The Effect of Job Displacement on Mental Health, When Mental Health Feeds Back to Future Job Displacement

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Abstract

This paper investigates the link between job displacement and mental health problems. The econometric model allows for the possibility that mental health troubles, once present, feed back to future job displacement. The results show evidence of statistically significant and nontrivial feedback, and that feedback is an important part of the link between job displacement and mental health problems. Specifically, once feedback is taken into account, the link between job displacement and mental health problems shrinks by approximately 45 percent. That conclusion points to an unfortunate loop in which job loss begets mental health troubles, which, in turn, hinder future job prospects. Consequently, policymakers should aim to improve mental health and job prospects by breaking that loop, perhaps through mental health assistance to aid those who experience job displacement, or by easing the job search process for people with mental health troubles.

JEL Codes: I12; J63; C33

Keywords: correlated random effects; numerical integration; average partial effects

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1. Introduction

This paper considers the effect of job displacement on mental health, while accommodating the possibility that mental health “feeds back” to future employment status. The econometric approach appends a feedback mechanism to a standard dynamic random effects probit model. Results show that, not only is feedback from mental health to future employment status evident, both statistically and substantively, but once that feedback is taken into account, the effect of job displacement on mental health is 45 percent smaller than when feedback is ignored.

Mental health problems represent one of the leading causes of disability among people 15 and older (Siu, 2016), and those problems come with high costs to society. In 2005, the U.S. spent $135 billion on mental health care, or approximately 1.1 percent of gross domestic product in that year (Mark et al., 2011). Insel (2008) argues that the true costs of mental health problems are even larger once one accounts for numerous “indirect” costs, a point echoed in many works by Kessler (2012). In light of those large expenses, policymakers need accurate estimates of how job displacement contributes to mental health problems.

Uncovering the link between job displacement and mental health must confront several econometric challenges. First, mental health likely displays intertemporal
persistence, with current mental health influenced by previous mental health. Such persistence calls for a dynamic specification, adding complexity to panel data estimators. Second, unobserved person-specific factors that correlate with the likelihood of job displacement likely also relate to mental health. For example, people with physical ailments might struggle to find employment, and those same physical problems also might contribute to mental health troubles.

A third complication, and the main point of emphasis in this paper, is that mental health problems, once present, likely hinder future employment prospects. But such “feed back” from mental health to future employment violates the assumption of strict exogeneity crucial for consistency in dynamic panel models. If job displacement harms mental health, and then deteriorating mental health subsequently hinders job prospects, then panel estimators that ignore that feedback loop will overestimate the true causal impact of job displacement on mental health.

A number of studies examine the effects of job loss on physical or overall health (Browning et al., 2006; Sullivan and Von Wachter, 2009; Strully, 2009; Black, Devereux, Salvanes, 2015; Browning and Heinesen, 2012). A few studies outside of economics attempt to link job loss and mental health (Caplan, Vinokur, Price, and Van Ryn, 1989; Drydakis, 2015). Within economics, the nearest related
study – and the one to which this paper attempts to compare its results – uses panel estimators and Medical Expenditure Panel Survey data to find that job displacement leads to an approximate 41 percent increase in “fair or poor” mental health (Schaller and Stevens, 2015).

Ignoring feedback, this paper also finds that job displacement increases the likelihood of “fair or poor” mental health. Accounting for dynamics, controls, and unobserved heterogeneity, the magnitude of that effect is slightly smaller than Schaller and Stevens (2015), but nonetheless in their ballpark. But taking into account that mental health might feed back to future employment prospects, this paper finds that that relationship, while still present, shrinks by 45 percent.

That conclusion should not be interpreted as downplaying the effects of job loss on mental health. Rather, the point is that part of the observed link between job loss and mental health problems owes to the finding that mental health problems, once present, appear to hinder future job prospects, creating an unfortunate loop. Policymakers can short circuit that loop, and improve both employment and mental health numbers, by providing mental health services for people displaced from their jobs, or by easing the job search process for those with mental health problems.

