Living in the Shadow of the Past: Financial Profiles, Health and Well-Being

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Living in the Shadow of the Past: Financial Profiles, Health and Well-Being*

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Abstract. We consider the link between individual financial profiles over time and well-being, as measured by life satisfaction. We in particular look at annual self-reported financial worsening and improvement information for over 24,000 individuals in Australian panel data from 2002 to 2016. We first find that satisfaction falls (rises) with a contemporaneous major financial worsening (improvement), with worsening having the larger effect. Second, the experience of these financial events in the past continues to scar current well-being. Last, only the order of financial improvement spells matters for well-being: a given number of past years where finances deteriorated has the same effect on current well-being whether the deterioration occurred in one continuous spell or was interrupted. We also find that these effects are heterogeneous over the distribution of well-being and that they affect individual smoking, drinking, exercise and sleep quality.

JEL Classification Codes: I31, I32, D60.

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1 Introduction

The last few decades have witnessed a fast-growing economic research literature on the causes and consequences of various measures of subjective well-being (Di Tella and MacCulloch, 2006; Dolan et al., 2008; Lane, 2017; Clark et al., 2018). Particular attention has been focussed on the role of individual income, both within and across countries and in cross-section and time-series data (Easterlin, 1995; Clark and Oswald, 1996; Blanchflower and Oswald, 2004; Ferrer-i Carbonell, 2005; Luttmer, 2005; Clark et al., 2008, 2009). This well-established literature has produced three main conclusions (Clark et al., 2016): (i) within each country at a given point in time, richer people are more satisfied; (ii) on average, individuals living in richer countries are more satisfied with their lives than are their counterparts in poorer countries; and (iii) rising average income within country over time is generally not associated with higher life satisfaction.[1]

As acknowledged in Brown and Gray (2016), however, only a limited number of contributions have looked at the effect of monetary factors beyond income on individual well-being. Headey and Wooden (2004) have shown that life satisfaction is positively related to household net wealth. Regarding debt, Keese and Schmitz (2014) find that this is negatively related to mental well-being, and Brown et al. (2005) emphasise the role of unsecured, as opposed to secured, debt in this respect. Bridges and Disney (2010) explore the link between self-reported depression and both objective and subjective debt measures, concluding that it is the latter rather than the former that is most associated with depression. Brown and Gray (2016) also show that subjective well-being is positively associated with net wealth and assets, but negatively correlated with both total and unsecured debt. They further find evidence of comparisons, with the financial situation of households in a reference group also being correlated with individual life satisfaction and financial well-being.

This extant research on financial situation and subjective well-being is however resolutely atemporal, with contemporaneous financial measures being correlated with current well-being. We here instead focus on the time profiles of both major financial improvements (e.g., having won a lottery or having received an inheritance) and major financial worsening (e.g., having gone

[1] See, for example, Figure 2.3 in Clark et al. (2018).

bankrupt) in determining life satisfaction, using longitudinal data from the Household Income and Labour Dynamics in Australia (HILDA) Survey. In contrast to existing research on contemporaneous correlations with financial variables, our analysis is intertemporal. Although where individuals are now (financially) is important, how they got there is also key in understanding their current well-being. Conditional on the present, the past matters here for at least two reasons. The first is the scarring effect of past negative events, which can continue to affect current well-being even conditional on the current situation: this has been demonstrated for both past poverty (Clark et al., 2015) and past unemployment (Clark et al., 2001; Clark and Lepinteur, 2018). An analogous 'anti-scarring' effect may well be at play for past positive effects. Second, the sum of previous financial events may provide us with some measure of wealth. The order of financial events may also matter, with the experience of an additional consecutive event being lived differently by the individual, in a sense that we will clarify below.

We thus relate well-being at time t to both individual variables at the same point in time (t) and their past values up to time t–1. For the latter we use two intertemporal measures from the recent literature on economic inequality: (i) the *chronicity* index of Foster (2009) (which measures the frequency of financial shocks) and (ii) the *persistence* index in Bossert et al. (2012) (which considers the continuity of financial-shock spells). Showing how well-being is related to the *chronicity* and *persistence* of financial profiles is our first contribution.

Our second contribution is to look at the effect of financial profiles over the entire distribution of subjective well-being. Existing work on the role of income and other financial variables has almost exclusively dealt with average effects by focussing on the mean of the distribution of subjective well-being. However, these average effects likely conceal considerable heterogeneity. From the policy perspective, the distributional analysis of subjective well-being can also help policy-makers to develop policies that target specific groups rather than the entire population, which is arguably a more efficient use of resources. In this context the distribution of well-being may well itself be a policy goal.[2] We here employ the panel data quantile regression model with fixed effects developed by Canay (2011). This allows us to provide a complete picture of the relationship between financial profiles and the

[2] Clark et al. (2016) underline that growing GDP per capita over time has not changed the average level of satisfaction, but has led to a fall in its variance.

entire distribution of well-being, controlling for individual fixed effects.

Finally, we contribute to the literature on the impact of financial situation on health-related life styles. Among the existing work, Kim and Ruhm (2012) find that large inheritances, which are an exogenous variation in wealth, increase alcohol consumption, but do not affect smoking or exercising. van Kippersluis and Galama (2014) find evidence that the wealth shocks from inheritances or lottery wins increase the prevalence of drinking alcohol, but not the number of drinks or the incidence of heavy drinking; they also find that greater wealth increases the likelihood of smoking in the US, but not in the UK. In addition, Apouey and Clark (2015) show that lottery winnings are associated with greater smoking and social drinking in UK panel data. This work has focussed on the relationship between current wealth and current health behaviours. We do so also here, but in addition add the intertemporal influence of the *chronicity* and *persistence* of past financial profiles on current health behaviours.

The remainder of the paper is organised as follows. Section 2 describes the HILDA data and variables. Section 3 introduces our empirical analytical approach, and the results appear in Section 4. Last, Section 5 concludes.

2 Data and descriptive statistics

We use panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Beginning in 2001, HILDA is a nationally-representative household panel survey in Australia that collects annual information on economic well-being, income, life events and labour-market dynamics. As the first wave (2001) does not include information on financial improvement or worsening over the past year, we concentrate on the remaining 15 HILDA waves (2002–2016). Following Clark et al. (2016), we focus on individuals who are aged over 16. We also impose an upper age bound of 65, which is the current qualifying age for the Australian Age Pension. After dropping observations with missing information on the core variables our final sample comprises 159,926 observations on 24,436 Australians. The descriptive statistics of our main variables for this sample are summarised in Appendix Table A1.

We use life satisfaction as the main measure of subjective well-being (Di Tella and MacCulloch, 2006; Clark et al., 2008). In each wave, HILDA respondents are asked the following question: "*All things considered, how satisfied are you with your life?*". Subjects answer on a scale of 0 to 10, where 0 refers to Not Satisfied at All and 10 to Completely Satisfied.

