Modelling financial satisfaction across life stages: a latent class approach

Abstract

We explore the determinants of financial satisfaction using a modelling framework which allows the drivers of financial satisfaction to vary across life stages. Given that financial satisfaction is measured as an ordered variable, our modelling approach is based on a latent class ordered probit model with an ordered probit class assignment function. Our analysis of household survey data indicates that four life stages are supported by the data. Our results suggest that such flexibility is important in understanding the drivers of financial satisfaction over the life cycle since there is a substantial amount of parameter heterogeneity across the four classes.

Keywords: Financial Satisfaction; Latent Class; Life Cycle; Ordered Probit.

JEL Classification: C3; D1; D6.

1 Introduction and Background

Over recent years, there has been increasing interest in the determinants and implications of wellbeing and overall life satisfaction from a number of disciplines including economics and psychology, as well as from policy-makers across a range of countries. Rather than the potentially opaque concept of "happiness", research tends to discuss individuals' subjective well being: that is, how they feel about themselves and their lives (Dolan, Peasgood, and White (2008)). There is evidence that individuals' incomes have a positive yet diminishing role in their overall subjective well being (Dolan, Peasgood, and White (2008)). In Australia, for example, longitudinal data indicates that life satisfaction has declined from 2001 to 2010, a period of strong economic performance (Ambrey and Fleming (2014)); such a finding is consistent with the international evidence (see, for example, Blanchflower and Oswald, 2004). When we consider the components of subjective well being, however, we find that financial satisfaction has an important influence on overall life satisfaction (see, for example, Easterlin, 2006, and Van Praag and Ferrer-i Carbonell, 2007). Thus, in order to understand the determinants of wellbeing and overall life satisfaction, it is important to identify what influences financial satisfaction. Consequently, there has been increasing interest in exploring the determinants of financial satisfaction. In addition, the growing literature on household finances as well as the recent financial crisis has led to increased interest in furthering our understanding of financial wellbeing and vulnerability at the individual and household level (see the recent review of the household finance literature by Haliassos, Jappelli, Pagano, and Zechner, 2011).

While research on the determinants of financial satisfaction nevertheless remains relatively scarce, "findings on the association between money and happiness have implications for investor behavior...[but there is] limited direct research on money and happiness pertinent to investor behavior" (Xiao, 2014, p. 184). Therefore, the motivation for the research presented in this analysis is drawn from the Behavioural Finance literature on feelings rather than the economics literature on general happiness. Our feelings about our finances determine our investment choices. Dissatisfaction with one's finances is psychologically arousing (see Foote (2000), p. 237) and drives action to remedy matters to achieve financial satisfaction. People who are satisfied, on the other hand, have little incentive to change (Isen (1987)). Studies show that individual investors should be dissatisfied with their portfolios; they tend not to be economically optimal (Barber and Odean (2013)). Furthermore, financial satisfaction is more than a consequence of the decisions we make or a spur to making those decisions, it is a core input in making those decisions (Schwarz (1990); Loewenstein, Hsee, Weber, and Welch (2001)). Given the same objective information, financially satisfied and dissatisfied people will make different financial decisions.

Theories on changes in the drivers of financial satisfaction appear in the economics literature as early as Ando and Modigliani (1963), with their introduction of life-cycle theories to financial behaviour. Ando and Modigliani (1963) hypothesised that individuals may be more comfortable with debt when they are young and their income is low, as they expect their future income to be much higher, and to be able to pay off the debt at a later stage. While theories of financial behaviour have been discussed in great detail since then (for example, by Laibson, 1997; Thaler, 1994; Loewinstein and Prelec, 1992; Nagatani, 1972; Shefrin and Thaler, 1988), the premise of individuals having different marginal utilities from various financial circumstances has remained. For example, Davies and Lea (1995) consider degrees of financial satisfaction among indebted university students, and argue that the life-cycle hypothesis might help explain unchanged satisfaction among students whose debt vastly outweighs their present earning capacity. In addition, heterogeneity in financial satisfaction has been studied across other dimensions, including religion (Van Praag, Romanov, and Ferrer-i Carbonell, 2010), race and gender (DePianto, 2011) and retirement pathways (Elder and Rudolph, 1999).

Not surprisingly, given the extent to which income varies over the life cycle, the role of income in determining financial satisfaction has attracted considerable attention in empirical studies in the existing economics literature, with, in general, a positive, albeit moderate, influence being reported (see, for example, Johnson and Krueger, 2006, and Xiao, Tang, and Shim, 2009). However, as pointed out by Plagnol (2011), despite the focus on the role of income in the existing literature, evidence for a number of countries suggests that financial satisfaction increases with age, (see, for example, Plagnol and Easterlin (2008)) whilst income over the life-cycle is characterised by an inverted U-shaped pattern peaking mid-life. Such findings suggest that the pattern of financial satisfaction over the life-cycle may not follow that of income alone. Thus, financial satisfaction is found to be relatively high amongst older retired individuals despite lower levels of income generally being observed at this stage of the life-cycle. In a comparison of life course patterns associated with financial satisfaction and household income, Plagnol (2011) comments that "it is impossible to reconcile these two life course profiles with the assumption that income is the primary determinant of financial satisfaction" (p.52). Studies have thus sought to expand the set of explanatory variables included in models of financial satisfaction, incorporating additional controls such as household assets and liabilities (see Plagnol (2011)).

Given the findings in the existing literature, an interesting line of enquiry relates to exploring the drivers of financial satisfaction for individuals at different stages of their lives. For instance, the influence of income may be apparent at early stages of the life-cycle, as compared to its effect at later stages when individuals may have, for example, paid-off mortgage debt and accumulated financial assets. The finding of a modest influence of income in the existing literature may reflect a more restrictive econometric approach which does not allow the influences of financial satisfaction to vary with life stages. In this paper, we thus extend the literature on modelling financial satisfaction by applying a latent class approach, which does allow the determinants of financial satisfaction to vary across life stages. Thus, our contribution lies in introducing a new flexible framework for modelling financial satisfaction, which is based on the latent class approach.

