Gender and Mental Depression: Analyzing Census Data Through Statistical Methods*

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Mental health poses a significant global health threat. This threat existed before the pandemic, and recent studies have shown that it has become even more prevalent after the pandemic. Our study developed a noble method to identify severe psychological depression using survey data that can be used as an early alert system to identify nonspecific psychological distress.

1 Introduction

Mental health issues, particularly depression, have emerged as a significant public health concern globally. Among other factors influencing mental health, gender and education stand out as critical determinants. Recent studies have also indicated that educational attainment may play a protective role against depression, suggesting that individuals with higher education levels experience lower rates of mental health issues. Conversely, gender disparities in depression prevalence remain pronounced, with research consistently showing that women report higher rates of depression than their male counterparts, even when controlling for education levels.

This study employs a statistical approach in R to examine the relationships between gender, educational attainment, income and reported cases of mental depression. By exploring these dynamics, we hope to contribute to a deeper understanding of how education and gender intersect to influence mental health, providing valuable insights for policymakers and mental health practitioners.

Therefore our key questions underpinning this research include: does higher education correlate with lower rates of depression? Are women disproportionately affected by depression compared to men at the same educational level? Can we develop a model that predicts the likelihood of psychological distress (Kessler et al. 2012) given certain characteristics of an individual

*Code and data are available at: https://github.com/Nguyen-Ar-Rakib-Barnes/downturns-household-insurance-and-poverty.

such as sex, education or age? To address these questions, we analyze national census data through various statistical methods, focusing on the intersection of gender, education, and mental health outcomes (Blewett et al. 2023).

Predictive models - even simplified ones like the one we present below - are helpful for understanding complex issues like mental health. They allow researchers and policymakers spot trends and make smarter decisions. By looking at how factors like gender and education connect to depression, these models show patterns which lets us identify at-risk groups early, and lets us provide tailored support and resources to those who need it most. Plus, predictive models help direct future research by pointing out where more exploration is needed, ensuring we keep learning and improving our approach to mental health. In a time when mental well-being is more important than ever, being able to predict and tackle what affects it is key to building healthier communities.

The remainder of this paper is structured as follows: Section 2 presents the data and methodology, detailing the statistical techniques used for analysis. Section 3 discusses the modeling strategy and expected outcomes, followed by a presentation of results in Section 4. Finally, Section 5 engages in a critical discussion of our findings, addressing their implications for future research and policy.

2 Data

2.1 Overview

We used the Medical Expenditure Panel Survey(MEPS) dataset from the Integrated Public Use Microdata Series, which contains microdata from different time points related to U.S. healthcare expenditures (Blewett et al. 2023). We performed all analysis using a popular statistical language called R (R Core Team 2023). Our dataset contains age, sex, marital status, race, highest level of education attainment, total personal income, and K6 score (Kessler et al. 2012).All the variable definitions can be found in the Appendix A.

Our goal was to identify respondents, based on gender and education, who were suffering from non-specific psychological distress based on the Kessler scale before and after the COVID-19 pandemic. To support our analyses, we split into two datasets for 2018 and 2021. We also excluded the respondents whose ages are below 19 and over 80. After enforcing our inclusion criteria, we had 15716 respondents for 2018 and 12685 for 2021. To give a preview of our data, Table 1 and Table 2 show the first five rows for each row for 2018 and 2021, respectively.

Table 1: Year 2018

year	age	sex	marstat	racea	educ	inctot	k6sum
2018	27	2	10	100	400	32000	3

Table 1: Year 2018

year	age	sex	marstat	racea	educ	inctot	k6sum
2018	34	2	10	100	201	25000	4
2018	39	1	10	100	201	30000	0
2018	36	2	10	100	501	30217	0
2018	30	1	10	100	301	31644	0

Table 2: Year 2021

year	age	sex	marstat	racea	educ	inctot	k6sum
2021	59	2	10	100	201	9508	2
2021	73	1	10	100	201	25508	2
2021	21	1	50	100	115	20000	2
2021	41	1	10	100	201	41500	1
2021	32	1	10	100	201	41600	1

2.2 Measurement

2.2.1 Gender and Mental Health

Research consistently shows that women report higher rates of depression than men (Van De Velde, Bracke, and Levecque 2010). Biological, social, and psychological factors contribute to this disparity. Women may experience unique stressors, such as role strain from balancing work and family obligations, as well as being subject to gender-based discrimination. Townsend et al. see this as, “competing demands between work and the gendered expectations of domestic labor for women”, which can “result in relatively more work–family conflict.” Plus, they note that “this tension between work and family tends to increase among women over their lifetime” (Townsend, Kray, and Russell 2024). These pressures can exacerbate mental health issues, leading to higher rates of depression among women, particularly those in lower socioeconomic or educational strata.