Starting in 2002, HILDA respondents are asked at each wave which major life events from a list of 21 have occurred to them over the past 12 months. Two of these 21 refer to financial events: (i) "*a major improvement in the financial situation, including having won a lottery or having received an inheritance*" (which we will denote by MIF_{it}); and (ii) "*a major worsening in the financial situation, including having gone bankrupt*" (denoted by MWF_{it}). The two key financial variables in our analysis MIF_{it} and MWF_{it} are thus dummies generated based on self-reported events. Ideally, we would want to construct these measures based also on actual financial information. However, the HILDA wealth module only appears in waves 2002, 2006, 2010 and 2014. It is moreover widely recognised that wealth is difficult to measure in surveys and exhibits considerable item-nonresponse and under-reporting. For example, Headey and Wooden (2004) can only calculate net household wealth for 61 percent of the households that responded in the 2002 wave of HILDA. Juster et al. (1999) find that wealth reported in surveys is underestimated by about 25 percent when the National Accounts are taken as the benchmark. In addition, what constitutes a major improvement or worsening of the financial situation can well also be unrelated to wealth: an individual may consider a job change to a more secure position as a major financial improvement; equally, illness or a change in the number of household members might be felt as a major financial worsening. For these reasons, self-reported measures of major financial shocks may arguably be more reliable than the seemingly desirable objective measures based on incomplete and underreported wealth levels in HILDA. The use of such subjective financial measures is supported by the recent literature. As noted above, Bridges and Disney (2010) find that subjective (rather than objective) debt measures have the greatest effect on individual depression.

Both MIF_{it} and MWF_{it} are contemporaneous, in that they take place in the same year as the individual reports their subjective well-being. In addition to the current financial situation, financial profiles over time (i.e. including past values of MIF_{it} and MWF_{it}) may also affect individual well-being conditional on their current values. We explicitly include time in a number of different ways when considering financial profiles. We first calculate two dummy variables for ever having had a major financial improvement or major financial worsening in the $past$ observational period (up to time t–1) covered by the HILDA data (denoted by $Past_{it-1}^{MIF}$ and $Past_{it-1}^{MWF}$).

We also distinguish *chronic* financial improvement (or worsening) from what we think of as being in a state of *persistent* financial improvement (or worsening). In the recent literature on economic inequality (Bossert et al., 2012; Clark et al., 2015) the former refers to the frequency of occurrence, while in the latter the financial events occur in periods that are more linked together, conditional on their frequency. Using financial improvement as an example, *chronicity* applies to a situation in which an individual experiences financial improvement for a certain proportion of the time periods under consideration, without paying any attention to the durations of *unbroken* financial-improvement spells. On the contrary, *persistence* explicitly takes the continuity of financial-improvement spells into account. We use a simple example to illustrate the importance of accounting for persistence. Assume that two individuals experience a major financial improvement this year, but the first also experienced this last year (but not the year before), while the second did not last year but rather in the year before that. It is clear that the intertemporal financial improvements are not the same for the two individuals. Both individuals experienced financial improvement twice, but the first in two consecutive periods while the second did not. The *chronicity* and *persistence* indices for financial improvement and worsening allow us to uncover the impact of financial profiles on well-being in an intertemporal context, which is largely absent in previous literature.

Our empirical analysis will first consider the *chronicity* measure of Foster (2009), which is simply the average financial improvement (or worsening) that an individual has experienced over time. That is:

$$Foster_{it}^{MIF} = \frac{1}{t}\sum_{\tau=1}^{t} MIF_{i\tau} \tag{1}$$

where $Foster_{it}^{MIF}$ is the chronicity measure of major financial improvement up to date t, with $MIF_{i\tau}$ being the dummy for a major financial improvement for individual i in period τ. The chronicity index of major financial worsening, $Foster_{it}^{MWF}$, is defined analogously.

We measure *persistence* in major financial improvements using the index proposed by Bossert et al. (2012), which weighs each spell by its length (denoted by l_τ). The BCD_{it}^{MIF} index is the weighted average of major financial improvements up to date t, with the weight being given by the length of the spell to which the period belongs:

$$BCD_{it}^{MIF} = \frac{1}{t}\sum_{\tau=1}^{t} l_\tau MIF_{i\tau}. \tag{2}$$

The persistence index for major worsening in finances, BCD_{it}^{MWF} is constructed analogously.

We here provide a simple example to illustrate how these two indices are calculated. Take $MIF_{i\tau}$, the dummy for a major financial improvement for individual i in period τ. Then the contiguous sequence (1, 1, 0, 1, 1) indicates that this person experienced a major financial improvement in periods 1, 2, 4 and 5, but not in period 3. The *chronicity* index is $Foster^{MIF}$=$\frac{1}{5}$(1+1+0+1+1)=$\frac{4}{5}$=0.8, so that 80 percent of the five consecutive years in which individual i was surveyed were characterised by financial improvement. The *persistence* index BCD^{MIF}=$\frac{1}{5}$[2(1+1)+1(0)+2(1+1)]=$\frac{8}{5}$=1.6. The BCD^{MIF} value here is larger than $Foster^{MIF}$, as the MIF_{it} value in each period is now weighted by the length of the continuous spell in which person reports the same value of the financial variable. On the contrary, the values of $Foster^{MIF}$ and BCD^{MIF} for someone with the contiguous sequence (1, 0, 0, 1, 0) are the same, as no improvement spell is of length greater than one.

In the empirical analysis we will always use lagged values of $Foster$ and BCD, so that these do not include contemporaneous (i.e. period-t) values of MWF or MIF: this will help identify the causal impact of these variables in fixed-effect analyses. Note also that $Foster$ and BCD are not necessarily automatically correlated. The addition of a singleton "one" value to a spell will always weakly increase the $Foster$ score, but can easily reduce that of BCD.[3]

The descriptive statistics of our main sample appear in Appendix Table A1. Our 159,926 observations correspond to 24,436 individuals, who are thus observed on average for between six and seven years each. Table A1 shows that, on average, in each year about three percent of individuals reported a major improvement in finances, with the same percentage experiencing a

[3]Calculating the lagged values, this occurs at observation five of the first example we gave in the text.

major worsening in finances. Moreover, around 14 percent of Australians reported at least one major financial improvement over the 2002–2016 period, with 12 percent reporting a major financial deterioration over the same period. Last, the *chronicity* index of Foster (2009) and the *persistence* index of Bossert et al. (2012) are also calculated to have similar values for financial improvements and financial worsening. The *chronicity* index turns out to be similar to the *persistence* index for both major improvements and worsening in finances. As expected, the pairwise correlation coefficients between the two indexes are very high (over 0.95 for both financial improvements and financial worsening): Table A1 indicates that both types of financial events are rare (just above three percent per year). While there are not that many cases where the *persistence* index is different from the *chronicity* index, our empirical results in Section 4 suggest that we do have sufficient cases to separately identify the well-being effects of the *chronicity* and *persistence* of financial profiles, with a reasonable level of precision.

