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Quantifying welfare costs of relative income concerns: a revealed preference approach

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Quantifying welfare costs of relative income concerns: a revealed preference approach*

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Abstract

We analyze relative income concerns and their impact on individual welfare using detailed data on Dutch households' consumption and labor supply. Our unique data set includes perceived mean incomes, allowing us to assess the welfare effects of income misperceptions. Using a nonparametric revealed preference approach, we quantify these effects in money metric terms. Our results reveal that relative income concerns impose a welfare cost of at least 142 EUR per month (approximately 8% of personal net income) on the average individual, with about one quarter of this cost attributable to income misperceptions. Additionally, we find that relative income and welfare effects vary by age, education, earnings, and household composition, with notable gender differences.

Keywords: relative income concerns, individual welfare, money metric measures, revealed preference analysis, Dutch household data, income (mis)perceptions.

JEL classifications: C14, D12, D91.

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1 Introduction

Relative income concerns refer to the phenomenon where individuals compare their income or consumption levels to those of others, which in turn impacts their own well-being and decision-making (Luttmer (2005), and Clark et al. (2008) for a review). The existing theoretical literature has shown that (negative) externalities from income comparisons have important implications for policy, with stronger relative income concerns typically associated with higher income taxes.[1] These policy implications depend on the strength and heterogeneity of relative income concerns, yet structural analyses of the presence and welfare effects of income comparisons across heterogeneous individuals remain scarce. In the current study, we assess the presence of such relative income effects in a structural modeling of individuals' labor supply behavior; and we measure the associated impact on individuals' welfare. Using unique observational data on Dutch households we are specifically able to quantify the welfare impact of individuals' (mis)perceptions of mean income.

Our contribution. We use a parsimonious model specification that is inspired on a recent study of Lewbel, Norris, Pendakur, and Qu (2022).[2] These authors propose to model the influence of interdependent preferences on an individual's utility through perceived needs. While Lewbel et al. (2022) focus on peer effects in a consumer demand setting, we adapt their model for examining relative income concerns in a labor supply setting. An attractive feature of the model in our context is that it offers a direct way of incorporating information on perceived mean incomes into the analysis, facilitating measurement of relative income effects. Moreover, and importantly, the model enables us to quantify the welfare impact of these relative income concerns in money metric terms. Lewbel et al. (2022) used a parametric household demand specification to bring the model to observational data. A main distinguishing aspect of our study is that we develop a revealed preference characterization of the model that is intrinsically nonparametric. This makes it possible to conduct an empirical

[1] Frank (1985) makes a distinction between positional goods (e.g., income and consumption) and less positional goods (e.g., leisure), arguing that taxes on positional goods help mitigate the distortions from negative consumption externalities. The general view in this literature is that greater concern for comparisons with average consumption in the population requires more income guarantees and higher marginal tax rates (Aronsson and Johansson-Stenman, 2018; Boskin and Sheshinski, 1978). Ireland (2001) shows that while status-seeking indeed implies a steeper tax schedule, it does not necessarily require more progressive taxes unless the rich care more about status than the poor. Aronsson and Johansson-Stenman (2021) allow for involuntary unemployment among low-skilled workers and demonstrate that in such context positional concerns imply even higher marginal tax rates for the high-skilled.

[2] Lewbel et al. (2022) themselves build on the early works of Samuelson (1948) and Gorman (1976), and on Blackorby and Donaldson (1994) and Donaldson and Pendakur (2006), who used a similar model in the context of equivalence scale measurement. Lewbel et al. (2022) provide an extensive discussion of the desirable welfare properties of their model of individual preferences with peer effects, referencing Blackorby and Donaldson (1994) and Donaldson and Pendakur (2006), as well as of the associated demand functions.

welfare analysis without imposing any (nonverifiable) parametric structure on the observed behavior, thus maximally avoiding functional specification error. To enhance the empirical bite of the model we (only) impose normality of household demand for consumption and leisure, along the lines of Cherchye, Demuynck, De Rock, and Surana (2020).

Despite its nonparametric orientation, our revealed preference methodology does allow for an informative empirical analysis. We show this through an empirical application that makes use of rich data that are drawn from the LISS (Longitudinal Internet studies for the Social Sciences) panel, which is representative for the Dutch population.[3] A unique feature of these data is that they include information on the individuals' perceptions of the distribution of income, in the population and among social contacts. By using our structural model, this effectively allows us to quantify the relative income/welfare effects of individuals' (mis)perceptions of mean income. More specifically, our empirical analysis will focus on three different research questions. First, we check whether a model with relative income concerns provides a better empirical fit of individual consumption and labor supply behavior than a standard model without income comparisons. Second, we quantify the welfare impact of relative income (and misperceptions of mean income) driving individuals' consumption and labor supply behavior. This procedure fits in a broader research approach that expresses the welfare effects of psychological phenomena in standard economic terms using money metrics; see, for example, Butera et al. (2022) for a recent application to shame and pride. Finally, we relate these welfare effects to individuals' observable characteristics. Even though our sample of individuals is fairly small and our revealed preference methodology imposes minimal prior structure, we do obtain meaningful results. For instance, our empirical findings reveal that the welfare cost of relative income concerns amounts to at least 142 EUR per month (about 8% of personal net income) for the average individual, with roughly one quarter of this cost stemming from income misperceptions. Notably, we also obtain that these relative income and welfare effects vary by age, education level, individual earnings, and household composition, with significant differences across genders.

A particular feature of our analysis is the recovery of relative income effects through a structural labor supply model, in which individuals balance leisure and consumption.[4] Our

[3] See https://www.lissdata.nl/ for more details on this LISS panel.

[4] In our set-up, leisure time is to be interpreted as available time that is not spent on market labor. Our parsimonious model specification implicitly assumes that individuals' consumption and leisure time allocations result from a two-stage budgeting process. In the first stage, individuals decide how to allocate their resources between leisure time and material consumption. In the second stage, they distribute the leisure time and material consumption budgets determined in the first stage across more specific categories of time use and consumption expenditures. This framework assumes that the allocations of leisure time and material consumption budgets in the second stage are separable from each other. In our modeling of relative income concerns, we assume that these concerns influence individuals' decisions during the first stage of the two-stage budgeting process.

structural welfare analysis complements previous research examining peer effects in labor supply behavior (see, for example, Card, Mas, Moretti, and Saez, 2012, Jäger, Roth, Roussille, and Schoefer, 2024, and van Rooij et al., 2024).[5] In our context, an advantage of this labor supply framework is that it enables us to exploit the considerable wage variation in our sample as price variation, significantly strengthening our analysis. In our empirical application, we define leisure as the difference between total available time and the time spent on market labor. For singles, we equate consumption with labor income. We proceed similarly for individuals in couples, thus making the assumption that these individuals (only) consume their own labor income. Admittedly, this is a strong assumption given the rich literature on multi-person household decision making (see, for example, Browning, Chiappori, and Weiss, 2014). Therefore, we also conduct separate analyses for single men and women in our empirical application. Interestingly, our findings highlight particularly strong relative income concerns for singles, despite the relatively small sample sizes.

A common focus in the broader literature on interdependent preferences is the identification of the effect of others' outcomes on an individual's own outcome. Following Lewbel et al. (2022), we do not directly observe *exogenous* shifts in others' behavior or detailed information about the network structure.[6] Instead, Lewbel et al. adopt a modeling strategy where the reference point depends on *expected* group behavior rather than the observed group averages. This approach breaks the direct link between individual behavior and group behavior, thereby mitigating the reflection problem described by Manski (1993). In our framework, the reference point is also modeled as an income expectation, but we use respondents' self-reported perceived values rather than model-based expectations. This has the advantage of directly capturing the —potentially biased— beliefs that underlie decision-making, which allows us to examine the welfare implications of such misperceptions. Moreover, it enables us to exploit the rich heterogeneity in individual perceptions. However, we acknowledge that correlated unobserved characteristics may also shape these perceptions. We leave a detailed exploration of this issue for future research. Consequently, our analysis does not allow for a strict causal interpretation of the relative income effects. Nevertheless, we argue that quan-

[5] van Rooij, Coibion, Georgarakos, Candia, and Gorodnichenko (2024) also utilized Dutch household data, employing reduced form techniques to examine how beliefs on average income and debt of similar individuals influence spending and happiness of the households under study. In particular, these authors conduct a randomized controlled study where treated households are informed about either the average income or debt of similar individuals, to assess how peer effects influence their beliefs and spending behavior. Our study complements this study by providing a structural analysis of households' behavior using observational data, in which we assess the presence of relative income effects and measure the associated impact on individual welfare of income comparisons and misperceptions. We also relate the magnitude of these relative income effects to observable characteristics of the individuals.

[6] For a recent review of the fast growing literature that utilizes network structure information to empirically identify peer effects, see, for example, Bramoullé, Djebbari, and Fortin (2020).

tifying welfare losses from income comparisons remains an important and valuable exercise in its own right.

Related literature. The interplay between income comparison, happiness, and consumption has been extensively explored in the economics literature.[7] Clark and Senik (2010) highlight the significance of relative income concerns in shaping individual happiness, emphasizing that people's well-being is not solely determined by their absolute income, but also by how it compares to others'. Bertrand and Morse (2016) investigate how income comparisons drive consumption patterns, noting that individuals often engage in conspicuous consumption to keep pace with their peers. Neumark and Postlewaite (1998) show that relative income concerns can explain why women's employment rose faster than predicted by standard neoclassical models. These studies collectively underscore the profound impact of income comparisons on both happiness and economic behaviors, including consumption and labor supply.

A more applied literature has attempted to measure social comparisons using econometric techniques or with direct survey questions. Ferrer-i-Carbonell (2005) conduct econometric analyses of subjective well-being and find a negative impact of the average income of the reference group on individual self-reported happiness. Other papers use surveys to quantify positional concerns in a broad range of product categories. The surveys present respondents with a choice between hypothetical societies with different combinations of individual outcomes and mean outcomes in the population (Carlsson et al., 2007; Johansson-Stenman et al., 2002; Solnick and Hemenway, 1998). Akay and Martinsson (2019) use a similar methodology to also study individual heterogeneity. They find that positional concerns gradually increase with age, particularly for income. One systematic insight from these studies is that income appears to be more positional than leisure (Carlsson et al., 2007; Solnick and Hemenway, 1998). Translated to our set-up, it means that unfavorable (income) comparisons are expected to make people work harder, causing them to deviate from their purely material optimum. To the best of our knowledge, we are one of the first to adopt a structural approach that offers deeper empirical insights into the welfare consequences of income comparisons.

A key feature of analyses of interdependent preferences is the need to define a peer group or reference point. Studies of peer effects in consumption typically rely on a predefined social group for comparison. For instance, the insightful studies by Agarwal, Qian, and Zou (2021), Bailey, Johnston, Kuchler, Stroebel, and Wong (2022), and De Giorgi, Frederiksen, and Pistaferri (2020) attribute significant multiplier effects to the influences of neighbors,

[7] For an early contribution, see Duesenberry (1949), who incorporates social comparisons into the theory of consumption and savings. See also Easterlin (1974) for early empirical evidence supporting the relative income hypothesis.

friends, and coworkers, respectively. Lewbel et al. (2022) define peer groups at a very local geographic level —small neighborhoods. In contrast, in relative income analyses the reference point is frequently defined in terms of mean outcomes in the economy as a whole (Aronsson and Johansson-Stenman, 2021; Clark et al., 2008; Johansson-Stenman et al., 2002). We follow this approach, which also enables us to examine the welfare cost of misperceptions about objective population means. Importantly, we validate this approach by conducting a complementary analysis in which the reference point is based on mean income among social contacts.[8] Our unique LISS module inquires directly about individuals' social contacts, obviating the need for assumptions about peer group definitions based on demographic characteristics and geography, which Lewbel et al. (2022, p. 1260) discuss as a limitation of their analysis.

At the methodological level, a main novel feature of our analysis is that we adopt a nonparametric revealed preference approach, providing a flexible framework that avoids stringent functional form assumptions. The nonparametric analysis of demand has a rich tradition in economics, with foundational work by Afriat (1967), Diewert (1973), and Varian (1982) on revealed preference analysis. Our approach aligns with closely related papers on nonparametric revealed preference methods. For instance, Blow and Crawford (2023) conduct a nonparametric analysis of reference-dependent preferences, where reference points are defined as vectors of consumer goods that alter the utility function. Their general approach imposes less structure but at the cost of reduced empirical applicability. In contrast, our method imposes more structure on the reference point, enabling a more informative empirical analysis. Additionally, Deb, Gazzale, and Kotchen (2014) employ a revealed preference methodology to test motives for charitable giving using experimental data. Their model is more general than ours in accounting for other-regarding preferences based on relative consumption and donations among individuals, but they do not address welfare analysis.

