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Experienced versus Decision Utility: Large-Scale Comparison for Income-Leisure Preferences

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Abstract

Subjective well-being (SWB) data is increasingly used to perform welfare analysis. Interpreted as 'experienced utility', it has recently been compared to 'decision utility' using small-scale experiments most often based on stated preferences. We transpose this comparison to the framework of non-experimental and large-scale data commonly used for policy analysis, focusing on the income-leisure domain where redistributive policies operate. Using the British Household Panel Survey, we suggest a 'deviation' measure, which is simply the difference between actual working hours and SWB-maximizing hours. We show that about three-quarters of individuals make decisions that are not inconsistent with maximizing their SWB. We discuss the potential channels that explain the lack of optimization when deviations are significantly large. We find proxies for a number of individual and external constraints, and show that constraints alone can explain at least half of the deviations. In our context, deviations partly reflect the inability of the revealed preference approach to account for labor market rigidities, so the actual and SWB-maximizing hours should be used in a complementary manner. The suggested approach based on our deviation metric could help identify labor market frictions.

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JEL: C90, I31, J22.

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July 6, 2022

Abstract

Subjective well-being (SWB) data is increasingly used to perform welfare analysis. Interpreted as 'experienced utility', it has recently been compared to 'decision utility' using small-scale experiments most often based on stated preferences. We transpose this comparison to the framework of non-experimental and large-scale data commonly used for policy analysis, focusing on the income-leisure domain where redistributive policies operate. Using the British Household Panel Survey, we suggest a 'deviation' measure, which is simply the difference between actual working hours and SWB-maximizing hours. We show that about three-quarters of individuals make decisions that are not inconsistent with maximizing their SWB. We discuss the potential channels that explain the lack of optimization when deviations are significantly large. We find proxies for a number of individual and external constraints, and show that constraints alone can explain at least half of the deviations. In our context, deviations partly reflect the inability of the revealed preference approach to account for labor market rigidities, so the actual and SWB-maximizing hours should be used in a complementary manner. The suggested approach based on our deviation metric could help identify labor market frictions.

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1 Introduction

In Economics, the standard approach to measure well-being relies on the observation of decisions made by supposedly rational (utility-maximizing) agents. The object derived from the 'revealed preference' approach is sometimes referred to as a *decision utility*. For more than two decades, some authors have claimed that this decision utility is not always consistent with the well-being associated with different experiences. They recommend developing measures that focus more directly on *experienced utility* (e.g. Dolan and Kahneman, 2008), such as self-reported information on happiness, life satisfaction or mental health. A growing amount of evidence has shown that such subjective well-being (SWB) information is not pure statistical noise: it reflects some individual heterogeneity that is closely associated with objective measures of well-being and, to some extent, with behavior.[1] Yet, SWB is still seen by many as one argument, among others, in the grand utility function of an individual (Rayo and Becker, 2007, Benjamin et al., 2012, Glaeser et al., 2016).[2] Other studies postulate that SWB answers, commonly provided in survey questionnaires, are consistent with people's revealed preferences (Oswald and Wu, 2010, Decancq et al., 2015).

Whether there is congruence between individual decisions and the SWB derived from these choices is still an open question. This is especially disputable for key economic decisions (such as labor supply), which imply a trade-off between several important dimensions of a good life (e.g. consumption vs. leisure). On the one hand, observed choices may reflect heuristics, optimization errors, or the fact that people have imperfect information about what is good for them. Choices are also potentially limited by many personal constraints (e.g., family obligations) and external factors (e.g., market imperfections), the importance of which is difficult to assess in welfare analyses. On the other hand, SWB may not encompass the totality of what humans are trying to achieve when they make decisions. Individual choices may reflect other life goals (e.g., fame) or values (e.g., helping others) that partly differ from, or sometimes conflict with, the

[1] See Krueger and Schkade (2008) and Oswald and Wu (2010), as well as critical reviews in Senik (2008), Clark et al. (2008), Kahneman and Krueger (2006) or Fleurbaey and Blanchet (2013).

[2] Köszegi and Rabin (2008) argue that both subjective and choice-based measures of well-being contain unique information on a person's true welfare, so that the ideal measure should perhaps combine both types of data.

pursuit of well-being as we measure it in subjective data. Despite these sources of discrepancy, it seems crucial to test whether there is (at least) minimal consistency between decision utility and experienced utility.

This paper proposes a tangible approach to address this question in the context of labor supply decisions. Rather than confronting the ordinal preferences consistent with decision-based versus experience-based welfare metric,[3] we directly compare *actual* working hours (consistent with decision-utility maximization) and *optimal* working hours (from the perspective of experienced utility, i.e. hours that maximize income-leisure satisfaction). The comparison is done on a large scale using nationally representative data (the British Household Panel Survey, BHPS). We necessarily focus on single people, because the joint decision in couples is difficult to apprehend for individual welfare comparisons. Our single-value 'deviation' metric is a practical and convenient representation of the potential discrepancies between decision and experienced utilities, which can be used for inference and for exploring the determinants of these discrepancies – here in the context of labor supply or more generally in analyses which traditionally rely on the revealed preferences approach.

The suggested procedure goes as follows. We start by calculating the distribution of deviations in the sample. To this end, we combine income and leisure satisfaction domains to construct a proxy of experienced utility in the income-leisure domain. We use this SWB measure to estimate an experienced utility function, adopting a flexible approach borrowed from the labor supply literature. Using the estimated parameters and discretized income-leisure bundles, we numerically search for the amount of working hours that would maximize experienced utility and compare them with actual choices. We find a broad overlap between actual work hours and SWB-maximizing work duration. The average deviation is close to zero (-2.9 hours). The negative sign implies that people 'overwork' on average according to SWB maximization, but the deviation is not significantly different from zero for 72% of the individuals in the sample. In other words, for a majority of people, actual decisions are not inconsistent with the maximization of their income-leisure satisfaction. We then attempt to describe the large discrepancies

[3] This alternative approach is used in Akay et al. (2020) where money metrics are derived from ordinal preferences consistent with either decisions or subjective experience.

observed for specific population subgroups (e.g., by gender, family composition, region of residence, etc.), either characterized as 'overworking' (a negative mean deviation) or 'underworking' (a positive mean deviation) from a SWB perspective. Results suggest intuitive patterns regarding the direction of the deviations. For instance, those living in London significantly overwork (suggesting social norms or labor market constraints) while those with children tend to work too little (suggesting childcare constraints or labor contracts that are not flexible enough). A detailed analysis by levels of worked hours suggests that significant deviations are primarily due to those at the two ends of the hours distribution, i.e. those out of work or engaged in overtime. We discuss the broad varieties of factors that can explain discrepancies: constraints, optimization errors and non-hedonic life goals. The presence of constraints seems to be the prominent explanation in the labor supply context, as suggested by simple regressions of deviations on a broad set of variables associated with individual constraints (e.g., poor health, family obligations) and labor market constraints (e.g., high local unemployment). The proxies for these constraints, as identified from the survey, can explain around half of the variance in individual deviations. These results are robust to alternative measures of experienced utility, alternative functional forms for experienced utility functions, alternative sample selection (e.g., adding job-seekers and the self-employed), the modeling of individual heterogeneity in SWB levels (either proxied by personality traits or panel data fixed effects) or the addition of heterogeneity in preferences for leisure (alternative sets of 'taste shifters' in work preferences).

The present exercise makes several contributions. *First*, comparison between experienced and decision utility remains rare in the literature. Small-scale experiments in behavioral economics or psychology have greatly contributed to explain some of the difference between subjective and revealed preferences (e.g., Kahneman and Thaler, 2006), notably in the field of public good valuation (Kahneman and Sugden, 2005). The present work is an original attempt to transpose this comparison in large-scale and non-experimental surveys, which are commonly available and used for policy analysis. In this way, it is very complementary to Benjamin et al. (2012) or earlier experiments (Kahneman et al., 1997). While we cannot experimentally control and manipulate the parameters that possibly explain why people do not maximize SWB, we show how to take advantage of a rich household panel survey to pinpoint a set of factors that could potentially explain discrepancies related to constraints.[4] *Second*, our approach is different from the first large-scale comparison suggested by Benjamin et al. (2012), who proxy experienced utility with SWB (as we do) but elicit decision utility using 'stated' preferences.[5] In the present study, we consider actual decisions rather than hypothetical life scenarios underlying stated preferences, which bring the decision-experienced utility comparison closer to the context traditionally used for policy and welfare analyses.[6] *Third*, we focus on a relevant domain for that purpose. Indeed, even though we focus on two dimensions only, the income-leisure domain is crucial for welfare analyses since this is where second-best redistributive policies operate.[7] *Fourth*, our contribution combines different perspectives. Methodologically, we propose a practical way to measure the degree of congruence between decision and experienced utility by means of a deviation metric. Conceptually, we discuss the different channels that can generate large discrepancies, in particular variables related to individual and external constraints. Quantitatively, survey data can explain a reasonable amount of deviations between actual and SWB-maximizing choices. *Finally*, our analysis highlights that experienced utility supplies complementary information that can help investigating the shortcomings of the revealed preference approach, at least in the context of labor supply decisions. We derive implications for future research, notably the fact that deviations derived from SWB could provide a new way to characterize labor market frictions in the labor supply context. Also, the strategy employed

[4] Our work also relates to studies that use panel data to check people's expectations regarding the future implications of their current choices or of major life events (Dolan and Kahneman, 2008, Odermatt and Stutzer, 2019, Frijters et al., 2009), or their ability to adjust behavior when reported SWB indicates that actual choices are sub-optimal (Clark et al., 1998, Frijters, 2000).

[5] In their application, people are asked to decide between virtual jobs with different work hours-earnings bundles. Other recent studies also use hypothetical situations. For instance Clark et al. (2015) elicit the relative weights placed by people on their own income versus on others' income. Benjamin et al. (2014a) evaluate the trade-offs between a large set of potential well-being measures.

[6] Other studies also consider actual choices: Benjamin et al. (2014b) or Glaeser et al. (2016) with residency choices, Fleurbaey and Schwandt (2015) for a whole set of decisions that can potentially affect SWB, Perez-Truglia (2015) for consumption decisions. Frijters (2000) investigate whether a low satisfaction level in a particular area is correlated with the plan to change current conditions in that area. Clark et al. (1998) find that a lower job satisfaction level (slightly) increases the chances of quitting in the future.

