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Introduction

In this paper, I seek to examine the effects of income deprivation and income inequality on mental health. As mental health concerns continue to take center stage in the recent news and our world becomes increasingly divided by poor versus rich, we must consider what outcomes, anticipated or unanticipated, arise from such issues as rampant inequality, unlivable wages, or rising unemployment—especially where they are created or exacerbated by public policy. The effects of absolute poverty on mental health are well-supported, but we continue to learn more about the mechanisms by which it works. Inequality is more controversial—while "popular" theory today states that inequality creates all types of negative outcomes, the actual research is mixed on this subject, and we have yet to create comprehensive theory in this area.

I used Poisson regression to examine the effects of income deprivation and inequality on self-reported mental health in two separate models, utilizing county level data from the early 2000s. My findings support the absolute poverty hypothesis (that absolute poverty diminishes mental wellness) and the income inequality hypothesis (inequality itself, apart from poverty, also diminishes mental wellness). An alternative model examining inequality with income as a control also produced significant results. Research denying the income inequality hypothesis often states that the effect only exists until controlling for income, and/or that it only exists at the macro-level (i.e., nations). By finding that inequality significantly impacts mental health while using this control at the county level, I have further confirmed the viability of the income inequality hypothesis, contributing to the broader conversation. In this paper, I will first offer a review of the literature connecting poverty, inequality, and mental health; following, I will state my hypotheses and introduce my methods, datasets, variables, and models. I will then share the results of my analysis, along with a discussion of what measures were taken to ensure their robustness. In conclusion, I will reiterate the main takeaways of this paper and their implications.

Literature review

Faris and Dunham's 1938 *Mental Disorders in Urban Areas* was one of the earliest studies to examine the social causes of mental health issues. This, along with E. Gartly Jaco's 1960 *The Social Epidemiology of Mental Disorders* and Hollingshead and Redlich's 1958 *Social Class and Mental Illness*, was among the first to explicitly detail a negative link between social class and mental disorders. These findings have been supported repeatedly since, particularly in the last 25 years. Scholars have studied the negative effects of poverty on mental health via socio-economic status (Lorant et al 2003, Muntaner et al 2004), income (Sturm & Gresenze 2002, Dashiff et al 2009, Jacob & Kuruvilla 2007, Weich & Lewis 1998, Kahn et al 2000), unemployment (Murali & Oyebode 2004, Weich & Lewis 1998), material hardship (Heflin & Iceland 2009), and neighborhood disadvantage (Leventhal & Brooks-Gunn 2003, Ross 2000). I focus on the effects of poverty via income deprivation; a key component of social class and SES. However, multiple measures bear noting, as they are often the mediators of the effects of income poverty and may thus be invisibly inherent to the model, turning income-based variables into proxies of poverty effects as a whole. Studies like Leventhal and Brooks-Gunn's "Moving to Opportunity" experiment (2003) provide evidence that poor neighborhoods, in and of themselves, affect mental health via factors like lack of social cohesion (the importance of social support for mitigating the effects of poverty is stressed throughout the literature, and is the rationale behind my social support control variable). Considering my data is county-level, the results may indeed include such an impact. Material hardship, such as food and housing insecurity, is closely connected to income deprivation (Iceland & Bauman 2007), and may also mediate a large part of the income effect (Heflin & Iceland 2009). Due to space constraints, I have not included a material hardship model, but encourage this as an area for further research. When considering what it is about poverty that precisely affects health, it is variables like these we must consider, along with other potential mediators, such as status' effect on identity or limited personal resources (coping mechanisms, self-esteem, parents' parenting style, etc.) (Dashiff 2009, Siegel 2008, Lorant 2003, Muntaner et al 2004). I discuss these to explore by what complex mechanisms my hypotheses may operate. Causality between poverty and mental health is not always clear; the concept of those with mental disorders “drifting” down the socioeconomic ladder appears often (Siegel 2008, Murali & Oyebode 2004, Jacob & Kuruvilla 2007). However, most acknowledge that, while this may occur, the poverty/mental health relationship is still very real. Some have found variation in that relationship—for example, poverty impacting persistence or experience more than onset (Lorant 2003, Weich & Lewis 1998, Fryers et al 2003). However, most of the literature agrees that it plays an important role, even if varying precisely in how it does so.