Outline. The remainder of this paper is structured as follows. Section 2 describes our data and the set-up of our empirical analysis. Section 3 introduces our structural model of individuals' consumption and labor supply behavior with relative income concerns, derives its testable revealed preference conditions, and assesses the empirical fit of our model for the LISS data. Section 4 quantifies the welfare impact of relative income effects, with particular attention for the welfare costs that follow from mean income comparisons and misperceptions. Section 5 relates these welfare costs to individuals' observable characteristics. Section 6 concludes.

[8]The results of our two analyses align very well. This is not surprising: Galesic et al. (2012) argue that the social environment of individuals helps construct their beliefs. The incomes of social contacts thus shape the individuals' perceptions of the income distribution in the population.

2 Empirical set-up

This section starts by describing the LISS data that we use. We pay specific attention to the survey questions on individuals' perceptions of mean income in the population and among social contacts. This also allows us to show the patterns of misperceptions that will play an important role in our empirical welfare analysis. Finally, we describe a data partitioning procedure that we use to subdivide our cross-section of individuals into observably homogeneous subgroups, which we will use in our following empirical analysis.

Data. The basic LISS panel, which is gathered by CentERdata, consists of 5000 households (comprising 8000 individuals) and is representative for the Dutch population. The first wave of the LISS panel was gathered in 2008. The LISS Core Study is a longitudinal study, which is repeated yearly and is designed to follow changes in the life course and living conditions of the panel members. It is comparable in content to standard social surveys. In addition to the LISS Core Study, researchers can collect their own data via online questionnaires presented to the panel members.

We merge individual characteristics and income data from the *Background variables* module of the LISS panel, labor supply data from Core module 6: *Work and schooling*, and information on individual perceptions from Study 21: *Effect of perceived social distributions on subjective well-being*. The latter study was only conducted in July 2008, so we focus on this wave for our data selection. Respondents with missing values for key variables such as income and income perceptions are excluded. We further remove individuals younger than 25 or older than 65, and we limit our analysis to singles and couples without children. Because our empirical analysis relies on a structural labor supply model, we include only individuals in paid employment. We finally drop four individuals who have a net wage rate beyond 67 EUR per hour (i.e., the top percentile). Our final sample consists of 343 individuals. Appendix A.1 provides more details on the sample selection, showing that the most restrictive criteria are participation in Study 21, household type, and being in paid employment at the time of the survey.

Study 21 of the LISS inquires about individuals' perceptions of the distribution of income, in the population and among social contacts. More specifically, respondents were asked what percentages of adults living in the Netherlands fall into the following personal net income categories: less than 1000 EUR, from 1001 to 1500 EUR, from 1501 to 2000 EUR, from 2001 to 2500 EUR, from 2501 to 3000 EUR, from 3001 to 5000 EUR, 5001 EUR or more. A similar question was asked about the percentages of *social contacts* falling into these categories.[9]

[9]Study 21 of the LISS introduces social contacts as follows: "*We would now like you to think of all adults you were in personal, face-to-face contact with at least twice this year. There are probably many such people:*

We use the reported percentages and the category midpoints to construct the individual's perception of mean personal income in the population and among social contacts. These perceptions differ by individual, so we can exploit rich heterogeneity in reference points based on perceived mean income.[10]

Table 1: Summary statistics

	mean	sd	min	max
Wage	12.09	5.71	1.50	46.15
Leisure	332.62	50.56	182.00	463.67
Income	1741.99	747.38	250.00	5400.00
Refpoint	2212.63	440.97	875.00	4460.00
Socialrefpoint	2142.98	736.10	500.00	5000.00
Age	45.20	11.22	25.00	65.00
Observations	343			

Notes: Wage is expressed in EUR/hour, Leisure in hours/month, and Income, Refpoint, and Socialrefpoint in EUR/month. Refpoint is the individual's perception of mean income in the population, Socialrefpoint is the individual's perception of mean income among social contacts.

Table 1 presents summary statistics on individual wages, monthly leisure, monthly earnings, the individual's perception of mean income in the population (*Refpoint*) and the individual's perception of mean income among their social contacts (*Socialrefpoint*), as well as the individual's age. On average, individual perceptions of mean income in the population do not differ much from individual perceptions of mean income among social contacts.[11] However, these perceptions considerably exceed the true mean income in the population,

your friends, family, colleagues, and other acquaintances. Some people may have such contacts with only a few other people, and others with several hundred. [...] *In the rest of the questionnaire, we will call these people your social contacts.*"

[10] In our analysis, we use the mean of the perceived income distribution as the reference point. Alternatively, the reference point could be defined as a specific percentile of the perceived income distribution, but this would require data with sufficiently narrow personal income categories. Moreover, it is important to note that, by construction, our measure of an individual's perception of the population's mean income is negatively correlated with the probabilities assigned to the lowest income category (-0.61) and positively correlated with those assigned to the highest income category (0.72). Finally, as we will explain in the following sections, incorporating the perceived mean income into our structural model of individuals' consumption and labor supply behavior with relative income concerns provides a good fit for our data. In our view, this further validates the use of perceived mean incomes as reference points.

[11] Unsurprisingly, the correlation between (Income minus Refpoint) and (Income minus Socialrefpoint), which represent the perceived positions in the income distribution under the two scenarios, is also high; in particular, it amounts to 0.62.

which amounts to 1565 EUR per month.[12,13]

This is also reflected in Figure 1, which shows the distribution of perceptions around the true mean income in the population. The figure reveals substantial misperceptions of mean income, generally implying an upward bias. Figures 2 and 3 provide complementary information. Figure 2 shows the joint distribution of perceived mean income and individual earnings, indicating that there is no clear relationship. Figure 3 displays the cumulative distributions of individual earnings and perceived mean incomes in the population and among social contacts. The figure confirms that the *Refpoint* and *Socialrefpoint* distributions are fairly close to each other, while the perceived incomes are generally above the actual incomes in the population.

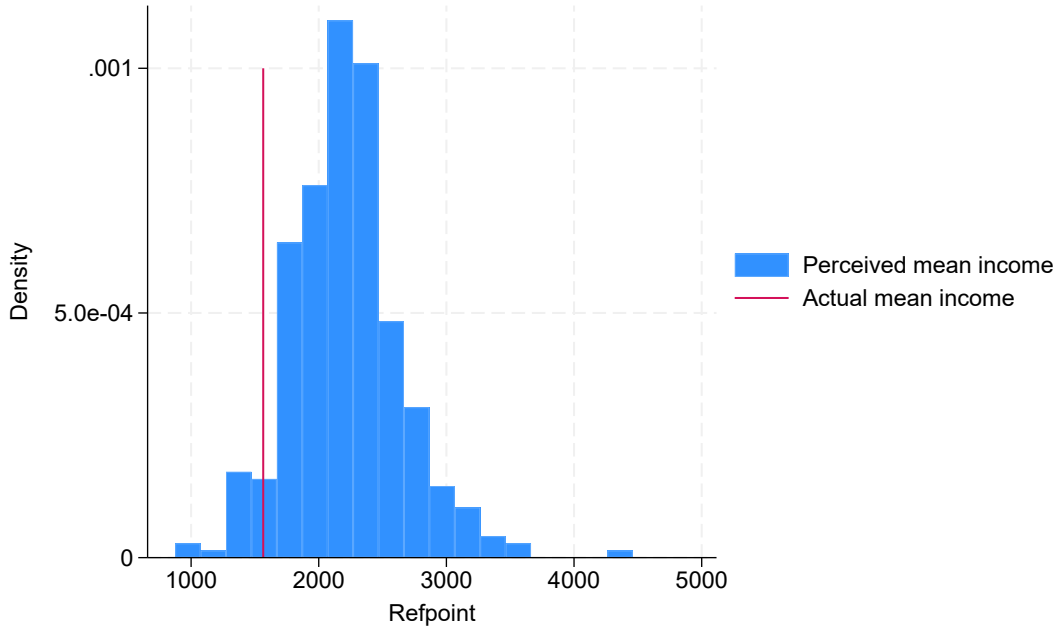


Figure 1: Histogram of individuals' perceived mean income (reference points $\bar{c}_r$)

Notes: The red line indicates the objective mean income in the population ($\bar{c}$) drawn directly from Study 21 of the LISS.

[12]To clarify, the mean Income in Table 1 (i.e., 1741.99 EUR per month) refers to the average income of all respondents in our specific sample, based on the reported incomes of our 343 participants. In contrast, the "mean income in the population" (i.e., 1565 EUR per month) is drawn directly from Study 21 of the LISS, which includes information on the objective income distribution in the Netherlands. We compare this objective average to the averages of the subjective/perceived income distributions. Further, Appendix A.2 provides additional information by regressing individual perceptions of mean income in the population on the individuals' observable characteristics. We find that perceived mean income increases significantly with age while it decreases significantly with individuals' wages (both at the 10% level).

[13]Using US data, Page and Goldstein (2016) also find systematic biases in individual beliefs with an overestimation of average household incomes. See Bursztyn and Yang (2022) for a meta-analysis of the literature on how misperceptions about others impact people's behavior.

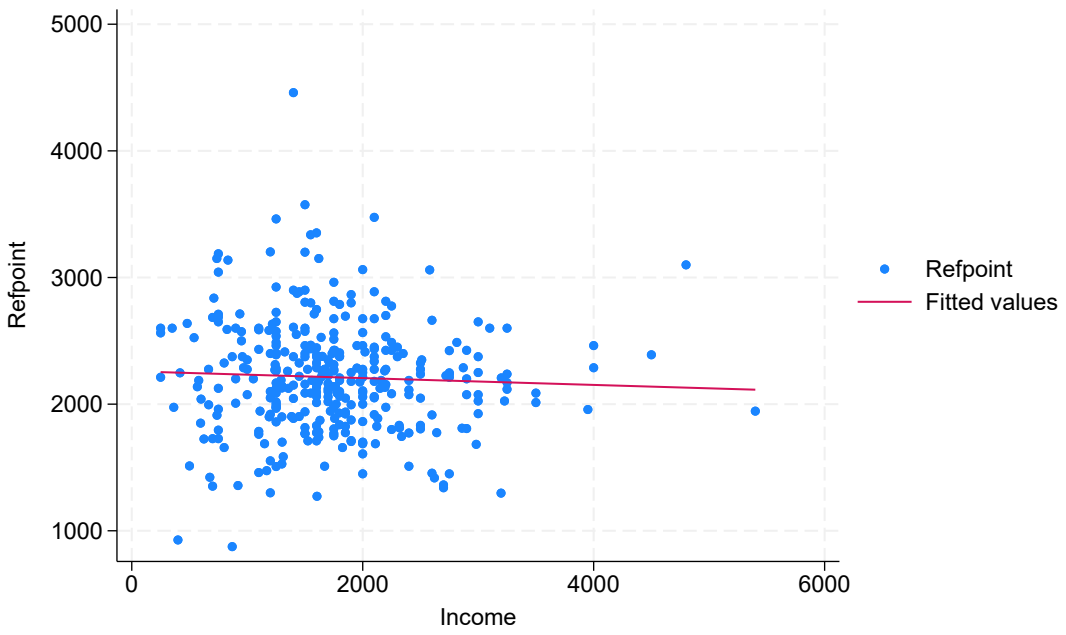


Figure 2: Scatter plot of individual earnings and reference points

Notes: The reference points are the individual perceptions of the mean income in the population

In what follows, we will use these data to conduct a relative income analysis at the individual level. We will study how income comparisons affect individual welfare, with special attention for the impact of income misperceptions. In our core analysis, we will use the individuals' perception of the mean income (*Refpoint*) as individuals' reference incomes that can influence labor supply. However, as we will indicate, our main qualitative findings are robust for using *Socialrefpoint* instead of *Refpoint*. As explained in the Introduction, we adopt a labor supply model where individuals allocate their entire income between leisure and consumption. Leisure is defined as the difference between the total available time and the hours spent on market labor. We set total available time at 16 hours per day, assuming that individuals require 8 hours daily for sleeping and eating. For singles, we define consumption as equal to labor income. We apply a similar approach for individuals in couples, assuming that each person consumes (only) their own labor income.

