MENTAL HEALTH POLICY OUTCOMES: AN EXAMINATION
OF OLDER ADULTS’ MENTAL HEALTH SERVICE USE,
2002-2012

by

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ABSTRACT

The underutilization of mental health services (MHS) by older adults – and especially by racial/ethnic minority elders – is a well-recognized problem. Though several national-level mental health policies have been enacted and implemented over the past decade, rates of underutilization remain high. Guided by the Socio-Ecological Theory of public health policy, we aimed to examine individual- and community-level factors that have fostered the most successful implementations of national mental health policies in recent years.

This dissertation conducted a multilevel growth curve analysis in order to examine older adults’ MHS use using a large, nationally-representative panel survey (the Medical Expenditure Panel Survey – Household Component, or MEPS-HC). We considered MHS use in the MEPS-HC for the period of 2002-2012, during which members of MEPS Panels 6-17 provided responses. This analysis revealed that rates of older adults’ MHS use did not increase significantly over our examination period, regardless of race/ethnicity or rurality of location. Only insurance status was a significant predictor of change in MHS use rates over the years 2002-2012. Our findings highlighted several important issues for policy implementation and future research of MHS use and mental health policy, and we make suggestions for ensuring greater efficiency and efficacy of efforts to improve older adults’ MHS use in the coming decade.
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INTRODUCTION

Untreated mental illness is estimated to cost the United States more than $100 billion annually (Insel, 2008; Pew Charitable Trust, 2015) and adults 60+ account for nearly half that cost (Cameron, 2004), due to their disproportionately low utilization of mental health services (MHS) (Bogner, de Vries, Maulik, & Unützer, 2009; Institute of Medicine, 2012; Karlin, Duffy, & Gleaves, 2008; Klap, Unroe, & Unützer, 2003; Mackenzie, Pagura, & Sareen, 2010; Wang et al., 2005). Statistics like these have prompted some to proclaim that the projected geriatric mental health crisis (Karel, Gatz & Smyer, 2012; Qualls, Segal, Norman, Niederehe, & Gallagher-Thompson, 2002) is at hand (Molinari, 2012).

Prevalence rates for psychiatric illnesses are only marginally lower for older adults than for the general population, with past-year prevalence rates for mood disorders at about 5% for adults 55+, and 12% for anxiety disorders (Byers, Yaffe, Covinsky, Friedman, & Bruce, 2010; see also Administration on Aging [AOA], 2001). Further, research reveals inconsistencies in the rates of mental illness and psychological distress among older adults from different racial/ethnic minority groups (González, Haan, & Hinton, 2001; Kim, Bryant, & Parmelee, 2012; Sorkin, Nguyen, & Ngo-Metzger, 2011; Sorkin, Pham, & Ngo-Metzger, 2009; and U.S. Department of Health and Human Services [USDHHS], 2001). Unfortunately, the underutilization of MHS by older adults is even more pronounced among racial/ethnic minorities (Akincigil et al., 2012; Byers, Arean, & Yaffe, 2012; Neighbors et al., 2008). Recent research into the phenomenon of “frequent mental distress” (or FMD) has revealed rates at around 6.9% for American adults 65+ (Segal, Qualls, & Smyer, 2011) to 7.7% for women 65+ and even higher for racial/ethnic
minority older adults (CDC, 2004). Although they have received some attention, older adults’ mental health and their mental health service (MHS) use remain problematic. This dissertation represents an attempt to identify factors contributing to the failure of previous attempts to achieve rates of MHS use that are proportionate to the prevalence of psychological illness among older adults. We review recent changes in policy and clinical practice intended to address the problem, as well as potential explanations for their shortcomings; first, however, we detail the public health theory which underpins our approach to the topic.

**Theoretical Perspective**

Although research into public health issues has traditionally focused on individual-level determinants of illness and health behaviors, more recent evaluations of health-related public policy have increasingly focused on contextual and environmental factors (DiClemente, Crosby, & Kegler, 2002; Eyler, Chriqui, Russell, & Brownson, 2016). The ecological theories underlying these more recent studies highlight the importance of various levels of factors in a health problem and its solution (Rimer & Glanz, 2005), including not only individual characteristics, but also interpersonal phenomena, community characteristics, environmental factors, and past and current policies at the local, state, and national levels. Specifically, we adopt the Socio-Ecological Model outlined by McLeroy, Bibeau, Steckler, & Glanz (1988), which posits that interventions and efforts targeting the broader levels are likely to have greater impacts on public health than those at the individual level. The Socio-Ecological model also posits that changes in the overall health (or some other characteristic) of a population can interact with the policies enacted to target that same characteristic in such a way that its effects are altered (McLeroy et al., 1988; Richard, Gauvin, & Raine, 2011). Without considering individual, community, population, and policy level factors, it is impossible to evaluate the
public health effects of any one component (see Figure 1, below; Phillips, Morrison, Andersen, & Aday, 1998). If the relevant factors underlying a health behavior phenomenon (in this case, effects of MHS use-targeting policies) are interrelated in such complex ways, it is understandable that there is little consensus among studies focusing on different levels of factors. This is complicated further by the increasingly rapid accumulation and expansion of policy changes relevant to older adults’ MHS use.

Figure 1: The Complex Interrelationships between Levels of Influence on Public Health

Adapted from Moreland Russell, Zwald, & Glissman, 2016, in Eyler, Chriqui, Russell, & Brownson, (Eds.).

Guided by this Socio-Ecological Model, we believe that individual changes (such as those in rates of MHS utilization) will not occur without appropriate changes at the larger social-
environmental level (like public policy). Conversely, large-scale improvements in the behaviors or status of a population cannot be achieved without changes at the individual level, and many factors intervene. Policy dictates the structural organization of service delivery, which in turn affects the success of individual level change – but societal attitudes influence and are influenced by each of these components. This is represented by the relationships between the elements in Figure 1, above. Change (or movement) of any one element cannot occur in isolation. Thus, a close examination of the complex interactions of population characteristics and individual behaviors is necessary for the evaluation of the effects of any public health policy.

**Mental Health Policy**

Attention to the topic of MHS underutilization, broadly, and to patterns of use among older adults specifically, has spurred policy changes aimed at increasing access to services for as many people as possible. We detail the most important of these changes below; these are also depicted in a timeline in Figure 2. As the overwhelming majority of U.S. adults over 65 are Medicare enrollees (Federal Interagency Forum on Aging Related Statistics, 2012), the most relevant policy changes are those affecting Medicare. This national insurance program for older Americans and younger adults with disabilities is administered by the Center for Medicare and Medicaid Services (CMS), a component of the federal government’s Department of Health and Human Services (DHHS). With the passing of the Medicare Improvements for Patients and Providers Act (MIPPA; P.L. 110-275) in 2008, Medicare has begun to cover outpatient mental health services at the same rate at which it covers physical health services (that is, at 80% of the CMS-approved fee for services, while the enrollee is responsible for the remaining 20%) (Center for Medicare and Medicaid Services, 2012). This parity of MHS with physical health services was phased in from its original 50% copayment rate during the years 2010-2014. That is, prior
to 2010, out-of-pocket copayment rates for MHS were 50% for Medicare enrollees. Beginning on January 1, 2010, the copayment rate was reduced to 45% (so that Medicare covered 55% of outpatient MHS). The copayment rate was reduced to 40% in 2012, to 35% in 2013, and the final rate of 20% was effective beginning January 1, 2014. This is the first time in its history that Medicare will have provided mental health care coverage on par with other medical health care services.

Figure 2: Timeline of Mental Health Service-Relevant Events and Policy Changes, 1998 – 2014

Even more recently enacted (2010), the implementation of the Patient Protection and Affordable Care Act (PPACA; P.L. 111-148) will also entail expansion of the types of services and numbers of visits for mental health issues covered by Medicare. For example, enrollees will be eligible for free preventive services, including a yearly depression screening. A subcomponent of the PPACA, the Medicare Shared Savings Program (MSSP), outlines a plan for
the formation of Accountable Care Organizations (ACOs) and incentives for their successful application (PPACA § 3022); ACOs are designed to facilitate increased interprofessional collaboration among health care providers, a change promoted by many researchers and influential professional organizations in recent years to be an effective solution to the underutilization of MHS by older adults (see, for example, APA Presidential Task Force on Integrated Health Care for an Aging Population, 2008; and Zeiss, 2003).

**Structural barriers to policy implementation.** Despite their promise, some barriers to the successful implementation of these legislative provisions are anticipated. For example, Ndumele & Trivedi (2011) point out that managed-care organizations and health insurance providers can limit enrollees’ access to MHS in a variety of ways – many of which are not addressed by existing policies. These can include tactics such as prior authorization, MHS carve-outs, physicians as gatekeepers, and utilization review (Ndumele & Trivedi, 2011). Furthermore, the implementation of MHS-friendly policies will likely meet resistance in the form of high startup costs, political opposition, and difficulties associated with overhauling the infrastructure of existing health service institutions and networks of providers (O’Donnell, Williams, Eisenberg, & Kilbourne, 2013) – especially in areas already low in health care resources. Because rural and low-income areas already have low concentrations of mental health professionals (Ellis, Konrad, Thomas, & Morrissey, 2009), these areas are likely to encounter the most difficulty in implementing mental health policies.

Geographical location has been shown to have a significant impact on the utilization of MHS (Baicker, Chandra, & Skinner, 2005; Kim et al., 2013; New Freedom Commission on Mental Health, 2004) and quality of MHS (as indicated by perceived benefits of and satisfaction with MHS) (Kim, et al., 2014). Specifically in the United States, state of residence can influence
the outcomes of health policies. First, rates of mental illness vary widely by state, and of course these rates correlate to different total numbers of people (USDHHS/SAMHSA, 2017; see Tables 1-2, below).

