The Role of Adverse Physical Health Events on the Utilization of Mental Health Services

Jangho Yoon and Stephanie L. Bernell

Objective. To test the degree to which adverse physical health events may subsequently increase the utilization of mental health services.

Methods. A quasi-experimental pretest–posttest design was employed on a nationally representative sample of adults from the Medical Expenditure Panel Surveys for years 2004 and 2005. We constructed a 2-year balanced-panel dataset on 6,017 U.S. adults who did not have any adverse physical health events in 2004. We calculated difference-in-differences estimators that capture the effect of adverse physical health events on provider visits and prescription drug use for the treatment of mental health conditions.

Principal Findings. Our most rigorous analytic model shows that an adverse physical health event is significantly associated with more than a threefold increase in the likelihood of provider visits and prescribed medication use for the treatment of mental health problems. These increases are mainly through office-based physician visits for nonsevere mental health conditions. This relationship is greater among those who experience more severe physical health events.

Conclusion. An adverse physical health event substantially increases the utilization of mental health care. Mental health service use increases with the severity of a physical health condition.

Key Words. Mental health care utilization, physical and mental health interplay, quasi-experiment, difference-in-differences estimators, propensity scores

When individuals are confronted with a new diagnosis, unexpected hospitalization, major surgery, or other physical health events, a change to their mental health state, either development of new symptoms or worsening of existing conditions, such as feeling anxious or being depressed, may arise for some individuals. These emotional distress or psychiatric disorders may be linked to the uncertainty of health outcomes associated with the new medical event or may be a result of financial strain such as medical bankruptcy, the inability to do everyday tasks without becoming overly tired, or something

else related to the health event such as mediation side effects. It is also possible that with a new health event, untreated mental health problems are simply identified via contacts with the health care system.

To put this association in perspective, a prospective study of 285 patients hospitalized for acute myocardial infarction reports that approximately one-fifth of the patients have major depression, most of whom continue to have depression several months after their initial hospital discharge (Bush et al. 2001). A recent review of psycho-oncology literature finds that about half of all patients with advanced cancer suffer from serious mental health problems, such as depression, anxiety, and adjustment disorders (Miovic and Block 2007). Likewise, co-morbid mental health problems are widespread among HIV-positive patients (Ellis, Collis, and King 1994), and clinical depression is more prevalent among diabetes patient compared with the general population (Egede, Zheng, and Simpson 2002).

Despite the frequent association between physical and mental health in the literature, the extent to which an individual's adverse physical health event actually influences the utilization of mental health services remains unanswered. Understanding this association has implications for patients, acute care physicians, mental health providers, and the health care system as a whole.

Adverse physical health events do not always affect demand for mental health services. Some individuals may not seek out mental health treatment due to stigma (Sussman, Robins, and Earls 1987; Cooper-Patrick et al. 1997; Department of Health, Human Services [DHHS] 1999; Sirey et al. 2001), financial constraints (Wang et al. 2005), and lack of coordination between the physical health and mental health system (Institute of Medicine [IOM] 2001). In addition, the link between physical health events and mental health service use may differ by the severity of the events. For example, Kokkonen, Kokkonen, and Moilanen (2001) report the same prevalence of depressive symptoms in Finnish young adults ages 19–25 who have had chronic health conditions since their childhood and their counterparts who did not, but they also document more serious psychiatric problems for those with more severely disabling conditions.

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The primary purpose of this research is to explore the relationship between adverse physical health events and subsequent utilization of mental health services. Specifically, using a nationally representative sample of adults from the Medical Expenditure Panel Survey for years 2004 and 2005, we empirically examined whether, and to what extent, physical health events would alter use of provider visits and prescription medication for the treatment of mental health problems. Given that such relationship might vary by an individual's heterogeneous experience with physical health events, we also tested the extent to which an individual's perception of severity related to the variation in the use of the mental health services.

METHODS

Difference-in-Differences Model

We estimated a relationship between a physical health event and the use of mental health services via the difference-in-differences approach (henceforth, "DD" model). As we will discuss below, our study sample included persons who reported that they had no important medical condition during the pre-event period (i.e., 2004). Therefore, our DD model compares average changes in mental health care utilization between the pre-event and postevent periods among persons who reported any adverse physical health event in the post-event period (henceforth, physical health event group) to average changes in outcomes between the pre-event and postevent periods among those who did not report any physical health event in either the pre-event or postevent period (henceforth, the reference group).

