Hedonic Recall Bias
Why You Should Not Ask People How Much They Earn

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Abstract
The empirical literature which explores the effect of wage on job satisfaction typically uses data drawn from social surveys. In these surveys, the amount of wage is reported by the respondents themselves: thus, the explanatory variable of the econometric models may differ from the true wage people earn. Our paper shows that the use of survey data can lead to considerable over-estimation of the importance of wage as a determinant of wage satisfaction. In particular, responses seem to be affected by a recall bias: people who are satisfied with their wage are more likely to over-report their wage in questionnaires. The more satisfied they are the more they over-report (and vice-versa unsatisfied people). We name this behavioral disposition “hedonic recall bias”. We finally suggest possible indirect links with a more comprehensive well-being variable: life satisfaction.

Keywords: recall bias; job satisfaction; wage satisfaction; measurement error; survey income.

JEL codes: D03; J28.

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1 Introduction

“The soul is and becomes what it remembers”
Plotinus

1.1 Asking people how much they earn: how bad could it be?

During the last two decades, the number of inquiries about the observable determinants of subjective well-being has substantially grown. The majority of this literature has considered the effect of income on subjective well-being (Kahneman & Deaton, 2010; Diener & Biswas-Diener, 2002; Gardner & Oswald, 2007; Dunn et al., 2008; Layard et al., 2008, Li et al., 2011; Easterlin, 2003). In particular, relative income, i.e. income with respect to some reference point, seems to play a fundamental role (Clark & Senik, 2010; Clark & Oswald, 1996). Much research has found a consensus on the fact that richer people tend to be more satisfied with numerous aspects of their lives, including their job.

Typically, empirical results on job satisfaction rely on data from social surveys and labor force surveys, where people are asked questions like “How satisfied are you with your income? [options: very satisfied; rather satisfied; rather unsatisfied; very unsatisfied]”. Data on income satisfaction are then compared with some other useful information on the respondent, like sex, age, years of schooling, marital status, job type and, of course, income. The problem with these data is that they are self-reported: the subjects declare their own income, which allows a significant margin of error compared to the true income they earn. It seems difficult to answer the central question *Can money buy happiness?* if we are not sure about how much money people earn.

This consideration falls within the current, lively debate on the use of administrative records. The increasing use of administrative data and their merging with survey data is one of the core transitions promoted by Eurostat and some European statistical institutes (Bakker & Daas, 2012). Indeed, the access to administrative records can improve the quality of the data (at a lower cost). The central issue is that the variable “income” widely changes if it refers to “self-reported” income or if it refers to income “declared to fiscal authority”. In a 2013 study for INE (Spanish Statistical Office) on the “Reconciliation of income data from survey and from administrative sources”, Méndez Martín explores the introduction of administrative data in the context of the Spanish SILC survey. The difference between self-reported income and fiscal income is so important that the author concludes the transition to administrative data broke the time series. In another study for Eurostat, Di Meglio & Montaigne (2013) reach similar conclusions for France and Latvia.

The potential inaccuracy of self-reported income represents the starting point of our paper: a significant discrepancy between self-reported income and real income may bias the coefficients stating the impact of income on satisfaction measures. We will focus our attention on wage satisfaction. Our research provides evidence that the estimated effect of wage on wage satisfaction is 20% to 50% lower when we use reliable fiscal data on wage instead of survey data.

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¹For example, Statistics Netherlands developed a micro-integration system which allows matching records from administrative registers and household sample surveys. The countries involved in EU-SILC (European Survey on Income and Living Conditions) are progressively adopting a similar approach.
1.2 Why is self-reported income different from fiscal income?

The direction of the bias is surprising. If misreporting behaviors were random, an attenuation bias in the estimated coefficients would appear (see Green, 2007, p.324-325). Instead, we observe an upward bias which suggests some endogeneity of the error. Hence, we explore the psychological co-determinants of the discrepancy between fiscal and self-reported wage.

The incongruity between the two measurements may be due to different factors (cf. Bakker, 2010; Daas & Ossen, 2011), which we summarize in table 1.

Table 1: Possible explanations for the discrepancy between self-reported income and fiscal income.

<table>
<thead>
<tr>
<th>Category</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical issues</td>
<td>Mislinking the data</td>
<td>Two sources are mislinked, meaning two non-matching elements are combined.</td>
</tr>
<tr>
<td></td>
<td>Miscoding the data</td>
<td>Miscoding can occur in both sources: surveys and administrative registers.</td>
</tr>
<tr>
<td></td>
<td>Mislinking the concept</td>
<td>The concept of “income” as stated in the survey does not match the administrative definition.</td>
</tr>
<tr>
<td>Voluntary misreporting</td>
<td>Misreporting to the tax agency</td>
<td>Respondents voluntarily misreport their income to the Tax Agency.</td>
</tr>
<tr>
<td></td>
<td>Misreporting to the survey</td>
<td>Respondents voluntarily misreport their income in the survey.</td>
</tr>
<tr>
<td>Involuntary misreporting</td>
<td>Recall bias</td>
<td>Respondents do not know exactly how much they earn.</td>
</tr>
</tbody>
</table>

Mislinking and miscoding data are quite rare and should only affect few observations in the sample. These errors usually lead to huge discrepancies which are easily detectable as outliers (for a discussion, see Fellegi & Sunter, 1969; Arts, Bakker & Van Lith, 2000). Mismatching the “income” concept can be a severe bias for some variables which can create confusion, like property income (Méndez Martín, 2013) or investment income (Di Meglio & Montaigne, 2013); however net employment income is unlikely to fall into this category, except for some confusion between net and gross wage. The second error category is misreporting. There is empirical evidence that misreporting to the Tax Agency

\[^2\] For a discussion about the confusion between net and gross wage, see section 6.1.
is a major problem for self-employment income, since tax evasion motifs can encourage under-reporting. Concerning wages, widespread under-reporting in surveys significantly scales down wage data, while administrative data on wages are much more reliable (Bakker & Daas, 2012, Jäntti et al., 2013). In general, questions about income are perceived as particularly intrusive and tend to generate comparatively higher nonresponse rates and higher measurement errors than other topics (Tourangeau and Yan, 2007). The classic explanation of this tendency is the fear of disclosure to a third part and the possible subsequent fiscal checks (Cifaldi & Neri, 2013; Jäntti & Törmäleht, 2013).

The last possible explanation is the simplest, but also the least explored in the literature. Recall errors may occur: people can simply not know exactly how much they earn. This situation is very common. When people are asked to report their monthly net wage, it is very unlikely they will know the exact amount. Thus, their answer will be an approximation, whose quality depends on psychological factors affecting the recall process. Indeed, we show that the error in self-reported wages is not random, but it is endogenous with respect to the level of satisfaction experienced by the respondents. People who are more satisfied with their wage tend to overestimate their true wage while unsatisfied people tend to underestimate it. To our knowledge this behavioral pattern, which we name “hedonic recall bias”, has never been observed in the literature.

This recall bias can have harmful consequences on the estimation of the determinants of satisfaction measures. We will explain this with a simple example: let us imagine two people both earning 2000€ per month, but having different levels of satisfaction about their payrolls. If the error term is positively correlated with wage satisfaction, the gratified person will report a pay of 2000€ + u while the disappointed person will report a pay of 2000€ – u, with u strictly positive. As a consequence, researchers would infer an effect of the wage on wage satisfaction while the true effect is of wage satisfaction on the declarative error. Researchers could fall in a similar trap if they look at the role of relative wage and infer that the first person is satisfied because she is relatively richer than the second one, whereas in fact, the relative order of the two wages is purely due to misreporting.

In the next section we present our theoretical model. After the description of the databases, we discuss some statistics on the discrepancy between fiscal and self-reported wage in our sample (section 3). The discrepancy turns out to be large, so much that the use of self-reported wage significantly affects the estimation of the effect of wage on wage satisfaction (section 4). The empirical features of misestimation suggest some endogeneity of the recall error. This issue is discussed in section 5, where we explain and provide evidence of the existence of a hedonic recall bias. In section 6 we check the robustness of our empirical findings. In section 7 we provide a discussion on the causal validity of the hedonic recall hypothesis and on its potential extension to life satisfaction. We present the conclusions of our work in the last section.

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3We treat the capacity to store and recall information as involuntary. For an imperfect recall model with voluntary limitation, see for instance Bénabou & Tirole (2005).
2 The model

For research and policy purposes, we would like to know the relationship between the true amount of income a person receives and her subsequent satisfaction. We use a two-period model to describe this situation. Let us name:

- $h_i^s$: satisfaction reported in the survey by individual $i$ about some aspects $s$ of her job.
- $y_i^*: $ truly earned wage
- $y_i$: wage declared to fiscal authorities (henceforth, “fiscal wage”)
- $\tilde{y}_i$: wage declared in the survey (henceforth, “self-reported wage”)

In period 1, each individual $i$ learns her wage $y_i^*$. In other words, in period 1 people read their current pay slips and find out how much they earn. According to their wage and other characteristics (such as their age), individuals experience some utility $h_i^y$, which should be understood as the satisfaction of individual $i$ with respect to her income $y_i^*$.

In period 2, people are interviewed and asked to report their wage. We assume both experienced utility and truly perceived income to be constant over time. We expect respondents to answer imperfectly, since in period 2 the available information is no more the pay slip, but the memory of the pay slip $\tilde{y}_i$. This assumption stems from the fact that people do not usually have their pay slip available during surveys. They had some precise information on their income at some time (period 1) and they can recall this piece of information later (period 2). $\tilde{y}_i$ is the inter-temporal mapping of the true income $y_i$, according to the recall function $m(y_i^*, u)$, where $u_i$ is the recall error. Therefore in period 2, the individual $i$ does not know exactly how much she earns but she does know approximately her wage, with some approximation $u_i$.

2.1 The recall error

In order to assess the relationship between the wage a person receives and her level of wage satisfaction, we want to estimate the generalized linear regression model:

$$ h_i^y = f(y_i^*, \beta) + X_i' \gamma + \epsilon_i $$

where $y_i^* \in R_+$ is the wage of person $i$, $f(y_i^*, \beta)$, $f: R_+ \rightarrow R$ is a function which is monotonically positive in its first argument and which depends on a parameter vector $\beta$. $\beta$ is a vector of length 2 ($\beta_1, \beta_2$), where $\beta_1$ is interpreted as the effect of absolute wage on wage satisfaction and $\beta_2$ as the effect of relative wage. $X_i$ is a set of control variables, which includes the constant vector, $\epsilon_i$ is a normally distributed error term.

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4The assumption that the information on job satisfaction does not change from period 1 to period 2 - in contrast to the information on income - is a central assumption of our model. We base our assumption on the distinction between episodic memory (or pure memory) and semantic memory (or habitude memory) (Tulvieg, 1972; Bergson, 1896). The first system can recall a specific event in time, e.g. the last time you had oysters. The second system treats information which does not refer to a particular point in time, e.g. you dislike oysters. According to this distinction, the last time people saw their payslip pertains to the episodic system; their satisfaction with respect to their income pertains to the semantic system. Tulvieg explains that, while the episodic system “is probably quite susceptible to transformation and loss of information, [...] retrieval of information from the [semantic] system leaves its content unchanged” (Tulvieg, Episodic and semantic memory, p.386). Accordingly, we assume $m(y_i) \neq y_i$ and $m(h_i^s) = h_i^s$.  

5
As we already mentioned, administrative data on wages have been shown to be very close to the true earned wage (Bakker & Daas, 2012; Jäntti et al., 2013). Following this assessment, let us assume that the wage from fiscal sources is a truthful piece of information, i.e.:

\[ y_i^* = y_i; \]

and so:

\[ f(y_i^*, \beta) = f(y_i, \beta) \]  

By substituting (3) into (1), the true impact of the wage level on wage satisfaction can be estimated by:

\[ h^y_i = f(y_i, \beta) + X_i' \gamma + \epsilon_i \]  

But typically records on income come from the social survey itself and not from fiscal data. Therefore, the equation which is usually estimated in the literature is:

\[ \tilde{h}^y_i = f(\tilde{y}_i, \tilde{\beta}) + X_i' \tilde{\gamma} + \epsilon_i \]  

where \( \tilde{y}_i \) is the self-reported wage. It is customary to assume the error term \( \epsilon_i \) to be drawn from \( \epsilon \sim N(0, \sigma) \) with \( \epsilon \perp h^y \); however, in the next sections we will challenge this assumption. The relationship between \( y_i \) and \( \tilde{y}_i \) is determined by some recall function \( m(.) \), which generates a recall error \( u \). We describe the relationship between fiscal and self-reported wage as follows:

\[ \tilde{y}_i = m(y_i^*, .) = m(y_i, .) = y_i e^{u_i} \]  

By taking the logarithm on both sides of the previous equation we obtain the more practical log-linear form:

\[ \log \tilde{y}_i = \log y_i + u_i \]  

As far as \( u_i \neq 0 \), then \( \tilde{y}_i \neq y_i \). To understand the source of the recall error \( u_i \), we need to examine which arguments enter the recall function \( m(.) \).