Table 1: Rates of Mental Illness for Selected States, from the 2014-2015 NSDUH

| Rates of Mental Illness for Selected States, from the 2014-2015 NSDUH (USDHHS/SAMHSA, 2017) |
|----------------------------------|------------------|
| **Any Mental Illness, Adults 18+** |                  |
| Hawaii (lowest among states)     | 15.91%           |
| New Hampshire (highest among states) | 21.67%          |
| Overall U.S. rate                | 18.01%           |
| **Serious Mental Illness, Adults 18+** |                  |
| Maryland (lowest among states)   | 3.05%            |
| New Hampshire (highest among states) | 5.42%           |
| Overall U.S. Rate                | 4.05%            |

(USDHHS/SAMHSA, 2017)

Table 2: Estimated Total Numbers of Persons with Mental Illness for Selected States, from the 2014-2015 NSDUH

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>Any Mental Illness, Adults 18+</strong></td>
<td></td>
</tr>
<tr>
<td>Wyoming (lowest among states)</td>
<td>85,000</td>
</tr>
<tr>
<td>California (highest among states)</td>
<td>4,997,000</td>
</tr>
<tr>
<td>Overall U.S. estimate</td>
<td>43,486,000</td>
</tr>
<tr>
<td><strong>Serious Mental Illness, Adults 18+</strong></td>
<td></td>
</tr>
<tr>
<td>Wyoming (lowest among states)</td>
<td>19,000</td>
</tr>
<tr>
<td>California (highest among states)</td>
<td>1,035,000</td>
</tr>
<tr>
<td>Overall U.S. estimate</td>
<td>9,973,000</td>
</tr>
</tbody>
</table>

(USDHHS/SAMHSA, 2017)
This variation translates to an array of different mental health needs across states, which cannot all be addressed equivalently by blanket federal policies. Although Medicare is a federal program, and Medicaid has a federal component, each state has its own mental health agency (SMHA) responsible for meeting mental health needs of adults and children who would not otherwise have access to mental health care. These SMHAs also provide low-cost community mental health services to those who are covered by Medicare or private insurance. Although federal funds for SMHAs are dependent on some regulations, they are largely free to “set eligibility criteria for SMHA services based on various standards, including severity and duration of mental illness, sickness, insurance status, and income,” (Pew Charitable Trust, 2015).

SMHAs vary widely in their sources of funding and the extent to which they rely on federal funds. The agencies are also situated and organized differently, resulting in vastly different levels of staffing and patients served. Thus, although the national mental health policies described above were enacted for all states, they undoubtedly affect the states’ mental health care infrastructures differentially (SAMHSA, 2011). Further, states were given some freedoms in their implementation of the Patient Protection and Affordable Healthcare Act (ACA), including the extent of Medicaid expansion and cost/availability of insurance plans provided by their state Marketplaces (Cauchi, 2017), resulting in differential outcomes of the ACA by state. Finally, community characteristics (e.g., percentage of the population unemployed or living in poverty) differentially affect the MHS use patterns of racial/ethnic minority adults versus non-Hispanic white adults (Cook, Doksum, Chen, Carle, & Alegria, 2013), and these population densities vary widely even within states.

**Attitudinal barriers to policy implementation.** Beyond these structural and external variables, individual and societal attitudinal barriers to the utilization of MHS may persist,
regardless of increased accessibility. Although some studies indicate that older adults are no less likely than their younger counterparts to endorse stigmatizing views of mental illness (Bechtel, 2007; Kobau & Zack, 2013; Sirey et al., 2001) or to benefit from MHS (Ford, Bryant, & Kim, 2012), attitudes among elders do vary by age (becoming more negative with aging; Webb, Jacobs-Lawson, & Waddell, 2009), by cohort (with older cohorts having more negative attitudes toward mental illness and MHS; Currin et al., 1998), and by race/ethnicity (with African American having more negative attitudes toward mental health issues than White counterparts; Conner et al., 2010; Jimenez, Bartels, Cardenas, & Alegria, 2013). Within the ecological theory framework, attitudes are important at both the individual and community/society levels.

Individual and societal views of mental illness and mental health treatment impact the degree to which a person in need of MHS will perceive a need for those services; and perceived need is one of the strongest predictors of older adults’ MHS use (Karlin, Duffy, & Gleaves, 2008; Mackenzie, Pagura, & Sareen, 2010). Unfortunately, older adults with probable psychiatric diagnoses are much less likely than their younger counterparts to perceive a need for help – 28% of older adults with psychiatric diagnoses as opposed to 49% of younger adults and 43% of middle-aged adults (Klap, Unroe, & Unutzer, 2003). Aside from stigmatization of mental illness, the underlying causes of this lack of perceived need may range from the inability to identify certain symptoms (like boredom, for example) as indicative of serious mental disorders (Yang & Jackson, 1998) to confusion of mental illness symptoms with normal age-related changes (Pettigrew, Donovan, Pescud, Boldy, & Newton, 2010; Quinn, Ladlaw, & Murray, 2009).

Other barriers may prevent older adults from seeking MHS even if they do perceive a personal need; research demonstrates the influences of attitudinal barriers such as the desire to
handle issues independently (Mackenzie, Pagura, & Sareen, 2010) and the stigma attached to mental illness, using MHS, and medications (Pettigrew, Donovan, Pescud, Boldy, & Newton, 2010). Furthermore, upon perceiving a need for MHS, most older adults consult their general practitioners (James & Buttle, 2008), and these medical doctors can sometimes hold the same stereotypes or implicit biases as the older adults themselves. For example, Teasdale and Hill (2006) demonstrated ageist trends in doctors’ patient preferences which may affect the amount of time and effort they put into identifying and treating mental illness in their patients. Further, research by Callahan (2001) has shown that the mental health treatments general practitioners (GPs) provide their patients is largely ineffective. As many as 30% of depressed elders showed no improvement in response to treatment from their regular medical doctors.

As suggested by the ecological theory we have adopted (McLeroy, Bibeau, Steckler, & Glanz, 1988; Phillips, Morrison, Andersen, & Aday, 1998; Richard, Gauvin, & Raine, 2011), the attitudes of older adults and the practices of health professionals are likely interrelated. This phenomenon is demonstrated in a study by Tai-Seale et al. (2005), which revealed that GPs may be unlikely to assess for mental illness in their appointments with older adult patients (as they were for depression, here) when their primary concerns are for physical health (see also Harman, Edlund, Fortney, & Kallas, 2005). Perhaps because older adults are less likely to breach the topic with their GPs themselves, these doctors are less likely to refer older patients they suspect of mental illness to appropriate MHS than younger patients (Alvidrez & Arean, 2002).

**Previous research on policy implementation.** Some research has identified specific barriers to the successful implementation of MHS-targeting policies. For example, Ndumele and Trivedi (2011) identified a subset of Medicare plans which decreased enrollees’ copayment amounts for outpatient MHS, and examined these cost-sharing changes on the enrollees’ rates of
MHS utilization. They found that, overall, Medicare enrollees’ MHS utilization rates did not change substantially even when copayment amounts were reduced by 25% or more; however, for Black enrollees, the increased cost-sharing did have a positive effect. Similarly, in an examination of health service use data in the state of Iowa (with one of the highest older adult population concentrations in the United States), Kaskie & Szcecei (2011) demonstrated the degree to which contextual variables may influence quality of care. In their study, living in a more rural location or a community with a higher density of older adults was associated with lower likelihood of receiving a primary psychiatric diagnosis; among those who did receive such diagnoses, the use of specialty MHS was significantly less likely in rural counties and in those with fewer available MHS providers. These disparate results, focusing on highly specific samples, simultaneously highlight the need for a comprehensive examination of large-scale policy changes and the potential for variability in the effects of those policies across differing populations and locations.

**Purpose of the Study**

As described above, there is a great need for further research on the large-scale effects of recent Medicare policy changes. The current study addresses this need by utilizing several years of panel data from a large, nationally representative dataset (the Medical Expenditure Panel Survey, or MEPS) to examine variations in older adults’ MHS utilization over the course of the past half-decade of policy development and implementation. We utilized multilevel modeling to allow for the examination of the relationships between potentially influential factors as the various levels outlined by the Socio-Ecological theory of public health, as well as these factors’ main and interactive effects on the policy-influenced MHS utilization rates (see Figure 3, below). These analyses yielded a comprehensive picture of the large-scale changes in MHS
utilization that occurred over the course of implementation of various mental health policies, including facilitating and interfering factors.

Figure 3: Levels of Socio-Ecological Public Health Theory as Addressed in this Dissertation

Research Questions and Hypotheses

We hypothesized that contextual variables, such as a county’s rurality, would significantly impact the degree to which mental health policies have increased older adults’ MHS utilization. Further, we hypothesized that these effects operated differentially on non-Hispanic White versus racial/ethnic minority older adults. Based on previous research and our theoretical approach, we proposed to examine the following research questions, and anticipated the following outcomes:
Research Question 1: Did MHS use by older adults change over the course of the implementation of mental health parity policies during 2002-2012? Improving rates of service utilization and decreasing rates of unmet mental health need among older adults were goals of many of the policy changes that have been made over the past several years. It is important to evaluate, on a large scale, whether these goals have been met.

Hypothesis 1:

H₁: The rate of MHS use among older adults in the U.S. will have a significant, positive relationship with time over the years of 2002-2012.

H₀: There will be no significant positive relationship between MHS use and time for the years 2002-2012.

Research Question 2: How does rural versus suburban/urban location influence the effects of mental health policies on older adults’ MHS use over the period in question? Rural disparities in mental health were highlighted early in the period of interest; however, on a relatively small scale (the state of Iowa; Kaskie & Szsecei, 2011), researchers have demonstrated less success in the implementation of policies to improve older adults’ MHS use in rural areas. Thus, it is likely that any positive effects of the various recent MHS policies on the national level will be stunted in rural areas.

Hypothesis 2:

H₁: When rates of change in MHS utilization in rural counties are compared with those in urban and suburban counties, the rates of change in MHS utilization among older adults in rural counties will be significantly smaller (less positive) than those in urban and suburban counties.
H₀: There will be no significant differences between the rates of change in older adults’ MHS utilization in rural and urban or suburban counties.

Research Question 3: Do the changes in mental health policy over the period of 2002-2012 have different effects on the MHS utilization of racial/ethnic minority older adults than on the MHS utilization of non-Hispanic white older adults? Previous examinations of Medicare’s MHS-copay policies’ effects have demonstrated exaggerated improvements in minorities’ MHS use rates when compared to their White counterparts (Ndumele & Trivedi, 2011). However, to our knowledge, no such investigation has been conducted on a national scale, aiming to capture the effects of multiple policy and societal changes over a number of years.

Hypothesis 3:

H₁: Rates of change in MHS use over the period 2002-2012 among racial/ethnic minority older adults will be significantly greater than rates of change among non-Hispanic whites.

H₀: There will be no significant differences in the rates of change in MHS utilization between racial/ethnic minority and non-Hispanic white older adults.

Research Question 4: Do the effects of living in a rural county differ for racial/ethnic minority older adults versus non-Hispanic white older adults?