We estimated the following:

$$\Pr(Y_{it} > 0) = F(PHE_i \times POST_t, PHE_i, POST_t, X_{i,t}, Z_{i,t-1}, \varepsilon_{i,t}) \quad (1)$$

where F is a logit cumulative distribution function. The subscripts i and t index an individual and a year (2004 or 2005), respectively. ε_{it} is a random error component.

Y_{it} refers to one of our main outcomes including provider visits and the use of psychiatric drugs for the treatment of mental conditions. PHE_i refers to a physical health event and $POST_t$ represents the postevent period (i.e., year 2005). Therefore, we controlled for the fixed group effect and pre-post time effect. $PHE_i \times POST_t$ is the interaction term of the physical health event and the postperiod indicator. Its coefficient captures the magnitude of changes in mental health care use from the pre-event period to the postevent period for

the physical health event group, compared with pre-post differences in the outcomes for the reference group.

X_{it} includes time-varying individual characteristics that otherwise would bias the relationship between physical health events and the likelihood of receiving mental health treatment. We controlled for factors that may produce mental health and may also influence mental health care utilization, including demographic and socioeconomic characteristics, a measure of mental health endowed from the preceding period (e.g., initial mental health status at the beginning of each period), smoking status, and insurance status. We also included in X_{it} a measure of initial physical health status to capture the influence that physical health has on mental health.

$Z_{i,t-1}$ includes additional time-invariant individual characteristics for which panel information is not available. We controlled for physical activity and obesity status as well as additional indexes for physical and mental health status available just before or in the beginning of the postevent period.

Fixed-Effects Difference-in-Differences Model

Despite the comprehensive sets of covariates, an estimated effect of an adverse physical health event on mental health care utilization may still be biased if, for example, our measures of initial physical and mental health status insufficiently capture initial physical and mental health endowed from the preceding period. There are also additional sources of bias such as genetic factors that may jointly determine physical and mental health. In this context, it may improve accuracy in our estimates to control for the influence of temporally invariant unobservables. To explore this possibility, we extended the above DD specification and estimated difference-in-differences model with person fixed-effects (henceforth, “DD/Fixed-Effects” model) as follows:

$$\Pr(Y_{it} > 0) = F(PHS_i \times POST_t, POST_t, X_{it}, \mu_i, \varepsilon_{it}), \quad (2)$$

where μ_i is unobserved individual heterogeneity and is included to control for all time-invariant differences between persons. Variables that do not vary over time in equation (1) were not included such as the health event dummy variable (PHE_i) and time-invariant demographic factors in X_{it} (e.g., sex and race/ethnicity) as well as the additional time-invariant pre-event characteristics ($Z_{i,t-1}$).

Propensity-Score Matching

We further extended our models using a propensity-score matching approach. A fundamental assumption in the DD and DD/Fixed-Effects models is that if a person had actually not experienced a physical health event, then the pre-event difference between the two groups serves as a reasonable proxy for the postevent difference. However, our estimates would be biased if, for example, the physical health event heterogeneously influences the pattern of mental health service utilization between the physical health event and reference groups (Heckman, Ichimura, and Todd 1997). In this context, our propensity-score matching extension can increase the accuracy of our estimates because it pairs persons in the physical health event group with counterparts in the reference group with similar baseline observable attributes and thereby eliminates the additional source of bias (Rosenbaum and Rubin 1983).

We obtained propensity scores by estimating a propensity-score model, applied the radius matching algorithm (with a caliper of 0.001), and then repeated our analyses on matched cases. To obtain propensity scores and matched cases, we estimated a propensity-score (probit) model in which the binary physical health event was regressed on pre-event baseline individual characteristics. Covariates included the full set of covariates in the DD model, factors describing pre-event histories of mental health treatment, and measures of access to care and preventive care. All propensity-score models were estimated over regions of common support to avoid a poor-match problem (Heckman, Ichimura, and Todd 1997). Our results are robust to different propensity-score matching techniques. We defer a detailed discussion to the Results section.

Perceived Severity of Adverse Physical Health Events

One of the main purposes of this article is to examine whether the perceived severity of an event alters the pattern of mental health service use. We created two dummy indicators for the severity of a physical health event: “Severe” for being affected very severely and “Moderate” for being affected in a less severe manner. Being unaffected or being affected very little served as the reference category.