2.2.2 Educational Attainment and Mental Health

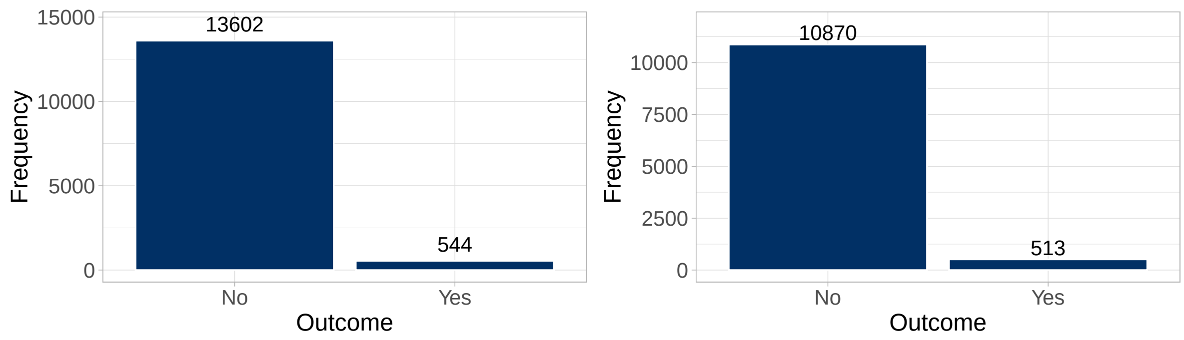
Education is often seen as a protective factor against mental health issues. Studies have mixed results when studying if higher levels of education correlate with improved mental health outcomes (Tabor, Patalay, and Bann 2021). Educated individuals do, however, tend to have better access to mental health resources, higher socioeconomic status, and greater job security, all of which contribute to lower rates of depression. Indeed, socioeconomic factor “is a consistent and reliable predictor of a vast array of outcomes across the life span, including physical and psychological health." ("Education and Socioeconomic Status," n.d.). Conversely, those with lower education levels may face more financial strain, reduced employment opportunities, and limited access to healthcare, increasing their vulnerability to depression.

2.2.3 Intersection of Gender, Education, and Depression

Despite the protective nature of education, the gender gap in mental health persists even at higher levels of educational attainment. Some studies suggest that women with high education levels still experience depression due to external stressors, including workplace discrimination and societal expectations. Acording to Ross et.al., "Academics report stress and waning resilience, fatigue and exhaustion, and a destabilization of the work-life balance. Furthermore, these impacts are unequally experienced by women with children and those with caring responsibilities" (Ross, Scanes, and Locke 2023). Additionally, the mental health benefits of education may differ between genders, with men benefiting more from the social status and economic opportunities that education provides, while women may continue to face challenges related to gender roles.

2.3 Outcome variables

The MEPS survey collects participants' K6 score for nonspecific psychological distress. The K6 score is a summed scale value, also known as the Kessler 6 Scale, which considers six manifestations of nonspecific psychological distress. A score of 13 or higher indicates likely severe mental illness (Kessler et al. 2012). The variable called K6SUM represents the score in our dataset A. We constructed a new variable called "outcome," where 0 represents the score below 13 and 1 represents the score above 13. We considered zero as a person who is not experiencing psychological distress, denoted as "No," and one as a person experiencing severe psychological distress, denoted as "Yes." Figure 1 represents the number of respondents we have in the dataset who were suffering from psychological distress. In 2018, 601 respondents were suffering severe psychological distress, where the number of total respondents was 15716. In 2021, 573 respondents were suffering from nonspecific psychological distress over the 30-day recall period, where the total number of respondents was 12685.