Hypothesis 4:

H₁: There will be a significant interaction effect of county rurality and racial/ethnic minority status, such that the effect of living in a rural county functions differentially for racial/ethnic minority older adults compared to non-Hispanic whites.
H₀: There will be no significant interaction of county rurality and racial/ethnic status.

We do not make any specific hypotheses about mental health service use rates as they vary by U.S. State, but will include this information in our analyses as an exploratory factor.
METHODS

Dataset

Data were drawn from the Medical Expenditure Panel Survey – Household Component (MEPS-HC), and merged with data from the U.S. Census Bureau. MEPS-HC is a nationally representative survey of the noninstitutionalized U.S. population that aims to provide representative information about the nation’s level and distribution of health care expenditures and utilization, as well as users’ sources of payment and insurance coverage. It is cosponsored by the National Center for Health Statistics (NCHS) and the Agency for Health Care Policy and Research (AHCPR) and its sample frame is drawn from the NCHS’s National Health Interview Survey (NHIS). The NHIS collects data from a nationally representative sample of households, oversampling Hispanic and African American persons. From the NHIS’s data pool, a subset of households are chosen to participate in the MEPS-HC. These data provided individual-level variables for our analyses, including individuals’ health status, demographic information, sources of funding for health care, and MHS utilization. Access to the restricted MEPS-HC data files allowed us to use Federal Information Processing Standard (FIPS) codes for participants’ main county of residence in order to link them to the appropriate community level variables, provided by the U.S. Census Bureau. To investigate changes in MHS use in response to various policy changes, we compared data for the years 2002 to 2012; in these years, data were collected from Panels 6-17 within the MEPS-HC surveys.

Panel design. The panel design of the MEPS-HC data creates a quasi-longitudinal data set that allows for the examination of both small- and large-scale changes over time. The panel
survey is conducted in five rounds, with each panel’s collection period spanning approximately 2 1/2 years. A new panel is selected each year, so that two panels are being surveyed simultaneously. The data for any given year or data collection round represent a unique combination of new, first-year respondents and returning second-year respondents. Considering all rounds of data collected during the years 2002-2012, there are 33 unique data collection points. Further, although similar sampling techniques are used to recruit each cohort, and similar questionnaires administered across time points and cohorts, the data for a single individual can be tracked only for about 2 1/2 years. The panel design is depicted below in *Figure 4*.

Figure 4: Illustration of MEPS Panel Design

Sample

Mental health need. We were primarily interested in the unmet need for mental health services. Thus, we restricted our analyses to those with an apparent need for mental health care, as indicated by a self-reported or physician-reported psychiatric diagnosis. Previous studies (Cook et al., 2014; Zuvekas, 2001), have included diagnoses with ICD-9 codes 291, 292, or 295-314. However, the MEPS datasets offer a more inclusive variable. That is, based on the Clinical Classification Codes outlined by Elixhauser and colleagues (1998), the 14,000+ ICD-9 clinical codes and V-codes were collapsed into 260 clinically meaningful, mutually exclusive categories. This categorization was used for all of the panels included in the present analyses. Of the 260 categories, we considered Clinical Classification Codes 65-75 to be indicative of probable need for mental health services. Full documentation of the included ICD-9 clinical codes and V-codes is available from the AHRQ website.

Age and cohort effects. We were interested in examining patterns of MHS use by older adults with mental health need, and thus chose to include only responses from participants who were age 65 or older at the time their data was collected. An individual participant’s MHS use pattern could only be observed over the course of 2 ½ years, which is not a sufficient sample of time to examine the effects of the aging process on MHS use. However, due to the quasi-longitudinal nature of our data, we were able to pool data across participants who were born in the same year, but participated in MEPS at varying points over the course of 2002-2012. Further, with the addition of each new panel, a new cohort of older adults was sampled (those crossing the minimum age threshold, age 65). This design lent itself to answering both cross-sectional (Are there any differences between 65-year-olds’ MHS use in 2002 and 65-year-olds’ MHS use in 2012?) and longitudinal questions (How did patterns of MHS use change among
those who were age 65 in 2002 as they aged?), achieved by examining the fixed and random effects of our age variable (see Data Analysis section, below).

Measures

Dependent variable. In accordance with previous research, the main outcome variable of interest will be the percentage of participants with mental health need who used any MHS in the given time period (see Alegria et al., 2008; Alegria et al., 2007; Cook, McGuire, & Miranda, 2007; Wang et al., 2007), where MHS use is defined as one or more visits to an MHS provider or one or more visits to another health care professional primarily for treatment for a psychological problem in a given year. As others utilizing MEPS-HC data have done (Cook, et al., 2014; Cook, McGuire, & Miranda, 2007), we will define “visits to an MHS provider” as reported visits to a counselor, psychiatrist, psychologist, or social worker, or stays in inpatient psychiatric facilities. Because physicians and other health care professionals provide information to supplement patient responses to the MEPS-HC, visits to other types of providers will be counted as use of MHS if the primary diagnosis under which the visit was classified was a behavioral health condition or mental/psychological illness. In our variable, having made any visit to a MHS provider or any visit to another health care professional attributable to a psychological problem (as defined above) in the past 12 months will be designated “Yes (used services).” Reports of no such health service visits will be designated “No (did not use services).” The percentage of “Yes” responses will be compared across time, racial/ethnic group, and level of rurality.

Individual level independent variables. At the individual level, we controlled for various demographic available in the MEPS-HC data. Covariates of interest included participants’ self-reported sex reported at birth (male or female), birth year, age at the time of the
data collection period (measured in years), health insurance status (covered by any health insurance plan during the data collection period or not covered), race/ethnicity (non-Hispanic White, Black/African American, Hispanic/Latino, Asian, Native American/American Indian, Native Hawaiian/Pacific Islander, and multiple races), and poverty status. Poverty status was a categorical variable developed by MEPS by dividing a participant’s household income by the corresponding poverty line for the participant’s household size and year of data collection. Categories included “poor” (household income less than 100% of poverty line); “near poor” (household income = 100% to less than 125% of poverty line); “low income” (household income = 125% to less than 200% of poverty line); “middle income” (household income = 200% to less than 400% of poverty line); and “high income” (household income greater than 400% of poverty line).

**Contextual level independent variables.** Participants’ state of residence during the data collection period was of interest to us. However, MEPS only provides location information for those participants from the states with the 29 greatest response rates, in order to protect confidentiality. Other states are distinguished, but labeled with encrypted codes. As such, we included only participants from those top 29 states in our analyses. The states included and number of responses per state in our sample are detailed below, in Table 3.

Rurality of participants’ counties of residence were also of interest. These were determined by using the Rural/Urban Continuum Code (RUCC) assigned to each county in 2003 by the Economic Research Service, Department of Agriculture (USDHHS, 2010). On this continuum, counties are assigned a number, 01-09, with higher numbers generally denoting a higher level of rurality. This coding scheme accounts not only for population size and density of a county, but also for the county’s adjacency to a metropolitan area.
Table 3: Observations by State, Including Those with and without Objective Need

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</table>

| TOTALS | 2283 | 3274 | 3537 | 3224 | 3460 | 3786 | 2738 | 3483 | 3610 | 3238 | 5794 | 38427 |

For our analyses, we followed the convention of previous studies (see Hall, Kaufmann, & Ricketts, 2006) and grouped counties into three categories according to their RUCC: Counties with a code of 01-03 were classified as “urban,” counties with a code of 04-06 were classified as “suburban,” and counties with a code of 07-09 were classified as “rural.” We were not allowed access to the actual FIPS codes, so we were forced to link our rurality variable to subjects within states. This means that some counties will be grouped together in terms of the examination of their unique effects on rates of change in MHS over the period in question, but we believed that
this information, coupled with state identity, would provide useful information. That is, rural counties in Alabama are likely to be similar enough in their effects on rates of change in MHS use that they could be considered a coherent group – as are urban counties in Alabama. Rural counties in California will be collapsed, yet considered their own unique group, as will urban counties in California (and so on, for each individual state).

Data Analyses

**Power analysis.** Power analyses were conducted prior to our accessing the MEPS data using G*Power software (Faul, Erdfelder, Lang, & Buchner, 2007). Power to detect effects at one level of a multilevel model is distinct from the power at other levels. At the lowest level, we aimed to detect change in rates of MHS use across 11 time points (once each year, 2002-2012). Given our sample size of \( n = 8,416 \) (4,673 individuals, sampled on multiple occasions) and alpha level of \( \alpha = 0.01 \), our prospective power analysis indicated that power to detect effects of small size across 11 time points is 0.999.

**Data access and data manipulation.** Once the application for access to restricted MEPS data was approved, data were accessed at the AHRQ Data Center in Rockville Maryland on two occasions for data set-up and preparation. We were provided with 9 separate files for each year of data we requested from the MEPS. For each year of the survey, we were provided one file with public use data (basic demographics), two with information about participants’ medical conditions, and six with information about participants’ different types of health service utilization. Each of these separate files were merged by participants’ unique subject ID codes, such that any reported instance of health service utilization could be attributed to a specific diagnosis, and participants had one observation in the dataset for every reported instance of service utilization (maximum number of observations per participant was 103). Next, we
merged all eleven years of data on demographics, conditions, and service use together. This resulted in a “stacked” master dataset with multiple observations per participant (one for each data collection round during which the participant provided responses).

Additionally, we were provided with the Area Resource File dataset that listed information about each participant’s county of residence (aside from the actual county’s FIPS code). This dataset was merged with our master file (again, by participants’ subject ID codes), so that every observation for every participant contained their collection-period-relevant geographical information. Due to the importance of state of residence to our results’ interpretation, we limited our sample to only those with identified (non-encrypted) state names.

Next, the full sample was limited to only those responses for which the subject was at least 65 years old at the time the data was collected. Finally, we further limited our sample to include only those participants who had an objective need for MHS, as indicated by at least one self- or provider-reported mental health-related diagnosis (see Mental Health Need section, above), although the full older adult sample from the previous step was retained, to allow for descriptive comparisons between those who needed services and those who did not.

Once our data was properly set up at the AHRQ Data Center, subsequent analyses were conducted remotely by emailing statistical programs to the Data Center representative, who returned logs and output files via email. All data preparation and analyses were conducted using SAS version 9.4© (2013).