The following section discusses the estimation sample, drawn from the Medical
Expenditure Panel Survey. That data discussion is followed by two sections that outline dynamic random effects probit estimators, one the ignores feedback and another that explicitly takes it into account. After discussing the main results, the paper then uses the econometric setup to explore state dependence in mental health, and the role that feedback to future employment prospects plays in that state dependence. The paper then concludes with some policy implications.

2. Data

Data used in this study come from the Medical Expenditure Panel Survey (MEPS), collected and published by the Agency for Healthcare Research and Quality, a unit of the U.S. Department of Health and Human Services. Along with the parent survey from which it is drawn, the MEPS enjoys a reputation as the most complete source of individual-level information on health conditions, health insurance, and health care spending and consumption. In addition to its health focus, the MEPS also includes detailed information on employment activities.

Each MEPS respondent is interviewed in five rounds over an approximate two-year period, with the rounds spaced approximately six months apart. Owing to that survey design, the MEPS allows for the construction of panel estimation samples, with a large number of cross-sectional units (persons) but a relatively
short time dimension (rounds). This paper considers subjects who entered the MEPS during the 2013, 2014, and 2015 waves of the survey.

The estimation sample focuses on subjects between ages 18-59 upon entry in the survey who were employed during the first round of the survey. The estimation sample deletes subjects who experienced job displacement because they took maternity/paternity leave, returned to school, or wanted time off. That sample restriction aims to remove as many “voluntary” job separators as possible. The final estimation sample includes 18,412 unique subjects, each observed for five rounds, for a total of 92,060 person/round observations.

The main outcome variable of interest is a dummy indicator for whether the subject self-reports “fair or poor” mental health. For succinctness, the remainder of this paper refers to “fair or poor” mental health as mental health “problems.” (Bound (1991) provides a detailed analysis which speaks to the appropriateness of using self-reported health measures in place of seemingly more accurate, but more difficult to obtain, objective measures.)

As explained in more detail in the following section, the empirical methods focus on data from rounds 3, 4, and 5, with information from rounds 1 and 2 used to account for various aspects of dynamics. Therefore, sample means, reported in Table 1, apply only to rounds 3-5. Recalling that all subject enter the survey
employed, approximately 7.2 percent of person/round observations in rounds 3-
5 experience job displacement. And among subjects displaced from their jobs,
approximately 12 percent report mental health problems during the round of
displacement, compared to only 4 percent among those who remain employed.
That difference is statistically significant according to a standard two-sample t-
test.

The remainder of Table 1 shows that displacers and non-displacers differ along
several other observable dimensions. For example, displacers are younger, less
educated, less likely to be married, and more likely to be female or minority
compared to their non-displacing counterparts. The final row of Table 1 shows,
not surprisingly, that job displacers are less likely to have health insurance.

Panel data estimators, such as those outlined in the following section, require
sufficient intra-person variation in key time-varying measures. Although it is not
obvious what constitutes “sufficient,” Table 2 reports within-person coefficients of
variation (within-person standard deviations divided by overall means) for time-
varying measures. Most importantly, the two key variables in this study – mental
health problems and job displacement – show within-person standard deviations
that exceed their respective means by several orders of magnitude. That amount
of intra-person variation should allow for precise estimation of the key magnitudes
of interest.

3. Dynamic Random Effects Model

This section outlines a probit model for the presence of mental health problems, with the main emphasis being the effect of job displacement. The model incorporates potential intertemporal persistence in mental health and the possibility of unobserved confounding factors. This section does not address feedback from mental health to future job displacement; that feature comes in the next section.