(a) 2018 (b) 2021

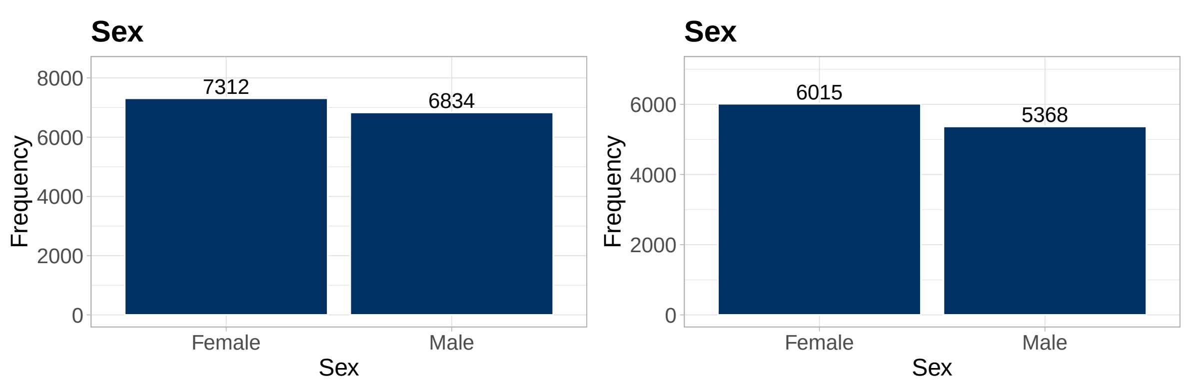
Figure 1: Number of Respondents Suffering Severe Psychological Distress

2.4 Predictor variables

We discuss the predictor variables in this section. We primarily use sex and education variables for our analysis. However, we also discuss marital status, race, and total income to understand our dataset better.

2.4.1 Sex

Our dataset has 8209 female respondents and 7507 male respondents for 2018. In 2021, the total number of respondents is lower compared to 2018. We have 6784 female respondents and 5901 male respondents for 2021 Figure 2.



(a) 2018 (b) 2021

Figure 2: Distribution of Respondents by Sex

2.4.2 Education

There are 36 categories in the education variable. Five of them represent the missing value or refused to answer. We discarded these values. We also discarded the 500, 504, and 505 codes as they represent overlap (e.g., 500 represents a Master's, Professional, or Doctoral Degree). We also merge the categories of education. Details are available in the Section A.2.

Figure 3 and Figure 4 depict the overall education status of our respondents. For both 2018 and 2022, a majority of respondents have at least a high school degree, followed by a bachelor's degree.

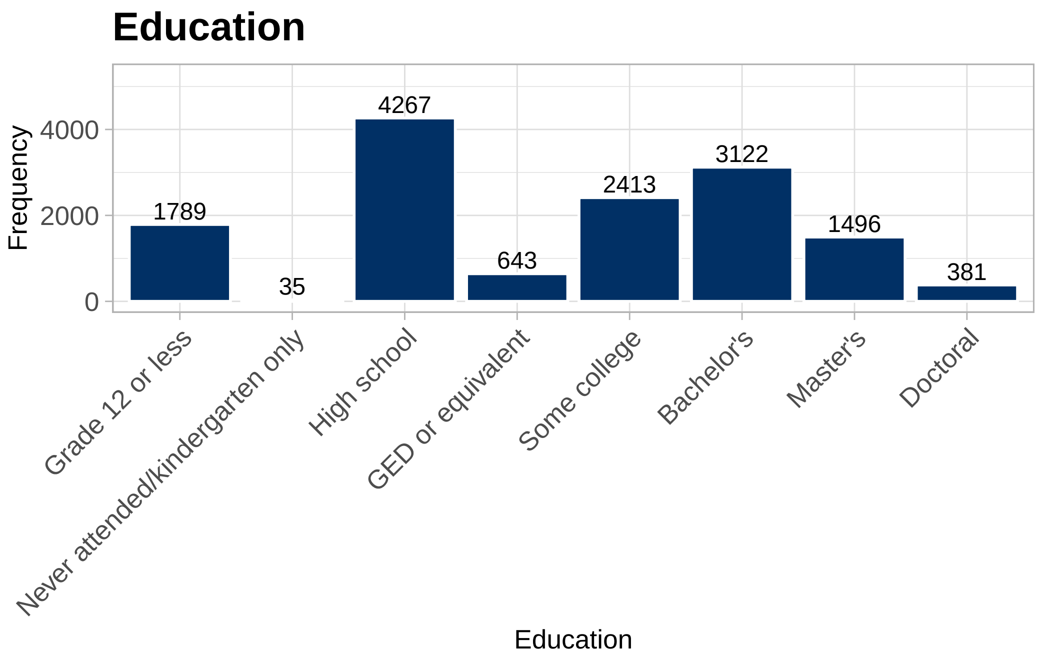


Figure 3: Distribution of Respondents by Education (2018)

