Accepted Manuscript

A link between labor participation, mental health and class of medication for mental well-being

N. Vecchio, G. Mihala, J. Sheridan, M.F. Hilton, H. Whiteford, P.A. Scuffham

PII: S0313-5926(14)00064-2
DOI: http://dx.doi.org/10.1016/j.eap.2014.11.006
Reference: EAP 42

To appear in: *Economic Analysis and Policy*

Received date: 27 May 2014
Revised date: 10 November 2014
Accepted date: 10 November 2014

Please cite this article as: Vecchio, N., Mihala, G., Sheridan, J., Hilton, M.F., Whiteford, H., Scuffham, P.A., A link between labor participation, mental health and class of medication for mental well-being. *Economic Analysis and Policy* (2014), http://dx.doi.org/10.1016/j.eap.2014.11.006

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

ACCEPTED MANUSCRIPT

*Title Page [include author details]

TITLE PAGE

Full title: A link between labor participation, mental health and class of medication for mental well-being

Short title: Labor participation, mental health and class of medication

N. Vecchio, G. Mihala, J. Sheridan, M. F. Hilton, H. Whiteford, P. A. Scuffham

Nerina Vecchio (Corresponding Author), BA, BEc, PhD
Griffith Business School
Griffith Health Institute
Griffith University Gold Coast Campus
PMB 50, Gold Coast Mail Centre
Queensland 9726 Australia
Tele: +61 7 5552 8284
Fax: +61 7 5552 8068
n.vecchio@griffith.edu.au

Gabor Mihala
Senior Research Assistant – Statistics
School of Medicine
Griffith Health Institute
Griffith University Logan Campus
Queensland 4131 Australia
g.mihala@griffith.edu.au

Judith Sheridan
D. Clinical Psychology
The Prince Charles Hospital
Chermside, 4032, QLD, Australia
jsheridan6@gmail.com

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Harvey A Whiteford, MBBS, MPH, FRANZCP
Kratzmann Professor of Psychiatry
School of Population Health,
The University of Queensland
Queensland Centre for Mental Health Research,
Wacol, Queensland 4076 Australia
h.whiteford@uq.edu.au

Paul A Scuffham BA, PhD
Professor of Health Economics & Director, Centre for Applied Health Economics
Griffith Health Institute & School of Medicine
Griffith University Logan Campus
Queensland 4131 Australia
p.scuffham@griffith.edu.au

Acknowledgements

The authors would like to thank Dr Michael Hilton for his helpful comments.

Competing interests

The authors declare that they have no competing interests.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

A link between labor participation, mental health and class of medication for mental well-being

N. Vecchio[a,]*, G. Mihala[b], J. Sheridan[c], M. F. Hilton[c], H. Whiteford[c] , P. A. Scuffham[b]

[a] Griffith Business School, Griffith Health Institute, Griffith University Gold Coast Campus, PMB 50, Gold Coast Mail Centre, Queensland 9726 Australia

[b] Griffith Health Institute & School of Medicine, Griffith University Logan Campus, Queensland 4131 Australia,

[c] School of Population Health, The University of Queensland, Queensland Centre for Mental Health Research, Wacol, Queensland 4076 Australia

* Corresponding Author. Tele: +61 7 5552 8284. Fax: +61 7 5552 8068. E-mail: n.vecchio@griffith.edu.au

Abstract: We examined the relationship between mental health and labor participation. Analysis was based on the Australian National Health Survey, providing a nationally representative sample using 14788 observations. Accounting for endogeneity, analysis revealed that females were almost twice more responsive to changes in mental health on labor participation compared to males. Among Australians who did not take medication for mental wellbeing, poorer levels of mental health was associated with a reduction in the probability of labor participation. Among females with poorer mental health, taking any medication for mental well-being led to a decrease in the probability of labor participation. This relationship was not significant for males.

JEL: J22; J24; I1

Keywords: Mental health; Labor participation; Medication; Australia; Instrumental variables.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT
*Blinded Manuscript [no author details]
Click here to view linked References

A link between labor participation, mental health and class of medication for mental well-being

I. INTRODUCTION

The World Health Organization estimate that in developed countries the cost of mental health problems is between 3 percent and 4 percent of Gross National Product (GNP) (World Health Organisation, 2003). Although the cost of treatment of mental illness is often offset by an increase in productivity, in developed countries with well-organized health care systems, between 44 percent and 70 percent of patients with mental disorders do not receive treatment (World Health Organisation, 2003).

An inverse relationship exists between mental illness and productivity (Australian Bureau of Statistics, 2012; Chatterji, Alergria, Lu, & Takeuchi, 2007; Dewa & Lin, 2000; French & Zarkin, 1998; Kessler & Frank, 1997; Lim, Sanderson, & Andrews, 2000; Marcotte & Wilcos-Gok, 2003). Poor mental health can impair workplace productivity through increased absenteeism, deteriorating work performance, poorer staff attitude and behavior, and weaker relationships at work (Chatterji et al., 2007). Analysis of US worksite data found that workers with reported symptoms of emotional/psychological problems recorded higher absenteeism levels and lower earnings than others (French & Zarkin, 1998). The findings are supported by Chatterji et al. (2007) who found psychiatric disorders and mental distress were associated with detrimental effects on employment and absenteeism. Hilton and colleagues estimated psychological distress resulted in $5.9b lost employee productivity in Australia in 2009 (Ettner, Frank, & Kessler, 1997). A similar Australian study that investigated the education and health industry calculated a total presenteeism (suboptimal work performance) cost of $A2.68 billion for the state of Queensland, when measured in 2006 dollars (Laaksonen, Lallukka, Lahelma, & Partonen, 2012).

While existing research confirms that mental illness is negatively associated with productivity (Chatterji et al., 2007; Dewa & Lin, 2000; Frijters, Johnston, & Shields, 2010; Marcotte & Wilcox-Gok, 2001; Zhang, Zhao, & Harris, 2009), the labor productivity effects of drug therapies designed to alleviate the debilitating aspects of mental illness have received less attention. The majority of studies focus on the medication/treatment for depression (e.g. (Australian Institute of Health and Welfare, 2010, 2012; DeRubeis, Siegle, & Hollon, 2008).

ACCEPTED MANUSCRIPT

Fewer studies have allowed for comparisons across a variety of prescription medications, possibly reflecting their lower prevalence among the population (Australian Bureau of Statistics, 2007).