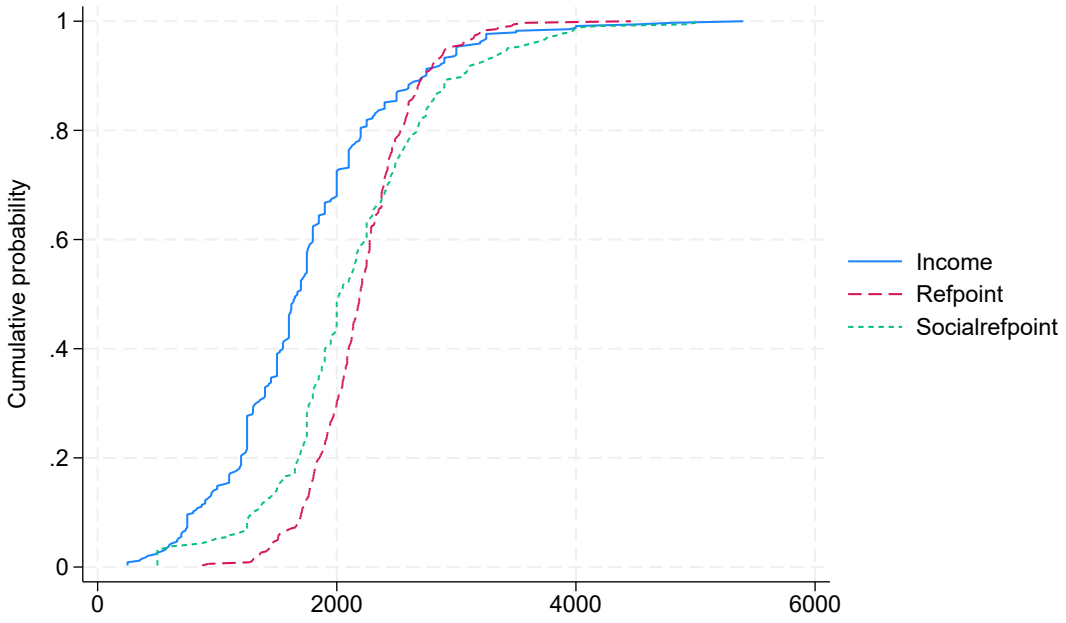


Figure 3: Cumulative distributions of individual earnings and reference points

Notes: The reference points are the individual perceptions of the mean income in the population (Refpoint) or among social contacts (Socialrefpoint)

Clustering. To conduct our following analysis, we form small groups of observably similar respondents.[14] We first split our sample based on two binary characteristics: gender of the respondent (male or female) and household composition (single or couple). This gives us four large groups of respondents: 49 single men, 68 single women, 109 men in couples, and 117 women in couples. Within each respondent type, we divide the subsamples further based on education. We classify individuals who finished (at most) primary school or intermediate secondary education into low education [Education=1], individuals who finished higher secondary education or intermediate vocational education into intermediate education [Education=2], and individuals who finished higher vocational education or university into high education [Education=3]. This yields three education classes of roughly equal size. Table 2 summarizes the frequency of the different types of respondents.

Finally, we further group the individuals, within each household composition—gender—education cell, based on their age. We sort individuals by age and then assign them to con-

[14]See Cherchye, Saelens, and Tuncer (2024) for a revealed preference analysis that examines the observable consumer characteristics influencing the heterogeneity in individuals' allocation of money and time. These authors highlight gender, age, education, household composition, and employment as key preference factors, identifying household composition and age as the most significant for their sample. This aligns with our clustering procedure, which is based on the same personal characteristics (i.e., gender, household composition, education and age)

secutive clusters of at most four individuals. We end up with 91 clusters in total. Appendix A.1 provides additional details on the clustering procedure and shows the distribution of clusters by average age. Even though our clusters are small, they do allow for an informative empirical analysis, as we will show in the following sections.

In our empirical analysis, we will assume that (observably similar) individuals in the same cluster are characterized by homogeneous utility functions defined over leisure and consumption. Obviously, such a preference homogeneity assumption is inescapable in a cross-sectional data setting like ours. At this point, it is worth to indicate that we will account for individual-specific relative income concerns, so inducing a channel of inter-individual heterogeneity in our structural model. Furthermore, in Appendix A.3 we show robustness of our revealed preference results with respect to the size of the groups that we define in our data partitioning procedure.

Table 2: Summary of clustering

	Singles		Couples		Total
	Men	Women	Men	Women	
Low edu	14	18	31	46	109
Med edu	14	22	38	38	112
High edu	21	28	40	33	122
Total	49	68	109	117	343

Notes: Low edu refers to primary school or intermediate secondary education (Education = 1), Med edu refers to higher secondary education or intermediate vocational education (Education = 2), and High edu refers to higher vocational education or university (Education = 3).

3 Relative income concerns and consumer rationality

We next turn to our theoretical model of rational consumption and labor supply behavior that is characterized by relative income concerns. As we explained in the introduction, we adopt a parsimonious model specification that is based on Lewbel et al. (2022), which models interdependent preferences by considering how the average outcomes of others influence an individual's utility through perceived needs. We establish the model's revealed preference characterization, which specifies the model's testable implications for the observed consumer behavior. We then apply these testable implications to the LISS data that we presented in the previous section. Our empirical results reveal that the model with individual-specific relative income concerns provides a good fit of the observed behavior. Importantly, the model significantly outperforms the model without relative income concerns and the model

that assumes homogeneous relative income concerns for observably similar individuals.

Theoretical model. We assume that consumers are characterized by continuous and strictly increasing utility functions U defined over leisure l and consumption c. As explained in the previous section, we cluster observably similar individuals, assuming that those within the same clusters share homogeneous utility functions. A consumer's time endowment equals T, and the consumer receives the wage w_r in a given situation r. Furthermore, our relative income model assumes that individuals compare their income or consumption level c with the needs $f_r(\bar{c}_r)$, which are specific to the situation r. These needs depend on the individual's perception of the mean income level (i.e., $\bar{c}_r$) and the consumer's observable and unobservable characteristics (shaping the function f_r).

Importantly, by incorporating individual-specific relative income effects, we introduce a source of inter-individual heterogeneity into our structural model. In principle, the function f_r can depend on demographic variables such as gender, type of household, education and age (which we used to define our clusters in Section 2), as well as on taste shifters that vary across decision-making situations. The latter also implies that the strength of income comparisons may vary depending on the individual's wage. Furthermore, our model accounts for unobserved factors (such as the rise of social media) that influence not only perceptions of mean income in the population (i.e., $\bar{c}_r$) but also the significance assigned to income comparisons (through f_r).

Let consumer r refer to the individual in situation r. We assume that consumer r chooses leisure and consumption quantities that solve the following problem:

$$(l_r, c_r) = \arg\max_{l,c} U(l, c - f_r(\bar{c}_r)) \text{ s.t. } w_r l + c \leq w_r T,$$

where $U(l, c - f_r(\bar{c}_r))$ represents the utility function, indicating that the individual values both leisure l and the difference between consumption c and their needs $f_r(\bar{c}_r)$. The needs function $f_r(\bar{c}_r)$ depends on the individual's perception of the mean income $\bar{c}_r$.

In our practical implementation of the general model, we will assume a linear structure $f_r(\bar{c}_r) = \alpha_r \bar{c}_r$, where $\alpha_r \in [0, 1]$ represents the strength of the relative income effect in situation r. Note that when $\alpha_r = 0$, relative income effects are entirely absent, while $\alpha_r = 1$ implies that a one-euro increase in mean income has the same impact on the individual's welfare as a one-euro decrease in the own consumption budget, assuming all else constant.[15]

[15] More generally, α_r indicates the importance of positionality considerations vis-a-vis pure consumption since $c - \alpha_r \bar{c}_r$ can be written equivalently as $(1 - \alpha_r)c + \alpha_r(c - \bar{c}_r)$.

With this linear structure, the consumer's optimization problem becomes:

$$(l_r, c_r) = \arg\max_{l,c} U(l, c - \alpha_r \bar{c}_r) \text{ s.t. } w_r l + c \leq w_r T.$$

In what follows, we will assume that leisure and consumption are normal goods. Normality implies that the expansion paths $l_r(x)$ and $c_r(x)$ are weakly increasing in $wT = x$, conditional on the prices and needs of situation r. In our opinion, normality is a natural assumption to make in a labor supply setting like ours. We refer to Cherchye et al. (2020) for a revealed preference analysis that provides empirical support for this normality assumption in a labor supply setting.

Testable implications. In our empirical application, each cluster of R consumers (defined in Section 2) represents a data set S. As outlined above, we will assume that (observably similar) individuals in the same cluster are characterized by homogeneous utility functions U defined over leisure and consumption. For each consumer r ($\leq R$), we observe the wage w_r, the leisure amount l_r, the consumption quantity c_r, and the relevant mean income $\bar{c}_r$, which gives:

$$S = \{w_r, l_r, c_r, \bar{c}_r\}_{r \leq R}.$$

We have the following definition of rationalizable behavior with relative income concerns:

Definition 1. *Consider a data set $S = \{w_r, l_r, c_r, \bar{c}_r\}_{r \leq R}$ and time endowment T. We say that S is rationalizable by relative income concerns if there exists a utility function U and numbers $\alpha_r \in [0, 1]$ such that each bundle (l_r, c_r) solves*

$$\max_{l,c} U(l, c - \alpha_r \bar{c}_r) \text{ s.t. } w_r l + c \leq w_r T.$$

The next result provides a nonparametric revealed preference characterization of rationalizable behavior for a given data set S. It allows us to check data consistency with our theoretical model of labor supply behavior with relative income concerns without requiring a functional specification of the utility function U.[16]

Proposition 1. *Suppose that the data set S is rationalizable by relative income concerns. Then, for all $t, v, r, s \leq R$ there must exist utility numbers U_t, (Hicksian) demand bundles*

[16] In Appendix A.4 we show that we can reformulate the testable conditions in Proposition 1 in Mixed Integer Linear Programming (MILP) terms, which is what we use in our following empirical exercises.

$H^l_{r,v}, H^c_{r,v}$, *and variables* $\alpha_r \in [0,1]$ *so that:*

$$\begin{aligned} H^l_{t,t} &= l_t, \\ H^c_{t,t} &= c_t, \end{aligned}$$

$$\begin{aligned} U_t &\geq U_v \Rightarrow w_r H^l_{r,v} + (H^c_{r,v} - \alpha_r \bar{c}_r) \leq w_r H^l_{s,t} + (H^c_{s,t} - \alpha_s \bar{c}_s), \\ U_t &> U_v \Rightarrow w_r H^l_{r,v} + (H^c_{r,v} - \alpha_r \bar{c}_r) < w_r H^l_{s,t} + (H^c_{s,t} - \alpha_s \bar{c}_s), \end{aligned}$$

$$\begin{aligned} U_t &\geq U_v \Rightarrow H^l_{r,v} \leq H^l_{r,t}, \\ U_t &\geq U_v \Rightarrow H^c_{r,v} \leq H^c_{r,t} \end{aligned}$$

Proof. Let $(H^l_{r,v}, H^c_{r,v})$ solve:

$$(H^l_{r,v}, H^c_{r,v}) = \arg\min_H w_r H^l_{r,v} + H^c_{r,v} \text{ s.t. } U(H^l_{r,v}, H^c_{r,v} - \alpha_r \bar{c}_r) \geq U_v$$

To show that $U_t \geq U_v \Rightarrow w_r H^l_{r,v} + (H^c_{r,v} - \alpha_r \bar{c}_r) \leq w_r H^l_{s,t} + (H^c_{s,t} - \alpha_s \bar{c}_s)$, the reasoning is as follows.[17] Let $U_t \geq U_v$. Towards a contradiction, assume that $w_r H^l_{r,v} + (H^c_{r,v} - \alpha_r \bar{c}_r) > w_r H^l_{s,t} + (H^c_{s,t} - \alpha_s \bar{c}_s)$. By definition, $(H^l_{r,v}, H^c_{r,v})$ minimizes earnings needed to reach utility level U_v with prices w_r and needs $\alpha_r \bar{c}_r$. Also by definition, bundle $(H^l_{s,t}, H^c_{s,t})$ produces utility level U_t when needs are $\alpha_s \bar{c}_s$. When needs are in fact $\alpha_r \bar{c}_r$ (instead of $\alpha_s \bar{c}_s$), buying $(\tilde{H}^l, \tilde{H}^c) = (H^l_{s,t}, H^c_{s,t} - \alpha_s \bar{c}_s + \alpha_r \bar{c}_r)$ must also produce utility U_t. To see this:

$$\begin{aligned} U(H^l_{s,t}, H^c_{s,t} - \alpha_s \bar{c}_s) &\geq U_t \\ &\Leftrightarrow U(H^l_{s,t}, (H^c_{s,t} - \alpha_s \bar{c}_s + \alpha_r \bar{c}_r) - \alpha_r \bar{c}_r) \geq U_t \\ &\Leftrightarrow U(\tilde{H}^l, \tilde{H}^c - \alpha_r \bar{c}_r) \geq U_t \end{aligned}$$

If $(\tilde{H}^l, \tilde{H}^c) = (H^l_{s,t}, H^c_{s,t} - \alpha_s \bar{c}_s + \alpha_r \bar{c}_r)$ was strictly cheaper than $(H^l_{r,v}, H^c_{r,v})$ at prices w_r, but $U_t \geq U_v$, the consumer should have chosen $(H^l_{s,t}, H^c_{s,t} - \alpha_s \bar{c}_s + \alpha_r \bar{c}_r)$ instead of $(H^l_{r,v}, H^c_{r,v})$. This gives the conclusion:

$$U_t \geq U_v \Rightarrow w_r H^l_{r,v} + (H^c_{r,v} - \alpha_r \bar{c}_r) \leq w_r H^l_{s,t} + (H^c_{s,t} - \alpha_s \bar{c}_s).$$

□

As a concluding note, we point out that Proposition 1 presents our testable implications

[17] Similarly for $U_t > U_v \Rightarrow w_r H^l_{r,v} + (H^c_{r,v} - \alpha_r \bar{c}_r) < w_r H^l_{s,t} + (H^c_{s,t} - \alpha_s \bar{c}_s)$.

as necessary conditions for rationalizable behavior. In other words, if the data set S can be rationalized by relative income concerns, these conditions must be satisfied. Demonstrating necessity is sufficient for our subsequent testing analysis. Moreover, it also motivates the use of these conditions in the identification analysis that follows, which is the primary focus of our empirical exercise. Specifically, as explained in Section 4, they allow us to nonparametrically identify the welfare impact of relative income concerns, under the maintained assumption that the observed behavior is rationalizable by relative income concerns. In principle, we may establish that these testable conditions are not only necessary but also sufficient for rationalizability, following the approach of Cherchye, Demuynck, De Rock, and Surana (2020, Proposition 2), who build on a general result from Nishimura, Ok, and Quah (2017). However, for the sake of brevity, we will not address this issue in the present paper.