2.2 The hedonic recall hypothesis

In the introduction, we discussed several possible causes of the discrepancy between true wage and self-reported wage. In this paper we suggest that this discrepancy is partly due to the level of wage satisfaction itself. Our central hypothesis is that the recall error is not random, but is instead increasing in the utility \( h^y_i \). This means that for a given income \( y^* \), if two individuals \( i \) and \( j \) experience different satisfaction levels with respect to their income, say \( h^y_i > h^y_j \), then \( i \) will declare a higher income than \( j \), ceteris paribus. In other words, people who are satisfied with their wage tend to overestimate it and vice-versa people who are not satisfied with their wage tend to underestimate it.

We call this hypothesis, *hedonic recall hypothesis*, from ηδονη, “pleasure” in ancient Greek. Consistently with the concern of high income under-reporting (Atkinson et al., 2001), we allow the declarative error to be affected by the size of the true income itself, in addition to some other observable characteristics of the respondent.

We describe the recall function as:

\[ \tilde{y}_i = m(y_i, h^y_i, X_i) = y_i^{1+\mu_3} \exp(\mu_1 h_i + X_i' \mu_2 + v_i) \]  

6
which is equivalent to the log-linear form:

\[
\log \tilde{y}_i = (1 + \mu_3)\log y_i + \mu_1 h_i + X_i'\mu_2 + v_i
\]  

(9)

We assume the residual \( v_i \) to have a standard normal distribution. If we rearrange equations (7) and (9), we obtain:

\[
u_i = \mu_1 h_i + X_i'\mu_2 + \mu_3 \log y_i + v_i
\]  

(10)

To empirically evaluate our hedonic recall hypothesis we look at the size, sign and significance of coefficient \( \mu_1 \) in the regression model (10). To simplify, \( \mu_1 \) can be interpreted as the sensitivity of the recall error to wage satisfaction. We expect \( \mu_1 \) to be positive, in compliance with the idea that the recall error is increasing in satisfaction \( h_i \).

3 Data

3.1 Survey data and administrative data: SalSa and DADS

For our analysis, we need a database where three pieces of information are simultaneously available:
- wage from a questionnaire
- a reliable measurement of true wage
- a measurement of wage satisfaction

Thanks to a common identifier variable, we are able to create such a database by matching two records: one from the “Enquête sur les Salaires Auprès des Salariés” (SalSa) and one from the “Déclaration Annuelle des Données Sociales” (DADS). The merged dataset is the same already used by Godechot & Senik (2015).

The first record contains the answers to the first wave of the SalSa social survey by 3055 employees, which took place in France from November 2008 to January 2009. The sample of employees is drawn from both the private and public sector. Interviews were run either by phone or face-to-face within the following regions: Alsace, Auvergne, Centre, Languedoc-Roussillon, Lorraine, Midi-Pyrénées, Basse-Normandie, Pays de Loire, Picardie, Rhône-Alpes and Ile-de-France (in the Essonne county only). The non-response rate due to refusal is relatively low (12% of the initial population). The survey asks several questions about job satisfaction under different points of view: stress, physical effort, working schedule among others and, luckily, wage satisfaction. In the interview, subjects are also asked to report their net monthly wage. We refer to this piece of information as “self-reported wage” and we distinguish it from the “fiscal wage”, drawn from the DADS records.

The DADS is an administrative document which every employer (included public companies) must produce. The document contains, inter alia, information on the net annual wage of the employees. Since it is the employer who provides the wage information, data are particularly reliable. The section of the dataset which interests us is the one containing the yearly fiscal wage of the respondents to the SalSa survey. We do not have the fiscal records for 62 observations, which went lost in the matching process.

We should highlight that SalSa provides information on monthly wage, and DADS on yearly wage. In order to compare the two pieces of information, we multiply the
monthly self-reported wage by 12. The multiplication by a higher factor (13 or 14), to account for extra monthly payments, generates a larger absolute discrepancy between the two records. Some clear outliers are present. Following up the Godechot & Senik (2015) strategy, we assume 6 outliers in the SalSa to be mistyped and we modify them accordingly.

We remove a further 283 observations where the relative discrepancy between fiscal and self-reported wage is incongruent (higher than 2/3 of the wage) or where the absolute discrepancy is very high (beyond 40000€). We believe that it is not reasonable to explain these huge errors as recall biases, so they fall outside our domain of interest. We could have generated them during the necessary transformation of the SalSa records from monthly to annual (if a respondent worked only one month during the past year, the annualized SalSa wage will be 12 times higher than the true annual wage); furthermore, they may be due to miscoding or by mislinking the data. The sample restriction allows us to obtain a 95% correlation between SalSa and DADS income records. We offer a further discussion on alternative rules for outliers in section 6.2.

Finally, we must take into consideration that a small noise was added to the DADS records by the data provider. This process is applied to most income records in order to preserve the privacy of the respondents and is designed to minimize the impact on data analysis. In section 6.3 we test (and strongly reject) the hypothesis of a misleading effect from the artificial noise.

3.2 The measurement of job satisfaction and wage satisfaction

Before describing our data set, we should discuss what “job satisfaction” and “wage satisfaction” mean. A classic definition of job satisfaction is the one offered by Locke (1957), who describes this concept as “a pleasurable or positive emotional state resulting from the appraisal of one’s job or job experiences”. This definition has the merit to stress the importance of the evaluation process. Job satisfaction does not represent someone’s emotional state at work, i.e. during working hours. We believe that it renders the evaluation of the idiosyncratic representation of a job in its different dimensions (wage, schedule, physical effort, nervous effort, etc), according to some subjectively weighted criteria (comparative schemes, physical capability, consumption motifs, etc). The nature and the heterogeneity of these criteria are not under debate here. On the contrary, we must assume some inter-personal consistency in the different dimensions which determine job satisfaction.

A critique we could receive is that we intend to analyze some variables which are intrinsically subjective and not observable a posteriori. Four decades of studies support our choice by showing that job satisfaction predicts observable behaviors such as job quits (Clark, 2001; Freeman, 1978; Akerlof et al, 1988, McEvoy & Cascio, 1985), absenteeism (Clegg, 1983), productivity (Mangione & Quinn, 1975): if job satisfaction was pure noise or purely idiosyncratic, these results would be unlikely to happen.

The SalSa survey does not contain a question asking respondents’ general satisfaction with regards to their job. However, it contains a question which refers directly to wage satisfaction:

\[\text{For instance, we change the monthly wage to 1100€ whereas the record is 21100€.}\]
Table 2 summarizes data on average wage satisfaction by category. This data are compared both with the average self-reported wage and with the answers to another 4-scaled job satisfaction question, which is intended to capture “task satisfaction”:

**[WPLAIT]** Do you like what you do in your job? [yes, almost all the time; yes, most of the time; yes, sometimes; usually no]\(^7\)

It is worth noting that young workers are much more satisfied with their wage than the average, although they tend to have relatively low wages. This pattern is quite intuitive if we consider that many of the less-than-26-years-olds have just entered the labor market, entailing a transition from null to positive income. Also men are on average more satisfied of their wage than women, but they earn more too. Finally, we should underline that the previous remarks on wage satisfaction do not extend to task satisfaction: neither male workers, nor young workers like what they do at work more often than the others.

### 3.3 How much does self-reported wage differ from fiscal wage?

Once the two datasets - SalSa and DADS - have been merged, we can compare the annual self-reported net wage (from SalSa) and the fiscal net wage (from DADS). Fiscal and self-reported wage are well correlated (see fig. 1), but not identical.

We remind that, following from equation 7, the recall error \( u \) was defined as \( \log \tilde{y} - \log y \). To make the descriptive statistics clearer, we avoid the log form and we look at the difference between the two wage measurements, \( \tilde{y} - y \). We name “discrepancy” this difference:

\[
\text{discrepancy} = \text{self-reported wage} - \text{fiscal wage} = \tilde{y} - y; \tag{11}
\]

we will always designate with the term “discrepancy” the difference between surveyed and fiscal wage. By “mean error” we will refer to the normalized value of this difference:

\[
\text{mean error} = \frac{\text{self-reported wage}}{\text{fiscal wage}} - 1 = \frac{\tilde{y}}{y} - 1; \tag{12}
\]

by “absolute error” we will refer to the absolute value of the mean error:

\[
\text{absolute error} = |\frac{\text{self-reported wage}}{\text{fiscal wage}} - 1| = |\frac{\tilde{y}}{y} - 1|; \tag{13}
\]

Table 3 summaries the differences between fiscal and self-reported wage, by category. Respondents’ imprecision is far from negligible: on average, the absolute error is almost

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\(^6\)The original questions are:

\([SALSATI]\) = Concernant votre salaire, diriez-vous que vous êtes? [Très satisfait; plutôt satisfait; plutôt mécontent; très mécontent]

\(^7\)[WPLAIT] Ce que vous faites dans votre travail vous plaît-il ?[oui, presque toujours; oui, la plupart du temps; oui, parfois; généralement non]
<table>
<thead>
<tr>
<th></th>
<th>Wage satisfaction*</th>
<th>Task satisfaction**</th>
<th>Self-reported wage***</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>2.47</td>
<td>3.44</td>
<td>20346</td>
</tr>
<tr>
<td>male</td>
<td>2.54</td>
<td>3.45</td>
<td>23014</td>
</tr>
<tr>
<td>female</td>
<td>2.40</td>
<td>3.42</td>
<td>17524</td>
</tr>
<tr>
<td>French</td>
<td>2.47</td>
<td>3.44</td>
<td>20412</td>
</tr>
<tr>
<td>foreigner</td>
<td>2.41</td>
<td>3.35</td>
<td>18413</td>
</tr>
<tr>
<td>full-time</td>
<td>2.49</td>
<td>3.45</td>
<td>21916</td>
</tr>
<tr>
<td>part-time</td>
<td>2.40</td>
<td>3.39</td>
<td>13615</td>
</tr>
<tr>
<td>Age:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-25</td>
<td>2.64</td>
<td>3.35</td>
<td>14093</td>
</tr>
<tr>
<td>26-40</td>
<td>2.47</td>
<td>3.45</td>
<td>19607</td>
</tr>
<tr>
<td>41-55</td>
<td>2.45</td>
<td>3.43</td>
<td>21739</td>
</tr>
<tr>
<td>56-65</td>
<td>2.45</td>
<td>3.45</td>
<td>22381</td>
</tr>
<tr>
<td>Diploma</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No diploma (1)</td>
<td>2.37</td>
<td>3.24</td>
<td>15309</td>
</tr>
<tr>
<td>General high school certificate (6)</td>
<td>2.53</td>
<td>3.44</td>
<td>19448</td>
</tr>
<tr>
<td>Graduated (9)</td>
<td>2.49</td>
<td>3.40</td>
<td>22482</td>
</tr>
</tbody>
</table>

* 4 = very satisfied; 3 = rather satisfied; 2 = rather dissatisfied; 1 = very dissatisfied
** 4 = yes, almost all the time; 3 = yes, most of the time; 2 = yes, sometimes; 1 = usually no
*** Nominal annual net wage, expressed in euros.

13% (about 2640€ per person). Consistently with the literature, we observe a downward bias: on average people declare about 1000€ less than what is reported in the fiscal registers (1st column) and about two thirds of the respondents under-report their wage (4th column).

The bottom of the wage distribution has a higher absolute error. This is not a surprise. By its definition, \( \frac{\text{discrepancy}}{\text{fiscal wage}} \), this measure is mechanically boosted when the income shrinks. If rounding the value of the annual wage of 500€ seems an acceptable approximation for the respondent, it represents a big distortion for a low wage, and a small one for a high wage. Thus, if we consider a part of the error to be non-proportional to the wage, this part is relatively over-weighted for low wages.