In the health production model (Grossman, 1972), health capital can be maintained and improved through economic resources and time. Among those experiencing mental illness, medication is expected to improve health capital. Since the mid 1990s there is growing evidence that impaired work performance from mental illness would respond to currently available treatments (Australian Institute of Health and Welfare, 2010, 2012; DeRubeis et al., 2008; Goldberg, 1972). Previous research highlights the positive impact of medications such as antidepressants on productivity (Australian Institute of Health and Welfare, 2010). Rizzo et al., (1996) conducted one of the first studies to investigate labor productivity that separated the effects of chronic depression from the effects of prescription medications taken to alleviate the condition. Using data taken from the National Medical Care Expenditure Survey, the study concluded that the net benefits to employers from having workers take prescription medicines were substantial.

An endogenous relationship exists between health and work outcomes (Grossman, 1972); that is, mental health impacts on labor participation and labor participation impact on mental health. For example, possible feelings of isolation, loss of identity and a reduction in income associated with non-participation in the work force may lead to a deterioration of mental health. Alternatively, stress associated with employment may lead to a deterioration of mental health.

Recent studies have used instrumental variables to gain more reliable estimates between labor force participation and mental health (Chatterji et al., 2007; Ettner et al., 1997; Frijters et al., 2010; Zhang et al., 2009). Zhang (Zhang et al., 2009), for instance, used pooled cross-sectional data from the Australian National Health Surveys to estimate a joint system of equations modelling the relationship between chronic diseases, including mental disorders and labor market participation. The effect of mental illness was found to be large for men, with older males in particular having a decline in the likelihood of participation of around 25 percentage points (Zhang et al., 2009). Frijters and colleagues used panel data to estimate the effect of mental health on labor market participation (Frijters et al., 2010). Addressing the problems of reverse causality and selectivity the authors used the recent death of a close friend as the instrumental variable for mental health. A standard deviation decrease in mental health decreased the

ACCEPTED MANUSCRIPT

probability of participation in the labor force by around 17 percentage points. The effect was larger for females and for older individuals (Frijters et al., 2010).

Of the major disease groups in Australia, mental disorders is the leading cause of disease burden resulting from years lost due to disability (Australian Institute of Health and Welfare, 2010). In this study, data from the Australian Bureau of Statistics' (ABS) 2005 Australian National Health Survey (ANHS) is used to investigate the association between labor market outcomes and mental health. We take advantage of census data that captures information on class of medication for mental wellbeing. The contribution of this paper is twofold. One, we confirm the findings of previous empirical research that shows a negative impact of mental illness on labor market participation. Accounting for the endogenous relationship between mental health and labor force participation, we estimate the relationship using prescription medications for mental well-being as instrumental variables. Secondly, we extend the work of previous studies by isolating the impact of class of medication to obtain the effects of mental health on labor force participation. A major advantage of this study is that it captures information about individuals who have taken medication rather than those who have been prescribed medication (but may not comply). This has allowed the separation of the effects of mental illness from the effects of medication taken to alleviate this condition.

II. METHODS

The Data

The main variables under investigation include labor participation, mental health and class of medication. These variables are discussed in the subsections below.

Labor participation

Labor force participation describes the economically active population or the formal supply of labor. Labor force participation is defined as either being employed or else being unemployed but actively looking for work and available to begin. The remainder of the working age population is described as being not in the labor force.

Measuring mental health

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Given the lack of information relating to specific mental disorders in the ANHS, the Kessler Psychological Distress Scale (K10) became a proxy for mental health. The K10 score is a 10 item scale of non-specific psychological distress based on questions about negative emotional states in the 4 weeks prior to interview (Australian Bureau of Statistics, 2007). The K10 is scored from 10 to 50, with a K10 score of 10 being the lowest level of psychological distress and 50 indicating the highest level of psychological distress (Australian Bureau of Statistics, 2007).

The K10 score has been validated as a measure of psychological distress with excellent internal consistency and reliability (Frijters et al., 2010; Ware, Kosinski, & Keller, 1996). Andrews and Slade (2001) showed a significant association between the scores on the K10 and a) measures of symptoms (General Health Questionnaire – a symptom measure that can predict cases) (Goldberg, 1972); b) health-related quality of life (SF-12 – a measure of disability) (Ware et al., 1996); c) the number of consultations for a mental health problem in the previous 12 months. Thus, there is a high likelihood of a mental disorder among those with high psychological distress. As a measure of mental health, the K10 is preferred over the number of psychiatric-related consultations because consulting is a measure of met need rather than morbidity. Although the K10 score does not indicate directly those clinically diagnosed with mental illness, high scores indicate the likely presence of a mental disorder, including an undiagnosed or untreated disorder (Frijters et al., 2010; Ware et al., 1996) and as such highlights the labor force consequences of not seeking treatment.

Further support for the use of the K10 score as an indicator for the presence of mental illness is evidenced in the Australian Bureau of Statistics (ABS) summary findings. Adults reporting a long term mental or behavioural problem tend to record higher levels of current psychological distress (Australian Bureau of Statistics, 2007). Compared with 13 per cent of the total adult population, 48 per cent of people with a long term mental or behavioural problem reported high or very high levels of current psychological distress (d'Errico et al., 2011).

Class of Medication

The investigation captures information relating to prescription medications taken to improve mental wellbeing. The interviewer asked subjects *"Have you taken any of the following medications for your mental well-being in the last 2 weeks?"* (Australian Bureau of Statistics, 2007). In this study the categories of medication are sedatives (hypnotics), anxiolytics,

ACCEPTED MANUSCRIPT

tranquilizers, antidepressants, mood stabilizers, non-specified prescription medications and natural remedies (vitamins, minerals, herbs). The classification developed by the ABS for the National Health Survey was based on the WHO Anatomical Therapeutic Chemical Classification. The framework underlying the listing of medications was derived from the Australian Medicines Handbook (Australian Bureau of Statistics, 2007).

Data Analytic Procedures

Data were extracted from the ABS Remote Access Data Laboratory and analyses conducted remotely using Stata (Australian Bureau of Statistics, 2006b). All the results are calculated using the person weights provided in the ANHS dataset. These weights indicate how many persons in the population are represented by persons in the survey, and take into account the individual's probability of being selected into the sample. Standard errors of population estimates are calculated using the jackknife method (Virtanen et al., 2007). Analyses were stratified by gender to allow for comparisons.

Binary regression

Initially, a binary probit regression is run to estimate the relationship between labor force participation and several risk factors. Labor force participation is assumed to depend on chronic mental illness and subject to specific individual and employment characteristics. The estimated equation is specified as:

$$LFP_i = \beta_0 + \beta_1 KESS_i + \beta_2 S_i + \varepsilon_i \qquad (1)$$

where LFP_i is a dichotomous dependent variable: 1 if in the labor force; 0 if not in the labor force. The potential explanatory variables used in the model were based on the availability of the data, the theoretical model and the usual socio-demographic characteristics identified in the literature. These explanatory variables are described below and presented in Table 1.