Empirical results. We test three hypotheses about relative income concerns. The first hypothesis assumes that such concerns are absent, consistent with the standard utility maximization model. The second hypothesis allows for relative income concerns but assumes they are homogeneous within our clusters of observably similar consumers (i.e., after controlling for gender, household composition, education, and age). The third hypothesis permits general unobserved heterogeneity in relative income concerns across the sample. In terms of our rationalizability concept in Definition 1, these three hypotheses boil down to adding the conditions $\alpha_r = 0$, $\alpha_r = \alpha \in [0,1]$ and variable $\alpha_r \in [0,1]$, respectively. The associated testable conditions follow readily from Proposition 1.

We use these testable conditions to assess our three hypotheses on the basis of three well-known empirical performance measures from the revealed preference literature: pass rates, power and predictive success. One may be inclined to compare the empirical performance of alternative revealed preference conditions by solely comparing their pass rate, namely the proportion of individuals passing the conditions. However, this practice can be very misleading if one rationalizability concept is structurally weaker than the other. For example, any model that imposes additional restrictions on α_r will naturally involve stronger testable implications, which can only yield a lower pass rate.

In order to solve this issue, one should account for the empirical stringency of the revealed preference conditions. A widely used measure for the power of revealed preference conditions is the so-called Bronars (1987) index, which computes the fraction of (simulated) random data sets that violate the rationalizability conditions subject to testing. A random data set is then constructed by randomly selecting bundles from each of the observed budget hyperplanes (i.e., given the observed wages). In general, higher power values reveal more stringent revealed preference conditions. In our setting, the power will automatically increase

with stronger restrictions for α_r.

Beatty and Crawford (2011) suggest to combine the pass rate and power of a given specification of revealed preference conditions into a single-dimensional measure of "predictive success", which is computed as:

$$\text{predictive success} = \text{pass rate} - (1 - \text{power}),$$

and always situated between -1 and 1.[18] A good performing labor supply model has a predictive success measure that is close to one, as this reveals both a high pass rate and high power; many observed individuals pass the testable conditions while almost no random behavior passes the conditions. A predictive success measure below zero implies that the pass rate for the randomly generated data exceeds the one for the observed data. This indicates the —obviously undesirable— situation that the revealed preference conditions fit random behavior better than actual behavior. In principle, the higher the measure of predictive success, the better the empirical fit of the model that is tested. Demuynck (2015) introduced statistical tests for differences in predictive success associated with alternative behavioral models. We will use these statistical tools in our following application.

Throughout, we will use the individual's perception of mean income in the population (*Refpoint* in Section 2) to specify the income reference level $\bar{c}_r$. However, it is worth indicating that our following findings are robust for using the individual's perception of the mean income among social contacts (*Socialrefpoint* in Section 2) instead of *Refpoint*; see Appendix A.5. As illustrated in Section 2, the *Refpoint* and *Socialrefpoint* distributions are close to each other. The advantage of using *Refpoint* is that it can be compared with the true mean income in the population, which we can use to assess the welfare effects of income misperceptions. We will do this in Section 5.

Our results are summarized in Table 3. Interestingly, we find that predictive success is lowest for the model that assumes away relative income concerns (with $\alpha_r = 0$). It is somewhat higher for the model with fixed relative income concerns (with $\alpha_r = \alpha$), and highest for the model with fully heterogeneous relative income concerns (with variable α_r restricted to lie within the interval $[0, 1]$). We also computed 95%-confidence bounds around our predictive success estimates, following the statistical procedure outlined in Demuynck (2015). The predictive success of the model without relative income concerns is situated between 0.04 and 0.22. Predictive success with fixed relative income concerns is between 0.10 and 0.30, and predictive success with variable relative income concerns is between 0.33 and 0.39. Interestingly, the 95%-confidence intervals of the model without relative income

[18] Beatty and Crawford (2011) build on an original proposal by Selten (1991).

concerns and the model with variable relative income concerns are non-overlapping, clearly favoring the latter specification.

This last model achieves an almost perfect pass rate, successfully rationalizing 90 out of 91 clusters, resulting in a pass rate of 99%. Notably, its power is also reasonably high. The model does not only do well empirically, it is also conceptually attractive. It implies that the effect of $\bar{c}_r$ on utility may depend not only on gender, household composition, age or education, which we used in our data partitioning procedure, but also on characteristics of the choice environment (wage w_r, perceived income of others $\bar{c}_r$, ...) or unobservables defining individual needs.

Our results reveal that modeling relative income concerns provides a significantly better explanation of the observed labor supply behavior in our sample. Given its favorable empirical support and conceptual appeal, we will focus exclusively on the variable relative income concerns model in the subsequent identification analysis. This restricts attention to the 90 (out of 91) clusters of individuals (339 individuals in total) that can be rationalized by this model.

Table 3: Summary of revealed preference results

	Models		
	No relative income concerns ($\alpha_r = 0$)	Fixed relative income concerns ($\alpha_r = \bar{\alpha}$)	Variable relative income concerns (Variable α_r)
Pass rate	0.29	0.40	0.99
Power	0.84	0.81	0.37
Predictive success	0.13	0.20	0.36

Notes: The pass rate shows the fraction of clusters that can be rationalized. Power is the fraction of simulated random data that violate the rationality conditions. Predictive success is the pass rate of actual data minus the pass rate of random data. There are 91 clusters with 3 or 4 observations each.

4 Quantifying welfare costs

A particularly appealing aspect of our structural model is that it enables us to quantify the welfare impact of relative income concerns in money metric terms. We begin this section by formalizing this argument. Next, we outline the methodology we use to identify these welfare effects in practice. Finally, we present the distribution of relative income concerns as identified in our LISS sample. This will reveal substantial cross-sectional heterogeneity, motivating our investigation in the following section.

Theory. A most important feature of our model is that it allows us to define a money metric measure of the relative income concerns.[19] To show this, we let $e(w_r, \alpha_r, \bar{c}_r, u)$ denote an individual's expenditure function: for a given wage w_r, relative income effect parameter α_r, and reference level $\bar{c}_r$, it gives the minimal expenditures to attain the utility level u. For an interior solution of the expenditure minimization problem, we obtain (using $\tilde{c} = c - \alpha_r \bar{c}_r$):

$$\begin{aligned} e(w_r, \alpha_r, \bar{c}_r, u) &= \min_{l,c}\{(w_r l + c) \text{ subject to } U(l, c - \alpha_r \bar{c}_r) \geq u\} \\ &= \min_{l,\tilde{c}}\{(w_r l + \tilde{c} + \alpha_r \bar{c}_r) \text{ subject to } U(l, \tilde{c}) \geq u\} \\ &= \min_{l,\tilde{c}}\{(w_r l + \tilde{c}) \text{ subject to } U(l, \tilde{c}) \geq u\} + \alpha_r \bar{c}_r \\ &= e(w_r, 0, \bar{c}_r, u) + \alpha_r \bar{c}_r, \end{aligned}$$

where $e(w_r, 0, \bar{c}_r, u)$ represents the expenditure level for the consumer to achieve the utility level u if relative income concerns were absent (i.e., $\alpha_r = 0$). It follows directly that the additional expenditures that are specifically due to the presence of relative income concerns are given by:

$$e(w_r, \alpha_r, \bar{c}_r, u) - e(w_r, 0, \bar{c}_r, u) = \alpha_r \bar{c}_r,$$

which gives us an intuitive money metric measure of the welfare cost associated with relative income concerns. Identifying these welfare costs requires identifying α_r.

Methodology. We can nonparametrically identify bounds on the welfare costs of relative income concerns (i.e., "set" identification of α_r) by using our rationalizability conditions in Proposition 1. We proceed in two steps. First, we define the parameter Δ, which minimizes individual-specific deviations from the model that excludes relative income concerns. Specifically, we solve the following program for each cluster with R consumers:

$$\begin{gathered} \min \Delta \text{ subject to} \\ \alpha_r \leq \Delta \\ \alpha_r, \Delta \in [0, 1], \end{gathered}$$

with α_r $(r = 1, ..., R)$ satisfying the conditions in Proposition 1. We denote the solution of this program by Δ^*. It represents the tightest possible limit on relative income concerns that still rationalizes the data. An alternative interpretation of Δ^* is that it serves as a lower bound for the strongest individual relative income effect within the cluster. Intuitively, this

[19] Our following argument closely follows Lewbel et al. (2022).

method minimizes the heterogeneity in relative income concerns between this individual and others in the group who do not experience relative income concerns.

In the second step, we minimize and maximize $\alpha = \sum_r \alpha_r / R$ subject to the same restrictions as in the above program and, in addition, $\alpha_r \leq \Delta^*$ (i.e., we fix the variation $\Delta = \Delta^*$). This gives us lower and upper bounds on the average relative income effect per cluster, which we denote by α^{lb} and α^{ub}, respectively.

Empirical results. Table 4 summarizes the results for α^{lb}, α^{ub}, and Δ^* across the 90 clusters of consumers that can be rationalized by the variable relative income concerns model. On average, the value of Δ^* is 0.17, indicating that α_s for the individual s with the largest relative income concerns is at least 17% for the average cluster. Furthermore, Δ^* reaches 0.89 for at least one cluster, suggesting that a one-euro increase in the average income of the population is perceived as equivalent to a decrease in own consumption of at least 89 cents. When examining the cluster-specific lower bounds α^{lb} and upper bounds α^{ub}, we find average values of 0.06 and 0.11. However, there is quite some variation across clusters. For instance, in one cluster the within-group relative income effect is bounded between 0.37 and 0.39.[20]

Table 4: Lower and upper bounds on relative income concerns

	mean	sd	min	max
alpha_lb	0.06	0.09	0.00	0.37
alpha_ub	0.11	0.14	0.00	0.61
delta	0.17	0.19	0.00	0.89
N	90			

Notes: alpha-lb α^{lb}, respectively alpha-ub α^{ub}, is the lower (upper) bound on average relative income effects conditional on delta. delta Δ^* is the tighest possible limit on relative income concerns that still rationalizes the cluster. The results are based on the 90 rationalizable clusters.

Table 5 complements Table 4 by showing summary statistics for the corresponding welfare costs that are due to relative income concerns, for the 339 individuals within the 90 rationalizable clusters. Specifically, we consider the measure $m = \alpha \bar{c}_r$ that we introduced above, for which we can identify the bounds $m^{lb} = \alpha^{lb} \bar{c}_r$ and $m^{ub} = \alpha^{ub} \bar{c}_r$. The measure m captures the

[20] Interestingly, the magnitude of our estimated relative income effects is comparable to the peer effect estimates reported by Lewbel et al. (2022), who use a formally similar structural model (though based on a parametric approach, as discussed in the introduction); see, for example, their Tables 2 and 3. Their conservative baseline estimate of 0.26 falls within our range of 0 to 0.61 (across heterogeneous consumer clusters). This is particularly noteworthy given that our study focuses on different consumer populations (the Netherlands versus India) and employs a different methodology.

individual welfare cost of relative income concerns driven by the (potentially misperceived) reference level $\bar{c}_r$. Our findings indicate that the average welfare cost is situated between 142 EUR and 253 EUR per month. For some individuals, the welfare losses due to relative income concerns are at least 1032 EUR per month (lower bound) and can be as high as 2063 EUR per month (upper bound). Figure 4 visualizes the distributions of the upper and lower bounds on our money metric measure m for our sample of consumers. Similar to before, we observe substantial variation in relative income concerns across individuals.