Interestingly, foreigners and young workers turn out to be the least precise when they are asked how much they earn (the absolute errors are respectively 16.4% and 17.5%). Respondents from these two categories are also the ones who tend to over-report their wage the most: their self-reported wages are respectively 2.9% and 7.4% higher than their true wages and about half of them over-reported their wage in the survey. This goes against the general propensity to under-report wage in questionnaires.

We mentioned that young workers are less precise in their answers.\(^8\) We should

\(^8\)We do not further analyze specificities of the group of foreigners because of the small size of the
Figure 1: Correlation between the income reported in the SalSa survey (x axis) and the income recorded in the DADS register (y axis)

Note: correlation is 95%

Consider that workers younger than 30 earn relatively less than older ones. However, a simple comparison of the conditional means suggests that the imprecision of young workers is not purely due to the correlation between age and wage (see appendix, table 8).

It is also worth recalling that young workers are the most enthusiastic about their pay (see table 2). The group of people who are the most satisfied with their wage is also the one which tends to over-report it. This remark is the first hint of some correlation between wage satisfaction and the recall error. We will explore this correlation in the next sections.

4 The problem of using self-reported income as a proxy for truly perceived income

So far we saw that wages drawn from surveys can significantly differ from the true wage a person earns. The value of wage self-reported in surveys is the one typically adopted to infer the relationship between wage and some satisfaction variables. However, researchers usually estimate the impact of self-reported wage on satisfaction, from which they derive the impact of true wage on satisfaction. This passage may generate an important bias. Probably all practitioners of satisfaction surveys have this concern in their mind. Nevertheless, self-reported income is often the only available measure.

---

9 We do not claim that the effect of self-reported wage on job satisfaction is uninteresting: quite the opposite, self-reported income can be a precious source of information. Nevertheless we criticize the lack of distinction between subjectively perceived income and true income in empirical works. This difference must not be neglected, in particular for labor policies, where the latter is the only control variable.
4.1 The misestimation of the effect of absolute wage

Consistently with common intuition, the amount of wage has been shown to have a strong positive effect on job satisfaction measures (Clark, 1996; Gazioglu & Tansel, 2006). Let us begin by testing this correlation in our sample. From the generalized equation 4, we assume a standard log-linear relationship between wage satisfaction and wage:

\[
h_i^y = \beta_1 \log y_i + X_i'\gamma + \epsilon_i
\]  

(4')

We start by using Ordinary Least Squares and we regress wage satisfaction on self-reported annual wage. The estimation of the model provides results in line with the previous literature. The coefficient of annual wage is significantly different from zero (t-statistic = 15.22) and this conclusion holds when we progressively add some regressors to control for demographic characteristics (age, sex, nationality) and professional characteristics (education, part-time worker). Age operates in a concave fashion, where young workers tend to be more satisfied. The only remarkable difference with the previous literature is that the sex of the respondent does not seem to affect the level of job satisfaction.
Figure 2: Estimated coefficients of the regression of wage satisfaction on wage: self-reported wage vs fiscal wage

† indicates estimation by OLS. ‡ indicates estimation by Ordered Probit. “all” indicates the whole sample. “young” indicates under 31-year-olds. The vertical bars indicate the standard deviations. All regressions control for the following characteristics: sex, age, age$^2$, nationality, education, part-time schedule.

Reading note: when we regress wage satisfaction on self-reported wage, the associated OLS coefficient is 0.631. When the explanatory variable is fiscal wage instead, the associated OLS coefficient is 0.515.

We also test this same model using a common non-linear estimation technique for discrete regressands: Maximum Likelihood Ordered Probit. The main interest of this alternative approach is that it relaxes the assumption of cardinality in satisfaction records. Consistently with the findings of Ferrer-i-Carbonell & Frijters (2004), we find no qualitative difference between assuming ordinality or cardinality of the scores. Regardless of the estimation technique, we can conclude that the level of self-reported wage is a strong explanatory variable for wage satisfaction.

However, the econometric model we just used is nothing but a particular form of regression model (5):

$$h_Y = \tilde{\beta}_1 log \tilde{y} + X' \gamma + \varepsilon_i$$

Where $\tilde{y}_i$ is self-reported wage and $h_Y$ is wage satisfaction. This is the equation researchers usually estimate. Nevertheless, conclusions are often drawn on $y_i$, i.e. the true wage, as if the estimated parameters were from equation 4'.

The straightforward way to get an idea of how severe the bias is consists in comparing estimations from equations (4') and (5'). Formally, we check if $\tilde{\beta}_1$ is significantly different from $\beta_1$. Therefore, we compare the regression of wage satisfaction on self-reported wage with the regression of wage satisfaction on fiscal wage. We use both OLS and Ordered Probit. The results of the estimations are displayed in table 9 in the appendix, while figure 2 gives a graphic intuition of the misestimation.

Both OLS and Ordered Probit suggest the same conclusion: coefficients estimated from survey data suffer from a big upward bias. The OLS estimated coefficient for wage is 0.632 when we use self-reported wage and 0.515 when we use fiscal wage. The Ordered Probit estimator gives similar results: $\beta_1^{op} = 1.036$, while $\beta_1^{op} = 0.828$. This means that the estimated impact of wage on wage satisfaction is about 20% lower when we use fiscal sources instead of survey sources. A t-test rejects the null that $\tilde{\beta} = \beta$ at 1% level for
both estimation techniques, OLS and Ordered Probit. Results hold when we use robust standard errors (White, 1980) to control for heteroskedasticity.

As we discussed in the previous section, wage self-reported by young workers (under 31-year-olds) has some peculiarities. When reporting their wage in surveys, young people are particularly imprecise and tend to over-report their true pay. This is why we are not surprised to find the bias for young workers to be particularly bad. When we compare $\beta_1$ and $\beta_1$ from a restricted sample of only young workers, survey data over-estimate the effect of wage on wage satisfaction by about 50%.

The magnitude of the misestimation is relevant to the economic analysis, both in terms of marginal effects and of predicted satisfaction. For example, we could be interested in the marginal effect of a 20% increment of the salary on worker’s satisfaction. According to the Ordered Probit regression on self-reported wage, a 30-years-old full-time worker who used to earn 40 000€ is now 11% more likely to be very satisfied with his pay. The predicted marginal effect drops to 4% when fiscal wage is used. If we are interested in the probability this worker reports a high satisfaction level, we expect such a probability to be about 39% if we use self-reported wage. When fiscal wage is used instead, this probability is only 19%.

4.2 The misestimation of the effect of relative wage

In addition to the absolute level of wage, wage satisfaction seems to be largely determined by the relative level of wage, i.e. one’s wage with respect to some comparison wages (Cappelli & Sherer, 1988; Clark & Oswald, 1996). Many approaches has been suggested in the literature to model satisfaction reference dependence.10

We adopt the rank-dependent approach, promoted by Brown, Gardner, Oswald & Qian (2008), which focuses on the relative position of the worker within the pay scale of a reference group. We decide to focus on the rank because misreporting could change the relative position of wages within an ordered set. If we look at equation (10):

\[ u_i = \mu_1 h_i + X_i \mu_2 + \mu_3 \log y_i + v_i \]  

the two hypotheses that (i) high wage earners tend to under-report their pay (i.e. $\mu_3 < 0$) and (ii) more satisfied people tend to over-report their pay (i.e. $\mu_1 > 0$) cast some doubts on the reliability of the wage scale deduced from survey data. Mapping from fiscal wage to self-reported wage could be non-monotonic. In other words, the relative position in the pay scale of an individual could be different if it is measured using fiscal or self-reported wage. Of course, the rank mismeasurement would lead to misestimating the effect of the rank on wage satisfaction.

We define the reference group according to geographical proximity (region) and category of occupation (managers, intermediate, clerks, workers): two individuals $i$ and $j$ belong to the same wage reference group if they work in the same region and in a

10Research has focused on determining both the reference group (Bygren, 2004; Law & Wong, 1998; Senik, 2009; Clark & Senik, 2010) and the underlying comparative mechanism (Brown et al., 2008; Godechot & Senik, 2015). These questions are still under debate among experts.
hierarchically-comparable position.11 We obtain 40 potential reference groups (5 categories x 8 regions), from which we filter out groups with less than 5 individuals. We end up with 33 reference groups, having a mean size of 120 individuals each.

We define “normalized rank” as:

\[ w_i = \frac{r - 1}{N_R - 1} \] (14)

where \( r \) is the ordered position - within the wage scale - of individual \( i \) in her reference group \( R \) of size \( N_R \). Smaller \( r \) indicates the worker is higher up the pay scale of her reference group. As a consequence, normalized rank \( w_i \) is constrained between 0 and 1, where 0 (1) means the worker is at the very top (bottom) of the pay scale. For a larger discussion of equation 14 we refer back to Brown et al. (2008), which develops this approach.

We regress wage satisfaction on the vector of normalized ranks, defined above. We start by using the rank deduced from self-reported wages, so that the estimated equation is:

\[ h_s^i = \tilde{\beta}_1 \log \tilde{y}_i + \tilde{\beta}_2 \tilde{w}_i + X_i' \tilde{\gamma} + \epsilon_i \] (5")

The first column of table 4 displays the Ordered Probit coefficient \( \tilde{\beta}_2 \) associated to \( \tilde{w}_i \).12 We obtain a negative coefficient, consistent with the idea that a higher position in the pay scale (small \( \tilde{w}_i \)) associates with a higher wage satisfaction. We test this relationship for three population sub-groups too: workers under 30 years old, workers in the bottom half of the wage distribution and workers in its top half. The estimated coefficient is significantly different from zero across the population subgroups.

When we repeat the same regression analysis using fiscal data, results change considerably. The estimated equation is now:

\[ h_s^i = \beta_1 \log y_i + \beta_2 w_i + X_i' \gamma + \epsilon_i \] (4")

The complete Ordered Probit regression table is presented in the appendix (table 10). Here we report only the estimated coefficients for \( \beta_2 \), displayed in the second column of table 4. The use of fiscal wage suggests a smaller effect of rank comparisons on satisfaction: the associated coefficient is systematically smaller when we use fiscal wage instead of self-reported wage.13 This remark supports the idea that the rank of self-reported wage is partially artifactual. If two workers \( i \) and \( j \) earn the same wage, but \( i \) is more satisfied than \( j \) and over-reports her wage, we can wrongly deduce a positive effect of the rank on \( i \)'s satisfaction. When the true rank is considered instead, no effect is found.

11 Numerous studies agree on the local dimension of wage comparisons, see for instance Caporale et al. (2009) for Europe. People seem to compare mostly with workers in the same occupation category rather than in the same firm or in the same sector (Bygren 2004).

12 We repeat the same regression analysis by assuming cardinality of wage satisfaction records, but once again the results are qualitatively the same.

13 For the coefficients estimated in the whole sample and in the sample of young workers, a Wald test rejects the null that \( \tilde{\beta}_1 \) and \( \tilde{\beta}_2 \) are jointly equal to \( \beta_1 \) and \( \beta_2 \) at 1%. For the bottom and top 50% the test fails to reject the joint hypothesis. However, when the two restrictions on \( \tilde{\beta}_1 \) and \( \tilde{\beta}_2 \) are tested independently, \( \tilde{\beta}_1 \) is statistically different from \( \beta_1 \) in the first population subgroup; \( \tilde{\beta}_2 \) is statistically different from \( \beta_2 \) in the latter population subgroup.
In addition, we can see that the effect of normalized rank on wage satisfaction is statically null for two population subgroups: young workers and the top 50% of the wage distribution. These findings are consistent with relative income theory. On the one hand, the professional future of young workers is both longer and more uncertain, so that they are particularly sensitive to signal-effects: the higher wage of their peers represents a positive signal for their career which can offset frustration (Clark & Senik, 2010). On the other hand, according to Duesenberry’s relative income theory (Duesenberry, 1948), upward comparisons matter more than downward ones, so that richer people are less sensitive to their position in the wage scale. The use of self-reported wages overlooks these two interesting outcomes.

In this section we showed that the use of self-reported wage led to overestimating the effect of wage on wage satisfaction and overlooking some features in the analysis of wage comparisons. If we consider that most of the literature on job satisfaction is built on survey data, these results are somewhat alarming.