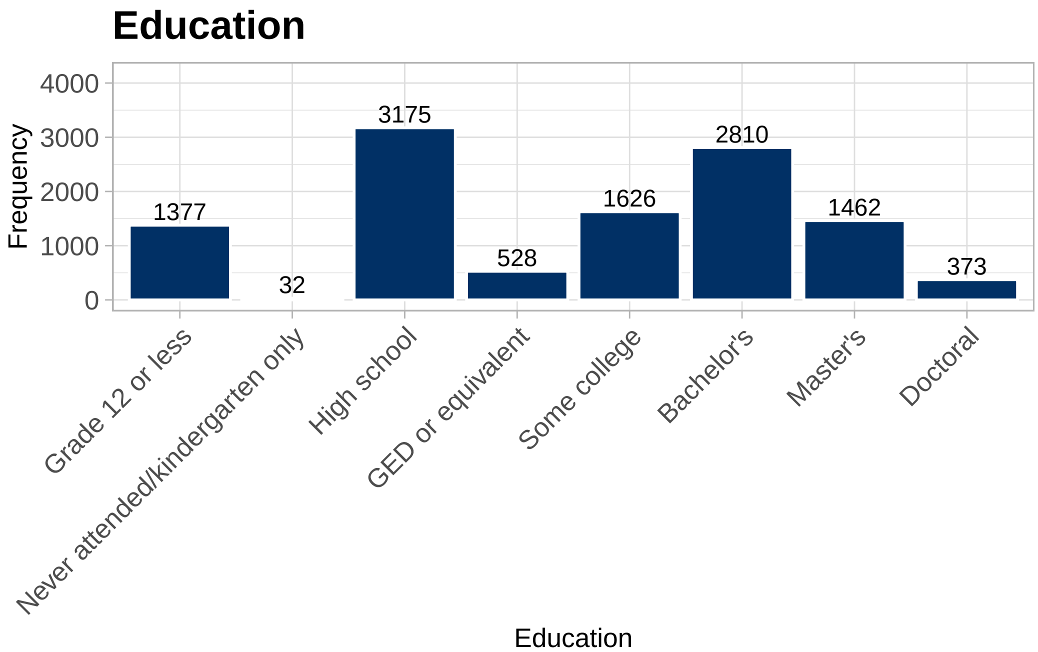


Figure 4: Distribution of Respondents by Education (2021)

2.4.3 Age

Figure 5 The histogram demonstrates the overview of the age data distribution, depicting the high and low frequencies. The highest concentration of respondents is above the age of 60. Our dataset has a relatively low representation of the younger population.