Table 5: Lower and upper bounds on welfare cost of relative income concerns

	mean	sd	min	max
mincost	141.57	192.98	0.00	1031.66
maxcost	252.74	307.58	0.09	2063.62
N	339			

Notes: mincost m^{lb}, respectively maxcost m^{ub}, is a lower (upper) bound on the individual welfare cost of relative income concerns. The results are based on the 339 individuals within the 90 rationalizable clusters.

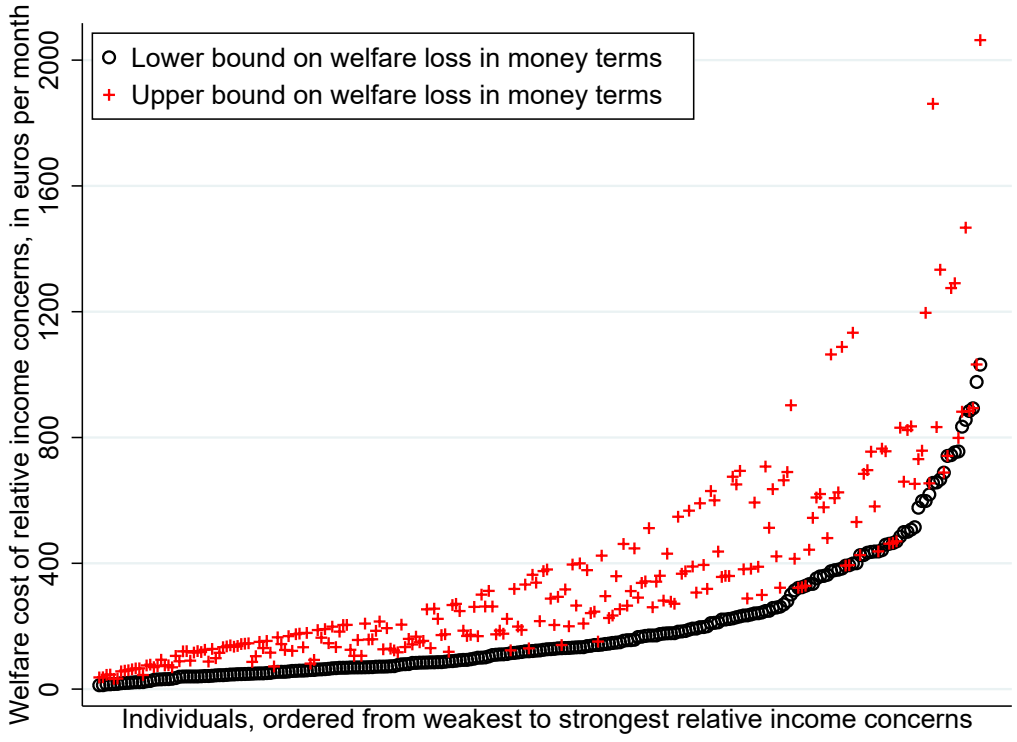


Figure 4: Distribution of welfare cost of relative income concerns

Notes: Individuals are ordered according to the lower bound on the cost of relative income concerns m^{lb}. The results are based on the 243 individuals within the 64 clusters that need $\Delta^* > 0$ for rationalizability.

5 Observable heterogeneity in relative income concerns

This section relates the cross-sectional heterogeneity in relative income/welfare effects that we described in the previous section to consumers' observable characteristics. In a first exercise, we specifically assess which types of individuals suffer most frequently from relative income concerns. In a following step, we relate the associated welfare costs to observable consumer characteristics. We conclude by investigating to what extent these welfare costs are driven by misperceptions of mean income.

Who suffers from relative income concerns? We begin by relating the presence of relative income concerns to observable individual characteristics, by conducting two different exercises.[21] We first perform a probit regression to estimate the probability that an individual has strictly positive relative income concerns (i.e., $\Delta^* > 0$). In our second exercise, we conduct interval regressions for the strength of the relative income effect. By construction, α^{lb} and α^{ub} bound the mean relative income effect in the group/cluster to which the individual belongs. We then use $[\alpha^{lb}, \alpha^{ub}]$ as the dependent variable in these regressions.[22]

We regress our outcome variables on education (with low levels of education as the benchmark), the wage of the individual (in EUR per hour), age (in years), gender (with male gender as the benchmark), and household composition (where being single is the benchmark). We can use 339 consumer observations. We consider six different categorizations of the individuals in our sample: all individuals, all men, all women, all singles, single men and single women.

Table 6 reports on the presence of relative income concerns, namely the probability that $\Delta^* > 0$. We find a particularly strong age effect; older men and women are systematically more prone to relative income concerns. Further, middle and higher educated single women are, respectively, 39.7% and 27.5% more likely to be characterized by at least some relative income concerns than lower educated single women. By contrast, we find no significant education effect for single men. Specifically, relative income concerns appear somewhat less among single men with intermediate education, but this effect is not significant at conventional levels. Finally, the relative income effect is also gender-specific: relative income concerns are 13% more likely for women.

[21] As a robustness exercise, in Appendix A.6 we report the results when performing the same two exercises at the group/cluster level instead of the individual/consumer level. Comfortingly, the results of this group-level analysis are generally in line with those of the consumer-level analysis (of which the results are given in Tables 6 and 7 below). Not very surprisingly, significance levels are somewhat lower for the group-level analysis because of the smaller sample sizes.

[22] For this exercise, we use Stata's `intreg` command, which is well-suited for fitting linear regression models when the dependent variable is measured as interval data.

Next, Table 7 reports on the strength of relative income concerns, using interval regressions to explain $[\alpha^{lb}, \alpha^{ub}]$. Once more, we observe a systematically strong and positive age effect, particularly for males. Moreover, individuals experience strongly positive relative income effects when they have higher wages.[23] The relative income effect is again stronger among women. Finally, individuals in couples seem to be characterized by less strong relative income concerns, especially men.

Table 6: Regressions of strictly positive individual relative income effects

	All	Men	Women	Singles	SingleMen	SingleWomen
Education=2	0.044	0.049	0.050	0.170	-0.224	0.397***
	(0.062)	(0.098)	(0.080)	(0.108)	(0.172)	(0.137)
Education=3	0.068	0.033	0.111	0.220**	0.104	0.275*
	(0.061)	(0.099)	(0.078)	(0.100)	(0.148)	(0.147)
Age	0.009***	0.011***	0.008***	0.020***	0.021***	0.015***
	(0.002)	(0.004)	(0.003)	(0.004)	(0.006)	(0.005)
Wage	-0.003	-0.007	0.001	-0.003	0.017	-0.002
	(0.005)	(0.008)	(0.006)	(0.008)	(0.021)	(0.008)
Couple=1	0.053	0.009	0.097			
	(0.051)	(0.081)	(0.067)			
Woman=1	0.130***			0.036		
	(0.048)			(0.081)		
Observations	339	154	185	117	49	68

Notes: The dependent variable is a binary outcome indicating the presence of strictly positive relative income effects ($\Delta^* > 0$) for that individual. The table reports the marginal effects from a probit model.

[23] We may relate this wage effect to Lewbel et al. (2022)'s finding that relative income concerns are larger for higher socioeconomic status groups in India. They suggest that the poorest households in India are so close to subsistence that engaging in status competition incurs greater costs.

Table 7: Regressions of individual relative income concerns

	All	Men	Women	Singles	Single men	Single women
Education=2	-0.003	-0.013	0.004	0.050	0.083*	0.027
	(0.013)	(0.017)	(0.019)	(0.032)	(0.043)	(0.045)
Education=3	-0.001	-0.009	0.005	0.010	0.038	-0.016
	(0.013)	(0.017)	(0.019)	(0.030)	(0.039)	(0.043)
Age	0.001**	0.002***	0.000	0.003**	0.006***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Wage	0.003**	0.002	0.003**	0.005**	0.005	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)
Couple=1	-0.033***	-0.044***	-0.026			
	(0.011)	(0.014)	(0.016)			
Woman=1	0.026**			0.007		
	(0.010)			(0.023)		
Constant	0.012	-0.009	0.057	-0.093	-0.271***	0.064
	(0.027)	(0.032)	(0.043)	(0.065)	(0.083)	(0.099)
lnsigma	-2.399***	-2.543***	-2.313***	-2.153***	-2.354***	-2.079***
	(0.041)	(0.060)	(0.055)	(0.071)	(0.109)	(0.094)
Observations	339	154	185	117	49	68

Notes: The dependent variable is the interval $[\alpha^{lb}, \alpha^{ub}]$ where α^{lb}, respectively α^{ub}, is a lower (upper) bound on average relative income effects.

Welfare costs of relative income concerns. As a following step, we consider the welfare cost of relative income concerns, by using the money metric measure that we introduced in Section 4. Specifically, we consider the measure $m = \alpha \bar{c}_r$, with bounds $m^{lb} = \alpha^{lb} \bar{c}_r$ and $m^{ub} = \alpha^{ub} \bar{c}_r$. The summary results presented in Table 5 and Figure 4 revealed significant variation in these welfare costs across the individuals in our sample.

Table 8 shows the outcomes of interval regressions that relate these welfare costs (with bounds m^{lb} and m^{ub}) to individual consumer characteristics, for the same categorizations of consumers as in Tables 6 and 7. Consistent with our previous findings, the welfare cost of relative income concerns is systematically higher for older individuals, especially men. Wages further increase the welfare cost of relative income concerns, particularly for women. Finally, individuals in couples tend to incur smaller welfare costs, and women generally face larger costs than men.

Table 8: Regressions of individual money cost of relative income concerns

	All	Men	Women	Singles	Single men	Single women
Education=2	-14.211	-32.769	-1.862	87.810	173.920*	24.159
	(28.708)	(37.028)	(42.898)	(71.897)	(98.365)	(100.147)
Education=3	-14.278	-26.452	-5.078	-0.930	79.840	-75.977
	(29.405)	(38.147)	(43.674)	(67.103)	(90.793)	(95.509)
Age	2.398**	4.459***	0.860	6.041**	13.929***	0.241
	(1.130)	(1.493)	(1.672)	(2.977)	(4.426)	(4.008)
Wage	5.045**	3.661	5.720*	8.910*	10.914	6.653
	(2.384)	(3.309)	(3.385)	(4.762)	(8.678)	(5.874)
Couple=1	-76.468***	-98.960***	-62.762*			
	(24.181)	(31.584)	(36.169)			
Woman=1	59.555***			15.671		
	(22.811)			(51.904)		
Constant	42.898	-6.769	149.834	-174.198	-591.807***	192.526
	(60.790)	(70.088)	(96.353)	(147.879)	(192.006)	(221.121)
lnsigma	5.316***	5.165***	5.407***	5.571***	5.386***	5.638***
	(0.041)	(0.061)	(0.055)	(0.071)	(0.108)	(0.094)
Observations	339	154	185	117	49	68

Notes: The dependent variable is the interval $[m^{lb}, m^{ub}]$ where m^{lb}, respectively m^{ub}, is a lower (upper) bound on the individual welfare cost of relative income concerns.

Income misperceptions. An interesting feature of our data set is that it allows us to further decompose the welfare cost $m = \alpha \bar{c}_r$ into (i) a welfare cost that can be attributed to relative income concerns per se, and (ii) a welfare cost that follows from the deviation between the *perceived* reference level $\bar{c}_r$ and the *true* level, which we denote by $\bar{c}$ (with $\bar{c} = 1565$ EUR in our application; see Section 2). Formally, we have:

$$m = \alpha \bar{c}_r = \alpha \bar{c} + \alpha(\bar{c}_r - \bar{c}).$$

Because individual perceptions on average exceed the true mean income in the population, the extra welfare cost from misperceptions will mostly be non-negative.

Table 9: Share of the total welfare costs due to income misperceptions

	mean	sd	min	max
Single men, Low edu	0.292	0.127	0.073	0.550
Single men, Med edu	0.259	0.143	0.073	0.412
Single men, High edu	0.275	0.104	0.117	0.495
Single women, Low edu	0.307	0.150	-0.025	0.548
Single women, Med edu	0.281	0.143	-0.079	0.489
Single women, High edu	0.263	0.151	-0.157	0.439
Men in couples, Low edu	0.261	0.096	0.086	0.444
Men in couples, Med edu	0.263	0.139	-0.230	0.489
Men in couples, High edu	0.230	0.145	-0.168	0.423
Women in couples, Low edu	0.278	0.214	-0.687	0.511
Women in couples, Med edu	0.287	0.144	-0.008	0.533
Women in couples, High edu	0.254	0.124	0.026	0.460
Total	0.269	0.148	-0.687	0.550

Notes: The share of the costs due to misperceptions is the difference between perceived mean income and objective mean income, relative to the perceived mean income, thus $(\bar{c}_r - \bar{c})/\bar{c}_r$.