With respect to subjective well-being, the average value of life satisfaction in Appendix Table A1 is close to eight on the zero to ten scale, corresponding to the very typical left-skew found in many well-being measures. About 47 percent of observations come from men and 53 percent from women, and average years of education is 12. Most observations come from the married (65 percent) or never married (25 percent). Around 75 percent of observations come from the employed, 4 percent from the unemployed and 21 percent from those not in the labour force. The individual income measure we use for most of our analyses is real annual equivalent household income, which controls for differences in household size and therefore economies of scale. The equivalence scale used here has an elasticity of 0.5, given by the square root of household size. Average annual household disposable regular income in 2016 Australian dollars is just below A$98,000, with the equivalent figure for annual equivalent household disposable regular income (the ratio of annual household disposable regular income to the square root of household size) being A$57,483. Last, around 63 percent of observations come from individuals who live in a major Australian city.

Table 1 describes the frequencies of major financial shocks. About 85 percent of Australians experienced no major financial improvement over the 2002–2016 period, with a similar figure for major financial worsening. One major financial improvement was experienced by 11.5 percent of

Table 1: The frequency of major financial shocks

	Major financial improvement		Major financial worsening	
	Individuals	%	Individuals	%
Did not happen	20,704	84.7	21,041	86.1
Once	2,802	11.4	2,374	9.72
Twice	665	2.72	577	2.36
Three times	182	0.74	234	0.96
Four times	55	0.23	107	0.44
Five times or more	28	0.11	103	0.42
Total	24,436	100.00	24,436	100.00

Note: Data from HILDA 2002–2016.

respondents and one major financial worsening by 9.7 percent of respondents over the same period. The analogous figures for two financial shocks are 2.7 percent and 2.4 percent respectively, and for three or more shocks 1.1 percent and 1.8 percent.

3 Empirical methodology

3.1 Econometric approach

We assume that subjective well-being can be described by the following equation

$$WB_{it} = FP_{it}'\beta + X_{it}'\gamma + \mu_i + \epsilon_{it} \tag{3}$$

where WB_{it} is a well-being measure for individual i in period t, FP_{it} is a vector of individual-level financial-profile variables, X_{it} a vector of time-varying explanatory variables, including age (five age groups: 16–25, 26–35, 36–45, 46–55 and 56–65), years of education, marital status (married, single, divorced, widowed and separated), employment status (employed, unemployed and not in the labour force), number of children in the household, the log of annual equivalent household regular disposable income, a dummy for living in a major city, and State and wave dummies. The μ_i term here is the individual fixed effect, which picks up any time-invariant unobserved heterogeneity. Last, ϵ_{it} is the idiosyncratic error term.

The presence of μ_i in equation (3) indicates that we will use fixed effects (FE) panel estimation, which is preferred over OLS due to its ability to deal with any bias from unobserved individual heterogeneity.[4] The FE estimates are identified from within-subject changes in the variables of interest over time. β, the coefficient vector on FP_{it}, is thus identified from the different subjective well-being scores for the same individual over time as their financial-profile variables change: no comparisons between individuals are used to identify the coefficients.

We first establish the relationship between contemporaneous financial events and well-being; we then explicitly introduce time, and ask whether past financial events continue to affect current well-being. Last, we consider the role of persistence, whereby the order of spells matters: For a given number of years of financial improvement (worsening), is well-being higher (lower) when these years are joined together?

We thus introduce three different sets of financial-profile variables in our investigation: (i) contemporaneous financial improvement and worsening (MIF_{it}, MWF_{it}); (ii) contemporaneous (MIF_{it}, MWF_{it}) and past financial shocks up (to time t–1) ($Past^{MIF}_{it-1}$, $Past^{MWF}_{it-1}$); and (iii) current financial shocks (MIF_{it}, MWF_{it}), the lags of the Foster (2009) indices ($Foster^{MIF}_{it-1}$, $Foster^{MWF}_{it-1}$) and the lagged differences between the Bossert et al. (2012) and Foster (2009) indices (BCD^{MIF}_{it-1}–$Foster^{MIF}_{it-1}$, BCD^{MWF}_{it-1}–$Foster^{MWF}_{it-1}$).

3.2 Causality concerns

As is often the case in statistical analysis, we are careful about the causal interpretation of the coefficients on the subjective financial-position variables FP_{it} in equation (3) above.

The first point is that we control for individual fixed effects in the estimation, which picks up any individual-specific response style in the reporting of financial position or well-being. There is no interpersonal comparison here: the estimated coefficients are identified from the comparison of the financial position of an individual at time t, say, (FP_{it}) to the same individual at a different point in

[4]The use of a linear specification in equation (3) assumes the cardinality of life satisfaction answers. Ferrer-i Carbonell and Frijters (2004) show that estimation via ordinal and cardinal techniques generally leads to similar conclusions. Kristoffersen (2017) presents evidence in favour of treating the eleven-point life satisfaction scale in HILDA as being cardinally comparable across both time and individuals.

time ($FP_{it+\tau}$). It is this difference that is being correlated with the difference in the individual's health and well-being outcomes.

This approach takes care of individual-level fixed heterogeneity. There then remains individual-level time-varying heterogeneity. Here we do control for a number of time-varying variables via the vector X_{it} (including labour-market and marital status, and current income). Our remaining endogeneity bias comes from any time-varying unobservables that are independent of X_{it} but are correlated with both FP_{it} and the dependent variable. In the context of subjective variables, these are sometimes thought of as reflecting current mood, which will affect subjective responses. We should note in this respect that not all of our dependent variables are strongly subjective, and in particular those regarding smoking, drinking and physical exercise.

The time dimensions of our financial variables helps to reassure us as to the causality of the relationships we estimate in equation (3). Respondents report their *current* level of health or well-being at the time of survey, but whether a positive or negative financial event occurred *over the past 12 months*. The financial shocks may then be considered to largely pre-date the measure of the dependent variable.

Another important point regarding causality is that the main focus of our work here is on the impact of *past* financial profiles (*chronicity* and *persistence*, measured up to time t–1) on *current* subjective well-being (measured at time t). After accounting for individual fixed effects, it seems unlikely that the estimated coefficients here will be strongly affected by confounding time-varying unobserved individual heterogeneity.[5]

4 Results

4.1 The contemporaneous and the past effects of financial shocks on well-being

We start with the contemporaneous effects of major financial improvement and worsening on well-being. Satisfaction with life is the dependent variable, and robust standard errors clustered at the

[5]This would need to be correlated with well-being at time t, independent of X_{it}, and correlated with the lagged values of financial worsening or improvement but not with their current values (as these are controlled for in the regression).

individual level appear in parentheses. Table 2 reports the estimation results, controlling for individual fixed effects (FE).