Poverty and inequality are tightly linked in the literature, and many studies have found that the two together have compounding effects (Belle & Doucet 2003, Kahn et al 2000). However, inequality’s role in health has been far more controversial. The income-inequality hypothesis (IIH) holds that inequality has negative effects for all social strata,[1] via such factors as status anxiety. Studies have found the mental health IIH to hold at country (Wilkinson & Pickett 2009), state (Siegel 2008, Wilkinson & Pickett 2009, Kahn et al 2000), and county (Muramatsu 2003; the level of my dataset) levels. Other studies, however, have found the IIH to be unsupported (Rai et al 2013, Bechtel et al 2012, Sturm & Gresenze 2002), or conditional (Fiscella & Franks 2000, Fryers et al 2003, Fone et al 2013). Fiscella and Franks noted that inequality’s effect was more likely to be significant with self-reported health measures than more objective measures, and that the latter relationship disappears when controlling for income.[2] There are also potential ameliorating reasons for inequality not having a measurable impact on mental health, such as differing policies and institutions between nations mitigating the effect (Bechtel et al 2012, Sturm & Gresenze 2002), or the potential for the relationship to vary at different levels; Fone et al (2013) found that the effects of inequality were insignificant at smaller geographic levels, but often had a significant effect at larger levels (something to consider with our county-level data).

Hypotheses

Informed by aforementioned theory, we have developed two major hypotheses: that 1)

[1] In contrast, some focus more on the idea of relative poverty, without noting effects for the higher strata. In an interesting twist, Fone et al (2013) showed a significant relationship for inequality affecting mental health only for those in *low* deprivation neighborhoods, not high.
[2] This potential difference is important to note for my own study, which utilizes a self-rated measure of health.

as income deprivation increases, mental wellness decreases, and 2) as income inequality increases, mental wellness decreases. (The null hypotheses, of course, are that income deprivation and inequality have no effect on mental health.) Per the variables: as per capita income increases, reported mentally unhealthy days per month will decrease; as unemployment increases, reported days will increase; as the GINI index increases, reported days will increase. We will rigorously test these and relevant control variables, utilizing Poisson regression.

Data and models

Poverty and inequality present a variety of options when it comes to testing variables and relationships. I initially decided to run two separate models, in recognition of the conceptual differences between the two main areas of concern, including relevant control variables that have been thoroughly tested via literature and logic. My data is compiled from the Robert Wood Johnson's 2010 County Health Rankings and ICPSR's "County Characteristics, 2000-2007." Each possesses data for all U.S. counties, and aligned perfectly when combined. It bears noting, however, that as they came from different sources, there may be some unintended bias in the results (where different individuals were surveyed for different variables); however, due to the size of the sample and respected nature of the data, I believe that the results are still sound.

The dependent variable for each model is the average self-reported mentally unhealthy days experienced per month. I use this as a proxy for mental health; as a self-rated measure, it can never be objectively perfect; however, the subjective experience of mental health and the reality that far more people never seek treatment than do, making official treatment numbers suspect, makes it a sound option. The initial models I use to test the hypotheses are as follows:[3]

- Model #1: income deprivation. This model's primary independent variables are per capita income and the percent of residents unemployed.[4] Both of these measures are well-established as viable measures of poverty for assessing health outcomes, as they can

[3] A third major model was ultimately included as well; this will be discussed later in the paper.
[4] Concerns of multicollinearity prompted a pairwise correlation test; the result was only -0.3042, demonstrating that significant multicollinearity is not necessarily a concern, despite unemployment's potential role in determining income.

cause and/or encompass many of the mediating effects I mentioned earlier.

- Model #2: income inequality. The primary independent variable is the GINI index, which measures the disparity in income levels within a set geographic area. This is the most common measure of income inequality, used in the majority of empirical studies.

Both models include the same controls (with one exception), as follows.[5] Based on literature and scatterplots (which were run for each variable), we are confident that these are linear, and not quadratic or inverse relationships:[6]

- Mental health Health Professional Shortage Area (HPSA) (dummy). (+/-, relative to non-HPSA; see Table 2 for arguments for differing relationship directions)
- Median age. (+/-; see Table 2 for arguments for differing relationship directions)
- Percentage of the population self-identifying as white. (+)
- Sex ratio (measured as male-to-female ratio). (-)
- Percentage of residents stating a lack of social and emotional support. (+)
- Percentage of single parent households. (+)
- Metropolitan area (dummy). (+, relative to urban area)
- Rural area (dummy). (+, relative to urban area)
- Percentage of residents, aged 25+, with a four-year college degree. (-)[7]

All variables were measured at some point between 2000 and 2008. While timing may be a concern, the fact that the dependent variable is a composite of data compiled from 2002 to 2008 (the last six of the eight years) indicates that any other variable may be construed to be a causal variable at different points. Additionally, many of these variables are slow to change significantly (population demographics do not change overnight), and variations are likely to be very slight.