The K10 score, represented as KESS, is a continuous variable representing the level of mental health, a score of 10 being the lowest level (best mental health) and 50 being the highest (worst mental health). The vector S relates to control variables of respondent characteristics such as marital status, age, gender, education, health insurance, language and number of long term health conditions. Controlling for the number of long term health conditions reduced over-estimations from disease specific effects (Bonde, Munch-Hansen, Wieclaw, Westergaard-Nielsen, & Agerbo,

ACCEPTED MANUSCRIPT

2009). Since age may be correlated with the number of health conditions, the age variable is converted to categories.

The analysis also stratifies the sample by gender and by medication intake - those that take any medication for mental well-being and those that do not.

Simultaneous equations

Due to the endogenous relationship between the K10 score (that is, psychological distress) and labor force participation, prescription medications used for mental well-being are chosen as instruments for mental health status (represented by the K10 score). Model (1) is transformed to a simultaneous equation model where MED represents a vector of instrumental variables relating to prescription medications taken to improve mental well-being. The output from the instrumental probit models are presented in Table 2 and discussed in the results section of this paper.

$$LFP_i = \beta_0 + \beta_1 KESS_i + \beta_2 S_i + \varepsilon_i \quad (2a)$$

$$KESS_i = \beta_3 + \beta_4 LFP_i + \beta_2 S_i + \beta_5 MED_i + \varepsilon_i \quad (2b)$$

The rejection of the null hypothesis of the Wald test of exogeneity ($p<0.05$) indicates that the error terms in the structural equation (probit) and the reduced-form equation for the endogenous variable (instrumented regression) are correlated and therefore instrumenting the endogenous variable is appropriate.

Using class of medication for mental wellbeing as instrumental variables rather than the traditional specific health conditions avoids several issues reported by Kalwij and Vermeulen (Kalwij & Vermeulen, 2008). For example, an individual may justify their non-participation in the labor market by reporting to have worse health than their actual health status. In addition to justification bias, measures of self-reported health may suffer from measurement error. To reduce problems associated with these issues, in the model the class of medication indicates the actual intake of medication, an objective measure based on the diagnosis by a health professional. Although psychiatric medications may be prescribed ‘off label’ (i.e. for conditions that are not their primary indication) it never-the-less identifies an individual with a mental health condition.

The two basic conditions for a valid instrumental variable are that the instruments must be: 1) highly correlated with the variable to be instrumented; and 2) correlated with the outcome variable of interest only through the variable to be instrumented. Prescription medications for mental well-being are appropriate instruments since they are highly positive correlated with mental health status. While each measure of mental health (either medications used or K10 score) explains a significant amount of variation in labor force participation, K10 score and medications used are not perfect substitutes. Mental health as measured by the K10 score and reflecting the presence of a mental disorder is a composite of various factors such as genetic influences, adverse early life experiences, exposures to risk factors and events and social factors affecting mental health. It is expected that individuals with more severe and/or long term mental conditions are more likely to take prescription medications and in turn are more sensitive to labor force participation.

Reverse causality (i.e. employment may effect medication) is not expected to be an issue in this study for the reasons below:

1. While employment can be influenced by mental health as measured by medication, the reverse causality of employment causing medication use though work related stress and other factors is likely to be weak. Short term conditions such as work related stress are less likely to be treated with prescribed medications with employees more likely to take leave. Over time employees will move away from stressful jobs. This has certainly been the case in the nursing profession (Andrews & Dziegielewski, 2005; Eley, Buikstra, Plank, Hegney, & Parker, 2007; Shields & Ward, 2001). During the data collection phase of 2004/5, the Australian economy was in the boom phase of the business cycle. Employees at this time had opportunity to successfully seek alternative work.
2. Generally researchers have found that the impact of employment on the use of prescribed medication for mental wellbeing is rather weak (Bonde et al., 2009; Laaksonen et al., 2012; Virtanen et al., 2007). Investigating work stress, Virtanen and colleagues (Virtanen et al., 2007) showed that the association with future antidepressant use was evident only among male workers and not female workers (Virtanen et al., 2007). Bonde and colleagues (Bonde et al., 2009) found no relationship between poor psychosocial work environment among 21,129 Danish public service employees and prescription of antidepressant pharmaceuticals (Bonde et al., 2009). After exclusion of current and regular users of psychotropic drugs, Laaksonen and colleagues (Laaksonen et al., 2012) found that working conditions were only weakly associated with psychotropic

ACCEPTED MANUSCRIPT

medication. The workplace environment was of importance only among men. Working overtime was associated with sleeping pills among men but otherwise the associations were negligible. A Finnish study examining work stressors and antidepressant medication during a 3-year follow-up found that job demands and job strain were associated with antidepressant medication among men (Virtanen et al., 2007). No association was found for job control among male workers or any of the work characteristics among female workers. Only psychosocial working conditions demonstrated some, albeit inconsistent, associations with psychotropic drugs, especially with antidepressants.

3. The use of specific categories of medications in the model is expected to reduce reverse causality of labor participation on health status in a similar way as the use of specific diseases reduces the possible reverse causality (Zhang et al., 2009).
4. Potential endogeneity arises as employment may affect health insurance status, which in turn may affect the likelihood of obtaining medical treatment (Galárraga, Salkever, Cook, & Gange, 2010). This endogeneity is less likely among Australian studies as health services and medications are heavily subsidized by the Australian government, particularly for individuals from disadvantaged groups.
5. Low levels of cyclical unemployment[1] in Australia during the data collection year of 2004/5 imply high levels of employability were experienced among the study's sample. Employability strongly moderates the effects of unemployment and of job insecurity on mental health (Green, 2011). In contrast, periods of economic downturns and increases in the unemployment rate associates with worsening of psychological distress and self-reported prevalence of non-psychotic mental disorders (C.J. Ruhm, 2000; C.J. Ruhm, 2003).

Although medication has an effect on the measure of mental illness it may lead to either an improvement for those with mental illness or could be a sign of more severe mental illness. This violation of the monotonicity assumption is unlikely. That is, the taking of medication in this study is not necessarily an indication of more severe mental illness if the medication is able to manage an individual's mental health condition. It is assumed that the optimal level of prescribed medication is taken, thus leading to an improvement in mental health. Furthermore, this study

[1] Relates to the cyclical trends in growth and production that occur within the business cycle. When business cycles are at their peak, cyclical unemployment will be low because total economic output is being maximized.

