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Stick and Stay, Make it Pay? Time Preferences and Marginal (Dis)Utility of Relative Concerns

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Abstract

Individuals' preferences for immediate gratification versus their ability to postpone it, i.e., time preferences, might be related to their marginal utility or disutility stemming from an increase in the income of comparable others, i.e., relative concerns. We argue that while an increase in others' income might lead to a higher level of marginal disutility for those seeking immediate gratification, the disutility among patient individuals might be lower if they prioritise the future development of their income and consider catching up with others' income over the long run. To investigate whether time preferences might moderate marginal utility due to increased others' income, we use a subjective measure of individual patience and a life satisfaction measure observed over a long period of time (Socio-Economic Panel, SOEP). Using panel data fixed effects interaction models, we find highly consistent evidence that the well-documented disutility from relative income, the so-called "status effect" in the literature, is predominantly experienced by impatient individuals with higher discount rates. In contrast, patient individuals with lower discount rates, high self-control, and the ability to regulate their stress and anxiety levels experience lower disutility or even gain utility due to their relative income, the so-called "information effect," which is significantly different from that of impatient individuals. The results are robust across a variety of checks, including income types, savings, reference groups, and time preference measures obtained from incentivised time preference experiments. We discuss the implications of these results for behavioural and welfare economics.

JEL classification

C90, D63

Keywords

time-preferences, patience, life satisfaction, relative income, information effect

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1 Introduction

How individuals discount the future relative to the present, i.e., time preferences, has been shown to influence a wide range of emotions, behaviours, and economic outcomes (e.g., Shoda et al., 1990; Casey et al., 2011; Sutter et al., 2013; Golsteyn et al., 2014; Bradford et al., 2017; Sunde et al., 2022; Meier, 2019; Horn and Kiss, 2020). One important and underexplored question is whether the (dis)utility associated with income comparisons is moderated by the time preferences of individuals. A substantial literature suggests that people derive utility not only from their absolute income but also from how their income compares to that of others, i.e., relative concerns (e.g., Frank, 1985; Ferrer-i-Carbonell, 2005; Clark et al., 2008; Akay and Martinsson, 2011; Akay et al., 2017). Yet, the marginal utility or disutility resulting from others' income may also depend on how individuals evaluate their current and future standing in the income distribution, i.e., how they discount the future (Friehe and Pannenberg, 2021). For example, individuals with strong present bias or impatience may experience anxiety or stress in response to income comparisons, driven by an immediate desire to improve their socio-economic status. In contrast, more patient individuals may better regulate their emotional responses and mentally distribute the process of "keeping up with the Joneses" over time. Recent studies in behavioural economics and happiness research have employed subjective well-being (SWB) data to evaluate these relative concerns through the lens of experienced utility, something that traditional revealed preference methods cannot easily capture (e.g., Clark et al., 2008). To our knowledge, for the first time, this paper uses SWB data as a proxy for experienced utility and measures of patience (e.g., discount rates, delayed gratification) as proxies for time preferences to examine how the degree of discounting influences the marginal disutility associated with others' income (e.g., Kahneman and Sugden, 2005; Burks et al., 2012; Vischer et al., 2013; Gauly, 2017; Meier, 2019; Tawiah, 2022).

Original ideas related to relative concerns were developed by scholars such as Adam Smith and Thorstein Veblen, but testing them empirically had to wait until more recent decades. Today, the literature draws primarily on either stated preference experiments or subjective well-being (SWB) datasets to assess the utility consequences of relative concerns (e.g., Carlsson et al., 2007; Clark et al., 2008; Akay et al., 2012). Both approaches suggest that individuals exhibit significant concern for relative positions in income and the consumption of goods such as luxury cars and houses (Ferrer-i-Carbonell, 2005; Solnick and Hemenway, 1998; Solnick et al., 2007). Each approach has its advantages and limitations, which are widely discussed in the literature. The SWB approach is particularly useful for identifying associations directly in relation to experienced utility, whereas stated preference experiments allow researchers to explore relative concerns across various goods using hypothetical comparison goods with tailored reference groups (Kahneman and Sugden, 2005; Solnick et al., 2007).[1] By regressing the mean income or consumption levels of comparable others, i.e., the reference group, on the well-being of individuals, the SWB literature finds that people tend to lose significant levels of well-being in response to the higher income of others, e.g., "status effect" due to envious feelings as predicted by the social comparison theory (e.g., Festinger, 1954; Ferrer-i-Carbonell, 2005; Layard et al., 2010; Clark et al., 2008). The literature has since expanded, with further findings that negative externalities from income differences have implications for broader economic issues, including economic growth and the Easterlin Paradox (Easterlin, 1995), optimal taxation (Aronsson and Johansson-Stenman, 2014), poverty experience (Fafchamps and Shilpi, 2008), labour supply decisions (Neumark and Postlewaite, 1998), and migration (Akay et al., 2017). At the same time, the literature has also identified "positive externalities" associated with relative income (e.g., Senik, 2004; Knight et al., 2010b; Akay and Yilmaz, 2025). These arise when individuals perceive the income of others not as a threat, but as a signal of upward mobility, especially if they believe that, through effort and perseverance, they too can achieve similar outcomes. This interpretation, known as the "information effect" or "Tunnel Effect" (Hirschman and Rothschild, 1973), suggests that others' success may generate 'hope' rather than envy.[2]

There is also parallel and fastly growing literature on relative concerns that investigates how the marginal disutility of relative income varies across individual characteristics, including personality traits (Budría and Ferrer-i-Carbonell, 2019; Boyce and Wood, 2011;

[1]The stated preference approach is used in several studies to investigate relative concerns via alternative functional forms of utility and different comparison goods (Solnick et al., 2007; Akay and Martinsson, 2011). This method uses hypothetical scenarios in which people are asked to choose between combinations of absolute and relative consumption levels, implicitly revealing their utility function. However, it has been criticised for relying on small samples and hypothetical, non-incentivised choices (Murphy et al., 2005).

[2]The positive relative income effect is also observed in small, close-knit communities, where others' income may be closely tied to shared consumption (see Akay and Martinsson, 2011; Knight et al., 2010a; Knight et al., 2010b). The information effect is particularly prominent in transition economies experiencing rapid income growth (see Senik, 2004, 2008, 2009).

Akay and Karabulut, 2020) and age (Akay and Martinsson, 2019; FitzRoy and Nolan, 2022). As suggested by Clark et al. (2008), considerations related to time and future orientation may also explain differences in how individuals respond to income comparisons (see Page 134 in Clark et al. (2008) for a detailed discussion and the theoretical foundations). These considerations may give rise not only to variation in the emotional cost of comparisons but also to a positive interpretation of others' income as a form of motivational information. Building on this insight, this paper is the first to examine whether individuals' time preferences, or their level of patience, influence how they experience the utility consequences of income comparisons. The main idea is that the discomfort, stress, or dissatisfaction caused by income differences may depend on whether individuals can tolerate or defer emotional reactions related to their economic position. Individuals with high discount rates tend to exhibit a strong preference for immediate consumption and may feel a greater sense of urgency to improve their current status. When exposed to others with higher consumption, they may experience more envy, anxiety, and dissatisfaction. This may also lead them to engage in behaviours such as unnecessary borrowing or spending, which is aimed at displaying status. Therefore, individuals with low patience are more likely to experience a dominant status effect, resulting in a substantial reduction in life satisfaction due to income comparisons.

In contrast, individuals who place greater value on the future, that is, those who are more patient, often have higher self-control and a lower tendency to focus only on immediate gains. These individuals are more likely to postpone desires related to income and consumption and may be better equipped to cope with short-term status disadvantages. Psychological research supports this view, showing that people with high levels of patience tend to regulate emotions more effectively and maintain psychological stability when faced with challenging circumstances (Schnitker, 2012). In addition, patient individuals are less likely to overestimate their future income or position, which makes them more realistic about their current standing and less vulnerable to discouragement caused by others' success (Friehe and Pannenberg, 2021). We suggest that patient individuals may even find encouragement in the success of others. Observing higher incomes among similar individuals may serve as a source of useful information or as a signal of opportunity, guiding their own long-term efforts. In such cases, comparisons may inspire rather than discourage. This pattern reflects the idea known as the information effect, where upward comparisons are interpreted with optimism and hope for future mobility (Hirschman and Rothschild, 1973; Senik, 2004, 2005; Clark et al., 2008). For patient individuals, this information-driven interpretation may weaken or offset entirely the typical negative impact of relative income, and in some cases, even lead to an improvement in well-being.

To investigate this research question, we use individuals' subjective reports of their own *patience* levels as a proxy for time preferences. In our robustness analysis, we also elicit discount rates from a large group of respondents who participated in a series of time preference experiments (e.g., Burks et al., 2012; Vischer et al., 2013; Pinger, 2017). The patience measure is considered a reliable proxy for time preferences, as demonstrated by comparisons with standard time-preference experiments involving trade-offs between earlier and later rewards (e.g., Becker et al., 2012; Vischer et al., 2013; Meier, 2019). Our empirical analysis is based on the nationally representative Socio-Economic Panel (SOEP) dataset, which covers the years 2000 to 2019. The dataset includes extensive SWB data, in particular life satisfaction, as well as information on subjective patience across three waves and an incentivised time-preference experiment in one wave. We construct a sufficient statistic for the time-invariant patience level by averaging reported patience across these waves and use it as the primary measure in our empirical analysis. The literature is not uniform on the temporal stability of time preferences. While some evidence points to substantial persistence over medium horizons (e.g., Meier and Sprenger, 2015; Preuss, 2021), other studies show that patience may evolve with age and major life circumstances (e.g., Haushofer and Fehr, 2019; Kureishi et al., 2021). This construction is therefore best viewed as a practical summary of individuals' longer-run orientation toward the future, rather than as a literal claim that patience is unchanged at every point in time. In the robustness analysis, we show that the main pattern is preserved when we use alternative patience measures, experimentally elicited discount rates, specifications that absorb age-related variation in patience, and time-varying versions of the measure.