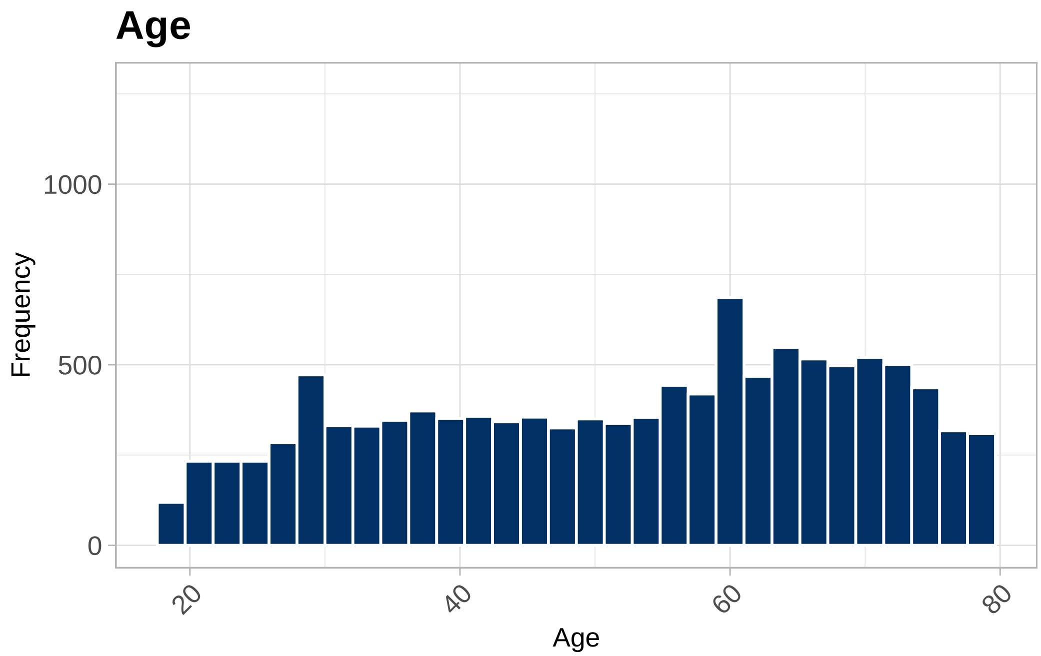


Figure 5: Distribution of Respondents by Education (2021)

3 Model

We leverage the logistic regression model to identify the association between suffering from psychological distress with sex and education. We set our model following the Alexander (2023) guidelines with the rstanarm package Brilleman et al. (2018) in R (**citer?**).

Logistic regression is a commonly used regression model when the outcome variable is binary (Alexander 2023). For our dataset, we introduce an outcome variable, which represents whether an individual is suffering from psychological distress. As a predictor variable for the logistic regression, we will use the sex and education variables discussed in the Section 2.

3.1 Model set-up

For logistic regression, we are using the equation below:

$$y_i \sim Bern(\pi_i) \tag{1}$$
$$logit(y_i) \sim \beta_0 + \beta_1 \times sex_i + \beta_2 \times education_i \tag{2}$$
$$\beta_0 \sim Normal(0, 2.5) \tag{3}$$
$$\beta_1 \sim Normal(0, 2.5) \tag{4}$$
$$\beta_2 \sim Normal(0, 2.5) \tag{5}$$

Here, y_i represents whether a respondent suffers from psychological distress. sex_i represents the respondent's gender, and $education_i$ represents the maximum education attained by the respondent. We randomly select 5000 samples from our entire dataset to simplify the model for lower execution time.

4 Results

Our results are summarized in Table 3 and Table 4.

Table 3: Model Results for Year 2018

	Severe Mental Illness
(Intercept)	-2.492
	(0.178)
sexMale	-0.490
	(0.161)
educationNever attended/kindergarten only	1.804
	(0.864)
educationHigh school	-0.450
	(0.213)
educationGED or equivalent	0.074
	(0.305)
educationSome college	-0.673
	(0.255)
educationBachelor's	-1.319
	(0.282)
educationMaster's	-2.982
	(0.749)
educationDoctoral	-2.516
	(1.152)
Num.Obs.	5000
R2	0.017
Log.Lik.	-711.613
ELPD	-722.5
ELPD s.e.	41.9
LOOIC	1444.9
LOOIC s.e.	83.8
WAIC	1443.4
RMSE	0.18

Table 4: Model Results for Year 2021

	Severe Mental Illness
(Intercept)	−2.938
	(0.183)
sexFemale	0.692
	(0.137)
educationNever attended/kindergarten only	−30.726
	(26.950)
educationHigh school	−0.173
	(0.197)
educationGED or equivalent	0.165
	(0.283)
educationSome college	−0.413
	(0.239)
educationBachelor's	−0.806
	(0.224)
educationMaster's	−1.363
	(0.336)
educationDoctoral	−2.755
	(1.120)
Num.Obs.	5000
R2	0.016
Log.Lik.	−943.918
ELPD	−953.4
ELPD s.e.	44.5
LOOIC	1906.7
LOOIC s.e.	89.0
WAIC	1905.2
RMSE	0.21

5 Discussion

5.1 Gender Differences in Depression

Table 3 and Table 4 demonstrate that the odds of being female and having psychological depression are higher compared to males. The findings are consistent both before and after the pandemic.

5.2 Educational Differences

We have not found any notable differences between education and psychological distress. Research indicates a strong connection between emotional well-being and education, as emotional learning is believed to be nurtured within the school environment and through the curriculum (Norwich et al. 2022; Billington et al. 2022).