Table 4: Estimated coefficients of the regression of wage satisfaction on normalized wage rank: self-reported wage vs fiscal wage

<table>
<thead>
<tr>
<th>population</th>
<th>self-reported</th>
<th>fiscal</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>-0.787(***)</td>
<td>-0.499(***)</td>
</tr>
<tr>
<td></td>
<td>(-6.94)</td>
<td>(-4.34)</td>
</tr>
<tr>
<td>young</td>
<td>-0.645(**)</td>
<td>-0.174</td>
</tr>
<tr>
<td></td>
<td>(-2.37)</td>
<td>(-0.60)</td>
</tr>
<tr>
<td>bottom 50%</td>
<td>-0.661(***)</td>
<td>-0.476(**)</td>
</tr>
<tr>
<td></td>
<td>(-3.51)</td>
<td>(-2.42)</td>
</tr>
<tr>
<td>top 50%</td>
<td>-0.591(***)</td>
<td>-0.247</td>
</tr>
<tr>
<td></td>
<td>(-3.41)</td>
<td>(-1.57)</td>
</tr>
</tbody>
</table>

*Reading note: when we regress wage satisfaction on the normalized self-reported rank, the associated Ordered Probit coefficient is -0.787. When the explanatory variable is the normalized fiscal rank instead, the associated Ordered Probit coefficient is -0.499.*

5 The hedonic recall bias hypothesis

To better understand the empirical results of the previous section, it is useful to think the problem in terms of a proxy, a latent and a measurement error. The self-reported
wage is a *proxy* for the truly earned wage, which is a *latent* unobserved variable. Ideally, what we would like to estimate is the impact of the latter on wage satisfaction. Given that this information is rarely available, we use self-reported wage as a proxy. The recall error - namely the deviation of self-reported wage from the true wage - is nothing but a *measurement error*.

A good proxy must respect two conditions: a high correlation with the latent variable (relevance) and the exogeneity with respect to the residuals (exogeneity). Relevance is surely met by self-reported wage, then again exogeneity is questionable: it depends on the relationship between the measurement error and the other variables of the model.

Measurement error is a common problem in econometric analysis: sometimes such errors are minor; often they are ignored. When taken into account, measurement error is usually assumed to be a *classical measurement error* (CME), i.e. to have a zero-mean and to be independent from the true value of the underlying variable (e.g., Klepper & Leamer, 1984; Li & Vuong, 1998; Chesher & Schluter, 1999; Grilliches, 1987; Angrist & Krueger, 2000), although some authors have considered the consequences of dropping this simplistic assumption, showing no or limited support to the CME (Card, 1996; Bollinger, 1996; Hyslop & Imbens, 2001). If we acknowledge the regressor to be subject to a CME, the coefficient estimated through OLS is inconsistent with a persistent bias toward zero (attenuation). Under CME, the estimated impact of self-reported wage on wage satisfaction is:

\[
\hat{\beta}_{CME} = \frac{\text{cov}(h^s; \tilde{y})}{V(\tilde{y})} = \frac{\text{cov}(h^s; y)}{V(y) + V(u)} < \hat{\beta}
\]  

(15)

However, in figure 2 we observe the opposite: the coefficient associated to the mis-measured variable \( \tilde{y} \) is upward biased. This can happen whether the measurement error is not random, but endogenous. In this case, the estimated linear relationship between wage and wage satisfaction could be biased either upward or downward:

\[
\hat{\beta} = \frac{\text{cov}(h^s; \tilde{y})}{V(\tilde{y})} = \frac{\text{cov}(h^s; y) + \text{cov}(h^s; u)}{V(y) + V(u) + 2\text{cov}(y; u)} \leq \hat{\beta}
\]  

(16)

Hence, the observed result \( \hat{\beta}_1 > \hat{\beta}_1 \) strongly suggests the CME assumption does not hold. In particular, two reasons can explain the over-estimation of the impact of wage on wage satisfaction (cf. equation 16):

1) The recall error could be endogenous with regards to the true wage (\( \text{cov}(y, u) \neq 0 \))
2) The recall error could be endogenous with regards to the satisfaction variable (\( \text{cov}(h^y, u) \neq 0 \))

The first case refers to parameter \( \mu_3 \) in equation 10. If this parameter is negative - as we will show - it means that richer people tend to further under-report their wage. This remark already violates the classical measurement error hypothesis: if the measurement...
error negatively depends on the underlying wage, OLS estimated coefficients could be upward biased.

The second possible source of endogeneity is more original and could have fecund implications. It suggests some dependence of the recall error with respect to wage satisfaction. This could explain, for instance, why we find an artificial effect of wage ranking for young workers. The intuition is the following. Let us take two young workers, \(i\) and \(j\) who earn the same wage. \(i\) is very satisfied with her wage while \(j\) is disappointed about it. When asked to report their wage, \(i\) slightly over-reports her wage, while \(j\) under-reports it. Hence, when the self-reported wage is the only available information, we could wrongly infer some positive effect of the amount of wage on wage satisfaction. In addition, we could infer that \(i\) is more satisfied because she is relatively richer than \(j\), while this effect does not exist neither.

This intuition is the core of the hedonic recall bias hypothesis. We talk about “recall bias” in the sense of Tversky & Kahneman (1976). Tversky & Kahneman define psychological bias as systematic errors which occur under specific conditions. According to our model, the recall error is indeed not random, but psychologically determined. The next paragraphs are devoted to the empirical validation of this hypothesis. Our empirical analysis of this behavioral bias cannot achieve the ambitious target of understanding human memory. Nevertheless, its existence would have important implications in terms of satisfaction data analysis and data collection strategies.

### 5.1 Least squares with cardinal satisfaction

According to the hedonic recall hypothesis, the amplitude of wage satisfaction directly affects both the size and the direction of the recall bias. In this scenario, more satisfied people tend to over-estimate their wage; less satisfied people tend to under-estimate their wage. The illustration below offers an intuitive view of the mechanism.

![Illustration of the mechanism](image)

As a first step to test the validity of our hypothesis, we investigate the explanatory power of wage satisfaction as a linear predictor of the recall error. The econometric model is the one we described in section 2. We then look at the significance of coefficient \(\mu_1\) in equation (10), estimated by OLS:

\[
 u_i = \mu_1 h_i + X_i' \mu_2 + \mu_3 \log y_i + v_i; \quad (10)
\]

where matrix \(X_i\) controls for the following covariates: age, age^2, nationality, sex, part-time job and education level.

Results, reported in the first two columns of table 5, suggest that wage satisfaction is a robust predictor of the recall error. Results hold with and without controls and

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16It is important to stress that the econometric concept of “bias” and the psychological concept of “bias” are clearly separate and must not be confused with one another.
suggest that, *ceteris paribus*, more satisfied people tend to declare a higher wage. More specifically, an additional point in the 1-4 scale of wage satisfaction is associated with a 3.7% increase in the ratio: self-reported wage / fiscal wage.

Table 5 also offers interesting insights on the other sources of the discrepancy between self-reported and true wage. Men tend to underestimate their wage more than women and full-time workers tend to underestimate it more than part-time workers. In addition, there is a clear tendency of high wage earners to under-report their wage, compared to low wage earners. On average, an additional euro on the payroll increases the income reported in surveys of 83 cents only.

The effect of satisfaction on misreporting is substantial. According to our estimation a man, who works full-time, earns 20 000€ per year and is very dissatisfied with his wage, estimates his annual salary quite accurately: 19960€. His colleague, who earns the same income and works full-time as well but is very satisfied with his wage, estimates his annual salary to be much higher: 22280€. Hence, if we compare the survey data on these two employees, we detect an effect of wage on wage satisfaction which actually does not exist.

5.2 Least squares with ordinal satisfaction

In the previous section, our analysis of the hedonic recall bias assumed cardinality of wage satisfaction records. This means we considered that the marginal effect of the increment from “rather satisfied” to “very satisfied” is the same as the marginal effect of the increment from “rather dissatisfied” to “rather satisfied”. This is open to criticism because it may unduly restrict the regressions. Therefore, we alternatively choose a more flexible functional form and we reshape the recall function as follows:

\[ u_i = \delta_1 VU_i + \delta_2 RU_i + \delta_3 VS_i + X_i' \mu_2 + \mu_3 \log y_i + v_i \]  

(10’)

where \( VU_i \), \( RU_i \) and \( VS_i \) are dummy variables which take value 1 when respondent \( i \) declares to be respectively “very unsatisfied”, “rather unsatisfied” and “very satisfied” with her wage. As a reference group, we take people who declared themselves as “rather satisfied” since this was the most common answer. Results are summarized in table 5, column (3) and confirm that the effect of satisfaction on misreporting is non-linear.

Estimation outcomes say that, on average, the marginal increment in self-reported wage subsequent to a transition from “rather satisfied” to “very satisfied” is about +4%. The magnitude of this effect is comparable to the effect of a transition from “rather unsatisfied” to “rather satisfied”. While, among unsatisfied people, the effect of a transition from “very unsatisfied” to “rather unsatisfied” appears to be lower. These results are consistent with the idea of a monotonic effect: the more satisfied a person is, the larger the over-reporting is (and *vice-versa* for unsatisfied people).

5.3 Bivariate regression analysis

So far, our empirical investigation told us that a person who is satisfied with her their wage tends to report a higher wage relative to her true wage. This could either mean
that she \textit{under-reports} her pay \textit{less} or that she \textit{over-reports} her pay \textit{more}, compared to an unsatisfied person. However, this analysis does not enable us to say if a more satisfied person is also \textit{more likely} to over-report her wage than to under-report it. This inference is made possible by a bivariate analysis of the recall error, i.e. a regression where we dichotomize the independent variable $u$. Therefore we carry on a Probit estimation,\footnote{The normality of the residuals is a critical assumption for us to carry on our Probit analysis.} by assuming the stochastic under-lying latent relation of equation (10).

Probit estimation allows us to assess if more satisfied people tend to over-report their wage and less satisfied people tend to under-report it. According to our estimates, showed in columns (4) and (5) of table 5, this is what actually happens. Indeed, the Probit estimation suggests that, on average, a one-point increment in the wage satisfaction scale increases the probability of over-reporting by about 10\%. For instance, a 40 year old French woman, working full-time for a 40 000\euro{} salary and “very dissatisfied” with her wage, has a 60\% probability of under-reporting her wage in the survey. The probability of her under-reporting drops to 38\% if she is “rather satisfied” with her wage and to 28\% if she is “very satisfied”.

We repeat the same exercise without the cardinality assumption of satisfaction measures. The last column of table 5 displays the results. Estimated effects lay qualitatively unchanged and quantitatively stronger. The dummy variables for “rather unsatisfied” and “very unsatisfied” attract a negative coefficient, the dummy for “very satisfied” has a positive one. According to the new estimates, the same 40 year old French employee, “very dissatisfied” with her wage, has a 55\% probability of under-reporting her wage in the survey. The probability of under-reporting her wage drops to 23\% if she is “very satisfied” with it.

\subsection{5.4 Quantile regression analysis}

We want to examine if the hedonic recall bias homogenously affects big errors and small errors on one hand, and underestimation and overestimation on the other hand. In sections 5.1 and 5.2 we used OLS models to estimate the \textit{conditional mean} of the recall error given certain values of the explanatory variables. Now we use quantile regression models to estimate the \textit{conditional quantiles} of the recall error.\footnote{The minimized conditional quantile function is:}

\begin{equation}
Q_{\tau}(u_i|h_i^y) = \arg \min_{q(h_i^y)} E[\rho_{\tau}(u_i - q(h_i^y))] \tag{17}
\end{equation}

Estimation results are displayed in figure 3. Table 11 in the appendix details the estimation for the first and last decile, the median and the third quartile.

The explanatory power of wage satisfaction is significantly different from zero across the whole distribution of recall errors. However, the size of the coefficients changes in a \textit{✓}-shape fashion, which brings up two kinds of heterogeneity in the hedonic recall bias.

