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ABSTRACT

Well-Being and Ill-Being: A Bivariate Panel Data Analysis*

The aim of this paper is to estimate in a multivariate context the factors associated with well-being and ill-being without making the assumptions that they are opposite ends of the same continuum, and that the factors uniformly affect both well-being and ill-being. Using the first five waves of panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, we jointly model positive and negative well-being in a two-equation dynamic panel data model. We found that while past ill-being had significant effect on current well-being there was no support for a reverse relationship (i.e. lagged effect of well-being on current ill-being). In addition, we also found support for asymmetry in how certain factors affect well-being and ill-being. The implication of the findings in this paper for the happiness literature is that for future empirical work, it would perhaps more prudent to begin with the notion that well-being and ill-being are distinct dimensions, that the unobservables that affect well-being and ill-being are correlated, and to specify econometric models that allow for these concepts to be reflected.

JEL Classification: I31, C33

Keywords: well-being, happiness, ill-being, dynamic panel models, bivariate probit

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"The deeper that sorrow carves into your being, the more joy you can contain."
Kahlil Gibran, "On Joy and Sorrow" from The Prophet

1. Introduction

An implicit assumption used in the happiness literature in economics is that well-being and ill-being are opposite ends of the same continuum. The aim of this paper is to estimate in a multivariate context the factors associated with well-being and ill-being without making the assumptions that they are opposite ends of the same continuum, and that the factors uniformly affect both well-being and ill-being. Assuming that reliable measures of positive and negative well-being exist (e.g., life satisfaction versus psychological stress), it is possible to empirically test if there are indeed asymmetries in how factors are associated with well-being and ill-being. One approach is to perform two separate analyses with the same set of regressors. This was the approach adopted in Headey and Wooden (2004) who estimated two independent cross-sectional regressions. However, by ignoring a possible correlation between unobserved factors that jointly affect well-being and ill-being, the results from their estimated regressions might be inconsistent. An alternative approach is to adopt a multi-index ordered probit panel data model with varying thresholds. Boes and Winkelmann (2006) argue that despite having only single-item measures of subjective well-being, based on rank ordering the subjective well-being measure, such a model can help identify asymmetries in well-being and ill-being. In this paper, a third approach is used. Using the first five waves of panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, we jointly model positive and negative well-being in a two-equation dynamic panel data model. An analysis of similarities and differences in how individual characteristics affect well-being and ill-being is then made. We believe this will help shed more light on the appropriate dimension to use in future studies of well-being.

Section 2 provides a brief review of the literature that supports the notion that well-being and ill-being are distinct dimensions. Section 3 describes the data. The econometric model is presented in section 4. Results are discussed in section 5. Finally, section 6 concludes.

2. Dimensionality of Subjective Well-Being

Research on subjective well-being is now arguably a major subfield in economics, with research appearing to increase at an exponential rate (Kahneman and Krueger 2006). The conventional viewpoint is that good moods and bad moods are inversely related – the more time one spends up the less time one can spend down. However, the idea that well-being and ill-being are distinct dimensions and not bi-polar opposites has found increasing support in the psychology literature. Knowing the amount of good feeling a person experiences over time does not indicate the global amount of bad feeling the person experiences. Empirical evidence has found that people who experience happiness intensely tend similarly to experience negative well-being more intensely. For some people, high highs alternate with low lows.

Bradburn (1969) and Bradburn and Caplovitz (1965) were the first to offer evidence that subjective well-being is not a unitary construct, but is composed of two separate feelings: positive and negative affect (i.e., moods and emotions).[1] They found that the correlation between positive and negative affect items was very low and that the two dimensions of affect correlated differently with various external variables. These findings have stirred considerable interest as if true, would imply that well-being must be measured along two dimensions that vary relatively independently of each other.

Although the degree of independence between momentary positive and negative affect is still debated, there is less controversy regarding the separability of long-term affective dimensions (Diener et al. 1999). For example, Diener et al. (1995) found that long-term pleasant and unpleasant affect are moderately inversely correlated but clearly separable. This is an important finding as research in economics on subjective well-being is generally interested in long-term moods rather than momentary emotions. More recently, using data from the British Health and Lifestyle Survey, Huppert and Whittington (2003) find support for a certain degree of independence between well-being and ill-being since important determinants of well-being are found to have less influence on negative well-being, and vice versa. They find in their study that over one third of their sample obtained either low scores on both positive and negative well-being measures or high scores on both measures. Other research that argues in favour of

[1] Positive affect refers to a dimension in which high levels are characterized by high energy, full concentration, and pleasurable engagement, whereas low positive affect is characterized by sadness and lethargy. In contrast, negative affect refers to a distress dimension that can be described by a variety of mood states including anger, contempt, disgust, guilt, fear and nervousness, with low negative affect being a state of calmness and serenity.

regarding measures of well-being and ill-being as distinct dimensions are Diener (1984), Diener and Emmons (1984), Headey et al. (1993) and Myers and Diener (1995).

Finding that well-being and ill-being are not bi-polar opposites can have practical and theoretical implications. For example, from an economics perspective, there are implications on public policies that attempt to make all individuals in a society absolutely better off (e.g., building a better public transport system, providing a lump sum tax refund to all tax payers etc.). Even if interventions raise the overall levels of well-being in society, it is not necessarily the case that there will be a corresponding decrease in feelings of ill-being or discontents that lead to crime and other forms of deviant behaviour. Other policies aimed specifically at reducing such incidents must also be simultaneously implemented (e.g., more law enforcement).

3. Data

The data used in this study come from the first five waves of the HILDA Survey. Described in more detail in Watson and Wooden (2004), the HILDA Survey began with a large national probability sample of Australian households occupying private dwellings in 2001. All members of those responding households in wave 1 form the basis of the panel to be pursued in each subsequent wave (though interviews are only conducted with those household members aged 15 years or older), with each wave of interviewing being approximately one year apart.

