth. PMHD are indeed found to have a statistically significant and negative association with growth.

Our results have important implications for several public policy issues related to mental health in the United States. The Mental Health Parity Act law of 1996 ended the long-standing practice of providing less insurance coverage for mental illnesses, or brain disorders, than what was provided for equally serious physical disorders. The Mental Health Parity and Addiction Equity Act of 2008 (MHPAEA) extends this act and mandates that group health plans and insurance issuers ensure that financial requirements (co-pays, deductibles) and treatment limitations (e.g., visit limits) applicable to mental health or substance use disorder benefits are on par with the basic requirements or limitations applied to all medical/surgical benefits (U.S. Department of Labor, 2015). While advances in public policy have addressed direct treatment costs associated with mental health, these policies do not capture the full costs of the disorder (e.g., income and productivity loss associated with increased mental issues). These indirect costs can substantially exceed costs of treatment and insurance coverage, as reaffirmed by the findings of the present study. Moreover, as suggested by the prior literature, if the mentally ill are less likely to find and maintain employment, the policy targeted at the inclusiveness and quality of insurance, primarily available through employers, may be inadequate (see Marcotte and Wilcox-Gok, 2001).

The MHPAEA could be enhanced through other policies targeted at mitigating causes of mental health problems. For example, Goetz et al. (2015) recently estimated that reducing poverty may be a more important policy strategy than reducing income inequality to address mental health problems in the U.S. (see also Heflin and Iceland, 2009). Evaluating the effect of state-level mental health expenditures on suicide rates, Ross et al. (2012) find no significant effect and suggest that policies aimed at income growth, divorce prevention or support, and assistance to low income individuals could be more effective. Mental health problems tend also to differ by race and ethnicity (see Bratter and Eschbach, 2005) and closer attention to each racial segment of the population will enhance policy debates related to the issue.

The incidence of certain mental health problems in the U.S., such as suicide, tends to be more prevalent among the middle-aged working age population, and they emerge during periods of adverse labor market conditions (Mohseni-Cheraghlou, 2013). Policies targeting the prime age population during labor market downturns can thus potentially mitigate these consequences. Furthermore, recent research indicates that social safety programs designed to improve the well-being of recipients may actually make them worse off. Heftin and Ziliak (2008) find that emotional distress associated with food insufficiency is higher among food stamp participants in the U.S. This effect is explained by the size of monthly benefits, the length of program participation or feelings of dependency. Re-evaluating the performance metrics for some of the major social safety programs could address major contemporary policy challenges related to mental health.

For mental health programs, it should be highlighted that both federal and state-level prevention programs and funds are fragmented across the U.S. The largest program funded by the federal government is the Community Mental Health Services Block Grant (MHSBG), which provides supplementary funds to state governments to target both adults with serious illness as

[11] These are: (1) direct and indirect cost of illness estimates; (2) value of lost output or economic growth; and (3) value of a statistical life.

well as children with significant emotional disturbances (SAMHSA, 2015). Based on the Consolidated Federal Funds Reports (CFFR, 2013), over the 1993-2010 period, average annual spending per treatment facility on the MHSBG program approached $7.6 million (in 2002 prices) and has remained at the same level for years despite a significant spike in mental health problems. The MHSBG program also appears to be considerably underfunded relative to the Substance Abuse Prevention and Treatment Block Grant (SABG) program that annually averages over $49 million per facility. Unlike to the SABG program, the MHSBG is aimed at ex-post treatment rather than ex-ante illness prevention (O'Connell et al., 2009). Given the scope of this research, we do not aim to evaluate how much these prevention programs could contribute to reducing non-trivial income losses forgone due to mental illness. However, the important question remains of evaluating their effectiveness in terms of avoidance of long-term income losses.

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