

When did it happen?

Reconstructing wage evolution in light of current wage satisfaction

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Abstract

Although satisfaction measures strongly depend on personal history, the relationship between memory and current well-being is still unclear. This article is dedicated to empirically investigating if current wage satisfaction affects the ability to date past wage changes. We match answers from a French national survey with administrative records, to compare the recalled and actual wage history. Our data support and extend some previous findings from the psychology literature: relatively remote events are recalled as closer in time, while relatively recent events are recalled as further in time. An instrumental variable strategy shows that these effects – respectively known as “forward” and “backward telescoping” – are partially caused by current satisfaction, so that, *ceteris paribus*, people who are satisfied with their wage tend to date wage cuts as more remote than they actually are. We suggest that this pattern of imperfect recall, which we denote as *hedonic telescoping*, opens a new perspective in the understanding of the transient effect of income changes on well-being.

Keywords:

recall bias, response bias, wage satisfaction, hedonic adaptation, hedonic telescoping, telescoping effect

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“To be able to enjoy one’s past life is to live twice”

Martial, Epigrams, X, 23,7

1. Introduction

Personal history is arguably one of the most important determinants of subjective well-being. Past events provide a reference which current outcomes are evaluated against, they trigger emotions such as regret and deception and are a precious baseline to form expectations from. In their study on the determinants of subjective well-being, Ross et al. (1986) find that people mention past comparisons up to four times more frequently than social comparisons to explain their satisfaction rate.¹

Accordingly, when we talk about wage satisfaction, wage history matters. Some years ago, the survey “Enquête sur les Salaires Auprès des Salariés” (SalSa) asked 3,000 French workers if they were satisfied with their wage and why. Textual factorial analysis of their answers (Baudelot et al., 2014) shows that the terms “year”, “at the end of” and “raises” are among the most significant drivers of dissatisfaction, even more than words associated with justice or social comparisons, such as “fair” or “colleagues”.² An important feature of these judgments is that they are based on the *memory* of the wage history. And memory, despite its prominent role in shaping well-being, is known to be limited and fallacious.

In this paper, we explore the relationship between current wage satisfaction and the way people recall their wage history. We focus on people’s ability to form retrospective temporal judgments, i.e. to recall the date of their last wage raise and wage cut. Do people recall this information differently according to how satisfied they currently are with their wage?

We do this by matching the aforementioned SalSa survey with administrative records. The matched dataset allows us to compare the personal wage history reconstructed by the respondents with the one observed in the administrative panel. We then analyze recall behaviors to understand their relationship with current satisfaction. For the purpose of causal inference, we instrument wage satisfaction using people’s relative wage with respect to peers.

We find evidence of memory distortions. Our data corroborate previous findings on the so-called “telescoping effects”: relatively remote events are recalled as closer in time, while relatively recent events are recalled as further in time. Moreover, we show misdating patterns to correlate not only with the recency of the wage change, but also with respondents’ wage satisfaction, so that people who are more satisfied with their wage tend to date wage raises as more recent than less satisfied people, and wage cuts as more remote.

¹On the dominance of intrapersonal comparisons over interpersonal comparisons see also Steffel and Oppenheimer (2009).

²The original terms from the survey are, respectively, “ans”, “au but de”, “augmentations”, “juste”, “collègues”. See Baudelot et al. (2014), p.80.

Instrumental variable analysis confirms current satisfaction to cause the temporal displacement of recalled wage cuts. We denote this recall bias as *hedonic telescoping*.³

We conclude that current subjective well-being indeed affects the reconstruction of wage history. We believe this evidence to be particularly relevant to a long-lasting question in happiness economics, namely the phenomenon of adaptation. Several empirical studies (Clark, 1999; Grund and Sliwka, 2007; Di Tella et al., 2010), support the adaptation hypothesis: people quickly adapt to income changes and generally maintain a baseline level of satisfaction throughout their career (aka *homeostatic happiness*). However, inasmuch as satisfaction depends on the comparison with the past and past information can be manipulated, hedonic telescoping offers an original perspective on adaptation: it might be that people not only get *passively adapted* to income changes, but also *actively adapt* the recollection of income changes.

Although both subjective well-being topics and imperfect memory frameworks have been gaining considerable interest among economists (e.g. Deaton and Stone, 2013; Wilson, 2014), the link between the two is still quite unexplored. On the one hand, albeit satisfaction measures refer to experienced utility, the role of memory has been poorly taken into account in empirical works. On the other hand, imperfect memory research has been eminently theoretical, with only few empirical applications, mostly in laboratory experiments. In this study, we draw from these two strands of research, to shed light on one of the (potentially many) ways present well-being influences information about the past.

We restrain our analysis to wages and wage satisfaction, but, in principle, extension to other domains is possible. The main advantage of wages and income in general is mainly operational: they offer an easily quantifiable object, both in the present and in the past. We focus on temporal judgments since this type of information is particularly hard to recollect (see section 2.3). As a consequence, it offers a sufficiently large *wiggle room* to remove or distort past information.

The next section discusses our research question in light of the related literature. In section 3, we introduce our hypothesis, which suggests that the date recollection process is affected by current well-being, according to a recall bias. We move on to the empirical application in section 4, where we describe our dataset and strategy to identify recall errors. Section 5 presents our main results from regression analysis and the evidence of hedonic telescoping of wage cuts. Section 6 discusses the economic implications and limits of this work. Section 7 concludes.

³We use the expression “recall bias” in the sense of Schacter (2001, 2003), who defines it as a memory failure where “current knowledge and beliefs distort our memories of the past” (Schacter et al., 2003, p.228). We use the adjective “hedonic” consistently with previous studies on motivated memory and satisfaction (Prati, 2017). “Telescoping” refers to the mnemonic temporal displacement of an event (see section 4.1).

2. Related literature

Our paper is linked to a few literatures, which are at the intersection of economics and psychology: happiness economics, imperfect memory and retrospective temporal judgments.

2.1. Happiness economics

Among the many dimensions of happiness, satisfaction is certainly the most studied in economics. By “satisfaction” we mean a measure which is deduced from questionnaires, where people are asked to give an assessment of how satisfied they are with their overall life or a particular aspect of their life.⁴ The answers to these questions are then used to understand the determinants of satisfaction, its different dimensions and its distribution across social groups (for an overview of economics of happiness see e.g. Frey and Stutzer, 2002; Senik, 2014b; Graham, 2016).

