Cotten, S.R., Ford, G., Ford, S., & Hale, T.M. (2014). Internet use and depression among retired older adults in the united states: a longitudinal analysis. *Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, doi:10.1093/geronb/gbu018

Internet Use and Depression Among Retired Older Adults in the United States: A Longitudinal Analysis

Shelia R. Cotten,[1] George Ford,[2] Sherry Ford,[3] and Timothy M. Hale[4]

[1]Department of Telecommunication, Information Studies, and Media, Michigan State University, East Lansing.
[2]Phoenix Center For Advanced Legal & Economic Public Policy Studies, Washington, District of Columbia.
[3]Department of Communication, University of Montevallo, Alabama.
[4]Center for Connected Health, Partners HealthCare, Harvard University, Boston, Massachusetts.

Objectives. The purpose of this study is to examine the association between Internet use among retired older adults in the United States and changes in a commonly used predictor of depression (the CES-D).

Method. Analyzing data from four waves (2002–2008) of the Health and Retirement Survey, we assess whether an available and commonly used index of a depression state was affected by prior values of the index and Internet use. The sample includes 3,075 respondents observed over 4 waves of data, yielding a total of 12,300 observations. We analyzed the effect on depression of Internet use and past depression in a full sample and a matched sample. We also conducted informal tests for confounders. Finally, we tested a basic mediation model to determine whether Internet use affected depression through its relationship with loneliness and social isolation.

Results. Across methods, we found a positive contribution of Internet use to mental well-being of retired older adults in the United States, where Internet use reduced the probability of a depression state by one third. We found no evidence of confounding. Some evidence of mediation was found.

Discussion. Our dynamic probit model indicates that for retired older adults in the United States, Internet use was found to reduce the probability of a depressed state by about 33%. Number of people in the household partially mediates this relationship, with the reduction in depression largest for people living alone. This provides some evidence that the mechanism linking Internet use to depression is the remediation of social isolation and loneliness. Encouraging older adults to use the Internet may help decrease isolation and depression.

Key Words: Depression—Internet—Older adults—Well-being.

DEPRESSION is a serious health issue among older adults in the United States. Late-life depression affects between 5 and 10 million Americans aged 50 and older, with nearly 8% of the aged population reporting current depression. The percentage is even higher, almost 20%, when examining a lifetime diagnosis of depression (National Institute of Mental Health [NIMH], 2009, p. 6), some type of mental disorder (U.S. Department of Health and Human Services [USDHHS], 1999), or clinically relevant depressive symptoms (Federal Interagency Forum on Aging-Related Statistics [FIFARS], 2004). Suicide rates, often associated with depression, are highest among older adults (Hoyert, Kochanke, & Murphy, 1999; Trocchia & Janda, 2000). In addition to bereavement, disability/health declines, and prior depression (Cole & Dendukuri, 2003), dominant, and potentially modifiable, risk factors for depression in older adults include social isolation, decreased social contact, and lack of emotional support (Bradley & Poppen, 2003; Cacioppo et al., 2006; Eastman & Iyer, 2004; George, 1996; Wright, 2000).

Using the Internet can help to reduce social isolation, loneliness, and depression, as well as enhance social support among older adults (Blit-Cohen & Litwin, 2004; Cotten, 2009; Cotten, Anderson, & McCullough, 2013; Cotten, Anderson, Berkowsky, Yost, & Winstead, 2012a; Choi, Kong, & Jung, 2012; McMellon & Schiffman, 2000, 2002; White et al., 1999; Xie, 2007). Although the mechanisms linking Internet use to depression are less clear, using the Internet to communicate with social ties is one of the key conduits. Internet usage among older adults results in increased social support, social contact, social connectedness, and greater satisfaction with that contact (Bradley & Poppen, 2003; Cotten, Goldner, Hale, & Drentea, 2011; Gatto & Tak, 2008; Mellor, Firth, & Moore, 2008; Sum, Mathews, Hughes, & Campbell, 2008; Sum, Mathews, Pourghasem, & Hughes, 2009; Trocchia & Janda, 2000).

Given that older adults often face mobility and activity limitations, the relative importance of the Internet for interpersonal communication to overcome social and spatial boundaries may be greater for older adults than for younger age groups (Climo, 2001; Cotten, 2009; Hogeboom, McDermott, Perrin, Osman, & Bell-Ellison, 2010; McMellon & Schiffman, 2000; O'Hara, 2004; Winstead et al., 2012). Theoretically, Internet usage by older adults enables them to maintain contact with their social networks, exchange social support, and gather information to

Received January 28, 2013; Accepted February 9, 2014
Decision Editor: Merril Silverstein, PhD

help them make decisions, which all enhance well-being. Berkowsky (2012) has shown that even when accounting for the potential mediating effects of social integration, Internet use is still positively associated with well-being among older adults.

With few exclusions (Berkowsky, 2012; Cotten, Ford, Ford, & Hale, 2012b), the conclusions from prior research have been challenged due to small sample sizes (Dickinson & Gregor, 2006; Huang, 2010). In attempting to overcome sample size challenges, Cotten and coworkers (2012b), using a large cross-sectional sample (n = 7,839) from the Health and Retirement Survey (HRS), find that Internet use substantially reduces the incidence of depression among retired older adults in the United States. A variety of statistical and econometric methods all confirmed a favorable effect, with Internet use reducing depression categorization by 20%–28%. Although the large sample permitted more advanced techniques, the findings were based on a single, cross-section of data (year 2006). Unlike some health issues, however, research indicates that depression, at least in some forms, is a highly recurrent condition that may persist over a number of years (Burcusa & Iacono, 2007; Solomon et al., 2000). As a consequence, a current depression state may depend on a past depressive state; thus, the estimated relationship between Internet use and depressive symptoms reported in that study could be biased.