[7] In Akay et al. (2020), we suggest a related approach to discuss the implications of using different types of preference elicitation methods for welfare analysis. We estimate ordinal preferences, consistent with either actual choices or income-leisure satisfaction, in order to compute equivalent incomes from the 'fair allocation theory' (Fleurbaey and Maniquet 2006) in both cases and characterize how welfare ranks change when moving from one set of preferences to the other. This analysis is more normative since conclusions depend on ethical priors regarding the degree of individual responsibility upon work aversion.

here can be extended to investigate deviations in other economic areas that rely on the revealed preference approach (e.g., transportation or consumption studies).

The rest of the paper is organized as follows. In the next section, we present the data, sample selection and our empirical approach. Section 3 presents the results in terms of mean deviations, as well as heterogeneity across subgroups, a discussion on the potential channels explaining deviations, and extensive robustness checks. Finally, Section 4 concludes by deriving the methodological and welfare policy implications of our results.

2 Data and Empirical Framework

2.1 Data and Sample Selection

Data. Our analysis is based on data from the British Household Panel Survey (BHPS), a large-scale nationally representative survey collected in the United Kingdom between 1991-2008. It contains information on labor market status and different domains of satisfaction (overall life satisfaction, income and leisure satisfaction) since 1996. This dataset also provides standard information on individual and household characteristics (gender, age, education, health, psychological traits) as well as regional characteristics that shall be used in our empirical analysis. As the SWB information is missing for the years 2006-7, we focus on the period 1996-2005.[8]

Sample Selection. In order to compare decision and experienced utilities in a non-experimental context, we necessarily restrict our analysis to *single* individuals. For individuals living in a couple, comparing their actual working hours to SWB-maximizing hours would be much more complex for several reasons. First, their individual SWB measure, constructed as a combination of income and leisure satisfactions (see below), may be interpreted differently than for singles, especially if, when answering the income satisfaction question, each partner expresses her/his satisfaction about the household total budget rather than referring to the resources

[8] See https://www.iser.essex.ac.uk/bhps for more detail on the dataset.

available to her/him in the household. Second, a person's income-leisure satisfaction would then be estimated on income and leisure variables, but only leisure is individual while income corresponds to total household resources. Indeed, the level of resources accruing to each adult is not observed and is very hard to estimate, as discussed in the literature on collective models of labor supply with nonlinear taxation (see Chiappori and Donni, 2011). Third, the underlying model would be even more complicated since the optimal work duration of a person would depend on her/his spouse's working hours, so that SWB equations for both spouses should be estimated jointly while accounting for an implicit household optimization mechanism. Finally, the reasons discussed above also mean that the interpretation of SWB-maximizing hours – and thus the interpretation of our 'deviation' metric – would be very different than for singles.[9]

We also focus on employed or voluntarily inactive workers in our baseline sample. Indeed, we necessarily apply the same logic as in labor supply models (see van Soest, 1995) as we must assume that income-leisure satisfactions result from a trade-off between consumption and free time. People who are not able to arbitrate between these dimensions should show larger deviations between actual and SWB-maximizing hours than the average. Thus, we exclude people who appear as fully rationed from the labor market, using a standard definition of job seekers,[10] and those not available for work (disabled individuals, full-time students and pensioners). We retain other inactive people, i.e. those who 'voluntarily' choose to be out of work (e.g., for childcare or other activities). The self-employed represent a specific population, with labor supply decisions that may considerably differ from those of salaried workers. Also, in their case, information on worked hours and income may be more prone to measurement errors or misreporting.[11] For these reasons, we do not include them in the baseline sample. Yet, we suggest robustness checks where we re-incorporate job seekers and self-employed in the analysis, increasing the external validity of our demonstration. Finally, we only retain individuals for whom all key characteristics (including socio-demographics) are available for all years. Our

[9] Further work should explore ways to include couples in the analysis, addressing each of the challenges outlined above, but it is likely that further progress in modeling collective labor supply is needed first.

[10] They answer negatively to at least one of the following questions: "Have you actively looked for a job within the last four weeks?" and "Are you ready to take up a job within the next two weeks?"

[11] For a specific study on entrepreneurs and how their expected life satisfaction deviates from future life satisfaction, see Odermatt et al. (2021).

selected sample includes $5,501$ person $\times$ year observations.

2.2 Setup and Measures

Key Variables. The key variables for our analysis are leisure (or, equivalently, working hours) and disposable income. Weekly working hours drawn from the data are denoted h_{it} for an individual i at time t. Assuming a maximum working time of 80 hours per week, we normalize leisure time as the residual, namely $l_{it} = 80 - h_{it}$. Disposable income of an individual y_{it} is calculated as:

$$y_{it} = G_t(w_{it}h_{it}, \mu_{it}, \zeta_{it}), \tag{1}$$

using reported gross labor income $w_{it}h_{it}$ (hourly wage rates w_{it} $\times$ weekly work hours h_{it}), unearned income μ_{it} and a set of individual characteristics ζ_{it}.[12] Function G_t represents the aggregation of all incomes and the imputation of taxes and benefits, using numerical simulations of tax-benefit rules of each period $t = 1, \ldots, T$. The set ζ_{it} represents individual characteristics that matter for tax-benefit calculations and are extracted from the data, for instance the presence of children (which conditions the calculation of child benefits, increment of income support, tax credits, etc.).[13]

Measures of Experienced Utility. In order to predict SWB-maximizing work hours, we must first compute an individual SWB measure focusing on income and leisure dimensions. We denote V_{it}^E such an experienced utility of income and leisure for individual i at period t. Our data contains satisfaction on life domains including income and leisure, which can be combined

[12] Unearned income refers to income not derived from labor such as capital income, property income, rents, and private transfers, etc.

[13] For hourly wage rates, we follow a fairly standard approach, i.e. we calculate them as weekly earnings divided by worked hours for workers, then use this information to estimate Heckman-corrected wage equation (instruments are non-labor income and the presence of children aged 0-2) in order to predict a wage rate w_{it} for non-workers. We assume that gross hourly wage rates do not depend on working duration. This assumption is standard (but sometimes relaxed, for instance in Ilmakunnas and Pudney, 1990). In general, when wages are determined by collective bargaining within branches or sectors, discrimination between full-time and part-time workers is less likely to occur.

for our purpose (see also van Praag et al., 2003). We use the questions "How dissatisfied or satisfied are you with the income of your household / with the amount of leisure time you have?". The answers, measured on an ordered scale between 1 ("not satisfied at all") and 7 ("completely satisfied"), are denoted S_{it}^y for income satisfaction and S_{it}^l for leisure satisfaction. To obtain a proxy for the experienced utility V_{it}^E, we need to combine these domains of satisfaction into a single measure. Yet the relative weight to be put on each of these domains is unknown. Thus, we use the overall life satisfaction question, with the answer S_{it} recorded on a similar 1-7 scale, to infer these weights. We simply estimate

$$S_{it} = \gamma^y S_{it}^y + \gamma^l S_{it}^l + e_{it} \tag{2}$$

and use the estimated coefficients as weights on each domain to compute the experienced utility $V_{it}^E = \widehat{\gamma}^y S_{it}^y + \widehat{\gamma}^l S_{it}^l$. It turns out that the two dimensions play a relatively balanced role, as we find that $\widehat{\gamma}^y/(\widehat{\gamma}^y + \widehat{\gamma}^l) = 0.468$. This combined or *concentrated* income-leisure satisfaction measure, extracted from overall life satisfaction, is our baseline proxy for experienced utility, but alternative approaches will be suggested in the robustness checks.

2.3 A Structural Subjective Well-Being Estimation

To calculate deviations between actual and SWB-maximizing hours, we estimate SWB on income and leisure plus other covariates. Given that this empirical model is then used to predict 'optimal' hours in terms of SWB, it must be specified in a relatively more structural way than usual SWB equations, i.e. we impose some structure similar to the one used in labor supply models. At the same time, we condition SWB on additional determinants of well-being in order to 'clean' the potential noise inherited by subjective measures and following the recommendations in the literature.[14]

[14] Several authors have insisted on the necessity to purge individual SWB measures from idiosyncratic variation in well-being responses and individual-specific circumstances, in order to recover a meaningful preference structure (see Decancq et al., 2015).

Functional Form. First, we assume that V^E can be modeled as a deterministic function $U_{it}^E(y_{it}, l_{it}; x_{it})$ of income y_{it} and leisure l_{it}. Several sources of heterogeneity enter the model. The deterministic utility is conditioned on a vector x_{it} of heterogeneity in terms of underlying income-leisure preferences. Additional controls z_{it} and α_i account for individual observed and unobserved heterogeneity in reported *levels* of well-being. The model is written:

$$V_{it}^E = U_{it}^E(y_{it}, l_{it}; x_{it}) + \lambda' z_{it} + \alpha_i + \epsilon_{it} \tag{3}$$

For the deterministic part, $U_{it}^E(y_{it}, l_{it}; x_{it})$, note that relatively simple functional forms are usually employed in the SWB literature (e.g., empirical models are usually linear, or log-linear in income to capture the concave relationship with well-being, cf. Clark et al., 2008). Few empirical studies add leisure (or working hours) as we do.[15] Since our model must come close to the structure of labor supply models, we suggest a relatively flexible functional form for our baseline estimations, namely a quadratic form in income and leisure with an interaction term (Blundell et al., 2000):

$$U_{it}^E(y_{it}, l_{it}; x_{it}) = \beta_{yy} y_{it}^2 + \beta_{ll} l_{it}^2 + \beta_y y_{it} + \beta_l(x_{it}) l_{it} + \beta_{yl} y_{it} l_{it}. \tag{4}$$

Preference heterogeneity is accounted for by linear variation in the leisure coefficient:

$$\beta_l(x_{it}) = \beta_{l,0} + \beta_{l,1}' x_{it}. \tag{5}$$

In the baseline, the vector x_{it} is composed of individual characteristics that possibly influence work preferences. For simplicity, we use binary variables in x_{it} including male, age above 40, presence of children, and living in London. To allow further heterogeneity, we also introduce personality traits. Among the 'big five', we select conscientiousness and neuroticism as they are shown to be those that matter the most for labor supply choices (see Wichert and Pohlmeier, 2010).[16] We include dummies indicating above-average conscientiousness and

[15] An exception is Knabe and Rätzel (2010) who use a log form on income and a linear or quadratic form for leisure, without interaction terms.

[16] Neuroticism is a fundamental personality trait in the study of psychology characterized by anxiety, fear,

neuroticism. In robustness checks, we will present alternative specifications, for instance using continuous (rather than binary) taste shifters in x_{it} or including the full set of 'big five' personality traits.