Let \( y_{it} \) equal 1 if person \( i \) (\( i = 1, \ldots, n \)) reports “fair or poor” mental health in round \( t \) (\( t = 1, \ldots, 5 \)), and 0 otherwise. The probability that \( y_{it} \) equals 1 follows

\[
\Pr(y_{it} = 1) = \Phi(\beta_1 y_{i,t-1} + \beta_2 d_{it} + X_{it}' \beta + c_i)
\]

(1)

where \( \Phi \) represents the cumulative distribution function of the standard normal distribution. The vector \( X_{it} \) includes control variables, some of which vary across time periods, with estimable coefficients \( \beta \). The control variables include age, gender, race, ethnicity, educational attainment, marital status, family size, and health insurance status. (Of course, health insurance status might correlate with job displacement, but similar results were obtained when health insurance was omitted from the list of controls. Health insurance is included in \( X_{it} \) to account for the possibility that access to care affects the likelihood of being diagnosed with
mental health problems.) The variable \( d_{it} \) is a binary indicator for whether the person is displaced from his job in round \( t \). The coefficient \( \beta_2 \), which captures the extent to which job displacement affects mental health, represents the main focus of this paper.

Equation (1) allows dynamic persistence in mental health through two channels. First, previous-round mental health, \( y_{i,t-1} \), appears on the right-hand side as a conditioning variable. Thus, the coefficient \( \beta_1 \), often called a measure of true state dependence, captures whether the previous-period mental health state influences the current one. A lagged dependent variable specification is appropriate if, following a change in mental health, mental health returns partly, but not entirely, to its original state. Such a pattern would be evident if, for example, mental health problems tend to beget subsequent mental health problems. A lagged dependent variable setup also captures (potentially time-varying) unobserved heterogeneity, to the extent that such heterogeneity affected previous-period mental health (Angrist and Pischke, 2009, pp. 243-246).

The second channel of persistence in mental health comes via the inclusion of the term \( c_i \), which represents time-invariant person-specific unobserved heterogeneity that affects mental health in all periods. For example, perhaps the person is genetically or medically predisposed toward mental health problems, and those
predispositions, while impossible to observe in household surveys, clearly affect mental health in all rounds. It is possible, post estimation, to decompose the separate contributions to observed persistence in mental health of true state dependence (described in the previous paragraph) and time-invariant unobserved heterogeneity (described in this paragraph).

Honore and Tamer (2006) explore the behavior of dynamic nonlinear panel estimators like the one shown in equation (1). They show that, in general, such models do not produce point-identified parameter estimates, especially for the coefficient attached to the lagged outcome. However, they also show that, in most cases, in addition to correctly capturing signs of parameters, the bounds of parameter estimates fall in very tight regions around “true” values, such that lack of point identification is of little practical concern.

Nonlinear panel setups usually treat the term $c_i$ as a random effect, but that introduces two problems. First, a person’s initial mental health state, $y_{i1}$, likely correlates with $c_i$. That “initial condition problem” is most easily addressed by specifying the term $c_i$ as a function of $y_{i1}$ (Wooldridge, 2005). The second problem is that the random effect $c_i$ must not correlate with right-hand side variables, a restriction that seems tenuous in the current setting. For example, it seems possible that unobserved traits that affect mental health also correlate with marital
status and family size, both of which appear in the vector $X_{it}$. Such correlation biases random effects estimators. A common approach to this problem is to specify the term $c_i$ as a function to intra-person averages of (time-varying) explanatory variables (Mundlak, 1978). The inclusion of those time averages introduces correlation between the random effect term and the control variables, thus allowing a random effects estimator to capture the spirit of a fixed effects model.

Combining the initial condition and Mundlak terms, the term $c_i$ becomes

$$c_i = \delta y_{i1} + X_i' \delta + \alpha_i$$

(2)

where the vector $X_i$ includes intra-person time averages of the time-varying measures in $X_{it}$. (Note that, for now, $c_i$ does not include time-averaged job displacement. Endogeneity of that variable is addressed in the following section.) The term $\alpha_i$ represents time-invariant white noise heterogeneity.