Regressions

My measure of mental health is a count variable, which runs the risk of violating the OLS assumptions of homoskedasticity and normally distributed errors. Therefore, I utilized a Poisson regression. Poisson standard errors are often heteroskedastic, and scatterplots revealed this to be likely (see the supplementary appendix); I thus included robust standard errors in both mod-

[5] I list them and the expected direction of their relationships briefly here; for a more comprehensive explanation of my rationales for inclusion and the expected relationship, see Table #1 in the supplementary appendix.
[6] One exception is age, whose relationship is unknown and mostly omitted by the literature, even as it is always included as an important control; different mental disorders are more common at different ages, and not necessarily in a discernible statistical pattern. Thus, I make no prediction as to its direction and linearity.
[7] Due to multicollinearity concerns, the college variable was dropped from Model #1 (recognizing the distinct relationship between college degrees and income levels). The pwcorr result was 0.7298, indicating severe multicollinearity.

els. Poisson's "extra" assumption is equidispersion—that mean count and variance are equal. If overdispersion is present, as is common, standard errors will be understated, thus affecting significance and necessitating the use of a different type of regression. However, by utilizing negative binomial regression as a comparison, I determined that this was not the case in this data—the results were identical between the two sets of models and the likelihood ratio tests were significant, ensuring us that the equidispersion assumption has been met. Unlike many count data (often zero-heavy), the data is fairly normally distributed, with only slight rightward skew.

<insert Graph #1: Distribution of Mentally Unhealthy Days (see main results appendix)>

Poisson does not allow VIFs; thus, I did an initial search for multicollinearity issues by running pairwise correlations between each primary independent variable and its control variables, and found none at a level of severity that would be cause for concern, except for income and education—education was thus dropped from the income deprivation model.

<insert Table #1: Regression Results (see main results appendix)

Model #1: income deprivation

I tested per capita income and unemployment's effect on reported mentally unhealthy days, with each of the previously listed control variables (except college education). Both of the key independent variables were significant at the 99% level. The beta for per capita income is minute, with a reported 0% change in reported days for a one-unit increase—initially discouraging. I generated a new variable—per capita income in thousands—to determine if a smaller continuous range would raise the visibility of the effect. This slightly increased the beta, while keeping the significance and all other variables' results the same—a $1,000 increase in per capita income thus resulted in a 1.1% increase in reported mentally unhealthy days per month. An even easier place to see the effect is with the standard deviation factor; one standard deviation increase ($6,834.85) results in a 7% decrease in reported days per month (this is the measure we will use for the rest of our results). One standard deviation in unemployment (2.056%) results in a 4.9% increase in reported days. Each of these results is concurrent with the initial hypotheses. Each control variable is also significant at the 99% level (except for single parent households, at the 90% level)—a potential effect of multicollinearity, which I will discuss momentarily. Mental health HPSAs decrease reported days, relative to non-HPSA counties; increases in median age increase reported days; increases in white residents increase reported days; higher sex ratio decreases reported days; reported lack of social support increases reported days; increases in single-parent households increase reported days; metropolitan areas increase reported days relative to urban areas; and rural areas decrease reported days relative to urban areas. These are mostly consistent with my predictions, except for rurality—I had predicted it would increase reported days, relative to urban areas. I made no predictions for mental health HPSA and age, due to conflicting theory. In assessing the model as a whole, we see that the Wald chi-squared statistic is significant at the 99% level, indicating joint significance.