Additive and Stochastic Terms. Experienced utility based on SWB measures may reflect individual heterogeneity in the way people perceive and/or report levels of leisure and income satisfactions. This makes it more difficult to assume interpersonal comparability in SWB responses when our aim is to extract subjective preferences on income and leisure. To 'clean' SWB measures, however, we can model heterogeneity in SWB levels through the additive shift represented by $\lambda' z_{it} + \alpha_i$ in equation (3). The first term z_{it} is a vector of the usual determinants of well-being found in the literature (cf. Clark et al., 2008). The second, α_i, correspond to time-invariant unobserved heterogeneity. It can be proxied in several ways. In our baseline approach, we rely on the complete set of personality traits (the 'big five' on a 1-4 scale). These traits are usually seen as capturing a large part of the time-invariant unobserved heterogeneity in SWB (Boyce, 2010, Ravallion and Lokshin, 2001). Residuals ϵ_{it} are i.i.d. and normally distributed error terms so the model can be estimated by standard linear estimation methods on pooled year; in robustness checks, maximum likelihood is used when nonlinear specifications of U_{it}^E such as Box-Cox, are tried. We will also examine alternative modeling of α_i including quasi-fixed effects à la Mundlak and fixed effects in panel estimations.

Identification. The estimation of the β parameters, interpreted as underlying preferences, may be biased due to omitted variables. This will be the case if actual unobserved heterogeneity in work 'preferences' (e.g., to be morally obliged to work a lot to support the family or, inversely, to stay home to care for a sick parent) is correlated with other unobserved determinants of well-being (e.g., experiencing stress due to moral obligations). Two modeling choices tend to reduce these concerns and support the identification of the model. First, we account for individual heterogeneity – notably in the form of relevant personality traits – both in work preference

moodiness, worry, envy, frustration, jealousy, and loneliness. Conscientiousness is the personality trait of being thorough, careful, or vigilant, implying the desire to do a task well.

parameters through x_{it} and in (separately additive) well-being terms z_{it}. Second, as used in the labor supply literature (Blundell et al., 1998), we avail of spatial and temporal variation in net wages due to variation in tax-benefit rules in function G. In particular, when pooling different years of data, the same individual may not make the same labor supply choice because she faces different work incentives due to different tax-benefit schedules, i.e. different functions G_t, over the periods $t = 1, ..., 10$.[17] These approaches are the best we can do in the present setting but we cannot exclude that some biases remain.

2.4 Construction of the Deviation Metric

Our approach focuses on a direct comparison between 'actual' hours (consistent with decision utility) and 'optimal' hours (in the perspective of SWB-maximization). The deviation between these measures can be seen as a 'projection error' in the sens of Loewenstein et al. (2003) and Loewenstein and Adler (1995), but that would entail a particular interpretation whereby SWB-maximizing errors represent failures of individuals to decide optimally according to their genuine preferences. More generally, deviations cannot be taken *prima facie* as errors if people face some types of constraints (due to health, family, labor market rigidities, social norms, etc.) or pursue other goals than maximizing their short-term SWB (which we can refer as non-hedonistic objectives, by simplification).

Our statistic of interest is a deviation D_{it} defined, for each individual i at time t, as

$$D_{it} = h_{it} - h^*_{it}, \tag{6}$$

namely the observed actual working hours h_{it} minus the experienced utility maximizing hours

[17] By pooling 10 years of data, we obtain much variation in the British tax-benefit schedules, compounded with spatial variation (e.g. council taxes are specific to England, Scotland, Wales and Northern Ireland). Indeed, the British system has experienced deep changes over the years under study, notably with the important reforms undertaken by the "New Labour" government regarding income tax, social insurance contributions, council taxes, income support and tax credits for working poor families (an extensive description of these reforms can be found in Blundell et al., 2000, and Adam and Browne, 2010).

h^*_{it} formally defined as:

$$h^*_{it} = \arg\max_{h_{it}} U^E_{it}\left(G_t(w_{it}h_{it}, \mu_{it}, \zeta_{it}), 80 - h_{it}; x_{it}\right). \tag{7}$$

In practice, we first estimate the model described by equations (3)-(5) and obtain the parameters of the deterministic part of the experienced utility function U^E_{it}. Thus, we can calculate h^*_{it} by means of numerical optimization of a discrete version of the model.[18] To investigate statistical significance of the estimated D_{it}, the standard errors are calculated using bootstrap, which goes as follows. We first draw $R = 200$ random bootstrap samples from our overall dataset and estimate model (3)-(5) repeatedly. Then, we calculate the bootstrapped standard error of D_{it} for each individual i and period t.

3 Results

We briefly discuss the estimation of the experienced utility function. We then move to the overall distribution of deviations D_{it} and analyze the heterogeneity in deviations with respect to observed individual characteristics and for different levels of working hours. Next, we provide a discussion on the potential explanations for large deviations and attempt to measure the extent to which they are associated with individual and external constraints that may hinder choices. Finally, we present an extensive robustness analysis in terms of sample selection, SWB definition/measure, preference heterogeneity, treatment of the unobserved heterogeneity and estimation methods.

[18] First, an agent i at period t is assumed to face J income-labor pairs, denoted (y_{ijt}, h_{ijt}), $j = 1, ..., J$. In the baseline, we opt for $J = 7$ discrete options corresponding to weekly work hours h_{ijt} from 0 ($j = 1$) to 60 ($j = 7$) with a step of 10 hours. With total time available for work normalized to 80 hours per week, leisure $l_{ijt} = 80 - h_{ijt}$ ranges from 80 to 20 hours per week. As seen later, our results do not change much when using a thinner grid ($J = 13$). For each hour option j, disposable income $y_{ijt} = G_t(w_{it}h_{ijt}, \mu_{it}, \zeta_{it})$ is easily calculated using gross hourly wage rates w_{it} and discretized values of hours h_{ijt}. Then, we numerically search the option j, hence the hour h_{ijt}, which maximizes U^E_{it}.

3.1 Estimation Results

Baseline estimations of experienced utility, used to calculate deviations, are presented in model (I) in Table A.1 in the appendix. We only report the estimates of the deterministic part U_{it}^{E} since we are mainly interesting in the respective roles of income and leisure in the variation of SWB between individuals. As expected, we observe a significant, increasing and concave effect of income on income-leisure satisfaction. Results for leisure are less clear, and most coefficients are insignificant, but this is due to the fact that many leisure terms enter the model. If we restrict the deterministic utility to a simple quadratic form without interaction and taste shifters on leisure, we find that both leisure terms are significant, as shown in model (II). Leisure has a positive and concave effect in this case. If we add taste shifters, in model (III), we do not reject the significance of the whole set of leisure terms, i.e. the quadratic term and the various linear terms (p-value of 0.022). Turning back to the complete model (I), we also see that preference shifters on leisure are broadly insignificant, which is also due to the fact that these variables enter the model additively through z_{it} (for socio-demographic variables) and α_i (for psychological traits). If we ignore these additive controls, as in model (IV), the role of preference shifters reappears more distinctively. Their effects tend to increase the value of leisure for men, Londoner or people with high conscientiousness. Inversely, it puts a lower weight on leisure for women and especially single mother. This result anticipates the characterization that comes next: those who tend to overwork (underwork) value leisure more (less) in their actual income-leisure situation.

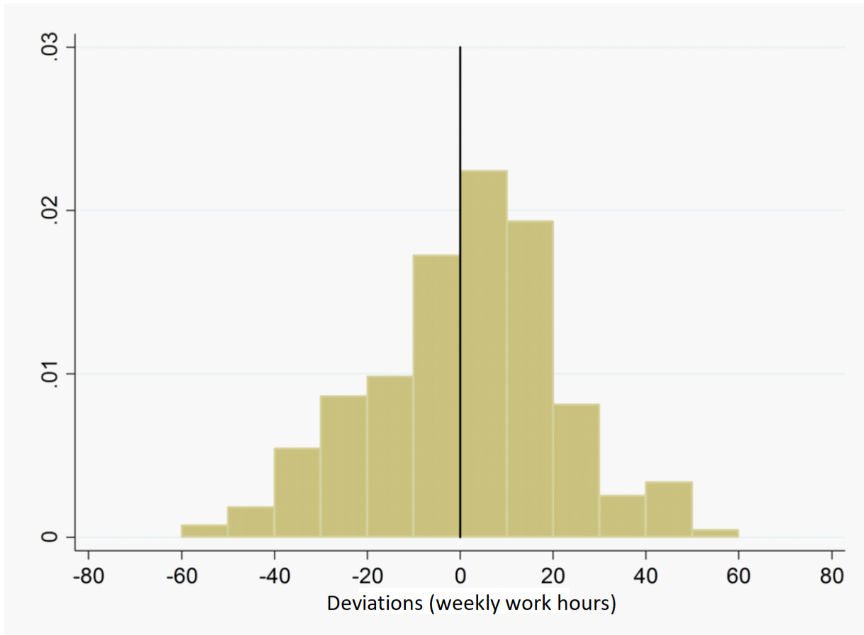
3.2 Deviations

Distribution of Deviations: Overall Characterization. We now present deviations between actual and SWB-maximizing hours using the baseline model. We calculate deviations $D_{it} = h_{it} - h_{it}^{*}$ for every person-time units of observation. Figure 1 shows their distribution: it is single-peaked, relatively symmetrical and with a mode close to zero. As reported in the first row of Table 1 (first column), the mean D_{it} is -2.9 weekly hours. That is, on average, individuals work 2.9 hours less than their SWB-maximizing work duration. The bootstrapped standard errors in parentheses indicates that overall, the mean deviation is not significantly different from zero at conventional levels. This means that on average, actual labor supply choices – implying maximization of decision utility – are consistent with choices that maximize experienced utility. Note, however, that the mean D_{it} is the result of positive or negative deviations, which differ for each individual and period in the sample. Thus, we also calculate the bootstrapped standard error for each observation in the sample and report in the next columns the frequency of observations for which deviations are significantly different from zero, negative or positive at the 5% level. For the whole sample, the deviations are significantly nonzero in 28% of cases, and correspond mostly to significantly negative deviations, which is consistent with the slightly negative average deviation. In other words, for 72% of the observations, there is no strong dissonance between actual choices and hours that would maximize SWB.[19]

Comparison with the Literature. Despite the non-experimental context, our results are close to the conclusions of controlled experiments. Namely, the bulk of observed choices are consistent with the pursuit of individual satisfaction. In particular, Benjamin et al. (2012) show that most (but not all) individuals are able to predict their SWB at the moment of deciding about (hypothetical) job opportunities. Benjamin et al. (2014b), looking at actual residency choices, show that SWB scores are correlated with the ranking of actual choices (even if the tradeoffs between aspects of residency tend to be different). Fleurbaey and Schwandt (2015) ask people if they can think of changes that would increase their SWB score. About 60% cannot think of an easy improvement, i.e. feel as if they currently maximized SWB. Clark et al. (2015) also find similar relative concerns in SWB regressions and in hypothetical-choice experiments. Our results are in line with the optimistic view that there is overall congruence

[19] Compared to studies people's views on what would be their best option for maximizing SWB (see Fleurbaey and Schwandt, 2015), we rely on a prediction of this optimal choice using our estimated experienced utility model. This means that some of the deviation may come from prediction errors. We argue that this issue is limited given our rich structure in terms of preference heterogeneity. Also, it is unlikely that unobserved heterogeneity drives the deviation measures upward or downward systematically, either for the whole sample or for broad population groups. Thus, comparing the sign and size of deviations across these groups may still reveal different exposures to the factors that limit the ability to maximize SWB. This is what we check in the next sub-sections.