The survey question on financial satisfaction that we analyse, in accordance with the measures of financial satisfaction commonly used in the existing literature, yields an ordered variable. Hence, an ordered probit model is the appropriate starting point for analysis. The novelty of our modelling approach is that it is based on an *ordered latent class specification*, whereby the natural ordering in the class specification is in accordance with the individual's age (discretised into "life stages"). Not only is this approach well-suited to the question at hand, it also represents, to the best of our knowledge, the first application of such a model.[1] Indeed, the analysis of our household survey data indicates that four life stages are supported by the data. The results suggest that such flexibility is important in understanding the drivers of financial satisfaction over the life cycle since there is a substantial amount of parameter heterogeneity across the four classes. Key empirical findings include: the effect of labour income on financial satisfaction being largely limited to the earliest life stage; with investment income and housing equity playing a more important role later on in the life cycle. In addition, gender appears to have an important influence on financial satisfaction, with males and females found to value different aspects of their financial circumstances at various different stages of their lives.

2 Econometric framework

As discussed above, we are interested in the drivers of financial satisfaction for individuals and how these vary at different stages of their lives. As is common in the economics literature, see for example Headey and Wooden (2004); Van-Praag and Ferrer-i Carbonell (2010); Plagnol (2011), the financial satisfaction measure that we analyse is based on a survey question which leads to an ordered variable.[2] In our specific application, the

[1] From a purely statistical perspective not driven by any underlying economic motivations as here, Brown, Greene, and Harris (2014), do also consider an ordered set-up within a latent class framework.

[2] Alternative approaches to measuring financial satisfaction are based on multiple item measures, see for example Draughn, LeBoeuf, Wozniak, Lawrence, and Welch (1994); Hayhoe and Wilhelm (1998), which include information relating to a range of influences. The single item measures tend to be more commonly available in large scale representative surveys.

survey question asks individuals to evaluate their financial situation from zero to ten, with higher numbers corresponding to higher levels of financial satisfaction. This implies that an appropriate model for the outcome variable (and the one used here) is an ordered probit.

The approach we follow here, is a modified version of a “latent class” ordered probit. Such an approach, in general, attempts to introduce unobserved heterogeneity into the model by allowing for a finite number of *classes*, or *types*, of individuals, within which behaviour is relatively homogeneous. Indeed such a general approach has been considered by Clark, Etile, Postel-Vinay, Senik, and Van der Straeten (2005) and Plagnol (2011). Clark, Etile, Postel-Vinay, Senik, and Van der Straeten (2005) look specifically at heterogeneity in the effect of income on financial satisfaction. This is done by allowing the coefficient of income, as well as the model’s inherent threshold parameters, see Greene and Hensher (2010), to vary across classes in a latent class ordered probit model. In addition, employment status is controlled for, with the coefficients restricted to be the same across classes.

The current approach taken is most related to Plagnol (2011), who explores the determinants of financial satisfaction and how it changes with age. It is first assumed that financial satisfaction is a function of a range of financial circumstances, discussed in Section 3 below, but how these financial circumstances affect financial satisfaction is dependent on progression throughout one’s life course. It is assumed that there are Q unknown different life stages, each of which corresponds to a potentially different set of relationships between financial factors and financial satisfaction. These life-stages are ordered with respect to the individual’s age, by definition, and it is exactly this ordering that our approach takes advantage of. As we show below, the result is a latent class ordered probit model, but with an ordered probit model for the life-stage class-assignment function. We note that such an approach is different to that typically assumed in the literature, whereby (inherently unordered) multinomial logit (MNL) probabilities are assumed for class-assignment, and there is no ordering assumed, or allowed for, in these classes. Here, however, we explicitly acknowledge the ordering in these classes as defined by the individual's age. We also note that such an approach will however, only differ from the more traditional MNL latent class approach if: firstly there are covariates driving the class probabilities (here *age*); and secondly that there are three, or more, classes.[3]

Thus, following the literature, we will assume the existence of Q latent (unobserved and unknown) *classes*. Individuals are heterogeneous across classes with regard to how they react to observed covariates, but homogeneous within each class. The corresponding density is

$$g(y_i|x_i, \pi_1, \ldots, \pi_Q; \theta_1, \ldots, \theta_Q) = \sum_{q=1}^{Q} \pi_q . f(y_i|x_i, \theta_q),$$

where y_i is the outcome variable and x_i the vector of covariates thought to influence it; π_q is the probability of being in latent class q; $f(y_i|x_i, \theta_q)$ is the density of y_i conditional on being in class q; and θ contains all of the parameters that influence the function f (and which importantly, vary by class). π_q are subject to the constraints that $\sum_{q=1}^{Q} \pi_q = 1$ and $0 < \pi_q < 1$. By definition, the latent classes will be unobserved and the usual approach to

[3]Otherwise the two approaches are formally identical.

address estimation of π_q is to use the MNL form of the probabilities of these, given by

$$\pi_q = \frac{exp(\gamma_q)}{\sum_{a=1}^{Q} exp(\gamma_a)},$$

where γ_q $(= 1, ..., q)$ is a set of constants that are used to calculate class probabilities, and $exp()$ is the exponential function. The choice of functional form for this class assignment function, is clearly inconsequential when class probabilities are treated as constant across individuals. However, this is not so when one considers an extension to this model that is increasingly used when the researcher has some prior reasoning as to the determinants of class membership: this involves an explicit parameterisation of the class assignment equation. Again, along the lines of the MNL model this would become:

$$\pi_q = \frac{exp(z_i'\gamma_q)}{\sum_{a=1}^{Q} exp(z_i'\gamma_a)} \tag{1}$$

where z_i is a set of explanatory variables that help allocate individuals to each of the unobserved classes. The MNL specification is evident in most (if not all) studies where class assignments are generalised (expressed as a prior function of covariates). Indeed, all modern econometric software that we are aware of estimates generalised latent class models in this manner.

