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3 authors:

Dusanee Kesavayuth
Kasetsart University

Prompong Shangkhum

Vasileios Zikos
Chulalongkorn University

Building Physical Health: What is the Role of Mental Health?

Dusanee Kesavayuth[*] Prompong Shangkhum[**] Vasileios Zikos[***]

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Abstract

In recent years, significant advancements have been made in our understanding of how certain behaviors impact physical health. Yet, little continues to be known about how mental health relates to physical health. This paper considers a dynamic model and estimates the effect of mental health on physical health. The paper utilizes data on 11,277 individuals aged 15 years and older from twelve waves (2005-2016) of the Household Income and Labour Dynamics of Australia (HILDA) survey. Analysis reveals that better past mental health increases present physical health. There is also evidence that better past physical health has a positive effect on present physical health. Estimation by subgroups shows heterogeneous effects across age groups but no differences between men and women. Interventions that target complementarities between physical health and mental health are promising avenues for promoting better health.

Keywords: physical health, mental health, panel data, HILDA

JEL codes: D01, I10

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* Department of Economics, Faculty of Economics, Kasetsart University, Bangkok 10900, Thailand. Email: dusanee.k@ku.th.

** School of Economics, University of the Thai Chamber of Commerce, 126/1 Vibhavadee-Rangsit Road, Dindaeng, Bangkok, 10400, Thailand. Email: prompong.shangkhum@gmail.com.

*** *Corresponding author*: Faculty of Economics, Chulalongkorn University, 254 Phayathai Road, Pathumwan, Bangkok 10330, Thailand. Email: vasileios.z@chula.ac.th.

1. Introduction

Living standards continue to rise around the world. Yet modifiable risk factors are increasingly documented as leading causes of death in developed and developing economies alike. According to a recent report from the World Health Organization (2016), health behaviors such as tobacco use, physical inactivity, unhealthy diet, and excessive alcohol consumption are responsible for more than 36 million deaths annually. It is therefore not surprising that economic research has paid considerable attention to understanding the determinants of individuals' physical health with the intention to better inform policy interventions.

While significant advancements in our knowledge have been made on how certain behaviors impact physical health, little is known about how mental health relates to physical health. The aim of this paper is to fill this gap in the literature by considering a dynamic model and estimating the dynamic relationship between physical and mental health. Examining this relationship, and how it varies between population groups, is important as it informs us directly about the determinants of physical health. It would also be of value for policy makers in offering new insights to aid the design of interventions that promote people's health.

As well as being a potentially important determinant of physical health, the study of mental health is also an interesting topic in itself. One reason for this is that mental health disorders are becoming increasingly common around the world (e.g. Hidaka, 2012). In Australia in particular, which is the source of our data, the Australian Bureau of Statistics (2009) documented that about 20% of the people aged 16-85 experience a mental illness. Three types of mental illness appear to be most common: depression, anxiety and substance use. There is also evidence that about one half of the Australians with mental illness do not access any treatment (Australian Institute of Health and Welfare, 2014). But, in fact, approximately 75% of those who used public mental healthcare services improved considerably (Department of Health and Ageing, 2013). The study of mental health and how it relates to physical health, therefore, seems important both from an empirical and practical point of view.

A growing body of literature examines health dynamics. Contoyiannis et al. (2004), for example, use eight waves of the British Household Panel Survey (BHPS) to study the dynamics of self-assessed health. They find evidence of substantial state dependence and unobserved heterogeneity in health. Buckley et al. (2004) examine how socioeconomic factors influence transitions between good and poor health among older Canadians. Their analysis reveals strong evidence that people in initial good health are more likely to remain in good health in the future, and that such link tends to vary by age, education and income. In another related study, McDonough et al. (2010) utilize 13 waves of data from the BHPS and the Panel Study of Income Dynamics (PSID), and show that Britons have a health advantage in that they are more likely to have stable good health. In addition, socioeconomic inequalities, which tend to influence these health dynamics, are more pronounced in the US than in Britain.

The existing literature on health dynamics abstains from considering mental health as a potential determinant of physical health. To our knowledge, there is only one other economic analysis of the relationship between physical and mental health which also models the dynamics of physical health explicitly.[1] Using six waves of the English Longitudinal Study of Ageing (ELSA), Ohrnberger et al. (2017) find that better past mental health is positively related to present physical health. Past mental health is also shown to be more important in determining present physical health than physical activity or education.

Given there is only little study of the importance of mental health for physical health in a dynamic setting, there is a lot we do not yet understand about the nature of this relationship. Here, three questions suggest themselves. First, are the results found for the UK similar to those observed in other settings – in our case, Australia – and thus are broadly representative? Second, do the results found in the aforementioned study using ordinary least squares (OLS) and random effects models hold when dynamic panel estimators are employed? Dynamic panel estimators are increasingly popular in the literature (see e.g. Acemoglu et al., 2008; Powdthavee, 2009; Flannery and Hankins, 2013; Piper, 2015; Downward and Rasciute, 2016). And unlike more traditional estimators such as OLS and fixed effects, they are capable of dealing with the problem of "dynamic panel bias" in estimating coefficients of interest (Nickell,

[1] Some cross-sectional studies show that mental health is positively correlated with physical health (see e.g. Rowan et al., 2005; Surtees et al., 2008). However, because of their cross-sectional nature, these studies do not capture the dynamics of physical health, something that we are able to do in this paper.

1981; Angrist and Pischke, 2009). Third, does the relationship between mental and physical health vary across gender and age group? In contrast to our paper, Ohrnberger et al. (2017) focus on the older population; hence, they do not analyze whether their findings are applicable to younger age groups. Furthermore, whether and to what extent the implied effects differ between men and women is not examined in their paper, but doing so may provide more nuanced insights into the dynamic relationship between physical and mental health.

The primary aim of this paper is to combine current knowledge of dynamic panel analysis with the literature on physical health in order to bring new insights into the substantive question of how mental health relates to physical health. For the empirical analysis, we draw data from the Household Income and Labour Dynamics of Australia (HILDA) survey. The HILDA data are ideal for our purpose as they contain measures of physical and mental health alongside a wealth of information on socio-economic characteristics for a large, nationally representative sample. To preface our results, we find that better past mental health increases present physical health. Better past physical health is also shown to have a positive impact on present physical health. Estimation by subgroups shows heterogeneous effects across age groups but no differences between men and women. These findings are robust under alternative specifications and limitations on the data.