Although HILDA is primarily a longitudinal survey with a focus on work, income and family issues, it is useful for examining the correlates of well-being and ill-being because of questions asked in the Self-Completion Questionnaire. The measure used for subjective well-being is the single item measure of "overall life satisfaction" scored on a 0 (Very Unhappy) to 10 (Very Happy) scale. This follows the empirical approach in the happiness literature which views these responses as proxies for what economists call utility. For our analysis, we collapse well-being into a binary variable, with scores of eight and above on overall life satisfaction indicating happiness, and score of seven and below indicating a lack of happiness.[2]

For measuring ill-being, we use a summary score derived using factor analysis from the Medical Outcomes Study Short-Form General Health Survey (SF-36), one of the most widely used measures of subjective health (Ware 2004). All HILDA waves include the set of questions that make up the SF-36. The 36 survey items in the SF-36

[2] A score of eight on the overall life satisfaction question is the median in our sample.

are scored such that 8 scale scores are given: physical functioning, role physical, bodily pain, general health perceptions, vitality, social functioning, role emotional and mental health. Two summary measures can be calculated from these scales – these are called the physical component score (PCS) and the mental component score (MCS). For the purposes in this paper, we utilize the MCS as our measure of ill-being because it has been shown to be useful in screening for psychiatric disorders. For example, using a cut-off score of 42, Ware, Kosinski and Keller (1994) found that the MCS had a sensitivity of 74% and a specificity of 81% in detecting patients diagnosed with depressive disorder.[3] For our analysis, we classify those with a MCS score of 42 and above as depressed, and those with score of 41 and less as not being depressed.

3.1 Description of the Sample

Our sample consists of a balanced sample of people who were between 25-59 years of age for females and 25-64 for males during the first five waves of the HILDA survey. After dropping observations with missing values of variables, our final analysis sample includes a total of 2113 males and 2285 females.

Table 1 describes the variables that are used in this study. They include a standard set of demographic characteristics such as age, marital status, and ethnicity, whether one's native language is English, employment status, total income, and welfare receipt. Income is measured using imputed gross income. In addition, we also include a measure of social interactions. The variable *social* is based on the response to the question of how often one gets together socially with friends. We create a binary indicator that equals one if they have get togethers more than once a month and zero if less than once a month. The final two variables listed in Table 1 are measures of personality, which are used later as our exclusion restrictions (more on this in section 4.1). The personality variables that measure emotional stability and extroversion are based on an ordinal scale of one to seven, with seven indicating the greatest emotional stability and extroversion. An interesting finding in Table 1 is that women report both higher mean levels of well-being and ill-being as compared to men. In other words, women are on average happier as well as more depressed than men are on average.

[3] Sensitivity refers to how good a test is at correctly identifying people who have the disease. Specificity, on the other hand, is concerned with how good the test is at correctly identifying people who are well.

Table 1: Descriptive Statistics, By Gender

	Men		**Women**	
Variables	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
Well-being	0.65	0.48	0.68	0.47
Lagged Well-being	0.65	0.48	0.68	0.47
Ill-Being	0.17	0.37	0.20	0.40
Lagged Ill-being	0.17	0.37	0.20	0.40
Age	44.28	9.71	42.02	8.49
Age squared	2054.59	871.72	1837.91	718.72
Non-English speaking background	0.10	0.30	0.11	0.31
Aboriginal/Torres Strait Islander	0.01	0.09	0.01	0.12
City	0.61	0.49	0.61	0.49
Married	0.79	0.41	0.76	0.43
Bachelor plus	0.26	0.44	0.27	0.45
Disability	0.23	0.42	0.19	0.39
Employed	0.86	0.35	0.71	0.45
Unemployed	0.03	0.16	0.02	0.15
Income	51931.1	42761.9	29965.6	25014.2
Welfare receipt	0.14	0.35	0.19	0.39
Social	0.73	0.44	0.78	0.41
Emotional stability	5.12	1.05	5.23	1.06
Extroverted	4.21	1.02	4.53	1.12
Sample Size	10565		11425	

Note: Statistics are obtained by pooling 5 waves of HILDA.

Table 2 shows the correlation between well-being and ill-being in one period and well-being and ill-being in the next period. We first examine the frequency of the joint outcomes within each wave. For all waves, about a quarter of males and a fifth of females report being neither happy nor depressed, a state we refer to as “stoic.” The majority of individuals (approximately 60 percent) appear to be happy and not depressed (“happy”), while about 10 to 13 percent of individuals report being depressed and not happy (“depressed”). The smallest group (between 5 to 9 percent) are those that reported being both happy and depressed (“volatile”) in the same wave. This group would consist of individuals that alternate between high highs and low lows. Similar to Huppert and Whittington (2003), we find that about a third of our sample is in the stoic or volatile state.

Next, we examine the conditional outcome in period $t+1$ conditional on self-reported statuses of well-being and ill-being in period *t*. The raw data suggest that there is considerable persistence in well-being and ill-being, with slightly more persistence in well-being. For example, conditional on being happy and not depressed in Wave 1, about 81 percent of men report being happy in Wave 2. Similarly, conditional on not being happy and depressed in Wave 1, about 57 percent of men report being depressed in Wave 2. These results remain rather consistent across all waves and for both genders.

Table 2: Bivariate Transition Rates

	State in Wave t			Frequency, Wave t		Outcome Probability in Wave $t+s$			
				Men	Women	Men		Women	
Wave $t/t+s$	Well-Being	Ill-Being	Description			Well-Being	Ill-Being	Well-Being	Ill-Being
1/2	X	X	Stoic	24.2%	18.8%	0.38	0.11	0.39	0.17
	√	X	Happy	59.4%	60.9%	0.81	0.07	0.82	0.10
	X	√	Depressed	10.8%	12.3%	0.26	0.57	0.27	0.61
	√	√	Volatile	5.6%	8.0%	0.67	0.48	0.69	0.46
2/3	X	X	Stoic	26.1%	20.8%	0.41	0.15	0.47	0.15
	√	X	Happy	58.0%	58.4%	0.84	0.06	0.85	0.09
	X	√	Depressed	10.1%	13.4%	0.30	0.60	0.30	0.58
	√	√	Volatile	5.9%	7.5%	0.73	0.60	0.78	0.44
3/4	X	X	Stoic	22.9%	19.6%	0.40	0.11	0.41	0.19
	√	X	Happy	60.0%	61.3%	0.83	0.07	0.85	0.09
	X	√	Depressed	10.7%	11.3%	0.26	0.56	0.31	0.61
	√	√	Volatile	6.4%	7.8%	0.60	0.60	0.72	0.55
4/5	X	X	Stoic	24.1%	18.9%	0.37	0.14	0.36	0.15
	√	X	Happy	59.3%	60.5%	0.83	0.07	0.82	0.08
	X	√	Depressed	10.0%	11.9%	0.24	0.66	0.34	0.63
	√	√	Volatile	6.6%	8.8%	0.60	0.54	0.72	0.52