As a preliminary analysis, Table 9 reports the share of the total welfare loss due to income misperceptions.[24] This table presents summary statistics for the fraction $\alpha(\bar{c}_r - \bar{c})/m$ per consumer type. Here we limit the sample to consumers where α is strictly positive (i.e., $\Delta^* > 0$).[25] On average, between 23% and 31% of the total welfare loss comes from the fact that individuals overestimate the true mean income in the population. For some consumers these misperceptions explain up to 55% of their total welfare loss due to relative income concerns. However, there is also a small number of consumers who *under*estimate mean income in the population. Notably, for one consumer, the total welfare loss from relative income concerns would have been 69% higher if she did not underestimate the mean income in the population. But overall, the average welfare loss would be reduced by approximately one quarter if individuals were better informed about the true income distribution in the population.

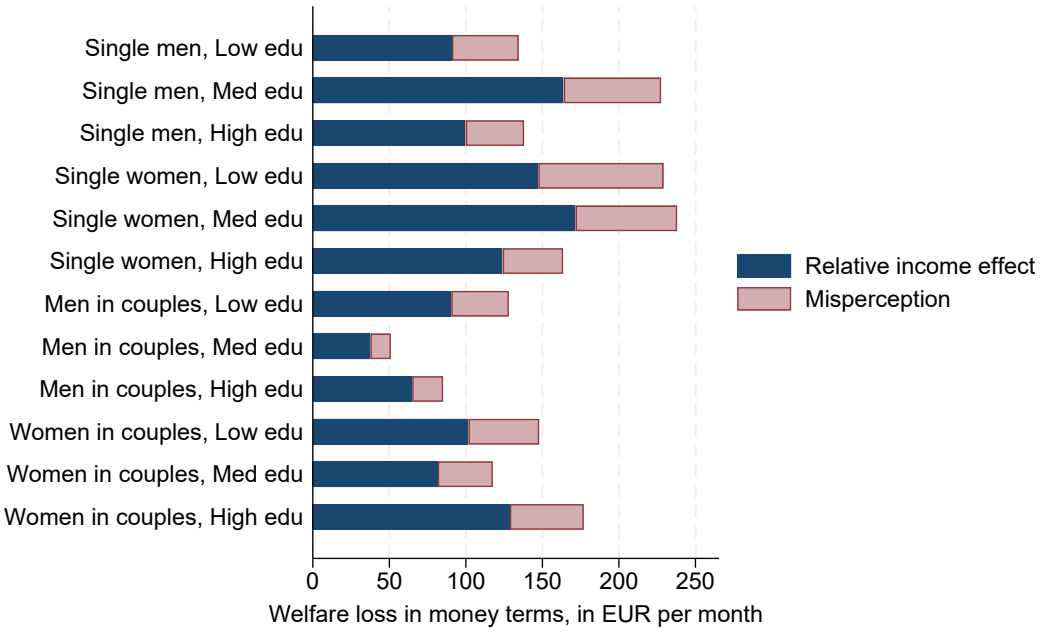
Figure 5 visualizes the decomposition of the welfare losses due to income comparisons into costs of relative income concerns per se (i.e., $\alpha\bar{c}$) and costs of income misperceptions (i.e., $\alpha(\bar{c}_r - \bar{c})$) per type of household composition—gender—education. When replacing α by its lower bound estimate α^{lb}, we take a conservative stance in that we consider the

[24] Appendix A.7 presents complementary regression results by linking the share of total welfare loss due to income misperceptions, as documented in Table 9, to individual consumer characteristics.

[25] Notably, by focusing on strictly positive α, this exploratory analysis is independent of the exact level of α, since $\alpha(\bar{c}_r - \bar{c})/m = \alpha(\bar{c}_r - \bar{c})/(\alpha\bar{c}_r) = (\bar{c}_r - \bar{c})/\bar{c}_r = 1 - \bar{c}/\bar{c}_r$ when $\alpha > 0$.

"minimal" welfare cost due to relative income concerns. Some interesting patterns emerge. For example, there appears to be quite some heterogeneity in welfare costs and these costs are often substantial. The effect of education appears to depend on the household composition. There is a U-shaped relationship between education of individuals in couples and their welfare losses due to relative income concerns. Medium educated individuals in couples experience the lowest total welfare losses compared to lower and higher educated individuals. The opposite seems to apply for medium educated single men, but this result stems from a minority of single men with disproportionately strong relative income concerns (see Tables 6 and 7). Overall, women tend to incur higher welfare losses than men. Notably, however, a significant fraction of the welfare costs is due to income misperceptions, for all types of individuals that we study.

Figure 5: Decomposition of welfare costs of income comparisons into costs of relative income concerns per se and costs of income misperceptions



Notes: The first component is the minimal welfare cost due to relative income concerns, measured as $\alpha^{lb}\bar{c}$. The second component is measured as $\alpha^{lb}(\bar{c}_r - \bar{c})$. The graph shows the average values across all (rationalizable) individuals per subgroup.

Our final exercise investigates in more detail the determinants of the welfare costs that are due to income misperceptions. As stated before, the individual's perception of mean income (i.e., $\bar{c}_r$) mostly exceeds the true mean income in the population (i.e., $\bar{c}$). However, there are some cases where $\bar{c}_r$ falls below $\bar{c}$. We quantify the associated welfare effects in money terms by using $\omega = \alpha(\bar{c}_r - \bar{c}) = m - \alpha\bar{c}$. If $\bar{c}_r \geq \bar{c}$, we replace α with α^{lb} (respectively α^{ub})

to construct a lower (upper) bound on ω. Conversely, if $\bar{c}_r < \bar{c}$, the misperception actually yields a welfare gain for the individual. In that case, we replace α with α^{ub} (respectively α^{lb}) to construct lower (upper) bounds on the negative welfare cost —hence benefit— of these misperceptions. Summarizing, we obtain:

$$\omega^{lb} = \begin{Bmatrix} \alpha^{lb}(\bar{c}_r - \bar{c}) & \text{if } \bar{c}_r \geq \bar{c} \\ \alpha^{ub}(\bar{c}_r - \bar{c}) & \text{if } \bar{c}_r < \bar{c} \end{Bmatrix}$$

$$\omega^{ub} = \begin{Bmatrix} \alpha^{ub}(\bar{c}_r - \bar{c}) & \text{if } \bar{c}_r \geq \bar{c} \\ \alpha^{lb}(\bar{c}_r - \bar{c}) & \text{if } \bar{c}_r < \bar{c} \end{Bmatrix}$$

Table 10: Regressions of individual money cost of income misperceptions

	All	Men	Women	Singles	Single men	Single women
Education=2	-10.388	-13.194	-8.969	8.103	43.226	-20.843
	(10.208)	(12.569)	(15.677)	(26.600)	(36.577)	(37.249)
Education=3	-13.085	-12.281	-14.808	-20.115	16.809	-55.287
	(10.431)	(12.927)	(15.917)	(24.699)	(33.356)	(35.541)
Age	0.764*	1.151**	0.408	2.012*	4.016**	0.398
	(0.401)	(0.506)	(0.610)	(1.097)	(1.623)	(1.491)
Wage	0.556	0.915	0.227	0.415	1.654	-0.729
	(0.840)	(1.121)	(1.221)	(1.751)	(3.137)	(2.179)
Couple=1	-24.693***	-31.046***	-22.424*			
	(8.568)	(10.691)	(13.159)			
Woman=1	17.952**			6.583		
	(8.086)			(19.097)		
Constant	25.602	8.502	62.649*	-22.489	-148.773**	98.257
	(21.560)	(23.773)	(35.098)	(54.428)	(69.728)	(82.235)
lnsigma	4.285***	4.090***	4.401***	4.582***	4.403***	4.653***
	(0.040)	(0.060)	(0.055)	(0.069)	(0.106)	(0.091)
Observations	339	154	185	117	49	68

Notes: The dependent variable is the interval $[\omega^{lb}, \omega^{ub}]$ where ω^{lb}, respectively ω^{ub}, is a lower (upper) bound on the individual welfare cost that stems from the difference $(\bar{c}_r - \bar{c})$ between perceived and objective mean income in the population.

Table 10 shows the results of interval regressions that relate this welfare cost of income misperceptions to observable consumer characteristics. We find that individuals in couples suffer significantly less from welfare costs due to relative income concerns. Furthermore, women experience greater welfare costs due to misperceived mean income than men. Next,

older individuals experience greater costs from misperceptions than younger individuals; this is particularly true for men, both in couples and single. This suggests that the gender and age effects on the welfare costs from relative income concerns are driven —at least partly— by misperceived mean income. However, we find no statistically significant relationship between welfare costs from income misperceptions and wages. Consequently, the significant effect of wages on welfare costs from relative income concerns (reported in Table 8) does not appear to be driven by misperceptions. As shown in Appendix A.2, higher wages are associated with slightly lower perceived mean income, which seems to offset the positive effect of wages on welfare costs from relative income concerns.

6 Conclusion

We have used rich data on the consumption and labor supply behavior of Dutch households to assess the presence of relative income concerns, and the associated impact on individual welfare. A unique feature of our data is that they report on perceived mean incomes, which enables us to quantify the welfare effects of income misperceptions. We analyzed these data through the lens of a parsimonious theoretical model of individual consumption and labor supply with income comparisons. An attractive feature of this model is that it allowed us to quantify the welfare effects in money metric terms. To bring the model to observational data, we developed its nonparametric revealed preference characterization.

Our empirical application showed that our revealed preference approach does allow for an informative empirical analysis, even though it imposes minimal prior structure. First, focusing on the predictive success of the alternative model specifications, we found that a model with individual-specific relative income concerns provides a substantially better fit of the observed behavior than a standard model without relative income concerns or a model that assumes homogeneous relative income concerns for observably similar individuals. Second, we obtained that the welfare impact of relative income concerns varies a lot across individuals and may be substantial in many instances. Finally, we related these welfare effects to observable heterogeneity across individuals.

More specifically, our results indicate that the welfare cost of relative income concerns ranges between 142 EUR and 253 EUR per month for the average individual in our sample. We also found notable variation by age, education, household composition, gender and earnings. For instance, relative income concerns are particularly pronounced among older individuals and higher-educated singles. In general, individuals in couples experience lower welfare costs from relative income concerns than singles, while women face higher costs than men. These costs are consistently greater for older men and high-wage women. On average,

roughly one quarter of the welfare costs associated with relative income concerns stem from misperceptions of mean income. These misperception-related costs are also higher for singles than for individuals in couples, and higher for women than for men. In addition, we again found a significantly positive age effect for men. Finally, wages no longer play a significant role in driving welfare costs due to income misperceptions.

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A Appendix

A.1 Sample selection and clustering

Sample selection. Table 11 shows how the sample size changes with each selection criterion. After merging individual characteristics and income data from the *Background variables* module with labor supply data from Core module 6 (*Work and schooling*), the full sample consists of 6891 observations. The Study 21 (*Effect of perceived social distributions on subjective well-being*) was conducted on a smaller subset of LISS panelists; merging this

study reduces the sample to 1425 observations. We then lose 62 and 151 observations due to missing or zero income data, and a further 39 observations due to missing reference point information, resulting in a sample of 1173 observations. Restricting the sample to respondents in paid employment at the time of the survey (even if only a few hours per week) yields 773 observations. After imposing age restrictions, the sample contains 700 respondents. Requiring respondents to be either single household heads or cohabiting without children further reduces the sample to 347 observations. Finally, we drop four observations with constructed wages exceeding 67 EUR per hour.

Table 11: Summary of sample selection

Condition	Observations
Core module 6	6891
Study 21	1425
No missing income	1363
Positive income	1212
No missing reference points	1173
Currently working	773
Age between 25 and 65	700
Household composition	347
No wage outliers	343

Clustering. When grouping individuals within each household type—gender—education cell into clusters of similar age, it is not always possible to form clusters of exactly four individuals. This occurs because the number of observations in a given cell is not always divisible by four. In such cases, we allow a small number of clusters to have size three. To minimize the number of three-person clusters while ensuring that each individual belongs to exactly one cluster, we proceed as follows. For each cell, we take the actual number of observations and identify the next larger number that is divisible by four. The difference between this number and the actual number of observations determines how many four-person clusters must be replaced with three-person clusters. This fixes the number of three-person clusters. We then sort the individuals within each cell by age and fill in the clusters sequentially. In this sequence, cluster size three is assigned to randomly selected clusters, but only until the total number of three-person clusters identified in the previous step has been reached. This random assignment avoids a mechanical correlation between cluster size and average age of individuals in the cluster. The resulting clustering is reported in Table 12. Our baseline data partitioning comprises 70 four-person clusters and 21 slightly smaller three-person clusters.