Like every non-random variable, satisfaction is strongly path-dependent: what happened in the past determines – at least to a certain extent – today’s outcome. If the object of evaluation is wages, wage satisfaction will depend not only on the *absolute wage* (primary evaluation), but also on the *relative wage* (non-primary evaluation) a person earns. “Relative” in at least two senses. Strong evidence exists that people compare their income to their peers (Clark and Oswald, 1996; Bygren, 2004; Clark and Senik, 2010), as well as to their own past income (Clark, 1999; Van Praag and Ferrer-i Carbonell, 2004).⁵

Comparison to one’s past is the milestone of the phenomenon of *adaptation*: people get used to changes so that the effect of positive or negative variations are only transitory. From an economist’s perspective, the question of income adaptation is paramount, since it raises the doubt that collective and individual efforts for richness are vain. A substantial empirical literature agrees on the fact that people (quickly) adapt to income changes and that the more recent the backward reference, the stronger the comparison effect (see Clark, Frijters and Shields, 2008, section 3.2 for a review). Economists have showed adaptation to appear in a variety of life domains, from durable goods (Emmerling and Qari, 2017), to disability (Oswald and Powdthavee, 2008), to marriage and divorce (Clark, Diener, Georgellis and Lucas, 2008). The usual interpretation of adaptive behavior is that well-being negatively depends on the comparison between the present and a brighter past and positively depends on the comparison with an inferior past.

Yet, the analysis of backward reference points calls for particular attention to be paid to the role of memory. In the evaluation process, most of the relevant information about the past is no longer directly

⁴In line with the tripartite model endorsed by the OECD, in addition to satisfaction we can distinguish two main aspects of subjective well-being: “affect”, denoting a person’s feelings or emotional states, and “eudaimonia”, intended as a sense of leading a meaningful and purposeful life (OECD, 2013).

⁵Another reference point, which is harder to measure and which we leave out of our analysis, is expected income (Stutzer, 2004; Senik, 2004).

available, but is available only through the mediation of memory. Thus, what matters to people’s evaluation is not only what *actually* happened, but mostly what they *recall* it happened. In the words of two famous psychologists: “your attitude toward events in the past matters more than the events themselves [...] because you cannot change what happened in the past but you can change your attitude toward what happened” (Zimbardo and Boyd, 2008, p.86). Accordingly, we might expect more satisfied people to deal with past information more efficiently for their well-being than less satisfied people. Although this hypothesis is uncommon in happiness research, it has already been adopted in several economic models of imperfect memory.

2.2. Imperfect memory

Imperfect memory has received considerable attention in bounded rationality research over the last two decades. A prominent theoretical literature in economics (Piccione and Rubinstein, 1997; Mullainathan, 2002; Bénabou and Tirole, 2002; Bernheim and Thomsen, 2005; Wilson, 2014) has rationalized behavioral phenomena using imperfect memory frameworks. A critical assumption of this literature is that individuals can, to a certain extent, endogenize their recall behaviors.

In their influential article, Bénabou and Tirole (2002) introduce a model of motivated memories, where individuals can affect the probability of remembering events in order to enhance their positive self-image. Although selective recall can be harmful in cases when it taints learning (Gottlieb, 2014), it also offers important advantages. Recall errors can foster utility through the pleasure of a positive self-image (egocentric recall bias); furthermore, they can improve a coherent identity by reducing the cognitive dissonance between a bad outcome and positive beliefs about the self (consistency bias). Some recent research in experimental economics partially confirms the existence of self-serving memory for trustful behaviors (Li, 2013), reference prices (Martin et al., 2018), personal performance (Zimmermann, 2019) and altruistic behaviors (Saucet and Villeval, 2018).

These studies have mostly focused on *selective memory*, that is the act of rationally forgetting past information. Scant attention has been devoted in economics to *manipulated memory*, i.e. the act of rationally modifying past information. However, psychologists maintain that much of our long-term memory is not an accurate recollection of what actually happened. Instead, it is in part a “creative process”, where reconstruction of the past is affected by what we think plausibly happened or should have happened (Carlson et al., 2009, p.258). In his pioneering study, Bartlett (1932) asks people to recall stories they previously read. When stories contain unexpected or incoherent passages, subjects tend to revise their memories and recollect details in a more coherent way with the overall interpretation of the narration. A similar phenomenon happens when people evaluate their *life narrative* (Ross, 1989; Bluck and Habermas, 2001).

Nevertheless, memory is not pure imagination and the human ability to modify one’s experience of the past is constrained by the vividness of the related memories. For instance, if it is very rare for people to

make a mistake about which school they went to, it is not so rare that they hesitate about the *date* they left school, especially if it happened a long time ago. Some types of information are more difficult to recollect than others and retrospective judgments about the temporal location of an event - i.e. its date - are among the most difficult. This is why we suspect temporal judgments to be particularly prone to recall biases. The higher the uncertainty about the past information, the higher the probability that the recollection process is at the mercy of present confounding factors.

2.3. Retrospective temporal judgments

It is surprisingly difficult to date past events: a curious experiment by the Dutch psychologist Willem Wagenaar illustrates well how hard this task is (Wagenaar, 1986).⁶ In the recent psychology literature, the act of dating a past event is usually referred to as a “retrospective temporal judgment” (RTJ). This is a quite general term and, according to the type of recollection task, we can distinguish different kinds of RTJ (see Friedman, 1993). People can be asked how long ago event x happened (*RTJ in relative time*) or if event x happened before or after event y (*RTJ in serial-order*). In this study, we focus solely on *RTJ in absolute time*, i.e. the answer to the question: “when did event x happen?”.

A copious literature (e.g. Linton, 1975; Brown, 1990; Burt, 1992; Friedman and Huttenlocher, 1997; Betz and Skowronski, 1997; Shimojima, 2002) sheds light on the different kinds of information people use to date past events. If people do not remember the exact date, they may either remember the temporal closeness to another event which they know the date of, or they may remember that the event belongs to a contextual period, or again they may use the clarity of memory to estimate how long ago the event occurred - just to mention a few possible explanations. Although several theories have been proposed to explain the mechanism behind RTJ, no consensus has been found yet on a unified model.