Using individual fixed effects regressions with interaction terms, we find that the disutility associated with others' income is strongly moderated by patience levels, which is highly consistent with our theoretical expectations. This result provides evidence of a robust pattern of heterogeneity in the relative-income gradient across individuals with different measured patience levels, while remaining cautious about claims that would require patience to be fully invariant over the entire observation window. On average, patient individuals do not experience a significant reduction in life satisfaction in response to an increase in the income of comparable others. We interpret these results to mean that, on average, neither the status effect nor the information effect dominates among patient individuals. The significant utility loss due to relative concerns is concentrated among less patient individuals, implying that the status effect dominates among these individuals. The differences in utility responses experienced by impatient and patient individuals are highly statistically significant. We also find consistent evidence that, depending on individuals' position in the relative income distribution and subsample – such as the working-age population – patient individuals may even experience a positive and statistically significant association, suggesting a dominant information effect. This implies that they may interpret the income of comparable others as a signal for their potential future income. The findings are highly robust to alternative estimators, definitions of comparison income, measures of time preference (discount rates obtained from incentivised time-preference experiments), age-adjusted and time-varying constructions of patience, measures of relative position, relative saving and consumption, samples with more stable life circumstances, definitions of reference group, and income inequality. Overall, our findings suggest that the "status effect" and the "information effect" may coexist, even in prosperous Western societies, and that time preferences shape the dominance of one over the other. These results have important implications for understanding the relative concerns and how they should be implemented in a variety of economic models (e.g., optimal taxation) and for the so-called Easterlin paradox, which we discuss in the final section (Senik, 2005; Clark et al., 2008; Akay and Martinsson, 2011).

The rest of the paper is organised as follows. In the next section, we present the panel data and describe the sample selection process. We also explain the measures for subjective well-being (SWB) and patience, and provide descriptive statistics. Section 3 outlines the econometric approach and discusses potential issues that may arise. Section 4 presents the main results, explores heterogeneity in the findings, and conducts an extensive robustness analysis. Finally, Section 5 concludes the paper.

2 Data

2.1 Sample Selection

The dataset used is the Socio-Economic Panel (SOEP), which has been conducted since 1984 in West Germany and since 1991 in East Germany.[3] The SOEP is frequently used in studies on well-being (Ferrer-i-Carbonell, 2005; Akay et al., 2017). It is nationally representative, and the sample has been periodically refreshed over time to maintain representativeness. Our sample selection strategy is as follows. We focus on native Germans to avoid migration-related selection effects that may be associated with differences in time preferences.[4] We analyse individuals aged 18 to 80. Since this age range is somewhat arbitrary, we test alternatives, such as restricting the sample to the working-age population or dividing it into younger and older cohorts, to assess the robustness of our findings. We primarily use data from 2000 to 2019. This time frame ensures that the number of observation years aligns with the number of waves for which patience was measured and avoids data from the pandemic period, which may introduce additional variation. We also estimate models using alternative year ranges. The baseline estimation sample includes 28,754 native German individuals and 283,671 individual$\times$year observations, after accounting for all missing values in the variables used in the regression analyses below.

The dataset is rich in individual socio-economic and demographic characteristics, including most key determinants of well-being such as marital status, education, household size, number of children, and health status. It also includes a consistent measure of life satisfaction available in all survey years. This measure is used as the dependent variable in our analysis and is based on the following question: "*How satisfied are you with your life in general?*" Responses are recorded on an 11-point scale, ranging from 0 ("*completely unsatisfied*") to 10 ("*completely satisfied*"). Life satisfaction is widely used as a proxy for experienced utility and is considered reliable in capturing overall well-being (Kahneman and Sugden, 2005; Krueger and Schkade, 2008; Oswald and Wu, 2010). It reflects an individual's evaluation of their life as a whole, encompassing both positive and negative

[3] The SOEP data can be obtained from www.diw.de upon application. For further information about the variables and samples, please visit www.paneldata.org.

[4] The dataset undergoes periodic sample refreshment and includes new groups of individuals in certain waves through innovation samples. Specifically, we exclude samples numbered 2, 4, 15, 16, 17, 18, 19, 21, 22, and 23, which include migrants, refugees, and high-income individuals.

affect across multiple life domains (e.g., health, employment, relationships, income). It is also strongly correlated with alternative indicators of well-being, such as happiness and mental health. Table 1 shows that the mean level of life satisfaction in our estimation sample is 7.16 (standard deviation = 1.71), which is in line with previous findings in the literature (Ferrer-i-Carbonell, 2005; Akay et al., 2017).

2.2 Income Sources, Reference Groups, and Reference Income

To investigate our research questions, we use per capita post-government household income (equivalized net household income) as the measure of *absolute income*. This is calculated using the modified OECD equivalence scale, which assigns a weight of 1 to the individual, 0.5 to other adults in the household, and 0.3 to each child aged 14 or younger.[5] This income measure is commonly used in the well-being literature and is positively and significantly associated with life satisfaction in previous studies based on the SOEP (e.g., Ferrer-i-Carbonell, 2005; Di Tella et al., 2010). This same income variable is also used to construct the measure of *reference income*, defined as the average income of the individual's *reference group*, the group with whom individuals are assumed to compare their income. The definition of reference groups in this study follows the standard approach in the literature and relies on practical criteria based on socio-demographic and economic characteristics (McBride, 2001; Ferrer-i-Carbonell, 2005; Luttmer, 2005; Akay and Martinsson, 2011).

Our baseline definition of the reference group is based on four dimensions: *age* (five categories derived from the quintiles of the age distribution), *years of education* (divided into high and low by the median value of 11.5), *gender*, and *federal states* (16 regions of Germany). These groups are constructed dynamically for each survey wave between 2000 and 2019.[6] This reference-group construction should be understood as an empirical approximation of the social environment in which both comparison and informational

[5]Postgovernment income equals the sum of pregovernment income, social security benefits, and annual public transfers, minus net household taxes. Household pre-government income includes gross annual labour income, asset income, private transfers, and private retirement income.

[6]The concept of a reference group is complex, as it may reflect a range of relevant life circumstances and may change over time. The literature uses several practical approaches, such as asking individuals directly (Clark and Senik, 2010) or identifying neighbours and acquaintances as comparison groups (Luttmer, 2005). Our approach follows the standard empirical strategy applied in the literature (e.g., McBride, 2001; Ferrer-i-Carbonell, 2005).

signals may operate. The psychologically relevant group for status comparison need not coincide exactly with the group from which individuals infer future prospects, but the present measure provides a standard and observable benchmark that plausibly contains both types of content. Using this approach, we form 1,021 reference groups with an average of about 296 individuals per group (standard deviation = 166). To reduce the potential bias from small or unstable group definitions, we exclude groups with fewer than 10 observations, which results in the removal of 139 individual-year observations. This leaves us with 998 reference groups in the final analysis. For each individual, we calculate the mean per capita income within their reference group to serve as their reference or comparison income. As part of the robustness analysis, we also test alternative comparison points, such as using the median instead of the mean, and we explore different reference group definitions by adding or removing observed characteristics, including education and marital status.

2.3 Patience: a Proxy for Time Preferences

The dataset includes three waves of a subjective patience measure used as a proxy for time preferences. The measure is extremely brief but has been found to be a reliable proxy for time preferences obtained using standard experimental tools (e.g., Vischer et al., 2013). It is also often used in studies investigating the relationship between time preferences and economic outcomes of individuals (e.g., Gauly, 2017; Meier, 2019; Tawiah, 2022). We also utilise a large-scale time preference experiment conducted among a subset of the same respondents during the year 2006 (Vischer et al., 2013) to compare our results with the baseline patience measure used in our analysis. The patience measure is simple and is obtained from every individual in the sample, generating a large sample size that is crucial for determining precise reference groups and income. The measure is obtained with the question asking respondents "*How patient are you in general?*", which is answered on an 11-point scale from 0 ("*very patient*") to 10 ("*very impatient*"). We reverse the scale so that a higher value on the scale implies a higher patience level. The measure is obtained only in three waves: 2008, 2013, and 2018. Although this self-reported item is necessarily parsimonious, it has two important advantages in our setting. First, it is available for a large number of respondents, which is essential for constructing sufficiently fine reference groups. Second, its broad wording is arguably more suited to capturing individuals' general orientation toward delayed gratification than a one-off situational choice would be. At the same time, we recognise that such a measure may still reflect both enduring dispositions and changes induced by age, stress, or major life circumstances.