To further test for multicollinearity beyond earlier efforts, I quickly utilized an OLS regression to run VIFs. There, I found the single parent and race variables had VIFs of 2.91 and 2.55, respectively—not extremely high (experts say the cutoff can be anywhere between 2.5 and 10), but high enough for concern. Running pairwise correlations between these two variables and the rest of the model, I found that these two variables were highly correlated (-0.728), and that each were also correlated with lack of social support, as well as single parent households with median age—all at around the 0.5 level (the most conservative cutoff point). Tradeoffs must always be considered when dealing with multicollinearity and omitted variable bias—correcting for one may cause the other. Due to the importance of these variables to theory, as well as the fact that each result was already significant at the 90% level or more, I chose to leave them in the regression. However, I ran an alternate regression (see the main results appendices) to see if dropping single parent households, the main offender, would wield an effect. While each z-statistic slightly increased, the model remained essentially the same, and we avoided unnecessary omitted variable bias. Finally, to further test the robustness of this model, I used “jackknifing,” rerunning the regression with the most egregious outliers removed from each key variable. I used graphs, as well as the sort/stem commands, to identify cutoff points, as Poisson does not allow studentized residuals. For the first model, reported days values of 7.5+ were removed; for the second, per capita income values $70,000+ were removed; for the third, unemployment percentages 15%+ were removed. None of the results changed significantly in these alternative models, upholding the robustness of the original.

Model #2: income inequality

Each of the results was significant at the 99% level, except for sex ratio and median age, and the Wald chi-squared statistic was once again significant at the 99% level. Analyzing the results, we see that, for every one standard deviation increase in the GINI index (3.414 points), average monthly reported mentally unhealthy days increase by 6.8%—a statistically significant change, concurrent with our initial hypotheses. College education was utilized in this model—increases in this percentage decreased reported days, concurrent with predictions. The directions are the same for each control as in the first model, except for median age, which switched. As mentioned earlier, the age relationship is complex; either outcome is theoretically viable. The change, however, does indicate bias—potentially omitted variable bias (perhaps the removal of the income or unemployment variables). The insignificance of both sex and age may indicate remaining multicollinearity concerns, or reflect that age may not be significant at all (while an important control in the literature, age's direct effects on mental health are controversial, and there may be no significant relationship). Sex ratio is more troubling, as this is well-supported by the literature to be significant. One possibility is that, because sex ratio varies so little at the county level (the mean for this variable is 0.993, with a minimum of 0.76 and a maximum of 2.01), it may be hard to infer too much of a significant relationship. As with the last model, I ran an OLS regression with VIFs, and found very similar results—single parent households and percent white having the highest scores, at 2.85 and 2.68. With the same logic (and pairwise results) as in the last model, I again decided to leave each variable in to honor theory and avoid omitted variable bias, while running an alternate regression. Once again, while this alternate regression increased the majority of the z-statistics, the effect was slight, and neither insignificant variable moved into significance. Again, I utilized jackknifing to help test the robustness of this model. For the first model, reported days values of 7.5 and over were removed; for the second, GINI values 55 and over were removed. The new results were nearly identical, in betas and significance, to the original, thus upholding the robustness of this model as well.

Alternative explanatory model: income *and* inequality

Upon reviewing the results, I decided to run an additional model—an inequality model with per capita income as a control (and again dropping education for collinearity). The two variables are not highly collinear (a pairwise score of -0.087), and a small subset of the literature identifies the need to control for income as the reason for the IIH being proved where it should not be. Upon running a new regression, I found that the majority of the model remained the same—the GINI index's effect on mental health had decreased very slightly (a 6.7% rise for every standard deviation increase, as opposed to 6.9%), in homage to the new variable, but the effect still persists. The effects of income actually increased (an 8.4% for every standard deviation increase, instead of 7%). The one noteworthy change was that median age, while still insignificant, had reversed its direction back to what we saw in the first model, signifying that income may have been the biasing omitted variable in the second model.

Discussion of results

The results are highly significant and operate in their predicted directions: income deprivation and income inequality both have statistically probable negative effects on mental health. While proving causality is always a concern (the "drift" hypothesis), it is also well-substantiated that poverty, and to some extent inequality, do wield their own direct influences on mental health. The control variables also generally operated in their expected directions. The HPSA variable, which we did not initially make a prediction for, introduces an interesting area for further research—how the mere presence of mental healthcare options, utilized or not, may affect understandings of mental health. Omitted variable bias is always a possibility; we can never be sure that we have included every important variable, and Poisson offers no Ramsey RESET equivalent. However, my variables were drawn from the literature, and no major frequently recurring variables were omitted, with the exception of physical health and, to some degree, marital status (single parent households, the most frequently highlighted variable, is included, however). Physical health was too multicollinear with the other variables—per the broader literature, many of the same factors affecting mental health also affect physical health. In sum, we were able to cover the majority of the primary control variables in the literature, but acknowledge the possibility that something was omitted. Also, in studying county-level over individual data, we may have lost some significant effects pointed to in the literature (i.e., gender), and this should be considered in interpreting the results. In short, my results remained significant even upon addressing imperfect multicollinearity issues with a very conservative standard (in fact, after running the VIFs, I ran pairwise correlations on every possible combination of control variables, just to ensure no more hidden issues existed—none did), applying robust standard errors, and jackknifing, thus showing my results to be consistent and robust, as well as in line with theory.