In an effort to account for the possibility of state dependence of depression symptoms, this study exploits the longitudinal nature of the HRS (2002–2008), including primarily the data prepared by the RAND Center for the Study of Aging, to study the role of past depression and Internet use on current depression in retired older adults in the United States. Given the large scope of the study, the goal is not to test a formal theoretical model specifying the pathways through which Internet usage may affect depression among older adults. Rather, we examine the role of past depression and Internet use on current depression. Quantification of these relationships was accomplished using a dynamic probit model, which in some cases is enhanced by matching algorithms. The longitudinal nature of the data also permitted informal testing for confounders, lending credibility to the causal nature of the relationships.

Method

Sample

The HRS is longitudinal household survey data for the study of retirement and health in the United States, surveying more than 22,000 persons over the age of 50 every 2 years, rendering a sample of about 21,000 observations in each wave. We employed four waves of biennial data covering the years 2002 through 2008. Like other studies that limit attention to subsets of the HRS population (Gallo et al., 2006; Siegal et al., 2003), the sample for this study is limited to retired, nonworking respondents (n = 30,413). Retired persons are a population of interest, particularly because one mechanism by which Internet use may affect depression is to counter the effects of isolation. Also, working individuals may be required to use the Internet rather than choosing to and may use the technology for different reasons than those not working. Unfortunately, the HRS data set does not include appropriate measures that would allow us to examine this differential in a satisfactory manner. Given these and many other reasons to suspect the pathway from Internet use to depression is heterogeneous across working and nonworking older adults in the United States, and the challenges of addressing such heterogeneity using the HRS data, this article focuses on the latter group, without precluding a study of the former in future research. Additional heterogeneity in the sample was limited by excluding from the sample proxy respondents (n = 1,614), respondents living in a nursing home (n = 329), respondents whose reported age is less than 50 years (n = 58), and respondents lacking data on the CES-D (n = 37) and Internet use (n = 17) variables. In light of the dynamic specification of the model, a sample was constructed by including only respondents with complete data records across the sample period. The final sample is 3,075 respondents in each of the four years data was collected or 12,300 (unweighted) observations in the full sample.

The HRS is a nonrandom and stratified sample, and we have limited the sample in a number of ways. In an effort to make our findings representative of population effects, a Raking algorithm was used to create respondent weights. National averages for education, gender, race (White, Black, and Hispanic, the latter are both oversampled in the HRS), and marital status were computed from the American Consumer Survey (year 2004) for nonworking persons over the age of 50. Weights are then computed with the Raking algorithm (using IPFWEIGHT in Stata), using the HRS respondent weights as starting values, so that the sample means of the covariates match the population averages. The use of lagged values in estimation and the effects of weighting leaves an estimation sample of 3,058 respondents and 9,174 observations.

Depressive Symptoms

Depression is measured using an eight-item version of the Center for Epidemiologic Studies (CES-D) scale calculated as the sum of dysphoric (yes/no) responses to eight question (McDowell & Newell, 1996; Radloff, 1977). The CES-D is a commonly used measure of depression in older adults (Gallo et al., 2006; Mezuk, Bohnert, Ratliff & Zivin, 2011; Radloff & Teri, 1986; Steffick, 2000) and is the only measure of depression included in the HRS. In the HRS, the CES-D has values ranging from 0 to 8, with a score of 8 indicating the most depressive symptoms. The eight-item CES-D has a dimension of 2^8 (or 256 unique outcomes), which is too large to reasonably accommodate as a dependent variable of a statistical model. Consequently, it is common for researchers to interpret the CES-D as a count variable, either evaluating the count itself (using, e.g., Poisson or ordered binomial regression) or converting the count into a dichotomous variable indicating depression "caseness" when the CES-D is "large." Research suggests that the appropriate cut point for depression "caseness," based on matching the 8-item to the 20-item CES-D, is CES-D ≥ 4 dysphoric responses (Steffick, 2000), and a threshold level of ≥ 4 is common in the literature (Blustein, Chan, & Guanais, 2004; Mezuk, Bohnert, Ratliff, & Zivin 2011; Mojtabai & Olfson, 2004; Nygaard, Turvey, Burns, Crischilles, & Wallace, 2003; Steffick, 2000).

Given the goal of assessing the effects of Internet use on the respondent being in a depressed state, the outcome of interest in this study is a dummy dependent variable with a value of 1 when the CES-D ≥ 4. The dummy variable is constructed for and is thus unique to each wave in the sample. Evaluating the CES-D in count form has valid motivations, but such interests are not the focus of this work. In count form, the statistics address the effect of Internet use on the mean CES-D score, not whether the CES-D count is large enough to reliably indicate a depressed state. The sample mean CES-D is 1.4, which is well below the commonly used threshold for a "depressed state." Also, given that only about 12% of the sample is classified as being in a depressed state (CES-D ≥ 4), it is very possible for Internet use to have a sizable effect on depression yet have only a small effect on the mean of the CES-D. Alternately, Internet use could be mean shifting, yet have a small effect on severe depressive systems. So, while the effect of Internet use on the mean CES-D may be of interest in certain contexts, our focus is rather on Internet use and its effect on a *depressed state*, which research implies is reliably indicated by a relatively large number of dysphoric responses to the CES-D questions. Preliminary analysis revealed that Internet use does reduce the mean of the CES-D in this sample (results available upon request). We also found that results were robust (though of different magnitudes) to alternative specification of the cutoff value of the CES-D (i.e., 3 or 5), and as would be expected, the size of the effect was only somewhat affected by the change.