5.3 Weaknesses and next steps

We randomly selected 5000 samples for our model. We have not used any prediction to find out how good our model is for detecting psychological depression. We also have not conducted any data augmentation to improve our model result. Our next steps are carefully curating the dataset, introducing several data validation techniques, and increasing the sample set.

6 Conclusion

This paper presented an overview of the educational attainment, sex, and psychological distress among participants. By looking at the Kessler 6 Scale for nonspecific psychological distress (K6SUM), we found complex relationships between education, sex, and mental health in the United States for our population. Firstly, the data revealed significant trends in educational attainment, highlighting disparities that exist among different demographic groups. Our constructed variable, EDUC, provided a clear understanding of individuals' highest completed education level through group lumping, which is important for identifying populations at risk of lower socioeconomic status. This knowledge can help inform targeted educational interventions and policies aimed at improving access to higher education, such as increasing funding for scholarships and grants for underrepresented groups, expanding community college programs, implementing outreach initiatives in underserved areas, providing mentorship opportunities, and enhancing financial literacy programs to help prospective students navigate the college application and funding processes.

Appendix

A Additional data details

A.1 Variable Definitions

Variable: "AGE"

Name:	AGE
Label:	Age
Variable Text:	AGE reports the individual's exact age, calculated from date of birth, as of the last day (12/31) of the survey year. Date of birth and age were asked for each reporting unit member, and then exact age was calculated from date of birth. Where the calculated age and the age provided did not match, inconsistencies were reviewed and resolved. When date of birth was not provided, but age was provided, the month and year of birth were assigned randomly from among the possible valid options. For any cases still not accounted, age was imputed using: (1) the mean age difference between MEPS participants with certain family relationships (where available) or (2) the mean age value for MEPS participants.
Concept:	Core Demographic Variables -- PERSON
Start Position:	99
End Position:	101
Width:	3
Variable Format:	numeric
Implied Decimal Places:	0

Coder Instructions:	CodesAGE is a 3-digit-numeric variable. 085: Top code for 85 years or older (2001-forward) 090: Top code for 90 years or older (1996-2000) 996: Missing

Variable: "Sex"

Name:	SEX
Label:	Sex

Variable Text:	SEX indicates whether the person was male or female. Collection of information on SEX in MEPS Data on the sex of each reporting unit (RU) member was determined during the NHIS interview, and was then verified, and, if necessary, corrected during each MEPS interview. If the respondent was a new RU member or their sex was not ascertained in the NHIS interview, MEPS initially used the first name of the respondent to assign their sex. If the first name gave no clear indication of sex, the reported family relationships were used to assign sex. If the sex of the respondent was still unclear, sex was randomly assigned. The NHIS method of ascertaining the sex of the respondent, which primarily informs the MEPS version of SEX, is similar to the MEPS method. First, sex of the respondent was inferred from the individual's first name or family relationships. If the sex of the respondent was unclear, the interviewer was instructed to explicitly ask the person's sex. Beginning in 1998, interviewers were told to ”enter your best guess” when the respondent either did not know or refused to answer the direct question that was asked about the person's sex.
Concept:	Core Demographic Variables -- PERSON
Start Position:	102
End Position:	102
Width:	1
Variable Format:	numeric
Implied Decimal Places:	0
Categories	

Value	Label
1	Male
2	Female
7	Unknown-refused
8	Unknown-not ascertained
9	Unknown-don't know

Variable: “MARSTAT”

Name:	MARSTAT
Label:	Legal marital status
Variable Text:	For persons age 16 and older, MARSTAT reports the person's legal marital status.
Concept:	Core Demographic Variables -- PERSON
Start Position:	103
End Position:	104
Width:	2
Variable Format:	numeric
Implied Decimal Places:	0
Categories	

Value	Label
00	NIU
10	Married
20	Widowed
30	Divorced
40	Separated
50	Never married
99	Unknown marital status

Variable: “RACEA”

Name:	RACEA
Label:	Main Racial Background (Pre-1997 Revised OMB Standards), self-reported or interv
Variable Text:	RACEA reports the race of the respondent. If not ascertained, the race and/or ethn
Concept:	Ethnicity/Nativity Variables -- PERSON
Start Position:	105
End Position:	107
Width:	3