Figure 1: Distribution of Individual Deviations



Note: Authors' own calculations from the BHPS. Deviations (horizontal axis) are defined as the distance between observed worked hours and SWB-maximizing hours. The mean deviations is -2.9 hours with a standard error of 5.7 hours. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrapped samples.

between revealed and subjective preferences,[20] but perhaps the most interesting aspect is when there is not, which is what we study below.

3.3 Discrepancies and Suggestive Explanations

Observed Heterogeneity. Deviations are small on average and infrequent. Yet, larger discrepancies appear for specific groups, as illustrated in Table 1 from the second row onwards. We observe that the average deviation is positive and large for men (11.5 hours, s.e. 7.2) and Londoners (19.9 hours, s.e. 7.4). This can be interpreted as if these two groups of individuals were working 'too much' from a SWB maximization perspective. Inversely, women and

[20] This is not always the case. Ferrer-i-Carbonell et al. (2011) compare the estimates on job characteristics in choice equations using vignettes to those on the same characteristics in determining the respondent's own job satisfaction, finding significant differences. Perez-Truglia (2015) shows that real consumption is well predicted by life satisfaction but not by economic satisfaction.

Table 1: Mean Deviations: Overall and by Group

		Mean deviation (working hours)	Proportion of deviations that are		
			nonzero	negative	positive
For the whole sample		-2.9	0.28	0.19	0.10
		(5.7)			
For specific groups:					
Gender	Female	-11.1	0.31	0.27	0.04
		(7.6)			
	Male	11.5	0.24	0.04	0.20
		(7.2)			
Age	Young	-7.6	0.31	0.25	0.06
		(6.2)			
	Old	3.4	0.25	0.10	0.15
		(6.1)			
Children	No	6.3	0.19	0.05	0.14
		(6.1)			
	Yes	-20.5**	0.46	0.45	0.02
		(9.3)			
London	No	-4.6	0.27	0.20	0.07
		(6.1)			
	Yes	19.9***	0.53	0.02	0.51
		(7.4)			
Conscientiousness	Low	0.9	0.29	0.16	0.13
		(5.9)			
	High	-7.7	0.28	0.22	0.06
		(6.4)			
Neuroticism	Low	-1.8	0.27	0.17	0.10
		(5.8)			
	High	-4.0	0.30	0.21	0.09
		(6.2)			

Note: Authors' own calculations from the BHPS. Deviations are defined as the distance between observed worked hours and SWB-maximizing hours. Standard errors in parentheses are calculated for each individual i and time t using estimates from 200 bootstrapped samples. *, **, and *** indicate significance levels at 10%, 5%, and 1% respectively.

single parents seem to work 'too little' as their mean deviation is negative on average. The fraction of statistically significant deviations ranges from 24% to 53% and is consistent across groups: large proportions of significant discrepancies are seen when the mean deviations is large in absolute terms (e.g. positively for Londoners or negatively for single parents). The last two columns confirm that the sign is right. For instance, the very large mean deviation for Londoners coincides with almost all of the significant deviations being positive.

These results are also consistent with the simple intuitions from the SWB estimates above, which already revealed the overworked or underworked groups to some extent. We provide more extensive interpretations on the nature of these discrepancies below. Beforehand, Table 2 reports the distribution of deviations by actual work duration (expressed by discretized weekly hours). People working a standard full time (30 or 40 hours per week) show small average deviations – and a low rates of significant deviations – compared to those at the extremes of the hour distribution (0-20 and 50-60 hours). As expected, those at zero hours tend to work 'too little' and those at 50-60 hours per week appear to work 'too much' from a SWB perspective. The remaining columns of Table 2 show the result by gender, which we comment later. We will also discuss the fact that zero or reduced work hours may largely reflect labor market constraints. Note that we have excluded job seekers from our baseline sample, who are possibly rationed out of the labor market because of keynesian or classic unemployment. With this interpretation, the extent of underworked situations would be even larger if we included them, which we do in robustness checks. That said, there may also be a fair amount of rationing in our baseline sample, namely among inactive people who declare not looking for a job. This could be the case of discouraged workers (people who have given up searching for a job because of labor market conditions) or of those financially disincentivized to work (due to low productivity and/or high childcare costs).

Broad Factors explaining Deviations. Large deviations may be explained by three broad types of mechanisms: constraints, mistakes and alternative life goals. First, the presence of *constraints* that prevent first-best choices pertains to indvidual factors (e.g., family obligations) or external ones (such as market imperfections for credit, labor or housing markets). This explanation is very likely in our context, especially the role of labor market constraints, as shown below.[21] Constraints may explain, at least partly, the contrasted pattern observed for men versus women in Table 1. The fact that women work 'too little' from a SWB perspective may result from under-employment due to labor market rationing, discrimination (Petrongolo,

[21] See also the evidence based on desired hour information (for instance in Bryan, 2007, Böheim and Taylor 2004 or Ilmakunnas and Pudney, 1990). Yet, note that when information on desired hours is available, it is difficult to make sure that individuals' answers to the preferred hours question only reflect preferences (and are not themselves affected by some constraints).

Table 2: Deviations: by Discrete Hour Level

Hours of work	All				Male				Female			
	Mean deviation	Proportion of deviations significantly			Mean deviation	Proportion of deviations significantly			Mean deviation	Proportion of deviations significantly		
		nonzero	negative	positive		nonzero	negative	positive		nonzero	negative	positive
0	-34.6***	0.78	0.78	0.00	-27.2***	0.66	0.66	0.00	-35.6***	0.80	0.80	0.00
	(7.8)				(7.6)				(8.7)			
10	-16.9**	0.31	0.31	0.01	-4.2	0.21	0.16	0.05	-18.3**	0.33	0.33	0.00
	(7.3)				(7.2)				(8.1)			
20	-14.4*	0.30	0.27	0.03	-0.8	0.14	0.08	0.06	-15.4*	0.31	0.28	0.02
	(8.1)				(7.6)				(8.6)			
30	-4.7	0.09	0.06	0.03	3.9	0.16	0.00	0.16	-6.2	0.08	0.07	0.01
	(7.1)				(6.3)				(8.0)			
40	7.9	0.10	0.00	0.10	12.8	0.14	0.00	0.14	2.6	0.06	0.00	0.06
	(5.5)				(7.2)				(7.6)			
50	19.8***	0.41	0.00	0.41	23.6***	0.58	0.00	0.58	13.8	0.13	0.00	0.13
	(6.1)				(7.6)				(8.7)			
60	31.9***	0.83	0.00	0.83	35.4***	0.96	0.00	0.96	25.5***	0.61	0.00	0.61
	(6.0)				(7.9)				(8.2)			

Note: Authors' own calculations from the BHPS. Deviations are defined as the distance between observed worked hours and SWB-maximizing hours. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrap samples. *, **, and *** indicate significance levels at 10%, 5%, and 1% respectively.

2004) and sticky floor, or low financial gains from work for low-skilled women and those facing high childcare costs (Blundell et al., 2000, 2008, Viitanen, 2005). More generally, constraints seem a good explanation for the pattern in Table 2, whereby large discrepancies are concentrated at extreme hours. Large negative (positive) deviations and a high frequency of people reporting underwork (overwork) situations are found for people with no or small activity (long working weeks) and especially for women (men).

The second type of factor explaining deviations pertains to *optimization errors* from a SWB perspective.[22] In our context, people may fail to predict the future satisfaction levels resulting from their choices when they had to make a labor supply decision (see also Odermatt et al., 2021, and Odermatt and Stutzer, 2019). They may work 'too much' due to peer pressure or to a 'focusing illusion' on the importance of income for instance.[23] This might explain some

[22] This aspect is extensively investigated through numerous experiments in the behavioral economics literature, exploring different dimensions of suboptimality (such as projection errors à la Loewenstein et al., 2003, and Loewenstein and Adler, 1995), excessive aspirations, heuristics or 'focusing illusions' (Kahneman et al., 2006).

[23] People may focus on one aspect (income) while ignoring the effect of hedonic adaptations to a certain level of wealth (Di Tella et al, 2010, Kahneman and Thaler, 2006). Kahneman et al. (2006) state that "despite the

of the differences between Londoners and the rest of the UK, if there are regional differences in aspirations and positional concerns (e.g., local norms may generate adaptive preferences leading to workaholism, cf. Golden and Altman, 2008). Gender differences in career-orientation or concern for status may also explain that men suffer from doing more excessive overtime, as illustrated in Table 2 (e.g., Frijters, 2000, consistently find that men are more likely to find their job important, indicating a higher level of ambition). Note that concepts are not mutually exclusive, which makes interpretations even more difficult. For instance, suboptimal behavior (e.g. excessive overtime or workaholism) may be due to a combination of ambition, status concerns and psychological biases (e.g., the need for recognition, etc.) and/or normative constraints or associated beliefs (e.g., demanding job rhythm due to social pressure on the high-skilled, the Londoners, etc.).[24]

The third mechanism is of a somewhat opposite nature: actual decisions may be more relevant than SWB if they reveal *other life goals* than the pursuit of short-term personal satisfaction (as we measure it). Life goals may be different because of altruism (e.g., working hard to provide for one's children, to leave a bequest, etc.), intertemporal optimization (e.g., working hard to save for later, to reach fame, etc.) or alternative objectives that diverge from SWB (e.g. moral objectives, honor, religious motives, recognition, etc.). It is more difficult to see how this type of factors could explain observed differences between men and women, Londoners and others in our results.[25] Moreover, experienced utility in our baseline is a 'concentrated' measure of income-leisure preferences, which is relatively specific and possibly distant from some of the other life goals.[26]

weak relation between income and global life satisfaction or experienced happiness, many people are highly motivated to increase their income. In some cases, this focusing illusion may lead to a misallocation of time".