Maximum likelihood estimation requires the joint density of $(y_{i3}, y_{i4}, y_{i5})$, where the first two rounds are omitted to accommodate lagged mental health in (1) and initial mental health in (2). That joint density follows

$$f(y_{i3}, y_{i4}, y_{i5} | X_i, c_i) = \prod_{t=3}^{5} (2y_{it} - 1)\Phi(\beta_1 y_{i,t-1} + \beta_2 d_{it} + X_{it}' \beta + c_i)$$

(3)

where $c_i$ is specified according to equation (2). The time-invariant white noise error $\alpha_i$ is numerically integrated out of the density (3) by drawing 100 quasi-
random Halton draws from \( \alpha_i \sim N(0, 1) \) and then averaging expression (3) across those draws. (Halton draws, as opposed to more familiar pseudo-random numbers, ensure more representative coverage of the target distribution, which, in principle, should allow for similar performance with fewer draws. Using more draws did not change the results.) The resulting integrated density is logged and summed over all \( i \) units to produce the log likelihood function, which is then maximized with respect to the estimable parameters \((\beta_1, \beta_2, \beta, \delta, \delta)\).

4. Dynamic Random Effects Model with Feedback

The panel model in the previous section relies on “strict exogeneity” of the control variables, which requires

\[
\Pr(y_{it} = 1|y_{i,t-1}, d_i, X_i, c_i) = \Pr(y_{it} = 1|y_{i,t-1}, d_{it}, X_{it}, c_i)
\]

where on the left-hand side \( d_i = (d_{i1}, \ldots, d_{i5}) \) and \( X_i = (X_{i1}, \ldots, X_{i5}) \). In words, strict exogeneity requires that, after controlling for previous-round mental health and unobserved heterogeneity \( c_i \), a person’s mental health state in round \( t \) may not correlate with control variables in rounds other than \( t \) (Wooldridge, 1997). The main concern in this study is that strict exogeneity rules out the possibility that mental health problems “feeds back” to future job displacement.

Strict exogeneity seems like a tenuous assumption in the current context, be-
cause mental health troubles, once present, might hinder a person’s ability to find work during subsequent periods. It is important to note that feedback is different from correlations induced by unobserved heterogeneity contained in \( c_t \). Whereas feedback implies a direct causal link from mental health to job prospects, unobserved heterogeneity concerns confounding factors, such as physical ailments, that might simultaneously influence mental health and job prospects.

This section seeks to relax strict exogeneity of \( d_{it} \) in order to allow feedback. First, mental health is specified identically to the previous section,

\[
\Pr(y_{it} = 1) = \Phi(\beta_1 y_{i,t-1} + \beta_2 d_{it} + \mathbf{X}_{it}'\mathbf{\beta} + c_i),
\]

(4)

where, as in the previous section, \( c_i = \delta y_{i1} + \mathbf{X}_{i}'\delta + \alpha_i \). Then, following Wooldridge (2000), a second conditional probability describes job displacement conditional on past mental health,

\[
\Pr(d_{it} = 1) = \Phi(\gamma_1 y_{i,t-1} + \gamma_2 d_{i,t-1} + \mathbf{X}_{it}'\gamma + \lambda c_i),
\]

(5)

where the heterogeneity term \( c_i \) is specified identically as in equation (4), but with an estimable “loading parameter” \( \lambda \) that allows the heterogeneity term to exert separate influences on mental health and job displacement. (A positive value for \( \lambda \) would indicate the unobserved person-specific traits that tend to lead to job displacement also contemporaneously correlate with mental health problems, as
opposed to the direct link captured by $\beta_2$.) Note that, similar to how mental health is modeled, current-round job displacement depends, in part, on possible displacement in the previous-round. But the main parameter of interest in equation (5) is $\gamma_1$, which captures to extent, if any, to which mental health problems feed back to future job displacement. Similar feedback type models have been applied to studies of poverty (Biewen, 2009), health insurance (Zimmer, 2010), and education (Welsch and Zimmer, 2015).