Conclusion

In conclusion, I found that both absolute poverty and inequality had significant negative effects on mental health. These effects are likely mediated by material hardships, lack of social cohesion, status anxiety, and other such variables, as described earlier, but the measures used are well-supported in the literature and in theory as being solid proxies for these effects. However, each of these effects is worthy of further study on their own independent merits. The alternative model's finding that inequality, while controlling for income and taking place at the relatively small county level, is still significant is this paper's most important contribution, but the confirmation of the absolute poverty hypothesis as well is still a substantial finding as we contemplate what future public policy endeavors should be undertaken to address our growing awareness of mental health issues in our nation, and at what levels interventions may be useful.

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APPENDICES

Table of contents

Main results

Graph #1: Distribution of Mentally Unhealthy Days

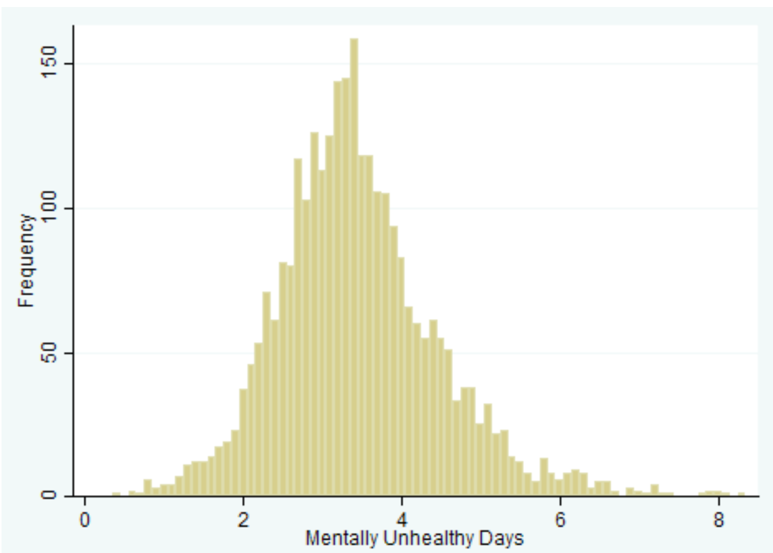

Table #1: Regression Results

Key:

*** indicates 99% p-value significance, ** indicates 95%, * indicates 90%

All results are expressed as:

%StdX***	(percent change per standard deviation with p-value significance)
SDofX	(standard deviation)
(z)	(z-statistic)

Exception: dummy variables are expressed as:

%***	(percent change per unit change with p-value significance)
(z)	(z-statistic)