[24] See Farzin (2009) and Hamermesh and Slemrod (2008) on beliefs and norms, Loewenstein et al. (2003) on 'projection biases' that can create a tendency to repeatedly increase labor and decrease leisure relative to earlier plans.

[25] We are going to investigate below further subgroups including caring for an elderly person at home (*Family care*, in Table 3), which might relate to this explanation more closely.

[26] Yet, our discussion is predicated on the idea that an individual's response to SWB questionnaires are about maximizing personal immediate gratification while even our income-leisure satisfaction might reflect some of the other life goals or values (for instance if people internalize the future benefits of working hard in the present, the satisfaction of spending time caring for someone else, etc.).

A Focus on Optimization Constraints. Explaining discrepancies between experienced and decision utility for some group is a daunting task. First, it may be difficult to disentangle the three set of factors outlined above. Interpretations of the role of specific factors may not be mutually exclusive. For instance, under-employment due to the care of an elderly parent may be seen as an alternative life objectives or as a 'constraint' (altruistic goal versus moral obligations). Second, it is certainly impossible to find variables that would comprehensively capture these three groups of factors. Non-hedonistic life goals and irrational behavior are especially hard to proxy with the information available in standard surveys such as the BHPS. Consequently, we suggest a simple exercise mainly focusing on constraints. We extract from the BHPS a number of proxies that potentially relate to different barriers on a person's ability to choose her desired working time. We distinguish between external constraints (e.g. pertaining to labor market conditions) and individual constraints (such as family obligations or health conditions). Results are reported in Table 3.

We first use variation in *local unemployment rates* across 12 regions $\times$ 10 periods to capture high versus low tension in the labor market. Recall that we exclude job seekers so that, in our sample, the proportion of underwork by those 'voluntarily' inactive or in small part-time is not very different across regions with high versus low unemployment. However, Table 3 shows that 20% of our observations correspond to people who tend to over-work when there is high unemployment. They may refrain from changing jobs, i.e., to adjust their working time to improve SWB, due to high local employment insecurity. This is consistent with past evidence for the UK using information on desired hours of work (Stewart and Swaffield, 1997, show that many workers would prefer to work less than they do when there is relative scarcity of alternative job opportunities).[27] Next, we see that *ethnic minorities* also seem to face high pressure to work more than what would be in line with income-leisure satisfaction. This seems to prevail over any form of discrimination in terms of access to jobs for the period under study.

We then exploit variation in individual constraints. Individuals' health status might be an important factor as we observe that those in *poor health* tend to work too little from a SWB

[27]

Table 3: Deviations by Proxies for Potential Explanatory Factors:
Optimisation Constraints

Explanatory Factor		Mean deviation	Proportion of deviations that are significantly		
			nonzero	negative	positive
Labor market conditions					
Regional unemployment rate	High	1.8	0.36	0.16	0.20
		(5.3)			
	Low	-4.1	0.26	0.19	0.07
		(6.0)			
Ethnicity	Non-white	9.4*	0.39	0.11	0.28
		(5.4)			
	White	-3.2	0.28	0.19	0.09
		(5.8)			
Personal circumstances					
Health	Poor	-9.5	0.41	0.32	0.08
		(6.2)			
	Good	-2.3	0.27	0.18	0.10
		(5.7)			
Previous unemployment spells	Long	-26.3***	0.62	0.60	0.02
		(6.0)			
	Short/none	-2.0	0.27	0.17	0.10
		(5.7)			
Education	Low	-8.0	0.34	0.27	0.07
		(6.5)			
	High	2.1	0.23	0.11	0.12
		(5.2)			
Family Care	Yes	-35.8***	0.81	0.81	0.00
		(9.1)			
	No	1.9	0.21	0.10	0.11
		(5.6)			
Commuting	High	7.6	0.22	0.02	0.20
		(4.9)			
	Low	-5.0	0.30	0.22	0.08
		(6.0)			

Note: Authors' own calculations from the BHPS. Deviations are defined as the distance between observed worked hours and SWB-maximizing hours. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrap samples. *, **, and *** indicate significance levels at 10%, 5%, and 1% respectively.

perspective. This is also the case of those who have *experienced long unemployment spells* in the past, which may reflect scaring effects or selection, and those with *low education*. Regarding the family, we consider a broader concept than just the presence of children (as some children may be old enough not to require care time). A '*family care*' dummy accounts more explicitly for the fact that a person must take time to care for a person, e.g. an elderly, who is not necessarily living in the household. In Table 3, this situation is associated with extremely large deviation denoting underwork (note that the fraction of negative deviations is even higher than when we use a dummy for the presence of children in Table 1). Admittedly, it could also be interpreted as other life goals (taking care of loved ones); yet, Fleurbaey and Schwandt (2015) show that "family obligations" are among the factors reported as most important for what prevents individuals from achieving greater SWB. Finally, we observe that *long commutes* entail the feeling of working 'too much' while living far from one's work may be due to housing market constraints.[28]

Although the set of explanations in terms of implicit constraints, as mobilized in the previous analysis, may not be exhaustive of all the constraints faced by British workers, we wish to test whether they already explain a substantial part of the observed variation in deviations. We regress D_{it} on these variables in a stepwise way and report the results in Table 4. Column (1) includes labor market conditions and individual factors related to health, past unemployment and education. The signs are in line with previous interpretations: high tensions on the labor market or being from ethnic minorities contribute to an upward pressure on work duration, health contributes to underwork situations and so does the scaring effects from past unemployment or being low-skilled. Column (2) isolates the role of gender, which may pertain, to a large extent, to differences in labor market constraints between men and women. It partly correlates with the low-skill effect (the associated coefficient decreases) but it has a strong independent contribution to under-employment (the R^2 increases by 27 points).[29] Further, Column (3) adds

[28] In Stutzer and Frey (2008), long commuting is indeed negatively correlated with SWB even after controlling for the endogenous sorting of individuals into location choice. Yet our result is also consistent with suboptimal decisions, if people who choose far-away jobs may not be able to correctly guess well-being implications (see Kimball and Willis, 2006). The consequences of a focusing illusion on work and money may include both overtime and lengthy commutes.

[29] We run additional multinomial logit estimations with three alternative: negative deviation, positive deviation and insignificant deviation (the reference category). We find that being female both increases the probability

family care: those in charge are compelled to work less than desired (the effect is substantial, as the R^2 increases by another 12 points). Column (4) refines the picture by adding detailed information on the number of children, which correlates with child age.[30] Column (5) adds high commuting as a potential constraint, which correlates with overwork. Interestingly, this set of 'constraint' variables alone explain in total more than half of the variation in individual deviations (final $R^2 = 0.504$).

3.4 Sensitivity Checks

Finally, we provide an extensive sensitivity analysis of our results. Our findings are summarized in Table 5 (the first row reproduces our baseline results) and discussed below. Detailed results are reported in the appendix.

Alternative Measures of Experienced Utility. Our baseline proxy for experienced utility was a 'concentrated' income-leisure satisfaction measure $V_{it}^E = \widehat{\gamma}^y S_{it}^y + \widehat{\gamma}^l S_{it}^l$, with weights obtained from a regression of life satisfaction S_{it} on income satisfaction S_{it}^y and leisure satisfaction S_{it}^l. In Table 5 (rows 2-5), we suggest alternative proxies for experienced utility. We first employ a more flexible specification of the first stage estimation (row 2), namely quadratic with an interaction term and heterogeneous coefficients (using the same variables x_{it} as in taste shifters for the experienced utility estimation:

$$S_{it} = \gamma_1^y(x_{it})S_{it}^y + \gamma_1^l(x_{it})S_{it}^l + \gamma_2^y S_{it}^{2,y} + \gamma_2^l S_{it}^{2,l} + \gamma^{y,l} S_{it}^y S_{it}^l + e_{it}. \tag{8}$$

We also extend the concentrated measure to other domains of satisfaction (row 3), which may somehow be correlated with the appreciation of one's income and time, namely satisfaction

of negative deviations and reduces the probability of positive deviations.

[30] Under-employment appears to be a stronger concern for those with only one child while it has a less depressing effect for larger families (i.e. probably when some children are older and can possibly care for their siblings).

Table 4: Explaining Deviations using Proxies for Constraints

	(1)	(2)	(3)	(4)	(5)
High regional unemployment	5.701***	6.664***	6.750***	6.798***	6.503***
	(1.059)	(0.926)	(0.832)	(0.827)	(0.806)
Non-white ethnic origin	11.40***	12.59***	12.00***	12.62***	12.27***
	(2.488)	(2.485)	(1.962)	(2.016)	(1.962)
Poor health	-3.892***	-2.313*	-0.724	-0.730	-0.830
	(1.486)	(1.185)	(1.031)	(1.011)	(0.978)
Long unemployment spells	-18.56***	-20.59***	-23.69***	-23.69***	-23.13***
	(1.470)	(1.358)	(1.339)	(1.336)	(1.325)
Low education	-7.478***	-4.308***	-0.973	-0.809	-0.515
	(0.964)	(0.746)	(0.664)	(0.665)	(0.665)
Female		-22.29***	-18.59***	-18.09***	-18.05***
		(0.691)	(0.647)	(0.717)	(0.711)
Family care			-22.44***	-23.18***	-22.68***
			(1.031)	(1.036)	(1.036)
One child				-3.720***	-3.505***
				(0.924)	(0.914)
Two children				0.151	0.380
				(0.973)	(0.973)
Three children				2.990*	3.287**
				(1.663)	(1.648)
Four or more children				10.40***	10.72***
				(3.111)	(3.071)
High commuting					4.039***
					(0.714)
Constant	-0.519	11.83***	10.74***	10.74***	9.798***
	(0.604)	(0.591)	(0.553)	(0.552)	(0.579)
R^2	0.108	0.375	0.490	0.499	0.504
#Obs	5,501	5,501	5,501	5,501	5,501

Note: Authors' own calculations from the BHPS. The dependent variable is the deviations. It is defined as the distance between observed worked hours and SWB-maximizing hours. The models are estimated using OLS with robust standard errors. *, **, and *** indicate significance levels at 10%, 5%, and 1% respectively.

with health (he) and housing (ho):

$$S_{it} = \gamma^y S^y_{it} + \gamma^l S^l_{it} + \gamma^{he} S^{he}_{it} + \gamma^{ho} S^{ho}_{it} + e_{it}. \tag{9}$$

We then suggest a measure based on a Principal Component Analysis (PCA) of income and leisure satisfactions (row 4). In all these cases, results are very close to the baseline, with salient groups affected by under-employment (women, those with poor health or previous experiences of long unemployment spells) or excessive overtime (Londoners). Detailed results are shown in Table A.2 in the appendix (columns 2-5). Note that a last variant (in row 5 of Table 5) takes overall life satisfaction S_{it} as a measure of experienced utility V^E_{it}. Overall satisfaction is noisy, mixes many life dimensions and absorbs much individual heterogeneity, so results are different and point to large deviations. Nonetheless, the aforementioned differences between groups (e.g. with or without family care) are still visible qualitatively (see column 5 of Table A.2). Yet the use of overall satisfaction is not very informative.