**Descriptive analyses.** We performed descriptive analyses to examine differences between our selected subsample (older adults with an objective need for MHS, as discussed above), and the full sample of older adults with identified states. Then, we performed descriptive analyses on the subsample of those with objective need to examine differences between those
who used any MHS during the relevant period and those who did not use any MHS. Comparisons of the continuous variable (age) were made using simple t-tests, and comparisons of the categorical variables (state of residence, racial/ethnic category, sex, insurance status, level of poverty, and rural/urban category) were made using chi-squared tests. All statistical comparisons were made using SAS 9.4. We also plotted the rates of MHS use (percent of those with objective need who DID use any services) by state, racial/ethnic category, and level of rurality in order to visually examine basic time trends and group differences. Plots were created using Microsoft Excel.

**Main analyses.** A multilevel growth curve analysis was utilized to analyze these data, which allowed for the examination of the complex relationships among variables at the individual and contextual levels across time. Growth curve analysis uses time as the primary predictor, but takes into account the inevitable correlations of observations across time that are collected from a single respondent (Garson, 2013; and Hoffman, 2015). Data for our outcome variable (any past-year MHS use) were collected annually, resulting in 11 distinct time points – one each year, for the years 2002-2012. Most individuals provided responses for two consecutive years sometime within that time frame (with Panel 7 participants providing responses once in 2002 and once in 2003; Panel 8 respondents once in 2003 and once in 2004; and so on). A single respondent’s past-year MHS use is unlikely to vary substantially from one year to the next, and growth curve modeling controls for such patterns, allowing for more accurate estimations of population-wide time trends (Wang, Xie, & Fisher, 2011). Further, multilevel growth curve modeling allows for the consideration of outcome dependency at even higher levels; for example, respondents who live in a similar geographical region (and, presumably, have access to similar resources) are more likely to have similar rates of MHS use.
than respondents from two completely different locations. In order to take advantage of multilevel growth curve modeling’s ability to handle nested data, our data will be organized conceptually as depicted in Figure 5, below.

Figure 5: Nesting Structure of Multilevel Model for Mental Health Service Use over the Period of 2002-2012: Measurement Occasions within Persons within States

The main analysis consisted of two major steps. The first (model fitting) addressed Hypothesis 1, examining the relationship of the primary outcome (past-year MHS use) with the primary predictor (year). This is analogous to “fitting a line to the data” in regression analyses.

The second step (predictor testing) addressed Hypotheses 2-4. This allowed for the addition of one predictor at a time to the base model (established in the previous step), and tested whether “fitting separate lines” for the data, based on predictor values (e.g., rural vs. urban counties) results in a better fit than using one line for the entire sample. These steps are described in further detail below.
Our analyses were somewhat complicated by the binary nature of the outcome variable (any MHS use during the period for which the participant had an objective need – “yes” or “no”). This means our outcome was not normally distributed, which is an underlying assumption of many common statistical processes, including most forms of multilevel modeling. In order to overcome this barrier, we utilized a generalized linear mixed model via the PROC GLIMMIX procedure (SAS Institute, 2013), which was able to account for the Bernoulli distribution of our outcome variable. Additionally, we were able to model linear relationships between our outcome and predictor variables by transforming the outcome via a logit-transformed identity link function. For all multilevel analyses, we utilized the restricted maximum pseudo-likelihood estimation method. Although this method has received some criticism in the recent longitudinal MLM literature (Hoffman, 2015), others have endorsed it (Garson, 2013; Littell, Milliken, Stroup, Wolfinger, & Schabenberger, 2006; Wang, Xie, & Fisher, 2011), and it reduced computer processing time for each analysis from 70-110 hours to 15-30 hours. Other options specified for all PROC GLIMMIX analyses included the between-within method for computing denominator-degrees of freedom for fixed effects, and the ridge-stabilized Newton Ralphson algorithm optimization technique for parameter estimation, which is recommended for binomial outcome distributions (Wang, Xie, & Fisher, 2011).

Further, in multilevel modeling, nested models are usually compared to one another via various fit statistics, including a deviance statistic called the -2 Log Likelihood (-2LL), which is essentially a measure of badness-of-fit. As significant predictors are added to the model and appropriately explain some of the variance in the outcome, the -2LL is significantly reduced, indicating a better fit, while the addition of non-significant predictors results in little change in the -2LL. Computation of the -2LL is based on the assumption that the outcome variable is
continuous. For models with binary outcomes, a deviance statistic called the -2 Residual Log Pseudo-likelihood (abbreviated -2RLL here, for clarity) is computed instead. Due to the non-normal distribution of our binary outcome variable, however, residual variances at the lowest level cannot be estimated, so the -2RLL is computed by fixing residual variance to a known value ($\pi^2/3$, or 3.29) across all models (Hoffman, 2015; Wang, Xie, & Fisher, 2011). As a result, adding random effects to a model cannot reduce its residual variance or its -2RLL (although adding fixed effects to the model may reduce -2RLL). Thus, for binary-outcome MLMs, we can assess the appropriateness of our hypothesized random effects in two ways. First, if the addition of a random effect to the model does not result in a significant increase in the -2RLL, this indicates that the model with random effects is not a significantly worse fit, and can be adopted for subsequent steps. Second, the intra-class correlation coefficient (or ICC) for a model can be used to evaluate the extent to which a particular random effect explains the variance in the outcome variable. For binary-outcome MLMs, SAS does not provide intra-class correlation coefficients (or ICCs) for comparison between different models. However, similarly to the -2RLL, the ICC for logit-transformed binary outcome data can be estimated by assuming that the residual variance for the logit of the outcome variable is $\pi^2/3$, or 3.29 (Hoffman, 2015; Wang, Xie, & Fisher, 2011). This value can be substituted into ICC calculations, such that

$$
\text{Logistic ICC} = \frac{(\text{group variance})}{(\text{group variance} + 3.29)}
$$

We hand-calculated the logistic ICC for model comparisons in our analyses.

**Model fitting.** The first step of our main analysis comprised fitting a base or “null” model for the data that characterized the overall pattern of MHS use in our sample of older adults with mental health need. As we made no specific hypotheses concerning state of residence and our demographic covariates (age at time of observation, birth year, sex, insurance status, and
poverty status), these variables were included as fixed effects in our null model. Our goals for this step were to identify which variables affected the model for the means and which affected the model for the variance; and to simplify the null model by removing non-influential covariates. The effects were evaluated by consulting the “Solutions for Fixed Effects” and “Test of Covariance Parameters” tables produced by the SAS PROC GLIMMIX procedure. Those that were non-significant were removed, and the null model was re-run. This pared-down null model and its fit statistics (specifically, the logistic ICC and the -2 residual log pseudo-likelihood, or -2RLL) were used for all subsequent model comparisons.

Next, to test Hypothesis 1, we included the variable “Year” in our model, in order to examine its effect on the model for the means of MHS use in our sample. This allowed us to fit a single line to the data to represent the change in MHS use over time. Then, in a subsequent step, we examined the effect of “Year” on the model for the variance. This allowed us to determine whether separate lines should be fitted for MHS use over time for each individual and for each state, and (if so) whether these lines should be allowed to vary by their intercepts, slopes, or both. Together, these models provided us with an understanding of the linear relationship between time and MHS use, as well as the ways in which this relationship varied in response to the other factors retained in our model. The effects of time were evaluated by consulting the “Solutions for Fixed Effects” and “Test of Covariance Parameters” tables for each new model, and by comparing the fit statistics of these new models to those of the null model (specifically, examining the increase in -2RLL, or -2ΔRLL, over the null model).

**Predictor testing.** Once the effects of time were appropriately accounted for, we could begin to examine our variables of interest (race/ethnicity and rurality) and their effects on the relationship of time with MHS. To test Hypothesis 2, we examined the effects of rurality by
adding our categorized rural-urban code into the model for the means and then the model for the variances from the previous step, evaluated the resulting statistics and compared the model fit to the previous model. The same process was followed for Hypothesis 3 by including racial/ethnic category in the model for the means and model for the variances in separate steps. Again after consulting the SAS procedure’s output tables and comparing the models’ fit statistics to those of the previous model, we retained only those terms which had a significant effect on the relationship of time with MHS use.

Finally, for Hypothesis 4, an interaction term of rurality by race/ethnicity was added into the model, in separate steps for the model for the means and the model for the variance. Significance of these terms and the -2ΔRLL were considered, and non-influential terms were removed, leaving us with our final model for MHS use over time with relevant determinants.
RESULTS

Descriptive Analyses

Racial/Ethnic composition of sample. Pooling the data from the selected Panels (Panels 6-17) allowed for a total sample of \( n=38,427 \) older adults whose data could be examined across the period of 2002-2012, though of these, only \( n=8,416 \) had an objective need for MHS. The racial/ethnic breakdown of the full sample (those with and without need for MHS) was as follows: non-Hispanic whites, \( n=24,717 \); Blacks, \( n=6,332 \); Hispanic/Latinos, \( n=5,041 \); and Asians, \( n=1,706 \). As sample sizes for American Indians/Alaska Natives (AI/ANs), Native Hawaiians/Pacific Islanders (NH/PIs), and those identifying as Multiple-race were too small to make generalizable observations about each of those groups, we have collapsed these participants into a racial/ethnic category “Other” \( (n=628) \). Three observations had missing values for race/ethnicity from the full sample. For those with an objective need for MHS, the breakdown was as follows: non-Hispanic whites, \( n=5,716 \); Blacks, \( n=1,156 \); Hispanic/Latinos, \( n=1,172 \); Asians, \( n=199 \); and “Other” race, \( n=173 \). There were no missing values for the race/ethnicity variable among those with an objective need for MHS.

Other demographics and objective need for mental health services. The overall demographic breakdown of our sample and descriptive comparisons of those with and without objective need are both summarized below, in Table 4. There were significant differences between those with and without mental health needs on several of the variables tested. Those who needed MHS were likely to be significantly older (born in late 1931 versus 1933; \( t=10.670; p<0.0001 \)). However, it should be noted that although this difference amounts to statistical
significance, this difference in birth year does not relate to practically different cohorts of older adults. Other variables showed more practical significance. Our total sample was 58.16% female. Of the 22,347 females, 25.75% had objective need for mental health services, while only 16.55% of the 16,077 males had objective need for MHS ($\chi^2=462.789; p<0.0001$). The majority of respondents were insured (97.94%). Of insured respondents, 22.13% needed MHS, while only 11.01% of the uninsured reported a need ($\chi^2=55.923; p<0.0001$). Our sample was distributed across income levels as follows: 9,313 respondents, or 24.24% of the sample, fell into the “poor” category; 3,505 respondents, or 9.12%, were “near poor”; 7,732 or 20.12% had “low income”; 10,085 or 26.25% had “middle income”; and 7,789, or 20.27% had “high income”. Higher levels of poverty were associated with increased likelihood of needing MHS. Among the “poor” group, 26.05% needed MHS, compared to 24.59% of the “near poor”, 23.05% of those with low income, 20.01% of those with middle income, and 17.05% of those with high income (across-groups $\chi^2=242.747; p<0.0001$).