Variable Format: numeric
Implied Decimal Places: 0
Categories

Value	Label
100	White
200	Black/African-American
300	Aleut, Alaskan Native, or American Indian
310	Alaskan Native or American Indian
320	Alaskan Native/Eskimo
330	Aleut
340	American Indian
350	American Indian or Alaskan Native and any other group
400	Asian or Pacific Islander
410	Asian
411	Chinese
412	Filipino
413	Korean
414	Vietnamese
415	Japanese
416	Asian Indian
420	Pacific Islander
421	Hawaiian
422	Samoan
423	Guamanian
430	Other Asian or Pacific Islander
431	Other Asian or Pacific Islander (1992-1995)
432	Other Asian or Pacific Islander (1996)
433	Other Asian or Pacific Islander (1997-1998)
434	Other Asian (1999 forward)
500	Other Race
510	Other Race (1963-1977)
520	Other Race (1978)
530	Other Race (1979-1991)
540	Other Race (1992-1995)
550	Other Race (1996)
560	Other Race (1997-1998)
570	Other Race (1999-2002)
580	Primary Race not releasable
600	Multiple Race, No Primary Race Selected

610	Multiple Race, including Asian, excluding Black and White
611	Multiple Race, including Asian and Black, excluding White
612	Multiple Race, including Asian and White, excluding Black
613	Multiple Race, including Black, excluding Asian and White
614	Multiple Race, including Black and White, excluding Asian
615	Multiple Race, including White, excluding Asian and Black
616	Multiple Race, including Asian, White, and Black
617	Multiple Race, excluding Asian, White, and Black
900	Unknown
970	Unknown-refused
980	Unknown-not ascertained
990	Unknown (1997 forward: Don't know)

Variable: “MARSTAT”

Name:	MARSTAT
Label:	Legal marital status
Variable Text:	For persons age 16 and older, MARSTAT reports the person's legal marital status.
Concept:	Core Demographic Variables -- PERSON
Start Position:	103
End Position:	104
Width:	2
Variable Format:	numeric
Implied Decimal Places:	0
Categories	

Value	Label
00	NIU
10	Married
20	Widowed
30	Divorced
40	Separated
50	Never married
99	Unknown marital status

Variable: “EDUC”

Name:	EDUC

Label:	Educational attainment
Variable Text:	EDUC reports the highest level of schooling an individual had completed, in terms of completed grades for persons with less than a high school degree, and in terms of degrees attained for high school graduates and those with higher education. EDUC is available for all survey participants age 5 and older at the time of their first MEPS interview. It is an IPUMS MEPS constructed variable. See Comparability section for more information on the construction of EDUC. Education Variables offered through IPUMS MEPS In addition to EDUC, there are several other educational attainment variables offered through MEPS. Unlike EDUC, these variables are not available for every MEPS year. EDUCYR: Years of education completed (available 1996-2011 and 2014 forward) HIDEG: Highest degree completed (available 1996-2011 and 2014 forward) EDUYRDG: Years of education and highest degree completed (available 2011-2015) EDRECODE: Years of education, recode (available 2011-2015)
Concept:	Education Variables -- PERSON
Start Position:	108
End Position:	110
Width:	3
Variable Format:	numeric
Implied Decimal Places:	0
Categories	

Value	Label
000	NIU
100	Grade 12 or less, no high school diploma or equivalent
101	Grade 8 or less (no further detail)
102	Never attended/kindergarten only
103	Grades 1-11 (no further detail)
104	Grade 1
105	Grade 2
106	Grade 3
107	Grade 4
108	Grade 5
109	Grade 6
110	Grade 7
111	Grade 8
112	Grade 9-12, no diploma (no further detail)
113	Grade 9
114	Grade 10
115	Grade 11
116	12th grade, no diploma
200	High school diploma or GED
201	High school graduate
202	GED or equivalent
300	Some college, no 4yr degree
301	Some college, no degree
302	AA degree: technical/vocational/occupational
303	AA degree: academic program
400	Bachelor's degree (BA,AB,BS,BBA)
500	Master's, Professional, or Doctoral Degree
501	Master's degree (MA,MS,Med,MBA)
502	Professional (MD,DDS,DVM,JD)
503	Doctoral degree (PhD, EdD)
504	Other degree
505	Professional School or Doctoral degree, topcoded (MD, DDS, DVM, JD, PhD, EdD)
996	No degree, years of education unknown
997	Unknown--refused
998	Unknown--not ascertained
999	Unknown--don't know

Variable: “INCTOT”

Name:	INCTOT

Label:	Total personal income

Variable Text:

INCTOT reports the sum of all person-level income for the current calendar year, excluding income from tax refunds and capital gains.