Measuring the accuracy of RTJ is also a methodological question. The main obstacle is represented by the accessibility to a reliable piece of information on the true dates of personal events. To solve this problem, the most common experimental design implies that subjects record some personal events for a certain period and, later, they are asked to recall the date the events occurred on (Gibbons and Thompson, 2001; Burt et al., 2003; Skowronski et al., 2003). The main issue with this design is that the period which recollection

⁶For 157 days, every evening Wagenaar wrote down one or two memories about his day. For each event he recorded four details: what, where, when and with whom the event happened. He wrote each piece of information on a different card. Six years later, he tested his memory by drawing one card and trying to recollect the missing pieces of information. For instance, if it was written that he had a nice walk in a park, he tried to recollect where, with whom and when it happened. Not surprisingly, the best hint to recollect the full memory was provided by the card on “what” he did. In sharp contrast, the information on “when” was mostly useless. Wagenaar also tried to recall which other event occurred the same day as the one he drew. What else did he do on the same day he had that nice walk in the park? Although temporal proximity may be a useful hint for recollection, it did not help Prof. Wagenaar much: he successfully performed the task only 22 times out of 314 experiments and only twice for events which did not happen in the same place.

judgments are made over is relatively scarce. An alternative method is to ask participants about verifiable events. For example, Loftus et al. (1990) ask people to date their medical examinations and then check their answers against official medical records; in Prohaska et al. (1998)'s study, subjects date previous laboratory experiments they took part in; Shimojima (2002) asks students how long ago they graduated and when they started university. In a similar vein, we ask people to date their last wage raise and wage cut and then compare their answers to the actual evolution of their payrolls.

The literature on memory and recollection is massive and we are not the first to model the relationship between dating errors and well-being. The closer hypothesis is probably the *mood congruency model* (Blaney, 1986), which has also been applied to explain economic behaviors (Bodoh-Creed, 2019). According to this model, people better recall information which is in line with their current emotional state. Our model is related but different to mood congruency. The hedonic telescoping hypothesis asserts that the *bias* (not the *variance*) in the recalled temporal location of an event is influenced by the current *satisfaction* (not the *affect*). To the best of our knowledge, we are the first ones to relate telescoping effects to self-reported satisfaction.

3. Model and empirical strategy

In “The Impact of Past and Future on Present Satisfaction” (2004), Van Praag and Ferrer-i-Carbonell model financial satisfaction as being determined by a weighted sum of the personal income history, where weights are a decreasing function of the temporal distance of each annual income. The authors corroborate this path-dependent model through an estimation on the German Socio-Economic Panel. In a similar vein, we model wage satisfaction as depending on three main factors:

w_0 = the current wage

w_{-1} = the previous wage

t_{-1} = the date the wage changed

where the indexes 0 and -1 refer respectively to the current and previous period. However, if we account for uncertainty in temporal judgments, the available information is no more the date of the last wage change t_{-1} , but the *current memory* of the last wage change $m(t_{-1})$, where the function $m(\cdot)$ is an intertemporal mapping from the past to the present. Hence, we can express wage satisfaction in the very general form:

$$\text{wage satisfaction} = f(w_0, w_{-1}, m(t_{-1}), \cdot) + \xi \quad (1)$$

where $f(\cdot)$ is a function to be specified and ξ is an additive error term. In section 5.1, we document a significant conditional correlation of wage satisfaction with the recency of a wage change, thus endorsing the assumption of path-dependency.

Building on the premises that personal wage history matters for satisfaction and that temporal judgments are prone to errors, in section 5.2 we move to our main research question: is the recalled temporal location of workers’ last wage change endogenous with respect to their current well-being?

Let us define the recall error, RE , as the difference between the true and the recalled date of the last wage change. Our hypothesis is that the recall error is not random, but described by a hedonic function $\eta(\cdot)$:

$$RE = t_{-1} - m(t_{-1}) = \eta(\text{wage satisfaction}, \cdot) + \epsilon \quad (2)$$

If ϵ was assumed to be independent from the set of regressors, the estimation of the reduced form 2 would yield the effect of wage satisfaction on the recall error. However, in this setting, such assumption contradicts eq.1, since wage satisfaction is an explanatory variable which is jointly determined with the explained variable $m(t_{-1})$, through the process described in eq.1.

We face a usual simultaneous equations framework. A standard regression of the recall error on wage satisfaction captures the simultaneous effects of the recalled event on current satisfaction and of current satisfaction on the recalled event. For instance, someone who thinks her wage raise happened later than it actually did may benefit from a lower hedonic adaptation; is she more satisfied because she is misdating the

event or is she misdating the event because she is satisfied? The estimation of the reduced form (2) does not let us disentangle the two channels of causality.

The usual approach to solve the endogeneity issue is by an instrumental variable. Instrumenting satisfaction variables is a difficult, somewhat heroic task. It is arguably one of the reasons why causality in happiness studies is so uncertain (Veenhoven, 1991). In our setting, we need a variable which directly affects wage satisfaction, but has no direct relationship with the temporal judgment about the last wage change. We believe that workers' relative wage with respect to their peers suits our frame, as we justify in section 4.3. For the moment, let us add peers' wage w_{others} in our system as an exogenous determinant of wage satisfaction, which becomes:

$$\text{wage satisfaction} = f(w_0, w_{-1}, m(t_{-1}), w_{others}, \cdot) + u \quad (3)$$

We will estimate the system of equations (2) and (3) after a standard linear specification of the functions $f(\cdot)$ and $\eta(\cdot)$, the inclusion of suitable psychological, socio-demographic and job-related regressors and some credible assumptions on the distribution of the error terms. Our ultimate aim is to evaluate the credibility, direction and size of the effect of wage satisfaction on the recall error.

4. The data

To carry on our empirical analysis, we use a unique French dataset which contains at the same time declarative and administrative information on the respondents. Thanks to a common identifier variable, we match the survey “Enquête sur les Salaires Auprès des Salariés” (SalSa) and the administrative panel “Déclaration Annuelle des Données Sociales” (DADS). This combined dataset represents a precious basis for the empirical analysis of recall phenomena. Indeed, it includes both self-reported answers on personal history (from the survey) and the observed personal history (from the administrative records). Although matching with administrative data is routinely implemented for some social surveys (e.g. EU-SILC), it is very rare to have redundant information from the two sources: typically, if a piece of information is contained in the administrative register, it is directly drawn from there and it is not asked to the respondent. In this respect, SalSa stands out as an exception.

The SalSa survey is a national job satisfaction survey which was carried out in France from November 2008 to January 2009. Interviews took place either by phone or face-to-face on a sample of employees from both the private and public sector. In the SalSa questionnaire, people are asked to report various information about their current, past and expected work situation and evaluate their well-being with respect to different aspects of their jobs. The DADS panel collects administrative information on the workers and their careers from the 1970s up to today. The sector of activity, the category of occupation, the hierarchical position (managers, intermediate, clerks, workers) and - of course - the net wage are among the recorded facts.⁷

Henceforth, we use the term “wages” to refer to net wages including bonuses.⁸ From the SalSa survey we have available declarative wage satisfaction and the self-reported date of the last wage raise and wage cut. We can then verify the latter in the DADS, which includes the true net wage trajectory over the past 30 years. The sample, which consists of 3,055 individuals, contains hundreds of retrospective temporal judgments on the last wage change. In the remainder of the section, we define and describe the relevant variables of our analysis.