First of all, there is some convexity of the coefficients curve. However the convexity is so light that we cannot deduce a substantive change in the size of the coefficients. For instance, the marginal effect of wage satisfaction on a heavy under-reporter ($\tau = 0.1$) is
Table 5: **Hedonic recall bias**: OLS and Probit regressions of recall error on wage satisfaction

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) OLS</th>
<th>(3) OLS</th>
<th>(4) Probit</th>
<th>(5) Probit</th>
<th>(6) Probit</th>
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<tbody>
<tr>
<td>Dependent variable: recall error</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>wage satisfaction</td>
<td>0.0156***</td>
<td>0.0368***</td>
<td></td>
<td>0.133***</td>
<td>0.276***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.55)</td>
<td>(8.55)</td>
<td></td>
<td>(3.77)</td>
<td>(7.02)</td>
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</tr>
<tr>
<td>very dissatisfied?</td>
<td></td>
<td></td>
<td>-0.0619***</td>
<td>-0.438***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-5.80)</td>
<td>(-4.52)</td>
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</tr>
<tr>
<td>rather dissatisfied?</td>
<td>-0.0439***</td>
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<td>-0.306***</td>
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</tr>
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<td></td>
<td>(-6.73)</td>
<td>(-5.18)</td>
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<tr>
<td>very satisfied?</td>
<td>0.0402**</td>
<td></td>
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<td></td>
<td>0.417***</td>
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<td></td>
<td>(2.58)</td>
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<td>(3.05)</td>
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<tr>
<td>log (fiscal wage)</td>
<td>0.162***</td>
<td>0.162***</td>
<td>-1.045***</td>
<td>-1.047***</td>
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<tr>
<td></td>
<td>(-18.85)</td>
<td>(-18.91)</td>
<td>(-12.61)</td>
<td>(-12.71)</td>
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<tr>
<td>male?</td>
<td>-0.0262***</td>
<td>-0.0266***</td>
<td>-0.208***</td>
<td>-0.220***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.00)</td>
<td>(-4.06)</td>
<td>(-3.52)</td>
<td>(-3.74)</td>
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<tr>
<td>full-time?</td>
<td>-0.0662***</td>
<td>-0.0651***</td>
<td>-0.523***</td>
<td>-0.519***</td>
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<tr>
<td></td>
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<td>(-0.97)</td>
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<tr>
<td>age^2</td>
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</tr>
<tr>
<td></td>
<td>(0.93)</td>
<td>(1.09)</td>
<td>(1.11)</td>
<td>(1.34)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>French?</td>
<td>-0.0244</td>
<td>-0.0217</td>
<td>-0.283*</td>
<td>-0.260*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.45)</td>
<td>(-1.29)</td>
<td>(-1.96)</td>
<td>(-1.81)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>-0.0783***</td>
<td>1.664***</td>
<td>1.771***</td>
<td>-0.783***</td>
<td>10.79***</td>
<td>11.67***</td>
</tr>
<tr>
<td></td>
<td>(-6.90)</td>
<td>(17.99)</td>
<td>(18.87)</td>
<td>(-8.52)</td>
<td>(12.31)</td>
<td>(13.04)</td>
</tr>
<tr>
<td>N</td>
<td>2634</td>
<td>2596</td>
<td>2626</td>
<td>2634</td>
<td>2596</td>
<td>2626</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table does not display the coefficients associated with 14 binary variables for the education level.
3%, while this same effect decreases to 2.5% for a moderate under-reporter (τ = 0.5).

The second observed heterogeneity concerns under- and over-reporting and is much stronger. In figure 3 we can observe a sharp increase in the hedonic recall effect starting from the 7th decile. Something very clear happens to the recall errors at this point of the distribution. At this point - as we can see in figure 4 - errors turn from being a matter of under-reporting to be a matter of over-reporting: at the 67th percentile $u_i$ switches its sign. Hence, the hedonic recall bias seems to affect more over-reporting than under-reporting. For instance, the marginal effect of wage satisfaction on a heavy over-reporter ($τ = 0.9$) is almost double the marginal effect for a heavy under-reporter ($τ = 0.1$). These results can explain why we observe coefficients to be particularly badly biased for young workers: young workers are a group of highly satisfied workers and the hedonic recall seems to be stronger for over-reporters.

After the four empirical studies of this section, we can summarize some stylized facts on the recall error. People more satisfied with their wage tend to over-report their wage and vice-versa less satisfied people tend to under-report it. The more satisfied they are the larger the over-estimation is and vice-versa for less satisfied people. The hedonic recall bias affects more over-reporting than under-reporting. As a corollary, it also affects relatively more highly satisfied groups, like young workers.

6 Robustness tests

6.1 Accounting for confusion between net wage and gross wage

The relationship between wage satisfaction and the recall error could be affected by another factor, the respondents’ confusion between net wage and gross wage. In surveys, people are asked about their net wage because this piece of information is assumed to be more accessible: people usually know how much money they have available each month. Nevertheless, some confusion between pre-tax income and post-tax income may arise, particularly if we consider that answers in surveys are often given in a few seconds.

To detect the existence of such confusion, we suggest exploiting another question from the SalSa survey:

[SMICVAUT] Could you state the net wage of a full-time worker who is paid minimum wage (SMIC)?

Starting from this question, we construct a dummy variable which takes value = 1 if the amount of the net SMIC reported by the respondent is higher than the gross SMIC ($1321\text{€}$ in 2008). This variable may reflect a systematic tendency of some respondents to over-estimate income. We explain this tendency as a confusion between the concepts of net and gross income and we assume that respondents are also affected by this confusion when they report their own wage. 15% of the respondents seem to report the gross value of the SMIC when net value is asked.

19[SMICVAUT] Pouvez-vous m’indiquer combien gagne par mois, en net, un salarié payé au salaire minimum (SMIC) travaillant à plein temps ?
Figure 3: Coefficients of quantile regression of the recall error on wage satisfaction

Reading note: An additional point in the wage satisfaction scale raises median recall error by 2.5%.

Figure 4: Cumulative distribution of the recall error

Reading note: The recall error is negative up to the 67th percentile; it is positive beyond this threshold.
We include this variable in the set of controls and re-run OLS and Probit regressions of the recall error on wage satisfaction (see table 12 in the appendix). Albeit our new variable is a significant predictor of the discrepancy between self-reported and fiscal wage, the coefficient and significance level of wage satisfaction are almost unchanged. This suggests that the confusion between the concepts of “net” and “gross” wage can partially explain the error in self-reported wage, but that this part is not redundant in wage satisfaction. Hence, the hedonic recall bias is robust to taking confusion into account.

6.2 Outliers

In our study, we apply quite a large definition of “outlier”.\textsuperscript{20} We consider outlier errors beyond 40 000€ or beyond 2/3 of the initial income. This definition leads to suppressing 221 observations. The best strategy to dealing with outliers has long been part of the data analysis debate (see the discussion in Fox, 1991). The main issue is that the definition of what an outlier is heavily depends on two contingent criteria: the source of the data and the aim of the analysis. These two criteria guided our choice of what to consider as an outlier.\textsuperscript{21}

To answer possible blames of both over-sampling and under-sampling, in this section we propose two extreme definitions of “outlier”. In one case, we apply a very narrow rule: we remove only matches which have discrepancies of over 40 000€. This allows to zoom out and see the effect of big discrepancies. As an alternative, we also apply a very restrictive rule: we remove every observation which has an absolute discrepancy of over 5%. This definition leads to the suppression of 3/4 of the sample, but allows us to zoom in on small discrepancies. Summary statistics of the new samples are displayed in table 6.

To test our claim that survey data lead to an overestimation of the effect of wage on wage satisfaction, we repeat the regression analysis of section 4 on the under-restricted sample, where only 10 outliers were dropped. Clearly, our claim is not induced by our initial restriction of the data. On the contrary, in the under-restricted sample, the bias gets even stronger. The estimated impact of wage on wage satisfaction decreases by up to

\textsuperscript{20}We devote a whole section of our dissertation to the treatment of outliers to enhance transparency in data treatment, which we consider a fundamental aspect for the credibility and intellectual honesty of the research.

\textsuperscript{21}Our motivations below.

\textbf{Source of the data.} The matching between our two datasets, SalSa and DADS, required a conversion of the monthly wage self-reported in the SalSa survey to an annual value. This transformation may generate some big errors, first of all when the respondents did not work for the whole year: in this case, their annualized wage considerably overestimates their true annual wage. We have no means to detect such errors other than looking at the relative correspondence between fiscal wage and self-reported wage. Therefore, we adopt a criterion based on the correlation between the two wage measurements: we apply progressively extensive definitions of “outlier” until we reach a 95% Pearson correlation between the two variables.

\textbf{Aim of the analysis.} In the first part of the dissertation, we show that the discrepancy between fiscal wage and self-reported wage can heavily affect the analysis of job satisfaction. A large definition of “outlier” is then a \textit{minima} to detect such a distortionary effect. The narrower the definition is, the larger the distortion is, as we show below. In the second part of our dissertation we investigate the existence of a recall bias. We believe that errors beyond 40 000€ or beyond 67% cannot be explained as \textit{recall biases}, so they fall outside our domain of interest. Conversely, a further restriction of our sample would reduce the available information and weaken the validity of our conclusions.
Table 6: Descriptive statistics on the discrepancy between fiscal and self-reported wage for alternative definitions of “outlier”

<table>
<thead>
<tr>
<th></th>
<th>Under-reporters (%)</th>
<th>Mean error (%)</th>
<th>Absolute error (%)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Over-restricted sample</td>
<td>60</td>
<td>-0.7</td>
<td>2.6</td>
<td>789</td>
</tr>
<tr>
<td>Under-restricted sample</td>
<td>63</td>
<td>58.4</td>
<td>74.0</td>
<td>2938</td>
</tr>
</tbody>
</table>

Reading note: In the over-restricted sample 60% of respondents under-reported their wage; the average under-reporting was 0.7%.

Figure 5: Correlation between fiscal and self-reported wage for alternative definitions of “outlier”

(a) Under-restricted sample

   Correlation: 89%

(b) Over-restricted sample

   Correlation: 99.8%
70% when we use fiscal data instead of self-reported data. Of course, it is not meaningful to run a similar test on the over-restricted sample, since its information is artificially aligned on fiscal wage.

To test the hedonic recall hypothesis, we repeat the OLS and Probit regression analysis of sections 5 on the new samples. Results, detailed in the appendix (table 12), lay qualitatively unchanged. In the explanatory regression for the recall error, the sign and significance level of the coefficients are the same: a higher level of wage satisfaction is associated with a lower recall error and with a higher probability of over-reporting. The magnitude of the coefficients changes, due to the variation in the size of the explained variable (the recall error) and in the size of the covariates (fiscal wage in particular). It is interesting to note that wage satisfaction is the only significant predictor of the recall error in the over-restricted sample: no covariate manages to explain the variance of the error whether this is artificially tiny (table 12, columns (3) and (6)).

At the end of this section we believe we can conclude that previous results are not sensitive to specific definitions of the outliers.

### 6.3 Monte Carlo simulations for white noise effect

As we mentioned at the beginning of this dissertation, data from DADS have been slightly modified to protect the privacy of the respondents. The data provider added a white noise to the “pure” income data.\(^{22}\)

In order to test that this procedure has no impact on our previous results, we propose a Monte Carlo simulation. We create a pseudo-random log-normal distribution of values with the same first and second moment of the DADS data set: these are our simulated wages. We treat the simulated wages as a monotonic transformation of the observed wages. Therefore, the observed wage satisfaction records are associated with the simulated wages, while preserving the income ranking. This means that we have the same value of wage satisfaction for the higher-wage respondent of the simulated distribution and of the observed distribution; the same value of wage satisfaction for the second-higher-wage respondent of the simulated distribution and of the observed distribution; and so on. Table 7 helps to understand our simulation strategy.

This procedure gives us a credible simulated sample. We regress wage satisfaction on the simulated wage, using both OLS and Ordered Probit. The model is the same as the one expressed in equation (1), except that we do not add any set of covariates to wage

\(^{22}\) The white noise was generated as a standard normal random variable, weighted by the standard deviation of the wages. If we denote by \(y\) the original wage information and by \(y^{DADS}\) the DADS wage information, their relationship is the following:

\[
y^{DADS} = \exp(\log(y) + n \cdot 0.02 \cdot s);
\]

\[
n \sim N(0,1);
\]

\[
s = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\log y_i - \overline{\log y})^2}.
\]

where \(s\) denotes the empirical standard deviation, \(N\) the size of the sample, \(\overline{\log y}\) is the sample mean of the logarithm of the wages and \(n\) is a random variable.
Table 7: Monte Carlo simulations: strategy to simulate the sample

<table>
<thead>
<tr>
<th>Simulated sample</th>
<th>DADS sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>wage</td>
<td>wage</td>
</tr>
<tr>
<td>$v_1$</td>
<td>$y_1$</td>
</tr>
<tr>
<td>$v_2$</td>
<td>$y_2$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>$v_N$</td>
<td>$y_N$</td>
</tr>
<tr>
<td>$\overline{v}$</td>
<td>$\overline{y}$</td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td>$\sigma_y$</td>
</tr>
<tr>
<td>$h_1$</td>
<td>$h_1$</td>
</tr>
<tr>
<td>$h_2$</td>
<td>$h_2$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>$h_N$</td>
<td>$h_N$</td>
</tr>
</tbody>
</table>

Reading note: Same letters designate equal values. $v_1$ is the simulated wage of individual 1, $y_1$ is the DADS wage of individual 1, $h_1$ is 1’s wage satisfaction.