There are two ways of using the patience data. We can either use only these three waves and assume that patience is time-varying, or we can use all waves available from 2000 to 2019, assuming that patience is time-invariant. We prefer the latter in our baseline and present the results for the former in our robustness analysis in detail.[7] To generate a time-invariant patience dummy matched to the entire set of waves, we calculate the within-person mean patience level observed across the three waves. This averaging procedure is intended to reduce transitory measurement noise and to retain the informational advantage of the full panel, rather than to deny the possibility that patience may change gradually over time. Given that there are five years between waves, conditional on the mean value, the measure is assumed to be time-invariant and exhibit temporal stability for a certain period (Preuss, 2021). This choice also allows us to preserve the long panel dimension of the SOEP and thereby estimate relative-income effects using more precise reference-group measures than would be possible if the analysis were restricted to the three patience waves only. The mean level of patience is about 6.05 (s.d., 2.32). In our empirical approach, we use the measure as a time-invariant dummy for each individual, characterising whether they are impatient or patient using the median of 6 as the threshold. We also experiment with other thresholds using the third quartile, which is 8 (the third quartile patience level). Importantly, we assess the robustness of our baseline measure by using alternative measures of patience, including specifications

[7] The literature does not speak with one voice on the temporal stability of time preferences. A number of studies argue that preferences such as risk and time exhibit meaningful persistence over time (e.g., Hardardottir, 2017; Preuss, 2021; Drichoutis and Vassilopoulos, 2021; Drichoutis and Nayga Jr, 2022). Relatedly, Meier and Sprenger (2015) document substantial short- to medium-run stability in experimentally elicited discounting behaviour. However, other contributions show that patience may evolve systematically over the life cycle or in response to major life circumstances. For example, individuals tend to become more patient as they age (Falk et al., 2018; Kureishi et al., 2021), and temporal instability may also arise from changes in stress, resources, and exposure to adverse events. This interpretation is also consistent with the poverty and scarcity literature, which suggests that time preferences may themselves respond to deprivation, uncertainty, and constrained choice sets (Tanaka et al., 2010; Haushofer and Fehr, 2014; Bartoš et al., 2021). We therefore do not interpret our baseline construction as implying that time preferences are literally fixed at every point in time. Rather, the within-person mean across the three available waves is used as a practical summary of individuals' longer-run orientation toward the future. To address the concern directly, we will report additional robustness checks based on time-varying versions of the patience measure, age-adjusted constructions, alternative experimentally elicited discount-rate measures, and samples with more stable life circumstances.

Table 1. Descriptive Statistics of Key Variables

	Whole Sample	Impatient People (Patience measure (0-10) < Median=6)	Patient People (Patience Measure (0-10) ≥ Median=6)
SWB (life satisfaction, 0-10)	7.163	6.989	7.336
	(1.710)	(1.762)	(1.639)
Absolute income (per capita/year)	24,061.7	24,350.9	23,774.7
	(18,198.4)	(18,599.3)	(17,787.0)
Reference Income (per capita/year)	21,252.5	21,145.7	21,358.4
	(5,867.7)	(5,813.0)	(5,919.7)
Employment status (working = 1)	0.671	0.678	0.664
	(0.470)	(0.467)	(0.472)
Gender (female = 1)	0.532	0.536	0.528
	(0.499)	(0.499)	(0.499)
Age in years	49.802	48.821	50.775
	(15.660)	(15.774)	(15.486)
Years of education	12.618	12.645	12.591
	(2.702)	(2.721)	(2.682)
Marital status (married = 1)	0.629	0.625	0.633
	(0.483)	(0.484)	(0.482)
Household size	2.697	2.715	2.68
	(1.256)	(1.240)	(1.270)
# Observations (baseline sample)	283,671	141,285	142,386

Note: Authors' own calculations from SOEP from 2000 to 2019. Standard deviations are in parentheses.

that relax the time-invariance assumption, alternative constructions intended to account for age-related changes in patience, and measures designed to capture the effects of life shocks on patience.

2.4 Descriptive Statistics and Control Variables

Table 1 presents descriptive statistics for the patience measure and a set of control variables used in the subsequent econometric analysis. A striking pattern emerges: individuals classified as patient report significantly higher life satisfaction compared to their impatient counterparts (mean SWB = 7.34 vs. 6.99). This is despite patient individuals having slightly lower average absolute income levels (€23,774 vs €24,350). Interestingly, patient individuals also exhibit marginally higher reference income (€21,358 vs €21,145), suggesting that their well-being advantage is not merely due to economic resources, but possibly tied to differences in how they perceive or respond to income comparisons. Patient individuals report higher life satisfaction even in the absence of income advantages, which is consistent with the interpretation that they may experience less distress or even benefit from upward social comparisons due to a more future-oriented or resilient outlook.

Other observable characteristics are highly similar across the two groups, reducing concerns about systematic compositional differences. Approximately 53% of respondents are female, with an average age of around 50. Patient individuals are slightly older on average (50.8 vs 48.8), which is in line with evidence that patience tends to increase with age (Falk et al., 2018; Kureishi et al., 2021). Educational attainment and employment rates are nearly identical: both groups average about 12.6 years of schooling, and approximately two-thirds of respondents are employed during the observation period. Marital status, household size, and gender balance are also comparable across groups. In addition to the variables reported in Table 1, the regression models include a comprehensive set of controls to address potential confounding factors. These include household composition (number of children by age group), self-reported health status (on a 5-point scale), working hours, job tenure, non–labour income, place of residence (east–west), and homeownership.

3 Econometric Specifications

3.1 The Model

The model specification is a panel data fixed effects model, in which we assume that the unobserved characteristics (e.g., personality or genetic predisposition) are correlated with the observed characteristics (e.g., patience or income). The econometric model specification reads as follows:

$$\begin{aligned} SWB_{it} = \gamma D_i^P + \alpha_1^{Abs} log(Y_{it}) + \alpha_2^{Abs} D_i^P log(Y_{it}) + \beta_1^{Rel} log(\overline{Y}_{it}^R) + \beta_2^{Rel} D_i^P log(\overline{Y}_{it}^R) + \\ X'\gamma + S_c + T_t + \eta_i + \varepsilon_{it} \end{aligned} \tag{1}$$

In equation 1, the dependent variable is life satisfaction, SWB_{it}, which is latent and observed on a 0-10 scale for individual i in wave t. The model specification includes logs of absolute income Y_{it} (the per capita income based on the modified OECD scale) and reference income $\overline{Y}_{it}^{R_j}$. The model specification implies that the "relative income" is constructed as the ratio $Y_{it}/\overline{Y}_{it}^{R_j}$. The parameter of the logged reference income will directly relate to the relative income, as an increase in others' income will decrease the relative income of the individuals, conditional on the logged absolute income. Thus, we will call the log of others' income as the relative income in the analysis below. We calculate the reference/relative income using $\overline{Y}_{it}^{R_j} = \frac{1}{N_{R_j}-1}\sum_{i=1}^{N_{R_j}-1} Y_{it}$, which is the mean income in the reference group R_j. D_i^P is a time-invariant dummy variable indicating highly patient individuals, defined as one if the mean patience measure is equal to or higher than the median (i.e., median patience = 6) and otherwise zero, indicating impatient individuals.

The fixed effects model eliminates time-invariant unobserved heterogeneity and other time-invariant variables, including the high-patience dummy, D_i^P. Thus, the parameter of the patience dummy γ is not identified in the fixed effects specification. Yet, the model identifies the parameters of the interaction terms α_2^{Abs} and β_2^{Rel} involving D_i^P. We aim to test whether the marginal utility of absolute and relative income varies by patient and impatient people. For patient people, $D_i^P = 1$, the coefficient of absolute income on SWB is $\alpha_1^{Abs} + \alpha_2^{Abs}$ while the coefficient of relative income is $\beta_1^{Rel} + \beta_2^{Rel}$. For impatient people, the marginal utility of absolute and relative incomes is α_1^{Abs} and β_1^{Rel}. In our tables below, we present the marginal utility of absolute and relative income for patients and impatient people with the respective p-value of the difference between estimated coefficients. Accordingly, the main object of interest in the paper is not the standalone coefficient of income or patience, but the difference in the income gradient across individuals with different measured patience levels.

3.2 Specifications and Estimators

The model also includes several determinants of SWB, which are represented by the matrix X. These variables include marital status indicators (married, single, widowed, divorced, and separated), years of education, household size, and the number of children in the household (grouped by age ranges: 0–1, 2–4, 5–7, 8–10, 11–12, 13–15, and 16–18). Additional covariates include subjective health status dummies (very bad, bad, neither bad nor good, good, and very good), non-labour income (rents and dividends), home ownership, employment status (not working, part time, and full time), region of residence (East–West Germany), job tenure and weekly average working hours (see Table 1 and the note under Table 2). The error component also includes region indicators (S_c for the 16 federal states of Germany) and year indicators (T_t) to account for regional differences and common shocks to the economy. The term η_i represents the time-invariant unobserved individual effect, which is assumed to be correlated with the observed characteristics.

Controlling for unobserved individual effects through a fixed effects specification is crucial in SWB regressions to mitigate potential omitted variable bias. While SWB is measured on an ordinal scale and an ordinal response model is appropriate in theory, we estimate linear fixed effects models for ease of interpretation and comparability. To test the robustness of our findings, we also estimate a "blow-up and cluster" ordered logit fixed effects model, which captures the ordinal nature of the SWB (Baetschmann et al., 2015). We also estimate a correlated random effects model where the coefficient on the patience dummy and its interaction with relative income (Mundlak, 1978). The specification includes a flexible distribution of the unobserved individual effect defined as a function of the within-means of all time-variant characteristics in the baseline model specification.

One of the main concerns in this study is that both patience and income might be endogenous (Luttmer, 2005; Ifcher and Zarghamee, 2011; Lindqvist et al., 2020). While it is not possible to make definitive causal claims using observational data, the consistency of our findings across specifications, sample definitions, and alternative measures strengthens the case for a systematic moderating role of time preferences. To partially address the omitted variables, we allow for individual fixed effects that incorporate the complete set of individual characteristics. By controlling for a comprehensive set of time-varying individual characteristics, including labour market status, health, and household structure, we address a wide range of potential confounders that could otherwise bias our estimates. At the same time, fixed effects do not by themselves eliminate reverse causality, simultaneity, or measurement-based endogeneity. This caveat applies both to the income side of the model and to the measurement of patience. Absolute and relative income may still co-move with unobserved shocks to life satisfaction, while patience may itself respond over time to stress, adversity, expectations, or prior well-being. For this reason, the estimates below should be interpreted primarily as evidence on heterogeneity in the relative-income gradient, rather than as fully causal parameters.