There also appears to be useful asymmetric information contained in past measures of well-being and ill-being for helping predict current well-being and ill-being. Consider the case when we simply condition on happiness in period t and ignore information on depression. The raw data highlight that not being depressed in period t (e.g., the first two rows in Table 2) does not necessarily imply that one is happy in period $t+1$. For example, happy/not depressed ("happy") males in Wave 1 are about 43 percentage points more likely to be happy in Wave 2 than the not happy/not depressed ("stoic") males. Now consider the reverse case when we simply condition on depression in period t and ignore information on happiness. Not happy/depressed ("depressed") males in Wave 1 are about 9 percentage points much more likely to be depressed in Wave 2 as compared to happy/depressed ("volatile") males (see rows three and four in Table 2). There therefore appears to be useful information contained in both well-being and ill-being in period t that can be used for predicting well-being and ill-being in period $t+1$. In other words, the raw data leads us to believe that a correctly specified econometric model should allow past well-being and ill-being to affect current well-being, as well as allowing past well-being and ill-being to affect current ill-being.

4. Empirical Methodology

This paper builds on the approach adopted in Lee and Oguzoglu (2007) who employed a dynamic panel model to analyse dynamics in subjective well-being. In this paper, two extensions are made. First, we relax the implicit assumption made in Lee and Oguzoglu (2007) that positive and negative well-being can be measured in a single dimension. Second, we explicitly model the complex correlation structure of well-being and ill-being. By allowing past well-being levels to affect current ill-being levels, and past ill-being levels to affect current well-being levels, we aim to provide a more complete statistical picture of the dynamics of positive and negative well-being.

Despite the fact that psychologists have repeatedly found strong empirical support for the setpoint hypothesis, studies of well-being have generally not attempted to model such dynamic processes explicitly.[4] Lee and Oguzoglu (2007) find that lagged happiness is statistically significant in all the dynamic panel models that they estimate, highlighting the importance of state dependence in person-level happiness data. Allowing past well-being levels to affect current well-being levels in a dynamic panel setting is one way forward towards obtaining a better understanding of the dynamics of the adjustment process towards setpoint levels of happiness. In this paper, our use of distinct measures for well-being and ill-being and allowing past well-being levels to affect current ill-being levels, as well as allowing past ill-being levels to affect current well-being levels, can be regarded as yet another step forward in attempting to better understand the mechanics by which people adapt to changes in positive and negative well-being.

4.1 The Econometric Model

In attempting to model the dynamic process of well-being, we use a bivariate dynamic panel data model that allows for interactions between unobserved factors associated with current well-being and current ill-being[5]. Put another way, instead of modelling the effects of individual characteristics (age, education, marital status etc.) on well-being and ill-being in separate equations (i.e., the approach in Headey and Wooden 2004), we propose to *jointly* model the effects of individual characteristics on well-being and ill-being in a two-equation system, allowing individual characteristics to have

[4] The setpoint theory of happiness postulates that people react to or are affected psychologically by events but they eventually adapt back to their baseline level of well-being.

[5] The model used here is similar to the model employed by Allessie et al (2004), who used a bivariate panel data modele to analyse the ownership dynamics of stocks and mutual funds.

potentially different effects on each outcome and allowing unobserved characteristics that affect both outcomes to be correlated.

More specifically, the bivariate dynamic random effects panel probit model can be written as:

$$W_{it} = \beta_1 X_{it} + \gamma_1 W_{it-1} + \gamma_2 I_{it-1} + \alpha_i + \varepsilon_{it} \quad (1)$$
$$I_{it} = \beta_2 X_{it} + \gamma_3 W_{it-1} + \gamma_4 I_{it-1} + \eta_i + \nu_{it} \quad (2)$$

where W_{it} is a binary measure of life satisfaction that is equal to one if individual i is very satisfied about his/her life at time t, I_{it} is a binary measure of ill-being that is equal to one if the individual has a score on the MCS ≥ 42, X_{it} is a $k \times 1$ matrix of observed characteristics, and α_i and η_i represent time invariant unobserved heterogeneity (or random effects).[6] α_i and η_i are assumed to be distributed bivariate normal with variances σ_α^2 and σ_η^2. Their covariance matrix can be written as:

$$\Sigma = \begin{bmatrix} \sigma_\alpha^2 & \sigma_\alpha \sigma_\eta \rho \\ \sigma_\alpha \sigma_\eta \rho & \sigma_\eta^2 \end{bmatrix}$$

Finally, ε_{it} and ν_{it} are time varying error terms. They are assumed to be distributed standard bivariate normal with $E[\varepsilon_{it}, \nu_{it}] = \tau$.

A problem with random effect models is that the individual effects are assumed to be uncorrelated with the right hand side variables. In an attempt to control for the correlation between X_{it} and the random effects α_i and η_i, we follow Mundlak (1978) by including the time averages of all time varying exogenous variables. This approach simply indicates that $\bar{x}_i$ will be included in equations (1) and (2) as additional regressors.