Combining the probabilities given in (4) and (5), the (unlogged) likelihood for person $i$ is

$$f(y_{i3}, \ldots, y_{i5}, d_{i3}, \ldots, d_{i5}) = \prod_{t=3}^{5} \{(2y_{it} - 1)\Phi(\beta_1 y_{i,t-1} + \beta_2 d_{it} + X_i' \beta + c_i) \times (2d_{it} - 1)\Phi(\gamma_1 y_{i,t-1} + \gamma_2 d_{i,t-1} + X_i' \gamma + \lambda c_i)\}.$$ 

Estimation follows a similar approach to that described in the previous section, with the white noise heterogeneity term $\alpha_i$ numerically integrates out of (6).

5. Results

Appendix Table 1 shows results for dynamic probits that do not account for feedback. The coefficients of lagged mental health, shown near the top of the table, indicate, not surprisingly, that mental health problems show strong persistence across time periods. The control variables, while not the central focus of this paper, align with a priori expectations. That is, mental health problems negatively
correlate with being married, having larger families, and holding higher levels of educational attainment. Mental health problems appear to increase with age, but decrease with respect to health insurance coverage. Finally, females report more mental health problems, while blacks and Hispanics report fewer.

Turning to the main explanatory variable of interest, job displacement, Table 3 reports average partial effects (APE), which aim to simplify the hard-to-interpret coefficients in Appendix Table 1. The APE of job displacement is calculated as

\[ APE = \frac{\Phi(\hat{\beta}_1 y_{it-1} + \hat{\beta}_2 1 + \tilde{X}_i \hat{\beta} + c_i) - \Phi(\hat{\beta}_1 y_{it-1} + \hat{\beta}_2 0 + \tilde{X}_i \hat{\beta} + c_i)}{n \times 3} \]  

(7)

where \( c_i = \hat{\delta} y_{1i} + \tilde{X}_i \hat{\delta} \). The denominator reflects that each person has 3 APEs, one for each time period used in estimation. Circumflexes denote converged parameter estimates. The standard error for the APE is calculated by a Monte Carlo method, where, on each replication of the method, the parameter \( \beta_2 \) is randomly perturbed by drawing it from a normal distribution centered on its estimated value and with standard deviation equal to its estimated standard error, and the APE in (7) is recalculated. The standard deviation of several hundred replications serves as the standard error.

In the model that contains only a constant (in addition to lagged mental health), job displacement correlates with a 3.3 percentage point increase in the
probability of mental health problems. Compared to the overall sample mean of mental health problems (0.044), that 3.3 percentage point increase translates to a substantial 75 percent increase in the likelihood of mental health problems. Consequently, job displacement shows a sizable link to mental health problems.

The second row of Table 3 shows that including controls shrinks the APE of job displacement, but only slightly. In the third row, the addition of random effects shrinks the APE further, to 0.011, or about 25 percent relative to the overall sample mean. The interpretation is that some, but not all, of the observed link between job displacement and mental health problems stems from people predisposed toward job displacement having unmeasured traits that also tend to correlate with mental health problems.

But none of the first three APEs reported in Table 3 account for possible feedback from mental health to future job displacement. To that end, Appendix Table 2 presents results from the full feedback model from equation (6). The most important number from that table, appearing near the upper right, shows evidence of statistically significant feedback. The APE of mental health problems on future job displacement (not reported in the table) is 0.016 with a standard error equal to 0.006. That APE indicates that, compared to mean job displacement (0.072), mental health problems increase the likelihood of job displacement.
by 22 percent. Thus, feedback is statically significant and nontrivial in size. An-
other result worth noting in Appendix Table 2 is the loading parameter (λ), which
is positive and significant, indicating that unmeasured person-specific traits that
lead to job displacement also tend to contemporaneously associate with mental
health problems.

The bottom row of Table 3 reports the APE of job displacement on men-
tal health, after accommodating for feedback. The estimated APE is 0.006, or
about 14 percent relative to the overall mean. Compared to the APE from the
random effects model without feedback, the feedback model shrinks the APE by
approximately 45 percent. Consequently, feedback from mental health to future
job displacement appears to be a sizable part of the observed link between job
displacement and mental health problems.