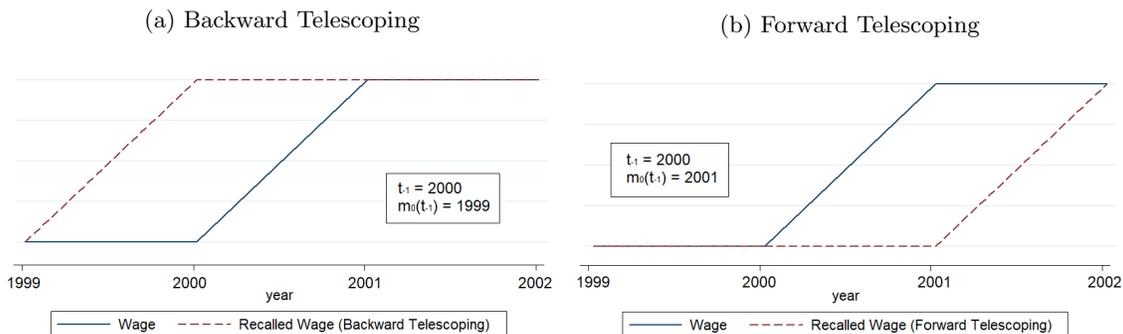
4.1. The explained variable

The variable we are aiming to explain in our model is the recall error, defined as the difference (in years) between the true date and the recalled date the wage changed for the last time. According to the direction of the temporal displacement, retrospective temporal judgments (RTJ) display two types of error: the event

⁷For a more comprehensive description of the data, refer to Godechot and Senik (2015), who also use this same merged dataset.

⁸In our analysis of administrative data, we always consider *nominal* wage and not *real* wage. Although there is no doubt that inflation may influence the perception of wage history, in the SalSa questionnaire people are explicitly asked to report information on the evolution of their nominal wage. It is stated that questions concern “nominal wage in euros and not purchasing power”.

Figure 1: Backward and forward telescoping



Reading note: The dotted lines and the full lines refer respectively to the recalled wage trajectory and the actual wage trajectory. The wage raise in figure *a* is recalled as more remote that it actually is. The wage raise in figure *b* is recalled as more recent that it actually is.

may be recalled as more recent than it actually is or as more remote. These two errors go, respectively, with the name of *forward telescoping* and *backward telescoping*.⁹

Let us take the example of a worker who experienced her last wage raise in 2000. If she thinks the wage raise happened in 1999, she is backward telescoping this event; on the contrary, if she remembers the wage raise took place in 2001, she is forward telescoping this event (see also fig.1a and 1b). Hence, our variable “recall error” takes negative values when answers display forward telescoping, positive values when answers display backward telescoping and it is equal to zero when people correctly report the date. In order to quantify the recall error, we need to compare the recalled year of the last wage raise/cut and the actual year of the last wage raise/cut, i.e. $m(t_{-1})$ and t_{-1} respectively.

We can elicit $m(t_{-1i})$ from the SalSa survey, where people are asked to report the year of their last wage raise and wage cut (see the appendix for the original questions in the survey). Once we have obtained the dates of the workers’ last self-reported wage raises/cuts, we can compare their answers with their actual wage trajectories, elicited from the DADS records, where workers’ net wages have been annually reported by the employers. Up to this point, the identification of the recall error may look straightforward. On the contrary, we face three important issues.

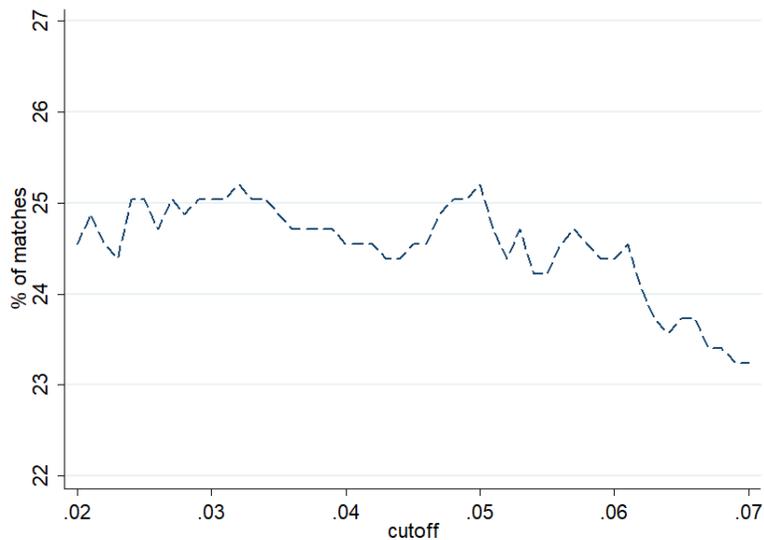
The first issue is that “what should be considered as a ‘wage change’?” is far from being a trivial question. Ideally, a wage w_{-1} should be stable over a certain period of time, then it may change to a new level w_0 at a date t_{-1} and should not vary for a while, until the next change to w_1 happens. In this ideal world, identifying a wage change would be easy. In practice things are more complicated. Net wages are quite volatile, due not only to small variations in payroll taxes, but also to bonuses, pay for piecework, allowances

⁹For a thorough discussion on forward and backward telescoping in survey research see Belli (2014).

and tips, to mention some of the unsteady factors contributing to volatility. These changes are usually small. However, the very fact that a worker almost never earns the same wage twice raises the issue of defining a cutoff point, i.e. how big a difference does it have to be for the worker to perceive it as a “wage change”. A 1% variation would probably be too small; a 10% cutoff would probably be too big.¹⁰

To address this concern, we simulate the number of perfect matches between t_{-1} and $m(t_{-1})$ that we would obtain according to the specification of different cutoff points. In other words, we look at the number of people who correctly date their last wage change, conditional on a wage change being a variation beyond, $\pm 2\%$, $\pm 2.1\%$, $\pm 2.2\%$ and so on. This strategy implicitly assumes that people tend to know the right date of the event, so that a good cutoff point is the one which maximizes the frequency of perfect matches. Visual results are displayed in figure 2. The graphic shows that the number of matches is quite stable up to $\pm 6\%$, but beyond this point it goes into a downward trend and fails to progressively identify more wage changes. Thus, we obtain a reasonable upper bound at 6% for our cutoff point. The lower bound is imposed by the second issue we face.

Figure 2: Percentage of matches between t_{-1} and $m(t_{-1})$, conditional on the definition of the cutoff point



Reading note: if we consider yearly variations beyond $\pm 4, 2\%$ as wage changes, we identify 24.5% of the sample as rightful reporters. If we consider yearly variations beyond $\pm 7\%$ as wage changes, we identify 23.2% of the sample as rightful reporters.