INCTOT includes annual earnings from wages, salaries, bonuses, tips, commissions; business and farm games and losses; unemployment and workers' compensation; interest and dividends; alimony, child support, and other private cash transfers; private pensions, IRA withdrawals, social security, and veterans payments; supplemental security income and cash welfare payments from public assistance, Temporary Assistance for Needy Families, and related programs; gains or losses from estates, trusts, partnerships, S corporations, rent, and royalties; and a small amount of ”other” income. Person-level income excluded tax refunds and capital gains.

Logical editing or weighted, sequential hot-deck imputation was used to impute income amounts for missing values (both for item non-response and for person in the full-year file who were not in round 3). Reported income components were generally left unedited.

Related Variables
INCWAGE: annual wage and salary income of individuals

INCBUS: annual business income of individuals

INCUNEMP: annual unemployment compensation income of individuals

INCWKCOM: annual workers' compensation income of individuals

INCINT: annual interest income of individuals

INCDIVID: annual dividend income of individuals

INCRETIR: annual pension income of individuals

INCSS: annual social security income of

Concept:	Total Income and Earnings Variables -- PERSON
Start Position:	111
End Position:	119
Width:	9
Variable Format:	numeric
Implied Decimal Places:	2
Coder Instructions:	CodesINCTOT is a 9-digit numeric variable with 2 implied decimals. That is, values of 012345678 should be interpreted as 123456.78. The command files delivered with IPUMS extracts automatically divide INCTOT by 100, so no further adjustment is needed. 9999999.96: Not in Universe 9999999.97: Unknown-refused 9999999.98: Unknown-not ascertained 9999999.99: Unknown-don't know

Variable: “K6SUM”

Name:	K6SUM
Label:	K6 score for nonspecific psychological distress: last 30 days

Variable Text:	For persons eligible for the self-administered questionnaire (SAQELIG), K6SUM is the summed scale value measuring nonspecific psychological distress over a 30-day recall period. This scale, developed by Ronald C. Kessler and known as the Kessler 6 Scale (K6), asks about six manifestations of nonspecific psychological distress. Kessler recommends scoring the scale by assigning 0 to 4 points for each of the six questions, based on the reported frequency of the feelings (i.e., 0 for ”none of the time”; 1 for ”a little of the time”; 2 for ”some of the time”; 3 for ”most of the time”; and 4 for ”all of the time”). The range for summed responses on the K6 Scale is thus 0 to 24, with 0 suggesting the lowest level of nonspecific psychological distress, and 24 suggesting the highest level of nonspecific psychological distress. According to the scoring criteria proposed by Kessler, persons with a score of 13 or greater are likely to be experiencing severe mental illness. Kessler's instrument asks how often, during the past 30 days, the respondent felt: So sad that nothing could cheer you up? (ASAD) Nervous? (ANERVOUS) Restless or fidgety? (ARESTLESS) Hopeless? (AHOPELESS) That everything was an effort? (AEFFORT) Worthless? (AWORTHLESS) As noted above, acceptable responses fell into five categories, ranging from ”none of the time” to ”all of the time.”

Concept:	Adult Mental Health Variables -- PERSON
Start Position:	120
End Position:	121
Width:	2
Variable Format:	numeric
Implied Decimal Places:	0
Categories	

Value	Label
96	NIU
98	Unknown-not ascertained

A.2 Education Recoding

100~"Grade 12 or less", 101~"Grade 12 or less", 102~"Never attended/kindergarten only", 103~"Grade 12 or less", 104~"Grade 12 or less", 105~"Grade 12 or less", 106~"Grade 12 or less", 107~"Grade 12 or less", 108~"Grade 12 or less", 109~"Grade 12 or less", 110~"Grade 12 or less", 111~"Grade 12 or less", 112~"Grade 12 or less", 113~"Grade 12 or less", 114~"Grade 12 or less", 115~"Grade 12 or less", 116~"Grade 12 or less", 200~"High school", 201~"High school", 202~"GED or equivalent", 300~"Some college", 301~"Some college", 302~"AA degree", 303~"AA degree", 400~"Bachelor's", 501~"Master's", 502~"Professional", 503~"Doctoral"

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