The outline of the paper is as follows. Section 2 reviews previous work on physical health, especially how it relates to subjective well-being which includes mental health. Section 3 describes the data. Section 4 discusses our model and empirical strategy. Section 5 presents the results, and Section 6 considers possible robustness checks. Section 7 concludes the paper.

2. Linking Subjective Well-Being and Mental Health to Physical Health

Why might better mental health be associated with better physical health? To answer this question, it is useful to consider possible mediators linking mental and physical health. That is, we need to better understand the pathways through which higher levels of mental health may benefit physical health. Diener et al. (2017) and Ong (2010) offer extensive reviews. They suggest that subjective well-being (which includes mental health) may influence physical health via three different pathways:

physiological systems (e.g. cardiovascular and immune systems), stress, and health behaviors (e.g. physical activity and diet).

Physiological systems, including the cardiovascular and immune system, appear to be affected by well-being. People high in well-being tend to have better cardiovascular functioning, which in turn is related to improved health and decreased mortality (e.g. Dockray and Steptoe, 2010; Kraft and Pressman, 2012; Tuck et al., 2017). In terms of people's physiological systems, studies have found associations between well-being and immune measures. Barak (2006), for example, reviewed a number of studies and concluded that two different types of subjective well-being, in particular positive affect and "eudaimonic" well-being,[2] can influence immune function. Furthermore, associations have been found between well-being and stress. Black and Garbutt (2002) suggest that higher stress levels may harm a person's health by increasing inflammation over time. Other studies provide evidence supporting the idea that well-being is associated with better health behaviors. People high in well-being tend to exercise more regularly, smoke less and consume a healthier diet (Boehm and Kubzansky, 2012; Kim et al., 2016). Across 21 nations, Grant et al. (2009) showed that life satisfaction predicted heathier behaviors: less smoking, more exercise, eating fruits and vegetables and limiting fat intake.

To better understand why subjective well-being affects a person's health, we would also need to look at how and why experiences of well-being influence the various physiological and behavioral outcomes discussed above (that ultimately lead to better health). Starting around 1998, Fredrickson developed the broaden-and-build theory (Fredrickson 1998, 2001). This theory, which is now well-established in positive psychology, proposes an evolved function of positive emotions.[3] It suggests that positive emotions *broaden* a person's awareness and thereby provide a wider set

[2] The notion of eudaimonic well-being, an important component of subjective well-being, captures meaning and purpose in life, which in turn may arise through supportive relationships and feelings of mastery. Diener et al. (2017) provide an excellent description of different types of well-being.

[3] The broaden-and-build theory has received substantial support from various randomized controlled lab studies. For more information the reader is directed to Fredrickson (2001). Isen (2000) provides strong evidence that positive emotions broaden people's thought-action repertoires, and reviews such evidence from two decades of experiments.

of thoughts and actions to draw upon.[4] Broader thought-action repertoires build resources over time, including psychological, intellectual, physical and social, and those accumulated resources tend to increase a person's well-being. Increased well-being leads to more positive emotions and helps build additional resources. This explains why individuals high in well-being (who also tend to have good mental health) may enjoy several advantages in terms of resources compared to those suffering from mental health problems such as anxiety disorders and depression.

In sum, subjective well-being has been found to positively alter a number of processes, including cardiovascular and immune function, stress and health behaviors, and these mediational pathways may in turn affect health. Thus, it is reasonable to expect that mental health, a key component of subjective well-being, will influence physical health. Indeed, we believe that people who have higher levels of mental health would be in better physical health simply because they are more likely to have better health behaviors and physiological functions. This paper uses nationally representative data for Australia in order to examine systematically the dynamic relationship between physical health and mental health for various population groups and for different empirical approaches.

3. Data

Our data come from waves 5-16 of the Household Income and Labour Dynamics of Australia (HILDA) survey.[5] HILDA is a nationally representative, longitudinal survey which started in 2001 with participation of almost 14,000 individuals from 7,682 households. These individuals aged 15 or older, set the basis of the panel pursued in subsequent waves. Annual re-interview rates are high, exceeding 95% in wave 8 and remaining as high since then. Watson and Wooden (2012) provide detailed information on the HILDA survey.

Our dependent variable originates from the answers to a series of questions based on the 36-item Short Form Health Survey (SF-36). Of the 36 questions, 22 concern physical health. Physical health is measured along four dimensions: physical

[4] According to Fredrickson (2004, p. 1367) "joy sparks the urge to play, interest sparks the urge to explore, contentment sparks the urge to savour and integrate, and love sparks a recurring cycle of each of these urges within safe, close relationships."

[5] We were not able to utilize data from waves 1-4 as one of our explanatory variables on private health insurance is available from wave 5 onwards.

functioning, role physical, bodily pain and general health. In the HILDA survey, the answers to each health dimension are provided in standardized form on 0-100 scale. It is worth noting that Cronbach's alpha is slightly above 0.83, indicating that the different dimensions of physical health are sufficiently closely related with one another. This enables us to construct a single index for physical health by computing the average of the four physical health dimensions for each observation (e.g. Zhu, 2016; Kesavayuth et al., 2019). Our physical health measure thus ranges from 0 to 100, with higher numbers indicating better health.

Our main independent variable of interest is also obtained from the SF-36. It is based on the answers to 14 questions which are intended to capture four dimensions of individuals' mental health: social functioning, role-emotional, mental health and vitality. Answers to each mental health dimension are available in the HILDA survey in standardized form and are again bounded between 0 and 100. As for physical health, the four dimensions of mental health are highly reliable with a Cronbach's alpha reliability statistic of 0.82. We thus generate a single index for mental health by computing the average of the four mental health dimensions for each observation.[6] The SF-36 measure is often used by medical scholars and other researchers and is considered a good proxy for a person's health status (e.g. Brazier, 1992; Hemingway et al., 1997). To aid the interpretation of our results, we standardized both our physical health and mental health measures so that the mean is 0 and standard deviation is 1.