We compared the effect of differing severity by including the interaction terms of $PHE \times POST$ and the two severity dummy indicators, “*Severe* $\times$ $PHE \times POST$ ” and “*Moderate* $\times$ $PHE \times POST$ ”. These triple-interaction terms capture the extent to which severely affecting and moderately affecting

physical health events may increase mental health care use, respectively. $PHE \times POST$ now captures the baseline effect of physical health events that were perceived to not affect overall health and well-being.

Estimation

We calculated logit estimators for the models without person fixed-effects. Coefficients on interaction terms in nonlinear models are likely to be misleading because the interaction effect cannot be examined by the sign and magnitude of the coefficient on the interaction term (Ai and Norton 2003). We computed marginal effects in the logit model as the mean interaction effect, which is the average change of predicted probabilities (Norton, Wang, and Ai 2004). Standard errors are based on 1,000 bootstrap repetitions. For the models with person fixed-effects, we estimated the fixed-effect linear probability model for computational tractability.

Data for this study were originally collected using a complex survey design. To obtain unbiased population parameters, we calculated survey-weighted estimators. To make correct statistical inference, standard errors were adjusted for geographical clustering and stratification based on the complex survey design of our dataset. All the analyses were performed in STATA, version 12.1 (Stata Corp., College Station, TX, USA).

DATA

Sample

The sample was derived from the household component of the Medical Expenditure Panel Survey (MEPS) for years 2004 and 2005. Respondents were preliminarily contacted in the beginning of 2004 and were followed by five rounds of interviews (Rounds 1–5) over the 2½-year period. Using information on survey interview dates, we created two-period balanced-panel observations for each person, so that an observation corresponds to either the 2004 or 2005 record for each person.

The main data file was merged with the medical condition files of the MEPS, which provided detailed information on *priority* medical conditions due to their prevalence, treatment costs, and policy relevance. Priority physical conditions include long-term, life-threatening conditions, such as cancer of any kind, ischemic heart disease (including acute myocardial infarction), stroke, HIV/AIDS, diabetes, emphysema, high cholesterol, and

hypertension, and chronic, manageable conditions, such as arthritis, asthma, gall bladder disease, stomach ulcers, and back problems of any type. The priority conditions also include Alzheimer's disease, dementia, depression, and anxiety disorders. See Supplementary Table S1 for the full list of priority conditions.

We excluded 5,693 individuals who reported symptoms for these priority physical and mental health conditions in 2004 from the sample. This allowed us to carry out a quasi-experimental pretest/posttest study where the priority physical conditions may only occur after the pretest period. Children under 18 were also excluded. The final analytic file included 12,034 observations on 6,017 individuals. Supplementary Table S2 reports summary statistics and definitions of variables.

Outcomes

Provider Visit refers to a binary indicator of office-based physician, outpatient department, or emergency room visit that involved mental health treatment. Psychiatric hospitalizations were rarely observed and not included. The other binary outcome measure, Medication, takes the value of 1 if a person purchased prescribed medication for the treatment of mental health problems. Approximately 3 percent of the sample had provider visits and 4 percent purchased prescription drugs for mental health treatment.

Data on mental health service use were retrieved from medical event files of the MEPS and were linked to the main dataset. The event files provided detailed information on health provider visits and prescribed medicines including the types of health care a person received and three-digit ICD-9 codes for each medical event or prescribed medicine. A provider visit was considered mental health treatment (1) if a person received psychotherapy or mental health counseling, (2) if a provider was a psychiatrist or psychologist, or (3) if a provider visit was associated with ICD-9-CM codes 295-316 except sexual deviations and disorders (302) and mental disorders specific to childhood and adolescence (299, 313-315). The same ICD-9 codes were used to identify prescribed drug purchases for mental health treatment.

Physical Health Event

Using ICD-9 codes provided in the medical condition files, we constructed a binary indicator of a physical health event (PHE). The physical health event variable equals 1 if a respondent reported the onset of any of the priority

physical conditions in 2005 and 0 otherwise. One thousand one hundred and six persons (approximately 18 percent of the entire sample) reported at least one priority condition in 2005.