Wages are sorted in descending order ($v_1 > v_2 > ... > v_N$; $y_1 > y_2 > ... > y_N$). Satisfaction records $h_i$ are not ($h_1 \leq h_2 \leq ... \leq h_N$).

satisfaction:

$$h_i = \beta_1 v_i + \epsilon_i \quad (1')$$

Where $v_i$ is the simulated wage. As expected, we obtain similar coefficients to the ones estimated through the original sample. To test the effect of the white noise, we add a residual to the simulated sample, according to the rule expressed in equation (20). Then, we run OLS and Ordered Probit again on the noisy sample. We iterate this procedure 500 times, using a simulated sample of 2634 observations. Clearly, the presence of the artificial white noise produces no effect on the coefficients. The value of the average estimated coefficient $\hat{\beta}_1$ across the iterations is displayed in the appendix (table 13).

6.4 Placebo variables

To understand the hedonic recall mechanism, it is useful to test if similar results can be obtained using different job satisfaction variables. Therefore, we systematically compare our hedonic recall model with four alternative specifications, where the estimated model is the same as in equation 10, except that we replace the explanatory variable $h_i$ (wage satisfaction) with some other satisfaction measures $h^s_i$, $s \in S = \{\text{task satisfaction}; \text{satisfaction with the working schedule}; \text{satisfaction with the nervous effort}; \text{satisfaction with the physical effort}\}$. The four satisfaction measures are deduced from the answers to the following questions in the SalSa survey:

[WPLAIT] Do you like what you do in your job? [yes, almost all the time; yes, most of the time; yes, sometimes; usually no]

[HCOMMOD] Is your work schedule practical? [yes; no]

[DURNER] Is your job nerve-wracking? [yes; no]

[DURPHY] Is your job physically demanding? [yes; no]

23[WPLAIT] Ce que vous faites dans votre travail vous plait-il? [oui, presque toujours; oui, la plupart du temps; oui, parfois; généralement non]
Estimation results are detailed in table 14 in the appendix. Satisfaction with the working schedule, with the nervous effort and with the physical effort clearly fail to predict the recall error, yet the estimated coefficient associated with task satisfaction is significantly positive. However, this result is very sensitive to model specification and it holds neither in a nested model where wage satisfaction is added (columns (6) and (7) in the table), nor in a model where task satisfaction is the only regressor (column (5)). In addition, task satisfaction does not add explanatory power to the set of covariates, as a comparison of the $R^2$ clearly shows. The correlation seems to be due more to a common latent factor than to task satisfaction itself. Overall, the explanatory power of task satisfaction looks small and spurious, and it seems unlikely that people who “like what they do” tend to overestimate their income.

[HCOMMOD] Vos horaires sont-ils pratiques ? [oui ; non]
[DURNER] Votre travail est-il dur nerveusement ? [oui ; non]
[DURPHY] Votre travail est-il dur physiquement ? [oui ; non]

24 Since the correlation between $h_1^*$ and $h_1^t$ is relatively low - 20% - there should be no risk of multicollinearity.
7 Discussion

In the next sections we pave the way for two discussions. First, we look beyond behavioral observations and we debate the underlying psychological mechanism of the recall bias, to understand why happy people should over-report their wage. Second, we explore possible indirect effects of the hedonic bias on a primary well-being variable: life satisfaction.

7.1 Possible explanations of the hedonic recall bias

Why should people more satisfied with their wage overestimate it and vice versa less satisfied people underestimate it? We can think of an explanation in terms of imperfect information recall. Although people do not know exactly how much they earn, they still have an idea of their wage: they know approximately how much they earn. For example, a respondent could know that her net wage ranges between 2400€ and 2600€ per month. She will give a response within this interval and the true value is likely to be within it. But which value to choose? 2450? 2500? More?

The correct information could be unavailable (i.e. forgotten) or could require a heightened cognitive effort. We can conceive that the mind makes a marginal adjustment as an immediate weighted average of available informative signals. This cognitive shortcut, albeit generally efficient, can lead to an estimation error, a bias. One of these signals is wage satisfaction. In the simple case where no other signal is available other than high wage satisfaction, a reasonable choice would be to guess in the upper part of the interval [1400€, 1600€]. This interpretation of the hedonic recall bias is in the fashion of the affect heuristics (Slovic et al., 2007), mental shortcuts which depend on some emotive status and influence people’s decisions. This explanation can answer why the recall process concerning the wage is affected only by wage satisfaction, but not by other satisfaction variables. Satisfaction with regards to the working task or the working schedule are not relevant signals in the estimation of the wage. Satisfaction with regards to the wage itself is a relevant signal indeed.

A possible critique could put the argument of consistency motifs forward. Consistency motifs refer to the respondents propensity to maintain consistency in their answers. In the questionnaire, people who claim to be satisfied with their wage could be tempted to inflate (more or less voluntarily) the value of their wage in the following question. However, since in the SalSa survey the respondents are asked to report their wage before they are asked to rate their wage satisfaction, the hypothesis of consistency motifs seems untenable.

In this article we present only correlations, without attempting any causal inference. The main problem is that our data do not contain a reliable instrument for wage satisfaction. In order to assess the causal relationships at stake, we would need some variables which affect the recall error only through wage satisfaction. Some good candidates to instrument wage satisfaction could be the so-called “common rater effects”. In survey method analysis, this locution denotes any artifactual covariance between the predictor and the predicted variable due to the fact that these variables are provided by the same respondent.

Among the common rater effects, Podsakoff et al. (2003) distinguish the mood state, which “refers to the propensity of respondents to view themselves and the world around
them in generally negative terms (negative affectivity) or the propensity of respondents to view themselves and the world around them in generally positive terms (positive affectivity)\textsuperscript{25} and the transient mood state which “refers to the impact of relatively recent mood-inducing events to influence the manner in which respondents view themselves and the world around them.” (Podsakoff et al., \textit{ibid}, p.882). During the survey, people may have a certain tendency to over- or under-rate satisfaction measures, due to their general mental attitude or their contingent emotional disposition, and independently from the true value of the rated dimension (wage). However, our data do not allow us to elicit a reliable measurement of the respondents’ mood state. SalSa is a social survey, not a psychological questionnaire. Moreover, we could not control for individuals’ heterogeneity because only cross-sectional data are available. In this context, any inference on the underlying psychological process is an uphill struggle: an economist would probably say it is ambitious, a psychologist would probably say it is wrong. Further experimental research could help clarifying the underlying cognitive process.

Should we conclude that the hedonic recall hypothesis is wrong? Not at all. Even if we refrain here from claiming the causal validity of this model, we firmly believe in its epistemological implications. Regardless of the truthfulness of the neuroscientific process described above, the hedonic recall model has powerful behavioral implications: people act \textit{as-if} a hedonic recall bias was at stake. This model allows us to predict how people behave, to correct for misreported information and to account for misestimated effects. We cannot prove that people tend to over-report their wage \textit{because} they are more satisfied with it; yet, they over-report \textit{when} they are more satisfied.

\section*{7.2 Hedonic recall bias and life satisfaction}

Much of the recent literature on happiness has been focusing on a very comprehensive declarative variable: life satisfaction. This measurement can be based on a single question or on a weighted index from many questions.\textsuperscript{26} Although the best way to measure declarative well-being is still under debate, life satisfaction has undeniably attracted a lot of attention, not only among scholars. This is why a spontaneous question arises: can the hedonic recall bias affect life satisfaction questions?

Theoretically, it is perfectly possible. Studies agree on some positive impacts of income on overall life satisfaction, at least up to a certain threshold (Kahneman & Deaton, 2010; Diener & Biswas-Diener, 2002). As a consequence, one’s life satisfaction is an informative signal about the true income and this piece of information could be exploited by people to approximate their income. Misreporting would be endogenous with life satisfaction in a similar fashion as it happens for wage satisfaction. Yet, the recall bias would probably be smaller and, according to its size, it may or may not be relevant to the analysis of life

\textsuperscript{25}Watson and Clark (1984) were the first to introduce the concept of “positive and negative affectivity”, defined as an emotive dimension that reflects individual differences in negative and positive moods and self-concepts.

\textsuperscript{26}The most common question uses the self-anchoring Cantril scale:

\textit{Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time? [0-10]}

For a discussion on life evaluation questions see the \textit{OECD Guidelines on Measuring Subjective Well-being} (2016).
satisfaction determinants. It follows the importance of empirically determining its size in life satisfaction replies.

Unfortunately, the SalSa survey does not contain questions on general life satisfaction: nor did we manage to find a data set containing - for the same individual - life satisfaction, self-reported income and a reliable objective measurement of the true income. However, here we suggest an indirect approach in order to have a rough approximation of the hedonic recall bias in life satisfaction answers. As suggested by Van Praag, Frijters and Ferrer-i-Carbonell (2003), we can think of life satisfaction as an aggregate of different subjective satisfaction domains, including income satisfaction. They assume the following linear relation:

$$LS = LS(\theta^1 h^1, \ldots, \theta^y h^y, \ldots, \theta^J h^J, z)$$ (21)

Where $LS$ is life satisfaction, $h^j$ is the satisfaction with respect to some domain $j$, $h^y$ is income satisfaction and $z$ is a latent common component the authors control for. Every domain satisfaction $h^j$ is expected to follow a linear relationship which is nothing but an extended form of equation 4':

$$h^j = log_i \beta^j_1 + X_i \gamma^j + \epsilon^j$$ (4*)

Where $X$ contains $z$ and observable relevant factors other than income. This is a general form: depending on the satisfaction domain, income can account or not, i.e $\beta_1$ can be different from 0 or not. According to this aggregate approach, the marginal effect of income on life satisfaction is given by:

$$\frac{\partial LS}{\partial y} = \sum_{j=1}^{J} \beta^j_1 \theta^j$$ (22)

However, when data on income are self-reported, like in the German Socio-Economic Panel (GSOEP) used by Van Praag and coauthors, the marginal effect of income on life satisfaction is estimated as:

$$\frac{\partial LS}{\partial \tilde{y}} = \sum_{j=1}^{J} \tilde{\beta}^j_1 \theta^j$$ (23)

In section 4.1 of this paper we estimated $\tilde{\beta}_1$ to be at least 20% bigger than $\beta_1$. Thus, under the restrictive assumption that income affects income satisfaction only ($\beta^j_1 = 0, \forall j \neq y$), the size of the over-estimation would be the same for life satisfaction. That is, the use of self-reported income would lead to over-estimating the effect of income on life satisfaction by 20%. We would reach this same conclusion whether income matters for several satisfaction domains but the recall bias applies to all these relevant domains: thus, the coefficient would be over-estimated by 20%.

Nevertheless, the two previous hypotheses are not very realistic. A more accurate assumption is that income affects several satisfaction domains, but the hedonic recall bias affects income satisfaction only. Following this assumption, the misestimation of the effect of income on life satisfaction is given by equation (24), displayed below.