To further address internal consistency, we provide an extensive set of robustness analyses. In our robustness analysis, we estimate alternative models within the correlated random effects framework that include several time-invariant measures (unidentified in the fixed effects), such as Big–5 personality characteristics, locus of control (internal and external), risk-taking behaviour, impulsivity, emotions (e.g., anger), and saving behaviour. We estimate models using alternative definitions of income variables, lags, sample selections, and time-preference measures obtained from incentivised time-preference experiments. In addition, several robustness checks are designed to address these identification concerns directly. On the income side, we re-estimate the main specification using windfall income within the reference group as a more plausibly exogenous source of variation in others' income. On the patience side, we move away from the strongest time-invariance assumption by using only waves in which patience is observed, employing experimentally elicited discount-rate measures, constructing auxiliary fixed-effects measures that absorb age-related and observable shock-related variation in patience, and restricting the sample to individuals with more stable life circumstances. We do not view these exercises as full solutions to the endogeneity problem, but they provide informative sensitivity checks that show the main moderation pattern is not tied to one particular income concept, patience measure, or sample composition.

4 Results

4.1 Baseline

First, we estimate a model without interaction terms to replicate the relative income results found in the literature (e.g., Ferrer-i-Carbonell, 2005). The fixed effects model includes the log of per capita absolute income (based on the modified OECD scale), the log of per capita reference income (mean per capita income in the baseline reference groups), the full set of observed individual characteristics, and year and state dummies. The results are presented in the first row of Table 2, Columns I(A) and I(B). Absolute income is positively associated with life satisfaction, with a coefficient estimate of 0.141 (s.e., 0.013), while relative income – measured as the mean income of the reference group – is negatively associated with life satisfaction, with a coefficient estimate of -0.119 (s.e., 0.022), as expected. Both coefficients are highly statistically significant. The relative magnitudes of the estimated coefficients are similar. This result suggests that, on average, there is a dominant "status" or "envy effect" due to income comparisons, as expected.

Our primary interest is to investigate whether the coefficients of absolute and relative income on well-being vary by patience levels, that is, by time discounting. The baseline fixed effects interaction model results are presented in the first row of Table 2. While Columns II(A) and III(A) show the absolute income coefficients for impatient and patient individuals, respectively, Columns II(B) and III(B) report the corresponding coefficients for relative income. The estimated coefficient of absolute income is positive for both patient and impatient individuals. Their relative magnitudes are very similar (0.131 vs 0.152), and the difference between the two is not statistically significant (p-value = 0.185). This result suggests that increases in absolute income yield similar gains in well-being for both groups.

However, in line with our conjectures, the relative income coefficients for patient and impatient individuals differ markedly. We find that the negative coefficient of relative income on well-being – indicating a dominant status effect – is experienced only by impatient individuals. The estimated coefficient of relative income for impatient individuals is -0.221 (s.e., 0.025), while for patient individuals it is -0.018 (s.e., 0.028). Notably, the average negative relative income coefficient reported in the literature is statistically significant and experienced only by *impatient* people. The difference between the relative income coefficients of patient and impatient individuals is also highly statistically significant (p-value < 0.001), which provides strong support for our central hypothesis.

4.2 Relative Income Distribution

We argue that individuals in different segments of the reference income distribution may also differ in their sensitivity to relative income depending on their patience levels. The key intuition is that the psychological meaning of a rise in reference income is unlikely to be the same for individuals below, near, or above their reference-group mean. For individuals below the reference-group mean, higher others' income may simultaneously intensify the negative feeling of being left behind and provide information about attainable future outcomes. The net effect is therefore ambiguous a priori and may depend on

Table 2. Main Results: Baseline and Heterogeneity across Relative Income Distribution

Dep Var. Life Satisfaction	I(A)	I(B)	II(A)	II(B)	III(A)	III(B)	IV(A)	IV(B)
	Baseline Model		Interaction with Patience Dummy					
			Impatient Individuals		Patient Individuals		p-value	p-value
	Absolute Income	Reference Income	Absolute Income (a)	Reference Income (c)	Absolute Income (b)	Reference Income (d)	H_0: $a = b$	H_0: $c = d$
1 Baseline (whole sample)	0.1408***	−0.1189***	0.1308***	−0.2213***	0.1521***	−0.0182	**0.1849**	**0.0000**
	(0.0131)	(0.0217)	(0.0187)	(0.0246)	(0.0110)	(0.0279)		
2 Upward comparators ($\leq Q1$)	0.1100***	0.0099	0.0889***	−0.0795**	0.1338***	0.0911**	**0.1069**	**0.0000**
	(0.0142)	(0.0318)	(0.0230)	(0.0394)	(0.0157)	(0.0358)		
3 Around the reference income ($> Q2$, $\leq Q3$)	0.2076***	−0.1521***	0.2234**	−0.2754***	0.1908***	−0.0300	**0.7052**	**0.0000**
	(0.0502)	(0.0374)	(0.0892)	(0.0658)	(0.0276)	(0.0341)		
4 Downward Comparators ($> Q3$)	0.0852***	−0.1266***	0.0615**	−0.2060***	0.1114***	−0.0451	**0.1588**	**0.0038**
	(0.0171)	(0.0267)	(0.0266)	(0.0379)	(0.0224)	(0.0392)		

Note: Authors' own calculations from SOEP from 2000 to 2019. The baseline model (Row 1, Columns I(A) and I(B)) is a linear fixed effects model using the whole sample (n = 283,671). Rows 2–4, Columns I(A) and I(B), report the linear fixed effects model with Q1, Q2–Q3, and Q4 dummies indicating quartiles in the distribution of the difference between absolute income and the reference income metric (n = 283,671). Row 1, Columns II(A)–III(B), is obtained from the baseline interaction model using the same sample size. Finally, Rows 2–4, Columns II(A)–III(B), present results from the double-interaction linear fixed effects model in which quartile dummies and the patience dummy are interacted with the income measures (n = 283,671). All model specifications include the full set of control variables: marital status dummies (married, single, widowed, divorced, and separated), years of education, household size, number of kids (aged 0–1, 2–4, 5–7, 8–10, 11–12, 13–15, and 16–18), subjective health status dummies (very bad, bad, neither bad nor good, good, and very good), non-labour income (rents and dividends), home ownership, employment level (not working, part-time, and full-time), working hours, job tenure, West Germany dummy, year dummies, and 16 federal state dummies. Age and gender are excluded as they are not identified in the fixed effects model. P-values are obtained from the t-test of whether the differences in the estimated absolute- and relative-income coefficients are equal to zero. Standard errors in parentheses are clustered within each reference group. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

how individuals weigh immediate status disadvantage against future-oriented information. We further hypothesise that this relationship varies systematically by time orientation. Patience is expected to matter precisely because it can shift the relative weight of these two channels. Individuals with shorter horizons may react more strongly to the immediate disutility of being below others, whereas more patient individuals may be better able to tolerate short-run disadvantages and place greater value on the informational content of others' success.

To investigate this hypothesis, we examine the distribution of the difference between individuals' absolute income and the mean income of their reference group. For upward comparators, that is, individuals whose income lies below their reference-group mean, the relative income effect is therefore expected to reflect the interaction of a negative status effect and a potentially positive information effect. For individuals with income close to the reference-group mean, comparison may be especially frequent, vivid, and behaviourally relevant. They are close enough to the local standard for changes in others' income to be salient in everyday life, but not secure enough to be insulated from status pressure. This makes the region around the mean a natural place for relatively strong negative comparison effects, especially for impatient individuals. For downward comparators, by contrast, the information channel is less central. Once individuals are already at or above the reference-group mean, higher reference income no longer naturally signals upward escape from a lower position. The more relevant psychology is one of status maintenance: others' gains reduce relative advantage, narrow the distance to those below, and may weaken the sense of being ahead. In this group, we still expect a negative relative income coefficient, but one that reflects the erosion of relative position rather than the standard upward-comparison mechanism. Patience may still matter here by weakening the psychological cost of comparison-driven stress and reducing the urge to defend current rank. We also hypothesise that individuals with incomes close to the average of their reference group may experience the strongest absolute and relative income effects (due to the concavity of absolute and relative income on well-being), and that among them, patience may again moderate the psychological impact of comparisons. Yet, whether the status or information effect dominates is unknown a priori.

We begin by calculating the distribution of the income difference metric and use it to classify individuals into three groups based on quartiles. Specifically, we define Q1 as the first quartile (the most deprived upward comparators), Q2-Q3 as the middle quartiles (those with income close to their reference group mean), and Q4 as the fourth quartile (the better-off downward comparators). We first estimate a fixed effects model where these quartile dummies are interacted with absolute and relative income. The results are presented in Rows 2-4 and Columns I(A)-I(B) of Table 2. Consistent with our expectations, upward comparators in Q1 do not show a statistically significant relative income coefficient on well-being. Individuals in Q2-Q3, with income around the reference group mean, experience the largest coefficients for both absolute and relative income (Row 3, Columns I(A)-I(B)). While absolute income remains positive among the better-off in Q4, the relative income coefficient remains sizable and negative (Row 4, Columns I(A)-I(B)). The weak coefficient in Q1 need not imply the absence of comparison. Rather, it may indicate that status and information effects potentially offset each other in this part of the distribution. It is also consistent with the idea that individuals below the reference-group mean are not homogeneous and that the strongest negative comparison effects may arise somewhat closer to the group average, where comparisons are most immediate and socially salient.

Next, we estimate a model with double interactions that includes quartile dummies (Q1, Q2-Q3, and Q4), the patience dummy (D^P), and both absolute and relative income variables. These results are shown in Rows 2-4 and Columns II(A)-III(B) of Table 2. The findings are highly consistent with our conjectures. Among upward comparators (Q1), patient individuals experience a statistically significant positive effect of relative income on well-being (0.091, s.e., 0.036), suggesting the presence of a dominant information effect (Row 2, Column III(B)). In contrast, impatient individuals in Q1 experience a significantly negative effect (-0.080, s.e., 0.039). The difference in the estimated coefficients is highly statistically significant (p-value $<$ 0.001). The absolute income coefficient is also larger for patient individuals in Q1 (0.134) compared to the impatient (0.089), although the difference is not statistically significant (p-value = 0.107). This contrast is consistent with the view that, within the upward-comparison region, patience shifts the balance between status and information.