However, the MNL is one of a large range of potential class assignment functions that could be used. One alternative to this standard approach arises when there is some inherent natural ordering in the classes. That is, class selection may arise from a single utility function, rather than competing utility functions for each class. In this case, an ordered probit class assignment function is appropriate, see Greene and Hensher (2010). The ordered probit class probabilities would be (Greene and Hensher, 2010)

$$\pi_{iq} = \Phi(\mu_q - z_i'\gamma) - \Phi(\mu_{q-1} - z_i'\gamma), \quad q = 1 \dots Q \tag{2}$$

where $\mu_0 = -\infty$, $\mu_1 = 0$ and $\mu_Q = \infty$. The corresponding log-likelihood function would therefore be

$$LogL = \sum_{i=1}^{N} log \left(\sum_{q=1}^{Q} \left[\Phi(\mu_q - z_i'\gamma) - \Phi(\mu_{q-1} - z_i'\gamma) \right] .f(y_i|x_i\theta_q) \right).$$

where, given the ordered categorical nature of our measure of financial satisfaction, $f(y_i|x_i\theta_q)$ also takes an ordered probit form.

The resulting specification is more parsimonious than a MNL class assignment specification in cases where there are more than two classes, and moreover is explicitly consistent with the prior view that these classes are ordered according to life-stages (proxied by an individual's age). Thus this approach is not only a parsimonious way of introducing more unobserved heterogeneity into the modelling framework, it is also an approach consistent with having unobserved classes of individuals that are ordered according to an individual's age, where the life-stages are not exogenously imposed by the researcher, but determined endogenously by the data.

A fundamental question concerns whether a simpler model could be applied. One possible alternative that might be considered to incorporate parameter heterogeneity is a pooled ordered probit model with interactions between age and each of the covariates. Another alternative is to split up the sample by ages and estimate a pooled ordered probit model for each age group. The latent class approach has distinct advantages over both of these methods. Firstly, considering the former, interacting age with each of the covariates would imply a linear gradient of each of the factors that influence financial satisfaction across different ages. In contrast, a latent class specification allows a much more flexible gradient, with the ability to distinguish between when particular factors have a significant effect on financial satisfaction and when they do not. The second alternative of splitting the population into subgroups may partly relax the strict parametric assumptions implied about the nature of the gradients (in favour of a step-like gradient for each variable). However, there is the serious issue of choosing where to split the population into groups. That is, it is difficult to determine at what age one life stage ends and another begins, and this may differ across individuals. This is a key output from the latent class ordered probit estimation process. In addition, the approach of subjectively splitting up the sample by age neglects the fact that age is intended to proxy life stages, and that actual life stages are unobserved.

It is useful here, to compare how our approach differs from that of Clark, Etile, Postel-Vinay, Senik, and Van der Straeten (2005), who also utilise a latent class framework in the context of explaining the drivers of financial satisfaction, and whose output equation (and accordingly statistical model), is an identical specification to the one employed in the current study. Clark, Etile, Postel-Vinay, Senik, and Van der Straeten (2005) employ a "standard" latent class approach: time invariant characteristics explain the class probabilities, *which* *are driven by the MNL form of equation (1) above.* Moreover, no explicit allowance is made for how these classes may change over, or be related to, the changing drivers of financial satisfaction over the life-cycle of the individual (with regard to financial satisfaction). Following the related literature, *ex post* Clark, Etile, Postel-Vinay, Senik, and Van der Straeten (2005) label the uncovered groups according to increasing levels of (predicted) levels of financial satisfaction within each group. *That is, they order the classes post estimation.* In our approach we explicitly define these class probabilities with reference to the individual's life-cycle by parameterising them directly as a function of their age. Our approach has the combined benefits of: 1) giving the classes a direct interpretation of distinct stages of the life-cycle with regard to financial satisfaction; 2) *ex post* and *ex ante* the classes have a direct interpretation - they are ordered according to increasing age (or according to the life-cycle); and 3) suggests a more parsimonious parametrisation of the class probabilities (it is possible, indeed probable, that a different optimal number of classes might have been found by Clark, Etile, Postel-Vinay, Senik, and Van der Straeten (2005) if they had specified the class probabilities differently).

3 Data

Our empirical analysis is based on nine waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey, which started in 2001 and is financed by the Australian Government and managed by the Melbourne Institute of Applied Economic and Social Research.[4] HILDA is a nationally representative panel data set which provides a wealth of socioeconomic information. Details on the study design are given in Wooden and Watson (2007). We analyse panel data drawn from the 2001 to 2009 waves, which comprises a total number of observations of 33,642 with 3738 individuals observed 9 times. Thus, we are able to exploit panel data over a relatively large number of waves.[5] In the HILDA survey, individuals are asked to indicate their level of satisfaction with their financial situation on a score from 0 to 10, where 0 indicates "totally dissatisfied" and 10 corresponds to "totally satisfied". The percentages of responses in each category are follows: 0 (1%); 1 (2%); 2 (3%); 3 (4%); 4 (4%); 5 (12%); 6 (13%); 7 (21%); 8 (22%); 9 (11%); and 10 (7%).

Progression through life stages is assumed to be driven primarily by age, although a simple extension could be to include factors such as whether an individual has children, their level of responsibility in their job, whether they have retired, as so on. Instead, age acts as a proxy for the other factors the analyst might want to explicitly include in this equation. The panel aspect of the data helps to identify transitions between life stages and the gradient associated with each financial factor over the life course. The factors utilised in the output variable function reflect different sources of income and financial status, including income derived from employment, government support, pensions, investment income, and housing equity, as well as whether the individual is renting or has a mortgage.[6] Our key

[4] Ambrey and Fleming (2014), as we have noted in the introduction, document a decline in overall subjective well being in Australia from 2001 to 2010 using the HILDA panel data set.

[5] In contrast Plagnol (2011) is restricted to analysing data from two waves of the US National Survey of Families and Households.

[6] In HILDA, over the time period that we focus on, detailed information on debt and asset holding is only available in waves 2002 and 2006. Thus, we focus on the role of housing equity, the difference between current house value and outstanding mortgage debt, arguably the most important asset in a household's financial portfolio, in order to maximise the number of waves analysed.

hypothesis is that different types of income (such as investment income versus income from employment) or financial assets, have different marginal impacts on financial satisfaction at different points in a person's life, with liquidity and cash-flow trade-offs tending to change over time. Marital status is also included in the analysis to reflect the financial implications associated with having a spouse. Marital status may affect income and create household economies of scale but it also exposes individuals to potential financial shocks such as the costs associated with children and the potential costs should the marriage fail (Love (2009)). These variables are chosen as they are indicative of different financial circumstances, and are reliably constructed in the HILDA data-set and are generally consistent with the existing literature. Summary statistics relating to the explanatory variables are presented in Table 1. It is apparent that just over half of the sample are married and are employed. Labour income is the dominant source of income with, as expected, income from government sources being, on average, the lowest. The average age of the individuals in the sample is 48 years.