¹⁰The issue of unstable past income trajectory is well-known and its solution represents a conceptual challenge to empirical studies. Van Praag and Ferrer-i Carbonell (2004) explain that “incomes always include a random element: windfall profits, etc.; many people do not even know their exact monthly net income, because it fluctuates from month to month, even for individuals with an essentially fixed income like civil servants. We assume that the past income levels which determine the evaluation of present income are not the real ones, but a smoothed-out version of them, where random fluctuations from year to year are ignored.” (*ibid*, p.142)

The second identification issue comes from the nature of our data. The data provider - the National Institute of Statistics and of Economic Studies (INSEE) - added a small white noise to the net wage records to protect workers' privacy. This artificial white noise is designed to minimize the impact on data analysis, yet it introduces some additional disturbance we should take care of.

Since we know the algorithm generating the white noise, we can compute its 95% confidence interval, to disentangle the small wage variations due to the artificial noise from the ones which actually took place. The calculation, detailed in the appendix, gives us an average confidence interval of $\pm 4.2\%$. It means that observed yearly variations smaller than $\pm 4.2\%$ may be purely due to the white noise and not correspond to an actual wage change. Left with the feasible interval [4.2;6], we arbitrarily choose $\pm 4.2\%$ as a cutoff point.¹¹ Hence, we identify as “wage raises” only yearly variations beyond $+4.2\%$ and as “wage cuts” only yearly variations below -4.2% .

The third and last issue we need to solve is that possibly people *rightly* date the *wrong* event. When asked about their last wage raise/cut, people may refer to their penultimate wage raise/cut, or an even earlier one. This *events mismatch* generates artificially big errors which add undesired noise to the variable of interest (which is instead *dates mismatch*). Moreover, events mismatch causes the recall error to be positive-biased, since the additional noise concerns backward telescoping only.

To control for events mismatch, we remove unreasonably big discrepancies (beyond 15 years) and we further filter out reported dates which correspond to a wage raise/cut which is not the last one. For instance, if a person reports that her last wage cut took place in 1995 but we actually observe a wage cut in 1995 and in 2003, we disregard this recall error. We end up with 597 observations for the recall error.¹² We test the robustness of this approach to outliers in section 7.

Figure 3 shows the distribution of the recall error for wage changes. People seem to be quite precise about their wage trajectories: 25% of the respondents correctly date their last wage change and zero is the median error; 50% of them misdate by at most 1 year.

4.2. The explanatory variables

Our key variable to explain RTJ is wage satisfaction. We deduce this dimension of evaluative well-being from the SalSa survey, where people reply to the question: *As for your wage, would you say you are? [very satisfied; rather satisfied; rather dissatisfied; very dissatisfied]*.¹³ Table 1 summarizes some descriptive

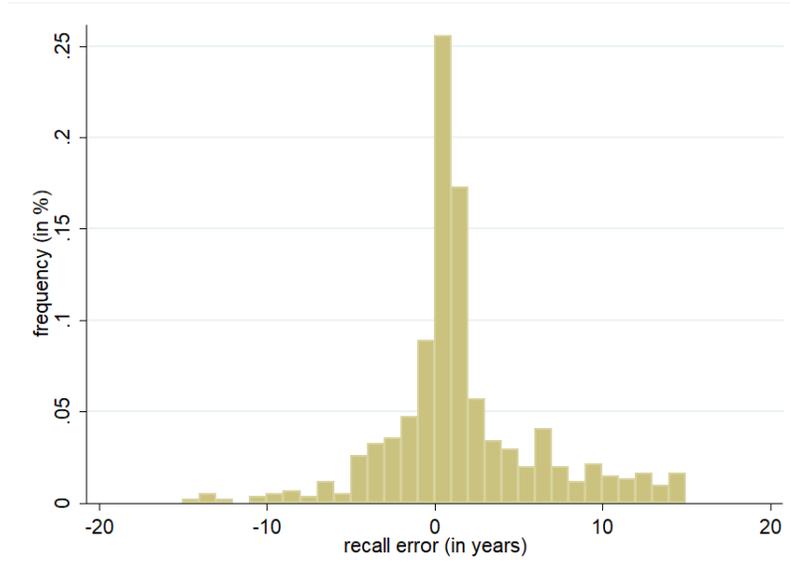
¹¹Results are substantially unchanged if we adopt $\pm 6\%$ instead, as figure 2 clearly suggests.

¹²From the original sample, we are able to match 803 RTJ from SalSa with their administrative counterparts in the DADS. By withdrawing mismatched events, we remove 127 wage cuts and 87 wage raises. We are left with 597 usable observations for wage changes.

¹³The original questions is:

Concernant votre salaire, diriez-vous que vous êtes? [Très satisfait; plutôt satisfait; plutôt mécontent; tres mécontent]

Figure 3: Distribution of the recall error for wage changes



Reading note: the recall error is equal to 0 for 25% of the respondents. In other words, 25% of the respondents correctly date their last wage change. The recall error is equal to +10 for 1.5% of the respondents. That is, 1.5% of them date the last wage change as 10 years more recent than it actually was.

statistics on wage satisfaction in our sample.

The psychology literature points out three aspects which mainly affect RTJ. Firstly, the *recency* of the event. As intuition suggests, recent events are dated more precisely than remote ones. For retrospective temporal judgments in absolute time, experiments show that median dating error exponentially increases with elapsed time (Janssen et al., 2006). This evidence is consistent with exponential decay, which is arguably the most common functional form for the loss of memory strength (Hinrichs, 1970). In keeping with the hypothesis of exponential decay, we include the logarithm of the temporal lag between the date of the survey and the actual date of the wage change as an explanatory variable.¹⁴ Yet, recency is known to affect not only the *size* of the recall error, but also its *direction*. It has been shown that relatively recent events tend to be displaced earlier in time (backward telescoping), while relatively remote events tend to be displaced later in time (forward telescoping).¹⁵ Figure 4 shows telescoping effects for recent and remote events in our

¹⁴The SalSa survey was carried out over two calendar years: 2008 (Nov-Dec) and 2009 (Jan). We disregard this issue and consider all temporal lags from 2009, so that the minimum value for recency is $\log(2)=0.7$, thereby avoiding null values from $\log(1)=0$. Hence, the variable takes value from 0.7 (if wage changed in 2007) to 3.5 (if the last wage change happened in 1976, the first year of the DADS panel).

¹⁵In spite of the empirical evidence of this effect (Thompson et al., 1988; Janssen et al., 2006; Wang et al., 2010), its explanation is still unclear. The initial theory of time compression (Sudman and Bradburn, 1973) has been criticized and partially replaced by the theory of reference period boundary (Huttenlocher et al., 1988; Rubin and Baddeley, 1989).