Table 2: The effects of financial profiles on well-being (FE estimates)

	Life satisfaction			
	(i)	(ii)	(iii)	(iv)
MIF_{it}	0.129***	0.170***	0.149***	0.150***
	(0.016)	(0.018)	(0.017)	(0.017)
MWF_{it}	–0.567***	–0.596***	–0.591***	–0.591***
	(0.025)	(0.029)	(0.028)	(0.028)
$Past_{it-1}^{MIF}$		0.117***		
		(0.020)		
$Past_{it-1}^{MWF}$		–0.130***		
		(0.027)		
$Foster_{it-1}^{MIF}$			0.167***	0.156***
			(0.052)	(0.052)
$Foster_{it-1}^{MWF}$			–0.368***	–0.361***
			(0.071)	(0.071)
BCD_{it-1}^{MIF}–$Foster_{it-1}^{MIF}$				0.769**
				(0.301)
BCD_{it-1}^{MWF}–$Foster_{it-1}^{MWF}$				–0.157
				(0.163)
Observations	159,926	135,716	135,716	135,716
Individuals	24,436	20,019	20,019	20,019
Overall R-Squared	0.048	0.065	0.066	0.066

Notes: *** p<0.01; ** p<0.05; * p<0.10. Robust standard errors clustered at the individual level are reported in parentheses. The full set of estimated coefficients appears in Appendix Table A2.

The FE estimates in Column (i) of Table 2 show that contemporaneous major financial improvements (MIF_{it}) are associated with higher life satisfaction of 0.129 points, which represents 0.09 of a standard deviation (0.129/1.435) of the latter. Consistent with our expectations, a major financial worsening (MWF_{it}) reduces life satisfaction by much more, accounting for 0.40 of a standard deviation (0.567/1.435). It is worth noting that all of these correlations are estimated holding the current level of household disposable regular income constant, so that we are not just picking up here the simple income consequence of financial shocks.

The control variables in the regressions attract the expected estimated coefficients and the full table of results is relegated to Appendix Table A2. Controlling for income, education is negatively correlated with life satisfaction.[6] Those who marry are more satisfied, while widowhood and separation are associated with lower well-being, as compared to the same individual when they were married or never married. In addition, compared to being employed, unemployment is associated with lower levels of life satisfaction but not being in the labour force is not.

We then introduce time, and ask whether past financial events continue to affect current well-being. We do so by first including two additional dummies into the regression: these indicate whether an individual has experienced major financial improvement and/or major financial worsening in the past observational period (up to time t–1) of the data.

The results appear in Column (ii) of Table 2. Conditional on current financial events, past financial worsening reduces current life satisfaction, whereas past financial improvements continue to exert a positive effect on well-being. Broadly speaking, the effect of past exposure to a financial change is smaller than the current experience of the same change p-value = 0.014 for the null hypothesis that the coefficients on MIF_{it} and $Past_{it-1}^{MIF}$ are the same; p-value = 0.000 for the analogous test for MWF_{it} and $Past_{it-1}^{MWF}$). The effect size of past improvement is around two-thirds of that of current improvement, with the analogous figure for worsening being much smaller at just under one quarter. Even so, all of the past financial-change variables are significant. Financial events are not then ephemeral but have well-being effects that extend beyond their contemporaneous impact.

Instead of looking at the simple existence of a past event in Column (ii), we can also take into account the individual's entire cumulated experience of major financial improvements and worsening. In this context, we not only consider the past average percentage of years of financial improvement/worsening (which reflects $chronicity$, as discussed in Section 2), but also whether a given number of years of financial improvements (worsening) increase (reduce) well-being more if they are consecutive (which picks up the separate effect of the $persistence$ of financial movements).

Our FE regressions then include both lagged average past cumulative events, given by the Foster (2009) index (measuring *chronicity*, $Foster_{it-1}$ defined in equation [1]), and the Bossert et al. (2012) index (measuring *persistence*, BCD_{it-1} defined in equation [2]), both calculated over all of the past

[6] In general, the relationship between education and subjective well-being is ambiguous (see Chapter 3 of Clark et al., 2018), with education improving some outcomes but also being associated with greater expectations.

years excluding the current year. As can be seen from equation [2], the BCD persistence index mechanically includes chronicity. In order to disentangle the two, our regressions introduce both the lagged $Foster$ index ($Foster_{it-1}$) and the difference between the two terms (BCD_{it-1}–$Foster_{it-1}$) as explanatory variables. This second term then picks up persistence conditional on any effect of the chronicity of the financial situation. If past persistence in financial improvement increases current well-being, we expect to find a positive estimated coefficient on the difference variable (BCD_{it-1}^{MIF}–$Foster_{it-1}^{MIF}$). On the contrary, if past persistence in financial worsening reduces well-being, we will find a negative estimated coefficient on (BCD_{it-1}^{MWF}–$Foster_{it-1}^{MWF}$). The FE results are reported in the last two columns of Table 2.

The results clearly show that the chronicity of financial situation, as measured by the lagged Foster index, matters for the measure of well-being. Chronic financial improvement attracts a positive estimated coefficient, while chronic financial worsening reduces well-being. It is not only contemporaneous financial shocks that matter, but also the proportion of past years experiencing a financial shock (as measured by the lagged $Foster$ index).

Column (iv) of Table 2 shows that the estimated coefficient on the (BCD_{it-1}^{MIF}–$Foster_{it-1}^{MIF}$) variable is positive, as expected. The sequence of a given number of years with positive financial shocks thus matters for life satisfaction, with consecutive years of financial improvement being better than the same number of years when interrupted. We do not however find this effect of consecutive shocks for financial worsening: a given number of years where finances deteriorated has the same effect on current well-being whether the deterioration occurred in one continuous spell or was interrupted. The inclusion of the BCD variables makes very little difference to the estimated coefficients on either current or past financial shocks.

4.2 The distributional well-being effects of financial profiles

One limitation of the above fixed-effects (FE) panel estimation is its restriction to mean well-being effects, without considering impacts at different points of the subjective well-being distribution. Binder and Coad (2011) and Fang and Niimi (2017) underline the importance of moving beyond average effects in the context of happiness research, allowing for the possibility of heterogeneity.

We apply the panel data quantile regression model with fixed effects (QR–FE) developed by Canay (2011). The life-satisfaction variable in HILDA is discrete on an eleven-point Likert scale (0–10), and can be considered as approximately continuous and used in quantile regressions.[7] The QR–FE model considers the individual fixed effects as location shift variables, and is implemented in Canay (2011) via the following two-stage estimation:

(i). Estimate equation (3) with FE panel regression to obtain consistent estimates of the coefficients ($\widehat{\beta}$, $\widehat{\gamma}$), and then calculate the unobserved fixed effect for each individual as

$$\widehat{u}_i = \frac{1}{T}\sum_{t=1}^{T}(WB_{it} - FP'_{it}\widehat{\beta} - X'_{it}\widehat{\gamma}). \tag{4}$$

(ii). Estimate the conditional quantile regression model of Koenker and Bassett (1978), using ($\widehat{SWB}_{it}$=$SWB_{it}-\widehat{u}_i$) as the dependent variable. Namely, we solve the following minimization problem

$$(\widehat{\beta}_\tau, \widehat{\gamma}_\tau) = arg \min_{(\beta_\tau,\gamma_\tau)} \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}[\rho_\tau(\widehat{WB}_{it} - FP'_{it}\beta_\tau - X'_{it}\gamma_\tau)] \tag{5}$$

where $\rho_\tau(u)$=$u[\tau-I(u<0)]$ and I is an indicator function. The estimated coefficient vector $\widehat{\beta}_\tau$ measures the effects of financial-profile variables on the τ-th percentile of the conditional distribution of well-being, controlling for individual fixed effects. Canay (2011) proves that this two-step estimator is not only consistent but also asymptotically normally-distributed under regularity conditions.