INSERT TABLE 1 ABOUT HERE

Finally, in order to ascertain the existence of collinearity problems we present a correlation matrix as well as the variance inflation factors for the continuous variables included in our analysis. It is apparent that the degree of correlation between the continuous variables is generally relatively low and the variance inflation factors are small suggesting that collinearity is not problematic here.

INSERT TABLE 2 ABOUT HERE

4 Results

4.1 Overall Results

Coefficient estimates are summarised in Table 3. Pooled ordered probit models are estimated with and without age in the regressor set, to provide appropriate comparisons with the latent class model. Some results from the population pooled ordered probit models are briefly considered first. Firstly, all variables are significant in the pooled ordered probit model without age. However some coefficients imply counter-intuitive directional effects. For example, income is found to have a negative effect on financial satisfaction. While this may be true for individuals who prefer to rely on investments or pensions, rather than wages, in accordance with the existing literature as discussed in Section 1, income would generally be expected to have a positive effect on financial satisfaction – especially for younger individuals. While including age in the model partials out some of the effect of income, the coefficient is still negative and significant at the 5% level. Similar reasoning pulls into question many of the other coefficient estimates. Lastly, age is found to have a positive effect on financial satisfaction, as found in the existing literature, see, for example, Plagnol (2011). Overall, these results suggest that the pooled ordered probit model is mis-specified in some respect. The current set of variables does not appear to be flexible enough to explain the influences of these different financial circumstances on financial satisfaction for all people. This motivates the use of a different modelling approach that allows for such flexibility.[7]

[7] We further explore the counter-intuitive results found in the case of the pooled ordered model by including additional proxies of wealth in the set of explanatory variables. Unfortunately, wealth modules are only available in three waves of HILDA (waves 2, 6 and 10), which severely restricts the number of waves

INSERT TABLE 3 ABOUT HERE

We now turn to the latent class specification. Four life stages are supported by the data (based on the usual Information Criteria metrics), with a substantial amount of parameter heterogeneity across these classes. The positive coefficient on age in the class allocation stage of the latent class model indicates that Class 1 reflects individuals at the earliest life stage, while Class 4 indicates individuals at the latest life stage. In the first life stage the most important factors for financial satisfaction (based on parameter significance) are: marital status; employment; and labour income. The evidence relating to marital status, which may reflect financial stability, has been inconclusive in the existing literature. For example, Hsieh (2001) reports a positive influence associated with being married, whereas Joo and Grable (2004) report a statistically insignificant effect. Our modelling approach highlights the importance of allowing parameter estimates to vary across life stages, with the statistical significance as well as the direction of the effect of some explanatory variables varying across the life stages. The next two life stages reflect a shift to dependence on other sources of income, with labour income losing statistical significance, housing equity and

used for analysis. We have re-estimated the pooled ordered probit model for waves 2, 6 and 10 including a comprehensive set of aspects of household wealth, namely: holding business equity; the value of cash investments; the value of collectibles and other assets; the value of trust funds; the value of equity investments; the value of life insurance and superannuation; cash held in bank accounts; the value of vehicles; amount of credit card debt; student loans; amount of other debt. The full results from this analysis are available on request. The findings related to the additional wealth proxies are in line with expectations with, for example, credit card and other debt being inversely associated with financial satisfaction and asset categories such as investments, trust funds and bank account balances being positively associated with financial satisfaction. After including these additional controls, the counter-intuitive negative effect of income remains, with an estimated coefficient of -0.0166 and a t-statistic of -4.4. In addition, there are several coefficients for which different signs or levels of significance (insignificance) would be expected for people of different ages. For example, a large superannuation balance would likely seem more important to older individuals than for younger individuals. The persistence of such counterintuitive findings suggests that exploring the actual modelling approach is a potentially important line of enquiry.

other investments becoming more important, and government support having a negative effect. Such findings indicate that the influence of labour income is particularly important at the early stage of the life-cycle, with a shift towards assets and asset-based income at later stages of the life-cycle. Such findings not only highlight the importance of allowing parameter estimates to vary by life stages, but also the importance of distinguishing between different income sources. In the final two life stages, in accordance with Plagnol (2011), having a mortgage is also associated with lower financial satisfaction, suggesting a strong preference for less debt in later years of respondents' lives, which may reflect expected decreases in income as individuals approach retirement. Having mortgage debt during the early stages of the life-cycle is not characterised by a statistically significant effect, which may be associated with expecting higher income in the future and being confident about being able to pay-off the debt in the future. Lastly, people in the final life stage who work are less financially satisfied, potentially reflecting those who are forced to work due to a lack of retirement savings and the associated financial insecurity.

In discrete choice models there is no ubiquitous measure of "goodness of fit" as there are in the linear regression world (see Greene (2012), for example). And indeed, many of the models we consider are not nested in the traditional sense of parameter restrictions, such that a standard hypothesis testing approach to (preferred) model selection is not available to us here. To address both of these concerns, we report the common Information Criteria (IC) metrics - B(Bayesian)IC and A(Akaike)IC in Table 3. These are often used in such situations with regard to model selection purposes: the model with the lowest IC (essentially the maximised log-likelihood penalised by the sample size and the number of parameters estimated) is the preferred one. As those for both AIC and BIC are lowest for the latent class ordered probit model (across all models) this would be the preferred model specification over both pooled ordered probit specifications (and also that the pooled ordered probit model including age is preferred over that without age).

Two estimates of the probability of individuals falling into any of the unobserved life-stages are available; see Greene (2008). Prior probabilities are evaluated using the expressions given in equation (2). "Posterior" probabilities, on the other hand, for class q are given by the density conditional on class q, weighted by the probability of being in class q, all divided by the overall likelihood across all classes. The posterior probabilities answer the question: *given that we observe* y_i what it is the probability that the individual belongs to class q? For an individual with average characteristics these prior probabilities are given in Table 4.