Functional Forms and Hour Discretization. We also check the sensitivity of our results to alternative parametric forms for the deterministic part of experienced utility $U^E(y_{it}, l_{it}; x_{it})$. Results are place in Table 5 (rows 6-9) (and detailed estimates shown in appendix Table A.3, columns 6-9). We first use a less flexible quadratic form whereby separability between income and leisure is imposed (row 6):

$$U^E_{it}(y_{it}, l_{it}; x_{it}) = \beta_{yy} y^2_{it} + \beta_{ll} l^2_{it} + \beta_y y_{it} + \beta_l(x_{it}) l_{it}. \tag{10}$$

That is, there is no income × leisure interaction term, as in Knabe and Rätzel (2010) or the alternative specifications discussed in section 3.1. Inversely, we suggest a more flexible polynomial form, namely a cubic specification including all possible interaction terms between income and leisure (row 7). Two other functional forms are popular in welfare economics, namely the log-linear utility (row 8):

$$U^E_{it}(y_{it}, l_{it}; x_{it}) = \beta_y \ln y_{it} + \beta_l(x_{it}) \ln l_{it}, \tag{11}$$

often used in SWB studies (e.g., Clark et al., 2008) and capturing some nonlinearity in income and leisure, and the Box-Cox utility (row 9):

$$U_{it}^{E}\left(y_{it}, l_{it}; x_{it}\right) = \beta_y \left(\frac{y_{it}^{\lambda_y} - 1}{\lambda_y}\right) + \beta_l(x_{it}) \left(\frac{l_{it}^{\lambda_l} - 1}{\lambda_l}\right) \tag{12}$$

used in numerous empirical studies (e.g. Decoster and Haan, 2015). All these models include taste shifters on the composite leisure term $\beta_l(x_{it})$. In all these cases, results are very similar to the baseline. There are small variations, especially in the log-linear case, which is arguably more restrictive. Yet, our conclusions are broadly robust to the choice of the functional form imposed on the deterministic part of the experienced utility function.

Regarding the discretization used to compute deviations, we account for $J = 7$ different income-leisure pairs (y_{ijt}, h_{ijt}) in the baseline, corresponding to weekly work hours from 0 ($j = 1$) to 60 ($j = 7$) with a step of 10 hours. This grid seems precise enough to accommodate any actual choices. However, the approximation may lead to measurement error when assessing the degree of deviations. Thus, we experiment with a thinner grid, namely $J = 13$ points with a step of 5 hours. Results show that the mean deviation increases slightly (row 10), but not the share of individuals with a significant error. The heterogeneity across groups is very similar to the baseline (see last column of Table A.3).

Treatment of Additive Individual Heterogeneity. In model (3), the part of the utility not related to income and leisure is supposed to capture individual heterogeneity in how people perceive and report their well-being. For that purpose, we have included observed individual characteristics as additive shifters z_{it} and a time-invariant individual effect α_i based on key psychological traits (as sometimes done in the literature, cf. Boyce, 2010). Alternatively, we can use panel estimations of the experienced utility function with α_i modeled as fixed effects (FE), random effects (RE) or quasi-fixed effects (QFE) à la Mundlak. Relying only on 'within' variation, QFE à la Mundlak are modeled as RE plus the time average of relevant time-varying controls in the estimation (time-variant variables in the auxiliary distribution of unobserved

Table 5: Robustness Checks

		Mean deviation	Proportion of significant deviations
1	Baseline	-2.9	0.28
		(5.7)	
Alternative Definitions of SWB			
2	Quadratic in income and leisure satisfactions, with demographic shifters	-3.5	0.25
		(4.7)	
3	Linear in income, leisure and additional satisfaction domains	-6.7	0.30
		(5.0)	
4	PCA income-leisure satisfaction	-5.1	0.28
		(5.9)	
5	Overall life satisfaction	-16.7***	0.48
		(6.4)	
Alternative Functional Forms			
6	Quadratic no interaction	-3.2	0.29
		(5.8)	
7	Cubic	-1.9	0.24
		(6.3)	
8	Log-linear	-6.0	0.44
		(7.4)	
9	Box-Cox	-7.5	0.36
		(10.1)	
10	Quadratic with alternative discretization (13 income-labor pairs)	-5.2	0.28
		(5.7)	
Alternative Treatments of Additive Heterogeneity			
11	Fixed-effects	-7.3	0.33
		(5.6)	
12	Random-effects	-4.7	0.28
		(5.4)	
13	Quasi-fixed-effects	-1.6	0.28
		(5.1)	
14	No additive observed heterogeneity	-12.0***	0.55
		(4.2)	
Alternative Specifications of Taste Shifters			
15	Continuous age and personality scores	-4.1	0.39
		(4.3)	
16	Baseline with all big 5	-3.1	0.27
		(5.7)	
17	Baseline with all big 5 and all other explanatory variables	-2.0	0.33
		(6.1)	
Additional Checks: Estimators and Sample Selection			
18	Cross-sectional ordered probit model	-8.6	0.27
		(7.5)	
19	Including job-seekers	-9.7	0.29
		(6.3)	
20	Including self-employed	-6.9	0.40
		(4.2)	

Note: Authors' own calculations from the BHPS. The deviation is defined as the distance between observed worked hours and SWB-maximizing hours. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrap samples. Detailed results for the subgroups are presented in Appendix Tables A.2, A.3, A.4, A.5, and A.6 in the appendix. *, **, and *** indicate significance levels at 10%, 5%, and 1% respectively.

heterogeneity are health status, number of children and region).[31] Estimates of the FE, RE and QFE models are reported in Table 5 (rows 11-13). Reassuringly, results are relatively close to the baseline. A specification without additive terms $\lambda' z_{it} + \alpha_i$ shows extremely noisy results and confirms the point made by Decancq et al. (2015) that an attempt to recover a meaningful preference structure requires to clean SWB from individual heterogeneity. Detailed results are reported in Table A.4 in the appendix.

Preference Heterogeneity (Taste Shifters). We test the sensitivity of our results with respect to the specification of preference shifters x_{it} used in the deterministic part of experienced utility function. In our baseline, the coefficient of leisure varied linearly with the set x_{it}. For the ease of exposition of heterogeneous results across population groups, these shifters were defined as binary variable (male, age above 40, presence of children, living in London, above-average conscientiousness or average neuroticism). In Table 5, we present additional results (rows 15-16), starting with the same set of variables but using intensive form of age (in years) and personality traits (1-4 scale), then expanding shifters to the whole set of personality traits. In both cases, results are similar to the baseline. Finally, we extend the set of shifters by including various variables used in our previous characterization of the potential factors explaining deviations (all characteristics appearing in Table 1 and 3). Many of these variables pertain to the demand side of the labor market or other sources of constraints, rather than preferences, so that this specification can be seen as the reduced form of a more complete model. With some exceptions, results are close to the baseline (row 17), which means that basic taste shifters – that comply more with a labor supply interpretation – also captured much of these other dimensions. Detailed results are presented in Table A.5 in the appendix.

Ordered Probit Estimation and Inclusion of Job Seekers and Self-Employed. We suggest three last sensitivity checks. The first one is the use of an alternative estimation

[31] Indeed, 'between' variation may attenuate differences (as it captures long-term trends possibly smoothed by adaptation) while "within" variation can lead to different estimates (in particular, subjective appreciation of transition in or out of work may be stronger for those who experience these changes over the course of the survey). See Fleurbaey and Blanchet (2013) for a discussion of SWB estimations in the context of panel data.

method. The 'concentrated' satisfaction measure has been treated as a continuous variable for linear estimations. Yet, the satisfaction measures are observed on ordinal scale and we aim to investigate whether the results are sensitive to the choice of estimator. Having calculated the concentrated measure of experienced utility, we transform the variable back to its original ordinal state, i.e., the nearest integer to reconstitute a 1-7 scale as the original income and leisure satisfaction answers. Doing so, we then estimate an ordered probit model (instead of OLS) using the discretized 'concentrated' SWB measure. Results are close to our baseline (row 18 in Table 5 and column 18 in Table A.6).

Our baseline sample has excluded job seekers and the self-employed. We now add these groups of individuals into our analysis for a better external validity. To be able to include job seekers without biasing our main results, we suggest an alternative estimation method based on a double hurdle model (Blundell et al., 2000). Table 5 shows that the intensity of negative deviations increases (row 19), with a mean deviation of -9.7 hours. This is expected since job-seekers are constrained, by definition, and contribute to our characterization of 'underwork'. Yet, they represent only a small percentage of (3%) of the initial sample, which explains why the share of significant deviations increases only slightly (from 28 to 29%). Heterogeneous effects, described in Table A.6, vary a little but do not lead to different conclusions. Among exceptions, we see that the mean error for men is now negative, which translates the fact that job seekers are mainly men rationed out of the labor market.

Finally, we add the self-employed to our baseline sample (the resulting sample is 6,088 observations with 9.6% of self-employed). The inclusion of self-employed workers yields a larger mean deviation (-6.9 hours), which remains statistically insignificant for the whole sample (row 20 of Table 5). However, for this group, the mean deviation is statistically significant and large (last rows of Table A.6). This is not surprising considering that working hours of the self-employed vary with several other factors potentially related to individual life goals (e.g., autonomy, personal ambition among many others). This is consistent with the literature suggesting that the self-employed might suffer from mispredicting their well-being in relation to their actual working hours (e.g., Odermatt and Stutzer 2019, Odermatt et al. 2021).

4 Concluding Discussion

This paper originally compares decision and experienced utility using a large household survey. We focus on labor supply decisions, motivated by the fact that income-leisure domains crucially matter for welfare analysis and the design of redistributive policies. To this end, we estimate a series of experienced utility functions, with a structure similar to that of labor supply models, and we derive for each individual the 'deviation' between the actual choice (consistent with decision utility) and the choice that would maximize her experienced utility. We find a high proportion of insignificant deviations, indicating a broad congruence between actual hours of work and SWB-maximizing decisions. However, deviations can be very large in some groups and explained by a variety of factors. Nonetheless, our analysis provides suggestive evidence that personal constraints (family obligations) and labor market constraints explain the bulk of these discrepancies.