Our sample was mostly urban (81.82%), with 14.63% of respondents living in suburban counties and 3.55% living in rural counties. Differences in objective need for MHS according to county rurality were statistically significant, with 21.56% of those living in urban counties needing MHS, compared to 23.64% of those in suburban counties and 22.73% of those in rural counties. Finally, there were significant differences in objective need for MHS among the various racial/ethnic categories. The proportion of respondents who had objective need for MHS for each group is as follows: 23.13% of non-Hispanic Whites, 18.26% of Blacks/African Americans, 23.25% of Hispanics/Latinos, 11.66% of Asians, and 27.55% of all others, including AI/AN, NH/PI, and multi-racial respondents (across-groups $\chi^2=192.411; p<0.0001$).
Table 4: Differences among Participants with and without Objective Need for Mental Health Services, from the Full Available Sample of Older Adults with Identified States

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Proportion of Total Sample (n=38,424) % or M±SD</th>
<th>Proportion of Group who Needed MHS (n=8,416) % or M±SD</th>
<th>$\chi^2$ or ($t$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birth Year</td>
<td>1933.05 ± 7.440</td>
<td>1931.9 ± 7.781</td>
<td>(10.670)***</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td>462.789***</td>
</tr>
<tr>
<td>Female</td>
<td>58.16%</td>
<td>25.75%</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>41.84%</td>
<td>16.55%</td>
<td></td>
</tr>
<tr>
<td>Insurance Status</td>
<td></td>
<td></td>
<td>55.923***</td>
</tr>
<tr>
<td>Insured</td>
<td>97.94%</td>
<td>22.13%</td>
<td></td>
</tr>
<tr>
<td>Uninsured</td>
<td>2.06%</td>
<td>11.01%</td>
<td></td>
</tr>
<tr>
<td>Poverty Category</td>
<td></td>
<td></td>
<td>242.747***</td>
</tr>
<tr>
<td>Poor</td>
<td>24.24%</td>
<td>26.05%</td>
<td></td>
</tr>
<tr>
<td>Near Poor</td>
<td>9.12%</td>
<td>24.59%</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>20.12%</td>
<td>23.05%</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>26.25%</td>
<td>20.01%</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>20.27%</td>
<td>17.05%</td>
<td></td>
</tr>
<tr>
<td>Rural/Urban Category</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>81.82%</td>
<td>21.56%</td>
<td>12.709*</td>
</tr>
<tr>
<td>Suburban</td>
<td>14.63%</td>
<td>23.64%</td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>3.55%</td>
<td>22.73%</td>
<td></td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td></td>
<td></td>
<td>192.411***</td>
</tr>
<tr>
<td>Non-Hisp. White</td>
<td>64.33%</td>
<td>23.13%</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>16.48%</td>
<td>18.26%</td>
<td></td>
</tr>
<tr>
<td>Hisp./Latino</td>
<td>13.12%</td>
<td>23.25%</td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>4.44%</td>
<td>11.66%</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>1.63%</td>
<td>27.55%</td>
<td></td>
</tr>
</tbody>
</table>

Note: *$p<0.05$, ***$p<0.001$
Comparison of those who did and did not use mental health services. Next, we considered only those with an objective need for MHS, and compared values on the demographic covariates of interest for those who used any MHS over the data collection period to those who did not use any services. Results for descriptive comparisons of those who did and did not use any MHS are described below, in Table 5. There were no significant differences in birth year, sex, or race/ethnicity between those who used services and those who did not. Those with insurance were more likely to utilize MHS compared to those with no insurance coverage (83.42% of those with coverage used MHS versus only 59.77% of those without coverage; \( \chi^2=34.411; p<0.0001 \)). Poverty status also had a significant impact on MHS use, with those having the lowest incomes being more likely to utilize MHS (84.71% of those with objective need in the “poor” category actually used MHS, compared to 85.15% in the “near poor” category, 82.32% of those with “low income, 82.46% in the “middle income” category, and 81.33% of those with “high income”; across-groups \( \chi^2=11.387; p=0.023 \)). There were also significant differences in rates of MHS use by county rurality. Those with objective need in urban counties were less likely to use services than their suburban and rural counterparts (81.89% of those living in urban counties with a need for MHS actually used services, compared to 87.89% of those in suburban counties and 90.97% of those in rural counties; across-groups \( \chi^2=42.464; p<0.0001 \)).
Table 5: Differences among Participants who Did and Those who Did Not Use Mental Health Services, from the Subsample of Older Adults with Mental Health Need

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Objective Need Sample (n=8,416)</th>
<th>Proportion of Group who Used MHS (n=7,000)</th>
<th>(\chi^2) or (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% or M±SD</td>
<td>% or M±SD</td>
<td></td>
</tr>
<tr>
<td>Birth Year</td>
<td>1931.91 ± 7.904</td>
<td>1931.8 ± 7.810</td>
<td>(2.020)</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td>0.801</td>
</tr>
<tr>
<td>Female</td>
<td>68.38%</td>
<td>82.64%</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>31.62%</td>
<td>83.42%</td>
<td></td>
</tr>
<tr>
<td>Insurance Status</td>
<td></td>
<td></td>
<td>34.411**</td>
</tr>
<tr>
<td>Insured</td>
<td>98.97%</td>
<td>82.56%</td>
<td></td>
</tr>
<tr>
<td>Uninsured</td>
<td>1.03%</td>
<td>59.77%</td>
<td></td>
</tr>
<tr>
<td>Poverty Category</td>
<td></td>
<td></td>
<td>11.387*</td>
</tr>
<tr>
<td>Poor</td>
<td>28.83%</td>
<td>84.71%</td>
<td></td>
</tr>
<tr>
<td>Near Poor</td>
<td>10.24%</td>
<td>85.15%</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>21.17%</td>
<td>82.32%</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>23.98%</td>
<td>82.46%</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>15.78%</td>
<td>81.33%</td>
<td></td>
</tr>
<tr>
<td>Rural/Urban Category</td>
<td></td>
<td></td>
<td>42.464**</td>
</tr>
<tr>
<td>Urban</td>
<td>80.53%</td>
<td>81.89%</td>
<td></td>
</tr>
<tr>
<td>Suburban</td>
<td>15.79%</td>
<td>87.89%</td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>3.68%</td>
<td>90.97%</td>
<td></td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td></td>
<td></td>
<td>3.179</td>
</tr>
<tr>
<td>Non-Hisp. White</td>
<td>67.92%</td>
<td>83.38%</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>13.74%</td>
<td>82.70%</td>
<td></td>
</tr>
<tr>
<td>Hisp./Latino</td>
<td>13.93%</td>
<td>83.62%</td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>2.36%</td>
<td>79.40%</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>2.06%</td>
<td>80.92%</td>
<td></td>
</tr>
</tbody>
</table>

Note: *\(p<0.05\), **\(p<0.01\)
Main Analyses

**Null model fitting.** First, an empty means, unstructured model was fit to the data in order to capture the total amount of variance in our outcome variable, MHS use. This provided a base against which to compare the amounts of variance explained by the predictors we later included as covariates and those in our hypotheses. The resulting empty model had a $-2$ Residual Log Pseudo-likelihood ($-2\text{RLL}$) of 41,454, and is summarized by column 1 in *Table 6*, below. Adding our level-2 grouping variable (person) into the model for the variances provided us with a between-persons null model (see column 2 of *Table 6*). This resulted in a $-2\Delta\text{RLL}$ of -1007 ($\chi^2=1007.21; p<0.0001$). The logistic ICC for the between-persons null model was 0.452, indicating that about 45% of the variance in MHS use in our sample was accounted for at the individual level or above (and 55% of the variance was accounted for at the “occasion” or time level).

Next, we added our level-3 grouping variable, state, into the null model, providing us with a three-level null model. This resulted in a $-2\Delta\text{RLL}$ of +53.78 ($\chi^2=53.78; p<0.0001$), compared to the empty 2-level model. This indicated that state was not a significant variable in our model, and the logistic ICC for the between-persons null model, 0.027, indicated that about less than 3% of the variance in MHS use in our sample was uniquely accounted for by participants’ states (see *Table 6*, column 3). However, because of its statistical significance and its importance to our results interpretation, the state level grouping variable was retained for subsequent analyses.

Finally, in forming our null model, we included the covariates sex assigned at birth, insurance status, birth year, and poverty status in order to control for their effects. The inclusion of this group of variables resulted in a $-2\Delta\text{RLL}$ of +67 ($\chi^2=66.92; p<0.0001$) from the three-level
null model with no covariates, indicating a significantly worse fit (*Table 6*, column 4). Solutions for fixed effects revealed that sex was not a significant predictor of likelihood to utilize MHS (*t*=0.190, df=38; *p*=0.8492), nor was birth year (*t*=1.09, df=8,383; *p*=0.2771), or level of poverty (*t*=1.83, df=8,383; *p*=0.0672). Insurance status was a significant predictor (*t*=3.79, df=19; *p*=0.0012). Adding these predictors did not significantly change the proportion of variance accounted for at the state (ICC=0.027) and individual (ICC=0.450) levels of the model. 