Row 3 presents results for individuals with income levels close to their reference group average. The relative income coefficient is large and negative for impatient individuals (-0.275), while it is statistically insignificant and close to zero for patient individuals (-

0.030). The difference in these coefficients is highly statistically significant (p-value $<$ 0.001), indicating that the status effect is concentrated among the impatient. This is also the segment in which the strongest negative relative income effect emerges, which fits the idea that comparison is particularly intense when individuals remain close to the local standard but still fall short of it. Finally, Row 4 shows that patience moderates the effect of relative income even among higher-income individuals. The large negative coefficient among the better-off is driven primarily by the impatient (-0.206 vs -0.045 for the patient; Row 4, Columns II(B)-III(B)). The difference is again statistically significant (p-value $=$ 0.004). While the absolute income coefficient is somewhat larger for patient individuals in Q4, the difference between the two estimates is not statistically significant (Row 4, Columns II(A) and III(A) of Table 2). For this group, the weaker response among patient individuals is more naturally interpreted as evidence that patience attenuates status-maintenance concerns. When others' income rises and relative advantage narrows, patient individuals appear less reactive to the erosion of rank than impatient individuals.

4.3 Heterogeneity

The findings above provide strong evidence in support of the conjecture that patient individuals with lower discount rates experience a smaller marginal disutility from relative income comparisons. However, this estimated relationship may not be uniform across all individuals. Instead, it may exhibit important heterogeneities across different population subgroups. In particular, we argue that for some individuals, the income of others may not only exert a weaker negative effect but could also produce a positive effect, enhancing utility rather than diminishing it. Two examples illustrate this idea. First, younger individuals at the early stages of their careers may perceive the income of comparable others as a valuable source of information about potential career trajectories and economic opportunities. If these individuals are sufficiently patient, observing others' success may reduce stress and anxiety about their own future prospects, thereby yielding a net positive utility effect. Second, parents may also interpret others' income in a more future-oriented way. One possible interpretation is that higher peer income signals better future opportunities for their children. Another, and perhaps more immediate, interpretation is that parents may view the income of comparable others as informative about

Table 3. Observed Heterogeneity

Dep Var. Life Satisfaction	I(A)	I(B)	I(C)	II(A)	II(B)	II(C)
	Absolute Income			Reference Income		
	Impatient (*a*)	Patient (*b*)	p-value H_0: $a = b$	Impatient (*c*)	Patient (*d*)	p-value H_0: $c = d$
Gender						
Male	0.1582***	0.1640***	0.8446	−0.2278***	−0.0418	**0.0120**
	(0.0231)	(0.0197)		(0.0607)	(0.0594)	
Female	0.0988***	0.1383***	0.2088	−0.2125***	0.0056	**0.0042**
	(0.0234)	(0.0223)		(0.0619)	(0.0594)	
Age						
Younger ($<$ 49 years)	0.1194***	0.1196***	0.9923	−0.1153***	0.1600***	**0.0000**
	(0.0202)	(0.0133)		(0.0402)	(0.0465)	
Older ($\geq$ 49 years)	0.1281***	0.1614***	0.1169	−0.0509	−0.0520	0.9863
	(0.0202)	(0.0145)		(0.0569)	(0.0384)	
Education						
Lower education ($<$ 11.5 years)	0.1581***	0.0966***	**0.0652**	−0.3413***	0.0778	**0.0000**
	(0.0291)	(0.0249)		(0.0698)	(0.0823)	
Higher education ($\geq$ 11.5 years)	0.1151***	0.1788***	**0.0028**	−0.1958***	−0.0788***	**0.0004**
	(0.0203)	(0.0109)		(0.0288)	(0.0285)	
Having kids						
Having kids	0.2081***	0.2005***	0.8554	−0.1862***	0.1609**	**0.0000**
	(0.0392)	(0.0244)		(0.0626)	(0.0671)	
Not having kids	0.1030***	0.1275***	**0.0924**	−0.1452***	−0.0314	0.1173
	(0.0157)	(0.0120)		(0.0437)	(0.0438)	
Marital Status						
Married	0.1028***	0.1514***	**0.0831**	−0.1409***	0.0670	**0.0001**
	(0.0189)	(0.0203)		(0.0328)	(0.0516)	
Not married	0.0932***	0.1316***	**0.0387**	−0.3443***	−0.1905	**0.0851**
	(0.0254)	(0.0226)		(0.0590)	(0.1230)	
Region of residence						
East	0.1617***	0.1874***	0.4456	−0.2396***	−0.2184***	0.7364
	(0.0258)	(0.0218)		(0.0904)	(0.0752)	
West	0.1172***	0.1404***	0.3312	−0.2996***	−0.0122	**0.0000**
	(0.0248)	(0.0107)		(0.0276)	(0.0285)	

Note: Authors' own calculations from SOEP from 2000 to 2019. The model specifications include the full set of control variables. P-values are obtained from the t-test by comparing whether the differences in the estimated absolute- and relative-income coefficients are zero. Standard errors clustered by the reference group are in parentheses. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

their own future income prospects once child-care constraints ease and labour supply becomes less restricted. In either case, for patient and forward-looking parents, the income of others may carry informational content that partly offsets the negative psychological cost of comparison. To examine these possibilities more systematically, we explore several dimensions of heterogeneity to identify the subgroups for whom the marginal disutility is weaker or the information effect dominates. Specifically, we estimate the baseline interaction model separately for subgroups defined by characteristics such as age, parental status, and education level. The results of these heterogeneity analyses are summarised in Table 3.

The analysis suggests that gender does not significantly moderate the effects. Individuals of both genders with low levels of patience experience a strong status effect. As expected, the results are primarily driven by younger individuals. Among the young and impatient, we find a substantial status effect (-0.115, s.e., 0.040), while among young and patient individuals, we observe a statistically significant information effect (0.160, s.e., 0.047) (Columns II(A) and II(B), Table 3). In contrast, among individuals aged 49 (median) and older, there is essentially no difference in the estimated coefficients for others' income, suggesting that the moderating role of patience is negligible in this group. This result may also relate to findings in the literature indicating that patience levels tend to be higher among older individuals, potentially mitigating differences in the estimated coefficients. We further investigate the role of age in the next section, where we examine the robustness of our analysis with respect to age selection. In our alternative estimations, we consistently find evidence of the information effect only among samples with relatively younger individuals. It is also worth noting that these subgroup patterns are unlikely to be driven simply by large unconditional differences in education or equivalised household income between patient and impatient individuals, since the descriptive differences in these variables are modest in our sample.

Among less-educated individuals, those with high impatience experience a strong status effect. The relative income coefficient among patient individuals in this group is positive but estimated with less precision, implying that the information effect only partially offsets the status effect. Interestingly, even highly educated patient individuals experience a significant status effect. However, the difference in the estimated coefficients for others' income between impatient and patient highly educated individuals remains statistically significant (p-value < 0.001). Another notable finding is that individuals with children, who may be more future-oriented, show clear evidence of the information effect. Specifically, patient parents exhibit a statistically significant positive association with peer income (0.161 vs. -0.186). This pattern is consistent with a future-oriented interpretation, but the present data do not allow us to distinguish sharply between different forward-looking channels. It may reflect more optimistic beliefs about children's future opportunities, as suggested above, but it may also capture parents' expectations about their own future income trajectory once current family-related constraints become less binding. Marital status also appears to play a moderating role: married individuals exhibit stronger coefficient differences than those who are not married. Finally, we find that the moderating effect of patience is significant only among individuals residing in West Germany, which may reflect historical and political differences between the East and West regions of the country. This regional heterogeneity is also broadly in line with Ferrer-i-Carbonell (2005), who documents East-West differences in the well-being consequences of relative income within Germany, although the East German estimates in the present analysis are less precise and should therefore be interpreted with caution.

4.4 Robustness

The rest of the paper investigates the robustness of the previous results with respect to the choice of estimators, measures and stability of time preferences, sample selection, absolute and relative income measures, reference group definitions, and income inequality within the reference group. The results are summarised in Table 4. In each case, we focus on the estimated coefficients of absolute and relative income, interacted with the high-patience dummy. We then present the p-values from t-tests comparing the differences between the estimated absolute and relative income coefficients.

Estimators We begin with the choice of estimators. Our baseline specification is the linear fixed effects model, which does not account for the latent and ordinal nature of SWB. This choice is made in order to accommodate unobserved individual effects, which are crucial in SWB regressions. As an alternative to the linear specification, we employ the "blow-up and cluster" fixed effects ordered logit model (Baetschmann et al., 2015), which allows for both fixed effects and non-linearity. This state-of-the-art model is estimated for the baseline sample, and the results are presented in Row 1 of Table 4. It should be noted that the estimated parameters from this model are not directly comparable to those from the linear specification without calculating marginal effects. Nevertheless, the signs and statistical significance (standard errors are not clustered) of the estimated relative income coefficients for impatient and patient individuals are similar to those found in the linear fixed effects model. The difference in the relative income coefficients between the two groups remains highly statistically significant (p-value < 0.001). Moreover, this specification provides partial evidence that the absolute income effect on well-being may also differ by patience level (p-value $= 0.095$).