ACCEPTED MANUSCRIPT

confines the sample to individuals who take only one type of medication for mental wellbeing. Doing so eliminates those with more complex mental health conditions. Regardless of the cause of poor mental health, taking medication for mental well-being is expected to improve health and therefore labor force participation rather than reduce labor force participation.

Interaction terms

Further regressions are run that add non-prescription medication (MED7) to the vector of medications. The model is then expanded to include interaction effects between the class of medication and level of mental health.

$$LFP_i=\beta_0+\beta_1 MnKESS_i+\beta_2 MED_i+\beta_3 S_i+\beta_4 MED*MnKESS_i+\varepsilon_i \quad (3)$$

KESS is centred for the analysis (mean of the K10 score of the sample is subtracted from each subject's K10 score so that the mean is now zero) and represented as MnKESS. The inclusion of the interaction term (MED*MnKESS) changes the interpretation of the coefficients for mental health (KESS) and the class of medication (MED) variables from unconditional (when there is no interaction term) to conditional, regardless whether the interactions are significant or not. The coefficient for MnKESS shows the mental health of individuals who do not take medication. The β2MEDi term now shows the difference between use of medication and non-medication at the mean of KESS for the sample. The variable MED*MnKESS represents a vector of interaction effects between each medication (MED = 0 is non-use, 1 is use) and the level of mental health (MnKESS). The interactions show the effect of the class of medication on labor force participation as the level of mental health rises/falls.

Data Source

The 2004-2005 ANHS is the fourth in a series of regular population surveys designed to obtain national benchmark information on a range of health-related issues and to enable the monitoring of trends in health over time. The cross sectional analysis is based on the ANHS (2005) data collected between August 2004 and July 2005. The ANHS includes information about people residing in urban and rural areas of all Australian States and Territories. Trained interviewers from the Australian Bureau of Statistics collected the household component of the data survey from a sample of 19,501 private dwellings selected throughout non-sparsely settled areas of Australia (Australian Bureau of Statistics, 2007).

ACCEPTED MANUSCRIPT

Within each selected household a random sub-sample of usual residents were selected for inclusion in the survey. Confidentialised data files were provided by the Australian Bureau of Statistics from a population survey. The ANHS contains individual statistical records with information about 25,906 persons.

The survey was conducted using personal interviews. Based on self assessment these interviews obtained data on respondents' own perceptions of their state of health, their use of health services and aspects of their lifestyle. The information obtained is not necessarily based on any professional opinion (e.g. a doctor, a nurse) or on information available from records kept by respondents (Australian Bureau of Statistics, 2006a). In responding to questions on medication use, interviewers encouraged respondents to collect and refer to medication bottles, packets, etc. This served to assist respondents in reporting all medications used for a particular condition, and assist interviewers in accurately recording the medication name.

Those aged 65 and over were excluded from the analysis because the minimum Age Pension for males was 65 years in Australia at the time of data collection. Persons aged under 18 years were omitted. To understand the direct impact of prescription medications on labor participation, individuals taking multiple medications were excluded from the analysis. It is likely that those who took more than one class of medication possessed more complex and difficult to treat mental health conditions. Within this group we would expect that the taking of more than one class of medication would negatively impact on the probability of participating in the labor market. After excluding those who did not fit this study's criteria, 14788 observations remained for analysis, resulting in an estimated weighted population of 11,907,704.

III. RESULTS

Descriptive Statistics

A statistical summary of the estimated weighted population is presented in Table 1. The analysis of the sample reports 79.2 per cent participate in the labor force. While the KESS mean score is 15.26, those in the labor force show a lower mean score compared to those not in the labor force. Those employed or actively seeking employment appear to possess better mental health. During the previous 2 weeks non-prescription medication (9.2 per cent), antidepressants (3.0 per cent) and sedatives (1.7 per cent) were the most commonly taken medications for mental well-being. A

ACCEPTED MANUSCRIPT

greater proportion of Australians not in the labor force take medication for their mental well-being.

INSERT TABLE 1 HERE

Regression models: Binary and simultaneous equations

The results of the regression models are presented in Table 2. The probit regressions for the total sample and stratified by gender (refer model (1), Methods section) are compared to the simultaneous models estimated using ivprobit (refer model (2), Methods section). The estimated coefficients for the control variables are as expected. For instance, being male, health insurance, English speaking, increasing educational attainment and decreasing number of health conditions significantly increase the probability of labor participation. Females aged 25 years and older are associated with lower participation in the labor force compared to females aged 18 to 24 years. As males age, labor force participation rates increases and then decreases after the age of 50 years. Responsiveness of labor force participation to mental health status (measured by KESS) is similar between females and males.

The ivprobit models that include the instrumental variables show similar magnitude and signs to that of the simple probit model. When endogeneity between mental health (KESS) and labor force participation is considered (refer Table 2, columns 6), the model shows that for the total sample, a marginal change in KESS from the average of 15.3 is associated with a 1.8 per cent decrease in labor force participation. Among the sample of males and females a marginal change in KESS from the average is associated with a 1.3 per cent and 2.1 per cent, respectively, decrease in labor force participation.

INSERT TABLE 2 HERE

Further analysis is stratified by medication status – did/did not take any medication[2] for mental well-being in the last 2 weeks (refer Table 3). Among the sample who took medication for mental well-being, females were more responsive to changes in mental health than males.

[2] Regressions were also run stratifying the sample by prescription medication rather than any medication that included over the counter medications. This produced similar results to those presented in Table 3.

ACCEPTED MANUSCRIPT

Among individuals who do not take medication, little difference in magnitude exist between the genders. However, being unmarried lowers labor force participation among males and increases participation among females.

INSERT TABLE 3 HERE

Regression models with interaction effects between mental health and class of medication

Implicit in the models presented in Tables 2 and 3 is the assumption that the differential effect of mental health is constant across the class of medication and that the differential effect of class of medication is constant across levels of mental health. For example, it is assumed that the likelihood of labor force participation is lower for those with higher levels of mental illness, regardless whether or not respondents take medication or not for their mental health. Interaction terms between mental health and class of medication are added to the models to isolate the impact of mental health on labor force participation.

INSERT TABLE 4 HERE

The analysis of model (3) uses 'no class of medication' (NoMED) as the base category. The results from the probit models that include the interaction terms (refer model (3), Methods section) are presented in Table 4 (columns 1, 2, 3). The estimated coefficients for MnKESS show that among individuals with poorer levels of mental health who <u>do not take</u> medication, there is a lower probability of participating in the labor market.