In addition to distinguishing between unobserved heterogeneity and genuine state dependence, the bivariate model can explain correlation between well-being and

[6] Winkelmann (2005) explores the potential the family has in shaping the intrinsic well-being of an individual by studying the joint distribution of subjective well-being within the family. Although adding an extra subscript to denote family membership, as Winkelmann does, would add to explaining variation in intrinsic well-being, it would be a big econometric challenge to incorporate such interdependent family effects in our bivariate setup. We therefore resort to the somewhat standard approach in the happiness literature of including marital status as an imperfect control for family effects.

ill-being from correlated unobserved heterogeneity as well as from state dependence across outcomes. The correlation between random effects in the two equations captures correlated unobserved heterogeneity. Dummies for the lagged dependent variable in each equation capture genuine state dependence effects. A key feature of this model is that lagged well-being and lagged ill-being are in both equations. If the coefficient on lagged ill-being for the well-being equation is zero, for example, then there is no gain to estimating a bivariate model and a univariate equation can be estimated.

In the bivariate model, if well-being in period t is correlated with ill-being in period $t-1$, this can be due to correlated unobserved heterogeneity (i.e., a non–zero covariance between α_i and η_i) or be due to state dependence across the two outcomes (i.e., a non–zero value of γ_2). For example, a positive value of γ_2 could mean that ill-being may make individuals more appreciative of the good things that happen in life in general. On the other hand, a positive correlation between the random effects would simply mean that the same people who are happier in general also experience more intense levels of ill-being. A negative correlation would imply that people who are happier in general are less likely to experience depression.

The consistent estimation of the models (1) and (2) requires a solution to the "initial conditions problem." The complication arises due to our lack of knowledge of the data generating process that governs the first observations of well-being and ill-being. One solution, originally suggested by Heckman (1981), is to approximate the unknown initial conditions with a static probit equation that utilizes information from the first wave. Our approach is to model the initial conditions for well-being and ill-being separately. In order to freely correlate the main equations and the initial condition equations, we follow Alessie et al. (2004) and add arbitrary linear combinations of the random effects α_i and η_i to the initial condition equations as follows:

$$W_{i1} = \delta_1 X_{i1} + \theta_1 \alpha_i + \theta_2 \eta_i + \varepsilon_{i1} \tag{3}$$

$$I_{i1} = \delta_2 X_{i1} + \theta_3 \eta_i + \theta_4 \alpha_i + \nu_{i1} \tag{4}$$

where X_{i1} includes all variables in X_{it} measured in the first wave, and the summary scores for extroversion and emotional stability from the Big Five personality test incorporated in Wave 5 of HILDA.[7,8] ε_{i1} and ν_{i1} are assumed to be uncorrelated with all other terms in equations (1) to (4) and they are assumed to follow a bivariate standard normal distribution with $E[\varepsilon_{i1}, \nu_{i1}] = \tau_1$.

Heckman (1981) suggests that the parameters of the models (1) to (4) can be jointly estimated with Full Information Maximum Likelihood to obtain consistent estimates. An individual's contribution to the log-likelihood can be expressed as:

$$L_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \Phi_2 \left[(2W_1 - 1)\mu_{11}, (2I_1 - 1)\mu_{21}, (2W_1 - 1)(2I_1 - 1)\tau_1 \right] \\ \times \prod_{t=2}^{T} \Phi_2 \left[(2W_{1t} - 1)\mu_{1t}, (2I_{1t} - 1)\mu_{2t}, (2W_{1t} - 1)(2I_{1t} - 1)\tau \right] \times \phi_2(\alpha, \eta, \Sigma) d\alpha d\eta \tag{5}$$

where Φ_2 is the bivariate normal cumulative distribution function, ϕ_2 is the bivariate normal density function of the random effects, μ_{11} and μ_{21} are the right hand side variables of the initial conditions equation, and μ_{1t} and μ_{2t} are the right hand side variables of the main equations. This model can be estimated using Maximum Simulated Likelihood.

5. Discussion of Empirical Results

In this section we represent estimation results from the dynamic bivariate model. The results are summarized in three sections. First, we discuss the impact of observed characteristics on measures of well-being and ill-being. Second, the results of estimating the initial conditions are discussed. Finally, we interpret the estimates of unobserved heterogeneity.

5.1 Dynamic Bivariate Models

The model described in the previous section was estimated using Maximum Simulated Likelihood based on 20 Halton draws.[9] The results in Table 3 indicates that

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[7] We treat personality as a time invariant feature; therefore personality scores that are only available in wave 5 are valid information for the initial conditions.

8 Much work in psychology (Costa and McCrae 1980, Tellegen 1985, Headey and Wearing 1992, Watson and Clark 1992, Lucas and Fujita 2000) emphasizes that extroversion and neuroticism provide the primary links between personality and subjective well-being. Little is known, however, about the social relevance and importance of the remaining summary scores; openness, agreeableness, and conscientiousness (Eysenck 1991).

both well-being and ill-being show considerable persistence. These findings are consistent with the findings in Lee and Oguzoglu (2007). A currently very satisfied individual is very likely to be satisfied with her life in the next period. In addition, in this paper, we find that the likelihood of depression in future periods increases with the prevalence of current depression. The finding that the effect of lagged ill-being on current ill-being is larger than the effect of lagged well-being on current well-being is supported by findings in the psychological literature.[10] Whereas chronic happiness is not a common phenomenon, chronic depression is a well-known medical condition that has been subject to much research (e.g., Kocsis and Klein 1995).[11] In other words, it is reasonably well established that depression is a persistent condition that is affected by previous episodes of depression. For example, based on an adult sample of 7076 individuals from the Netherlands Mental Health Survey, Spijker et al. (2002) found that the risk of chronic depression was considerable. Almost 20 percent of the participants with depression had not recovered 24 months after entering a spell of depression. Similar results are reported by Keller et al. (1992) based on 431 subjects from Institute of Mental Health Collaborative Depression Study.

In general, there appears to be an asymmetry in the effects of the variables on well-being and ill-being, supporting the hypothesis that well-being and ill-being measure are not bi-polar opposites. For both men and women, although lagged well-being has insignificant effects on current ill-being, lagged ill-being is highly significant and is associated with lower incidence of well-being in the current period. Such a finding is consistent with the notion that changes to equilibrium levels of ill-being are likely to be more permanent as they are rather immune to events that give rise to positive feelings. On the other hand, changes to equilibrium levels of well-being are more easily counteracted by events that lead to negative well-being, making such changes more transitory.