Table 1: Mean value of wage satisfaction, net wage and wage rank by population subgroups

	Wage satisfaction	Net wage	Wage rank	N
Overall	2.44	1,867€	0.54	599
female	2.39	1,518€	0.48	298
male	2.49	2,212€	0.60	301
Age:				
18-30	2.42	1,367€	0.44	67
31-50	2.42	1,914€	0.56	397
50-65	2.50	1,976€	0.55	135

Column 1: 4 = very satisfied; 3 = rather satisfied; 2 = rather dissatisfied; 1 = very dissatisfied.

Column 2: nominal monthly net wage including bonuses, expressed in euros.

Column 3: wage rank index, as defined in eq.4

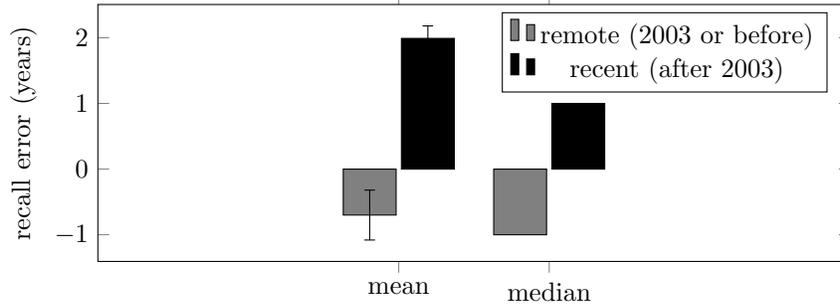
sample. In line with the literature, we find that recent events tend to be subject to backward telescoping and remote events to forward telescoping.

The second element which potentially affects RTJ is the *valence* (aka *affective valence*) of the recalled event, in the sense of its intrinsic attractiveness or averseness. The role of valence is controversial. In their seminal study on retention, Waters and Leeper (1936) conclude that, while saliency is positively related to retention, valence is not. Many other studies reveal valence asymmetries, but there is contradictory evidence on the direction and importance of the effects.¹⁶ In line with standard microeconomic theory, we assume wage raises to be associated with positive valence and wage cuts to be associated with negative valence. This assumption is likely to be violated in some cases: neither are all wage raises good news nor 100% of wage cuts bad news. For example, a wage raise after being promoted to a stressful position can be a disagreeable episode; a wage cut due to maternity leave or a voluntary reduction of the working load is likely to be associated with a pleasant event. We consider these and similar cases as exceptions from the general tendency to like higher than lower income.

The last element which is likely to affect the recall error is the *saliency* (aka *saliency*) of the recalled event. Emotional intensity of an event has been shown to be the best predictor of autobiographical memory (Talarico et al., 2004). This attention mechanism is intimately related with valence, at least in terms of loss aversion: since losses are generally more intense experiences than gains, we should expect wage cuts to be

¹⁶In their critical review, Baumeister et al. (2001) explain that there is limited evidence “for greater power of bad [information] over good, but this does not appear to be the dominant force” (p.344). The authors later underline the important relationship between valence and the current affective state: evidence exists of “a tendency for individuals to recall positive information (a self-enhancement effect), particularly when in a positive mood (a mood-congruent recall effect)” (p.344).

Figure 4: Mean recall error (in years) for recent and remote wage changes



Reading note: For an illustrative purpose, we take the mean year of the last wage change (2003) as an arbitrary cutoff to define recent events (happened after 2003) and remote events (happened in 2003 or earlier). On average, recent wage changes are backward telescoped by 0.7 years and remote wage changes are forward telescoped by 2 years. Half of recent (resp. remote) events are backward (forward) telescoped by at least one year.

more salient. Regardless of the *direction* of the last wage change, its *size* is a reasonable approximation of saliency, inasmuch as bigger wage changes can be considered perceptually more intense. Hence, in our set of explanatory variables, we include the absolute value of the annual rate of growth of wage corresponding to the last wage change: $(w_0 - w_{-1})/w_{-1}$.¹⁷

In our specifications, we further control for several socio-demographic characteristics (sex, age, age², diploma, French?) and job-related characteristics (long-term contract?, tenure, part-time?, working sector, private sector?).

4.3. The instrument

To infer the causal origin of variations of the recall error due to wage satisfaction, we instrument the latter through a non-declarative reference-dependent measure. More specifically, we adopt the index introduced by Brown et al. (2008). Brown and colleagues develop a simple measure which captures the relative position of a wage within a comparison group. Their index, $rank = \frac{r-1}{N_R-1}$, expresses wage rank as the ordered position r of individual i within her reference group R , normalized by the group size N_R . The index takes value within the (0;1) set. We reverse the original formulation, in order to have higher values associated with higher rank. We then use:

$$rank = 1 - \frac{r-1}{N_R-1} \quad (4)$$

$rank = 1$ means worker i is at the very top of the rank. Vice versa, $rank = 0$ means she is the worst paid within her reference group. The next step is to determine what a credible reference group is.

¹⁷It is important to highlight that, to our knowledge, the impact on telescoping effects has been shown for recency only. Saliency is known to affect the *precision* of RTJ, yet not the *bias* of RTJ. Our estimations, detailed in the next section, replicate this empirical evidence.

In line with the evidence that people mostly compare their income to their colleagues (Clark and Senik, 2010), we define the reference group according to geographical proximity (region) and category of occupation (managers, intermediate, clerks, workers). It is important to stress that we use the whole surveyed sample (3055 people) to define the groups, and not only the sub-sample of matched temporal judgments. We obtain 32 reference groups, each with an average size of 140 individuals. Two individuals belong to the same wage reference group if they live in the same region and work in a hierarchically-comparable position. The third column of table 1 summarizes some information on wage rank in our sample.

By using wage rank as an instrument, we are assuming that between-people variations in relative wage rank are associated with changes in wage satisfaction but do not lead *directly* to changes in the recall error. To justify this (strong) assumption, we must defend both the relevance and the exogeneity of our instrument. The first property can be statistically assessed. A simple regression of wage satisfaction on wage rank excludes any weak instrument issue (F-stat = 42.9). Wage rank is a strong significant predictor even when the wage level and other covariates are added to the set of explanatory variables (see tab. 2). This holds true not only in our sample, but also in the original study by Brown et al. (2008) on 16,000 British employees.

Exogeneity of wage rank cannot be statistically justified. However, we cannot think at any reasonable direct channel through which someone's relative wage directly impacts the way she recalls her wage history. Spurious correlation seems very unlikely too, given that wage rank is not a declarative variable: its co-movements with wage satisfaction should capture latent satisfaction, beyond any spurious declarative factor.