Table 3 displays the QR–FE results at the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the conditional distribution of life satisfaction. Panel A shows that the effects of negative financial shocks are very heterogeneous along the well-being distribution. The size of the detrimental impact of contemporaneous financial worsening falls monotonically as we move up the subjective well-being distribution. The QR–FE estimate of this impact at the 10^{th} percentile is twice the FE estimate, while that at the 90^{th} percentile is only about one-third of this latter figure. A focus on the average effect

[7] Binder and Coad (2011) show that even when the measure of subjective well-being is on a seven-point categorical scale (1–7) in the British Household Panel Survey (BHPS), quantile regressions are still capable of detecting the heterogeneity in the effects of covariates on the full distribution of subjective well-being.

Table 3: Quantile effects of financial profiles for life satisfaction (QR–FE estimates)

		Life satisfaction				
		$Q10$	$Q25$	$Q50$	$Q75$	$Q90$
Panel A	MIF_{it}	0.121***	0.109***	0.108***	0.107***	0.144***
		(0.024)	(0.018)	(0.008)	(0.015)	(0.023)
	MWF_{it}	–1.131***	–0.712***	–0.474***	–0.302***	–0.220***
		(0.070)	(0.034)	(0.022)	(0.020)	(0.026)
	Observations	159,872	159,872	159,872	159,872	159,872
	Individuals	24,433	24,433	24,433	24,433	24,433
	Overall R-Squared	0.044	0.056	0.059	0.0456	0.022
Panel B	MIF_{it}	0.178***	0.157***	0.140***	0.147***	0.192***
		(0.027)	(0.018)	(0.010)	(0.016)	(0.027)
	MWF_{it}	–1.164***	–0.757***	–0.467***	–0.341***	–0.281***
		(0.059)	(0.032)	(0.023)	(0.020)	(0.028)
	$Past^{MIF}_{it-1}$	0.083***	0.119***	0.127***	0.128***	0.144***
		(0.015)	(0.010)	(0.006)	(0.010)	(0.014)
	$Past^{MWF}_{it-1}$	–0.342***	–0.219***	–0.119***	–0.003	0.079***
		(0.024)	(0.011)	(0.008)	(0.013)	(0.017)
	Observations	135,688	135,688	135,688	135,688	135,688
	Individuals	20,018	20,018	20,018	20,018	20,018
	Overall R-Squared	0.049	0.058	0.060	0.044	0.016
Panel C	MIF_{it}	0.151***	0.137***	0.126***	0.131***	0.161***
		(0.025)	(0.020)	(0.010)	(0.016)	(0.024)
	MWF_{it}	–1.147***	–0.733***	–0.455***	–0.326***	–0.293***
		(0.061)	(0.036)	(0.023)	(0.019)	(0.025)
	$Foster^{MIF}_{it-1}$	0.087**	0.200***	0.165***	0.150***	0.200***
		(0.044)	(0.031)	(0.011)	(0.032)	(0.033)
	$Foster^{MWF}_{it-1}$	–0.935***	–0.614***	–0.363***	–0.134***	–0.174***
		(0.072)	(0.039)	(0.012)	(0.039)	(0.061)
	BCD^{MIF}_{it-1}–$Foster^{MIF}_{it-1}$	0.909***	0.782***	0.764***	0.771***	0.592
		(0.070)	(0.097)	(0.081)	(0.124)	(0.578)
	BCD^{MWF}_{it-1}–$Foster^{MWF}_{it-1}$	–0.218***	–0.309***	–0.156***	–0.068**	0.038
		(0.026)	(0.029)	(0.047)	(0.034)	(0.565)
	Observations	135,688	135,688	135,688	135,688	135,688
	Individuals	20,018	20,018	20,018	20,018	20,018
	Overall R-Squared	0.049	0.057	0.060	0.045	0.015

Notes: *** p<0.01; ** p<0.05; * p<0.10. Robust standard errors clustered at the individual level are reported in parentheses. The regressions include all of the other control variables used in Table 2.

then conceals substantial heterogeneity in the effects of negative financial shocks on life satisfaction. The effects of a major contemporaneous improvement in finances are positive and significant at the different points of the life-satisfaction distribution and vary less than those for financial losses, with the estimates suggesting a 0.107–0.144 point rise in life satisfaction.

Panel B of Table 3 additionally shows that past financial improvements have positive and somewhat heterogeneous effects along the life-satisfaction distribution, with the smallest impact on the bottom end of the distribution. As was the case for current MWF_{it}, $Past_{it-1}^{MWF}$ is notably heterogeneous with the largest adverse effect on those at the lower end of the well-being distribution.

Last, the chronicity of major improvement in finances ($Foster_{it-1}^{MIF}$) has a positive significant influence at all points on the life-satisfaction distribution (see Panel C of Table 3) The chronicity index of major financial worsening ($Foster_{it-1}^{MWF}$) reduces life satisfaction, with again negative financial shocks yielding a much larger adverse impact at the lower end of the life-satisfaction distribution than towards the top. The chronicity of financial worsening is estimated to have a small positive impact at the 90^{th} percentile of the life-satisfaction distribution. It could be argued that well-being for the happiest can be used to protect against adverse life events. Financial worsening may even provide an opportunity for individuals to draw closer to family members and close friends, improving satisfaction with some important life domains.[8] In the existing literature, individuals with high well-being scores are found not to be adversely affected by negative phenomena such as relative income comparisons (Budria, 2013) and expected declines in future household income (Fang and Niimi, 2017). Equally, research in Psychology, such as Tugade and Fredrickson (2004) and Cohn et al. (2009), argues that the resilient can use positive emotions to bounce back from negative emotional experiences. Here, we show that individuals who are mentally well-off seem to cope with financial losses in a more positive way than those with lower subjective well-being.

The QR–FE coefficient estimates of the persistence index, (BCD_{it-1}^{MIF}–$Foster_{it-1}^{MIF}$), are positive and of similar size at the 10^{th}, 25^{th}, 50^{th} and 75^{th} percentiles of the life-satisfaction distribution. On the contrary, persistence in financial losses measured by (BCD_{it-1}^{MWF}–$Foster_{it-1}^{MWF}$) affects life

[8] van Praag et al. (2003) postulate that the overall life satisfaction can be considered as a global conception of well-being that aggregates and depends on the happiness with different domains of life.

satisfaction towards the bottom of the life-satisfaction distribution.

Overall, Table 3 indicates that current negative financial shocks, past financial worsening, and the chronicity and persistence of financial losses hurt people at the lower end of well-being distribution more than those who are better off. On the contrary, current positive financial shocks, past incidence of financial improvement, and the chronicity of financial gains benefit people in a more uniform fashion across the well-being distribution.