The results also suggest that being born in a non-English speaking country significantly lowers the level of well-being of both men and women, but has no effect

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[9] The optimization is carried out using GAUSS CML library and the BFGS algorithm. The results are not significantly different when 50 draws were used. See Train (2003) for a detailed discussion on Halton draws. See also Alessie et al (2004) for more details on the estimation procedure.

[10] This is based on the average partial effects evaluated at the individual means of the independent variables. For both men and women, the effect of lag well-being on current well-being is approximately 5%, whereas the effect of the lagged ill-being on current ill-being is approximately 15%.

[11] A large body of research in psychology (see, for example, Diener et al. (1999) and the references therein) suggests that positive changes to happiness levels do not seem to have lasting effects because hedonic adaptation tends to return people back to their initial set point of happiness, which is genetically determined and assumed to be fixed and stable over time.

on levels of ill-being. Such a result appears to be intuitive as a language barrier might prohibit one from fully assimilating into society thereby not allowing one to reach one's full potential. But there is less reason to believe that a language barrier should lead to higher levels of ill-being as presumably, an immigrant society that speaks the same language will exist and immigrants are not socially isolated.

Table 3: Dynamic Bivariate Model, Main Equation

	Well-Being				**Ill-Being**			
	Men		**Women**		**Men**		**Women**	
Parameters	*Estimate*	*S.E.*	*Estimate*	*S.E.*	*Estimate*	*S.E.*	*Estimate*	*S.E.*
Constant	-1.437**	0.50	0.039	0.35	0.270	0.56	-0.936*	0.38
Well-Being$_{t-1}$	0.214**	0.06	0.371**	0.05	0.041	0.06	-0.108	0.06
Ill-Being $_{t-1}$	-0.268**	0.07	-0.173**	0.06	0.509**	0.07	0.469**	0.06
Age	0.082	0.37	0.096	0.35	0.436	0.47	-0.216	0.41
Age squared	0.009	0.09	0.016	0.09	-0.085	0.11	0.026	0.11
Non-English speaking background	-0.323**	0.09	-0.186*	0.08	0.145	0.10	0.052	0.08
Aboriginal/Torres Strait Islander	1.198**	0.43	-0.115	0.23	-0.270	0.35	0.399*	0.20
City	-0.206	0.14	-0.357*	0.15	-0.082	0.20	0.047	0.15
Married	0.499**	0.12	0.409**	0.11	-0.405**	0.12	-0.224	0.12
Bachelor plus	-0.982*	0.43	-0.277	0.45	1.006	0.78	0.320	0.40
Disability	-0.166*	0.07	-0.060	0.07	0.278**	0.07	0.359**	0.07
Employed	0.212	0.13	0.055	0.08	-0.190	0.14	-0.309**	0.08
Unemployed	-0.091	0.18	-0.086	0.14	-0.180	0.18	-0.136	0.15
Income	-0.122	0.39	-0.059	0.35	0.495	0.50	0.261	0.37
Welfare receipt	0.021	0.12	-0.060	0.09	-0.094	0.14	0.029	0.10
Social	0.142*	0.06	0.089	0.06	-0.206**	0.07	-0.128*	0.06
Time Averages								
m(Age)	-0.995	0.82	-0.704	0.84	-0.186	1.00	0.473	0.97
m(Age squared)	0.12	0.09	0.076	0.10	-0.011	0.11	-0.056	0.11
m(City)	0.10	0.15	0.211	0.16	0.084	0.21	-0.018	0.16
m(Married)	0.202	0.15	0.079	0.13	0.104	0.15	0.010	0.14
m(Bachelor plus)	0.753	0.44	0.111	0.46	-0.897	0.79	-0.366	0.40
m(Disability)	-0.290*	0.12	-0.592**	0.11	1.045**	0.13	0.940**	0.12
m(Employed)	-0.331	0.20	-0.356**	0.12	-0.457*	0.21	0.021	0.12
m(Unemployed)	0.163	0.34	-0.495	0.32	-0.362	0.36	0.813*	0.33
m(Income)	3.212**	1.18	0.519	0.87	-2.552	1.36	0.403	0.98
m(Welfare receipt)	-0.163	0.18	-0.188	0.13	0.284	0.20	0.262	0.13
m(Social)	0.311**	0.11	0.478**	0.10	-0.356**	0.12	-0.387**	0.10

Note: * and ** indicate significance at 5% and 1%. Reported standard errors in the table have been rounded to two decimal places. The variables m(.) denote the means of the variables in parentheses over time.

A particularly strong asymmetric result shows up for Aboriginal and Torres Strait Islanders (ATSI). Although being a male ATSI is associated with a significantly higher level of well-being and not associated with levels of ill-being, being a female ATSI is significantly associated with a higher level of ill-being and not associated with levels of well-being. This gender difference is likely accounted for by the experiences of ATSI women in Australia. Kimm (2004) documents the high levels of violence that ATSI women experience in their own communities. She argues that an underlying cause of such violence is the male dominated cultural heritage of modern indigenous society that provides women with few legal rights.

The most symmetric results are found for marital status and education, where it is found that the signs of the coefficients are opposite to each other in the well-being and ill-being equations and that the size of the coefficients are approximately the same. The positive effect of marriage on well-being is a well documented empirical regularity across many different data sets from different countries (Diener et al. 1999). The negative effect on well-being of having at least a bachelor's degree for males, however, is not a common result in the literature, although Headey and Wooden (2004) report a similar finding in their analyses based on Wave 2 of HILDA.

Having a disability significantly lowers the level of well-being for males, and to a greater degree significantly increases the level of ill-being for both males and females. Such a finding likely reflects the large inconvenience in daily activities that is a result of having a disability. Work appears to make women more depressed but has insignificant effects on men. This could reflect the additional stress that women have trying to juggle taking care of the family and working. Income levels are not found to be significantly associated with levels of well-being or ill-being. This finding is consistent with repeated empirical findings in the psychology literature that money does not buy happiness (e.g., Myers and Diener 1995; Diener et al. 1999). The finding that receipt of income support payments does not affect levels of adult well-being or ill-being is similar to the finding in Lee and Oguzoglu (2007) for young Australians using a different data set. Finally, it is also intuitively easy to understand why having frequent social activities leads to higher levels of well-being. Similarly, the negative coefficients on this variable obtained for the ill-being equation implies that more social activities leads to lower levels of ill-being.