Internet Use

Internet use is based on a direct question asking participants, "Do you regularly use the World Wide Web, or the Internet, for sending and receiving e-mail or for any other purpose…?" The response is dichotomous (1 = *Yes*, 0 = *No*).

Covariates

Potential confounders to include in the dynamic model were identified from prior research on the determinants of depression (Cotten et al., 2012a; Dooley & Prause, 2004; Gallo, Royall, & Anthony, 1993; Gallo et al., 2006; Link & Dohrenwend, 1989; Mezuk et al., 2011; Penninx et al., 1998). Descriptive statistics are summarized in Table 1. We divided the covariates into time-invariant and time-varying factors.

Time-invariant factors.—Variables fixed in the sample include (the natural log of) age (in years); gender (1 = *male*); three variables for race (1 = *Black*; 1 = *Hispanic*; 0 = *others*); and education (1 = *more than a high school education*).

Time-varying factors.—Variables updated for each wave include marital status (1 = *married and living with spouse*); the frequency of vigorous physical activity (1 = *physically active at least once weekly*); debilitating health condition (1 = *has a debilitating physical health condition*); (the natural log of) household size; seasonal affective disorder (1 = *survey taken in months of November, December, or January*). Also included are dummy variables for each wave (except the final wave).

Table 1. Means of Selected Variables

Variable	Full sample (*N* = 12,300)	Internet users (*N* = 3,880)	Internet nonusers (*N* = 8,420)	Internet users (Matched; *N* = 3,607)	Internet nonusers (Matched; *N* = 6,009)
Depression	0.140 (0.35)	0.091 (0.29)	0.161 (0.37)	0.075 (0.26)	0.109 (0.31)
Internet use	0.297 (0.46)	1.000 (0.00)	0.000 (0.00)	1.000 (0.00)	0.000 (0.00)
ln(age)	4.299 (0.11)	4.315 (0.11)	4.313 (0.11)	4.271 (0.09)	4.283 (0.10)
Married	0.551 (0.50)	0.704 (0.46)	0.487 (0.50)	0.761 (0.43)	0.711 (0.45)
High school	0.72 (0.45)	0.920 (0.27)	0.635 (0.48)	0.962 (0.19)	0.944 (0.23)
Physical activity	0.204 (0.40)	0.283 (0.45)	0.170 (0.38)	0.294 (0.46)	0.214 (0.41)
Debilitating health condition	0.078 (0.27)	0.052 (0.22)	0.089 (0.28)	0.033 (0.18)	0.050 (0.22)
ln(HH size)	0.555 (0.43)	0.602 (0.36)	0.535 (0.45)	0.603 (0.32)	0.583 (0.35)
Black	0.096 (0.29)	0.034 (0.18)	0.122 (0.33)	0.025 (0.16)	0.040 (0.20)
Hispanic	0.071 (0.26)	0.022 (0.15)	0.092 (0.29)	0.006 (0.07)	0.009 (0.10)
Male	0.395 (0.49)	0.402 (0.49)	0.392 (0.49)	0.491 (0.50)	0.499 (0.50)
November	0.014 (0.12)	0.013 (0.11)	0.014 (0.12)	0.013 (0.11)	0.012 (0.11)
December	0.007 (0.08)	0.007 (0.08)	0.007 (0.08)	0.007 (0.08)	0.005 (0.07)
January	0.004 (0.06)	0.003 (0.06)	0.004 (0.07)	0.003 (0.06)	0.004 (0.06)

Note. HH = household. Statistics computed using data from all four waves. The first wave is lost in estimation due to lags.

Statistical Analysis

As discussed earlier, a respondent is taken to be in a depressed state if his or her CES-D ≥ 4, so the outcome of interest is dichotomous. Because current depression may depend on a past depressive state, our model is dynamic in specification. Also, the sample includes data for a large number of respondents but only over a few years and some covariates are time invariant, so the effect of Internet use is estimated using a dynamic random effects probit model.

In order to control for the initial conditions problem, we used the Conditional Maximum Likelihood Estimator (CMLE; Wooldridge, 2005a). Estimation of the CMLE involves a probit regression where a bivariate measure of depression is regressed on a one-wave lag of depression, Internet use in the current wave, the covariates listed earlier, the dependent variable in the first wave of the sample (year 2002), and lead and lag values of the (time-varying) covariates including Internet use. Including two survey wave dummy variables, there were 41 total regressors. This augmented regression model was then estimated as a standard random effects probit model. Average partial effects were estimated in the manner detailed by Wooldridge (2002, p. 495; 2005b), conducting hypothesis tests using the bootstrapped standard errors and *t*-statistics (t_b) computed using 50 repetitions.

We evaluate the robustness of our findings in two ways. First, the HRS data are observational and Internet use is not randomly assigned. Even though the econometric model includes a large number of covariates, the estimated treatment effect on Internet use may still be poorly estimated if users and nonusers are demographically very different (Imbens & Wooldridge, 2009). This problem arises from the extrapolation inherent to regression models. Not surprisingly, there are some differences in the covariate distributions across Internet use, with Internet use being much higher for younger, married, and more educated respondents, and less likely among Blacks and Hispanics. To address this concern, we apply a matching algorithm to the data, thereby ensuring sufficient overlap of the covariates. Second, we address the unconfoundedness assumption, which states that there are no unobserved covariates affecting both Internet use and depression that would lead to spurious correlation. If the assumption is false, then we may contribute to Internet use the effect of some unobserved covariate that is influencing the level of both Internet use and depression. By exploiting the time series component of the data, we conduct an informal test of the unconfoundedness assumption by assigning pseudotreatments to nonusers. Figure 1 illustrates the steps taken to select the sample and conduct our data analysis.