Referring to the MED coefficients of the sample of males, there is no significant difference in the probability of actively participating in the labor market between those that take medication and those that do not when KESS is at the mean of the sample. However, of the sample of females, the estimated coefficients for other prescription medication (MED6) show a strong effect between taking and not taking medication when KESS is at the mean. Specifically, when mental health is at the mean, females taking other prescription medications for mental well-being are less likely to participate in the labor force. Although the level of distress may have decreased, females taking these medications may not be ready to participate in the labor market. Amongst

ACCEPTED MANUSCRIPT

males who take Anxiolytics (MED2*KESS), those with poorer mental health are less likely to participate in the labor force.

Converting the categories of medication into a dichotomous variable, MED (medication = 1, 0 otherwise) (refer Table 4, columns 4, 5, 6) we find that among females with poorer mental health (MED*KESS) taking medication is associated with a decrease in the probability of participating in labor force. No such significant relationship is found for males.

IV. DISCUSSION

This study achieved several objectives. First, consistent with previous research, we confirmed a negative relationship between mental illness and labor market participation. After accounting for the endogenous relationship between mental health and labor force participation, the stratification of the analysis by gender revealed that females were almost twice more responsive to changes in the level of mental health on labor force participation compared to males. This is consistent with the findings of Frijters et al. (Frijters et al., 2010)[3] and Marcotte et al. (Marcotte & Wilcox-Gok, 2001) Frijters et al. (Frijters et al., 2010) suggests the higher social demands made on men to keep working even when mental health deteriorates may explain this gender difference. Zhang et al., however, found that the effects of mental illnesses were higher for males than females (Zhang et al., 2009).

Also of interest in this study was the effect of mental health on labor force participation when isolating the impact of each class of medication used to alleviate mental illness. The results from this study showed that among Australians, those with poorer mental health who did not take medication for mental wellbeing were less likely to actively participate in the labor market. Among the sample of females, those with worse mental health that took any medication for mental well-being were less likely to participate in the labor force. This relationship was not significant for the sample of males. This adds further weight to the argument that men may be more duty bound than women to continue employment when they become unwell (Frijters et al., 2010).

[3] Difference in magnitude between our study (2.1 per cent) and Frijters et al. (17 per cent) reflects the difference in the mental health measure used in each study. Frijter and colleagues' health index is based on the SF-36 score (scale of 0 to 100) that takes the mean of individual's responses and then standardizing such that the index is mean zero and standard deviation one.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

We offer several explanations for the gender difference in the magnitude of the mental health coefficient. First, the dominance of women in the part-time workforce, 70% of all part-time workers in Australia (Australian Bureau of Statistics, 2012), provide opportunities for women to better adapt to changing circumstances and health conditions. The majority of men are employed on a full time basis which offers less flexibility. Another possible explanation is that with each incremental increase in labor attachment the marginal benefits of health output may be greater for males than females. Llena-Nozal and colleagues found that the rate of mental health deterioration slowed down when people worked and that this effect was strong for males and small for females (Llena-Nozal, Lindeboom, & Portrait, 2004). Employment status was also found to be important for males. Although males who were out of the labor force had substantially worse mental health, no such evidence was found for females. Llena-Nozal and colleagues reasoned that the dominant view of non-market activities (such as taking care of the home and children) as acceptable for females but not for males may explain these results. Also compared to males, females may be more likely to leave employment for reasons unrelated to their health, such as family care responsibilities.

Our study found that being married increased the chance of males participating in the labor force but decreased that for females. The ability to speak English was also an important indicator for labor force participation. In terms of educational level, as expected, the higher the educational level, the more likely the respondent participated in the labor force. Compared to males, females' labor participation were more likely to be influenced by education levels. These results are consistent with the findings reported by Zhang et al. (2009). Similar to our study, Zhang used the national weighted census data from the Australian National Health Survey.

Medication and labor force participation

Medication for mental wellbeing appeared to neutralize the negative impact of psychological distress on labor force participation. Among individuals that <u>did not take</u> medication for mental wellbeing, worse psychological distress associated with a significant decrease in the probability of labor participation (refer Table 4). Among Australians who <u>did use</u> any class of medication for mental well-being, a significant and negative relationship existed between the level of psychological distress and labor force participation for females but not for males when controlling for confounding variables (Table 4, columns 4 and 5). There was no significant

ACCEPTED MANUSCRIPT

difference in the probability of participating in the labor market between those that took medication and those that did not when psychological distress was at the mean.

V. CONCLUSION

This study investigated labor participation of mental illness. This study offered several advantages: the identification of medication variables as plausible instruments when taking into account the potential endogeneity between mental health and labor force participation; and the ability to isolate the impact of medications when testing the relationship between mental health and labor force participation. In line with previous studies we found evidence that worsening mental health led to a significant decline in the probability that an individual would actively participate in the labor force. Accounting for the endogenous relationship between mental health and labor force participation, we also found that the effect of poor mental health on participation rates was larger for females than males. Analysis that included interaction terms between mental health and medications revealed that as the level of mental health of individuals who took medication worsened, there was a lower probability of labor participation. This relationship was significant for the sample of females, not the sample of males.

The results show that the effect of poor mental health on labor force participation is larger for females than males. Given these findings, future research would benefit from an investigation of the relationship between mental health and measures such as presenteeism and absenteeism. This is likely to lead to telling findings of the impact of mental health on the productivity of males.

Psychological distress is a generic manifestation of all mental disorders which can interfere with a person's ability to function. Consequently worsening psychological distress is likely to lead to a deterioration of work performance and participation. While the personal benefits of taking medications to alleviate mental illness are obvious, the positive impacts on society are expected to be substantial. By reducing or preventing the occurrence of mental health conditions, greater incentives to participate in the labor force may be created. Social benefits of alleviating mental illness include not only increased national productivity but also a reduction in publicly funded disability and unemployment benefits. Publicly funded mental health strategies designed to combat mental illness within the community are expected to be cost effective. Advances in pharmacotherapy have led to progress in treating the most debilitating psychiatric disorders, such

ACCEPTED MANUSCRIPT

as depression, bipolar disorder and schizophrenia. Thus, the forgone labor market productivity associated with mental illness can be contrasted with the costs of treating the condition (Ettner et al., 1997).

REFERENCES

Andrews, D., & Dziegielewski, S. (2005). The nurse manager, job satisfaction, the nursing shortage and retention. *Journal of Nursing Management 13*, 286-295.

Australian Bureau of Statistics. (2006a). Census of Population and Housing, Queensland, 2006 (Vol. Cat. no. 2068.0). Canberra: Commonwealth Government of Australia.