5.2 Initial Conditions

Based on using summary scores for extroversion and emotional stability from the Big Five personality test as the exclusion restrictions, the results of estimation of the initial condition equations for well-being and ill-being are given in Table 4. Although we do not find that extroversion is statistically significant in the initial conditions equations, our other exclusion restriction – the measure of emotional stability – is highly significant and is signed in the correct direction. Individuals who are genetically predisposed to be more emotionally stable are likely to have higher initial levels of well-being and lower initial levels of ill-being.

In addition, it is also found that marriage and social activities are associated with higher levels of initial well-being and lower initial levels of ill-being, while having any disabilities or being in unemployment (for males) are associated with lower levels of initial well-being and higher initial levels of ill-being.

Table 4: Dynamic Bivariate Model, Initial Conditions

	Well-Being				**Ill-Being**			
	Men		**Women**		**Men**		**Women**	
Parameters	*Estimate*	*S.E.*	*Estimate*	*S.E.*	*Estimate*	*S.E..*	*Estimate*	*S.E..*
Constant	-1.122**	0.43	-0.412	0.34	0.434	0.48	0.234	0.37
Age	-0.345*	0.16	-0.220	0.17	0.344	0.18	-0.010	0.18
Age squared	0.143*	0.05	0.074	0.06	-0.112*	0.05	0.011	0.06
Non-English speaking background	-0.382**	0.13	-0.058	0.13	0.269	0.15	0.110	0.13
Aboriginal/Torres Strait Islander	0.403	0.51	0.107	0.37	0.317	0.49	0.314	0.35
City	0.002	0.09	-0.138	0.08	0.030	0.10	-0.024	0.08
Married	0.818**	0.10	0.788**	0.09	-0.555**	0.11	-0.506**	0.10
Bachelor plus	-0.154	0.10	-0.079	0.09	0.011	0.11	0.095	0.10
Disability	-0.289**	0.10	-0.367**	0.11	1.069**	0.12	0.968**	0.11
Employed	0.129	0.17	-0.239	0.10	-0.316	0.19	-0.274*	0.11
Unemployed	0.111	0.22	-0.56*	0.23	-0.819**	0.24	0.109	0.22
Income	1.063	0.68	-0.273	0.57	-0.687	0.78	0.285	0.62
Welfare receipt	-0.233	0.15	-0.116	0.11	0.421**	0.15	0.226*	0.11
Social	0.248**	0.09	0.410**	0.09	-0.302**	0.10	-0.328**	0.10
Extroverted	0.017	0.04	0.049	0.03	-0.012	0.05	-0.025	0.04
Emotional stability	0.078	0.04	0.105**	0.04	-0.198**	0.04	-0.153**	0.04

Note: * and ** indicate significance at 5% and 1%. Reported standard errors in the table have been rounded to two decimal places.

5.3 Unobserved Heterogeneity

Estimates of parameters for unobserved heterogeneity are given in Table 5. The results suggest that unobserved permanent characteristics play a crucial role in well-being and ill-being. For men, 52 percent of unobserved stochastic variation in well-being can be attributable to these unobserved individual characteristics.[12] Unobserved permanent characteristics of women are responsible for 48 percent of the unsystematic variation in well-being. For ill-being, random effects are also significant but slightly lower in magnitude. 47 percent of unexplained variation in men's ill-being can be

[12] This follows from the standard normality assumption of α_{it} and ν_{it}. For example, for the well-being equation in (1), the ratio of the variation due to random effects to the total stochastic variation is calculated as: $\hat{\sigma}_\alpha / \left(1+\hat{\sigma}_\alpha\right)$.

attributed to time invariant unobserved characteristics. For women, 43 percent of unsystematic variation in ill-being can be explained by random effects. These results suggest that the effect of unobserved permanent characteristics and stochastic life events (losing a job, death or illness of a loved one etc.) are approximately equally responsible for the majority of unobserved variation in well-being and ill-being.

The correlation of the random effects in the two equations is significant and negative (-0.499 for men and -0.392 for women). This implies that the cross lagged effects in the dynamic equations are endogenous and that omission of this correlation (i.e., by estimating two separate equations) would lead to inconsistent and biased estimates. For example, due to the negative correlation, the effect of lagged ill-being on well-being would be under-estimated in a single equation model. The sizeable correlation suggests that the unobserved characteristics that make an individual more likely to be happy and depressed overlap. However, the negative correlation suggests that the unobserved characteristics affect the two outcomes in opposite directions, which echoes the findings for many of the observed characteristics discussed in section 5.1.

Table 5: Dynamic Bivariate Model, Unobserved Heterogeneity

	Men		**Women**	
Parameters	*Estimates*	*S.E.*	*Estimates*	*S.E.*
σ_α	1.064**	0.05	0.907**	0.05
σ_η	0.884**	0.07	0.762***	0.05
ρ	-0.499**	0.05	-0.392**	0.05
τ	-0.27⁶**	0.04	-0.373**	0.03
τ_1	-0.431**	0.07	-0.437**	0.06
θ_1	0.997**	0.07	0.903**	0.07
θ_2	-0.035	0.07	-0.138*	0.06
θ_3	-0.349**	0.07	-0.307**	0.06
θ_4	0.724**	0.09	0.739**	0.08

Note: * and ** indicate significance at 5% and 1%. Reported standard errors in the table have been rounded to two decimal places.

Estimates of τ and τ_1 show that the random shocks that derive an individual's tendency to be very happy or depressed are rather highly correlated. The significance of the θ parameters suggest that the initial levels of well-being and ill-being are not exogenous. Put another way, their significance highlights the fact that an initial conditions problem exist. This reinforces the importance of using an estimation strategy that can account for such a problem.