Results

We performed all calculations and data management using Stata (Version 12), and all *p* values refer to two-tailed tests. The weighted mean of the dependent variable was found to be relatively stable across time (2002, 13.5%; 2004, 12.8%; 2006, 14.4%; 2008, 15.4%). The full sample mean of the dependent variable was 14.0%, with Internet users having a mean 9.1% and nonusers of 16.1%. About half (48.6%) of those categorized as depressed in the current wave were also depressed in the preceding wave. Internet use was also stable over the four waves (28.9%, 30.4%, 30.0%, and 29.6%), with 85% of users in a current wave also being users in the preceding wave.

The weighted dynamic random effects probit model is estimated with 9,174 observations. Estimated coefficients and their *t*-statistics are summarized in Table 2, Model 1 (excluding the lead and lag values of the covariates). Seven of the 9 demographic covariates in the model are statistically different from zero at the 5% level or better. Depression categorization declines with age and is less common among married persons, males, more educated persons, and those engaging in vigorous physical activity at least once a week. Having poor health, assessed as a debilitating physical health condition, has a strong positive effect on the likelihood of being depressed, and the positive signs on the survey month variables (with November being statistically significant) provide some support for Seasonal Affective Disorder (Lurie, Gawinski, Peirce, & Rousseau, 2006). Hispanics are more prone to depression than others. Household size does not appear to influence depression. Based on the period fixed effects, we find a slight increase in depression over time, though the coefficients are statistically significant only at the 10% level. Depression is highly persistent: Those in a depressed state in the prior

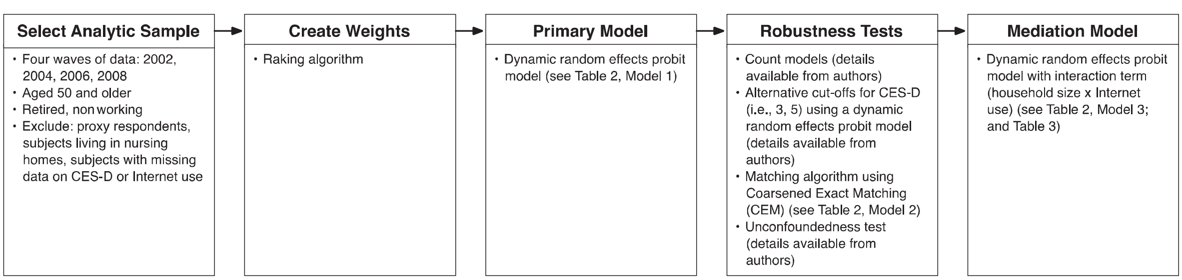

Figure 1. Sample selection and data analysis steps.

Table 2. Summary of Regression Results

	Model 1	Model 2	Model 3
	CMLE	CMLE, matched sample	CMLE, mediation
Internet use	−0.304** (0.122)	−0.478*** (0.136)	−0.510*** (0.148)
Internet use × Ln(HH size)	—	—	0.349** (0.138)
Depression lagged	0.319** (0.087)	0.306** (0.119)	0.315*** (0.087)
Depression first period	1.017** (0.101)	1.175*** (0.145)	1.024*** (0.101)
ln(age)	−0.789** (0.262)	−1.101** (0.392)	−0.791** (0.263)
Married	−0.512** (0.150)	−0.250 (0.201)	−0.543*** (0.151)
High school Education	−0.208** (0.060)	−0.225 (0.140)	−0.211*** (0.060)
Physical activity	−0.237** (0.079)	−0.235** (0.095)	−0.238** (0.079)
Debilitating health condition	0.540** (0.094)	0.925*** (0.137)	0.528*** (0.094)
ln(HH size)	−0.033 (0.119)	0.208 (0.192)	−0.090 (0.121)
Black	−0.060 (0.085)	−0.221 (0.170)	−0.066 (0.085)
Hispanic	0.465** (0.095)	0.589* (0.317)	0.480*** (0.096)
Male	−0.145** (0.057)	−0.127 (0.072)	−0.141* (0.057)
November	0.499** (0.205)	0.126 (0.261)	0.501* (0.205)
December	0.302 (0.298)	1.129** (0.395)	0.302 (0.299)
January	−0.282 (0.377)	−0.213 (0.430)	−0.295 (0.378)
Year 2006	0.088† (0.052)	0.026 (0.068)	0.088† (0.052)
Year 2008	0.102† (0.055)	0.058 (0.072)	0.102† (0.055)
Constant	−1.983† (1.140)	3.253† (1.689)	2.022† (1.144)
ρ	0.34	0.391	0.34
Confidence interval	[0.26, 0.43]	[0.29, 0.50]	[0.26, 0.43]
LLT ρ = 0	53.8***	42.6***	54.7***
N	9,174	7,212	9,174
Log-L	−2,897	−1,776	−2,894
Wald χ^2	812.6***	458.7***	810.8***

Notes. CMLE = Conditional Maximum Likelihood Estimator; HH = household; LLT = log-likelihood test.
Standard errors in parentheses unless otherwise noted.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. $^{\dagger}p < .10$.

wave are about 50% more likely to be depressed in the current wave (predicted means of 8.4% and 12.9%), and being in a depressed state in the first wave of the sample greatly increases the probability of later depression (predicted means of 0.062% and 25.3%).