Table 1: Reg Results	Model #1: income deprivation (baseline)	Model #1, income in thousands	Model #1, SPH removed	Model #2: income inequality (baseline)	Model #2, SPH removed	Alternate model: income & inequality
Variable results						
Per capita income (dollars)	-7.0%*** 6834.846 (-10.371)	N/A	-7.2%*** 6835.023 (-6.515)	N/A	N/A	N/A
Per capita income (1000s)	N/A	-7.0%*** 6.835 (-10.371)	N/A	N/A	N/A	-8.4%*** 6.835 (-13.748)
Percent unemployed	4.9%*** 2.056 (7.719)	4.9%*** 2.056 (7.719)	5.1%*** 2.055 (8.286)	N/A	N/A	N/A
GINI index	N/A	N/A	N/A	6.8%*** 3.414 (10.858)	6.9%*** 11.055 (3.414)	6.1%*** 3.406 (9.915)
Mental health HPSA	-6.9%*** (-4.854)	-6.9%*** (-4.854)	-6.7%*** (-4.715)	-5.4%*** (-3.838)	-5.0%*** (-3.540)	-6.1%*** (-4.346)
Median age	1.8%*** 4.438 (2.656)	1.8%*** 4.438 (2.656)	1.5%** 4.434 (2.277)	-0.4%* 4.440 (-0.659)	-1.0% 4.440 (-1.553)	2.5%*** 4.438 (3.889)
Percent white	5.8%*** 15.611 (7.05)	5.8%*** 15.611 (7.05)	5.0%*** 15.608 (6.857)	6.8%*** 15.623 (8.132)	5.3%*** 15.623 (7.394)	7.3%*** 15.611 (8.520)
Sex ratio (male to female)	-1.9%*** 0.067 (-2.863)	-1.9%*** 0.067 (-2.863)	-2.0%*** 0.067 (-2.917)	-0.9% 0.067 (-1.423)	-1.0% 0.067 (-1.557)	-0.7 0.067 (-1.190)
No social, emotional support	8.7%*** 5.114 (11.636)	8.7%*** 5.114 (11.636)	8.9%*** 5.113 (11.996)	7.5%*** 5.122 (10.336)	7.7%*** 5.122 (10.697)	8.4%*** 5.114 (11.747)
Single parent households	1.6%* 2.699 (1.895)	1.6%* 2.699 (1.895)	N/A	2.5%*** 2.696 (3.026)	N/A	3.1%*** 2.699 (3.830)
Metropolitan area	5.1%*** (4.304)	5.1%*** (4.304)	2.5%*** (4.384)	5.5%*** (4.885)	2.8%*** (5.122)	6.8%*** (5.823)
Rural area	-8.4%*** (-4.043)	8.4%*** (-4.043)	-3.2%*** (-4.348)	-9.9%*** (-4.833)	-3.8%*** (-5.373)	-10.1%*** (-5.083
College education	N/A	N/A	N/A	-8.1%*** 8.861 (-14.276)	-8.7%*** 8.861 (-16.583)	N/A
Model results						
(Wald) Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(Alpha score) Prob > chibar2	1.000	1.000	1.000	1.000	1.000	1.000

Supplementary

Table 2: Variables: measures, signs, and sources

Variable	Definition	Year(s) measured	Dataset	Expected sign	Justification
Dependent variable					
Mentally unhealthy days	Average number of mentally unhealthy days reported by survey respondents	2002-2008	CHR	N/A	See main paper.
Primary independent variables					
GINI index	GINI coefficient measuring local income inequality	2000	CHR	+	See main paper.
Income	Per capita personal income	2005	ICPSR	-	See main paper.
Unemployment	Percentage of population unemployed	2008	CHR	+	See main paper.
Control variables					
Mental health HPSA	Dummy; whole county designated as a mental health health profession shortage area (HPSA)	2007	ICPSR	+/-	This measure indicates that there is a severe shortage of mental health professionals, relative to the population. Poverty also influences what treatments are available to those with mental health disorders, and thus also their chances of improving or worsening their condition (Jokela 2013). This was influential in our decision to include mental health profession shortage areas as a control variable for mental health outcomes. This relationship could conceivably be positive or negative—less mental health treatment available may increase the incidence of mental disorders, but it also may mean that those suffering from mental disorders lack the language or knowledge to assess their condition in the terminology necessary for self-reporting, which would taint the survey results.
Age	Median age of total population	2005	ICPSR	+/-	This relationship could also go either way—while some of the literature identifies youth as a risk group for mental health issues, others point to the social isolation aging can bring. Thus, I leave my prediction open-ended for this variable as well, but acknowledge its importance as a control, per the literature.
Race	Percentage of population identifying as white	2005	ICPSR	+	This is also an important control variable in the literature, and per that literature, we theorize that as the percentage of the white population increases, so will reported mentally unhealthy days.
Sex ratio	Total male population divided by total female population, rounded to 2 decimal points	2005	ICPSR	-	This is an important control variable in all the literature, especially considering that women (especially when compounded by being a single parent) are far more prone to depression and anxiety relative to poverty and inequality models (Jacob and Kuruvilla 2007, Ross 2000, Belle and Doucet 2003, Kahn et al 2000); we thus theorize that as the ratio increases (more men relative to women), reported days will decrease.