4.3 Do financial profiles affect health-related life styles?

We now switch our focus from subjective to objective outcomes, and look at the relationship between the above financial profiles and four current health behaviours or outcomes: smoking, drinking, physical exercise and sleep quality. Information on smoking, drinking and exercise is available in HILDA waves 2002–2016; however, information on sleep quality only appears in the 2013 wave.

Appendix Table A3 shows the summary statistics for our four health variables. About 23 percent of observations in our estimation sample come from individuals who smoke cigarettes or tobacco products, and around 19 percent from those who smoke daily. In addition, 84 percent of observations come from individuals who drink alcohol, with 27 percent from those who drink at least three times per week. 74 percent of observations come from individuals who engage in physical activities at least once per week, and 50 percent from those who exercise at least three times per week. Furthermore, 66 percent of 2013 respondents reported that they could not get to sleep within 30 minutes in the past month, with 71 percent waking up in the middle of the night or early morning in the past month. 24 percent experienced difficulty in sleeping due to coughing or snoring, and 13 percent had taken medicine to help them sleep in the past month. Average nightly hours of sleep over a typical week were around 7.2.

The analysis is carried out using fixed-effects (FE) panel estimation for dummy variables indicating smoking, drinking and exercise, and Ordinary Least Squares (OLS) for sleep quality. Panel A of Table 4 shows the relationship between financial profiles and smoking: both positive and negative financial shocks are associated with greater smoking incidence here, with the latter having a somewhat larger impact. Persistence in financial improvement is also positively associated with smoking. Panel B of Table 4 considers the intensive margin of smoking (whether smokes daily). The contemporaneous incidences of financial shocks are mostly significant here. In addition, the chronicity of financial worsening (as measured by the lagged $Foster$ index) is significantly associated with being a daily smoker.

Table 4: Financial profiles and smoking (FE estimates)

	Panel A			Panel B		
	(a) Smoke			(b) Smoke daily		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
MIF_{it}	0.005	0.011***	0.009**	0.004	0.010***	0.007**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
MWF_{it}	0.014***	0.010**	0.011**	0.012***	0.010**	0.012**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
$Past_{it-1}^{MIF}$		0.008			0.010**	
		(0.005)			(0.005)	
$Past_{it-1}^{MWF}$		0.003			0.005	
		(0.006)			(0.006)	
$Foster_{it-1}^{MIF}$			0.003			0.010
			(0.012)			(0.012)
$Foster_{it-1}^{MWF}$			0.027*			0.039***
			(0.015)			(0.015)
BCD_{it-1}^{MIF}–$Foster_{it-1}^{MIF}$			0.137**			0.018
			(0.062)			(0.089)
BCD_{it-1}^{MWF}–$Foster_{it-1}^{MWF}$			–0.033			0.003
			(0.044)			(0.028)
Observations	159,872	135,688	135,688	159,872	135,688	135,688
Individuals	24,433	20,018	20,018	24,433	20,018	20,018
Overall R-Squared	0.000	0.003	0.004	0.001	0.000	0.000

Notes: *** p<0.01; ** p<0.05; * p<0.10. Robust standard errors clustered at the individual level are reported in parentheses. The regressions include all of the other control variables used in Table 2.

In Panel A of Table 5 there is no evidence that major financial worsening significantly affects drinking (the estimated coefficients are negative), while positive financial shocks are associated with more drinking. This positive correlation is also found in the literature using either aggregate shocks (Ruhm, 2000) or the individual-level positive shock of lottery winnings (Apouey and Clark, 2015). There is however no evidence that the chronicity, and persistence of financial improvement affects drinking. Panel B of Table 5 shows similar pattern of results for frequent drinking (at least 3 times per week), with the only exception that persistent financial worsening is more likely to result in heavy drinking.

Table 5: Financial profiles and drinking (FE estimates)

	Panel A			Panel B		
	(a) Drink			(b) Drink at least 3 times per week		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
MIF_{it}	0.010***	0.011***	0.011***	0.015***	0.015***	0.015***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
MWF_{it}	0.003	-0.002	0.001	0.002	-0.001	0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$Past^{MIF}_{it-1}$		0.000			0.001	
		(0.005)			(0.006)	
$Past^{MWF}_{it-1}$		–0.014**			–0.005	
		(0.006)			(0.007)	
$Foster^{MIF}_{it-1}$			0.002			0.003
			(0.011)			(0.015)
$Foster^{MWF}_{it-1}$			–0.002			0.010
			(0.015)			(0.016)
BCD^{MIF}_{it-1}–$Foster^{MIF}_{it-1}$			–0.025			0.048
			(0.107)			(0.164)
BCD^{MWF}_{it-1}–$Foster^{MWF}_{it-1}$			–0.008			0.079*
			(0.041)			(0.047)
Observations	159,872	135,688	135,688	159,872	135,688	135,688
Individuals	24,433	20,018	20,018	24,433	20,018	20,018
Overall R-Squared	0.010	0.015	0.015	0.010	0.015	0.015

Notes: *** p<0.01; ** p<0.05; * p<0.10. Robust standard errors clustered at the individual level are reported in parentheses. The regressions include all of the other control variables used in Table 2.

The profiles of major financial improvements do not have any impact on either the incidence or intensity of Australians' physical activities, as indicated in Table 6. However, current financial worsening leads to less exercise. Moreover, the chronicity of negative financial shocks reduces the propensity to engage in any physical exercise.

Finally, Panel A of Table 7 shows that negative contemporaneous financial shocks are associated with worse sleep quality on all five measures. For example, in the last column a negative financial shock is associated with about 17 minutes less sleep per night, and in column (d) individuals with major financial worsening are nine percentage points more likely to take medicine to help them sleep. In Panel B of Table 7 the chronicity in negative financial shocks (as measured by the lagged Foster (2009) index) and the persistence of financial worsening (as measured by the lagged difference between the Bossert et al. (2012) index and the Foster (2009) index), are also found to significantly reduce sleep quality.

Table 6: Financial profiles and exercising (FE estimates)

	Panel A			Panel B		
	(a) Exercise			(b) Exercise at least 3 times per week		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
MIF_{it}	0.004	0.007	0.006	–0.002	0.002	–0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
MWF_{it}	–0.019***	–0.028***	–0.026***	–0.014**	–0.025***	–0.020***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
$Past^{MIF}_{it-1}$		0.008			0.011	
		(0.007)			(0.008)	
$Past^{MWF}_{it-1}$		–0.019**			–0.023**	
		(0.008)			(0.009)	
$Foster^{MIF}_{it-1}$			0.025			0.014
			(0.017)			(0.020)
$Foster^{MWF}_{it-1}$			–0.043**			–0.006
			(0.021)			(0.022)
$BCD^{MIF}_{it-1}–Foster^{MIF}_{it-1}$			0.034			0.101
			(0.087)			(0.127)
$BCD^{MWF}_{it-1}–Foster^{MWF}_{it-1}$			–0.005			–0.035
			(0.039)			(0.041)
Observations	159,872	135,688	135,688	159,872	135,688	135,688
Individuals	24,433	20,018	20,018	24,433	20,018	20,018
Overall R-Squared	0.005	0.009	0.008	0.007	0.008	0.007

Notes: *** p<0.01; ** p<0.05; * p<0.10. Robust standard errors clustered at the individual level are reported in parentheses. The regressions include all of the other control variables used in Table 2.