INSERT TABLE 4 ABOUT HERE

Average ages in each class (shown in Table 3) are calculated by weighting the age of each individual in the sample by their prior probability of participating in that class. Therefore, the formula used in constructing the average age is:

$$\hat{Age}_j = \frac{\sum_{i=1}^{N}(Pr(\hat{Class}_i = j) \times Age_i)}{\sum_{i=1}^{N} Pr(\hat{Class}_i = j)}$$

Table 4 also presents the latent class posterior class probabilities, which are also shown in Figure 1 in the Appendix.

The prior probabilities suggest that an individual with average characteristics is most likely to belong to either Class 2 or Class 3. However, with regard to the posterior probabilities, conditional on the individual reporting high financial satisfaction (eight or above), the individual is estimated to have a much higher probability of being in Class 4. In addition, the higher the reported financial satisfaction, the lower the likelihood of the individual being in Class 1. However, the posterior probabilities of being in Class 2 or Class 3 are less straightforward. While both posterior probabilities decrease as financial satisfaction increases, life stage two becomes more likely than the third life stage for very high levels of financial satisfaction. This suggests that although financial satisfaction generally improves as individuals get older, the average level of the output variable is not necessarily an increasing function of the latent class index. Overall, it is clear that ordering in the latent classes does not necessarily mean ordering in the average value of the output variable. The positive association of age and financial satisfaction is consistent with research showing that with age comes experience: "...older and more experienced investors hold less risky portfolios, exhibit stronger preference for diversification, trade less frequently, exhibit greater propensity for year-end tax-loss selling, and exhibit weaker behavioral biases" (Korniotis and Kumar (2011), p. 245). After the age of 70, however, cognitive decline trumps experience and portfolios become worse (Korniotis and Kumar (2011)). Therefore, financial satisfaction may, before 70 be a function of better investments and, after 70, a function of not knowing any better.

Partial effects of the covariates on conditional probabilities are largely in line with the estimated coefficients (see Table 5). Some outcomes are grouped in order to reduce the complexity of the tables, namely outcomes 0 to 4 and outcomes 5 to 6. An interesting finding relates to income. Although some partial effects are significant at the five percent level for Class 3, the estimated coefficient on income is not. The effects indicate that individuals who earn higher wages in this life stage are more likely to report lower levels of financial satisfaction. This is consistent with the interpretation of individuals in Class 3 moving into retirement. The partial effects on overall probabilities also resemble coefficient estimates, with the exception of renting, which has significant effects across most outcome probabilities, despite having insignificant estimated coefficients in each life stage (see the overall outcome probabilities). Importantly, income from wages is found to have a relatively small overall effect on financial satisfaction for the average individual, compared to income from investments and housing equity, once again highlighting the importance of distinguishing between different sources of income. For purposes of comparison, we have attempted to estimate a comparable model based on a MNL class assignment equation, *i.e.*, the traditional latent class approach. The fact that this model failed to converge serves to endorse the modelling approach used in this paper.[8]

INSERT TABLE 5 ABOUT HERE

[8] A likely reason for the MNL version of the latent class model failing to converge could be around the lack of structure imposed on class-specific parameters in the MNL specification. While the ordered probit latent class assignment involves stronger assumptions around the manner through which age impacts on class assignment, more parameters are required for the MNL version of the model, and each parameter impacts a greater number of classes than in the case of the OP specification. Hence, we believe that the OP specification has indeed helped to identify the four classes evident in this empirical exercise, which the standard MNL approach would not have found.

4.2 The Impact of Gender

As mentioned above, existing research has considered the effects of gender on financial satisfaction. For example, Plagnol and Easterlin (2008) report that at the beginning of the life course women are more satisfied than men with their financial situation, whereas at the end of the life course, they are less satisfied, whilst DePianto (2011) found substantial differences in the partial effect of personal and family income on financial satisfaction between men and women of different races. However, changes in the gradient of income over different life stages, and the effect of other financial circumstances on financial satisfaction were outside the scope of the DePianto (2011) study. Here these two facets are examined via the estimation of the previous generalised latent class model on male and female sub-populations.

There is a growing body of evidence supporting gender trait differences in financial decisions (Stinerock, Stern, and Solomon (1991); Powell and Ansic (1997); Barber and Odean (2001); Dwyer, Gilkeson, and List (2002); Huang and Kisgen (2013)). Gender differences in finance have been linked to different risk-preferences. Male and female responses to risk have a pharmacological basis; for example, testosterone levels have been found to have a link with the risk adjusted returns of London traders (Coates and Herbert (2008)). Women have been found to have a lower preference for risk than men in other domains such as war games (Hudgens and Fatkin (1985)) and gambling (Levin, Snyder, and Chapman (1998); Johnson and Powell (1994)). Given a financial portfolio with the same characteristics, a man would be less likely to be financially satisfied than a woman. The analyses presented in this section suggest that the differences in financial satisfaction between men and women are not simply functions of different risk preferences. The analyses for men and women indicate that some variables significant for one gender are not significant for the other. When variables are significant for both men and women, the magnitudes of the estimated coefficients differ.

Table 6 shows the results from these estimations. As these models could be estimated by adding a gender interaction term with each of the variables, an overall likelihood-ratio test for heterogeneity can be performed by comparing the sum of the likelihoods to that of the original (constrained) model. Under the null hypothesis of no gender differences, the test statistic is distributed chi-squared, with fifty-three degrees of freedom (= 79.84 at the 1% level). As the sum of the unconstrained model likelihoods is 66,236, and the restricted likelihood is 66,413, the null hypothesis is rejected, and gender differences are found to exist.

INSERT TABLE 6 ABOUT HERE

Significant discrepancies in estimated coefficients are evident in a few variables. For example, income from wages is found to have a positive impact for males in the first class, but then no significant effect thereon. For females, income from wages has a significantly positive effect in Class 2 (perhaps reflecting a focus on material resources post child-bearing age). This is tempered by a significant negative effect in Class 3. Government and investment income is found to have a significant effect on female financial satisfaction earlier than for men (Class 2), and this effect is in line with that found in other classes. An earlier effect on financial satisfaction is also evident for employment status, with women gaining most of the benefit from employment in stage one, while men gain this benefit primarily in stage two.