We created binary variables of perceived severity based on answers to the survey question regarding how severely an adverse physical health event affected an individual's overall health and well-being. "Severe" equals 1 if an individual answered "very severely" for at least one physical health event in 2005 (approximately 4 percent of the sample). "Moderate" equals 1 if an individual replied "somewhat severely" for at least one event or did not have any health event that affected health and well-being severely (approximately 7 percent of the sample). The base group consists of persons who answered "not severely" or "not at all" for all physical health events in 2005. Among persons who reported any physical health conditions starting in 2005, about 22 percent had at least one severe physical health event and 31 percent experienced moderately severe events.

Covariates

Demographic and socioeconomic characteristics were extracted from Rounds 1 and 3 of the MEPS, which roughly correspond to the beginning of 2004 and 2005, respectively. These variables included age, sex, race/ethnicity (black, Asian, and Hispanic), marital status (married, widowed, and divorced), level of schooling (high school graduate and college-and-higher education), unemployment status, income levels (poor, low, and middle income), insurance coverage of any kind, perceived poor mental health status, smoking status, metropolitan residence, and geographic census regions.

Additional pre-event baseline characteristics available just before or in the beginning of 2005 included binary measures of smoking, obesity, and physical activity, as well as Physical and Mental Component Summary scores. Physical Component Summary scores are calculated by weighting the physical items of the Short-Form 12 Version 2 (SF-12v2) more heavily, whereas Mental Component Summary scores are calculated by weighting the mental responses to the SF-12v2 more heavily. Greater Physical and Mental Component Summary scores refer, respectively, to better physical and mental health/well-being.

To calculate propensity scores, we included five frequency indicators for mental health treatment in 2004 such as inpatient days, outpatient department visits, office-based physician visits, emergency room visits, and prescription drug use for psychiatric problems. We also included access measures in the

pre-event period, including the use of preventive care and the inability to obtain needed medical care.

RESULTS

Coefficient Estimates from the DD Model

Coefficient estimates from our DD model are reported in Table 1. The coefficient on the interaction term of physical health event and the postperiod indicator ($PHE \times POST$) is our primary interest. This coefficient is positive and statistically significant for both utilization outcomes, suggesting a potentially positive relationship between physical health event and the likelihood of receiving mental health treatment during provider visits and purchasing prescription drugs for mental health treatment.

Results on the covariates are consistent with the literature (e.g., Wells et al. 1982; Watts, Scheffler, and Jewell 1986; Wang et al. 2005). Age negatively relates to the probability of any provider visit. Women are more likely than men to visit providers and purchase medications for mental health treatment. Compared with whites, other races are less likely to obtain mental health treatment. A married person is less likely than a single person to obtain mental health treatment through provider visits. There was a positive association between unemployment status and the probability of obtaining prescription drugs. Having insurance coverage and poorer mental health status also positively relate to an increase in provider visits and prescription drug use. Living in a metropolitan area is positively associated with the probability of provider visits. Having higher Physical and Mental Component Summary scores (i.e., better physical and mental health) is negatively associated with the likelihood of obtaining mental health treatment.

Link between Physical Health Event and Mental Health Care Utilization

The marginal effect of physical health events on mental health care utilization is shown in Table 2. It is the degree to which an adverse physical health event is on average associated with the likelihood of using mental health services.

The first row of Table 2 presents results from the DD model. An adverse physical health event is associated with approximately 2.2 and 2.5 percentage-point increases in the likelihood of provider visits and prescribed drug purchase, respectively. These associations appear to be significant in magnitude. For instance, given that the average probability of provider visits and medication