Australian Bureau of Statistics. (2006b). User Manual: ABS Remote Access Data Laboratory (RADL) *1406.0.55.002* Retrieved January 24th, 2012, from http://www.abs.gov.au/ausstats/abs@.nsf/mf/1406.0.55.002

Australian Bureau of Statistics. (2007). National Health Survey 2005 Basic, Confidentialised Unit Record File (CURF) No. 2079. Canberra: Australian Bureau of Statistics.

Australian Bureau of Statistics. (2012). *Year Book Australia, 2012* Canberra: Commonwealth Government of Australia.

Australian Institute of Health and Welfare. (2010). *Australia's health 2010. Australia's health no. 12* Canberra.

Australian Institute of Health and Welfare. (2012). Australia's health 2012. In AIHW (Ed.), *Australia's health series*. Canberra: AIHW.

Bonde, J., Munch-Hansen, T., Wieclaw, J., Westergaard-Nielsen, N., & Agerbo, E. (2009). Psychosocial work environment and antidepressant medication: a prospective cohort study. *BMC Public Health, 9*, 262.

Chatterji, P., Alergria, M., Lu, M., & Takeuchi, D. (2007). Psychiatric disorders and labor market outcomes: evidence form the national Latino and Asian American study. *Health Economics, 16*, 1069-1090.

d'Errico, A., Cardano, M., Landriscina, T., Marinacci, C., Pasian, S., Petrelli, A., & Costa, G. (2011). Workplace stress and prescription of antidepressant medications: a prospective study on a sample of Italian workers. *Int Arch Occup Environ Health 84*, 413–424.

DeRubeis, R., Siegle, G., & Hollon, S. (2008). Cognitive therapy versus medication for depression: treatment outcomes and neural mechanisms. *Nature Reviews Neuroscience, 9*, 788-796.

Dewa, C. S., & Lin, E. (2000). Chronic physical illness, psychiatric disorder and disability in the workplace. *Social Science and Medicine, 51*, 41-50

Eley, R., Buikstra, E., Plank, A., Hegney, D., & Parker, V. (2007). Tenure, mobility and retention of nurses in Queensland, Australia: 2001 and 2004. *Journal of Nursing Management 15*, 285-293.

Ettner, S., Frank, R., & Kessler, R. (1997). The impact of psychiatric disorders on labor market outcomes. *Industrial and Labor Relations Review, 51*, 64-81.

French, M., & Zarkin, G. (1998). Mental health, absenteeism and earnings at a large manufacturing worksite. *The Journal of Mental Health Policy and Economics, 1*, 161-172.

ACCEPTED MANUSCRIPT

Frijters, P., Johnston, D., & Shields, M. (2010). *Mental health and labour market participation: Evidence from IV panel data models* IZA Discussion Paper No. 4883.
Galárraga, O., Salkever, D., Cook, J., & Gange, S. (2010). An Instrumental variables evaluation of the effect of antidepressant use on employment among HIV-infected women using antiretoviral therapy in the United States: 1996–2004. *Health Economics, 19*(2).
Goldberg, D. (1972). *The detection of psychiatric illness by questionnaire*. London: Oxford University Press.
Green, F. (2011). Unpacking the misery multiplier: How employability modifies the impacts of unemployment and job insecurity on life satisfaction and mental health. *Journal of Health Economics 30*, 265-276.
Grossman, M. (1972). On the concept of health capital and the demand for health *Journal of Political Economy 80*, 223-255.
Kalwij, A., & Vermeulen, F. (2008). Health and labour force participation of older people in Europe: What do objective health indicators add tot he analysis? *Health Economics, 17*, 619-638.
Kessler, R., & Frank, R. (1997). The impact of psychiatric disorders on work loss days. *Psychological Medicine, 27*(4), 861-873.
Laaksonen, M., Lallukka, T., Lahelma, E., & Partonen, T. (2012). Working conditions and psychotropic medication: a prospective cohort study. *Soc Psychiatry Psychiatr Epidemiol 47*, 663–670.
Lim, D., Sanderson, K., & Andrews, G. (2000). Lost productivity among full-time workers with mental disorders. *Journal of Mental Health Policy and Economics, 3*(3), 139-146.
Llena-Nozal, A., Lindeboom, M., & Portrait, F. (2004). the effect of woek on mental health: does occupation matter? *Health Economics, 13*, 1045-1062.
Marcotte, D., & Wilcos-Gok, V. (2003). Estimating earnings losses due to mental illness: A quantile regression approach. *The Journal of Mental Health Policy and Economics, 6*, 123-134.
Marcotte, D., & Wilcox-Gok, V. (2001). Estimating the employment and earnings costs of mental illness. Recent developments in the United States. *Social Science and Medicine, 53*, 21-27.
Ruhm, C. J. (2000). Are recessions good for your health? *Quarterly Journal of Economics, 115*(2), 617-650.
Ruhm, C. J. (2003). Good times make you sick. *Journal of Health Economics, 22*, 637–658.
Shields, M., & Ward, M. (2001). Improving nurse retention in the National Health Service in England: the impact of job satisfaction on intentions to quit *Journal of Health Economics, 20*, 677-701.
Virtanen, M., Honkonen, T., Kivimäki, M., Ahola, K., Vahtera, J., Aromaa, A., & Lönnqvist, J. (2007). Work stress, mental health and antidepressant medication findings from the Health 2000 Study
Journal of Affective Disorders, 98, 189–197.
Ware, J., Kosinski, M., & Keller, S. (1996). A 12 item short form survey. *Med Care, 34*, 220-233.
World Health Organisation. (2003). Investing in mental health (n.-c. d. a. m. h. Department of mental health and substance dependence, Trans.). Geneva: World Health Organisation.
Zhang, X., Zhao, X., & Harris, A. (2009). Chronic diseases and labour force participation in Australia. *Journal of Health Economics, 28*, 91-108.