Due to the significantly worse fit, we ran our null model again, including only the level-2 covariate which significantly accounted for some variation between persons – insurance status. This resulted in a -2ΔLL of -36 (*χ^2*=36.13; *p*<0.001) from the null model with all covariates included, indicating that this model, with only insurance status as a covariate, was a significantly better fit to the data. Insurance status retained its significance as a predictor of likelihood to use MHS in this model (*t*=3.89, df=19; *p*=0.0010). In this model, state accounted for about 3% of the variance in MHS use, while factors at the individual level accounted for about 45% of the variance (*see column 5, *Table 6*), leaving about 52% of the variance in the model to be accounted for by factors at the occasion level. This comprised our base model for all future analyses, in which we tested our main hypotheses.
Table 6: Comparison of Models Used in the Process of Selecting a Base Model for Hypothesis Testing

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>-2RLL</td>
<td>41,454.19</td>
<td>40,446.98</td>
<td>40,559.24</td>
<td>40,626.16</td>
<td>40,590.03</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>--</td>
<td>-1007.21**</td>
<td>112.26**</td>
<td>66.92**</td>
<td>-36.13**</td>
</tr>
<tr>
<td>Logistic ICC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-Persons (Level 2)</td>
<td></td>
<td>0.452</td>
<td>0.450</td>
<td>0.450</td>
<td>0.450</td>
</tr>
<tr>
<td>Between-States (Level 3)</td>
<td></td>
<td>--</td>
<td>0.027</td>
<td>0.027</td>
<td>0.029</td>
</tr>
<tr>
<td>t-value(df) for Fixed Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.190 (28)</td>
<td>--</td>
</tr>
<tr>
<td>Insurance Status</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>3.790 (19)*</td>
<td>3.890 (19)*</td>
</tr>
<tr>
<td>Birth Year</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>1.090 (8,383)</td>
<td>--</td>
</tr>
<tr>
<td>Poverty Level</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>1.830 (8,383)</td>
<td>--</td>
</tr>
</tbody>
</table>

Note: *p<0.01, **p<0.001

**Hypothesis 1.** The increase in attention to mental health issues and instatement of various mental health policies over the time we are examining led us to predict a significant, positive relationship of MHS use with time. Thus, our hypothesis was tested by fitting a model to the data in which time was assigned a fixed effect on the likelihood of any past year MHS use. First, we tested whether time had a singular linear effect on likelihood of using MHS for the entire sample; intercepts were allowed to vary by both individual and state, as indicated by the significance of those parameters in our base model, but this would create parallel slopes for all individuals and states. Results for Hypothesis 1 and all subsequent models are reported in Table 7, below. Adding time as a linear fixed effect into the model resulted in a -2$\Delta$RLL of +5 ($\chi^2$=5.18; $p<0.05$) over the base model, indicating that this new model was not a significantly
better fit for the data (see Table 7, column 1). Specifically, the year in which a participant responded did not account for a significant proportion of the variance in likelihood to utilize MHS ($t=1.42; p=0.1560$). When considering our entire sample of those with need for MHS, the probability of using any services changed very little over the course of the years 2002-2012. Figure 6, below, depicts the overall linear slope for likelihood of MHS use over time. Although this trend was slightly positive (the direction we predicted), the change over time was not significant, so we rejected the alternative hypothesis for Research Question #1.

![Figure 6: Linear Trend for Likelihood of MHS Use over 2002-2012](image)

Next, although we made no specific hypotheses regarding the effect of state on the rates of change in MHS use over the time period in question, we fitted a model that allowed for the slope of the linear effect of time to vary by state, by entering the interaction term TIME*STATE into our model. This resulted in a significantly worse fit, with a $-2\Delta RLL$ of +516 ($\chi^2=515.92$;
$p<0.001$) over the model with no random time-slope for states (see Table 7, column 2). This indicated that the change in MHS rates over time did not vary significantly by state. An examination of the fixed effects for each state included in our analyses revealed that no state’s rates of MHS use varied significantly from that of the overall model during the period of 2002-2012. Thus, the interaction term of YEAR*STATE was not included in subsequent analyses. However, because Hypotheses 2 and 3 aimed to examine the changes in the rates of MHS use over time based on specific characteristics (i.e., rurality and racial/ethnic category), we retained the fixed effect for time in our subsequent models. Therefore the models for Hypotheses 2 and 3 were compared to the original Hypothesis 1 Model represented in Table 7, column 1, below.

**Hypothesis 2.** To test our Hypothesis 2, we added the rural/urban category code into our model to test its effects on both intercepts and slopes of MHS use over time. This was accomplished by entering the interaction term TIME*RURALITY into our model. We predicted that the rate of change in MHS use over the years 2002-2012 would vary between rural and urban counties, such that MHS use increased more over time for urban counties than for rural counties. This resulted in a significantly worse fit, with a $-2\Delta$LL of +96 ($\chi^2=95.99; p<0.001$) over the model with fixed effects for time and insurance status only (see Table 7, column 3). Significance testing was conducted to compare the change in likelihood of using MHS over time among those living in suburban and rural areas to the rate of change in those living in urban counties. There were no significant differences among the rural/urban categories (Table 7, column 3). Attempts to examine the interaction of rurality and state (to determine whether rurality might have more significant impact on MHS use rates in certain states, compared to others) resulted in non-convergence. We rejected the alternative hypothesis for Research Question #2.
Hypothesis 3. To test our Hypothesis 3, we added the categorical predictor of “Race/ethnicity,” by entering the interaction term TIME*RACE/ETHNICITY into our model. We predicted that the rate of change in MHS use over time would be significantly greater for non-Hispanic whites than for other racial/ethnic groups. This model was a significantly worse fit, with a \(-2\Delta\text{RLL}\) of +82 ($\chi^2=81.68; p<0.001$) compared to the model with fixed effects for time and insurance status only (see Table 7, column 4). Significance testing indicated that the rates of change in likelihood of MHS use did not differ significantly when comparing Black, Hispanic/Latino, Asian, or other-race older adults to the non-Hispanic White comparison group (see Table 7, column 4). Thus, we rejected the alternative hypothesis for Research Question #3. As with rurality, attempts to determine whether the effects of race/ethnicity varied by state resulted in non-convergence.

Hypothesis 4. Because the simple effects of rurality and race/ethnicity were shown to be non-significant in testing Hypotheses 2 and 3, examination of the interaction effect was inappropriate, and tests were not conducted for this hypothesis.
Table 7: Comparison of Models Used in Hypothesis Testing

<table>
<thead>
<tr>
<th>Parameter or Statistic</th>
<th>Hypothesis 1a: Fixed Effect of Time</th>
<th>Hypothesis 1b: Effect of Time, Variation by State</th>
<th>Hypothesis 2: Fixed Effect of Rural/Urban Category</th>
<th>Hypothesis 3: Fixed Effect of Race/Ethnicity</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2RLL</td>
<td>40,595.21</td>
<td>41,111.13</td>
<td>40,691.20</td>
<td>40,676.89</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>5.18</td>
<td>515.92**</td>
<td>95.99**</td>
<td>81.68**</td>
</tr>
<tr>
<td>Logistic ICC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-Persons</td>
<td>0.450</td>
<td>0.462</td>
<td>0.451</td>
<td>0.451</td>
</tr>
<tr>
<td>(Level 2)</td>
<td>(Level 2)</td>
<td>(Level 2)</td>
<td>(Level 2)</td>
<td></td>
</tr>
<tr>
<td>Between-States</td>
<td>0.029</td>
<td>0.000</td>
<td>0.022</td>
<td>0.030</td>
</tr>
<tr>
<td>(Level 3)</td>
<td>(Level 3)</td>
<td>(Level 3)</td>
<td>(Level 3)</td>
<td></td>
</tr>
<tr>
<td>t-value (df) for Fixed Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Insurance Status</td>
<td>3.93 (19)**</td>
<td>4.04 (19)**</td>
<td>3.91 (19)**</td>
<td>1.00 (19)**</td>
</tr>
<tr>
<td>Time</td>
<td>1.42 (8,381)</td>
<td>0.88 (8,353)</td>
<td>1.27 (8,377)</td>
<td></td>
</tr>
<tr>
<td>Rurality</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Comparison group: Urban)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time*Suburban</td>
<td>--</td>
<td>--</td>
<td>1.07(8,377)</td>
<td>--</td>
</tr>
<tr>
<td>Time*Rural</td>
<td>--</td>
<td>--</td>
<td>0.80(8,377)</td>
<td>--</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Comparison group: Non-Hisp. Whites)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time*Black</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.08(8,373)</td>
</tr>
<tr>
<td>Time*Hisp./Latino</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.88(8,373)</td>
</tr>
<tr>
<td>Time*Asian</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>1.03(8,373)</td>
</tr>
<tr>
<td>Time*Other</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>1.10(8,373)</td>
</tr>
</tbody>
</table>

Note: *p<0.01, **p<0.001

**Post hoc analysis of insurance status.** Because insurance status was the only statistically significant predictor across all models in our analyses, we sought to identify descriptive difference between those who were insured during the period of 2002-2012, and those who were never insured from our full sample of older adults ($n=38,424$). We conducted chi-squared tests to reveal which groups of individuals in our study were more likely to be uninsured. We found no significant sex differences in insurance status. However, there were significant differences on every other categorical variable. The wealthiest were least likely to be uninsured (2.76% of those in the “poor” category were uninsured, compared to 2.82% of the
“near poor,” 2.56% of the “low income” group, 1.55% of “middle income,” and 1.03% of “high
income”). Those in suburban counties were less likely to be uninsured than their urban and rural
counterparts (2.13% of those living in urban counties were uninsured, versus 1.57% of those in
suburban and 2.35% of those in rural counties). Finally, Hispanics/Latinos and Asians were
significantly more likely than other racial/ethnic groups to be uninsured, while non-Hispanic
Whites were least likely (0.97% of non-Hispanic Whites were uninsured, compared to 2.20% of
Blacks/African Americans, 6.43% of Hispanics/Latinos, 4.22% of Asians, and 2.55% of those in
the “other” racial/ethnic category). See Table 8, below.