Inadequate social/emotional support	Percentage of population reporting no social or emotional support	2005-2008	CHR	+	Social isolation was one of the key takeaways of Faris and Dunham's 1938 work, as an influencer of mental health often brought on by poverty via neighborhood disorder and disadvantage. Social support is also frequently mentioned in the literature as a mitigator of the effects of poverty where present—where strong social networks are present, mental health issues are less likely. Thus, I predict that as lack of reported social support increases, so will reported days.
Single parent households	Percentage of population in single parent households	2000, 2005-2007	CHR	+	Family structure is an important control variable in the literature. While it does not fully encompass all family structures, such as those without children, it does mark one of the most important factors; single mothers in particular are prone to the mental health effects of poverty. Thus, I predict that as this percentage increases, so will reported days.
Urban/rural continuum	Dummies; using the rural/urban continuum codes, I created 3 dummy areas for metropolitan, urban, and rural areas.	2000	ICPSR	+	The negative effect of inner city areas on mental health is mentioned frequently in the literature; while rural areas are mentioned frequently, with the social isolation hypothesis in mind, it is possible that very rural areas could have a negative effect as well. Therefore, I predict that reported days will increase in metropolitan areas *and* rural areas, relative to urban (the catch-all in-between the extremes) area, representing a pseudo-quadratic relationship.
College education	Percentage of population aged 25+ with 4-year degree	2000, 2005-2007	CHR	-	Education is also a very important variable in the literature; and I predict that as education increases, reported days will decrease.

Summary statistics of all variables

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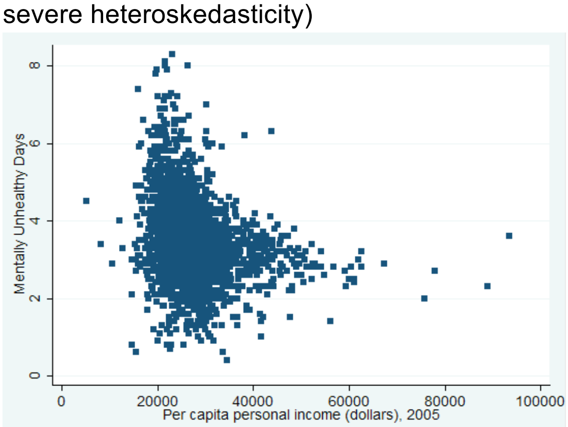
. sum mentallyunhealthydays CA05N0030_05 unemployed gini M_HPSA_Cty07 MedianAge05 PctWhite05 SexRa
> tio05 nosocialemotionalsupport singleparenthouseholds metro1 rural1 college
```

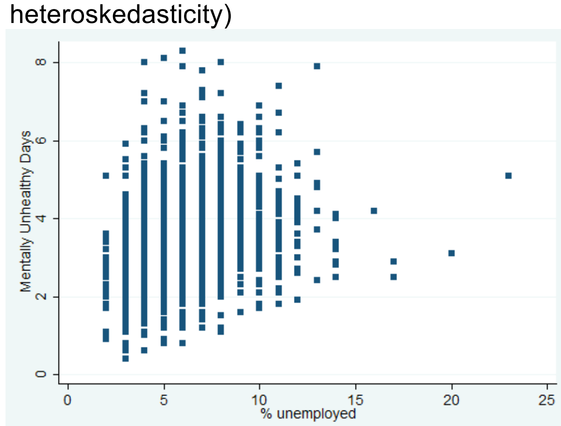
Variable	Obs	Mean	Std. Dev.	Min	Max
mentallyun~s	2905	3.456695	1.028729	.4	8.3
CA05N0030_05	3086	27366.97	6604.393	5148	93377
unemployed	3140	5.852548	2.14486	1	23
gini	3140	43.3051	3.573901	33	60
M_HPSA_Cty07	3141	.1391277	.3461348	0	1
MedianAge05	3141	38.60917	4.425648	20.1	55.3
PctWhite05	3141	87.01721	16.15113	4.73	100
SexRatio05	3141	.9929895	.0944522	.76	2.01
nosocialem~t	2096	18.96088	5.121288	6	51
singlepare~s	3140	8.813376	2.767895	1	29
metro1	3141	.3470232	.476099	0	1
rural1	3141	.2133079	.4097085	0	1
college	3140	17.77038	8.412347	5	70

Scatterplots of relationships

Model #1a: mentally unhealthy days and per capita income (note appearance of severe heteroskedasticity)



Model #1b: mentally unhealthy days and unemployment (note appearance of potential heteroskedasticity)



Model #2: Mentally unhealthy days and the GINI index