5.4 Linear Probability Model

As a check for the sensitivity of the findings based on the random effects assumptions, we estimate a linear dynamic panel model with fixed effects. Fixed effects models allow one to be agnostic about the distributional properties of the unobserved heterogeneity.

We estimate models (1) and (2) separately by the one-step system GMM approach (Blundell and Bond 1998).[13] The same regressors that are used in the random effects model are included in the linear probability model. In the system GMM approach, the dynamic panel data model is estimated along its first differenced version in a system. The equations in levels are based on following moment conditions:

Well-being equation:

$$E\left[\Delta W_{it-1}, \varepsilon_{it}\right] = 0 \qquad \text{for t = 3, … , T} \qquad (6)$$

$$E\left[\Delta X_{it}, \varepsilon_{it}\right] = 0 \qquad \text{for t = 2, … , T} \qquad (7)$$

Ill-being equation:

$$E\left[\Delta I_{it-1}, v_{it}\right] = 0 \qquad \text{for t = 3, … , T} \qquad (8)$$

$$E\left[\Delta X_{it}, v_{it}\right] = 0 \qquad \text{for t = 2, … , T} \qquad (9)$$

where Δ is the first difference operator. The equations in first differences, on the other hand utilize the following moment conditions:

Well-being equation:

$$E\left[W_{it-s}, \Delta\varepsilon_{it}\right] = 0 \qquad \text{for t = 3, … , T and s≥2} \qquad (10)$$

$$E\left[X_{it-s}, \Delta\varepsilon_{it}\right] = 0 \qquad \text{for t = 2, … , T and s≥1} \qquad (11)$$

Ill-being equation:

$$E\left[I_{it-s}, \Delta v_{it}\right] = 0 \qquad \text{for t = 3, … , T and s≥2} \qquad (12)$$

$$E\left[X_{it-s}, \Delta v_{it}\right] = 0 \qquad \text{for t = 2, … , T and s≥1} \qquad (13)$$

The results reported in Table 6 reveal that the findings are very similar to the ones previously obtained from the random effects model. In particular, it is found that

[13] The linear probably models are estimated using xtabond2 command in Stata version 9.

the effect of lagged ill-being on current ill-being is larger than the effect of lagged well-being on current well-being. In addition, marriage again appears to be an important factor for both well-being and ill-being while receipt of income support has little effects. The main difference in the results of the linear probability model and the bivariate probit model is the magnitude of the cross effects. Whereas lagged ill-being has a significant effect on current well-being in the bivariate probit model, in the linear probability model this relationship is found to be insignificant.

Table 6: Linear Probability Model with Fixed Effects

	Well-Being				Ill-Being			
	Men		Women		Men		Women	
Parameters	*Estimate*	*S.E.*	*Estimate*	*S.E..*	*Estimate*	*S.E*	*Estimate*	*S.E..*
Constant	0.365**	0.12	0.4134**	0.11	0.234*	0.09	0.438**	0.09
Well-Being$_{t-1}$	0.056*	0.02	0.0728**	0.02	0.002	0.02	-0.006	0.02
Ill-Being $_{t-1}$	-0.054	0.03	-0.0466	0.02	0.110**	0.02	0.100**	0.02
Age	0.015	0.09	-0.0382	0.09	0.083	0.07	0.004	0.07
Age squared	0.005	0.02	0.0148	0.02	-0.021	0.02	-0.004	0.02
City	-0.115	0.06	-0.0450	0.06	0.004	0.05	-0.066	0.05
Married	0.211**	0.05	0.2409**	0.04	-0.107**	0.04	-0.120**	0.04
Bachelor plus	-0.066	0.11	0.0337	0.11	0.151	0.09	0.029	0.09
Disability	-0.06*	0.02	-0.0256	0.02	0.085**	0.02	0.104**	0.02
Employed	0.105*	0.04	0.0437	0.03	-0.102	0.03	-0.103**	0.02
Unemployed	-0.032	0.06	0.0115	0.05	-0.081	0.05	-0.055	0.04
Income	-0.007	0.07	0.0285	0.06	-0.012	0.05	-0.052	0.05
Welfare receipt	0.031	0.04	-0.0529	0.03	0.062	0.03	0.048	0.03
Social	0.060**	0.02	0.0192	0.02	-0.037	0.02*	-0.036*	0.02
Sargan Test p-value	0.553		0.188		0.135		0.281	
AR(2) Test p-value	0.117		0.263		0.593		0.400	

Note: * and ** indicate significance at 5% and 1%. Models include time dummies. The instruments are selected according to Sargan's test of over identifying restrictions and test of no second order serial correlation.

6. Conclusion

This paper examined the dynamics of well-being and ill-being without making the assumption that the two constructs lie on opposite ends of the same spectrum. The idea that well-being and ill-being should be regarded as distinct dimensions has found increasing support in the recent psychology literature.

Based on the HILDA data, descriptive analyses were suggestive of a complex inter-relationship between past and current levels of well-being and ill-being. We therefore chose to specify a dynamic bivariate panel data model which allowed for own lagged and cross lagged effects, and unobserved heterogeneity. It was found that both lagged well-being and lagged ill-being were statistically significant in predicting their own respective current levels. The finding that the effect of lagged ill-being on current ill-being is larger than the effect of lagged well-being on current well-being is supported by findings in the psychological literature. Whereas chronic happiness is not a common phenomenon, chronic depression is a well-known medical condition that has been subject to much research. The cross effects of lagged well-being on current ill-being and lagged ill-being on current well-being were also noteworthy. The results from the bivariate random effect model suggest that while past ill-being has a significant effect on current well-being, there was no support for a reverse relationship (i.e. lagged effect of well-being on current ill-being). The asymmetric cross lag effects reinforce the notion that depression is a more chronic state than happiness, with changes to levels of well-being more easily influenced by past levels of ill-being. The unobserved factors that drive well-being and ill-being were also found to be highly influential. The significant correlation between random effects in the well-being and ill-being equations suggest that even if well-being and ill-being are treated as separate constructs, estimating well-being and ill-being in separate equations (as opposed to estimating them jointly) may lead to biased results.