6. State Dependence of Mental Health

Although not the main focus of this paper, the econometric setup in this paper
can inform upon the extent of state dependence in mental health, including the
role that feedback to future job displacement plays in that state dependence. The
probability of mental health problems, presented in equation (1), and repeated
here,

\[ \Pr(y_{it} = 1) = \Phi(\beta_1 y_{i,t-1} + \beta_2 d_{it} + X'_{it}\beta + c_i), \]  

(8)

allows for mental health problems to show intertemporal persistence through two channels. The first channel, called “true state dependence,” is captured by the coefficient \( \beta_1 \). The second channel stems from unobserved heterogeneity that remains constant across time periods and affects mental health in each time period. That form of persistence is captured by the inclusion of \( c_i \), which, recall, is specified to permit (some) correlation with elements of \( X_{it} \).

Table 4 shows APEs of lagged mental health calculated similarly to equation (7), but with emphasis on the coefficient \( \beta_1 \). The first row includes only lagged health, job displacement, and a constant, effectively setting \( \beta \) and \( c_i \) equal to zero in equation (8). (The constant element of \( \beta \) is not set equal to zero.) That APE shows that previous-period mental health problems increase the likelihood of current-period mental health problems by 12.9 percentage points. Compared to the mean (0.044), that percentage point increase amounts to an increase of almost 300 percent in the probability of mental health problems. The second row in Table 4 adds controls to \( X_{it} \), with barely any reduction in the large APE estimate.

The third row introduces unobserved heterogeneity via the term \( c_i \). That inclusion shrinks the APE to 0.022, or about 50 percent relative to the sample mean.
The fourth row adds feedback, and the APE increases slightly to 0.035, likely because job displacement and mental health troubles appear to reinforce each other, both contemporaneously and dynamically. Thus, comparing the APE of 0.035 to those reported in the first two rows, state dependence accounts for approximately 27-30 percent of observed persistence in mental health, with the remainder due to unobserved heterogeneity. And comparing the two APEs reported in the bottom two rows, state dependence increases by almost 60 percent once feedback is taken into account.

7. Conclusion

This paper investigates the link between job displacement and mental health problems. The econometric model allows for the possibility that mental health troubles, once present, feed back to future job displacement. Results find evidence of statistically significant and nontrivial feedback, and that feedback is an important part of the link between job displacement and mental health problems.

A dynamic correlated random effects setup finds that job displacement increases the likelihood of mental health problems by approximately 25 percent, which is slightly smaller, but still in the ballpark, of the most closely-related study on this topic (Schaller and Stevens, 2015). However, after accounting for feedback,
that estimate shrinks to approximately 14 percent. The model also sheds light on state dependence in mental health. Specifically, state dependence accounts for approximately 27-30 percent of observed persistence in mental health, with the remainder due to unobserved heterogeneity. State dependence also increases by almost 60 percent once feedback is taken into account.

In sum, this paper’s main finding is that, after accounting for feedback, the link between job displacement and mental health problems, while still present, shrinks in magnitude. However, that conclusion should not be interpreted as downplaying the link between job loss and mental health. Quite to the contrary, the results of this paper point to an unfortunate loop in which job loss begets mental health troubles, which, in turn, hinder future job prospects. Consequently, policymakers should aim to improve mental health and job prospects by breaking that loop, perhaps through mental health assistance to aid those who experience job displacement, or by easing the job search process for people with mental health troubles.
References