Our analytical sample consists of respondents aged 15 and older over our sample period. After excluding observations with missing answers to the questions required for our analysis, the final sample corresponded to an unbalanced panel of 11,277 individuals (4,910 males, 6,367 females) and 68,372 observations (28,865 males, 39,507 females). Table 1 provides summary statistics.

3. Empirical Model and Strategy

Letting PH_{it} be physical health of individual *i* at time *t*, our model can be specified as follows:

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[6] Section 5 shows that qualitatively equivalent results can be obtained if, alternatively, factor analysis is used to construct our physical and mental health indexes.

$$PH_{it} = \beta_0 + \beta_1 PH_{i,t-1} + \beta_2 MH_{i,t-1} + \beta_3 X_{it} + \beta_4 T_t + v_{it} \tag{1}$$

where v_{it} is a composite error term that consists of a person-specific error a_i and an idiosyncratic error ε_{it}:

$$v_{it} = a_i + \varepsilon_{it} \tag{2}$$

In equation (1), $PH_{i,t-1}$ refers to the one period lag of physical health. The inclusion of this lagged value captures dynamic behavior in physical health and follows a first-order Markov process as it is often assumed in the literature (e.g. Contoyannis et al., 2004). $MH_{i,t-1}$, our key explanatory variable of interest, is the one-period lagged value of mental health; X_{it} is a vector of time-varying predictor variables including binary indicators for Australian state and territory of residence; and T_t are year fixed effects which account for any time trends in physical health that are common to all individuals.

Achieving estimation of equation (1) presents the challenge that $PH_{i,t-1}$ is correlated with the fixed effects in the error term. This implies that using either OLS or fixed effects estimators give rise to "dynamic panel bias" (e.g. Nickell, 1981; Angrist and Pischke, 2009; Roodman, 2009). To overcome this empirical issue, we utilize a well-established identification strategy which is based on the dynamic panel estimators of Arellano-Bond (Arellano and Bond, 1991) and Blundell-Bond (Blundell and Bond, 1998). The former is also known as 'difference' generalized methods of moments (GMM) estimator while the latter is often referred to as 'system' GMM. Both estimators rely on internal instruments – namely appropriate lags of variables already included in the model – whose validity can be tested. This approach has been successfully implemented by others scholars in a variety of settings ranging from general microeconomics to macroeconomics, health economics and finance (e.g. Acemoglu et al., 2008; Powdthavee, 2009; Flannery and Hankins, 2013; Piper, 2015; Downward and Rasciute, 2016).

Arellano-Bond estimation starts by transforming all regressors by differencing in order to eliminate the individual fixed effects. It then uses lagged values of the endogenous variables as instruments. Blundell-Bond estimation, on the other hand, builds a system of two equations – the original equation and the first differenced one – and modifies the estimator to include lagged levels and lagged differences as instruments. In the level equation, the endogenous variables are then instrumented with their own first differences. The methodology assumes that there is no second-order autocorrelation in the differenced residuals.

Estimation of the dynamic model in equation (1), along with a test for second-order serial correlation, and the Sargan/Hansen test for joint validity of the instruments can be conveniently implemented in STATA using the *xtabond2* command of Roodman (2009). For comparative purposes, we also report estimates based on OLS and fixed effects models.

4. Results

4.1 Preliminary Analysis

Before turning to the econometric estimation, Figure 1 sheds some light on the nature of the relationship between past mental health (horizontal axis) and present physical health (vertical axis). Consistent with our initial expectations, the relationship is overall positive. This implies that those who had better mental health in the previous wave are more likely to report higher levels of current physical health. Furthermore, Figure 2 shows a positive relationship between past physical health and present physical health. This is our first tentative evidence of a positive link between past physical health or past mental health and current physical health. Nonetheless, it is important to control of a variety of personal, economic and social factors that may confound any associations observed in the raw data.

Table 2 presents benchmark econometric estimates based on simple OLS and fixed effects models. The dependent variable is physical health and has been standardized to mean 0 and standard deviation 1. In addition to the one period lag of mental health, which is the main explanatory variable of interest, we control for a variety of factors that have been found in the literature to be correlated with both mental health and physical health. These include age, gender,[7] lagged physical health,

[7] Gender is controlled for only in the OLS model.

household size, real household income,[8] the number of children living in the household, educational attainment, the frequency of physical activity, the frequency of social interaction, private health insurance,[9] living as a couple, employment status, regional fixed effects, and time (waves).

The OLS estimates reported in column 1 suggest that past mental health enters the physical health regression equation in a positive a manner. This implies that individuals with better past mental health are more likely to report higher levels of current physical health. The corresponding coefficient estimate is highly significant at p-values < 0.01. It is also interesting to note that better past physical health is positively associated with present physical health. Qualitatively similar results are obtained in column 2 where we use the fixed effects estimator in order to address potential bias emanating from unobserved heterogeneity at the individual level, that is, the presence of a_i.[10] As might be expected, however, the estimates are now smaller in magnitude. This seems to suggest that the coefficients on both past physical health and past mental health picked up individual fixed effects, thus causing an upward bias to the OLS estimates in column 1. These findings, which are generally consistent with the exploratory analysis above based on the raw data, provide some initial evidence in support of a positive relationship between better past physical health or past mental health and present physical health.

4.2 GMM Estimates

The results reported so far should be taken with caution. This is because the presence of dynamic panel bias tends to confound both the OLS and fixed effects estimates, as explained earlier. Estimation of the parameter β_1 in equation (1) by OLS, for instance, would impart upward bias due to a positive correlation between the lagged dependent variable and the individual fixed effects. One common way of overcoming this endogeneity problem is to employ the Arellano-Bond and the

[8] The base year is 2012.

[9] This is captured by a dummy variable that takes the value 1 if the respondent is responsible for any of the annual household expenditures on private health insurance.

[10] A test of first-order serial correlation of the residuals of the static fixed effects model (the model which does not include $PH_{i,t-1}$ as an explanatory variable) can also be used to assess the validity of dynamic analysis. The corresponding F statistic (F(1, 9066) = 352.494; Prob > F = 0.0000) rejects the null hypothesis of no first-order serial correlation and indicates the presence of dynamic behavior in physical health (see e.g. Wooldridge, 2002; Downward and Rascuite, 2016).