Table 8: Differences Among Participants Who Were Insured at Any Time and
Participants Who Were Never Insured during 2002-2012

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Insured (n=38,424)</th>
<th>Uninsured (n=8,416)</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>97.84%</td>
<td>2.16%</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>98.09%</td>
<td>1.91%</td>
<td></td>
</tr>
<tr>
<td>Poverty Category</td>
<td></td>
<td></td>
<td>96.889***</td>
</tr>
<tr>
<td>Poor</td>
<td>97.24%</td>
<td>2.76%</td>
<td></td>
</tr>
<tr>
<td>Near Poor</td>
<td>97.18%</td>
<td>2.82%</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>97.44%</td>
<td>2.56%</td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td>98.45%</td>
<td>1.55%</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>98.97%</td>
<td>1.03%</td>
<td></td>
</tr>
<tr>
<td>Rural/Urban Category</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>97.87%</td>
<td>2.13%</td>
<td>8.1645*</td>
</tr>
<tr>
<td>Suburban</td>
<td>98.43%</td>
<td>1.57%</td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>97.65%</td>
<td>2.35%</td>
<td></td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td></td>
<td></td>
<td>664.966***</td>
</tr>
<tr>
<td>Non-Hisp. White</td>
<td>99.03%</td>
<td>0.97%</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>97.80%</td>
<td>2.20%</td>
<td></td>
</tr>
<tr>
<td>Hisp./Latino</td>
<td>93.57%</td>
<td>6.43%</td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>95.78%</td>
<td>4.22%</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>97.45%</td>
<td>2.55%</td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.05, **p<0.01, ***p<0.001
DISCUSSION

Objective Need for Mental Health Services

Descriptive analyses revealed significant group differences in rates of mental health need. The interpretation of these results is complicated by our limiting the definition of need to “objective” need. As described above, we limited our sample to those who had a recorded ICD-9 diagnosis, either self-reported or verified by their MEPS-interviewed physician or by medical records. Thus, many of the respondents who were positive for objective mental health need had already been informed of their diagnosis by a health care provider, indicating that our measure of “objective need” is somewhat confounded with access to health care. The strongest evidence for this confounding is the finding that those who were insured were significantly more likely to have objective need for MHS than their uninsured counterparts. Though those who had no perceived need for MHS may have been less likely or motivated to obtain insurance, this finding may conversely indicate that those without insurance are less likely to report or even be aware that they have any mental health needs. They are also less likely to have a doctor who can report their diagnosis when they are unable to report it themselves.

Other factors that appeared to correlate with increased likelihood for needing MHS were being female, having lower income, living in a suburban county, and being non-Hispanic White, Hispanic/Latino, or falling into the “other” racial/ethnic category. However, due to the potential confounding mentioned above, it is difficult to say whether these groups were actually more likely to have mental health need than their counterparts, or whether they simply had better access to health care and were therefore more likely to report having a mental health-related
diagnosis. Future studies could help to parse out the effects observed here, but this was outside the scope of this particular dissertation.

**Rates of Mental Health Service Use**

Overall, older adults’ MHS use rates in our study were high in comparison to previous research (Bogner, de Vries, Maulik, & Unützer, 2009; Institute of Medicine, 2012; Karlin, Duffy, & Gleaves, 2008; Klap, Unroe, & Unützer, 2003; Mackenzie, Pagura, & Sareen, 2010; Wang et al., 2005). As discussed above, these observed rates may have been higher than expected because we limited our sample to only those who reported (or whose doctors reported) a mental health diagnosis.

Another factor affecting observed rates was the metric of "use." We sought to identify those who had used *any* MHS in the reference period for which they had a need, but we made no distinctions based on type of provider or facility, number of visits, or quality of care. In fact, due to our classification system, those reporting a diagnosis and “using MHS” by filling prescriptions only may not have seen a doctor at all during the reference period, yet still received a positive value on our outcome variable. Considering this, our outcomes are consistent with other recent research, which shows a dramatic shift in mental health treatment toward psychotropic medications (Pew Charitable Trust, 2015). Using the metric described, we identified those who received at least acknowledgment and/or minimal treatment for their mental health need(s). If we had been able to measure it, the rates of "sufficiently" met needs may have been more similar to those observed in previous studies. Given this potential bias in our results, the number of participants who did *not* receive any treatment for their mental health needs (1,416 of 8,416 with need, or 16.83%) is even more concerning.
On the other hand, we can optimistically consider the high rates of MHS use among our older adult sample. Although rates did not increase significantly over the period we examined, the consistently high use rates should offer some encouragement. Although the Medicare Improvements for Patients and Providers Act (MIPPA; P.L. 110-275) and its counterpart for non-Medicare enrollees, the Paul Wellstone and Pete Domenici Mental Health Parity and Addiction Equity Act (MHPAEA; H.R. 6983, 110th Congress [2008]) were not passed until 2008, other factors may have begun to positively affect rates of MHS use earlier on in the period of interest and even before it. Indeed, as outlined by our underlying theory, the Socio-Ecological Model, multiple levels of influence can contribute to overall changes in public health and health behaviors, including factors such as general awareness of the problem and availability of services. Both of these factors had improved throughout the second half of the twentieth century (Pew Charitable Trust, 2015; Schomerus et al., 2012), potentially improving rates of MHS use by the beginning of our examination period and possibly even inspiring the lawmakers behind the Wellstone Domenici Act and MIPPA to develop and enact these policies.

**Group differences in overall rates of use.** Without consideration of change over time, descriptive analyses showed significant group differences in *overall rates* of MHS use (that is, respondents’ likelihood of using MHS at any point over the period of examination). Unsurprisingly, those with objective mental health need who were insured were significantly more likely to use MHS than those who were uninsured. About 40% of uninsured older adults who had objective need at some point during their data collection panel (which spanned about one year) failed to receive any treatment over that time. Although the uninsured portion of our sample was relatively small, the costs of unmet mental health need can be extremely large
(Demyttenaere et al., 2004; Hu, 2006; Insel, 2008). Our finding highlights the importance of insurance coverage in reducing those costs to individuals and society.

**Stagnant Rates over Time**

Our main analyses revealed that the rates of mental health service use among our sample did not increase over time, as we had predicted. This stagnation may also be understood in terms of the Socio-Ecological Model. That is, the renewed focus on mental health urged by the Surgeon General’s Report (USDHHS, 1999) may have been taken up by lawmakers and public health researchers, but it is unlikely that this mindset had diffused to all levels of society, even by the end of the period we examined. In fact, studies have shown that despite growing mental health literacy, stigma remains high nearly two decades after the Surgeon General’s report (Schomerus et al., 2012; Wu et al., 2017); some studies have even shown that attitudes toward those needing help for mental illness have become more negative (Mackenzie, Erickson, Deane, & Wright, 2014).

Further, even after the passing of the relevant MHS parity policies in 2008, implementation was a gradual process (Pew Charitable Trust, 2015). Implementation of a policy entails the dissemination of knowledge and action to all other layers outlined by the Socio-Ecological model, from communities to individuals (Eyler, Chriqui, Russell, & Brownson, 2016). This requires education about the policy’s specifications for relevant parties (including at least state and local governments, care providers, insurance providers, and consumers), distribution of funds to the appropriate service organizations, hiring or additional providers and staff, and enforcement, and evaluation. Although passed in 2008, the final rules for implementation of the Wellstone Domenici Act were not released until 2013 (Pew Charitable Trust, 2015), and, as mentioned, mental health parity under MIPPA was phased in over the years.
of 2010-2014. At the end of our sample period (2012), copayments for mental health services were still 40%, meaning that Medicare enrollees were still paying twice as much for MHS as for other health care services. Rates of MHS use by older adults may have increased more sharply after parity was more fully achieved. The finalization of both of these laws lies outside the time covered by our analyses, and may have slowed the progress of MHS utilization rates. Even after rules were finalized and distributed to state governments and other relevant parties, some states and insurance providers were slow to implement the new parity practices (Honberg, Diehl, Kimball, Gruttadaro, & Fitzpatrick, 2011; Horgan et al., 2015). Some of the lag in implementation may be attributable to the economic recession of 2007-2009, which correlated with the onset of these parity policies as well as with increased need for MHS among many American citizens (Catalano, 2009; Cooper, 2011; Modrek, Hamad, & Cullen, 2015).

The effectiveness of MHPAEA (H.R. 6983, 110th Congress [2008]) and MIPPA (P.L. 110-275) may also have been thwarted by lack of public awareness about mental health parity. A survey conducted by the American Psychological Association in 2014 revealed that only 4% of Americans were aware that insurers and Medicare are required to provide equitable coverage for mental health issues. Additionally, the use of MHS by older adults may have remained stagnant due to the consistent shortage of mental health care providers. The insufficient supply of MHS providers was documented prior to the period we examined (Goldman, 2001) and during the time our data was collected (Thomas, Ellis, Konrad, Holzer, & Morrisey, 2009), and it remains notable today (Nguyen, Hellebuyck, Halpern, & Fritze, 2017).

Overall, while this finding may represent a disappointing lack of improvement, the trend may change in years that follow our period of analysis, as long as mental health parity laws remain in place (or are expanded). Efforts toward expanding awareness of mental health parity
and aiding states, organizations, insurers, and providers to continue to implement the parity policies will be vital. Data from 2012 to present is needed to verify this possibility in order to ensure further endorsement of MIPPA and future parity-friendly policies.

**Uniformity of Mental Health Service Use Rates**

Although the full sample’s rates of MHS use did not change over time, we had hypothesized that rates of MHS use would change differentially based on rural/urban location and on racial/ethnic group. Our analyses showed no significant differences, however, indicating that none of the groups showed any significant change in their likelihood of using MHS over the period 2002-2012. Racial/ethnic and rural/urban disparities in mental health and mental health services have been targets of research and policy change for decades now, so while the absence of any disparities in our results may suggest cause for optimism, we argue that this may not be the case. Instead, it should be noted that our main analyses indicated that there were no changes in the likelihood to use MHS by those who already had an identified, objective need for MHS. However, our descriptive analyses identified significant rural/urban and racial/ethnic differences between those with and without identified objective need. Specifically, those living in urban counties were less likely to have mental health need than their suburban and rural counterparts, and non-Hispanic Whites, Hispanic/Latinos, and those in the “other” racial/ethnic category were more likely to have need than Blacks/African Americans and Asians. The potential complexity of the “objective need” variable described above limits our interpretation of these findings, but this highlights the possibility of disparities that are glossed over by our (and possibly others’) research.
Insurance Coverage

Insurance coverage was the only factor that retained significance across descriptive analyses and all models used in our main analyses. There were significant differences by level of poverty, rurality, and race/ethnicity in insurance status, and despite the selectiveness of the objective need sample employed for our main analyses, insurance status stood out as a significant factor impacting likelihood of using MHS and even becoming an increasingly important factor over time. Follow-up analyses allowed us to get a clearer picture of those adults over 65 who were not insured at any time while providing responses to the MEPS-HC, and the findings were concerning.