27On the one hand, we found no evidence of the hedonic recall bias on other satisfaction questions (see the section on the placebo variables). On the other hand, income has been shown to affect other satisfaction domains, such as housing satisfaction and job satisfaction.
We can quantify the value of this equation by applying our estimated ratio \( \tilde{\beta}_1 / \beta_1 \) into Van Praag et al.’s model. This extrapolation is meaningful as far as we assume the hedonic recall bias acts equally on the two samples: GSOEP and SalSa. We have no reason to discredit this hypothesis. The population from which the German sample comes can be considered the same as the population the French sample is drawn from, with regards to misreporting behaviors.\(^{28}\) When we use Van Praag et al.’s estimated parameters, the misestimation of the effect of income on life satisfaction is:

\[
\frac{\tilde{\beta}_1^y \theta^y + \sum_{j=1,j \neq y}^J \beta_1^j \theta^j}{\sum_{j=1}^J \beta_1^j \theta^j} - 1 = 13\% \quad (24)
\]

Equation (24) - the computation of which is detailed in the appendix - suggests that the hedonic recall bias may indirectly affect life satisfaction in a non-negligible way. The effect of income on life satisfaction could be over-estimated by 13% when self-reported data on income are used, due to the endogeneity of misreporting behaviors. Our extrapolation exercise does not attempt to reliably estimate the size of the bias; still it shows this bias is not negligible: even if here we provide only a rough approximation of the indirect effect of the hedonic recall bias on life satisfaction, we hope this section will stimulate further research on this subject.

\(^{28}\)Van Praag et al. estimate the relationship between life satisfaction and domain satisfaction by least squares, using about 8,000 individuals from the German Socio-Economic Panel (GSOEP), from the 1992 to 1997 period. We base our estimation on about 3,000 individuals from the SalSa survey, 20 years later. We do not see any particular reason to suspect time-specific effects on misreporting behaviors. As for differences in the labor participation status and in the national labor market, Van Praag et al. restrict the sample to workers (no unemployed or inactive people), from both the private and public sector (like in SalSa) from West Germany only (where the economic structural characteristics overlap quite well with France).

Some important differences with the SalSa survey appear, though. Firstly, in the GSOEP people are asked to report their net monthly household income (and not their net monthly wage) and to estimate their financial satisfaction (and not their wage satisfaction). However, we can reasonably approximate the relationship between household income and financial satisfaction with the relationship between wage and wage satisfaction. Secondly, in the GSOEP satisfaction is measured on a 0 to 10 numeral scale (and not 1 to 4 verbal scales). Yet, the assumed latent relation of equation (10) is not affected by this difference of scales.
8 Conclusions

This dissertation was devoted to the description of a behavioral bias in survey answers about wage and its consequences in the analysis of job satisfaction. Researchers and policy makers are increasingly interested in the elements which affect the quality of jobs. Directly asking workers is arguably the best way to know their satisfaction regarding several aspects of their work. Indeed, matching these answers with observable characteristics can provide useful information on what matters to workers. However, when the amount of wage is self-reported by the respondents, their imprecision may lead to severe misestimations. In particular, this article provides empirical evidence of the endogenity of the measurement error of self-reported wage, with respect to wage satisfaction. This piece of evidence overturns the common assumption about mismeasured income: with survey data the estimated effect of wage is not attenuated, but raised.

Replies seem to be affected by some recall bias, which we designated as *hedonic* and we described in a simple non-linear model. We showed that people tend to relatively over-report their wages in questionnaires whether they also declare to be more satisfied with their wage; *vice-versa* unsatisfied people tend to under-report their wage. The existence of this bias downgrades the role of wage as a determinant of satisfaction for the worker. These results meet the recommendation by Eurostat to further integrate administrative records and survey records, in order to enhance data quality.

Finally, we discussed some possible implications of misestimating income effects on a more comprehensive declarative variable: life satisfaction. We argued that the effect of income on life satisfaction could be over-estimated when self-reported income data are used. In addition to this indirect approach, we can reasonably conjecture that the hedonic recall bias directly involves the mismeasurement of other satisfaction domains, such as *transport satisfaction* - where the misreported measurement would be the commuting distance - or *satisfaction with the working schedule* - where the misreported measurement would be the amount of weekly working hours. Investigating the extensions of the hedonic recall bias is beyond the objectives of this paper, but could lead to interesting new research paths.
9 Appendix

Computation of the OLS estimator with and without CME assumption

By definition, the linear estimation of $\beta_1$ (the coefficient associated with fiscal wage) from equation (4'), is:

$$\hat{\beta}_1 = \frac{\text{cov}(h^*_s; y)}{V(y)}$$ (25)

While, the linear estimation of $\tilde{\beta}_1$, (the coefficient associated with self-reported wage) from equation (5'), is:

$$\hat{\tilde{\beta}}_1 = \frac{\text{cov}(h^*_s; \tilde{y})}{V(y)}$$ (26)

Under the CME assumption, $\text{cov}(u, h^*_s) = 0$ and $\text{cov}(u, y) = 0$. The expected value and the variance of self-reported wage are respectively:

$$E(\tilde{y}) = E(y + u) = E(y) + E(u) = E(y)$$ (27)
$$V(\tilde{y}) = V(y + u) = V(y) + V(u) - 2\text{cov}(y; u) = V(y) + V(u)$$ (28)

Hence, if the CME assumption holds, the covariance between self-reported wage and wage satisfaction is the same as the covariance between true wage and wage satisfaction:

$$\text{cov}(h^*_s; \tilde{y}) = \text{cov}(h^*_s; y + u) = \text{cov}(h^*_s; y) + \text{cov}(h^*_s; u) = \text{cov}(h^*_s; y)$$ (29)

And the estimated impact of self-reported wage on wage satisfaction is:

$$\hat{\tilde{\beta}}_1 = \frac{\text{cov}(h^*_s; \tilde{y})}{V(y)} = \frac{\text{cov}(h^*_s; y)}{V(y) + V(u)}$$ (15)

Given that $\text{cov}(h^*_s; y) > 0$ (the more you earn, the better it is), we can see from equation (15) that $\hat{\tilde{\beta}}_1 < \hat{\beta}_1$. The positive difference between $\hat{\beta}_1$ and $\hat{\tilde{\beta}}_1$ corresponds to the attenuation bias.

If we relax the CME assumption, the expected value and the variance of self-reported wage are respectively:

$$E(\tilde{y}) = E(y + u) = E(y) + E(u) \neq E(y)$$ (30)
$$V(\tilde{y}) = V(y + u) = V(y) + V(u) + 2\text{cov}(y; u) \neq V(y)$$ (31)

The covariance between self-reported wage and wage satisfaction is now different from the covariance between true wage and wage satisfaction:

$$\text{cov}(h^*_s; \tilde{y}) = \text{cov}(h^*_s; y + u) = \text{cov}(h^*_s; y) + \text{cov}(h^*_s; u) \neq \text{cov}(h^*_s; y)$$ (32)

Hence, the estimated linear relationship between wage satisfaction and wage is:

$$\hat{\tilde{\beta}}_1 = \frac{\text{cov}(h^*_s; y + u)}{V(\tilde{y})} = \frac{\text{cov}(h^*_s; \tilde{y})}{V(\tilde{y})} = \frac{\text{cov}(h^*_s; y) - \text{cov}(h^*_s; \epsilon)}{[V(y + u)]} = \frac{\text{cov}(h^*_s; y) + \text{cov}(h^*_s; u)}{[V(y) + V(u) + 2\text{cov}(y; u)]}$$ (16)
This result is the one we presented in section 5. It proofs that without the CME assumption the estimated coefficient \( \hat{\beta}_1 \) could be biased both upward or downward, according to the values \( \text{cov}(h^*; u) \) and \( \text{cov}(y; u) \) take.

**The data**

In order to disentangle the effect of age from the pure effect of income, we apply a simple two-steps comparison of conditional means.

1) We take the first quartile of the distribution and divide it into subgroups by age. We compare the absolute errors.

2) We take the group of workers under 30 and divide it into quartiles by income. We compare the absolute errors.

According to step 1), the absolute error decreases as age increases up to 55; according to step 2) the absolute error decreases as wage increases up to the 75\% threshold.

Table 8: Disentangle age and income effect on imprecision in self-reported wage

<table>
<thead>
<tr>
<th>Income effect conditional on age</th>
<th>Absolute error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quartile</td>
<td></td>
</tr>
<tr>
<td>1st quartile</td>
<td>15.6</td>
</tr>
<tr>
<td>2nd quartile</td>
<td>13.2</td>
</tr>
<tr>
<td>3rd quartile</td>
<td>11.5</td>
</tr>
<tr>
<td>4th quartile</td>
<td>12.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age effect conditional on income</th>
<th>Absolute error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td></td>
</tr>
<tr>
<td>&lt; 25</td>
<td>17.2</td>
</tr>
<tr>
<td>25 - 40</td>
<td>15.7</td>
</tr>
<tr>
<td>40 - 55</td>
<td>12.6</td>
</tr>
<tr>
<td>&gt; 55</td>
<td>15.7</td>
</tr>
</tbody>
</table>

*Reading note.* Within the group of workers under 30 years old, the poorest 25\% misreported their income of 15.6\%.

Within the bottom 25\% of the wage distribution, the under 25 year olds misreported their wage of 17.2\%.
The problem of using self-reported income as a proxy for truly perceived income

Table 9: Estimation results of the impact of wage on wage satisfaction: self-reported wage vs fiscal wage.

<table>
<thead>
<tr>
<th>population:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>0.632***</td>
<td>1.035***</td>
<td>0.906***</td>
<td>1.588***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>young</td>
<td>0.632***</td>
<td>1.035***</td>
<td>0.906***</td>
<td>1.588***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>young</td>
<td>0.632***</td>
<td>1.035***</td>
<td>0.906***</td>
<td>1.588***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>young</td>
<td>0.632***</td>
<td>1.035***</td>
<td>0.906***</td>
<td>1.588***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent variable: wage satisfaction</td>
<td>log (self-reported wage)</td>
<td>log (fiscal wage)</td>
<td>log (self-reported wage)</td>
<td>log (fiscal wage)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>age</td>
<td>-0.0627***</td>
<td>-0.0638***</td>
<td>-0.105***</td>
<td>-0.105***</td>
<td>-0.509***</td>
<td>-0.462***</td>
<td>-0.900***</td>
<td>-0.775***</td>
</tr>
<tr>
<td>age²</td>
<td>0.000671***</td>
<td>0.000688***</td>
<td>0.00113***</td>
<td>0.00114***</td>
<td>0.00899***</td>
<td>0.00890***</td>
<td>0.0159***</td>
<td>0.0135***</td>
</tr>
<tr>
<td>French?</td>
<td>-0.0286</td>
<td>-0.0403</td>
<td>-0.0656</td>
<td>-0.0806</td>
<td>0.113</td>
<td>0.179</td>
<td>0.184</td>
<td>0.302</td>
</tr>
<tr>
<td>male?</td>
<td>0.0281</td>
<td>0.0502*</td>
<td>0.0507</td>
<td>0.0853*</td>
<td>-0.0115</td>
<td>0.0244</td>
<td>-0.0122</td>
<td>0.0503</td>
</tr>
<tr>
<td>full-time?</td>
<td>0.268***</td>
<td>0.218***</td>
<td>0.447***</td>
<td>0.357***</td>
<td>0.211*</td>
<td>0.0494</td>
<td>0.380**</td>
<td>0.0909</td>
</tr>
<tr>
<td>constant</td>
<td>-2.705***</td>
<td>-1.494***</td>
<td>10.33***</td>
<td>8.181***</td>
<td>-0.485</td>
<td>1.953</td>
<td>6.914**</td>
<td>2.602</td>
</tr>
</tbody>
</table>

N = 2596

The constant displayed for Ordered Probit is the estimated value of the last threshold.

Note: The table does not display the coefficients associated with 14 binary variables for the education level.
Table 10: Estimation results of the impact of normalized wage rank on wage satisfaction: self-reported wage vs fiscal wage.