Table 1: Coefficients from the DD Model

<i>Variable</i>	<i>Provider Visit</i>	<i>Medication</i>
PHE × POST	0.41* (0.19)	0.43* (0.20)
PHE (physical health event)	1.29*** (0.21)	0.88*** (0.25)
POST (year 2005)	−0.01 (0.11)	−0.019 (0.082)
Age	0.23 (0.17)	−0.01 (0.11)
Female	0.34** (0.13)	0.58*** (0.13)
Race/ethnicity		
Asian	−0.02* (0.01)	0.003 (0.006)
Black	−0.49* (0.20)	−0.96*** (0.28)
Hispanic	0.30 (0.18)	0.55*** (0.16)
Marital status		
Married	−0.38* (0.15)	−0.21 (0.17)
Widowed	−1.15* (0.53)	−2.11** (0.73)
Divorced	0.28 (0.21)	0.14 (0.20)
Educational level		
High school	−0.93** (0.32)	−1.08*** (0.32)
≥ College	0.43* (0.20)	0.09 (0.21)
Household income level		
Poor income	−0.13 (0.24)	−0.21 (0.25)
Low income	−0.23 (0.20)	0.02 (0.2)
Middle income	0.004 (0.14)	−0.06 (0.15)
Region		
Northeast	0.20 (0.20)	0.17 (0.24)
South	0.36 (0.22)	0.20 (0.18)
West	0.16 (0.19)	0.19 (0.21)
Metropolitan	0.28 (0.30)	0.32 (0.26)
Unemployed	−0.21 (0.25)	−0.90*** (0.22)
Health insurance	−0.59 (0.66)	−0.19 (0.51)
Smoking status	0.56 (0.31)	0.31 (0.25)
Obesity status	−0.13 (0.13)	0.17 (0.14)
Physical activity	0.20 (0.21)	0.32 (0.17)
Poor mental health	0.70** (0.22)	0.67*** (0.19)
Physical component summary score	−0.0185** (0.0068)	−0.0248*** (0.0069)
Mental component summary score	0.30 (0.29)	0.04 (0.27)
Constant	−0.003 (0.64)	0.23 (0.61)

Notes. PHE × POST = interaction of physical health event and post dummy variables. Reported are survey-weighted results. Standard errors are reported in parentheses and are adjusted for geographical clustering and stratification used in the MEPS survey.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

use for the reference group was 1.6 percent and 2.4 percent in 2004, respectively, the estimates suggest that over a 1-year period an adverse physical health event may be associated with more than a twofold increase in the likelihood of receiving mental health treatment.

Table 2: Role of Adverse Physical Health Event on Provider Visits and Psychiatric Drug Use

<i>Model</i>	<i>Provider Visit</i>	<i>Medication</i>
DD ($N = 12,034$)	0.022* (0.011)	0.025* (0.012)
DD/Fixed-effects ($N = 12,034$)	0.036** (0.014)	0.049*** (0.011)
DD/Propensity-score matching ($N = 10,172$)	0.026* (0.013)	0.025* (0.013)
DD/Fixed-effects/Propensity-score matching ($N = 10,172$)	0.031** (0.014)	0.047*** (0.011)

Notes. DD = difference-in-differences. All estimates are survey-weighted. Standard errors are in parentheses and are adjusted for geographical clustering and stratification used in the MEPS survey. DD/Propensity-Score Matching and DD/Fixed-Effects/Propensity-Score Matching results are based on the radius matching with a caliper of 0.001. Only marginal effects of a physical health event are presented to preserve space (full results are available on request).

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Results from the extended DD/Fixed-Effects model are summarized in the second row of Table 2. Controlling for unobserved individual heterogeneity leads to larger estimates. Having physical health event is associated with 3.6 and 4.9 percentage-point increases in the likelihood of provider visits and prescription drug use, respectively.

We now turn our attention to estimates from the propensity-score matching extension. Before matching, there were moderate to large differences between the physical health event and reference groups on several covariates (see Supplementary Table S3). For instance, the mean age for the pre-event sample (i.e., 2004 observations) is 44 and 37 for the physical health event group and the reference group, respectively. Persons in the physical health event group, on average, are more likely than those in the reference group to be female, widowed, divorced, unemployed, insured, smoking, and obese. The likelihood of reporting poor mental health is greater for the physical health event group (twice as large as that for the reference group). Similarly, the physical health event group has lower Mental and Physical Component Summary scores (i.e., worse mental and physical health/well-being, respectively).

This observed imbalance between the two groups is effectively removed by the propensity-score matching technique. Two-sample t -tests clearly show that the observable characteristics become statistically indistinguishable for the propensity-score matching sample. The matching process dropped 16 percent of the original analytic sample ($N = 10,072$). Full results for the propensity-score model are reported in the Supplementary Table S4.

The marginal effects from the propensity-score matching models reported in the third and fourth rows of Table 2 are almost identical to those from the DD and DD/Fixed-Effects models. DD/Fixed-Effects/Propensity-score Matching results, arguably the most rigorous estimates, show that a physical health event is associated with an increase of 3 and 5 percentage points in the likelihood of provider visits and prescription drug purchase, respectively. These increases correspond to approximately a threefold increase from the pre-event period (2004) for the reference group.