4.4 Robustness checks

We have carried out a series of robustness checks. We first investigate whether our results are robust to alternative definitions of well-being. The mental-health index derived from the 36-item Short Form Health Survey (SF-36), which quantifies and measures respondent vitality, social functioning, emotional functioning and anxiety/depression, appears in HILDA and is standardised to lie between 0 and 100. We also have information on satisfaction with financial situation, which is answered on

Table 7: Financial profiles and sleep quality (OLS estimates)

		Quality of sleep				
		(a)	(b)	(c)	(d)	(e)
Panel A	MIF_{it}	0.034	0.012	–0.013	0.026	0.084
		(0.024)	(0.023)	(0.022)	(0.019)	(0.064)
	MWF_{it}	0.161***	0.110***	0.090***	0.089***	–0.281***
		(0.019)	(0.019)	(0.024)	(0.021)	(0.084)
	Observations	121,51	121,51	12,151	12,151	12,151
	R-Squared	0.015	0.022	0.036	0.015	0.046
Panel B	MIF_{it}	0.017	–0.008	–0.022	0.014	0.099
		(0.025)	(0.024)	(0.022)	(0.019)	(0.065)
	MWF_{it}	0.136***	0.084***	0.075***	0.068***	–0.236***
		(0.021)	(0.020)	(0.025)	(0.023)	(0.088)
	$Past^{MIF}_{it-1}$	0.002	0.031***	0.002	0.011	–0.004
		(0.012)	(0.011)	(0.011)	(0.009)	(0.032)
	$Past^{MWF}_{it-1}$	0.083***	0.086***	0.061***	0.059***	–0.217***
		(0.013)	(0.011)	(0.013)	(0.011)	(0.041)
	Observations	11,303	11,303	11,303	11,303	11,303
	R-Squared	0.018	0.026	0.037	0.019	0.044
Panel C	MIF_{it}	0.016	–0.007	–0.022	0.013	0.102
		(0.025)	(0.024)	(0.022)	(0.019)	(0.065)
	MWF_{it}	0.136***	0.083***	0.066***	0.061***	–0.240***
		(0.021)	(0.021)	(0.026)	(0.023)	(0.089)
	$Foster^{MIF}_{it-1}$	–0.000	0.113***	0.052	0.060*	–0.141
		(0.045)	(0.042)	(0.042)	(0.034)	(0.121)
	$Foster^{MWF}_{it-1}$	0.241***	0.272***	0.202***	0.180***	–0.709***
		(0.040)	(0.035)	(0.044)	(0.038)	(0.147)
	BCD^{MIF}_{it-1}–$Foster^{MIF}_{it-1}$	0.308	–0.217	–0.292	–0.036	0.790
		(0.188)	(0.237)	(0.236)	(0.152)	(0.625)
	BCD^{MWF}_{it-1}–$Foster^{MWF}_{it-1}$	–0.083	–0.120	0.109*	0.124**	–0.612***
		(0.076)	(0.080)	(0.058)	(0.058)	(0.217)
	Observations	11,303	11,303	11,303	11,303	11,303
	R-Squared	0.017	0.025	0.038	0.019	0.044

Notes: *** p<0.01; ** p<0.05; * p<0.10. Robust standard errors are reported in parentheses. The regressions include the control variables used in Table 2. (a) Cannot get to sleep within 30 minutes in the past month. (b) Wakes up in mid-night or early morning in the past month. (c) Cannot sleep because coughs or snores loudly in the past month. (d) Takes medicine to help sleep in the past month. (e) Hours of sleep per day in a typical week.

the same scale as life satisfaction. We find similar results when these two alternative measures of well-being are used as the dependent variable.

Second, we use equivalent household disposable total income (rather than equivalent household disposable regular income) as a control variable. Third, we further include those aged above 65 in our analysis. Fourth, instead of constructing the *chronicity* and *persistence* indexes based on financial variables up to time t-1, we also use the information at time t for the calculation of the two indexes. These three checks yield very similar results.

Fifth, we check that our results in fixed effects linear regressions are the same in the fixed effects ordered-logit model in Dickerson et al. (2014), which takes into account the ordered nature of well-being responses. This is consistent with the findings in Ferrer-i Carbonell and Frijters (2004) and Kristoffersen (2017) that the assumption of cardinality in well-being produces the same results as that of ordinality.

Last, we assess whether the well-being effects of financial profiles can be entirely captured by movements in disposable income. In Table A1, 3.2 percent of observations experienced a recent major financial improvement on average over 2002–2016, with an analogous figure of 3.3 percent for a major financial worsening. Using information on household equivalent disposable total income, we create a dummy variable for the 3.2 percent of observations with the largest disposable income growth over the past year; an analogous dummy indicates the 3.3 percent of observations with the largest disposable income fall. The profile variables in Section 2 can then also be generated for these two disposable income-shock variables. We include these income-profile variables as additional controls in our regressions. The results are similar to those in Tables 2–7, suggesting that our results are not driven by income drops/gains and that profiles of financial elements beyond income are important factors influencing both subjective well-being and health in a dynamic and heterogeneous fashion.[9]

[9]The detailed results from these analyses are available upon request.

5 Conclusion

We have here used panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey to examine the link between financial profiles over time and both subjective (life satisfaction) and objective (health behaviour) individual outcomes. Our fixed effects panel regressions first highlight that satisfaction falls with a contemporaneous major financial worsening and rises with contemporaneous major financial improvement (controlling for current household income), with the former having a much larger effect than the latter. Second, past financial experiences continue to affect current well-being. Third, both current and past negative financial shocks hurt individuals at the lower end of well-being distribution more than those at the top, while current and past positive financial shocks provide a much more uniform benefit. The order of financial improvement spells also matters. For example, for a given number of financial improvement years, current life satisfaction is higher when these past improvement years were consecutive. The results differ for financial worsening: a given number of years where finances deteriorated has the same effect on current well-being whether the deterioration occurred in one continuous spell or was interrupted.

We also conclude that current and past financial shocks are correlated with current health behaviours and outcomes. Any type of financial shock is associated with more smoking, while positive financial shocks lead to increased drinking, and negative financial events are associated with less physical activity and worse sleep quality. It might be thought that these health behaviours mediate the effect of financial movements on life satisfaction. This turns out not to be the case (their inclusion in the life-satisfaction regressions makes little difference to the estimated coefficients on the various financial-profile variables). This could reflect that the relationship between smoking and drinking, on the one hand, and life satisfaction on the other is not particularly clear (Grant et al., 2009; Vermeulen-Smit et al., 2015). Alternatively, the health consequences of risky behaviours may become apparent only a considerable time later (Cawley and Ruhm, 2012).