Turning to the key question of the relevance of Internet use, the coefficient on Internet use is −0.304 (t-statistic = −2.49 [p = .013]). Internet users are less likely to be in a depressed state than are nonusers. Other things constant, Internet users have an average predicted probability of depression of .07, whereas that probability for nonusers is .105. Based on the difference, Internet use leads to a 33% reduction in the probability of depression ($t_b = 1.98$, $p < .05$). This effect is comparable to, though larger than, the results from the cross-sectional analysis (year 2006) reported by Cotten and coworkers (2012b).

Coarsened Exact Matching

In an effort to evaluate whether covariate imbalance between Internet users and nonusers influences the estimated treatment effect, we employed Coarsened Exact Matching (CEM), which has several advantages over more traditional propensity score matching algorithms, to ensure comparable covariate distributions across Internet users and nonusers (Iacus, King, & Porro 2012). The matching algorithm is applied to the 2004 cross-section and the weights then distributed across all waves. All demographic variables are used in the matching algorithm. The balanced, weighted estimation sample was 7,212 observations (2,404 for each wave). The results are presented in Table 2, Model 2. For Internet use, the CEM-weighted results from the CMLE model were larger than those obtained from the full sample. The coefficient on Internet use is −0.48 (t = −3.52, p < .01), for a percentage reduction in the dependent variable of 48% (with a predicted probability of depression of .045 for Internet users and .086 for nonusers). Covariate imbalance attenuates the estimated treatment effect of Internet use on depression.

Unconfoundedness

A core assumption required for the estimation of causal effects is that of unconfoundedness (Imbens & Wooldridge, 2009; Pearl, 2009). Although there is no direct test of unconfoundedness, there are indirect means by which to assess its presence, usually by testing the null hypothesis that an average treatment effect is zero when the effect is known to be zero. For example, if one wanted to test whether or not a training class had an effect on job performance, there could be a concern that those receiving the training were hand-picked because of an expectation of superior performance (i.e., a nonrandom selection). A result suggesting the program was effect may, in fact, merely reflect the nonrandom selection into the program of better employees. By testing for group differences in performance prior to the class, the presence of an unobserved cause of superior performance can be determined. In the presence of time series data, it is possible to evaluate the effect of future treatment on an outcome determined prior to the treatment (Imbens & Wooldridge, 2009, p. 48). We used that approach.

For our informal test, we first took the data from period t and exclude all Internet users from that period. Then, for these nonusers, we divided the sample into two groups, g_0 and g_1, based on observed Internet use in period $t + k$, with g_1 being Internet users in $t + k$ and g_0 remaining nonusers. Presumably, those nonusers in period t who become users in period $t + k$ (group g_1) are those most likely to have high values of the potential unobserved factor. By assigning a pseudotreatment to group g_1, we are, in essence, testing for the influence of a confounder and not the treatment because the treatment has yet to be applied (it is applied in the future). In the first case, we took nonusers from the 2004 cross-section and assigned values to the pseudotreatment based on actual future Internet use in year either 2006 or 2008. With this data, we ran a cross-section probit model to test the null hypothesis that the pseudotreatment has no effect; a null hypothesis we know to be true in the absence of confounders. We also assigned pseudouse to nonusers in the 2006 wave based on actual use from the 2008 wave.

In all, there were three probit models, and we summarize the key findings here (details are available upon request.) First, we estimated the model using data for the full sample from 2004 and include actual Internet use data to confirm that the effect of Internet use is negative and statistically different from zero (n = 3,058). The coefficient on Internet use is −0.165 with a t-statistic of −2.16 ($p < .05$), giving a reduction in depression categorization of 23%. Dropping all Internet users from the 2004 period and assigning 2006 Internet use as a pseudotreatment to nonusers (6.5% of 2,082 observations), the estimated coefficient on use is 0.21 with a t-statistic of 1.34 ($p = .18$). The null hypothesis of "no effect" is not rejected (and the coefficient is positive). Using the 2008 Internet use data as a pseudotreatment for the 2004 sample of nonusers (8.0% of the sample), the estimated effect on Internet use is 0.151 with a t-statistic of 0.98 ($p = .33$). In both cases, the estimated coefficient is small, of the wrong sign, and the null hypothesis of "no effect" cannot be rejected. Although we cannot claim that these findings represent a formal statistical test of the unconfoundedness assumption, the results add credibility to the causal nature of our findings on Internet use and depression.

Mediation

Although the literature suggests Internet use may affect depression through isolation and loneliness, an extension of the model is to test for mediating factors related to isolation between Internet use and depression. A full investigation of mediation is beyond the scope of this article, but we provide some potentially supportive evidence of mediation here. Generally speaking, we expect persons living alone, or at least living with very few persons, to be more vulnerable to isolation and loneliness than are those living in larger households that offer greater social interaction. A variable measuring (the natural log of) household size was included in the probit model above but was found to have no influence on the incidence of depression. To test for mediation of household size on depression, we augment the probit model with an interaction term between household size and Internet use. If Internet use operates on depression by reducing isolation, then we expect the treatment effect of Internet use on depression will be attenuated by increases in household size.

Table 3. Mediation Effects

HH size	Marginal effect	t-statistic	N
1	−0.510**	−3.45	3,524
2	−0.266**	−2.16	7,144
3	−0.126	−0.90	1,025
4	−0.021	−0.13	345
5	0.048	0.26	148
6	0.118	0.58	58
7	0.171	0.77	30
8	0.216	0.91	20
9	0.258	1.02	5

Notes. HH = household; N = 9,174.