Blundell-Bond dynamic panel estimators (Arellano and Bond, 1991; Blundell and Bond, 1998). In the current context, results from diagnostic tests indicate that using Arellano-Bond estimation – as opposed to Blundell-Bond estimation – is permissible. These tests include, first, examining the absence of first-order serial correlation in the idiosyncratic disturbances, and second, examining the validity of the instruments.

Arellano and Bond (1991) have developed a test for serial correlation in the idiosyncratic disturbance term, ε_{it}. By construction, $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$ and $\Delta\varepsilon_{i,t-1} = \varepsilon_{i,t-1} - \varepsilon_{i,t-2}$ are mathematically related given that they share the term $\varepsilon_{i,t-1}$. What this implies is that the differenced residuals are themselves serially correlated of order 1. In effect, to test for first-order serial correlation in levels, one has to look for second-order correlation in differences. Doing so allows us to detect correlation between $\varepsilon_{i,t-1}$ in $\Delta\varepsilon_{it}$ and $\varepsilon_{i,t-2}$ in $\Delta\varepsilon_{i,t-2}$ (Roodman, 2009). As can be seen at the bottom of Table 3, the null hypothesis of no first-order serial correlation can comfortably be rejected which is seen to be desirable; the corresponding p-value is zero to three decimal places. Additionally, the null hypothesis of no AR(2) in the differenced idiosyncratic disturbances cannot be rejected, thus lending further support for our empirical approach.

Next, the Hansen J test is used to assess the joint validity of the instruments. In the current analysis past mental health is treated as an endogenous variable; there may be omitted variables such as individuals' discount factors that correlate with their investments in both physical and mental health. Our analysis also treats past physical health as an endogenous variable for similar reasons. All other variables included in the model were treated as exogenous.[11] Importantly, the null hypothesis that all IVs are valid cannot be rejected, as can be seen at the bottom of Table 3.

Table 3 presents results of our dynamic model. Column 1 shows that better past mental health continues to predict current physical health in a positive and statistically significant manner. This implies that a standard deviation increase in past mental health leads to an approximately 0.033 standard deviation increase in current physical health. The corresponding coefficient estimate is significant at p-values <

[11] In a robustness check, we also considered other regressors as potentially endogenous variables. Thus, in addition to past physical and past mental health, we also instrumented the variables on physical activity and social interaction using the Arellano-Bond estimator. We found our results to be unchanged. The estimates are provided in the next section.

0.01. Furthermore, better past physical health has a positive effect on current physical health, which is also statistically significant with $p < 0.05$. Interestingly, the coefficient on the lagged dependent variable is 0.026 and indicates low state dependence (complete state dependence would require a coefficient close to unity). Alternatively, previous research has found moderate state dependence in physical health among older individuals in the UK, perhaps because physical health conditions are more prevalent in this age group compared to their younger counterparts (Ohrnberger et al., 2017).

To gain a better understanding of how large the estimated effects actually are, take for example the average person in terms of past physical health and the person who is one standard deviation above the average. Our findings in column 1 of Table 3 suggest that the difference between these two groups of individuals is 0.026 standard deviations. All things being equal, such difference is approximately 23% of the effect of being out of the labor force versus being employed. The estimated effects appear to be more substantial when it comes to mental health. Here, we find that the difference between the average person and the person who is one standard deviation above the average is 0.033 standard deviations. This amounts to about 29% of the effect that being out of the labor force (versus being employed) has on current physical health, *ceteris paribus*.[12]

4.3 Heterogeneous Effects by Gender and Age Groups

The analysis to this point has assumed that both past mental health and past physical health have the same effect on present physical health for men and women. The implied effects, however, are not necessarily uniform. Courtenay (2000), for example, reviewed the literature and concluded that, on average, women have a health advantage over men, which could be explained by the fact that they make consistently healthier lifestyle choices.

[12] A potential concern is that individuals with relatively low levels of physical or mental health are more likely to drop out of the panel survey over time. To shed some light on this issue, we re-estimated equation (1) using a balanced panel of those respondents who participated in all 12 waves used in our study. We find that even in this smaller sample (of approximately 33% of the initial observations), the estimates are very similar to those using an unbalanced panel. Since our results hold for a homogeneous sample with respect to individuals' participation in the panel survey, we believe that attrition bias that may be related to low levels of physical or mental health does not drive our main conclusions.

To test whether gender differences matter in the HILDA data, Table 3 provides separate estimates for men and women. Looking across the columns, we can see that both better past physical health and better past mental health are positively related to current physical health. The estimated effects appear not to be uniform; better past mental health exerts a larger positive impact on current physical health among men, while the opposite is true for past physical health, which appears to have a larger positive impact among women. Do the observed estimates represent any actual differences across gender? Using a two-sample z-test, we find that the null hypothesis of no gender differences cannot be rejected. Hence, in these data, men and women do not seem to differ systematically in how either past physical health or past mental health relates to current physical health.

A question of interest is whether heterogeneity in people's responses about their physical health reflects differences related to their age group. To examine this, Table 4 estimates equation (1) separately for four age groups: (i) 16-36, (ii) 37-57, (iii) 58-78 and (iv) 79+. Looking across the columns of Table 4, we observe some evidence of heterogeneity between age groups. It is interesting to note that the positive relationship between past mental health and current physical health is found only among those aged 16-36. In addition to this youngest age group, however, better past physical health also exhibits positive effects among those aged 58-78 as well as those aged 79+. Using a two-sample z-test to look for statistically significant differences in the estimates, we find that better past mental health exerts a larger positive impact on those aged 16-36 compared to those in any of the older age groups. Conversely, better past physical health is more important in determining present physical health among those aged 79+ compared to those in any of the younger age groups. We may conclude that both better past physical health and better past mental health have a positive effect on present physical health for some but certainly not all groups of individuals.