Self-employment only seems to improve the financial satisfaction of men, however, with no significant coefficients for females across the classes. While renting has little effect on the financial satisfaction of women (as found in the full model), for men the effect is positive early on, then negative in the later three life stages. The effect of mortgages on financial satisfaction is similar across genders, although the negative effect on the latest life stage is statistically significant only for women. Our findings thus serve to illustrate how the drivers of financial satisfaction over the life cycle differ by gender.

5 Conclusion

We have introduced a new modelling approach to allow for the different life stages in exploring the determinants of financial satisfaction. Given the extent to which both income and financial commitments vary over the life cycle, allowing the determinants of financial satisfaction to vary across life stages seems to be a potentially important approach in order to fully understand the drivers of financial satisfaction at the individual level. Four life stages are supported by the data. Our results suggest that such flexibility is important in understanding the drivers of financial satisfaction over the life cycle since there is a substantial amount of parameter heterogeneity across the four classes. Key findings include the effect of labour income on financial satisfaction being largely limited to the earliest life stage with investment income and housing equity playing a more important role later on in the life cycle, which suggests that the role of different sources of income varies across the life cycle. In addition, gender appears to have an important influence on financial satisfaction, with males and females found to value different aspects of their financial circumstances at various different stages of their lives. Our modelling approach, therefore, provides a more accurate picture of the determinants of financial satisfaction at different stages of the life cycle. Given the importance that the policy-makers in a number of countries over recent decades have placed on understanding the wellbeing and overall life satisfaction of individuals, as well as the significance of financial satisfaction for wellbeing and overall life satisfaction, it apparent that our modelling contribution may serve to shed further light in this area from a life cycle perspective.

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Table 1: Summary statistics

Variable	Obs.	Mean	Std. Dev.
Married	33642	0.572	0.495
Ln(income)	33642	8.330	4.078
Gov income	33642	3.181	4.376
Inv income	33642	4.412	3.985
House equity	33642	2.622	2.673
Employed	33642	0.541	0.498
Self Employed	33642	0.115	0.319
Renting	33642	0.188	0.391
Mortgage	33642	0.355	0.478
Age	33642	47.943	15.094

Table 2: Correlation matrix and OLS variance inflation factors

	Age	In(income)	Gov income	Inv income	House equity	Variance inflation factors (OLS)
Age	1					1.88
In(income)	-0.5299	1				2.34
Gov income	0.2989	-0.4868	1			1.63
Inv income	0.2419	-0.0536	-0.1246	1		1.3
House equity	0.2110	0.0013	-0.1421	0.3882	1	1.55

Table 3: Estimation results: financial satisfaction OP and latent class OP models

Covariate	Pooled OP 1	Pooled OP 2	Latent Class OP Class 1	Class 2	Class 3	Class 4
Constant	2.346**	1.823**	0.437	2.298**	2.367**	4.392**
	(0.048)	*(0.072)*	*(0.544)*	*(0.601)*	*(0.177)*	*(0.171)*
Married	0.196**	0.156**	0.544**	0.011	0.367**	-0.278*
	(0.022)	*(0.022)*	*(0.128)*	*(0.368)*	*(0.071)*	*(0.110)*
Ln(income)	-0.018**	-0.077*	0.046*	0.072	-0.038	0.020
	(0.003)	*(0.003)*	*(0.023)*	*(0.068)*	*(0.022)*	*(0.016)*
Gov income	-0.031**	-0.035**	-0.009	-0.046**	-0.060**	-0.013
	(0.003)	*(0.003)*	*(0.026)*	*(0.014)*	*(0.009)*	*(0.011)*
Inv income	0.058**	0.053**	0.019	0.022	0.098**	0.042**
	(0.003)	*(0.003)*	*(0.018)*	*(0.019)*	*(0.029)*	*(0.011)*
House equity	0.040**	0.033**	0.024	0.048*	0.076**	-0.023
	(0.005)	*(0.005)*	*(0.021)*	*(0.024)*	*(0.015)*	*(0.022)*
Employed	0.141**	0.170**	1.024**	0.262	0.108	-0.475*
	(0.029)	*(0.029)*	*(0.327)*	*(0.629)*	*(0.311)*	*(0.220)*
Self Employed	-0.082*	-0.055	0.861	0.100	-0.180	-0.082
	(0.039)	*(0.039)*	*(0.466)*	*(0.304)*	*(0.196)*	*(0.175)*
Renting	-0.303**	-0.243**	1.283	-0.974	-0.190	-0.312
	(0.033)	*(0.032)*	*(0.974)*	*(0.580)*	*(0.190)*	*(0.175)*
Mortgage	-0.266**	-0.210**	0.754	-0.482	-0.307*	-0.552*
	(0.025)	*(0.026)*	*(0.762)*	*(0.286)*	*(0.137)*	*(0.222)*
Age†		0.098**	0.450**			
		(0.011)	*(0.045)*			
Average Age	47.94	47.94	35.1	42.6	51.1	61.1
Log Likelihood	-67,491.7	-67,302.2	-66,413.8			
AIC	135,021	134,644	132,934			
BIC	135,181	134,813	133,380			

** Significant at the 1% significance level * Significant at the 5% significance level; Standard errors in parenthesis; †Refers to latent class equation in Latent Class OP model

Table 4: Financial satisfaction: class probabilities for individual with average characteristics

Class	Prior	Posterior (conditional on financial satisfaction): $0 \leq y_i \leq 4$	$5 \leq y_i \leq 6$	$y_i = 7$	$y_i = 8$	$y_i = 9$	$y_i = 10$
Class 1	9.18%	14.41%	11.20%	8.83%	6.55%	4.07%	1.92%
Class 2	34.44%	30.95%	35.37%	37.30%	35.86%	29.41%	18.15%
Class 3	44.19%	53.87%	50.38%	45.66%	38.29%	27.16%	14.54%
Class 4	12.20%	0.77%	3.05%	8.20%	19.29%	39.37%	65.40%