In the particular context of labor supply and policy analysis, the methodological implication of our work is that there should be ways to improve our modeling of employment decisions by combining information on actual choices and the self-reported well-being derived from individual situations. Our deviation metric could be used as an original way to elicit labor market frictions and could be compared to other attempts to account for restrictions in labor supply models (e.g. Altonji and Paxson, 1982, Ilmakunnas and Pudney, 1990, Dickens and Lundberg, 1993, van Soest, 1995, Aaberge et al., 1999, Dagsvik and Strøm, 2006, Bloemen, 2008, Beffy et al., 2016).[32] A more systematic characterization of how deviations vary across countries/regions and, above all, with business cycles may help to validate this measure, with larger deviations expected when frictions appear in places/times of strong demand-side constraints.

Many extensions and improvements can be suggested. First, our implicit comparison of decision and experienced utility in the context of nonexperimental data could easily be extended to other areas in economics such as transportation choices or savings (for consumption decisions, see Perez-Truglia, 2015). Second, deviations could be better explained – at least regarding observed

[32] Recent approaches characterize labor market frictions by comparing long- and short-term adjustments, assuming people are less constrained in the long run.

heterogeneity – using longer and richer household surveys. Third, our models are static and do not consider the intertemporal decisions and the dynamic nature of repeated occurrences of decision and experience. Modeling intertemporal decisions would require additional information, including actual consumption at each period (e.g., see Haan et al., 2008). More generally, further research should account for the potential time discrepancy and causal link between the observed decision (possibly made in the past) and the resulting income-leisure satisfaction. It could combine our approach with the panel dimension in order to check if people showing large deviations at one point in time are more likely to change job/contract in the future to adjust their working time (in the line of Frijters, 2000, Benjamin et al., 2012, Odermatt et al. 2021, Odermatt and Stutzer 2019, etc).

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A Appendix: Additional Empirical Results

Table A.1: SWB Estimations

	(I)	(II)	(III)	(IV)
Income^2	-4.61e-07***	-4.66e-07***	-4.94e-07***	-4.24e-07***
	(1.37e-07)	(1.36e-07)	(1.36e-07)	(1.43e-07)
Income	0.000762**	0.00117***	0.00123***	0.000825**
	(0.000374)	(0.000184)	-0.000185	(0.000417)
Income x Leisure	9.30e-06			7.32e-06
	(6.17e-06)			(6.91e-06)
Leisure^2	-4.22e-05	-0.000101**	-8.17e-05	-5.32e-05
	(5.82e-05)	(4.97e-05)	(5.17e-05)	(6.33e-05)
Leisure	0.00552	0.0140**	0.0116**	0.00788
	(0.00722)	(0.00561)	(0.00585)	(0.00812)
x male	0.00208		0.00197	0.00157**
	(0.00238)		(0.00238)	(0.000790)
x age	0.00111		0.00117	6.10e-05
	(0.000823)		(0.000825)	(0.000609)
x child	-0.00167		-0.00112	-0.00582***
	(0.00244)		(0.00244)	(0.000763)
x london	0.00571*		0.00581*	0.00869***
	(0.00300)		(0.00304)	(0.00301)
x high conscientiousness	-0.00146*		-0.00148*	0.00140**
	(0.000883)		(0.000886)	(0.000617)
x high neuroticism	0.000319		0.000321	-0.00542***
	(0.000834)		(0.000835)	(0.000607)
Additive controls z_{it} and α_i	YES	YES	YES	NO
Region and Year dummies	YES	YES	YES	YES
R^2	0.243	0.239	0.242	0.148
#Obs	5,501	5,501	5,501	5,501

Note: Authors' estimations of subjective well-being (i.e. income-leisure satisfaction) using the BHPS. In baseline model (I) and some of the variants, the subjective well-being equation includes additively separable controls z_i (same variables as in leisure interaction terms plus age squared, family size, health status, home ownership) and α_i (all personality traits). Standard errors in parentheses. *, **, *** indicate significance levels at 1%, 5% and 10% respectively.

Table A.2: Robustness Checks – Alternative Measures of SWB

		Concentrated life satisfaction				
		Baseline (linear in income and leisure satisfactions, no heterogeneity)	Quadratic in income and leisure satisfactions, with demographic heterogeneity	Linear in income, leisure and additional satisfaction dimensions	PCA income-leisure satisfaction	Life satisfaction
Corresponding **rows** in Table 5		1	2	3	4	5
Mean deviation		-2.9	-3.5	-6.7	-5.1	-16.7***
		(5.7)	(4.7)	(5.0)	(5.9)	(6.4)
Proportion of significant deviations		0.28	0.25	0.30	0.28	0.48
Gender	Female	-11.1	-5.5	-13.5**	-13.1*	-17.1*
		(7.6)	(5.6)	(6.1)	(7.6)	(8.8)
	Male	11.5	-0.2	5.1	8.8	-16.1**
		(7.2)	(5.9)	(6.1)	(7.3)	(6.3)
London	No	-4.6	-4.7	-7.7	-6.9	-19.0***
		(6.1)	(4.9)	(5.2)	(6.3)	(6.7)
	Yes	19.9***	11.2	5.5	18.2**	13.3
		(7.4)	(7.4)	(7.1)	(7.8)	(13.2)
Health	Poor	-9.5	-11.4**	-13.8***	-11.7*	-22.5***
		(6.2)	(5.3)	(5.4)	(6.3)	(7.3)
	Good	-2.3	-2.9	-6.2	-4.6	-16.3***
		(5.7)	(4.7)	(5.0)	(5.9)	(6.3)
Regional unemployment	High	1.8	-0.5	-5.6	-0.2	-10.4
		(5.3)	(4.8)	(5.0)	(5.5)	(6.8)
	Low	-4.1	-4.4	-7.0	-6.4	-18.5***
		(6.0)	(4.8)	(5.1)	(6.2)	(6.6)
Ethnicity	Non-white	9.4*	7.9	1.2	7.0	2.4
		(5.4)	(4.8)	(4.9)	(5.5)	(7.5)
	White	-3.2	-3.8	-6.9	-5.4	-17.2***
		(5.8)	(4.7)	(5.0)	(5.9)	(6.4)
Previous unemployment spells	Long	-26.3***	-29.5***	-31.6***	-28.0***	-41.5***
		(6.0)	(5.3)	(5.3)	(6.3)	(7.0)
	Short/none	-2.0	-2.6	-5.8	-4.3	-15.8**
		(5.7)	(4.7)	(5.0)	(5.9)	(6.4)
Education	Low	-8.0	-6.5	-12.7**	-10.3	-19.9**
		(6.5)	(5.2)	(5.7)	(6.7)	(7.7)
	High	2.1	-0.7	-1.0	-0.1	-13.7**
		(5.2)	(4.5)	(4.6)	(5.4)	(5.6)
Family Care	Yes	-35.8***	-24.9***	-34.5***	-37.8***	-30.6**
		(9.1)	(6.9)	(7.0)	(9.0)	(13.1)
	No	1.9	-0.4	-2.7	-0.4	-14.7**
		(5.6)	(4.7)	(5.0)	(5.8)	(5.8)
Commuting	High	7.6	2.2	3.3	5.5	-8.6
		(4.9)	(4.5)	(4.4)	(5.0)	(5.5)
	Low	-5.0	-4.7	-8.8*	-7.2	-18.4***
		(6.0)	(4.8)	(5.2)	(6.1)	(6.8)

Note: Authors' own calculations from the BHPS. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrap samples. *, **, and *** indicate significance level at 10%, 5%, and 1% respectively.

Table A.3: Robustness Checks – Alternative Functional Forms and Hour Discretization

		Baseline	Quadratic no interaction	Cubic	Log-linear	Box-Cox	Quadratic (alternative discretization)
Corresponding rows in Table 5		1	6	7	8	9	10
Number of discretized hours		7	7	7	7	7	13
Mean deviation		-2.9	-3.2	-1.9	-6.0	-7.5	-5.2
		(5.7)	(5.8)	(6.3)	(7.4)	(10.1)	(5.7)
Proportion of significant deviations		0.28	0.29	0.24	0.44	0.36	0.28
Gender	Female	-11.1	-11.1	-10.7	-17.3	-18.8*	-13.1*
		(7.6)	(7.4)	(8.0)	(10.6)	(9.8)	(7.6)
	Male	11.5	10.5	13.5*	13.7*	12.1	8.4
		(7.2)	(7.5)	(7.3)	(7.3)	(13.8)	(7.2)
London	No	-4.6	-5.0	-3.5	-6.9	-10.1	-6.9
		(6.1)	(6.1)	(6.7)	(7.6)	(10.0)	(6.1)
	Yes	19.9***	20.2**	20.0***	5.9	26.4*	17.0**
		(7.4)	(8.1)	(7.0)	(8.9)	(15.5)	(7.4)
Health	Poor	-9.5	-8.9	-8.7	-15.7*	-14.4	-11.2*
		(6.2)	(6.1)	(6.8)	(8.6)	(10.3)	(6.2)
	Good	-2.3	-2.8	-1.3	-5.3	-7.0	-4.8
		(5.7)	(5.8)	(6.3)	(7.3)	(10.1)	(5.7)
Regional unemployment	High	1.8	2.9	2.1	-3.6	0.9	-0.5
		(5.3)	(5.3)	(5.5)	(7.4)	(11.1)	(5.3)
	Low	-4.1	-4.9	-3.0	-6.7	-9.8	-6.5
		(6.0)	(6.1)	(6.6)	(7.5)	(9.9)	(6.0)
Ethnicity	Non-white	9.4*	8.9	10.8*	-1.6	12.8	5.9
		(5.4)	(5.7)	(5.6)	(7.3)	(12.6)	(5.4)
	White	-3.2	-3.5	-2.2	-6.1	-8.0	-5.5
		(5.8)	(5.8)	(6.3)	(7.4)	(10.1)	(5.8)
Previous unemployment spells	Long	-26.3***	-25.5***	-24.6***	-30.6***	-27.1**	-26.0***
		(6.0)	(6.0)	(6.7)	(7.7)	(11.2)	(6.1)
	Short/none	-2.0	-2.4	-1.0	-5.1	-6.8	-4.5
		(5.7)	(5.8)	(6.3)	(7.4)	(10.1)	(5.7)
Education	Low	-8.0	-6.8	-7.3	-14.9*	-13.1	-9.7
		(6.5)	(6.1)	(7.1)	(8.7)	(10.3)	(6.5)
	High	2.1	0.3	3.4	2.5	-2.1	-0.9
		(5.2)	(5.6)	(5.9)	(6.5)	(10.1)	(5.2)
Family Care	Yes	-35.8***	-35.5***	-35.2***	-56.0***	-49.8***	-35.7***
		(9.1)	(9.0)	(10.1)	(14.5)	(10.4)	(9.1)
	No	1.9	1.5	3.0	1.3	-1.4	-0.8
		(5.6)	(5.7)	(6.1)	(6.9)	(10.4)	(5.6)
Commuting	High	7.6	6.3	9.2	8.0	5.6	4.8
		(4.9)	(5.3)	(5.5)	(6.2)	(10.7)	(4.9)
	Low	-5.0	-5.1	-4.1	-8.8	-10.2	-7.2
		(6.0)	(5.9)	(6.5)	(7.7)	(10.0)	(6.0)

Note: Authors' own calculations from the BHPS. Standard errors are calculated using 200 bootstrap samples for each individual and then averages for the mean deviation. *, **, and *** indicate significance level at 10%, 5%, and 1% respectively.