5. Robustness Checks

5.1 Mortality Selection

A potential concern is that our results are driven by selection bias. This would be the case if, for example, individuals with relatively low levels of physical health or mental health face higher mortality rates. To mitigate this concern, we re-estimated equation (1) focusing our attention on those who are no older than 85 years of age. The estimates, reported in Table 5, suggest that better past physical health and better past mental health continue to have a positive and statistically significant effect on current physical health. In addition, men and women did not appear to differ systematically, consistent with our findings reported earlier in Table 3.

5.2 Endogeneity of Physical Activity and Social Interaction

The analysis to this point has treated past physical health and past mental health as endogenous variables. There is a possibility, however, that some of the other explanatory variables are not randomized across the sample. To address this concern, we re-estimated our model treating as endogenous variables – in addition to past physical health and past mental health – the frequency of physical activity, and the frequency of social interaction.[13] Looking across the columns of Table 6, we can see that our main findings remain unchanged: better past physical health and better past mental health continue to predict current physical health in a positive and statistically significant manner. Importantly, as can be seen at the bottom of Table 6, there is no evidence of AR(2) behavior in the differenced residuals and the Hansen J test does not reject the null hypothesis of joint validity of the instruments.

5.3 Alternative Physical and Mental Health Indexes

Our analysis utilizes physical health and mental health measures that assign equal weights to the four items of each scale. This assumption is not unreasonable, given that the Cronbach's alpha reliability statistics were slightly higher than 0.82, indicating that the four dimensions of both physical health and mental health had internal consistency that is highly reliable. Nonetheless, we conducted a sensitivity analysis by constructing an alternative physical health and mental health index. In particular, we first used factor analysis to confirm that the four items of each health

[13] The frequency of physical activity is drawn from responses to the question: "In general, how often do you participate in moderate or intensive physical activity for at least 30 minutes?" Answers are on a 6-point scale that ranges from 0 (not at all) to 5 (every day). The frequency of social interaction comes from asking the question: "In general, how often do you get together socially with friends or relatives not living with you?" with possible answers ranging from 0 (less often than once every three months) to 6 (every day).

measure load onto one factor. We then calculated the first predicted factor of physical health and mental health. The resulting indexes were standardized to have mean 0 and standard deviation 1. This approach relaxes that assumption of equal weights since the data determine the weight assigned to the items of each index (e.g. Cobb-Clark et al., 2014; Mohamad et al., 2017). Looking across the columns of Table 7, we can see that the estimates corroborate our previous findings in Table 3. Thus, using an alternative physical health and mental health index from factor analysis does not appear to matter for our conclusions.

5.4 The Role of Other Health Behaviors

An additional concern might be that heterogeneity in individuals' physical health is driven by their health behaviors. This would be the case if, for example, those who smoke or consume alcohol more frequently are more likely to report lower levels of physical health (US Department of Health and Human Services, 2010, 2014). At the same time, it is possible that smoking and drinking are related to individuals' mental health – those with mental health conditions such as mood disorders and anxiety may be more likely to smoke or drink in an effort to regulate the symptoms or emotions associated with their disorder (e.g. Cornah, 2006; Minichino et al., 2013). If that is the case, then the results reported in our study may have been significantly confounded by omitting information about individuals' smoking and drinking behavior from the physical health regression equation. To shed some light on this issue, we augmented the specification in equation (1) by including the frequency of smoking and the frequency of alcohol consumption as additional explanatory variables.[14] As shown in Table 8, the results remain unchanged, thus lending further support for our previous findings.

6. Concluding Remarks

In recent years, significant advancements have been made in our understanding of how certain behaviors impact physical health. Yet little continues to be known

[14] The frequency of smoking is taken from responses to the question, "Do you smoke cigarettes or any other tobacco products?" Possible answers include 0 (I have never smoked, or I no longer smoke) to 3 (I smoke daily). Respondents were also asked about drinking, with answers ranging from 0 (I have never drunk alcohol, or I no longer drink alcohol) to 6 (I drink alcohol every day).

about how mental health relates to physical health, especially in a setting which accounts for the dynamics of physical health. This paper's aim was to fill part of this gap in the literature by considering a dynamic model and estimating the effect of mental health on physical health. Examining this effect, and how it varies by gender and age group, is a novel contribution and important in developing a better understanding of the determinants of physical health.

Drawing longitudinal data from the HILDA survey, we showed that better past mental health increases present physical health. We also found that better past physical health has a positive impact on present physical health. While men and women did not appear to differ systematically, we found evidence of significant differences across age groups of the respondents. In particular, better past mental health exerted a larger positive impact on those aged 16-36 compared to those in any of the older age groups. Conversely, better past physical health was more important in determining present physical health among those aged 79+ compared to those in any of the younger age groups.

Complementing previous work in economics, two key implications emerge from these findings, the first empirical, the second for policy. First, earlier studies in this area typically abstain from considering mental health as a potential determinant of physical health and focus instead on other socio-economic factors such as income, education, retirement and lifestyle choices. While these factors are certainly important themselves in influencing a person's physical health, in this paper we shifted the focus to another, yet relatively unexplored factor – mental health – and examined its importance for physical health. Our finding that, at least for certain groups of individuals, past mental health matters for present physical health indicates that applied researchers in this area may find it worthwhile to augment their dynamic models of physical health by considering measures of mental health.

What are the policy options for promoting better health? Our results suggest that health promotion may need to target complementarities between physical health and mental health. For example, interventions that raise people's well-being and lower their levels of stress might be helpful in improving their physical health (e.g. Diener et al., 2017). While such interventions may not be effective across the entire population, we believe that at least some individuals may benefit from having higher levels of mental health.

The study of the link between physical and mental health is likely to continue being a topic of intensive research in social sciences as many intriguing questions remain. One fruitful direction for future research might be to examine the potential benefits of other dimensions of one's well-being, including life satisfaction, optimism and positive affect, in influencing physical health. The identification of such benefits (as hard it may be to isolate them due to substantial correlations between well-being measures) would further our understanding of the determinants of physical health. It would also be of value for policymakers in offering support for programs aimed to increase societal welfare (e.g. Stiglitz et al., 2010). In future work, we hope to explore some of the more nuanced effects of various types of well-being on physical health.