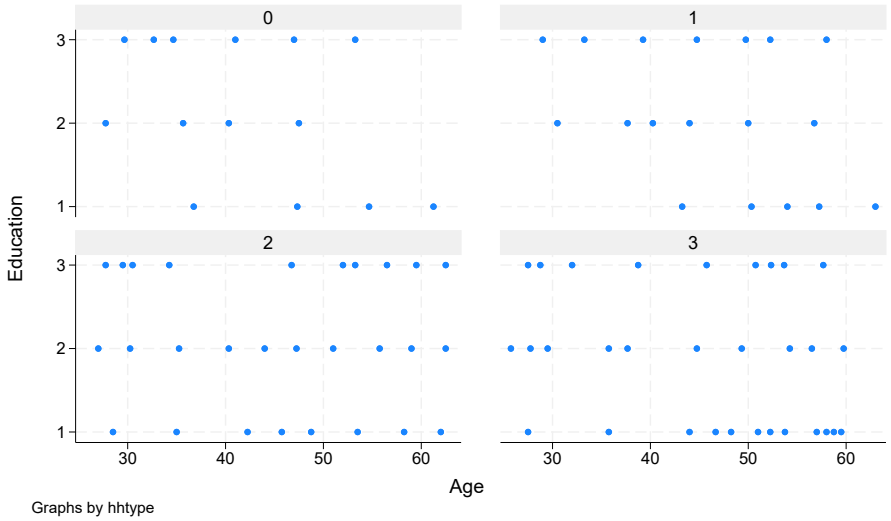
Table 12: Overview of cluster size

	Observations	Group sizes
Single men, Low edu	14	4/3/3/4
Single men, Med edu	14	4/3/3/4
Single men, High edu	21	4/4/4/3/3/3
Single women, Low edu	18	4/4/3/3/4
Single women, Med edu	22	4/4/3/4/3/4
Single women, High edu	28	4/4/4/4/4/4/4
Men in couples, Low edu	31	4/4/4/4/4/4/3/4
Men in couples, Med edu	38	4/4/4/4/4/4/3/4/4/3
Men in couples, High edu	40	4/4/4/4/4/4/4/4/4/4
Women in couples, Low edu	46	4/4/4/4/4/4/4/4/3/3/4/4
Women in couples, Med edu	38	4/4/4/3/4/3/4/4/4/4
Women in couples, High edu	33	3/3/3/4/4/4/4/4/4

Notes: The individuals within each row are sorted by age (in descending order) and then assigned to groups starting from the left.

Figure 6 visualizes the distribution of clusters by household composition—gender—education and by the average age of individuals within each cluster. The clusters clearly reflect the heterogeneity in the age distribution.

Figure 6: Distribution of clusters by age and education



Notes: Education and age capture the education class (1 is low, 2 is medium, 3 is high) and the average age of individuals in each cluster. Clusters are represented by dots. We distinguish between clusters with single men (panel $hhtype = 0$), single women (panel $hhtype = 1$), men in couples (panel $hhtype = 2$), and women in couples (panel $hhtype = 3$).

A.2 Regression of individual perceptions of mean income in the population

Table 13: Regression of individual perceptions of mean income in the population

	Refpoint
Education=2	29.616
	(60.926)
Education=3	-12.393
	(61.495)
Age	4.542*
	(2.379)
Wage	-8.492*
	(4.628)
Couple=1	-31.414
	(50.591)
Woman=1	51.878
	(48.092)
Constant	2097.470***
	(126.038)
Observations	343

A.3 Robustness of revealed preference results to group size

Table 14: Summary of revealed preference results with smaller clusters

	Models		
	No relative income concerns ($\alpha_r = 0$)	Fixed relative income concerns ($\alpha_r = \bar{\alpha}$)	Variable relative income concerns (Variable α_r)
Pass rate	0.50	0.61	0.99
Power	0.66	0.62	0.24
Predictive success	0.16	0.23	0.23

Notes: The pass rate shows the fraction of clusters that can be rationalized. Power is the fraction of simulated random data that violate the rationality conditions. Predictive success is the pass rate of actual data minus the pass rate of random data. There are 119 clusters with 2 or 3 observations each.

Table 15: Summary of revealed preference results with larger clusters

	Models		
	No relative income concerns ($\alpha_r = 0$)	Fixed relative income concerns ($\alpha_r = \bar{\alpha}$)	Variable relative income concerns (Variable α_r)
Pass rate	0.16	0.26	0.99
Power	0.93	0.91	0.50
Predictive success	0.09	0.17	0.48

Notes: The pass rate shows the fraction of clusters that can be rationalized. Power is the fraction of simulated random data that violate the rationality conditions. Predictive success is the pass rate of actual data minus the pass rate of random data. There are 74 clusters with 4 or 5 observations each.

A.4 Mixed Integer Linear Programming (MILP)

The following result presents the MILP characterization of Proposition 1, which we use in our empirical application.

Proposition 2. *Consider a data set* $S = \{w_r, l_r, c_r, \bar{c}_r\}_{r \leq T}$. *For all* t, v, r, s *there exist utility numbers* U_t, *Hicksian demand bundles* $H^l_{r,v}, H^c_{r,v}$, *binary revealed preference relations* $R_{t,v}$, *and variables* α_r *so that:*

1. $H^l_{t,t} = l_t$,

   $H^c_{t,t} = c_t$,

2. $U_v - U_t < R_{v,t}$,

   $(R_{t,v} - 1) \leq U_t - U_v$,

3. $w_r(H^l_{r,v} - H^l_{s,t}) + (H^c_{r,v} - \alpha_r \bar{c}_r - H^c_{s,t} + \alpha_s \bar{c}_s) < R_{v,t} A$,

   $A(R_{t,v} - 1) \leq w_r(H^l_{s,t} - H^l_{r,v}) + (H^c_{s,t} - \alpha_s \bar{c}_s - H^c_{r,v} + \alpha_r \bar{c}_r)$,

4. $B(R_{t,v} - 1) \leq H^l_{r,t} - H^l_{r,v}$,

   $B(R_{t,v} - 1) \leq H^c_{r,t} - H^c_{r,v}$,

with arbitrary large numbers A *and* B.

The explanation goes as follows. Conditions (1) are identical to the first set of conditions in Proposition 1. Conditions (2) and (3) implement the second set of conditions in Proposition 1. To see this, assume that (2) and (3) hold. The first part of Condition (2) states

that $U_t \geq U_v$ implies $R_{t,v} = 1$ and the second part of Condition (3) subsequently implies $w_r(H^l_{s,t} - H^l_{r,v}) + (H^c_{s,t} - \alpha_s \bar{c}_s - H^c_{r,v} + \alpha_r \bar{c}_r) \geq 0$. Now for the strict inequality in Proposition 2, suppose towards a contradiction that $U_t > U_v$ but $w_r(H^l_{r,v} - H^l_{s,t}) + (H^c_{r,v} - \alpha_r \bar{c}_r - H^c_{s,t} + \alpha_s \bar{c}_s) \geq 0$. Because of (3, first part), the latter implies $R_{v,t} = 1$ and because of (2, second part) this obtains $U_v \geq U_t$, a contradiction. Finally, Conditions (2) and (4) implement the last set of conditions in Proposition 1. Condition (2, first part) states that $U_t \geq U_v$ implies $R_{t,v} = 1$ and Condition (4) subsequently implies $H^l_{r,t} \geq H^l_{r,v}$ and $H^c_{r,t} \geq H^c_{r,v}$. We refer to Cherchye et al. (2020) for more details on the MILP characterization of rationalizable consumer behavior with normal demand.

A.5 Reference points based on social contacts

Figure 7 shows the relationship between individual earnings and perceived mean income *among social contacts*. This (positive) relationship is more pronounced compared to the one between individual earnings and perceived mean income *in society as a whole* (see Figure 2).



Figure 7: Scatter plot of individual earnings and reference points

Notes: The reference points are the individual perceptions of the mean income among social contacts

For the following analyses, we have replaced (perceived) mean income in the population with (perceived) mean income among social contacts as the individual's reference point. The

empirical performance of this alternative specification is summarized in Table 16. Predictive success is again lowest for the model that assumes away relative income concerns (with $\alpha_r = 0$) and highest for the model with fully heterogeneous relative income concerns (with variable α_r). There is however one group of observations that can no longer be explained by any model when the reference point is determined by social contacts. We also computed 95%–confidence bounds for our predictive success measure when the reference point is mean income among social contacts. The predictive success of the model without relative income concerns is bounded between 0.04 and 0.22. Predictive success with fixed relative income concerns is between 0.14 and 0.34, and predictive success with variable relative income concerns is between 0.34 and 0.41. This is very similar to our baseline specification.

Table 16: Summary of revealed preference results when mean income *among social contacts* is used as reference point

	Models		
	No relative income concerns ($\alpha_r = 0$)	Fixed relative income concerns ($\alpha_r = \bar{\alpha}$)	Variable relative income concerns (Variable α_r)
Pass rate	0.29	0.46	0.98
Power	0.84	0.78	0.40
Predictive success	0.13	0.24	0.38

Notes: The pass rate shows the fraction of clusters that can be rationalized. Power is the fraction of simulated random data that violate the rationality conditions. Predictive success is the pass rate of actual data minus the pass rate of random data. There are 91 clusters with 3 or 4 observations each. The reference point is each individual's perception of mean income among social contacts.

Table 17 summarizes the results for α^{lb}, α^{ub}, and Δ^* for the 89 clusters of consumers that can be rationalized. Correlations show that there are strong linear relationships between these results and the corresponding estimates for α^{lb} (correlation: 0.95), α^{ub} (correlation: 0.91), and Δ^* (correlation: 0.91) from our baseline analyses. Overall, income comparisons among social contacts seem to influence individual welfare only slightly more than income comparisons with the whole population.

Table 17: Lower and upper bounds on relative income concerns

	mean	sd	min	max
alpha_lb_social	0.06	0.09	0.00	0.43
alpha_ub_social	0.12	0.15	0.00	0.71
delta_social	0.18	0.21	0.00	0.94
N	89			

Notes: alpha-lb-social α^{lb}, respectively alpha-ub-social α^{ub}, is the lower (upper) bound on average relative income effects conditional on delta-social. delta-social Δ^* is the tighest possible limit on relative income concerns that still rationalizes the cluster. The results are based on the 89 rationalizable clusters. The reference point is each individual's perception of mean income among social contacts.

Table 18 reports on the presence of relative income concerns, namely the probability that $\Delta^* > 0$. Table 19 reports on the strength of relative income concerns, using interval regressions to explain $[\alpha^{lb}, \alpha^{ub}]$. Once more, we observe that older individuals are more prone to relative income concerns, and that relative income effects are stronger among women and individuals with higher wages.

Table 18: Regressions of strictly positive individual relative income effects

	All	Men	Women	Singles	SingleMen	SingleWomen
Education=2	0.029	0.017	0.050	0.128	0.000	0.397***
	(0.063)	(0.101)	(0.080)	(0.117)	(.)	(0.137)
Education=3	0.069	0.033	0.111	0.210**	0.048	0.275*
	(0.061)	(0.098)	(0.078)	(0.101)	(0.152)	(0.147)
Age	0.009***	0.011***	0.008***	0.019***	0.016**	0.015***
	(0.002)	(0.004)	(0.003)	(0.004)	(0.007)	(0.005)
Wage	-0.003	-0.008	0.001	-0.003	0.029	-0.002
	(0.005)	(0.008)	(0.006)	(0.008)	(0.029)	(0.008)
Couple=1	0.067	0.042	0.097			
	(0.052)	(0.086)	(0.067)			
Woman=1	0.141***			0.065		
	(0.049)			(0.086)		
Observations	335	150	185	113	35	68

Notes: The dependent variable is a binary outcome indicating the presence of strictly positive relative income effects ($\Delta^* > 0$) for that individual. The table reports the marginal effects from a probit model. The reference point is each individual's perception of mean income among social contacts.

Table 19: Regressions of individual relative income concerns

	All	Men	Women	Singles	Single men	Single women
Education=2	-0.019	-0.049***	0.004	-0.009	-0.054**	0.012
	(0.014)	(0.014)	(0.022)	(0.031)	(0.026)	(0.046)
Education=3	-0.002	-0.018	0.010	-0.006	-0.015	-0.010
	(0.014)	(0.014)	(0.023)	(0.028)	(0.021)	(0.044)
Age	0.001**	0.002***	0.001	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Wage	0.002*	0.001	0.003	0.004**	0.006***	0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Couple=1	-0.009	0.001	-0.012			
	(0.012)	(0.012)	(0.019)			
Woman=1	0.040***			0.044**		
	(0.011)			(0.022)		
Constant	0.003	-0.002	0.050	-0.022	-0.058	0.088
	(0.029)	(0.026)	(0.050)	(0.062)	(0.046)	(0.101)
lnsigma	-2.332***	-2.740***	-2.161***	-2.234***	-3.056***	-2.055***
	(0.042)	(0.066)	(0.056)	(0.073)	(0.132)	(0.093)
Observations	335	150	185	113	45	68

Notes: The dependent variable is the interval $[\alpha^{lb}, \alpha^{ub}]$ where α^{lb}, respectively α^{ub}, is a lower (upper) bound on average relative income effects. The reference point is each individual's perception of mean income among social contacts.