ACCEPTED MANUSCRIPT

Table

Table 1. Descriptive Statistics: Weighted Estimates on Labor Participation, 2004-05

Variable	Description	%/mean			
		Total	LF	Not in LF	p-value
LFP	In the labor force = 1; Not in the labor force = 0		79.21	20.79	
KESS	Psychological distress: continuous variable range: 10 (lowest) to 50 (highest)	15.26	14.93	16.53	<0.001
MED1	1 Sedatives used for mental well-being 2 weeks prior, 0 other	1.67	1.34	2.93	<0.001
MED2	1 Anxiolytics for mental well-being 2 weeks prior, 0 other	0.69	0.49	1.47	<0.001
MED3	1 Tranquilisers for mental well-being 2 weeks prior, 0 other	0.18	0.08	0.54	<0.001
MED4	1 Antidepressants for mental well-being 2 weeks prior, 0 other	3.00	2.60	4.55	<0.001
MED5	1 Mood stabilisers for mental well-being 2 weeks prior, 0 other	0.15	0.10	0.34	0.08
MED6	1 other prescription for mental well-being 2 weeks prior, 0 other	0.31	0.24	0.58	0.06
MED7	1 vitamins/minerals/herbal/natural for mental well-being 2 weeks prior, 0 other	9.16	9.15	9.20	0.94
NoMED	1 No medications for mental well-being 2 weeks prior, 0 other	84.83	85.99	80.39	<0.001
AGE	18-24=1	15.24	16.16	11.73	<0.001
	25-29=2	10.62	11.45	7.49	<0.001
	30-34=3	11.75	12.51	8.85	<0.001
	35-39=4	11.41	11.91	9.49	<0.001
	40-44=5	11.89	12.98	7.73	<0.001
	45-49=6	11.21	12.19	7.48	<0.001
	50-54=7	10.19	10.43	9.28	0.17
	55-59=8	9.34	8.05	14.27	<0.001
	60-64=9	8.36	4.33	23.70	<0.001
SEX	1 Male	50.42	55.77	30.04	<0.001
	2 Female	49.58	44.23	69.96	
ED	1 Higher degree, Postgraduate diploma	6.25	7.09	2.99	<0.001
	2 Bachelor degree	14.19	15.68	8.44	<0.001
	3 Undergraduate diploma, Associate diploma	12.58	13.45	9.22	<0.001
	4 Skilled vocational qualification	14.87	16.19	9.82	<0.001
	5 Basic vocational qualification	8.01	7.61	9.53	0.02
	6 No post-school qualification	44.11	39.98	59.99	<0.001
MARR	1 Married	55.51	54.38	59.84	<0.001
	2 Defacto	3.50	3.76	2.50	<0.001
	3 Not Married	40.99	41.86	37.66	<0.001
LANG	1 Main English Speaking	90.8	92.63	83.76	<0.001
	2 Other	9.22	7.37	16.24	
HINS	1 Private health insurance cover	51.99	54.95	40.67	<0.001
	2 No private health insurance cover	48.01	45.05	59.33	
COND	Number of long-term health conditions. Continuous variable range from 0 to 7	2.52	2.32	3.31	<0.001

Source: Derived from the ANHS, 2005

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Table 2. Probit Regression Models: Labor Force Participation by Gender - Marginal Effects

	Model Probit						Model ivprobit[a]					
Variable[b]	(1) Male		(2) Female		(3) Total		(4) Male		(5) Female		(6) Total	
	marg.eff	z	marg.eff	z	marg.eff	z	marg.eff	z	marg.eff	z	marg.eff	z
KESS	-0.004***	-5.49	-0.005***	-4.16	-0.005***	-6.63	-0.013***	-3.04	-0.021***	-2.89	-0.018***	-4.36
Sex (female)#					-0.171***	-17.83					-0.164***	-19.59
Age25-29#	0.042**	3.11	-0.089**	-2.53	-0.007	-0.41	0.044***	3.24	-0.086***	-2.71	-0.008	-0.42
Age30-34#	0.046***	3.85	-0.123***	-4.49	-0.021	-1.50	0.047***	3.77	-0.127***	-4.09	-0.026	1.42
Age35-39#	0.025*	2.15	-0.131***	-4.46	-0.036***	-2.70	0.025*	1.72	-0.129***	-4.27	-0.038**	-2.13
Age40-44#	0.032**	2.44	-0.059**	-2.32	0.004	0.26	0.034***	2.59	-0.069**	-2.25	-0.002	-0.10
Age45-49#	0.028*	2.19	-0.029	-1.09	0.017	1.28	0.025*	1.75	-0.042	-1.30	0.007	0.37
Age50-54#	-0.022	-1.23	-0.078**	-2.23	-0.041**	-2.12	-0.038	-1.62	-0.112***	-3.07	-0.067***	-2.90
Age55-59#	-0.107***	-4.19	-0.272***	-10.65	-0.184***	-9.63	-0.143***	-3.99	-0.315***	-8.66	-0.228***	-8.08
Age60-64#	-0.335***	-7.66	-0.541***	-24.38	-0.463***	-22.81	-0.390***	-8.57	-0.577***	-21.27	-0.512***	-18.68
Defacto#	0.016	0.63	0.039	1.23	0.031	1.59	0.018	0.79	0.050	1.56	0.037**	2.02
Not married#	-0.064***	-5.45	0.098***	5.90	0.016	1.60	-0.058***	-5.84	0.114***	7.50	0.028***	3.09
No HINS#	-0.047***	-6.49	-0.134***	-9.11	-0.091***	-11.62	-0.040***	-4.36	-0.116***	-6.81	-0.077***	-8.04
LANG other#	-0.070***	-4.79	-0.224***	-8.14	-0.143***	-8.49	-0.061***	-3.80	-0.202***	-7.16	-0.127***	-7.94
Ed Bachelor#	-0.008	-0.31	-0.068*	-1.69	-0.039*	-1.72	-0.005	-0.19	-0.056	-1.48	-0.031	-1.31
Ed Under Grad#	-0.017	-0.57	-0.063	-1.53	-0.038*	-1.59	-0.009	-0.36	-0.051	-1.34	-0.028	-1.14
Ed skilled#	-0.020	-0.80	-0.156***	-3.22	-0.078***	-3.45	-0.013	-0.56	-0.128***	-2.79	-0.062**	-2.45
Ed basic#	-0.040	-1.09	-0.191***	-4.65	-0.124***	-4.28	-0.026	-0.85	-0.170***	-4.00	-0.106***	-3.63
Ed no post qual#	-0.063**	-2.54	-0.234***	-7.49	-0.152***	-7.52	-0.053**	-2.27	-0.205***	-5.94	-0.132***	-6.21
Conditions	-0.015***	-6.69	-0.015***	-4.02	-0.015***	-6.83	-0.007	-1.58	0.000	-0.06	-0.002	-0.52
N	7067		7721		14788		7067		7721		14788	

Source: Derived from the NHS 2005

[a] Instrumented: KESS. Instrumental variable estimators are Sedatives, Anxiolytics, Tranquilisers, Antidepressants, Mood stabilisers and other prescription medication used for mental wellbeing.

[b] For categorical independent variables the base (reference) category are in the same variable order as in the table: Age 18-24; Married; Education Higher degree; NoMed. For dependent variable: 0=not in labor force; 1=in labor force.