Another alternative is the correlated random effects specification, which provides a richer structure for modelling unobserved individual heterogeneity.[8] This specification controls for the within-person means of all time-varying characteristics (e.g., age, working hours, health status, household size) as part of the distribution of unobserved individual effects. To further account for personality-related traits potentially correlated with patience, we additionally control for the Big–5 personality characteristics (i.e., extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience) (Costa and McCrae, 1999). These traits are considered stable and time-invariant after adolescence (Cobb-Clark and Schurer, 2012), and are theoretically linked to time preferences (Becker et al., 2012). Thus, allowing for the personality might also help reduce the omitted variables bias further. We compute the within-person means of these personality scores across the five waves in which they are available and include them in the correlated random effects model. The results, presented in Row 2 of Table 4, show that the relative income coefficient is negative and statistically significant only for impatient individuals, consistent with the findings from the baseline fixed effects model. The difference in the estimated coefficients for patient and impatient individuals is statistically significant at conventional levels (p-value $= 0.043$). Notably, this difference remains significant across all model variations, including those with different combinations of within means and whether or not the Big–5 traits, locus of control (internal and external), subjective risk preferences mea-

[8]The Hausman test supports the fixed effects model with p-value < 0.001. Nevertheless, we present results from the correlated random effects model as it allows identification of the time-invariant high-patience dummy and offers a more flexible treatment of unobserved effects.

sure (on a 0-10 scale), fequency of anger (on a 1-4 scale), and the degree of impulsivity (on a 0-10 scale) are included.

Measures of Time Preferences To examine the robustness of our findings to alternative measures of time preferences, we conduct two main exercises. First, we reconsider the definition of the "high-patience" dummy. Second, we employ an alternative measure of discount rates derived from incentivised time preference experiments. In the baseline specification, an individual is classified as "patient" if their reported patience level exceeds the median of the population distribution (median = 6). We now redefine the threshold using the third quartile (Q3 = 8) of the patience distribution. The results of the linear fixed effects interaction model, presented in Row 3 of Table 4, indicate that the baseline findings are robust to this alternative definition. The coefficient on relative income for impatient individuals remains negative, statistically significant, and of comparable magnitude, while relative income continues to be statistically insignificant for patient individuals. The difference in the estimated coefficients of relative income is highly statistically significant (p-value < 0.001). Among the unreported results, we conduct two further robustness checks. First, we divide the patience distribution into four quartiles and interact each quartile with the relative income. Second, we treat patience as a continuous variable. These specifications also yield results that are highly consistent with our main findings.

Our primary measure of time discounting is based on a subjectively reported patience scale, which has been shown to correlate with experimentally elicited discount rates (e.g., Vischer et al., 2013; Richter and Schupp, 2014; Pinger, 2017). A notable advantage of the SOEP dataset is that it includes an incentivised time preference experiment conducted on a randomly selected subsample of individuals during wave 2006. This experiment was designed to elicit an individual's 'internal rate of return' as a proxy for time preferences. In the experiment, respondents were presented with 20 choice situations, each offering a choice between receiving €200 immediately or a larger amount after 12 months. The future amounts reflected annual interest rate increments of 0.025. Choosing the immediate reward in all scenarios indicates high impatience, while opting for delayed rewards early on, e.g., choosing €205 over €200, indicates greater patience and a lower discount rate. The first switching point between immediate and delayed choices determines an individual's implied internal rate of return.[9]

A total of $n = 977$ respondents participated in the experiment.[10] The internal rate of return calculated from these choices and the patience self-reports observed in 2006 are correlated at approximately 0.1308, indicating reasonable validity.[11] The internal rate of return ranges from 0.025 to 0.558; thus, the switching point also serves as an indirect proxy for the degree of time discounting. We merge the experimental data with the main SOEP dataset for the year 2006. Assuming relative temporal stability in discount rates, we calculate within-individual means and use all available panel waves for these respondents. To identify particularly patient individuals, we generate a dummy variable equal to one for those whose internal rate of return is below the first quartile value (0.076), corresponding to a switching point at the third choice situation.

We then re-estimate our baseline model, replacing the original high-patience dummy with the experiment-based measure. Using the full sample from 2000 to 2019 ($n = 9,802$), the results, presented in Row 4 of Table 4, show that the experimentally derived time preference measure yields conclusions highly consistent with the baseline. The marginal utility of absolute income remains unaffected, while individuals with higher discount rates (greater impatience) experience a larger marginal disutility from relative income. However, the difference in the relative income coefficients between individuals with low and high discount rates is not statistically significant (p-value = 0.171). We acknowledge that extending the data from 2000 to 2019 based on a single wave observation of the discount rate in 2006 may introduce bias. To address this, we estimate alternative models using shorter time spans. In Row 5, we restrict the sample to the period from 2000 to 2015 and re-estimate the baseline model. In this specification, the difference in estimated relative income coefficients for individuals with low and high discount rates is statistically significant (p-value = 0.050). In unreported results, we narrow the sample period further and find even lower p-values, offering stronger evidence of heterogeneity in relative income

[9] The experimental payment procedure ensures incentive compatibility: each participant selects a number between 1 and 9, and if it matches a randomly generated number by the computer, the selected choice from a random decision round is paid out. See Richter and Schupp (2014) and the SOEP documentation (www.paneldata.org) for further details.

[10] The experiment was conducted using CAPI (Computer-Assisted Personal Interviews), with an enumerator present.

[11] For comparison, Vischer et al. (2013) report a similar correlation of about 0.15 between the two measures.

effects by experimentally elicited time preferences. Finally, in Row 6, we estimate the model using the baseline high-patience dummy but restrict the sample to individuals who participated in the experiment. The results are highly consistent with our main findings, again showing statistically significant differences in relative income coefficients between impatient and patient individuals (p-value = 0.034).

Income Types, Consumption, Savings, and Comparison points Next, we check whether the results hold for alternative income types, consumption, savings, and comparison points. First, working people might make comparisons with respect to their labour earnings. Row 7 presents the results for the *wage income* obtained from labour activities. The analysis is conducted among the working wage population aged 18-65 to prevent retirement-related confounders ($n = 183,289$). The results are similar to the baseline per capita equalised household income. The relative income coefficient is negative and significant only among the impatient. In the previous analysis, we have assumed that people consume all they earn without savings. Yet patient people might save more than impatient people, and the consumption levels might be the actual comparison good. We now calculate the *consumption* per capita using the discretionary saving levels of the individuals. The model specification additionally controls for the log per capita savings. The results in Row 8 suggest highly similar results with or without controlling for the saving per capita levels in the regression ($n = 184,699$). The estimated relative income coefficient differences are statistically significant (p-value < 0.001). We have also estimated an alternative specification with the relative savings in the reference groups as one of the omitted variables. The results hardly differ.

In the next estimation (Row 9), we replace the standard income measure with *windfall income* (per capita, equivalised using the modified OECD scale), which can be viewed as a more plausibly exogenous source of income variation than the other income concepts used in the analysis (n = 278,605 observations, of which n = 12,660 report positive windfall income). This exercise is particularly useful in light of the endogeneity concerns surrounding both absolute and relative income, since windfall income is less likely to be jointly determined with the respondent's contemporaneous well-being or longer-run economic choices in the same way as regular earnings or household income. We therefore calculate mean windfall income within each reference group and re-estimate the baseline model

Table 4. Robustness Checks

Dep Var. Life Satisfaction	I(A)	I(B)	I(C)	II(A)	II(B)	II(C)
	Absolute Income			Reference Income		
	Impatient (a)	Patient (b)	p-value H_0: $a = b$	Impatient (c)	Patient (d)	p-value H_0: $c = d$
Estimators						
1 "Blow-up and Cluster" Ordered Logit Model	0.2170***	0.2818***	**0.0952**	−0.4315***	−0.0556	**0.0002**
	(0.0290)	(0.0276)		(0.0800)	(0.0814)	
2 Correlated random effects with Big-5 personality	0.1756***	0.1727***	0.8250	−0.0697**	−0.0096	**0.0430**
	(0.0152)	(0.0108)		(0.0316)	(0.0241)	
Measures of time preferences						
3 High patience dummy = 1 if patience $\geq Q3$	0.1327***	0.1640***	0.1009	−0.1520***	−0.0276	**0.0002**
	(0.0169)	(0.0119)		(0.0240)	(0.0311)	
4 Time preference experiment (Years 2000–2019)	0.1107*	0.1348***	0.7075	−0.2864**	0.0295	0.1754
	(0.0602)	(0.0484)		(0.1263)	(0.2518)	
5 Time preference experiment (Years 2000–2015)	0.1544***	0.1215**	0.6086	−0.2993**	0.2408	**0.0504**
	(0.0541)	(0.0504)		(0.1289)	(0.2778)	
6 Patience with the same sample in Row 4	0.1849***	0.0666	0.1492	−0.4082***	−0.0637	**0.0335**
	(0.0432)	(0.0719)		(0.1515)	(0.1595)	
Income types, consumption, savings, and comparison points						
7 Wage (labour) income	0.0150	0.0155	0.9700	−0.0631***	0.0196	**0.0043**
	(0.0100)	(0.0098)		(0.0221)	(0.0222)	
8 Consumption per capita	0.0556***	0.0874***	0.1193	−0.1457***	0.0163	**0.0000**
	(0.0160)	(0.0104)		(0.0296)	(0.0369)	
9 Windfall income	0.0003	0.0040***	**0.0268**	−0.0181**	−0.0073	0.3900
	(0.0014)	(0.0012)		(0.0087)	(0.0095)	
10 Lagged per capita income	0.0304***	0.0379***	0.5872	−0.1854***	0.0410	**0.0000**
	(0.0107)	(0.0098)		(0.0487)	(0.0419)	
11 Median reference income	0.1291***	0.1525***	0.1258	−0.3001***	−0.0836***	**0.0000**
	(0.0180)	(0.0113)		(0.0322)	(0.0293)	
Sample selection, stability of patience, and endogeneity concerns						
12 All waves available (1993–2020)	0.1604***	0.1714***	0.4046	−0.2213***	−0.0195	**0.0000**
	(0.0167)	(0.0146)		(0.0223)	(0.0222)	
13 Working age population (18–65)	0.1300***	0.1513***	0.1867	−0.1629***	0.0696	**0.0000**
	(0.0190)	(0.0130)		(0.0533)	(0.0554)	
14 With only three waves (time-variant patience)	0.1692***	0.0812*	**0.0054**	−0.1522**	−0.0425	**0.0005**
	(0.0354)	(0.0455)		(0.0656)	(0.0671)	
15 Using only wave 2013 for the patience measure	0.1481***	0.1604***	0.6234	−0.1621***	−0.0580*	**0.0069**
	(0.0274)	(0.0112)		(0.0308)	(0.0300)	
16 Auxiliary fixed effects with age	0.1317***	0.1502***	0.3202	−0.2068***	−0.0328	**0.0000**
	(0.0204)	(0.0102)		(0.0260)	(0.0261)	
17 Auxiliary fixed effects with age and shocks	0.1385***	0.1433***	0.7503	−0.2071***	−0.0336	**0.0000**
	(0.0179)	(0.0121)		(0.0254)	(0.0268)	
18 Shock-free subsample	0.2282***	0.1976***	0.3142	−0.2046***	0.0755	**0.0000**
	(0.0296)	(0.0221)		(0.0508)	(0.0524)	
Reference groups and income inequality within the reference group						
19 Dropping small sized reference groups	0.1345***	0.1538***	0.2352	−0.2249***	−0.0145	**0.0000**
	(0.0198)	(0.0114)		(0.0248)	(0.0271)	
20 Alternative reference groups 1	0.1307***	0.1514***	0.1906	−0.3387***	−0.0973***	**0.0000**
	(0.0183)	(0.0108)		(0.0357)	(0.0317)	
21 Alternative reference groups 2	0.1282***	0.1550***	0.1033	−0.1371***	−0.0145	**0.0000**
	(0.0185)	(0.0104)		(0.0234)	(0.0213)	
22 Allowing Gini within reference groups	0.1306***	0.1523***	0.1748	−0.2195***	−0.0163	**0.0000**
	(0.0187)	(0.0111)		(0.0245)	(0.0275)	