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Figures and Tables

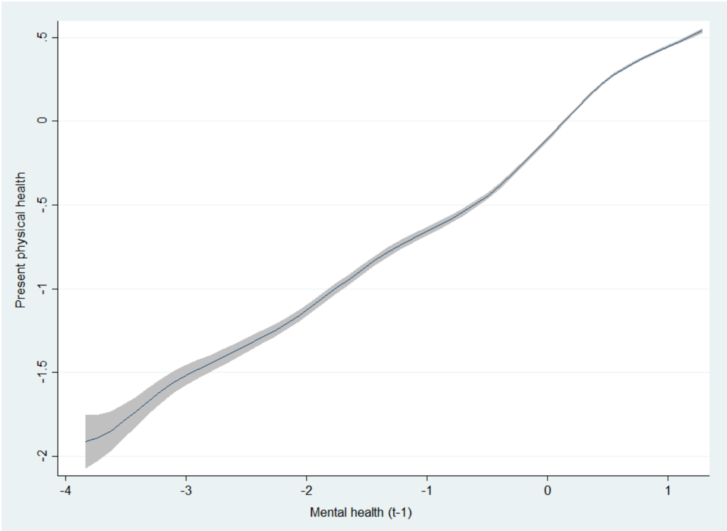

Figure 1: The relationship between past mental and present physical health.

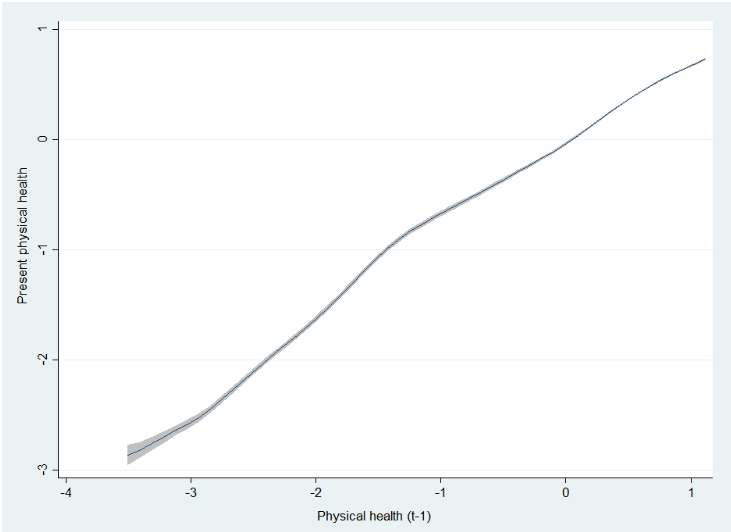

Figure 2: The relationship between past and present physical health.

Table 1
Summary statistics (non-standardized)

Variable	Mean	Std Dev.	Min	Max
Physical health	74.68	22.09	0	100
Mental health	75.38	19.37	0	100
Physical health (t-1)	75.24	21.72	0	100
Mental health (t-1)	75.62	19.14	0	100
Age	50.31	16.36	16	98
Male	0.42	0.49	0	1
Household size	2.58	1.35	1	17
Real household income (in thousands of AUS dollars)	82.29	60.64	-1,105.70	909.18
Number of children in the household	0.77	1.1	0	12
Private health insurance	0.59	0.49	0	1
Living as a couple	0.69	0.46	0	1
Higher education	0.61	0.49	0	1
Employed	0.65	0.48	0	1
Unemployed	0.02	0.14	0	1
Not in the labor force	0.33	0.47	0	1
Frequency of physical activity	2.54	1.53	0	5
Frequency of social interaction	3.43	1.43	0	6

Note: Number of observations 68,372.

Table 2
OLS and fixed effects regression models for physical health

	OLS	**Fixed effects**
Physical health (t-1)	0.636***	0.0426***
	(0.00424)	(0.00674)
Mental health (t-1)	0.0845***	0.0447***
	(0.00395)	(0.00491)
Age	-0.00524***	-0.00757
	(0.000198)	(0.00833)
Male	0.00182	
	(0.00487)	
Household size	-0.00912*	0.00555
	(0.0049)	(0.00666)
Real household income (in thousands of AUS dollars)	0.000289***	0.00000163
	(0.0000445)	(0.0000696)
Number of children in the household	0.0267***	0.0190**
	(0.00519)	(0.00795)
Private health insurance	0.0362***	-0.0102
	(0.00532)	(0.011)
Living as a couple	0.0290***	-0.00823
	(0.00702)	(0.0143)
Higher education	0.00711	0.0192
	(0.00524)	(0.0216)
Unemployed	-0.0213	0.0199
	(0.0186)	(0.0194)
Not in the labor force	-0.164***	-0.146***
	(0.00709)	(0.0124)
Frequency of physical activity	0.0693***	0.0803***
	(0.00174)	(0.00266)
Frequency of social interaction	0.0197***	0.0169***
	(0.00181)	(0.00249)
Constant	-0.00961	0.0432
	(0.0185)	(0.455)
Observations	68,372	68,372

Note: *p < 0.1, **p< 0.05, ***p< 0.01. Robust standard errors are in parentheses. All models included wave and Australian region of residence dummies as control variables.

Table 3
Difference GMM regression model for physical health

	Full sample	Males	Females
Physical health (t-1)	0.0260**	0.00741	0.0293**
	(0.0105)	(0.0164)	(0.0139)
Mental health (t-1)	0.0326***	0.0353***	0.0288***
	(0.00749)	(0.0127)	(0.00914)
Age	-0.0255***	-0.0290***	-0.0203***
	(0.00208)	(0.00292)	(0.00233)
Household size	0.0067	-0.000156	0.00669
	(0.00858)	(0.0124)	(0.0114)
Real household income (in thousands of AUS dollars)	-0.000205**	-0.000073	-0.000208*
	(0.0000875)	(0.000119)	(0.000117)
Number of children in the household	0.0102	-0.00286	0.0253*
	(0.0106)	(0.0159)	(0.0136)
Private health insurance	-0.0172	0.0124	-0.0348*
	(0.0137)	(0.0204)	(0.0179)
Living as a couple	-0.0337*	-0.00158	-0.0374
	(0.0193)	(0.0294)	(0.0247)
Higher education	-0.0595*	-0.0874	-0.0453
	(0.0336)	(0.0602)	(0.0392)
Unemployed	0.00485	-0.0323	0.0371
	(0.0225)	(0.0374)	(0.0274)
Not in the labor force	-0.113***	-0.129***	-0.0962***
	(0.0153)	(0.0276)	(0.018)
Frequency of physical activity	0.0600***	0.0567***	0.0593***
	(0.00291)	(0.00436)	(0.00379)
Frequency of social interaction	0.0125***	0.00357	0.0170***
	(0.00284)	(0.00435)	(0.00363)
Observations	53,396	22,363	31,033
Number of instruments	137	137	137
Hansen J test (p-value)	0.909	0.226	0.767
First-order serial correlation test (p-value)	0.000	0.000	0.000
Second-order serial correlation test (p-value)	0.700	0.884	0.972