Although the Centers for Medicare and Medicaid Services (CMS) regularly publishes data on the number of enrolled older adults, it is difficult to estimate the numbers of those living in the United States who are either ineligible for services or who are eligible but did not enroll. Moon (1996) estimated that 4% of eligible older adults did not enroll in Medicare in 1993, and we could not find more recent statistics. However, more recent studies have shown that less than one percent of Americans aged 65+ were uninsured, when all sources of health insurance were considered (Okoro, Young, Strine, Balluz, & Mokdad, 2005). As our insurance variable also included all types of insurance, it is concerning that many groups had rates much higher than 1%. Perhaps most concerning were the high rates of uninsurance among Hispanic/Latino (6.43%) and Asian (4.22%) older adults, but this is precedent; many studies have noted racial/ethnic minority status and limited English proficiency as barriers to adequate insurance coverage among older adults (Okoro et al., 2005; Ponce, Hays, & Cunningham, 2006).
Limitations of the Present Study

There are some limitations to the interpretability of our results, related mainly to the dataset, analyses, and the nature of policy research.

Dataset limitations. Although the MEPS dataset is large and informative, we faced the problem common to much secondary data research in that the dataset was not specifically designed to answer our research questions. The largest issues for our analyses were the availability and consistency of mental health need- and use-related variables. Our specificity with the definition of “objective mental health need” meant that those with undiagnosed symptoms of MHS were excluded from our sample, despite their potential need for MHS. That is, some who needed treatment and did not use services would not have been given a diagnosis by any provider; these same respondents may have also been hesitant or unable to self-report their diagnoses (Bartels et al., 2004; CDC, 2008). Even those who did see a doctor or other healthcare provider for a mental health-related problem may not have received a formal diagnosis from that provider; older patients’ mental health-related complaints are more likely to be explained away by physical diagnoses than younger patients’ (Bartels et al., 2004; IOM 2012). This definition of objective need also meant that respondents who had already seen a provider who assigned the diagnosis; therefore these respondents were more likely to report current MHS use during the data collection period, inflating our observed rates for MHS use among the objective need sample. The cautious approach to operationalizing “mental health need” we adopted gives us confidence in the results we found, but leaves part of the problem unexplored. While other studies have explored subjective well-being and subjective mental health need among older adults (Deiner & Lucas, 2000; Deiner, Suh, Lucas, & Smith, 1999; Lee,
2000), we are unaware of any studies that examine subjective need and use of MHS in response to the recent parity policy changes. This is a gap that should be addressed by future studies.

Also as described above, our metric for MHS use was extremely inclusive, counting even the reported receipt of one psychotropic prescription during the survey period as “positive” for MHS use. Despite this inclusivity, some types of providers (such as clergy members, psychiatric nurses, and others) were not available options in the MEPS-HC dataset. The inclusion of these more “non-traditional” sources of mental health care may also have influenced our findings. The dichotomous nature of our MHS use variable also served to oversimplify the grander picture of met versus unmet mental health need in our sample. Although it would have been ideal to measure “sufficient” use of MHS in the face of objective need, this would require a deeper knowledge of the respondents’ diagnoses and treatment plans, and more information from their providers. As such, it was outside the scope of this dissertation, but should be addressed by future research.

The second major problem we faced in regards to variable availability in the MEPS-HC dataset involved county rurality. As we were not allowed access to respondents’ actual county FIPS codes, we were forced to lump all individuals from rural counties into one category, and compare them to all individuals from suburban and urban counties, regardless of geographical location. Attempts to examine the interaction effect between respondents’ county rurality and their state (thus allowing for the comparison of rural counties in one state to rural counties in another state, and to suburban/urban counties in the same state) resulted in non-convergence. This would be valuable information to have, and could be a vital target for future studies, perhaps using different analytical methods.
Finally, the MEPS-HC dataset is subject to the same biases faced by all survey designs. That is, participants’ responses may spuriously vary from one collection point to another based on interview context, question clarity, respondents’ perceptions of interviewers, recording bias, desirability bias, and many others (Green, Krosnick, & Holbrook, 2001; Tourangeau, Rips, & Rasinski, 2000). However, we are confident that those who developed and conducted the MEPS-HC took reasonable efforts to prevent and address such biases to the best of their abilities based on their documentation.

**Analytical limitations.** We used a complex, logistic multi-level model design for our analyses, including 4,673 participants for the main analyses and several variables with multiple categories. This resulted in millions of iterations required by our statistical software for some tests, which ran for more than 150 hours each and occasionally led to non-convergence. We are confident in the results obtained, but were unable to explore some questions due to our commitment to using options and methods for these tests that were justifiable and precedent in other studies using similar approaches. Future research may be able to more fully explore some of our unanswered questions by using data from individual states or by employing different statistical methods.

**Policy research limitations.** As mentioned above, the lengthy and sometimes unsuccessful process of policy implementation may partially explain the lack of significant change in MHS use by older adults over the period we examined. Indeed, there are many issues affecting policy research that may have played a role in our project and outcomes. One of the largest of these is the constantly changing nature of health care policy. Although mental health parity has been a target for decades, research continues to inform lawmakers and advocates, public opinion continues to evolve, and policies are frequently re-evaluated and revised or
renewed. The Socio-Ecological model emphasizes the complex interactions between these factors, and highlights the difficulty of isolating any one of them to learn its effect. Our analyses were not immune to this. Whereas this dissertation focused on the effects of one major policy change (enactment of MIPPA), an examination of MHS use rates over a longer period of time might provide a clearer picture of the effects of the slow but steady policy shift toward mental health parity that has been taking place over the last several decades.

Conclusions and Future Directions

Despite these limitations, there is much to be gleaned from our results. Our findings indicate that early attempts at increasing met mental health need via mental health parity laws were largely unsuccessful with older adults. This indicates that more efforts toward decreasing unmet mental health need of Americans aged 65+ are needed. These should include (but not be limited to) continued improvement of mental health literacy among the public and among general health care providers (who refer older adult patients for MHS at lower rates than their younger patients); education for health care consumers about their rights, insurance benefits, and mental health parity; increased availability of mental health services in underserved areas; and stricter enforcement of mental health parity for health care payers (Eyler et al., 2016).

Another important finding of this dissertation is the complication that can arise from using the endorsement of a mental health diagnosis as an indicator for mental health need. As demonstrated, this may exclude individuals who have never received a diagnosis from a provider, those who have low mental health literacy and do not know their diagnoses, and those with internalized stigma or desirability bias who are unable or unwilling to report specific diagnoses. Future studies would benefit from the use of subjective mental health need measures,
or from including diagnostic interviews as part of their data collection, as these methods would provide a more accurate understanding of actual mental health need (met or unmet).

Finally, our findings on insurance status are vital to the current understanding of mental health parity policy. Policies that change the nature of insurance coverage are only applicable to those who have insurance, and this was clearly demonstrated in our outcomes. Despite the inclusive eligibility rules for Medicare and options for alternative or supplemental insurance, many older adults remain uninsured. Future research should target a better understanding of those older adults who are ineligible for Medicare as well as those who are eligible but unenrolled, with no other sources of health insurance. Until these groups are better understood and more fully accounted for by policy change, unmet health and mental health needs will remain burdensome.
REFERENCES


Callahan, C. M. (2001). Quality improvement research on late life depression in primary care. *Medical Care, 39*(8), 772-784.


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APPENDIX

June 1, 2018

Katy-Lauren Ford, M.A.
Department of Psychology
College of Arts & Sciences
The University of Alabama
Box 870348

Re: IRB # 17-OR-118-R1 "Mental Health Policy Outcomes: An Examination of Older Adults' Mental Health Service Use, 2002-2012"

Dear Ms. Ford:

Your renewal application has been given expedited approval according to 45 CFR part 46. You have also been granted the requested waiver of informed consent. Approval has been given under expedited review category 7 as outlined below:

(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

Your application will expire on May 31, 2019. If your research will continue beyond this date, complete the relevant portions of the IRB Renewal Application. If you wish to modify the application, complete the Modification of an Approved Protocol Form. Changes in this study cannot be initiated without IRB approval, except when necessary to eliminate apparent immediate hazards to participants. When the study closes, complete the appropriate portions of the IRB Study Closure Form.

Should you need to submit any further correspondence regarding this proposal, please include the above application number.

Good luck with your research.

Sincerely,

[Signature]

Carpanatia T. Myles, MSM, CIIP, CIP
Director & Research Compliance Officer
Office for Research Compliance

358 Rose Administration Building | Box 870127 | Tuscaloosa, AL 35487-0127
205-348-8460 | Fax 205-348-7189 | Toll Free 1-877-820-3066
April 20, 2017

Katy-Lauren Ford, M.A.
Dept. of Psychology
College of Arts & Sciences
Box 870348

Re: IRB#: 17-OR-118 “Mental Health Policy Outcomes: An Examination of Older Adults’ Mental Health Service Use, 2002-2012”

Dear Ms. Ford:

The University of Alabama Institutional Review Board has granted approval for your proposed research.

Your application has been given expedited approval according to 45 CFR part 46. You have also been granted the requested waiver of informed consent. Approval has been given under expedited review category 7 as outlined below:

(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies

Your application will expire on April 19, 2018. If your research will continue beyond this date, complete the relevant portions of the IRB Renewal Application. If you wish to modify the application, complete the Modification of an Approved Protocol Form. Changes in this study cannot be initiated without IRB approval, except when necessary to eliminate apparent immediate hazards to participants. When the study closes, complete the appropriate portions of the IRB Request for Study Closure Form.

Should you need to submit any further correspondence regarding this proposal, please include the above application number.

Good luck with your research.

Sincerely,

[Signature]

Carman Tate, M.S.W., C.I.M., C.I.P.
Director & Research Compliance Officer
March 10, 2015

Katy-Lauren Ford
Dept. of Psychology
College of Arts & Sciences
Box 8703-48

Re: IRB#: 15-OR-065 “Implementation and Outcomes of Mental Health Policy Changes: An Examination of Older Adults’ Mental Health Service Use”

Dear Ms. Ford:

The University of Alabama Institutional Review Board has granted approval for your proposed research.

Your application has been given expedited approval according to 45 CFR part 46. Approval has been given under expedited review category 7 as outlined below:

(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies

Your application will expire on March 9, 2016. If your research will continue beyond this date, complete the relevant portions of the IRB Renewal Application. If you wish to modify the application, complete the Modification of an Approved Protocol Form. Changes in this study cannot be initiated without IRB approval, except when necessary to eliminate apparent immediate hazards to participants. When the study closes, complete the appropriate portions of the IRB Request for Study Closure Form.

Should you need to submit any further correspondence regarding this proposal, please include the above application number.

Good luck with your research.

Sincerely,

Carpantier T. Myles, MSM, CIC, CIP
Director & Research Compliance Officer