Variation by Perceived Severity

The likelihood of mental health visits and prescription drug use is proportional to the perceived severity of the event (see Table 3). Compared with the event that does not affect or minimally affects perceived health or well-being, a severe event is associated with the approximately 5.2 and 5.6 percentage-point increase in the probability of provider visits and prescription drug use, respectively. There is no observed difference between moderate and unaffacting/minimally affecting events in terms of provider visits for mental health treatment. In contrast, a moderate event is associated with the 5.1 percentage-point increase in the likelihood of prescription drug use as compared with an event that does not influence perceived health or well-being.

Table 3: Role of Adverse Physical Health Event by Perceived Severity: Estimates from the DD/Fixed-Effects/Propensity-Score Matching Model ($N = 10,172$)

<i>Variable</i>	<i>Provider Visit</i>	<i>Medication</i>
Severe $\times$ PHE $\times$ POST	0.052*** (0.014)	0.056*** (0.014)
Moderate $\times$ PHE $\times$ POST	0.017 (0.012)	0.051*** (0.022)

Notes. Severe $\times$ PHE $\times$ POST = triple interaction of severe perception, physical health event and post (year 2005) dummies. Moderate $\times$ PHE $\times$ POST = triple interaction of moderate perception, physical health event, and post dummies. The estimates are survey-weighted. Standard errors are in parentheses and are adjusted for geographical clustering and stratification used in the MEPS survey. Presented are only marginal effects of a physical health event from the DD/Fixed-Effects/Propensity-Score Matching model to focus our attention on the estimates from the most rigorous model and to preserve space. Results from other less rigorous models have the same interpretation as those reported here. Full results are available on request.

*** $p < .001$.

Additional Analyses

In order for our findings to have more useful policy and clinical implications, we extended our analysis in several ways. We examined mental health service use by type of providers, including office-based physician (*OB*), outpatient department (*OP*), and emergency room (*ER*) visits. We also examined provider visits by diagnosis of mental illness, separately for mood disorders (*Mood*) such as depressive disorders and bipolar disorders, anxiety disorders (*Anxiety*), and schizophrenia and other psychotic disorders (*Psycho*).

We found statistically significant and positive marginal effects for office-based physician visits, anxiety disorders, and mood disorders (see Table 4). The DD/Fixed-Effects/Propensity-Score Matching results show that having physical health events is associated with an approximately 3.6 percentage-point increase in the likelihood of receiving mental health treatment from office-based providers. It is also associated with 2.5 and 4.3 percentage-point increases in the likelihood of receiving treatment for anxiety and mood disorders, respectively.

We examined whether a physical health event leads to a decrease in mental health status. We ran regressions using reported mental health status at the end of the pre- and postevent periods. The mental health outcome variable is a five-level ordered categorical variable ranging from 1 (poor) to 5 (excellent). We controlled for the same set of covariates in our main models, excluding initial physical and mental health status. Our propensity-score probit models included the same set of covariates but omitted the pre-event mental health utilization variables. We computed OLS estimators and found that a physical health event is significantly associated with a decrease in reported mental health status (see Supplementary Table S5).

We tested whether our results could be applied to nonfrequent users of the mental health system. If our findings are due mainly to persons experiencing severe psychiatric symptoms such as schizophrenia and bipolar disorders, we cannot easily apply our finding to the general population who do not have these persistent symptoms of mental illness. To explore this potential, we excluded persons with severe mental illness who received diagnoses or reported conditions of *ICD-9* 295-298 in either 2004 or 2005 (60 observations). We also re-estimated the models omitting persons who ever used any mental health services, either through a provider visit or prescription medication, during the pre-event period (1,766 observations). As shown in the first and second rows of Table 5, the results are almost identical to those reported in Table 2.

Table 4: Role of Adverse Physical Health Event by Type of Providers and Diagnosis of Mental Illness: Estimates from the DD/Fixed-Effects/Propensity-Score Matching Model ($N = 10,172$)

Variable	Types of Providers			Types of Mental Disorders Treated		
	Physician	Outpatient	ER	Anxiety	Mood	Psycho
PHE × POST	0.036*** (0.011)	0.0008 (0.0038)	0.0020 (0.0025)	0.0254** (0.0092)	0.0426*** (0.0074)	0.0002 (0.0026)

Notes. PHE $\times$ POST = interaction of physical health event and post (year 2005) dummies. The estimates are survey-weighted. Standard errors are in parentheses and are adjusted for geographic clustering and stratification used in the MEPS survey. Presented are only marginal effects of a physical health event from the DD/Fixed-Effects/Propensity-Score Matching model to focus our attention on the estimates from the most rigorous model and to preserve space. Results from other less rigorous models have the same interpretation as those reported here. Full results are available on request.