Note: Authors' own calculations from SOEP from 2000 to 2019. The model specifications include the full set of control variables. P-values are obtained from the t-test by comparing whether the differences in the estimated absolute- and relative-income coefficients are zero. Standard errors clustered by the reference group are in parentheses (except Row 1). *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

using this alternative comparison-income measure. The resulting estimates are similar to the baseline findings. The negative status effect remains concentrated among impatient individuals, whereas the corresponding coefficient for patient individuals is small and statistically insignificant. The difference between the two estimated coefficients is not statistically significant (p-value = 0.390). Since several reference groups under the baseline definition exhibit zero mean windfall income, we further re-estimate the model using broader reference groups that exclude education from the group definition, thereby increasing the sample size within each cell. These additional results, which are not reported in the table, align even more closely with the baseline pattern, and the difference between the estimated coefficients is estimated more precisely (p-value = 0.104). This exercise does not fully resolve the broader identification problem, but it does provide further reassurance that the main moderation pattern is not simply an artefact of the endogeneity inherent in more conventional income measures.

Next, we use the per capita income obtained during the *previous year*. The lagged relative income parameter estimate is negative and highly significant for individuals who are impatient (Row 10). The lagged relative income coefficient is positive but statistically imprecise for patient individuals ($n = 248,067$). The differences in the estimated coefficients are highly statistically significant in line with the baseline (p-value < 0.001). In Row 11, we change the definition of income comparison point to the *median*, which is robust in the case of smaller reference groups. The result of the median comparison income suggests that the relative income of the patient population is smaller but statistically significant. Yet, the main result holds, suggesting that impatient people experience very large relative income coefficients, which are statistically different from those of the patient people (p-value < 0.001).

Sample Selection, Stability of Patience and Endogeneity Concerns In Row 12, we investigate the sensitivity of the results concerning the *selection of sample waves*. Since patience is measured only in three waves, 2008, 2013, and 2018, we restrict the sample years to between 2000 and 2019 (dropping the years before 2000 and after 2019 due to the COVID-19 pandemic). This choice is arbitrary. We aimed to evenly distribute the waves to match those in which the patience is observed and to maintain a larger sample size to achieve higher degrees of freedom. We now use all waves from 1993 to

2020 and estimate the baseline linear fixed effects model ($n = 313,568$). The results in Row 12 are largely consistent with the baseline findings. The difference in the estimated relative income coefficients remains highly significant. Among the unreported results, we estimate models for alternative year selections, including 2007-2019 and 2013-2018. We obtain highly similar results for different sets of year combinations.

We also investigate the potential role of *age-related* sample selection. Our baseline sample covers the full population aged 18 to 80, but the inclusion of individuals who are still in education or already retired may affect the estimates. In Row 7, we partly address this issue by focusing on the working-age population (18 to 65) and using wage income. However, that specification excludes non-employed individuals. We therefore complement this exercise by re-estimating the baseline model with per capita household income for alternative age groups. The estimates reported in Row 13 are based on individuals aged 18 to 65 ($n = 228,270$). In this sample, impatient individuals continue to exhibit a negative relative income coefficient, whereas patient individuals display a positive, though statistically insignificant, coefficient. To examine this pattern more closely, we further restrict the sample to individuals aged 25 to 55 ($n = 160,703$). In this narrower age range, we find a statistically significant information effect. More generally, the positive relative income coefficient for patient individuals becomes significant and more precisely estimated as the sample is restricted to younger individuals (see also Table 3). These additional estimates are not reported in the table, but they suggest that our main findings are not driven by the inclusion of individuals at the margins of working life.

We then turn our attention to the *stability assumption* of the patience measure and its implications on the results. First, we use only the *three waves* in which the patience measure is available ($n = 45,257$), assuming that patience is time-variant, and estimate the baseline model on these three waves. The results in Row 14 suggest that the findings align with previous results. The negative coefficients of relative income are larger in magnitude for both impatient and patient individuals. The difference in the relative income coefficient remains statistically significant. This result indicates that the fixed effects model with a time-variant patience measure yields the same estimate, implying that the potential bias from the time-invariance assumption is relatively small. To go a step further, to assess how the stability of patience affects the results, we use only a *single* wave of patience measured in 2013 (instead of the mean over 2008, 2013, and

2018; $n = 193,333$ and 15,609 individuals). The rationale is that if patience is relatively stable, one wave of information should yield similar findings. Indeed, the results in Row 15 suggest that the relative income coefficient for impatient individuals is negative and larger in magnitude, and statistically different from that of patient individuals.

To investigate more directly whether our findings are sensitive to the temporal instability of patience and to potential endogeneity concerns, we estimate an auxiliary fixed-effects model in the spirit of Budría and Ferrer-i-Carbonell (2019). The purpose of this exercise is to recover an individual-specific component of patience that is purged of systematic age-related variation and major observable life-course shocks. Using the three waves in which patience is observed, we estimate the following auxiliary model:

$$Patience_{it} = \alpha_i + \sum_{k=1}^{4} \beta_k Age_{it}^k + \lambda_t + \delta' Shock_{it} + \varepsilon_{it}, \tag{2}$$

where α_i denotes the individual fixed effect, λ_t captures wave effects, and the fourth-order polynomial in age flexibly absorbs life-cycle variation in patience. The vector $Shock_{it}$ includes major time-varying life-course events and circumstances that may plausibly shift time preferences over time, such as labour-market status, marital status, disability, health shocks, and education-related transitions.[12] We then retain the estimated individual fixed effect, $\hat{\alpha}_i$, as an age-adjusted and shock-adjusted measure of the respondent's more stable patience component.[13]

We use this strategy in two steps. First, we estimate a parsimonious auxiliary specification that includes only the flexible age profile and wave effects, and use the resulting fixed effect to reconstruct the patient and impatient groups. The corresponding results are reported in Row 16. Second, we estimate the full specification above, which additionally absorbs major observable life-course shocks, and report the results in Row 17. In both

[12] At the individual level, unemployment exposure is identified from the labour-market-status history and captures whether the respondent is transitioned from employment to unemployment during the period under study. Educational change is defined as any observed change in educational attainment across waves. Marital instability is captured by changes in marital status from married to either divorced, seperated or widowed. Disability exposure is defined using reported disability status and flags respondents who report transition to disability during the observation period. Health shocks are constructed from large deteriorations in self-assessed health between consecutive waves (reduction in health status larger than two points on a five-point scale).

[13] Conceptually, this procedure isolates the persistent individual component of patience rather than the fitted value of observed patience at a particular age or shock profile. In this sense, it provides a practical summary of individuals' longer-run orientation toward the future after purging systematic age-related and observable shock-related variation.

cases, the results are remarkably stable and lead to the same substantive conclusion as in the baseline analysis. The disutility associated with others' income remains concentrated among less patient individuals, while the moderating role of patience remains. The estimated interaction terms, the implied patient–impatient differences, and the associated p-values are all highly similar across the two rows and to those obtained in the baseline specification.

As a further analysis to the concern that time preferences may shift with major life events, we construct shock-free subsamples following the logic in Budría et al. (2023), who restrict attention to individuals not exposed to major shocks in order to study more stable traits. Specifically, we exclude respondents who have ever experienced substantial changes in labour-market status, marital status, disability onset, health, or education-related transitions during the observation window. We implement both one-by-one exclusions and a stepwise cumulative restriction that removes respondents exposed to any of the identified shocks. Among the unreported results, across the one-by-one exclusions, the qualitative pattern remains unchanged: the relative-income effect is consistently negative for impatient individuals, while the corresponding coefficient for patient individuals remains small and statistically insignificant. Most importantly, in the most restrictive cumulative specification, reported in Row 18, the core sign pattern remains fully intact ($n = 65,992$). The relative-income effect remains negative and statistically significant for impatient individuals, whereas it becomes positive and statistically insignificant for patient individuals (p-value just above 0.10). This pattern is consistent with the idea that, once attention is restricted to individuals whose time preferences are more stable over the sample period, the estimated moderating role of patience remains visible and, if anything, becomes more precisely estimated. Part of this movement may also reflect changes in sample composition induced by the cumulative exclusions, since individuals who avoid major adverse shocks are likely to differ systematically from the full sample in ways that are themselves related to well-being and economic expectations. For this reason, we view the shock-free subsample analysis primarily as a stability check rather than as a preferred estimating sample. Its main contribution is not to strengthen the substantive magnitude of the positive coefficient, but to show that the central interaction pattern of the paper survives even under a stringent restriction to individuals whose patience is least likely to have shifted because of major life events.