The estimated model is provided in Table 2, Model 3. As expected, the sign on the interaction term is positive (0.349)—household size attenuates the treatment effect of Internet use on depression. Table 3 summarizes the findings by household size. The coefficient of Internet use is largest for those persons living alone (−0.510) and next largest for those living with one other person (−0.266), and both marginal effects are statistically significant at the 5% level or better. These two groups account for 87% of the respondents in the sample. About 8% of the respondents live with three persons, and although the coefficient for this group is negative, we cannot reject the hypothesis the effect is zero. In fact, the null hypothesis of no effect cannot be rejected for household sizes of three or more persons. We suspect small sample sizes for larger households make it difficult to precisely estimate coefficients for these types. Nevertheless, these results are comport with intuition and provide some evidence, albeit preliminary, that the pathway between Internet use and depression may, in part, be the remediation of isolation and loneliness.

Discussion

The aim of this study was to assess whether Internet use has any effect on depression categorization of retired older adults in the United States. Although some studies find a positive effect of Internet use on mental well-being, others do not, and some question the findings of earlier studies due to the limited samples typically employed. In a recent study, Cotten and coworkers (2012a) find a favorable effect of Internet use on mental well-being using a large sample from the HRS, but the study's findings are based on a single cross-section from the longitudinal HRS.

Exploiting the longitudinal nature of the HRS data, we permitted current episodes of depression to be a function of both Internet use and past depression. Our dynamic probit model indicates that depression is state dependent—current depression depends on past depression. Importantly, Internet use was found to reduce depression categorization by 33%. This estimated reduction is comparable to that found in Cotten and coworkers (2012b) in a 2006 cross-section (20%–28%).

This study makes significant contributions to the study of Internet use and depression in the older, retired population. First, the probative value of the existing literature was handicapped by small samples, which also limited the sophistication of the statistical procedures employed to quantify any effect. Our sample is large and drawn from data frequently used to study the mental well-being of older adults (and others). Second, depression is often a recurrent condition (Burcusa & Iacono, 2007; Solomon et al., 2000), and our statistical method allowed past depression to affect current depression. Third, Internet users are demographically different than nonusers. We applied a matching technique to ensure adequate covariate overlap and found that the effect of Internet use remained intact and unchanged. Fourth, the longitudinal nature of the data permitted an informal test of the unconfoundedness assumption. The results were highly favorable. Pseudotreatments were found to have small and statistically insignificant coefficients. These results lend credibility to the causal nature of our findings. Finally, we find that the effect of Internet use on depression is mediated by household size, a result consistent with prior research indicating that Internet use influences depression by reducing isolation and loneliness.

There are some potential limitations to our analysis. First, to reduce heterogeneity that could be difficult to account for, the sample was limited to nonworking retired persons, those not living in nursing homes, and other considerations. The role of Internet use for those excluded from the sample is an issue worthy of study. Second, the HRS contains only the simplest measure of Internet use—a yes/no response to use of any sort. As such, we could not distinguish between the use of high-speed and dial-up Internet services, which could be important (Davison & Cotten, 2009; Hale, Cotten, Drentea, & Goldner, 2010). The type, timing, function, and amounts of Internet usage may also be relevant to the depression outcome (Cotten et al., 2011), but we were unable to address such specifics.

Notwithstanding these limitations, this study makes some important contributions to research on the role of Internet use on mental health. We applied a dynamic econometric model to a large, longitudinal data set and found Internet use to have a sizeable effect on mental health; these results were robust to sample matching across users and nonusers; and we presented evidence supporting the causal nature of our results through an informal test of the unconfoundedness assumption. These are all new contributions to the research on Internet use and the mental well-being of older adults. Our findings also suggest that one pathway through which Internet use affects depression is through loneliness and social isolation. Researchers and those seeking to enhance the well-being of older adults will want to further pursue this potential pathway to determine which aspects of loneliness and isolation can be decreased through Internet use (Cotten et al., 2013).

Acknowledgments

G. Ford analyzed the data and wrote the initial draft of the paper. S. Ford contributed to the literature review. S. R. Cotten helped to write the manuscript and substantially edited the entire manuscript. T. M.Hale reviewed the statistical procedures and results, formatted the manuscript, and added additional literature as needed.

Correspondence

Correspondence should be addressed to Shelia R. Cotten, PhD, Department of Telecommunication, Information Studies, and Media, Michigan State University, 404 Wilson Road, East Lansing, MI 48824. E-mail: cotten@msu.edu.

References

Berkowsky, R. W. (2012). *Internet use, social integration, and psychological well-being in older adults* (Unpublished masters thesis). University of Alabama at Birmingham, Birmingham, AL.

Blit-Cohen, E., & Litwin, H. (2004). Elder participation in cyberspace: A qualitative analysis of Israeli retirees. *Journal of Aging Studies*, *18*, 385–398. doi:10.1016/j.jaging.2004.06.007

Blustein, J., Chan, S., & Guanais, F. C. (2004). Elevated depressive symptoms among caregiving grandparents. *Health Services Research*, *39*, 1671–1689. doi:10.1111/j.1475-6773.2004.00312.x

Bradley, N., & Poppen, W. (2003). Assistive technology, computers and Internet may decrease sense of isolation for homebound elderly and disabled persons. *Technology and Disability*, *15*, 19–25.

Burcusa, S. L., & Iacono, W. G. (2007). Risk for recurrence in depression. *Clinical Psychology Review*, *27*, 959–985. doi:10.1016/j.cpr.2007.02.005

Cacioppo, J. T., Hughes, M. E., Waite, L. J., Hawkley, L. C., & Thisted, R. (2006). Loneliness as a specific risk factor for depressive symptoms: Cross sectional and longitudinal analyses. *Psychology and Aging*, *21*, 140–151.