Note: *p < 0.1, **p< 0.05, ***p< 0.01. Two-step robust standard errors are in parentheses. All models included wave and Australian region of residence dummies as control variables.

Table 4
Difference GMM regression model by age group

	16-36	**37-57**	**58-78**	**79+**
Physical health (t-1)	0.0471**	0.0191	0.0551**	0.179***
	(0.022)	(0.0168)	(0.023)	(0.0581)
Mental health (t-1)	0.0649***	0.0082	0.00164	-0.0141
	(0.0203)	(0.0131)	(0.0152)	(0.0403)
Age	-0.00354	-0.0242***	-0.0376***	-0.0561***
	(0.00664)	(0.00302)	(0.00389)	(0.0136)
Household size	0.0277	-0.00446	-0.0242	-0.0486
	(0.0193)	(0.0158)	(0.0175)	(0.0671)
Real household income (in thousands of AUS dollars)	-0.000358	-0.000166	-0.000122	0.000744***
	(0.000314)	(0.000124)	(0.000153)	(0.000266)
Number of children in the household	0.0549*	0.0169	-0.0248	-0.0212
	(0.0324)	(0.0196)	(0.0175)	(0.03)
Private health insurance	-0.0466	-0.0166	0.00621	-0.0978
	(0.0297)	(0.0224)	(0.0302)	(0.0992)
Living as a coupled	-0.0756*	0.0197	-0.0683	-0.0552
	(0.0406)	(0.0336)	(0.054)	(0.133)
Higher education	-0.135**	-0.00727	-0.427	
	(0.0564)	(0.0666)	(0.285)	
Unemployed	0.200***	-0.0901**	-0.0186	
	(0.0529)	(0.0364)	(0.0477)	
Not in the labor force	-0.0318	-0.203***	-0.111***	0.102
	(0.0368)	(0.0301)	(0.0235)	(0.252)
Frequency of physical activity	0.0744***	0.0594***	0.0548***	0.0779***
	(0.00769)	(0.00486)	(0.00529)	(0.0133)
Frequency of social interaction	0.0137	0.00572	0.0170***	0.0286*
	(0.00848)	(0.00446)	(0.00498)	(0.0147)
Observations	11,447	21,295	13,967	1,996
Hansen J test (p-value)	0.794	0.530	0.090	0.177
Number of instruments	137	137	137	137
First-order serial correlation test (p-value)	0.000	0.000	0.000	0.000
Second-order serial correlation test (p-value)	0.864	0.995	0.332	0.855

Note: *p < 0.1, **p< 0.05, ***p< 0.01. Two-step robust standard errors are in parentheses. All models included wave and Australian region of residence dummies as control variables.

Table 5
Difference GMM regression model for physical health for individuals aged 15-85

	Full sample	Males	Females
Physical health (t-1)	0.0284***	0.00705	0.0327**
	(0.0106)	(0.0165)	(0.0141)
Mental health (t-1)	0.0317***	0.0356***	0.0272***
	(0.00761)	(0.0128)	(0.00933)
Age	-0.0239***	-0.0285***	-0.0214***
	(0.00169)	(0.00296)	(0.00253)
Household size	0.00639	0.00199	0.00476
	(0.00879)	(0.0128)	(0.0116)
Real household income (in thousands of AUS dollars)	-0.000231***	-0.0000820	-0.000248**
	(0.0000883)	(0.000121)	(0.000118)
Number of children in the household	0.0118	-0.00623	0.0311**
	(0.0111)	(0.0169)	(0.0140)
Private health insurance	-0.0200	0.0102	-0.0373**
	(0.0139)	(0.0206)	(0.0181)
Living as a couple	-0.0334*	-0.00320	-0.0347
	(0.0196)	(0.0299)	(0.0251)
Higher education	-0.0616*	-0.0883	-0.0470
	(0.0340)	(0.0607)	(0.0397)
Unemployed	0.00503	-0.0326	0.0374
	(0.0228)	(0.0377)	(0.0277)
Not in the labor force	-0.114***	-0.130***	-0.0972***
	(0.0155)	(0.0277)	(0.0183)
Frequency of physical activity	0.0602***	0.0564***	0.0599***
	(0.00298)	(0.00443)	(0.00388)
Frequency of social interaction	0.0127***	0.00367	0.0171***
	(0.00289)	(0.00443)	(0.00370)
Observations	52,743	22,094	30,649
Number of instruments	137	137	137
Hansen J test (p-value)	0.870	0.311	0.666
First-order serial correlation test (p-value)	0.000	0.000	0.000
Second-order serial correlation test (p-value)	0.592	0.825	0.876

Note: *p < 0.1, **p< 0.05, ***p< 0.01. Two-step robust standard errors are in parentheses. All models included wave and Australian region of residence dummies as control variables.