Another argument which could be addressed against the exogeneity of rank is that relative wage is likely to be correlated with (unobservable) cognitive skills which, in turn, determine recall capacity. Although cognitive skills represent a fair concern, they may affect the precision of the temporal judgments, not the direction of the telescoping effects. That is: they may affect the variance of the recall error, not its mean.

5. Regression analysis

The description of our dataset confirmed that retrospective temporal judgments are often subject to mistakes and that the dates of past wage changes are no exception. In this section, we adopt a regression approach to understand if these mistakes are random or systematic and, in the latter case, whether wage satisfaction can be at the origin of misdating behaviors. We will use the following notation:

h = wage satisfaction

$RE = t_{-1} - m(t_{-1})$ = recall error

t_{-1} = actual date of the last wage change

$m(t_{-1})$ = current recalled date of the last wage change

r = recency = $\log(t_0 - t_{-1})$

$m(r)$ = recalled recency = $\log(t_0 - m(t_{-1}))$

$rank$ = wage rank = $1 - \frac{r-1}{N_R-1}$

v = wage raise = 1 if $w_o - w_{-1} > 0$, 0 otherwise

$(1 - v)$ = wage cut = 1 if $w_o - w_{-1} < 0$, 0 otherwise

s = saliency = $|\frac{w_o - w_{-1}}{w_{-1}}|$

The example reported in figure A3 offers a graphical illustration of the variables. Before looking at the conditional correlation of the recall error with wage satisfaction, it is useful to inspect the path-dependency of the latter.

5.1. Path-dependency of wage satisfaction

As a preliminary step in our analysis, we check that the recalled date of the last wage change contributes to the explanation of current wage satisfaction. We use the recalled temporal distance from the event $m(r)$ and keep the log-form, in keeping with the idea that intertemporal effects of positive / negative events follow an exponential decay.¹⁸ Although it is true that the log-transformation already imposes a structure on perceived past time, this is not the driver of our results and we would come to similar conclusions if we used $(t_0 - m(t_{-1}))$ instead of $\log(t_0 - m(t_{-1}))$ (see appendix, tab A5, columns (3) and (4)).

By assuming additive separability of primary and non-primary evaluations, we can model wage satisfaction in a convenient linear form. The inter-temporal effects of wage cuts and wage raises on satisfaction are expected to go in opposite directions: a recent wage raise should enhance satisfaction, a recent wage cut

¹⁸Van Praag and Ferrer-i Carbonell (2004) use instead a half-normal distribution for the intertemporal effects from memory. Their justification for discarding the exponential distribution is operational: they need a two-sided distribution to account for both memory and expectations and the exponential one is not continuously differentiable at point 0. This concern does not apply here, since we do not take future expectations into account.

should lower it. Accordingly, we look at the conditional effects, by interacting $m(r)$ with the complementary dummies for the valence of the wage change. Equation 5 expresses the relationship between wage satisfaction, absolute wage, relative wage and the recalled dates of the last wage raise and wage cut:

$$h_i = \alpha_1 \log wage_i + \alpha_2 rank_i + \alpha_{31}(m(r_{ij}) \times v_{ij}) + \alpha_{32}(m(r_{ij}) \times (1 - v_{ij})) + x_i' \alpha_4 + \xi_{ij} \quad (5)$$

where h_i is the wage satisfaction reported by individual i . $m(r_{ij}) \times v_{ij}$ should be read as the “recalled recency of the last wage raise”, while $m(r_{ij}) \times (1 - v_{ij})$ is the “recalled recency of the last wage cut”. x_i is a vector which includes a constant, saliency, a binary indicator for wage cuts and relevant controls for socio-demographic characteristics (sex, age, age², diploma, French?) and job-related characteristics (long-term contract?, tenure, part-time?, working sector, private sector?). ξ_{ij} is the error term.

Under standard assumptions on the error term, we can estimate equation 5 by OLS (see table 2). Unsurprisingly, current absolute wage is the strongest predictor of wage satisfaction. When wage rank is added to the model, the contribution of absolute wage to explain wage satisfaction diminishes, since the comparative aspect is now captured by the new regressor. People who date wage cuts are 0.4 scale points less satisfied than those who date wage raises. Younger and full-time workers are happier with their wage than older and part-time ones. Finally, given the same salary, French people declare on average to be less satisfied than foreigners, consistently with previous studies on cultural transmission of happiness traits (Senik, 2014a). Instead, the coefficients associated with saliency are never significant. This fact is quite puzzling, but part of the explanation could be that here saliency refers to the difference between current and past wage and not to the difference between current and *recalled* past wage.

Results confirm a positive relationship between the temporal closeness of the wage raise and current wage satisfaction. A t-test fails to reject $\widehat{\alpha}_{31} < 0$ and $\widehat{\alpha}_{32} > 0$ at conventional 5% level. The negative sign associated with $\widehat{\alpha}_{31}$ means that the more recently the last wage raise took place, the more satisfied the person currently is with her wage. Vice versa, the positive sign associated with $\widehat{\alpha}_{32}$ tells us that the more recent the last wage cut was, the less satisfied the person is. Results hold when we relax the assumption of cardinal satisfaction and we estimate the models by ordered probit (see appendix, tab.A5, columns (1) and (2)).

The sign and significance of the estimated coefficients $\widehat{\alpha}_{31}$ and $\widehat{\alpha}_{32}$ support the idea that past events have a persistent effect, which decays over time. A Wald test confirms that the two coefficients are statistically different at a 99% confidence level. The opposite signs of the coefficients reflect opposite inter-temporal effects on satisfaction. Positive events related to an object (wage raises) positively affect the cognitive evaluation of this object (wage satisfaction) in a stronger way the more recent the event was: as time goes by, the positive effect fades away. Negative events follow a symmetric pattern.

This reduced form analysis has no pretension to tell the full path-dependent structure of wage satisfaction.

An important confounding factor may be the frequency of the wage cuts and wage raises. For instance, a person with a brilliant career, who experiences relatively frequent wage rises, is likely to declare a high wage satisfaction. Part of her positive evaluation would be due to the high frequency of the wage raises, which in turn would reduce the average time elapsed from the last wage raise. Understanding the size and functional form of the effect of past wage changes on current satisfaction is beyond the scope of this study.¹⁹ Yet, the existence of intertemporal spill-overs is an important element to understanding the endogeneity of the recall error. In the next section, we move on to the empirical illustration of the endogeneity issue.

5.2. The endogeneity of the recall error

According to the hypothesis of hedonic telescoping, people date past positive and negative events differently depending on their current well-being. Here the positive and negative events are respectively the last wage raise and wage cuts and the related level of evaluative well-being is wage satisfaction. To test this hypothesis, we regress the recall error on wage satisfaction, controlling for other potential psychological and socio-demographic factors.