Table 1 – Sample means

<table>
<thead>
<tr>
<th></th>
<th>Job displaced in round</th>
<th>Job not displaced in round</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N = 3,982</td>
<td>N = 51,254</td>
</tr>
<tr>
<td>“Fair or poor” mental health in round</td>
<td>0.12</td>
<td>0.04*</td>
</tr>
<tr>
<td>Age upon entry in MEPS</td>
<td>36.9</td>
<td>39.0*</td>
</tr>
<tr>
<td>Female</td>
<td>0.59</td>
<td>0.48*</td>
</tr>
<tr>
<td>Black</td>
<td>0.23</td>
<td>0.18*</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.33</td>
<td>0.31*</td>
</tr>
<tr>
<td>Highest education upon entry in MEPS: high school</td>
<td>0.64</td>
<td>0.57*</td>
</tr>
<tr>
<td>Highest education upon entry in MEPS: college degree</td>
<td>0.16</td>
<td>0.28*</td>
</tr>
<tr>
<td>Marital status in round</td>
<td>0.42</td>
<td>0.53*</td>
</tr>
<tr>
<td>Family size in round</td>
<td>3.26</td>
<td>3.22</td>
</tr>
<tr>
<td>Insured during round</td>
<td>0.62</td>
<td>0.78*</td>
</tr>
</tbody>
</table>

* column 2 differs from column 1 at p < .05

Table 2 – Coefficients of variation (within-person standard deviation divided by overall mean)

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fair or poor mental health</td>
<td>3.25</td>
</tr>
<tr>
<td>Job displacement</td>
<td>2.00</td>
</tr>
<tr>
<td>Marital status</td>
<td>0.15</td>
</tr>
<tr>
<td>Family size</td>
<td>0.09</td>
</tr>
<tr>
<td>Insured</td>
<td>0.18</td>
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</table>
Table 3 – APE estimates of the effect of job displacement on mental health problems (Mean mental health problems = 0.044)

<table>
<thead>
<tr>
<th>Percentage compared to mean mental health problems</th>
<th>APE</th>
<th>St. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contant only</td>
<td>0.033</td>
<td>0.002</td>
</tr>
<tr>
<td>Including controls</td>
<td>0.030</td>
<td>0.002</td>
</tr>
<tr>
<td>Random effects</td>
<td>0.011</td>
<td>0.002</td>
</tr>
<tr>
<td>Random effects with feedback</td>
<td>0.006</td>
<td>0.002</td>
</tr>
<tr>
<td>Percentage compared to mean mental health problems</td>
<td>APE</td>
<td>St. Err.</td>
</tr>
<tr>
<td>-------------------------------------------------</td>
<td>-------</td>
<td>---------</td>
</tr>
<tr>
<td>Contant only</td>
<td>0.129</td>
<td>0.002</td>
</tr>
<tr>
<td>Including controls</td>
<td>0.121</td>
<td>0.002</td>
</tr>
<tr>
<td>Random effects</td>
<td>0.022</td>
<td>0.0002</td>
</tr>
<tr>
<td>Random effects with feedback</td>
<td>0.035</td>
<td>0.0004</td>
</tr>
</tbody>
</table>

Table 4 – APE estimates of state dependence in mental health problems (Mean mental health problems = 0.044)
## Appendix Table 1 – Dynamic probit estimates (without feedback)

<table>
<thead>
<tr>
<th></th>
<th>Constant only</th>
<th></th>
<th></th>
<th>Including controls</th>
<th></th>
<th></th>
<th>Random effects</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged “fair or poor” mental health</td>
<td>1.694 0.028</td>
<td>1.626 0.029</td>
<td>0.783 0.039</td>
<td>1.600 0.058</td>
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</tr>
<tr>
<td>Job displacement</td>
<td>0.437 0.031</td>
<td>0.404 0.032</td>
<td>0.496 0.048</td>
<td>0.083 0.140</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age/10</td>
<td>0.079 0.010</td>
<td>0.123 0.016</td>
<td></td>
<td>0.043 0.035</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.068 0.021</td>
<td>0.097 0.034</td>
<td></td>
<td>0.017 0.084</td>
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Components of $c_t$...

Initial “fair or poor” mental health 1.600 0.058
Time average married 0.083 0.140
Time average family size 0.043 0.035
Time average insured 0.017 0.084
### Appendix Table 2 – Dynamic probit estimates (with feedback)

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<td>Lagged job displacement</td>
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<td>0.182</td>
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Components of $c_i$:

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<td>Time average married</td>
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<td>Time average family size</td>
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