Table 6
Difference GMM regression model for physical health with additional regressors treated as endogenous variables

	(1)	(2)	(3)
Physical health (t-1)	0.0217**	0.0245**	0.0213**
	(0.0105)	(0.0105)	(0.0106)
Mental health (t-1)	0.0319***	0.0320***	0.0329***
	(0.00747)	(0.00745)	(0.00746)
Age	-0.0263***	-0.0251***	-0.0256***
	(0.00199)	(0.00194)	(0.00195)
Household size	0.00577	0.00597	0.00609
	(0.00857)	(0.00862)	(0.00865)
Real household income (in thousands of AUS dollars)	-0.000211**	-0.000186**	-0.000196**
	(0.0000868)	(0.0000872)	(0.0000873)
Number of children in the household	0.0126	0.0101	0.011
	(0.0105)	(0.0105)	(0.0105)
Private health insurance	-0.0167	-0.0136	-0.0126
	(0.0138)	(0.0137)	(0.0138)
Living as a couple	-0.0303	-0.0245	-0.0244
	(0.0193)	(0.0193)	(0.0193)
Higher education	-0.0583*	-0.0632*	-0.0620*
	(0.0336)	(0.0339)	(0.034)
Unemployed	0.00612	0.00901	0.01
	(0.0227)	(0.0228)	(0.0228)
Not in the labor force	-0.110***	-0.113***	-0.109***
	(0.0154)	(0.0154)	(0.0155)
Frequency of physical activity	0.0476***	0.0587***	0.0463***
	(0.00412)	(0.00293)	(0.00413)
Frequency of social interaction	0.0125***	0.0111***	0.0114***
	(0.00284)	(0.00409)	(0.00407)
Observations	53,396	53,396	53,396
Number of instruments	201	201	265
Hansen J test (p-value)	0.570	0.314	0.239
First-order serial correlation test (p-value)	0.000	0.000	0.000
Second-order serial correlation test (p-value)	0.909	0.783	0.912

Note: *p < 0.1, **p< 0.05, ***p< 0.01. Two-step robust standard errors are in parentheses. All models included wave and Australian region of residence dummies as control variables. In column (1), the frequency of physical activity is treated as an endogenous variable. In column (2), the frequency of social interaction is treated as endogenous. In column (3), both the frequency of physical activity and the frequency of social interaction are treated as endogenous.

Table 7
Difference GMM regression model for physical health using an alternative physical and mental health index from factor analysis

	Full sample	Males	Females
Physical health (t-1)	0.0315***	0.0163	0.0349**
	(0.0106)	(0.0166)	(0.0141)
Mental health (t-1)	0.0333***	0.0358**	0.0273**
	(0.00930)	(0.0161)	(0.0115)
Age	-0.0227***	-0.0255***	-0.0198***
	(0.00181)	(0.00250)	(0.00197)
Household size	0.00543	-0.000864	0.00349
	(0.00744)	(0.0105)	(0.0104)
Real household income (in thousands of AUS dollars)	-0.000176**	-0.0000803	-0.000198*
	(0.0000754)	(0.0000996)	(0.000106)
Number of children in the household	0.00992	-0.000889	0.0246**
	(0.00916)	(0.0133)	(0.0125)
Private health insurance	-0.0152	0.0139	-0.0322**
	(0.0119)	(0.0172)	(0.0163)
Living as a couple	-0.0304*	0.000701	-0.0339
	(0.0168)	(0.0248)	(0.0226)
Higher education	-0.0502*	-0.0795	-0.0435
	(0.0295)	(0.0519)	(0.0358)
Unemployed	0.00890	-0.0162	0.0394
	(0.0195)	(0.0315)	(0.0251)
Not in the labor force	-0.0952***	-0.104***	-0.0855***
	(0.0133)	(0.0233)	(0.0163)
Frequency of physical activity	0.0525***	0.0478***	0.0544***
	(0.00253)	(0.00373)	(0.00345)
Frequency of social interaction	0.0115***	0.00374	0.0161***
	(0.00246)	(0.00371)	(0.00330)
Observations	53,396	22,363	31,033
Number of instruments	137	137	137
Hansen J test (p-value)	0.746	0.227	0.692
First-order serial correlation test (p-value)	0.000	0.000	0.000
Second-order serial correlation test (p-value)	0.720	0.981	0.889

Note: *p < 0.1, **p< 0.05, ***p< 0.01. Two-step robust standard errors are in parentheses. All models included wave and Australian region of residence dummies as control variables.

Table 8
Difference GMM regression model for physical health with smoking and drinking alcohol as additional control variables

	Full sample	Males	Females
Physical health (t-1)	0.0267**	0.00718	0.0313**
	(0.0106)	(0.0167)	(0.0142)
Mental health (t-1)	0.0327***	0.0377***	0.0285***
	(0.00763)	(0.0129)	(0.00936)
Age	-0.0243***	-0.0281***	-0.0190***
	(0.00196)	(0.00298)	(0.00237)
Household size	0.00620	0.0000451	0.00628
	(0.00874)	(0.0129)	(0.0115)
Real household income (in thousands of AUS dollars)	-0.000191**	-0.0000758	-0.000184
	(0.0000893)	(0.000125)	(0.000118)
Number of children in the household	0.00936	-0.00493	0.0240*
	(0.0107)	(0.0165)	(0.0137)
Private health insurance	-0.0150	0.0115	-0.0327*
	(0.0139)	(0.0206)	(0.0181)
Living as a couple	-0.0288	0.00319	-0.0314
	(0.0197)	(0.0302)	(0.0253)
Higher education	-0.0639*	-0.0824	-0.0524
	(0.0343)	(0.0614)	(0.0399)
Unemployed	0.00414	-0.0362	0.0374
	(0.0228)	(0.0380)	(0.0277)
Not in the labor force	-0.113***	-0.126***	-0.0977***
	(0.0155)	(0.0278)	(0.0183)
Frequency of physical activity	0.0608***	0.0577***	0.0601***
	(0.00295)	(0.00443)	(0.00387)
Frequency of social interaction	0.0119***	0.00384	0.0165***
	(0.00288)	(0.00446)	(0.00370)
Smoking	0.0169**	0.0169	0.0140
	(0.00683)	(0.0108)	(0.00858)
Drinking alcohol	0.0295***	0.0173***	0.0372***
	(0.00426)	(0.00668)	(0.00540)
Observations	52,101	21,893	30,208
Number of instruments	139	139	139
Hansen J test (p-value)	0.863	0.121	0.525
First-order serial correlation test (p-value)	0.000	0.000	0.000
Second-order serial correlation test (p-value)	0.662	0.744	0.976

Note: *p < 0.1, **p< 0.05, ***p< 0.01. Two-step robust standard errors are in parentheses. All models included wave and Australian region of residence dummies as control variables.