** $p < .01$.

*** $p < .001$.

Table 5: Additional Analyses and Robustness: Marginal Effects of Physical Health Event from DD/Fixed-Effects/Propensity-Score Matching Models

<i>Analysis</i>	<i>Provider Visit</i>	<i>Medication</i>
(1) Remove persons with severe mental illness ($N = 10,024$)	0.031* (0.013)	0.037*** (0.013)
(2) Remove persons who ever received mental health treatment in 2004 ($N = 9,962$)	0.055*** (0.010)	0.070*** (0.012)
(3) Remove cancer, ischemic heart disease, stroke, and HIV ($N = 9,942$)	0.033* (0.013)	0.054*** (0.012)
(4) Remove outlying observations ($N = 9,998$ for VISIT; $N = 9,899$ for RX)	0.023* (0.011)	0.023* (0.011)
(5) Different propensity-score methods		
5.1 Nearest neighbor matching		
a. One to one ($N = 4,086$)	0.030* (0.014)	0.050*** (0.013)
b. Five-nearest neighbors ($N = 7,152$)	0.031* (0.013)	0.049*** (0.012)
c. Caliper of 0.001 ($N = 7,004$)	0.029* (0.013)	0.048*** (0.012)
5.2 Kernel weighting		
a. Use normal density function ($N = 12,034$)	0.040*** (0.012)	0.060*** (0.011)
b. Use biweight kernel function ($N = 12,034$)	0.050*** (0.013)	0.062*** (0.011)

Notes. All estimates are survey-weighted except for the propensity-score-weighting estimates. Standard errors are in parentheses and are adjusted for geographical clustering and stratification used in the MEPS survey. Presented are only marginal effects of a physical health event from the DD/Fixed-Effects/Propensity-Score Matching model to focus our attention on the estimates from the most rigorous model and to preserve space. Results from other less rigorous models have the same interpretation as those reported here. Full results are available on request. Each row for different propensity-score methods reports estimates from different matching/weighting algorithms: nearest neighbor matching using one nearest neighbor (5.1.a); nearest neighbor matching using five-nearest neighbors (5.1.b); and nearest neighbor matching using five-nearest neighbors with a caliper of 0.001 (5.1.c), as well as kernel weighting using normal density function (5.2.a) and biweight kernel function (5.2.b).

* $p < .05$.

*** $p < .001$.

We also analyzed whether our results were driven only by certain catastrophic physical health events. We re-estimated our models excluding persons with cancer of any kind, ischemic heart disease, stroke, and HIV for which a strong association with mental health problems has been reported (Ellis, Collis, and King 1994; Bush et al. 2001; Miovic and Block 2007). As shown in the third row of Table 5, dropping these persons (162 observations) did not alter our main results.

We tested whether our main results are robust to the removal of outlying observations on Provider Visit and Medication. We ran OLS using continuous Provider Visit and Medication as dependent variables and calculated the DFITS statistic of Welsch and Kuh (1977). This method guided us to identify influential observations. Following the DFITS criterion in Belsley, Kuh, and

Welsch (1980), we removed 174 observations (about 1.7 percent of the PSM sample) and 273 observations (about 2.7 percent of the PSM sample) for Provider Visit and Medication, respectively. Running the model without the outliers did not change the results (see the fourth row of Table 5).

Finally, we compared our main results to estimates from different propensity-score algorithms. As noted earlier, the propensity-score matching technique involves dropping unmatched cases. We used the radius/caliper matching algorithm to create the propensity-score matching sample because among different matching algorithms, it resulted in the largest matched cases ($N = 10,072$ or 84 percent of the original sample).

We calculated different propensity-score matching estimators, including one-to-one nearest neighbor (greedy) matching, which dropped 7,948 unmatched cases (or 66 percent of the entire 12,034 observations); five-nearest neighbor matching, which deleted 4,882 (or 41 percent) observations; and five-nearest neighbor matching with a caliper of 0.001, which dropped 5,030 (or 42 percent) observations.