Choi, M., Kong, S., & Jung, D. (2012). Computer and Internet interventions for loneliness and depression in older adults: A meta-analysis. *Healthcare Informatics Research*, *18*, 191–198. doi:10.4258/hir.2012.18.3.191

Climo, J. (2001). *Distant parents*. Piscataway, NJ: Rutgers University Press.

Cole, M. G., & Dendukuri, N. (2003). Risk factors for depression among elderly community subjects: A systematic review and meta-analysis. *American Journal of Psychiatry*, *160*, 1147–1156.

Cotten, S. R., Anderson, W. A., Berkowsky, R., Yost, E., & Winstead, V. (2012). Can information and communication technology usage by older adults decrease stress, social isolation, and loneliness? Results from a randomized trial. Presented at the 13th International Conference on Social Stress Research, Dublin, Ireland.

Cotten, S. R., Ford, G. S., Ford, S. G., & Hale, T. M. (2012b). Internet use and depression among older adults. *Computers in Human Behavior*, *28*, 496–499. doi:10.1016/j.chb.2011.10.021

Cotten, S. R. (2009). Using ICTs to enhance quality of life among older adults: Preliminary results from a randomized controlled trial. Paper presented at the Annual Meeting of the Gerontological Society of America.

Cotten, S. R., Anderson, W., & McCullough, B. (2013). Impact of Internet use on loneliness and contact with others among older adults: Cross-sectional analysis. *Journal of Medical Internet Research*, *15*, e39. doi:10.2196/jmir.2306

Cotten, S. R., Goldner, M., Hale, T. M., & Drentea, P. (2011). The importance of type, amount, and timing of internet use for understanding psychological distress. *Social Science Quarterly*, *92*, 119–139. doi:10.1111/j.1540-6237.2011.00760.x

Davison, E. L., & Cotten, S. R. (2009). Connection disparities: The importance of broadband connections in understanding today's digital divide. In E. Ferro, Y. Dwivedi, J. Gil-Garcia, & M. D. Williams (Eds.), *Handbook of research on overcoming digital divides: Constructing an equitable and competitive information society* (pp. 346–358). Hershey, PA: Information Science Reference.

Dickinson, A., & Gregor, P. (2006). Computer use has no demonstrated impact on the well-being of older adults. *International Journal of Human-Computer Studies*, *64*, 744–753. doi:10.1016/j.ijhcs.2006.03.001

Dooley, D., & Prause, J. (2004). Settling down: Psychological depression and underemployment. In D. Dooley & J. Prause (Eds.), *The social costs of underemployment* (pp. 134–157). Cambridge, MA: Cambridge University Press.

Eastman, J. K., & Iyer, R. (2004). The elderly's uses and attitudes towards the Internet. *Journal of Consumer Marketing*, *21*, 208–220. doi:10.1108/07363760410534759

Federal Interagency Forum on Aging-Related Statistics (FIFARS). (2004). *Older Americans 2004: Key indicators of well-being. Federal Interagency Forum on Aging-Related Statistics*. Washington, DC: U.S. Government Printing Office.

Gallo, J. J., Royall, D. R., & Anthony, J. C. (1993). Risk factors for the onset of depression in middle age and later life. *Social Psychiatry and Psychiatric Epidemiology*, *28*, 101–108. doi:10.1007/BF00801739

Gallo, W. T., Bradley, E. H., Dubin, J. A., Jones, R. N., Falba, T. A., Teng, H. M., & Kasl, S. V. (2006). The persistence of depressive symptoms in older workers who experience involuntary job loss: Results from the health and retirement survey. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *61*, 221–228.

Gatto, S. L., & Tak, S. H. (2008). Computer, Internet, and e-mail use among older adults: Benefits and barriers. *Educational Gerontology*, *34*, 800–811. doi:10.1080/03601270802243697

George L. K. (1996). Social factors and illness. In R. H. Binstock, & L. K. George (Eds.) Handbook of aging and the social sciences (4th ed., pp. 229–253). San Diego, CA: Academic Press.

Hale, T. M., Cotten, S. R., Drentea, P., & Goldner, M. (2010). Rural-urban differences in general and health-related internet usage. *American Behavioral Scientist*, *53*, 1304–1325. doi:10.1177/0002764210361685

Hogeboom, D. L., McDermott, R. J., Perrin, K. M., Osman, H., & Bell-Ellison, B. A. (2010). Internet use and social networking among middle aged and older adults. *Educational Gerontology*, *36*, 93–111. doi:10.1080/03601270903058507

Hoyert, D. L., Kochanke, K. D., & Murphy, S. L. (1999). *Deaths: Final data for 1997. National Vital Statistics Reports*. Hyattsville, MD: National Center for Health Statistics.

Huang, C. (2010). Internet use and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior and Social Networking*, *13*, 241–249. doi:10.1089/cyber.2009.0217

Iacus, S. M., King, G., and Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, *20*, 1–24. doi:10.1093/pan/ mpr013

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, *47*, 5–86. doi:10.1257/jel.47.1.5

Link, B. G., & Dohrenwend, B. P. (1989). The epidemiology of mental disorders. In H. E. Freeman & S. Levine (Eds.), *Handbook of medical sociology* (4th ed., pp. 102–127). Englewood Cliffs, NJ: Prentice Hall.

Lurie, S. J., Gawinski, B., Pierce, D., & Rousseau, S. J. (2006). Seasonal affective disorder. *American Family Physician*, *74*, 1521–1524. doi:10.1016/S0140-6736(98)01015-0

McDowell, I., & Newell, C. (1996). *Measuring health: A guide to rating scales and questionnaires* (2nd ed.). New York, NY: Oxford University Press.