(#) dy/dx is for discrete change of dummy variable from 0 to 1

* p<.1; ** p<.05; *** p<.01

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Table 3. Probit Regression Models: Labor Force Participation by Medication Status by Gender – Marginal Effects

	Any medication[1] for mental well-being						No medication for mental well-being					
Variable[a]	(1) Male		(2) Female		(3) Total		(4) Male		(5) Female		(6) Total	
	marg.eff	z	marg.eff	z	marg.eff	z	marg.eff	z	marg.eff	z	marg.eff	z
KESS	-0.005***	-3.34	-0.010***	-4.21	-0.009***	-5.51	-0.003***	-3.79	-0.004***	-2.58	-0.004***	-4.51
Sex (female)#					-0.154***	-6.29					-0.172***	-20.72
Age25-29#	-0.122	-0.97	-0.129	-1.58	-0.150**	-2.14	0.047***	4.39	-0.080**	-2.33	0.007	0.41
Age30-34#	-0.144	-1.41	-0.108	-1.35	-0.137**	-2.16	0.054***	5.66	-0.124***	-3.69	-0.007	-0.42
Age35-39#	-0.072	-0.89	-0.161**	-2.19	-0.154***	-2.64	0.029**	2.29	-0.121***	-3.62	-0.022	-1.19
Age40-44#	-0.156	-1.53	-0.036	-0.50	-0.098*	-1.64	0.042***	3.88	-0.059*	-1.75	0.015	0.92
Age45-49#	-0.126	-1.25	-0.054	-0.73	-0.098*	-1.68	0.036***	3.05	-0.018	-0.54	0.030*	1.78
Age50-54#	-0.349***	-2.62	-0.039	-0.52	-0.155***	-2.37	-0.002	0.09	-0.087**	-2.36	-0.028	-1.33
Age55-59#	-0.351***	-2.83	-0.301***	-4.00	-0.320***	-4.94	-0.092***	-3.27	-0.261***	-6.77	-0.166***	-6.29
Age60-64#	-0.697***	-7.15	-0.578***	-9.80	-0.624***	-12.45	-0.297***	-7.30	-0.529***	-16.43	-0.432***	-14.61
Defacto#	0.047	0.77	0.076	1.03	0.065	1.29	0.011	0.50	0.034	0.97	0.025	1.32
Not married#	-0.092***	-3.20	0.065**	1.98	0.008	0.33	-0.059***	-5.98	0.108***	7.06	0.019**	2.14
No HINS	-0.076**	-2.52	-0.148***	-4.75	-0.124***	-5.30	-0.045***	-5.31	-0.134***	-8.86	-0.085***	-9.89
LANG other	-0.026	-0.40	-0.200***	-3.42	-0.129***	-2.77	-0.071***	-4.80	-0.230***	-8.30	-0.143***	-9.35
Ed Bachelor#	-0.002	-0.03	-0.125	-1.32	-0.091	-1.27	-0.005	-0.19	-0.057	-1.39	-0.029	-1.19
Ed Under Grad#	-0.076	-0.80	-0.214**	-2.23	-0.171**	-2.23	-0.009	-0.36	-0.033	-0.80	-0.018	-0.72
Ed skilled#	-0.057	-0.74	-0.288***	-2.87	-0.200***	-2.64	-0.014	-0.59	-0.129***	-2.61	-0.058**	-2.22
Ed basic	-0.206	-1.49	-0.369***	-3.89	-0.313***	-3.69	-0.019	-0.65	-0.150***	-3.26	-0.091***	-3.00
Ed no post qual#	-0.161**	-2.09	-0.328***	-4.45	-0.277***	-4.79	-0.048**	-2.16	-0.215***	-6.28	-0.131***	-6.16
Conditions	-0.027***	-4.34	-0.016**	-2.01	-0.021***	-3.77	-0.013***	-5.74	-0.015***	-3.72	-0.014***	-5.99
N	883		1601		2484		6184		6120		12304	

Source: Derived from the NHS 2005

[a] For categorical independent variables the base (reference) category are in the same variable order as in the table: Age 18-24; Married; Education Higher degree; NoMed. For dependent variable: 0=not in labor force; 1=in labor force.

(#) dy/dx is for discrete change of dummy variable from 0 to 1

* p<.1; ** p<.05; *** p<.01

[1] Includes non-prescription medication.

ACCEPTED MANUSCRIPT

Table 4. Probit Regression Models include Interaction Terms: Labor Force Participation by Gender

	Model includes categorical medication variable						Model includes dichotomous medication variable					
Variable[a]	(1) Male		(2) Female		(3) Total		(4) Male		(5) Female		(6) Total	
	coeff	z	coeff	z	coeff	z	coeff	z	coeff	z	coeff	z
Sex (female)					-0.704***	-20.72					-0.700***	
MnKESS	-0.024***	-3.74	-0.011**	-2.55	-0.016***	-4.56	-0.024***	-3.70	-0.011**	-2.49	-0.016***	-4.51
MED1	-0.160	-0.83	-0.082	-0.66	-0.109	-1.04						
MED2	0.127	0.35	-0.044	-0.13	0.018	-0.07						
MED3	-0.660	-1.06	-0.175	-0.45	-0.506	-1.39						
MED4	-0.226	-1.37	0.025	0.23	-0.040	-0.44						
MED5	-0.564	-0.97	-0.944	-1.27	-0.828	-1.60						
MED6	0.120	0.28	-1.243***	-3.15	-0.656**	-2.98						
MED7	0.085	0.72	0.125*	1.78	0.106*	1.76						
MED							-0.037	-0.44	0.040	0.73	0.013	0.29
MED1*KESS	-0.014	-0.67	-0.002	-0.13	-0.008	-0.63						
MED2*KESS	-0.107***	-2.87	-0.053	-1.46	-0.066**	-2.28						
MED3*KESS	-0.072	-1.20	-0.060	-1.21	-0.058	-1.35						
MED4*KESS	0.004	0.24	-0.018	-1.46	-0.010	-0.97						
MED5*KESS	0.021	0.46	0.085	1.18	0.033	0.78						
MED6*KESS	-0.057	-1.18	0.078**	2.28	0.029	1.24						
MED7*KESS	-0.010	-0.67	-0.019*	-1.75	-0.011	-1.34						
MED*KESS							-0.015	-1.49	-0.017**	-2.36	-0.015**	-2.47
_cons	3.089***		2.797***		3.929***		3.102***		2.816***		3.943***	
N	7067		7721		14788		7067		7721		14788	

Source: Derived from the NHS 2005

[a] Variables omitted from the table and included in the model: age, marital status, health insurance, language, education and health conditions.

* p<.1; ** p<.05; *** p<.01