Table 5: Partial effects

	Class 1						Class 2						Class 3					
Variable	Pr0-4	Pr5-6	Pr7	Pr8	Pr9	Pr10	Pr0-4	Pr5-6	Pr7	Pr8	Pr9	Pr10	Pr0-4	Pr5-6	Pr7	Pr8	Pr9	Pr10
Married	-0.148**	-0.070**	0.067**	0.104**	0.036**	0.011**	-0.002	-0.002	0.000	0.002	0.001	0.000	-0.083**	-0.063**	0.033**	0.073**	0.030**	0.011**
	(0.039)	(0.022)	(0.021)	(0.024)	(0.009)	(0.004)	(0.068)	(0.077)	(0.017)	(0.074)	(0.038)	(0.016)	(0.017)	(0.014)	(0.009)	(0.014)	(0.007)	(0.003)
Ln income	-0.012*	-0.006	0.006*	0.009	0.003	0.001	-0.013	-0.015	0.003	0.014	0.007	0.003	0.009	0.007*	-0.003	-0.007	-0.003*	-0.001*
	(0.006)	(0.004)	(0.003)	(0.004)	(0.002)	(0.001)	(0.010)	(0.016)	(0.002)	(0.013)	(0.008)	(0.004)	(0.005)	(0.003)	(0.002)	(0.004)	(0.002)	(0.001)
Gov income	0.002	0.001	-0.001	-0.002	-0.001	0.000	0.008*	0.010**	-0.002	-0.009**	-0.005**	-0.002	0.014**	0.010**	-0.005**	-0.012**	-0.005**	-0.002**
	(0.007)	(0.003)	(0.003)	(0.005)	(0.002)	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)
Inv income	-0.005	-0.002	0.002	0.004	0.001	0.000	-0.004	-0.005	0.001	0.004	0.002	0.001	-0.022**	-0.017**	0.009**	0.019**	0.008**	0.003*
	(0.005)	(0.003)	(0.002)	(0.004)	(0.001)	(0.000)	(0.003)	(0.004)	(0.001)	(0.004)	(0.002)	(0.001)	(0.006)	(0.006)	(0.002)	(0.006)	(0.003)	(0.001)
House equity	-0.006	-0.003	0.003	0.004	0.002	0.000	-0.009	-0.010*	0.002	0.010	0.005*	0.002*	-0.017**	-0.013**	0.007**	0.015**	0.006**	0.002**
	(0.005)	(0.003)	(0.002)	(0.004)	(0.001)	(0.000)	(0.006)	(0.005)	(0.003)	(0.005)	(0.002)	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)
Employed	-0.273*	-0.129**	0.125*	0.192**	0.066**	0.020**	-0.048	-0.055	0.012	0.052	0.027	0.011	-0.024	-0.019	0.010	0.021	0.009	0.003
	(0.106)	(0.033)	(0.055)	(0.055)	(0.016)	(0.006)	(0.127)	(0.123)	(0.042)	(0.127)	(0.060)	(0.023)	(0.072)	(0.052)	(0.029)	(0.061)	(0.025)	(0.009)
Self Employed	-0.230	-0.109	0.105	0.161	0.056	0.017	-0.018	-0.021	0.005	0.020	0.010	0.004	0.041	0.031	-0.016	-0.036	-0.015	-0.005
	(0.132)	(0.058)	(0.063)	(0.085)	(0.030)	(0.010)	(0.058)	(0.062)	(0.017)	(0.061)	(0.030)	(0.012)	(0.043)	(0.036)	(0.016)	(0.039)	(0.017)	(0.006)
Renting	-0.342	-0.162	0.156	0.240	0.083	0.025	0.178*	0.204	-0.044	-0.195	-0.101	-0.042	0.043	0.033	-0.017	-0.038	-0.016	-0.005
	(0.266)	(0.125)	(0.124)	(0.181)	(0.064)	(0.020)	(0.084)	(0.145)	(0.038)	(0.114)	(0.078)	(0.039)	(0.045)	(0.031)	(0.019)	(0.037)	(0.015)	(0.005)
Mortgage	-0.201	-0.095	0.092	0.141	0.049	0.015	0.088	0.101	-0.022	-0.097	-0.050	-0.021	0.070*	0.053*	-0.027	-0.061*	-0.025*	-0.009*
	(0.203)	(0.101)	(0.092)	(0.143)	(0.051)	(0.016)	(0.060)	(0.060)	(0.029)	(0.058)	(0.031)	(0.014)	(0.034)	(0.022)	(0.016)	(0.027)	(0.010)	(0.003)

** Significant at the 1% significance level   * Significant at the 5% significance level

Note: Standard errors in parenthesis

Table 5: Partial effects (cont.)

	Class 4						Overall outcome probabilities					
Variable	Pr0-4	Pr5-6	Pr7	Pr8	Pr9	Pr10	Pr0-4	Pr5-6	Pr7	Pr8	Pr9	Pr10
Married	0.006*	0.038*	0.046*	0.019	-0.036*	-0.072*	-0.050**	-0.031*	0.026**	0.045**	0.013*	-0.003
	(0.003)	(0.015)	(0.018)	(0.016)	(0.014)	(0.031)	(0.006)	(0.012)	(0.005)	(0.009)	(0.006)	(0.003)
Ln income	0.000	-0.003	-0.003	-0.001	0.003	0.005	-0.002	-0.003	0.000	0.002*	0.002	0.001*
	(0.000)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Gov income	0.000	0.002	0.002	0.001	-0.002	-0.003	0.009**	0.008**	-0.003**	-0.008**	-0.004**	-0.002**
	(0.000)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Inv income	-0.001	-0.006**	-0.007**	-0.003	0.005**	0.011**	-0.012**	-0.010**	0.004**	0.010**	0.005**	0.003**
	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
House equity	0.000	0.003	0.004	0.002	-0.003	-0.006	-0.011**	-0.009**	0.004**	0.011**	0.004**	0.001
	(0.000)	(0.003)	(0.004)	(0.002)	(0.003)	(0.006)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employed	0.010	0.065*	0.078*	0.032	-0.061*	-0.124*	-0.051**	-0.031	0.029**	0.049**	0.012	-0.008
	(0.006)	(0.033)	(0.036)	(0.025)	(0.030)	(0.059)	(0.009)	(0.019)	(0.007)	(0.016)	(0.008)	(0.005)
Self Employed	0.002	0.011	0.013	0.006	-0.010	-0.021	-0.009	-0.002	0.006	0.007	0.001	-0.002
	(0.004)	(0.025)	(0.029)	(0.011)	(0.023)	(0.045)	(0.010)	(0.012)	(0.006)	(0.011)	(0.006)	(0.005)
Renting	0.006	0.043	0.051	0.021	-0.040	-0.081	0.050**	0.075**	-0.002	-0.059**	-0.039**	-0.025**
	(0.005)	(0.028)	(0.028)	(0.015)	(0.025)	(0.044)	(0.015)	(0.016)	(0.014)	(0.010)	(0.009)	(0.006)
Mortgage	0.011	0.075*	0.090*	0.037	-0.071*	-0.144**	0.044**	0.059**	0.000	-0.043**	-0.033**	-0.027**
	(0.007)	(0.038)	(0.036)	(0.024)	(0.034)	(0.055)	(0.009)	(0.009)	(0.008)	(0.010)	(0.004)	(0.006)
Age							-0.012**	-0.024**	-0.008**	0.012**	0.016**	0.015**
							(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)