McMellon, C. A., & Schiffman, L. G. (2000). Cybersenior mobility: Why some older consumers may be adopting the internet. *Advances in Consumer Research*, *27*, 139–144.

McMellon, C. A., & Schiffman, L. G. (2002). Cybersenior empowerment: How some older individuals are taking control of their lives. *Journal of Applied Gerontology*, *21*, 157–175. doi:10.1177/07364802021002002

Mellor, D., Firth, L., & Moore, K. (2008). Can the Internet improve the well-being of the elderly? *Ageing International*, *32*, 25–42. doi:10.1007/s12126-008-9006-3

Mezuk, B., Bohnert, A. S., Ratliff, S., & Zivin, K. (2011). Job strain, depressive symptoms, and drinking behavior among older adults: Results from the health and retirement study. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *66*, 426–434. doi:10.1093/geronb/gbr021

Mojtabai, R., & Olfson, M. (2004). Cognitive deficits and the course of major depression in a cohort of middle-aged and older community-dwelling adults. *Journal of the American Geriatrics Society*, *52*, 1060–1069. doi:10.1111/j.1532-5415.2004.52302.x

National Institute of Mental Health (NIMH). (2009). Older adults: Depression and suicide facts (fact sheet). Retrieved November 2, 2009, from http://www.nimh.nih.gov/health/publications/older-adults-depression-and-suicide-facts-fact-sheet/index.shtml

Nygaard, I., Turvey, C., Burns, T. L., Crischilles, E., & Wallace, R. (2003). Urinary incontinence and depression in middle-aged United States women. *Obstetrics and Gynecology*, *101*, 149–156. doi:10.1016/S0029-7844(02)02519-X

O'Hara, K. (2004). "Curb Cuts" on the information highway: Older adults and the Internet. *Technical Communication Quarterly*, *13*, 426–445. doi:10.1207/s15427625tcq1304_4

Pearl, J. (2009). Causal inference in statistics: An overview. *Statistics Survey*, *3*, 96–146. doi:10.1214/09-SS057

Penninx, B. W., Guralnik, J. M., Ferrucci, L., Simonsick, E. M., Deeg, D. J., & Wallace, R. B. (1998). Depressive symptoms and physical decline in community-dwelling older persons. *JAMA: The Journal of the American Medical Association*, *279*, 1720–1726. doi:10.1001/jama.279.21.1720

Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, *1*, 385–401. doi:10.1177/014662167700100306

Radloff, L. S., & Teri, L. (1986). Use of the Center for Epidemiological Studies-Depression scale with older adults. *Clinical Gerontologist*, *5*, 119–136. doi:10.1300/J018v05n01_06

Siegel, M., Bradley, E. H., Gallo, W. T., & Kasl, S. V. (2003). Impact of husbands' involuntary job loss on wives' mental health, among older adults. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *58*, 30–37. doi:10.1093/geronb/58.1.S30

Solomon, D. A., Keller, M. B., Leon, A. C., Mueller, T. I., Lavori, P. W., Shea, T., … Endicot, J. (2000). Multiple recurrences of major depressive disorder. *American Journal of Psychiatry*, *157*, 229–233.

Steffick, D. E. (2000). *Documentation of Affective Functioning Measures in the Health and Retirement Study HRS/AHEAD Documentation Report* (pp. 98). Ann Arbor, MI: HRS Health Working Group.

Sum, S., Mathews, R. M., Hughes, I., & Campbell, A. (2008). Internet use and loneliness in older adults. *CyberPsychology & Behavior*, *11*, 208–211. doi:10.1089/cpb.2007.0010

Sum, S., Mathews, R. M., Pourghasem, M., & Hughes, I. (2009). Internet use as a predictor of sense of community in older people. *Cyberpsychology & Behavior*, *12*, 235–239. doi:10.1089/cpb.2008.0150

Trocchia, P. J., & Janda, S. (2000). A phenomenological investigation of Internet usage among older individuals. *Journal of Consumer Marketing*, *17*, 605–616. doi:10.1108/07363760010357804

U.S. Department of Health and Human Services (USDHHS). (1999). *U.S. Surgeon General's Report: (1999) Mental health: A report of the Surgeon General*. Washington, DC: U.S. Surgeon General's Office.

White, H., McConnell, E., Clipp, E., Bynum, L., Teague, C., Navas, L., … Halbrecht, H. (1999). Surfing the net in later life: A review of the literature and pilot study of computer use and quality of life. *Journal of Applied Gerontology*, *18*, 358–378. doi:10.1177/073346489901800306

Winstead, V., Anderson, W. A., Yost, E. A., Cotten, S. R., Warr, A., & Berkowsky, R. W. (2012). You can teach an old dog new tricks: A qualitative analysis of how residents of senior living communities may use the web to overcome spatial and social boundaries. Journal of Applied Gerontology. doi:10.1177/0733464811431824

Wooldridge, J. (2005a). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, *20*, 39–54. doi:10.1002/jae.770

Wooldridge, J. M. (2005b). Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models. *Review of Economics and Statistics*, *87*, 385–390. doi:10.1162/0034653053970320

Wooldridge, J. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

Wright, K. (2000). Computer-mediated social support, older adults, and coping. *The Journal of Communication*, *50*, 100–118. doi:10.1111/j.1460-2466.2000.tb02855.x

Xie, B. (2007). Older Chinese, the internet, and well-being. *Care Management Journals: Journal of Case Management; The Journal of Long Term Home Health Care*, *8*, 33–38. doi:10.1891/152109807780494122