Table 20 and Figure 8 show the distributions of the upper and lower bounds on m for our sample of consumers. This is in line with the patterns found in Figure 4. Table 21 shows the outcomes of interval regressions that relate these welfare costs (with bounds m^{lb} and m^{ub}) to individual consumer characteristics, for the same categorizations of consumers as in Tables 18 and 19.

Table 20: Lower and upper bounds on welfare cost of relative income concerns

	mean	sd	min	max
mincost_social	136.84	190.03	0.00	1053.11
maxcost_social	256.37	321.68	0.04	1861.31
N	335			

Notes: mincost-social m^{lb}, respectively maxcost-social m^{ub}, is a lower (upper) bound on the individual welfare cost of relative income concerns. The results are based on the 335 individuals within the 89 rationalizable clusters. The reference point is each individual's perception of mean income among social contacts.

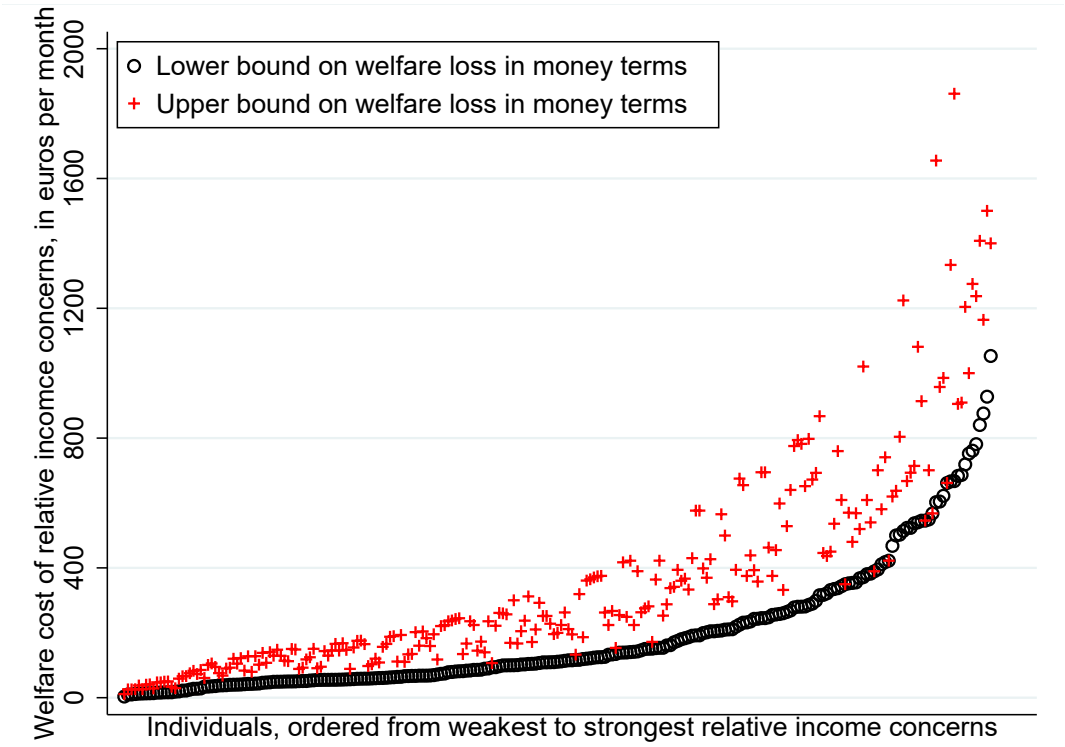


Figure 8: Distribution of welfare cost of relative income concerns for individuals in groups where $\Delta^* > 0$

Notes: Individuals are ordered according to the lower bound on the cost of relative income concerns m^{lb}. The results are based on the 239 individuals within the 63 clusters that need $\Delta^* > 0$ for rationalizability. The reference point is each individual's perception of mean income among social contacts.

Table 21: Regressions of individual money cost of relative income concerns

	All	Men	Women	Singles	Single men	Single women
Education=2	-18.918	-91.208***	34.756	14.092	-112.820*	59.628
	(29.385)	(33.631)	(45.797)	(64.439)	(66.372)	(92.992)
Education=3	15.227	-28.526	44.349	8.145	-9.228	-13.543
	(29.810)	(33.879)	(46.444)	(57.401)	(53.942)	(88.755)
Age	3.145***	3.495***	2.831	3.881	2.966	2.154
	(1.149)	(1.328)	(1.785)	(2.583)	(2.724)	(3.729)
Wage	4.524*	5.092*	3.764	7.637*	14.483***	5.906
	(2.413)	(2.952)	(3.568)	(4.109)	(5.481)	(5.472)
Couple=1	-17.635	-5.926	-21.567			
	(24.790)	(29.168)	(38.335)			
Woman=1	80.732***			77.379*		
	(23.297)			(45.908)		
Constant	-47.079	-41.942	34.234	-121.495	-136.945	55.232
	(61.869)	(62.641)	(102.547)	(128.467)	(122.551)	(205.163)
lnsigma	5.328***	5.042***	5.468***	5.405***	4.821***	5.563***
	(0.042)	(0.063)	(0.056)	(0.073)	(0.123)	(0.093)
Observations	335	150	185	113	45	68

Notes: The dependent variable is the interval $[m^{lb}, m^{ub}]$ where m^{lb}, respectively m^{ub}, is a lower (upper) bound on the individual welfare cost of relative income concerns. The reference point is each individual's perception of mean income among social contacts.

A.6 Group level analysis

We now repeat our analyses at the group level, thus aggregating over the different individuals belonging to a respondent type. We regress the outcome variables on average education (with low levels of education as the benchmark),[26] the average hourly wage of individuals in the group, average age, gender and composition (single or couple). We use 90 group observations.

We first run a probit regression where '$\Delta^* > 0$' is the (binary) outcome variable. We then apply interval regression to $[\alpha^{lb}, \alpha^{ub}]$.

[26] We set Education=1 if schooling of the representative member is strictly below higher secondary education, Education=3 if schooling of the representative member is strictly above intermediate vocational education, and Education=2 otherwise.

Table 22: Regressions of strictly positive group level relative income effects

	All	Men	Women	Singles	Couples
Education=2	0.055	0.059	0.071	0.180	0.042
	(0.121)	(0.196)	(0.156)	(0.200)	(0.142)
Education=3	0.093	0.067	0.132	0.267	0.053
	(0.125)	(0.208)	(0.152)	(0.189)	(0.163)
Age	0.010**	0.014	0.008	0.026**	0.007
	(0.005)	(0.009)	(0.006)	(0.011)	(0.006)
Wage	-0.008	-0.020	0.003	-0.017	-0.010
	(0.018)	(0.031)	(0.024)	(0.037)	(0.023)
Couple=1	0.077	0.059	0.120		
	(0.100)	(0.157)	(0.141)		
Woman=1	0.128			0.063	0.128
	(0.094)			(0.159)	(0.119)
Observations	90	41	49	32	58

Notes: The dependent variable is a binary outcome indicating the presence of strictly positive relative income effects ($\Delta^* > 0$) for that group. The table reports the marginal effects from a probit model. The main analysis sample consists of the 90 rationalizable groups.

Table 23: Regressions of group level relative income effects

	All	Men	Women	Singles	Couples
Education=2	-0.006	-0.018	0.007	0.036	-0.016
	(0.024)	(0.032)	(0.036)	(0.055)	(0.024)
Education=3	-0.012	-0.023	0.000	0.002	0.013
	(0.026)	(0.035)	(0.037)	(0.053)	(0.028)
Age	0.000	0.001	-0.000	-0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
Wage	0.009**	0.006	0.011**	0.023***	0.001
	(0.004)	(0.005)	(0.005)	(0.008)	(0.004)
Couple=1	-0.020	-0.036	-0.003		
	(0.021)	(0.026)	(0.032)		
Woman=1	0.034*			0.003	0.030
	(0.020)			(0.040)	(0.020)
Constant	-0.030	-0.029	-0.012	-0.151	0.008
	(0.054)	(0.061)	(0.089)	(0.122)	(0.051)
lnsigma	-2.418***	-2.569***	-2.334***	-2.255***	-2.627***
	(0.079)	(0.117)	(0.106)	(0.136)	(0.097)
Observations	90	41	49	32	58

Notes: The dependent variable is the interval $[\alpha^{lb}, \alpha^{ub}]$ where α^{lb}, respectively α^{ub}, is a lower (upper) bound on average relative income effects. The main analysis sample consists of the 90 rationalizable groups.

Table 24: Regressions of strictly positive group level relative income effects based on social contacts

	All	Men	Women	Singles	Couples
Education=2	0.041	0.024	0.071	0.133	0.042
	(0.123)	(0.202)	(0.156)	(0.216)	(0.142)
Education=3	0.095	0.074	0.132	0.257	0.053
	(0.124)	(0.206)	(0.152)	(0.190)	(0.163)
Age	0.010**	0.014	0.008	0.025**	0.007
	(0.005)	(0.009)	(0.006)	(0.012)	(0.006)
Wage	-0.009	-0.024	0.003	-0.020	-0.010
	(0.018)	(0.031)	(0.024)	(0.037)	(0.023)
Couple=1	0.090	0.095	0.120		
	(0.102)	(0.164)	(0.141)		
Woman=1	0.138			0.098	0.128
	(0.095)			(0.169)	(0.119)
Observations	89	40	49	31	58

Notes: The dependent variable is a binary outcome indicating the presence of strictly positive relative income effects ($\Delta^* > 0$) for that group. The table reports the marginal effects from a probit model. The main analysis sample consists of the 89 rationalizable groups. The reference point is each individual's perception of mean income among social contacts.

Table 25: Regressions of group level relative income concerns based on social contacts

	All	Men	Women	Singles	Couples
Education=2	-0.021	-0.051*	0.006	-0.014	-0.022
	(0.026)	(0.027)	(0.042)	(0.054)	(0.030)
Education=3	-0.009	-0.023	0.007	-0.011	0.011
	(0.028)	(0.030)	(0.043)	(0.049)	(0.035)
Age	0.000	0.001	-0.000	-0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)
Wage	0.007*	0.002	0.009	0.019***	0.000
	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)
Couple=1	0.001	0.006	0.008		
	(0.022)	(0.023)	(0.037)		
Woman=1	0.045**			0.039	0.034
	(0.021)			(0.039)	(0.025)
Constant	-0.028	-0.007	-0.009	-0.067	0.009
	(0.058)	(0.051)	(0.103)	(0.115)	(0.064)
lnsigma	-2.350***	-2.755***	-2.184***	-2.332***	-2.403***
	(0.081)	(0.127)	(0.108)	(0.139)	(0.100)
Observations	89	40	49	31	58

Notes: The dependent variable is the interval $[\alpha^{lb}, \alpha^{ub}]$ where α^{lb}, respectively α^{ub}, is a lower (upper) bound on average relative income effects. The main analysis sample consists of the 89 rationalizable groups. The reference point is each individual's perception of mean income among social contacts.

A.7 Regression of share of total welfare cost due to income misperceptions

Table 26: Regression of share of total welfare cost due to income misperceptions

	All	Men	Women	Singles	Single men	Single women
Education=2	-0.003	-0.001	0.002	-0.015	-0.028	-0.027
	(0.024)	(0.033)	(0.035)	(0.045)	(0.073)	(0.064)
Education=3	-0.021	-0.029	-0.017	-0.025	-0.011	-0.051
	(0.024)	(0.034)	(0.035)	(0.039)	(0.053)	(0.061)
Age	0.000	-0.001	0.001	0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Wage	-0.003	0.000	-0.004	-0.005*	-0.001	-0.006*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
Couple=1	-0.022	-0.033	-0.015			
	(0.021)	(0.029)	(0.030)			
Woman=1	0.011			-0.000		
	(0.019)			(0.032)		
Constant	0.308***	0.358***	0.284***	0.281***	0.282**	0.305**
	(0.053)	(0.066)	(0.079)	(0.092)	(0.133)	(0.137)
Observations	243	99	144	80	30	50

Notes: The dependent variable is measured as $(\bar{c}_r - \bar{c})/\bar{c}_r$. The linear model is estimated via OLS. The main analysis sample consists of the 243 individuals within the 64 clusters that need $\Delta^* > 0$ for rationalizability.

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