We also employed the propensity-score *weighting* analysis and thereby obtained estimates for the entire original analytic sample while benefiting from the spirit of the propensity-score approach. In particular, Frölich (2004) reports that, among other algorithms, kernel procedure produces the most precise estimates for a sample with a large number of control observations, which is the case for this study. We used normal density function and biweight kernel function. As reported in the fifth row of Table 5, our main results are quite robust to the choice of matching techniques.

CONCLUSION

This study presents strong empirical evidence that an adverse physical health event is significantly positively associated with the likelihood of obtaining mental health care. Our estimates suggest that there is a threefold increase in the likelihood of obtaining mental health treatment through office-based physician visits and prescription drugs following an adverse physical event. This finding is likely due in part to the worsening of mental health, not just due to the identification of untreated severe psychiatric symptoms. Additional analyses confirms that our results are not significantly influenced by certain types of catastrophic physical illness, heavy users of mental health services, outlying observations, and different estimation techniques.

The relationship between a physical health event and the utilization of mental health care appears greater for persons who have experienced more severe events. Therefore, our findings recommend closer screening of medical/surgical patients for attending mental health conditions particularly when patients experience higher perceived severity.

It is noteworthy that causal interpretation of our findings might be limited by the lack of randomization. For instance, selection bias may occur when significant mental health conditions lead to physical health events. We attempted to minimize this bias by applying the quasi-experimental methods such as the difference-in-differences and propensity-score methods. The fixed-effects specification was used to further eliminate bias from all unobserved person characteristics that do not change over time (e.g., chronic mental health problems). In the future, exploration of causal mechanisms may help better understand the dynamics between mental and physical health, including the question studied here.

The findings reported here have important implications, particularly for places where the partitioning of physical and mental health care remains the norm. In such places, physical and mental health services are financed separately and are loosely coordinated. As a result, many comorbid conditions may go undetected and untreated, thus increasing the unmet need of care for comorbid physical and mental health problems.

The Affordable Care Act will fundamentally change what services will be available to individuals that have mental health disorders. Various provisions will require benefit packages that include treatment for mental health and substance use disorder services and prescription drugs, among others. Given the significant association between physical health events and associated use of mental health services, our results can serve as a useful benchmark for the delivery of hopefully more coordinated physical and mental health care.

Given that individuals with a physical health event will have multiple contacts with health care providers each year, providers (who may or may not have training in mental illness) are encouraged to screen for potential mental illness and refer patients to the appropriate specialty care. For instance, research has shown that a 16-item substance abuse/mental illness screener (SAMISS), used in a busy clinical setting, is fairly successful in identifying mental illness (Pence et al. 2005). The SAMISS has a 95 percent (95 percent CI: 86–99 percent) sensitivity rate and a 49 percent (95 percent CI: 38–60 percent) specificity rate for mental illness. Although individuals who screen positive require a more rigorous confirmatory psychiatric evaluation, this screening tool can be viewed as the first step to attaining proper mental health treatment and might possibly prevent a spiral to severe mental illness in the future.

Addressing the need for mental health care associated with adverse physical health events may also prevent or reduce secondary conditions. For example, among survivors of a heart attack, post-heart attack depression has been linked to increased morbidity and mortality (Frasure-Smith et al. 1999; Bush et al. 2001; Carney et al. 2003). This underscores the need for proper mental health screening to prevent an exacerbation of physical and mental health problems.

Recent research also suggests that individuals with certain mental health problems are more likely to have positive employment outcomes if they receive early treatment (Berndt 1998; Simon et al. 2000, 2001). For example, adults with major depression, who exhibit clinical improvement associated with treatment, are more likely to maintain paid employment and report fewer days missed from work due to illness (Simon et al. 2000), and there is mounting evidence that as a result of effective mental health treatment, work productivity improvements may even offset the cost of the treatment (Goetzl et al. 2002). Future research that examines the financial and health benefits from integrating and coordinating the delivery and financing of physical and mental health care is clearly warranted.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Table S1. Priority Conditions in MEPS.

Table S2. Summary Statistics and Variable Definition.

Table S3. Comparison of Pre-Event Period (2004) Characteristics before and after Propensity-Score Matching.

Table S4. Probit Propensity-Score Model of Physical Health Event.

Table S5. Effect of Physical Health Event on Reported Mental Health Status, 1 (Poor) to 5 (Excellent): Coefficient on Physical Health Event.

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