** Significant at the 1% significance level * Significant at the 5% significance level

Note: Standard errors in parenthesis

Table 6: Coefficient estimates: LC financial satisfaction male/female comparison

	Class 1		Class 2		Class 3		Class 4	
Variable	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Constant	-0.134	1.558	1.585**	1.918**	2.641**	2.210**	4.922**	4.062**
	(0.589)	*(1.820)*	*(0.381)*	*(0.171)*	*(0.186)*	*(0.386)*	*(0.306)*	*(0.317)*
Married	0.841**	0.708**	-0.126	0.154	0.202**	0.497**	-0.362*	-0.177
	(0.203)	*(0.265)*	*(0.158)*	*(0.091)*	*(0.067)*	*(0.094)*	*(0.142)*	*(0.138)*
Ln income	0.165*	-0.115	-0.009	0.076**	0.001	-0.051*	-0.014	0.032
	(0.068)	*(0.180)*	*(0.022)*	*(0.020)*	*(0.009)*	*(0.025)*	*(0.019)*	*(0.017)*
Gov income	0.022	0.055	-0.019	-0.063**	-0.063**	-0.045**	-0.013	-0.023
	(0.034)	*(0.081)*	*(0.014)*	*(0.014)*	*(0.008)*	*(0.015)*	*(0.016)*	*(0.013)*
Inv income	0.000	0.016	0.033	0.032*	0.078**	0.100**	0.041*	0.045**
	(0.029)	*(0.051)*	*(0.019)*	*(0.014)*	*(0.010)*	*(0.017)*	*(0.016)*	*(0.015)*
House equity	0.033	-0.056	0.066*	0.052**	0.081**	0.070**	-0.031	-0.014
	(0.038)	*(0.061)*	*(0.033)*	*(0.016)*	*(0.018)*	*(0.022)*	*(0.039)*	*(0.024)*
Employed	0.258	1.447**	2.172**	0.228*	-0.154	0.138	0.142	-0.626**
	(0.571)	*(0.346)*	*(0.307)*	*(0.116)*	*(0.142)*	*(0.155)*	*(0.285)*	*(0.192)*
Self Employed	0.294	0.489	1.984**	0.252	-0.458**	-0.330	0.193	0.030
	(0.669)	*(0.705)*	*(0.361)*	*(0.160)*	*(0.153)*	*(0.197)*	*(0.233)*	*(0.235)*
Renting	1.674**	0.852	-0.768*	-0.286	-0.456**	-0.232	-0.505*	-0.292
	(0.605)	*(0.661)*	*(0.301)*	*(0.217)*	*(0.125)*	*(0.160)*	*(0.242)*	*(0.230)*
Mortgage	0.668*	1.203**	-0.345*	-0.272*	-0.248*	-0.348*	-0.611	-0.736**
	(0.314)	*(0.393)*	*(0.154)*	*(0.138)*	*(0.099)*	*(0.136)*	*(0.320)*	*(0.231)*
Average Age	34.2	30.6	40.8	40.5	50.9	50.8	63.1	61.1
Log-Likelihood	30073.0	36163.7						

** Significant at the 1% significance level   * Significant at the 5% significance level

Note: Standard errors in parenthesis

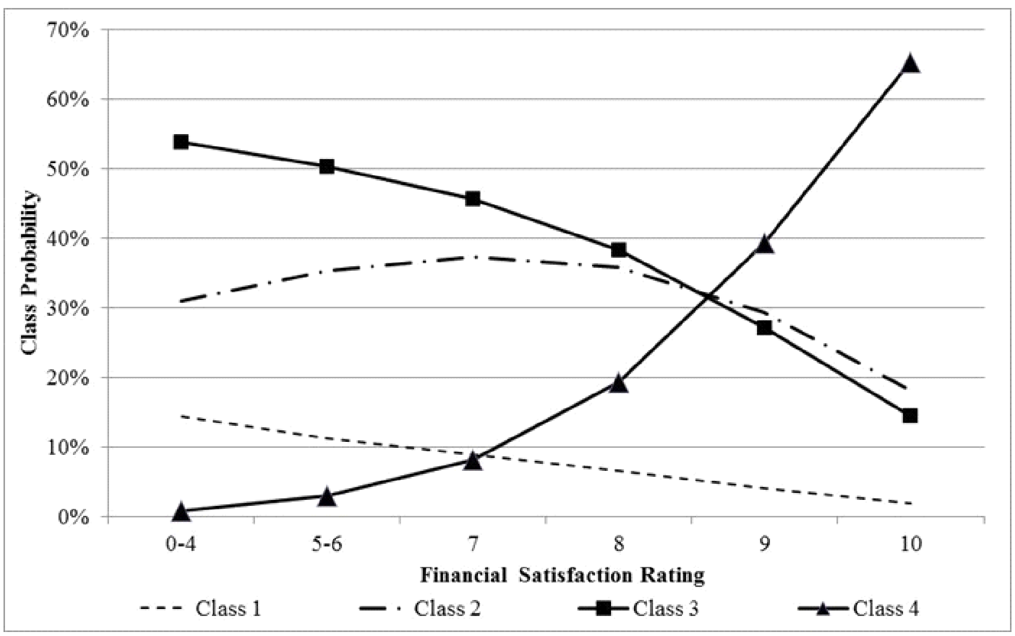

Figure 1: Financial satisfaction - latent class posterior class probabilities