Much of the current work in subjective well-being in economics begins with the implicit assumption that well-being is a unitary construct, with depression being the polar opposite of happiness. The implication of the findings in this paper for the happiness literature is that for future empirical work, such an implicit assumption should be revisited. The results in this paper suggest that many happiness equations in the literature are potentially misspecified because of a failure to model the dynamic relationship between well-being and ill-being. The findings in this paper suggest that it would perhaps more prudent to begin with the notion that well-being and ill-being are distinct dimensions, that the unobservables that affect well-being and ill-being are correlated, and to specify econometric models that allow for these concepts to be reflected.

References

Alessie, R., S. Hochguertel and A. van Soest. (2004). "Ownership of Stocks and Mutual Funds: A Panel Data Analysis." *Review of Economics and Statistics*, 86, pp. 783-796.

Blundell, R. and S. Bond. (1998). "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87, pp.115-143.

Boes, S. and R. Winkelmann. (2006). "The Effect of Income on Positive and Negative Subjective Well-Being." Socioeconomic Institute Working Paper No. 0605, University of Zurich.

Bradburn, N. (1969). *The Structure of Psychological Well-Being*. Chicago: Aldine.

Bradburn, N. and D. Caplovitz. (1965). *Reports on Happiness: A Pilot Study*. Chicago: Aldine.

Costa, P. and R. McCrae. (1980). "Influence of Extraversion and Neuroticism on Subjective Well-Being: Happy and Unhappy People," *Journal of Personality and Social Psychology*, 38, pp. 668-678.

Diener, E. (1984). "Subjective Well-Being," *Psychological Bulletin*, 95, pp. 542-575.

Diener, E. and R. Emmons. (1984). "The Independence of Positive and Negative Affect," *Journal of Personality and Social Psychology*, 47, pp. 1105-1117.

Diener, E., H. Smith and F. Fujita. (1995). "The Personality Structure of Affect," *Journal of Personality and Social Psychology*, 69, pp. 130-141.

Diener, E., E. Suh, R. Lucas and H. Smith. (1999). "Subjective Well-Being: Three Decades of Progress," *Psychological Bulletin*, 125, pp. 276-302.

Eysenck, H. (1991). "Dimensions of Personality: 16, 5, or 3? Criteria for a Taxonomic Paradigm," *Personality and Individual Differences*, 12, pp. 773-790.

Headey, B. and A. Wearing. (1992). *Understanding Happiness: A Theory of Subjective Well-Being*. Melbourne, Australia: Longman Cheshire.

Headey, B., J. Kelley and A. Wearing. (1993). "Dimensions of Mental Health: Life Satisfaction, Positive Affect, Anxiety and Depression," *Social Indicators Research*, 29, pp. 63-82.

Headey, B. and M. Wooden. (2004). "The Effects of Wealth and Income on Subjective Well-Being and Ill-Being," *Economic Record*, 80, pp. S24-S33.

Heckman, J. (1981). "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process" in C.F. Manski and D.L. McFadden (eds.), *Structural Analysis of Discreet Data with Econometric Applications*, London: MIT Press.

Huppert, F. and J. Whittington. (2003). “Evidence for the Independence of Positive and Negative Well-Being: Implications for Quality of Life Assessment,” *British Journal of Health Psychology*, 8, pp. 107-122.

Kahneman, D. and A. Krueger. (2006). “Developments in the Measurement of Subjective Wellbeing,” *Journal of Economic Perspectives*, 22, pp. 3-24.

Keller, M., P. Lavori, T. Mueller, J. Endicott, W. Coryell, R. Hirschfeld and T. Shea. (1992). “Time to Recovery, Chronicity, and Levels of Psychopathology in Major Depression. A 5-year Prospective Follow-up of 431 Subjects,” *Archives of General Psychiatry*, 49, pp. 809-816.

Kimm, J. (2004). *A Fatal Conjunction: Two Laws, Two Cultures*. Sydney: Federation Press.

Kocsis, J. and D. Klein. (1995). Eds. *Diagnosis and Treatment of Chronic Depression*. New York: The Guilford Press.

Lee, W. and U. Oguzoglu. (2007). “Income Support and Stigma Effects for Young Australians,” *Australian Economic Review*, forthcoming.

Lucas, R. and F. Fujita. (2000). “Factors Influencing the Relation between Extraversion and Pleasant Affect,” *Journal of Personality and Social Psychology*, 79, pp. 1039–1056.

Myers, D. and E. Diener. (1995). “Who is Happy?” *Psychological Science*, 6, pp. 10-19.

Spijker, J., R. De Graaf, R. Bijl, A. Beekman, J. Ormel and W. Nolen. (2002) “Duration of Major Depressive Episodes in the General Population: Results from the Netherlands Mental Health Survey and Incidence Study,” *British Journal of Psychiatry*, 181, pp. 208-213.

Tellegen, A. (1985). “Structures of Mood and Personality and their Relevance to Assessing Anxiety, with an Emphasis on Self-Report,” in *Anxiety and the Anxiety Disorders*, eds. A. Tuma, J. Maser, pp. 681-706. Hillsdale, NJ: Erlbaum.

Train, K. (2003). *Discrete Choice Methods with Simulation*. Cambridge University Press.

Ware, J. (2004). SF-36 Health Survey Update. The SF Community Website – www.sf-36.org.

Ware, J., M. Kosinski and S. Keller. (1994). *SF-36 Physical and Mental Health Summary Scales: A User’s Manual*. Boston, MA: The Health Institute.

Watson, D. and L. Clark. (1992). “On Traits and Temperament: General and Specific Factors of Emotional Experience and their Relation to the Five Factor Model,” *Journal of Personality*, 60, pp. 441-476.

Watson, N. and M. Wooden. (2004). “The HILDA Survey Four Years On,” *Australian Economic Review*, 37, pp. 343-349.

Winkelmann, R. (2005). “Subjective Well-being and the Family: Results from an Ordered Probit Model with Multiple Random Effects,” *Empirical Economics*, 30, pp. 749-761.