Reference Groups and Income Inequality Finally, we investigate the sensitivity of the results concerning the *reference groups* and the income inequality within the reference groups. The reference groups are defined using ad-hoc criteria, and adding more criteria decreases the precision of the comparison income estimates, as the sample size for each reference group becomes smaller. Therefore, we generate the reference groups using a short but fundamental list of characteristics. We now change the criteria by adding and removing some characteristics and check the robustness of our results. First, we examine the robustness with respect to the minimum sample size in the reference group. The minimum sample size in reference groups is 10 in our baseline sample. In Row 19, we present the results for a minimum of 35 observations ($n = 281,537$). We find highly similar results. Increasing the sample size in the reference groups directly improves the precision of estimating the mean and median of the income distribution in the reference groups. Our experiments suggest that the results hold for any allowed sample size and that the results using mean and median reference incomes are highly similar when the reference groups are sufficiently large.

We then assess robustness to the *alternative criteria* used in defining the baseline reference groups, which include age, gender, years of education, and region. In Row 20, we modify the baseline reference group by removing years of education to test the sensitivity of our findings to this particular dimension. The estimated coefficients differ in size, but the main results hold. The relative income coefficient for impatient individuals is about four times larger than that for patient individuals, and the difference in the estimated coefficients is highly statistically significant. Next, in Row 21, we add marital status to the reference group definition. The results remain highly similar to those of the baseline. We also experiment with different combinations of criteria (e.g., including patience, high and low saving, employment status, among many others) and find that the difference between the relative income coefficients of patient and impatient individuals remains large and statistically significant.

In the final check, we calculate reference group-specific *income inequality* using Gini coefficients. Estimating the baseline model while controlling for the Gini coefficient yields results that are highly consistent with the baseline findings (Row 22, Table 4). To complement this analysis, we also split reference groups into low- and high-inequality environments, defined by whether the group-specific Gini coefficient falls below or above the median across all (baseline) reference groups, and examine how the relative income coefficient varies by the patience dummy across these two settings. The pattern is again very similar across the two regimes. In low-inequality reference groups, the relative income coefficient is strongly negative for impatient individuals (-0.262, s.e. $= 0.037$, p-value < 0.001), whereas it is much smaller and statistically insignificant for patient individuals (-0.034, s.e.$= 0.036$, p-value $= 0.349$). In high-inequality reference groups, the same qualitative pattern remains: the coefficient is negative and highly significant for impatient individuals (-0.197, s.e.$= 0.025$, p-value < 0.001), but small and statistically insignificant for patient individuals (-0.017, s.e. $= 0.030$, p-value $= 0.564$). A direct comparison across inequality regimes shows that the coefficient for impatient individuals is somewhat more negative in low-inequality than in high-inequality reference groups, but this difference is only marginally significant (p-value $= 0.055$), while the corresponding difference for patient individuals is clearly insignificant (p-value $= 0.624$). We therefore interpret these results as indicating that the moderating role of patience is broadly stable across more equal and more unequal comparison environments. In other words, the heterogeneity we document does not appear to be driven by a particular level of within-group income dispersion. Rather, the main result, namely that relative income concerns are concentrated among less patient individuals, survives in both low- and high-inequality reference groups.

5 Conclusion

Using subjective well-being (SWB) data as a proxy for individual utility, recent literature reports a significant loss of well-being associated with socio-economic comparisons. This result is consistently observed across samples and in developed Western countries (e.g., Clark et al., 2008). Drawing on prior work that explores heterogeneity in the effects of relative concerns on well-being, this paper fills a notable gap by analysing how time preferences, or what we refer to as 'patience', relate to the utility or disutility generated by income comparisons. We use a long panel of life satisfaction data to proxy SWB, combined with a concise, validated survey measure of subjective patience to capture time preferences. Fixed effects interaction models, which control for unobserved time-invariant individual heterogeneity, reveal that the typical negative coefficient of relative income, the so-called status effect, is primarily driven by individuals with high discount rates, who seek immediate gratification and exhibit stronger present bias. In contrast, more patient individuals, who can delay gratification and focus on long-term goals, experience no significant utility loss from relative income and may even exhibit a positive association, known as the information effect. These individuals tend to have greater self-control and emotional regulation, which makes them more resilient to the psychological stress generated by lower socio-economic positions. Their lower discount rates enable them to view a higher income of others as a motivational benchmark, something they believe they can attain over time.

Further analysis shows heterogeneity in the effect of relative income depending on the direction of comparison. Among individuals at the lower end of their reference group's income distribution, i.e., upward comparators, impatient individuals suffer a significant status effect. In contrast, patient individuals exhibit a statistically significant information effect. This pattern is consistent with the idea that upward comparisons need not operate only through frustration or relative deprivation. For more future-oriented individuals, the higher income of similar others may also carry informational content about attainable trajectories, thereby softening the adverse emotional consequences of being below the group mean. The patient people who are at the higher end of their relative income distribution, i.e., downward comparators, also experience an insignificant relative income effect. This weaker response among downward comparators is also psychologically plausible, since comparisons directed toward lower-income others are less likely to provide new information about future prospects and may be less salient for individuals whose evaluations are not strongly anchored in immediate status ranking. We also find heterogeneity across several demographic characteristics. Notably, younger individuals and those with children experience a statistically significant information effect, suggesting that future orientation is especially relevant in these groups.

The results are robust to a wide range of checks. Time preferences elicited from a large-scale incentivised experiment yield highly similar results, supporting the reliability of subjective patience measures. Including controls for relative savings and consumption does not alter the main conclusions. The findings are also consistent across several alternative definitions of reference groups and remain unchanged when accounting for the reference group-specific income inequality. To assess the assumption of time-invariant patience, we restrict the analysis to three waves where patience was measured, and again, the results remain stable. More generally, the moderation pattern also remains intact when we use alternative patience constructions designed to relax the stability assumption and absorb age- or shock-related variation in patience, and when we address income-side endogeneity concerns using windfall-based comparison measures. Overall, the findings are highly robust and internally consistent.

These results demonstrate that the utility consequences of relative concerns are heterogeneous across individuals, depending on their time preferences. Since people with low and high discount rates coexist within the same population, both the status and information effects are present, even within affluent Western societies. This insight provides a new perspective on the Easterlin Paradox, which highlights the discrepancy between strong cross-sectional associations between income and well-being and the lack of a similar relationship over time at the macro level. Our findings suggest that this paradox may be driven primarily by impatient individuals. Patient individuals appear to respond to relative income in the opposite direction, potentially offsetting the aggregate effect. Future research could formally investigate the relative contributions of patient and impatient individuals in generating the Easterlin Paradox by estimating their population weights.

Information about individuals' patience levels may also serve as a valuable tool for identifying who suffers most from relative concerns. This has direct relevance for welfare analysis and for the design of behavioural and fiscal policies. For instance, individuals with high discount rates may be more susceptible to engaging in status-driven consumption or borrowing. Recognising this can inform the design of targeted luxury or positional goods taxes, credit regulation, or savings incentives. At the same time, these implications are more naturally interpreted as evidence on mechanisms and policy environments than as support for screening individuals on the basis of measured patience, especially since patience may itself be shaped by life circumstances and adverse events. Policymakers may therefore use this insight to design financial literacy or long-term planning interventions in settings where individuals are more vulnerable to the emotional costs of comparison. These findings suggest that the utility heterogeneity due to relative concerns, particularly in time preferences, should be more explicitly integrated into welfare evaluations, optimal taxation theory, and inequality assessments in modern public economics. More broadly, the results imply that economic models of welfare and redistribution may benefit from allowing the costs of relative deprivation to differ systematically across individuals with different intertemporal orientations. They also suggest that policies aimed at reducing comparison-driven welfare losses may be especially effective when they strengthen longer-term planning horizons and limit incentives for status-driven expenditure.

From a methodological point of view, this study shows that SWB data can be used to evaluate complex hypotheses that are not easily tested using revealed or stated preference methods. Nonetheless, the study has limitations. The results cannot be interpreted as causal. While we use fixed effects models to account for constant unobserved factors and include a wide range of control variables such as risk preferences, personality traits, relative savings behaviour, income inequality in the reference groups, endogeneity remains a concern. This concern applies both to the income side of the analysis and to the measurement of patience itself. Absolute and relative income may still be jointly related to unobserved shocks affecting life satisfaction, while patience may also respond over time to stress, adversity, expectations, or prior well-being. In addition, the empirical reference groups used in the analysis should be understood as observable approximations that may combine both status-comparison and informational content. The psychologically relevant group for current status comparison need not coincide exactly with the group from which individuals infer future prospects, especially when individuals differ in time horizon. Reverse causality and unobserved changes over time may still bias the results. However, the strength, consistency, and internal logic of the findings across multiple specifications and samples offer a compelling empirical foundation. Accordingly, we interpret the paper as documenting a robust moderation pattern in panel data, rather than as establishing a fully causal effect of income comparisons under an exogenously fixed preference parameter. This is the first study to systematically examine how time preferences relate to the effects of income comparisons on well-being, and it provides an original and empirically grounded benchmark for future research. Experimental or quasi-experimental studies will be needed to establish a clearer causal relationship between time preferences, income comparisons, and well-being.

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