<table>
<thead>
<tr>
<th>population:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>wage satisfaction</td>
<td>normalized rank</td>
<td>from survey</td>
<td>(-6.94)</td>
<td>-0.787***</td>
<td>-0.645**</td>
<td>-0.661***</td>
<td>-0.591***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>normalized rank</td>
<td>from fiscal records</td>
<td>(-4.34)</td>
<td>-0.499***</td>
<td>-0.174</td>
<td>-0.476**</td>
<td>-0.476**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>age</td>
<td>(-6.76)</td>
<td>-0.112***</td>
<td>-0.110***</td>
<td>-0.917***</td>
<td>-0.772***</td>
<td>-0.116***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>age^2</td>
<td>(5.90)</td>
<td>0.00120***</td>
<td>0.00118***</td>
<td>0.0162***</td>
<td>0.0135***</td>
<td>0.00131***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>male?</td>
<td>(1.07)</td>
<td>0.0527</td>
<td>0.0822*</td>
<td>0.0102</td>
<td>0.0649</td>
<td>-0.00109</td>
</tr>
<tr>
<td></td>
<td></td>
<td>log (self-reported wage)</td>
<td>(8.27)</td>
<td>0.689***</td>
<td>1.260***</td>
<td>0.188</td>
<td>1.036***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>log (fiscal wage)</td>
<td>(7.58)</td>
<td>0.611***</td>
<td>0.906***</td>
<td>0.0530</td>
<td>0.0530</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>constant</td>
<td>(6.95)</td>
<td>6.413***</td>
<td>5.670***</td>
<td>3.037</td>
<td>1.653</td>
<td>1.865</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N</td>
<td>2574</td>
<td>2574</td>
<td>533</td>
<td>533</td>
<td>1262</td>
<td>1278</td>
</tr>
</tbody>
</table>

* t statistics in parentheses.  * p < 0.10,  ** p < 0.05,  *** p < 0.01
The constant displayed for Ordered Probit is the estimated value of the last threshold.
Note: The table does not display the coefficients associated with nationality, full-time schedule and 14 binary variables for the education level.
The hedonic recall bias hypothesis

Table 11: Quantile regressions of the recall error on wage satisfaction

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>τ=0.1</td>
<td>τ=0.5</td>
<td>τ=0.75</td>
<td>τ=0.9</td>
</tr>
<tr>
<td>Dependent variable: recall error</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>wage satisfaction</td>
<td>0.0311***</td>
<td>0.0244***</td>
<td>0.0409***</td>
<td>0.0572***</td>
</tr>
<tr>
<td>log (fiscal wage)</td>
<td>-0.135***</td>
<td>-0.131***</td>
<td>-0.188***</td>
<td>-0.230***</td>
</tr>
<tr>
<td>age</td>
<td>0.00304</td>
<td>-0.00253</td>
<td>-0.00413</td>
<td>-0.0104*</td>
</tr>
<tr>
<td>age²</td>
<td>-0.0000314</td>
<td>0.0000390</td>
<td>0.0000574</td>
<td>0.000121*</td>
</tr>
<tr>
<td>French?</td>
<td>0.000333</td>
<td>-0.0344*</td>
<td>-0.0527**</td>
<td>-0.0563</td>
</tr>
<tr>
<td>male?</td>
<td>0.00171</td>
<td>-0.0268***</td>
<td>-0.0406***</td>
<td>-0.0519***</td>
</tr>
<tr>
<td>full-time?</td>
<td>-0.0840***</td>
<td>-0.0396***</td>
<td>-0.0520***</td>
<td>-0.0714***</td>
</tr>
<tr>
<td>no diploma?</td>
<td>-0.123***</td>
<td>-0.0687**</td>
<td>-0.0839**</td>
<td>-0.0856</td>
</tr>
<tr>
<td>high school certificate?</td>
<td>-0.0761*</td>
<td>-0.00493</td>
<td>-0.00392</td>
<td>0.0108</td>
</tr>
<tr>
<td>graduate?</td>
<td>-0.0155</td>
<td>0.00506</td>
<td>0.0452</td>
<td>0.0926</td>
</tr>
<tr>
<td>constant</td>
<td>1.144***</td>
<td>1.366***</td>
<td>2.059***</td>
<td>2.743***</td>
</tr>
<tr>
<td>N</td>
<td>2596</td>
<td>2596</td>
<td>2596</td>
<td>2596</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table does not display the coefficients associated with 11 binary variables for intermediate education levels.
### Robustness tests

Table 12: Robustness tests for the relationship between recall error and wage satisfaction

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
</tr>
<tr>
<td>Control for</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>confusion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Under-restr.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-restr.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent variable: recall error</td>
<td>0.0367</td>
<td>0.105***</td>
<td>0.00400**</td>
<td>0.276***</td>
<td>0.306***</td>
<td>0.203***</td>
</tr>
<tr>
<td></td>
<td>(8.54)</td>
<td>(13.19)</td>
<td>(2.37)</td>
<td>(7.02)</td>
<td>(8.08)</td>
<td>(2.78)</td>
</tr>
<tr>
<td>log (fiscal wage)</td>
<td>-0.163***</td>
<td>-0.666***</td>
<td>-0.00451</td>
<td>-1.051***</td>
<td>-1.301***</td>
<td>-0.235</td>
</tr>
<tr>
<td></td>
<td>(-18.90)</td>
<td>(-68.66)</td>
<td>(-1.21)</td>
<td>(-12.65)</td>
<td>(-18.23)</td>
<td>(-1.47)</td>
</tr>
<tr>
<td>age</td>
<td>-0.00197</td>
<td>0.0245***</td>
<td>0.000445</td>
<td>-0.0204</td>
<td>-0.0109</td>
<td>-0.00632</td>
</tr>
<tr>
<td></td>
<td>(-0.88)</td>
<td>(6.08)</td>
<td>(0.53)</td>
<td>(-1.03)</td>
<td>(-0.58)</td>
<td>(-0.18)</td>
</tr>
<tr>
<td>age(^2)</td>
<td>0.0000272</td>
<td>-0.000219***</td>
<td>-0.0000564</td>
<td>0.000286</td>
<td>0.000195</td>
<td>0.0000990</td>
</tr>
<tr>
<td></td>
<td>(1.00)</td>
<td>(-4.41)</td>
<td>(-0.56)</td>
<td>(1.18)</td>
<td>(0.84)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>male?</td>
<td>-0.0259***</td>
<td>-0.0806***</td>
<td>-0.000883</td>
<td>-0.205***</td>
<td>-0.223***</td>
<td>-0.0818</td>
</tr>
<tr>
<td></td>
<td>(-3.95)</td>
<td>(-6.57)</td>
<td>(-0.36)</td>
<td>(-3.47)</td>
<td>(-3.90)</td>
<td>(-0.78)</td>
</tr>
<tr>
<td>full-time?</td>
<td>-0.0649***</td>
<td>-0.327***</td>
<td>-0.00367</td>
<td>-0.515***</td>
<td>-0.628***</td>
<td>-0.274*</td>
</tr>
<tr>
<td></td>
<td>(-6.86)</td>
<td>(-20.06)</td>
<td>(-0.99)</td>
<td>(-5.86)</td>
<td>(-7.66)</td>
<td>(-1.71)</td>
</tr>
<tr>
<td>confusion</td>
<td>-0.0234***</td>
<td></td>
<td></td>
<td>-0.203***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>net / gross</td>
<td>(-2.82)</td>
<td></td>
<td></td>
<td>(-2.65)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>2596</td>
<td>2860</td>
<td>768</td>
<td>2596</td>
<td>2860</td>
<td>768</td>
</tr>
</tbody>
</table>

\(t\) statistics in parentheses

* \(p < 0.10\), ** \(p < 0.05\), *** \(p < 0.01\)

Note: The table does not display the coefficients associated with the constant, the nationality and to 14 binary variables for the education level.
Table 13: Monte Carlo simulations: estimated coefficients with and without artificial white noise

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OLS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without noise</td>
<td>500</td>
<td>0.225</td>
<td>0.0038</td>
</tr>
<tr>
<td>With noise</td>
<td>500</td>
<td>0.225</td>
<td>0.0038</td>
</tr>
<tr>
<td><strong>Ordered Probit</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without noise</td>
<td>500</td>
<td>0.343</td>
<td>0.0059</td>
</tr>
<tr>
<td>With noise</td>
<td>500</td>
<td>0.343</td>
<td>0.0058</td>
</tr>
</tbody>
</table>
Table 14: OLS regressions of the recall error on other satisfaction variables

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable: recall error</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sat. with the working schedule</td>
<td>-0.00854</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.07)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sat. with the nervous effort</td>
<td></td>
<td>-0.00490</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.75)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sat. with the physical effort</td>
<td></td>
<td></td>
<td>0.00224</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.34)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>task satisfaction</td>
<td>0.0108***</td>
<td>0.00212</td>
<td>0.00391</td>
<td>-0.00157</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.72)</td>
<td>(0.51)</td>
<td>(0.97)</td>
<td>(-0.37)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>wage satisfaction</td>
<td></td>
<td></td>
<td></td>
<td>0.0358***</td>
<td>0.0158***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(8.15)</td>
<td>(3.50)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log (fiscal wage)</td>
<td>-0.146***</td>
<td>-0.146***</td>
<td>-0.145***</td>
<td>-0.146***</td>
<td>-0.163***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-17.10)</td>
<td>(-17.10)</td>
<td>(-17.27)</td>
<td>(-17.31)</td>
<td>(-18.86)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>male?</td>
<td>-0.0304***</td>
<td>-0.0297***</td>
<td>-0.0296***</td>
<td>-0.0288***</td>
<td>-0.0262***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.53)</td>
<td>(-4.44)</td>
<td>(-4.46)</td>
<td>(-4.35)</td>
<td>(-3.99)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>full-time?</td>
<td>-0.0566***</td>
<td>-0.0568***</td>
<td>-0.0562***</td>
<td>-0.0574***</td>
<td>-0.0662***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.89)</td>
<td>(-5.96)</td>
<td>(-5.93)</td>
<td>(-6.05)</td>
<td>(-7.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>constant</td>
<td>1.653***</td>
<td>1.646***</td>
<td>1.639***</td>
<td>1.605***</td>
<td>-0.0467***</td>
<td>1.656***</td>
<td>-0.0733***</td>
</tr>
<tr>
<td></td>
<td>(17.48)</td>
<td>(17.05)</td>
<td>(17.58)</td>
<td>(17.22)</td>
<td>(-3.17)</td>
<td>(17.86)</td>
<td>(-4.34)</td>
</tr>
<tr>
<td>N</td>
<td>2578</td>
<td>2597</td>
<td>2609</td>
<td>2623</td>
<td>2662</td>
<td>2593</td>
<td>2631</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.141</td>
<td>0.139</td>
<td>0.142</td>
<td>0.140</td>
<td>0.000</td>
<td>0.160</td>
<td>0.005</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: The table does not display the coefficients associated with the constant, the nationality, age, age$^2$ and to 14 binary variables for the education level.
Hedonic recall bias and life satisfaction

To have a credible size of the misestimation of life satisfaction determinants due to income misreporting, we can exploit Van Praag et al’s estimations (2003). They estimate the relationship between life satisfaction and domain satisfaction ($\theta$) as well as the relationship between income and domain satisfaction ($\beta_1$) by least squares. Below are their estimated parameters on a sample of 7995 west German workers, drawn from the 1992-1997 GSOEP.

Table 15: Linear parameters estimated by Van Praag, Frijters and Ferrer-i-Carbonell (2003)

<table>
<thead>
<tr>
<th>Satisfaction domain</th>
<th>$\beta_1$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>financial satisfaction</td>
<td>0.382</td>
<td>0.637</td>
</tr>
<tr>
<td>job satisfaction</td>
<td>0.055</td>
<td>0.352</td>
</tr>
<tr>
<td>house satisfaction</td>
<td>0.299</td>
<td>0.148</td>
</tr>
<tr>
<td>environment satisfaction</td>
<td>0.211</td>
<td>0.050</td>
</tr>
<tr>
<td>leisure satisfaction</td>
<td>0.064</td>
<td>0.224</td>
</tr>
<tr>
<td>health satisfaction</td>
<td>0.101</td>
<td>0.501</td>
</tr>
</tbody>
</table>

Reading note: 0.382 is the permanent income effect on financial satisfaction; 0.637 is the level effect of financial satisfaction on life satisfaction.

We combine these estimates with our predicted bias in a linear regression of wage in wage satisfaction. We evaluate the coefficient associated with income to be over-estimated by 20%, when self-reported wage is used. Thus, we can extrapolate the bias in the estimation of the effect of income on life satisfaction:

$$
\sum_{j=1,j\neq y}^{J} \beta_1^j \theta^j = 0.055 \times 0.352 + 0.299 \times 0.148 + 0.211 \times 0.05 + 0.064 \times 0.224 + 0.101 \times 0.501 = 0.139
$$

(33)

$$
\sum_{j=1}^{J} \beta_1^j \theta^j = 0.382 \times 0.637 + 0.139 = 0.382
$$

(34)

estimation bias = \frac{\beta_1^y \theta^y + 0.139}{0.382} - 1 = \frac{0.382 \times 1.2 \times 0.637 + 0.139}{0.382} - 1 = 13\%

(24)
References


Acknowledgments

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