We believe that these results are important for at least two reasons. They first provide new information on the empirical link between financial profiles and individual well-being, explicitly taking the past into account: both the present and the past matter, even in a rich country. Second, we help to bridge the gap between theory and empirics, by showing that the recent literature on chronicity and persistence indices can be applied to well-known long-run panel data to determine the most salient dimensions of financial profiles in terms of current individual well-being. Future research may well consider taking a similar line with the vast number of different indices which are now available in the theoretical literature.

One limitation of our analysis is that our key variables of interest (major financial improvement and worsening) are self-reported. As HILDA question is subjective, respondents' answers may refer to changes in net worth of different sizes (even within subject). While Bridges and Disney (2010) find evidence that subjective financial measures matter more for well-being than do objective variables, it would likely be preferable to have both available to check the robustness of our findings. We leave this aspect for future research when suitable data become available.

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Table A1: Descriptive statistics for the main sample

Variables	Mean	Standard deviation
Measures of well-being		
Life satisfaction (0–10)	7.846	1.434
Measures of financial profiles		
Major improvement in finances	0.032	0.175
Major worsening in finances	0.033	0.179
Past major improvement in finances	0.142	0.349
Past major worsening in finances	0.121	0.327
Foster index (major improvement in finances)	0.033	0.111
Foster index (major worsening in finances)	0.034	0.122
BCD index (major improvement in finances)	0.033	0.115
BCD index (major worsening in finances)	0.036	0.140
Socioeconomic characteristics		
Age: 16–25	0.210	0.407
Age: 26–35	0.198	0.399
Age: 36–45	0.217	0.412
Age: 46–55	0.210	0.407
Age: 56–65	0.165	0.372
Male	0.470	0.499
Years of education	12.376	2.135
Married	0.650	0.477
Never married	0.251	0.434
Widowed	0.013	0.111
Divorced	0.058	0.234
Separated	0.028	0.164
Employed	0.745	0.436
Unemployed	0.041	0.197
Not in the labour force	0.215	0.412
Number of children in household	0.823	1.132
Household disposable regular income (A$000s, 2016)	97.896	66.123
Equivalent household disposable regular income (A$000s, 2016)	57.483	36.589
Living in a major city	0.632	0.482
Observations	159,926	
Individuals	24,436	

Note: Data from HILDA 2002–2016.

Table A2: The effects of financial profiles on well-being (FE estimates, full table)

	(i)	(ii)	(iii)	(iv)
MIF_{it}	0.129***	0.170***	0.149***	0.150***
	(0.016)	(0.018)	(0.017)	(0.017)
MWF_{it}	–0.567***	–0.596***	–0.591***	–0.591***
	(0.025)	(0.029)	(0.028)	(0.028)
$Past_{it-1}^{MIF}$		0.117***		
		(0.020)		
$Past_{it-1}^{MWF}$		–0.130***		
		(0.027)		
$Foster_{it-1}^{MIF}$			0.167***	0.156***
			(0.052)	(0.052)
$Foster_{it-1}^{MWF}$			–0.368***	–0.361***
			(0.071)	(0.071)
BCD_{it-1}^{MIF}–$Foster_{it-1}^{MIF}$				0.769**
				(0.301)
BCD_{it-1}^{MWF}–$Foster_{it-1}^{MWF}$				–0.157
				(0.163)
Log of equivalent household disposable regular income	0.064***	0.051***	0.050***	0.050***
	(0.008)	(0.009)	(0.009)	(0.009)
Age: 16–25	0.052*	0.093***	0.093***	0.093***
	(0.027)	(0.029)	(0.029)	(0.029)
Age: 26–35	0.017	0.039**	0.041**	0.041**
	(0.017)	(0.018)	(0.018)	(0.018)
Age: 46–55	0.031*	–0.006	–0.006	–0.006
	(0.017)	(0.018)	(0.018)	(0.018)
Age: 56–65	0.149***	0.077***	0.078***	0.078***
	(0.027)	(0.028)	(0.028)	(0.028)
Years of education	–0.038***	–0.020***	–0.020***	–0.020***
	(0.006)	(0.007)	(0.007)	(0.007)
Married	0.221***	0.202***	0.204***	0.204***
	(0.018)	(0.019)	(0.019)	(0.019)
Widowed	–0.259***	–0.244**	–0.243**	–0.242**
	(0.100)	(0.106)	(0.106)	(0.106)
Divorced	–0.135***	–0.126***	–0.129***	–0.129***
	(0.042)	(0.045)	(0.045)	(0.045)
Separated	–0.378***	–0.382***	–0.381***	–0.381***
	(0.040)	(0.042)	(0.042)	(0.042)
Unemployed	–0.131***	–0.132***	–0.130***	–0.130***
	(0.021)	(0.024)	(0.024)	(0.024)
Not in the labour force	–0.004	–0.023	–0.021	–0.021
	(0.014)	(0.015)	(0.015)	(0.015)
Number of children in household	–0.045***	–0.045***	–0.045***	–0.045***
	(0.007)	(0.007)	(0.007)	(0.007)
Living in a major city	–0.075***	–0.078***	–0.077***	–0.077***
	(0.021)	(0.022)	(0.022)	(0.022)
Constant	7.948***	7.830***	7.834***	7.834***
	(0.094)	(0.104)	(0.104)	(0.104)
Observations	159,926	135,716	135,716	135,716
Individuals	24,436	20,019	20,019	20,019
Overall R-Squared	0.048	0.065	0.066	0.066

Notes: *** p<0.01; ** p<0.05; * p<0.10. State dummies and wave dummies are also controlled for in the estimations. Robust standard errors clustered at the individual level are reported in parentheses.

Table A3: Descriptive statistics for smoking, drinking and sleeping

Variables	Mean	Standard deviation	Observations	HILDA wave
Smoking				
(a) Smokes cigarettes/tobacco products	0.226	0.418	159,926	2002–2016
(b) Smokes daily	0.185	0.388	159,926	2002–2016
Drinking				
(a) Drinks alcohol	0.843	0.363	159,926	2002–2016
(b) Drinks at least 3 times per week	0.266	0.442	159,926	2002–2016
Exercising				
(a) Physical exercise	0.741	0.438	159,926	2002–2016
(b) Takes physical exercise at least 3 times per week	0.499	0.500	159,926	2002–2016
Quality of sleep				
(a) Cannot get to sleep within 30 minutes in the past month	0.661	0.473	12,159	2013
(b) Wakes up in mid-night or early morning in the past month	0.709	0.454	12,159	2013
(c) Cannot sleep because coughs or snores loudly in the past month	0.240	0.427	12,159	2013
(d) Takes medicine to help sleep in the past month	0.129	0.335	12,159	2013
(e) Hours of sleep per day in a typical week	7.157	1.328	12,159	2013

Note: Data from HILDA 2002–2016.