Table A.4: Robustness Checks – Alternative Treatment of Additive Heterogeneity

		Baseline	Fixed effects	Random effects	Quasi-fixed effects	No additive observed heterogeneity
Corresponding rows in Table 5		1	11	12	13	14
Mean deviation		-2.9	-7.3	-4.7	-1.6	-12.0***
		(5.7)	(5.6)	(5.4)	(5.1)	(4.2)
Proportion of significant deviations		0.28	0.33	0.28	0.28	0.55
Gender	Female	-11.1	-8.4	-8.9	-5.2	-22.8***
		(7.6)	(6.8)	(6.5)	(6.1)	(4.3)
	Male	11.5	-5.3	2.7	4.7	6.9
		(7.2)	(8.3)	(7.1)	(7.3)	(4.6)
London	No	-4.6	-9.4	-6.7	-3.5	-11.8***
		(6.1)	(5.9)	(5.8)	(5.4)	(4.2)
	Yes	19.9***	20.1	22.2**	22.8**	-14.2***
		(7.4)	(14.1)	(9.0)	(8.9)	(4.6)
Health	Poor	-9.5	-10.9*	-10.9**	-7.7	-24.4***
		(6.2)	(5.9)	(5.5)	(5.1)	(4.2)
	Good	-2.3	-7.0	-4.2	-1.1	-11.0***
		(5.7)	(5.6)	(5.4)	(5.1)	(4.2)
Regional unemployment	High	1.8	1.8	3.0	5.4	-14.5***
		(5.3)	(5.9)	(4.8)	(4.6)	(4.3)
	Low	-4.1	-9.7	-6.7	-3.5	-11.3***
		(6.0)	(5.9)	(5.8)	(5.4)	(4.1)
Ethnicity	Non-white	9.4*	3.5	8.0	10.3*	-8.9**
		(5.4)	(9.4)	(6.1)	(6.1)	(4.3)
	White	-3.2	-7.5	-5.0	-1.9	-12.1***
		(5.8)	(5.6)	(5.4)	(5.1)	(4.2)
Previous unemployment spells	Long	-26.3***	-30.1***	-28.7***	-25.7***	-39.9***
		(6.0)	(5.7)	(5.4)	(5.1)	(4.3)
	Short/none	-2.0	-6.4	-3.8	-0.7	-11.0***
		(5.7)	(5.6)	(5.4)	(5.1)	(4.2)
Education	Low	-8.0	-11.2**	-8.8	-5.7	-19.0***
		(6.5)	(5.7)	(5.5)	(5.2)	(4.1)
	High	2.1	-3.4	-0.7	2.4	-5.2
		(5.2)	(5.8)	(5.5)	(5.3)	(4.3)
Family Care	Yes	-35.8***	-43.0***	-37.8***	-35.1***	-53.2***
		(9.1)	(9.1)	(8.6)	(8.5)	(3.7)
	No	1.9	-2.1	0.2	3.3	-6.0
		(5.6)	(5.6)	(5.3)	(5.1)	(4.3)
Commuting	High	7.6	3.9	5.5	8.4	-2.7
		(4.9)	(5.9)	(5.2)	(5.1)	(4.3)
	Low	-5.0	-9.5*	-6.7	-3.6	-13.8***
		(6.0)	(5.7)	(5.5)	(5.2)	(4.2)

Note: Authors' own calculations from the BHPS. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrap samples. *, **, and *** indicate significance level at 10%, 5%, and 1% respectively.

Table A.5: Robustness Checks – Alternative Specification of Preference Heterogeneity

		Baseline	Continuous age and personality scores	Baseline with all big 5	Baseline with all big 5 and all other explanatory variables
Corresponding **rows** in Table 5		**1**	**15**	**16**	**17**
Mean deviation		-2.9	-4.1	-3.1	-2.0
		(5.7)	(4.3)	(5.7)	(6.1)
Proportion of significant deviations		0.28	0.39	0.27	0.33
Gender	Female	-11.1	-10.3*	-11.3	-11.8
		(7.6)	(5.3)	(7.6)	(7.9)
	Male	11.5	6.7	11.3	15.0*
		(7.2)	(5.4)	(7.2)	(8.1)
London	No	-4.6	-5.6	-4.8	-3.6
		(6.1)	(4.5)	(6.1)	(6.5)
	Yes	19.9***	15.9**	19.9***	19.1***
		(7.4)	(6.8)	(7.5)	(6.7)
Health	Poor	-9.5	-8.9*	-10.4	-32.9***
		(6.2)	(4.6)	(6.3)	(7.4)
	Good	-2.3	-3.7	-2.5	0.4
		(5.7)	(4.3)	(5.7)	(6.4)
Regional unemployment	High	1.8	0.2	1.9	3.5
		(5.3)	(4.3)	(5.4)	(6.1)
	Low	-4.1	-5.2	-4.4	-3.5
		(6.0)	(4.5)	(6.0)	(6.5)
Ethnicity	Non-white	9.4*	6.9	8.0	-19.4
		(5.4)	(4.5)	(5.5)	(12.6)
	White	-3.2	-4.3	-3.3	-1.6
		(5.8)	(4.4)	(5.8)	(6.3)
Previous unemployment spells	Long	-26.3***	-23.1***	-26.4***	-30.5***
		(6.0)	(4.2)	(6.1)	(8.1)
	Short/none	-2.0	-3.4	-2.2	-1.0
		(5.7)	(4.3)	(5.7)	(6.2)
Education	Low	-8.0	-7.3	-8.2	-15.8*
		(6.5)	(4.6)	(6.6)	(8.5)
	High	2.1	-1.0	1.9	11.3*
		(5.2)	(4.3)	(5.2)	(6.7)
Family Care	Yes	-35.8***	-36.2***	-36.2***	-42.9***
		(9.1)	(6.6)	(9.1)	(9.4)
	No	1.9	0.6	1.8	3.9
		(5.6)	(4.2)	(5.6)	(6.2)
Commuting	High	7.6	4.5	7.5	8.8
		(4.9)	(4.1)	(4.9)	(5.7)
	Low	-5.0	-5.8	-5.2	-4.2
		(6.0)	(4.4)	(6.0)	(6.4)

Note: Authors' own calculations from the BHPS. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrap samples. *, **, and *** indicate significance level at 10%, 5%, and 1% respectively.

Table A.6: Robustness Checks – Alternative Estimator and Samples Selections

		Baseline	Ordered probit model	Job seekers included	Self-employed included
Corresponding rows in Table 5		1	18	19	20
Mean deviation		-2.9	-8.6	-9.7	-6.9
		(5.7)	(7.5)	(6.3)	(4.2)
Proportion of significant deviations		0.28	0.27	0.29	0.40
Gender	*Female*	-11.1	-16.1*	-13.7*	-6.9
		(7.6)	(8.8)	(7.1)	(4.3)
	Male	11.5	4.6	-3.0	-6.9
		(7.2)	(9.0)	(6.9)	(5.5)
London	*No*	-4.6	-11.1	-12.0*	-8.8*
		(6.1)	(7.9)	(6.8)	(4.6)
	Yes	19.9***	24.3***	20.8***	15.4**
		(7.4)	(7.6)	(6.5)	(6.1)
Health	*Poor*	-9.5	-14.7*	-15.9**	-12.0***
		(6.2)	(8.2)	(6.8)	(4.2)
	Good	-2.3	-8.1	-9.2	-6.5
		(5.7)	(7.4)	(6.2)	(4.2)
Regional unemployment	*High*	1.8	-1.7	-3.7	-0.1
		(5.3)	(6.7)	(5.3)	(3.5)
	Low	-4.1	-10.4	-11.4*	-8.8*
		(6.0)	(7.8)	(6.6)	(4.5)
Ethnicity	*Non-white*	9.4*	9.4	5.0	2.8
		(5.4)	(6.6)	(5.1)	(3.8)
	White	-3.2	-9.0	-10.1	-7.2*
		(5.8)	(7.5)	(6.3)	(4.2)
Previous unemployment spells	*Long*	-26.3***	-32.1***	-35.5***	-27.0***
		(6.0)	(8.2)	(6.9)	(4.3)
	Short/none	-2.0	-7.7	-8.5	-6.2
		(5.7)	(7.4)	(6.2)	(4.2)
Education	*Low*	-8.0	-13.9	-15.0**	-9.5**
		(6.5)	(8.5)	(7.2)	(4.4)
	High	2.1	-3.5	-4.5	-4.6
		(5.2)	(6.7)	(5.6)	(4.3)
Family Care	*Yes*	-35.8***	-39.0***	-34.8***	-31.0***
		(9.1)	(11.2)	(8.8)	(5.7)
	No	1.9	-4.2	-6.0	-3.8
		(5.6)	(7.2)	(6.1)	(4.2)
Commuting	*High*	7.6	3.2	2.3	5.3
		(4.9)	(6.1)	(5.1)	(3.9)
	Low	-5.0	-11.0	-12.0*	-9.1**
		(6.0)	(7.8)	(6.6)	(4.3)
Employment status	*Employee*				2.3
					(4.2)
	Self-employed				-37.3***
					(4.7)
#observations		5,501	5,501	5,689	6,088

Note: Authors' own calculations from the BHPS. Standard errors are calculated for each individual i and time t using estimates from 200 bootstrap samples. *, **, and *** indicate significance level at 10%, 5%, and 1% respectively.

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