We include wage satisfaction (h), the recency of the event (r), its valence (v) and its saliency (s) in the argument of the recall function $\eta(\cdot)$ (see eq.2). We assume the recall function to be linear in its arguments. Since we are interested in the effect of wage satisfaction conditional on the wage change being a raise or a cut, we interact the satisfaction level with the complementary indicator functions for valence. We specify the model as follows:²⁰

$$RE_{ij} = \beta_1 r_{ij} + \beta_2 s_{ij} + \beta_{31}(h_i \times v_{ij}) + \beta_{32}(h_i \times (1 - v_{ij})) + x_i' \beta_4 + \epsilon_{ij} \quad (6)$$

where RE_{ij} is the recall error of individual i with regard to event j ; x_i is a vector which includes a constant, a binary indicator for wage cuts, socio-demographic characteristics and job-related characteristics; ϵ_{ij} is the error term.²¹ We have good reason to suspect this error term to be heteroskedastic.²² Indeed, the

¹⁹See e.g. Bayer and Juessen (2015) for a recent study on the inter-temporal effects of different kinds of income shocks.

²⁰In equation 7, we omit unconditional wage satisfaction h_i to avoid multicollinearity with $h_i \times v_{ij} + h_i \times (1 - v_{ij})$

²¹This pooled regression treats all answers on wage raises/cuts as if they were from different individuals. Its shortcoming is that it does not control for unobserved heterogeneity with respect to the overall tendency to forward or backward telescope events. Nevertheless, this omitted variable would do some harm inasmuch as the estimated coefficients $\widehat{\beta}_{31}$ and $\widehat{\beta}_{32}$ have the same sign. As we will see, this is not the case.

²²Another fair concern is self-selection, which may arise because of non-response. The recall error is observed only insofar as people answer the survey question on temporal judgment. If propensity to respond is driven by heterogeneous characteristics, the sample of observed recall errors is biased, due to a classic self-selection issue. In the SalSa survey, among the subjects who declare they had a wage cut, 93 decline dating it. We estimate the probability to recall the date from a probit model. Contrary to our initial suspect, we fail to identify any pattern in the propensity to forget that date. Since the sample of respondents do not appear to be endogenously determined, we continue our analysis without any additional correction parameter.

explanatory variable “recency” could affect not only the mean of the recall error (telescoping effects), but also its variance (precision). A Breusch-Pagan test rejects the null hypothesis of homoskedasticity at 99%. As a consequence, we assume $\epsilon_{ij} \sim N(0, \sigma_{ij}^2)$. For a visual illustration of heteroskedasticity, we show the sample variance of the residuals in figure A1, in the appendix.

To account for heteroskedasticity, we use two techniques. As a first solution, we correct the estimated standard errors of the OLS models by using White’s robust standard errors (White, 1980). Results, with and without job-related controls, are reported in table 3, columns (1) and (2). An alternative way of dealing with heteroskedasticity is to model the skedastic function, i.e. the conditional variance of the error term. This approach can improve the efficiency of our estimation and it is particularly appealing in our case since the literature offers good insights for a suitable specification of the error variance. The econometric technique we apply goes with the name of Feasible Generalized Least Squares (FGLS). Our procedure is described step by step in the appendix. FGLS estimation results are reported in table 3, columns (3) and (4). Outcomes are substantially homogeneous regardless of the estimator: the size, sign and significance of the coefficients of interest are almost the same.

Let us first look at the psychometric covariates. Firstly, the recency of the event is confirmed to be a strong predictor of the recall error. The negative sign of the estimated coefficient $\widehat{\beta}_1$ means that the more remote an event is, the stronger forward telescoping is: this result corroborates previous findings from experimental psychology.²³ On the contrary, the size of the wage change, i.e. saliency, does not help explaining telescoping effects. This outcome is not anomalous since saliency may affect the precision of the recall, yet no evidence exists of its impact on telescoping effects.

None of the socio-demographic variables improves the prediction of the recall error, except for age, suggesting that older people display stronger backward telescoping.²⁴ A Wald test on the hypothesis that all the coefficients of the vector $\widehat{\beta}_4$ - except the one associated with age - are jointly equal to zero fails to reject the null at 5%. It may be surprising to see that the coefficient associated with log-wage is not significantly different from zero. Yet, the wage is likely to affect the saliency of a wage change and thus the precision of the recall process, not its bias. Indeed, relatively poor people will be more sensitive to a $n\text{€}$ -variation than richer ones, but with no implication for telescoping effects.

Let us now discuss the hypothesis of hedonic telescoping. When we regress the recall error solely on wage satisfaction, we find no significant relationship. However, this very parsimonious form - in particular the omission of relevant variables for recall such as recency and age - shall bias the coefficients. When we

²³We remind that, given our definition of the recall error, the explained variable takes negative values when RTJ display forward telescoping, positive values for backward telescoping and zero for correct dating.

²⁴The relationship between age and autobiographical memory has been conceptualized by several authors, see e.g. Carstensen’s *positivity effect* (Kennedy et al., 2004; Reed and Carstensen, 2012).

specify the full model, the explanatory power of wage satisfaction is significantly different from zero for both wage raises and wage cuts. The negative sign of the estimated coefficient $\widehat{\beta}_{31}$ means that wage raises tend to be displaced *forward* in time the higher the satisfaction level; the positive sign of $\widehat{\beta}_{32}$ means that wage cuts tend to be displaced *backward* in time the higher the satisfaction level. A Wald test confirms that the two coefficients are statistically different at 99%. Results hold after introducing job-related controls (columns (2) and (4)).²⁵

These regressions show the recall error to be endogenously determined and not purely random. It could be tempting to interpret $\widehat{\beta}_{31}$ and $\widehat{\beta}_{32}$ as the effects of current well-being on misdating behaviors. Nevertheless, we should be cautious when *causally* interpreting these coefficients. A Durbin-Wu-Hausman test of endogeneity rejects the exogeneity of wage satisfaction at a 99% confidence level. It means that regardless of the estimation method, $\widehat{\beta}_{31}$ and $\widehat{\beta}_{32}$ are correlations which capture the simultaneous effects of the recalled event on current satisfaction and of current satisfaction on the recalled event. More satisfied people recall wage cuts (raises) to be more remote (recent), but how much do they misdate because they are more satisfied and how much are they more satisfied because they misdate? So far, our analysis does not allow to disentangle the two channels of causality. For this reason, we go over to an instrumental variable analysis.

5.3. Hedonic telescoping

To assess the causal origin of the recall error, we use an instrumental variable approach. The underlying idea is to look at the variations of relative wage with respect to peers as a local predictor of the recall error, mediated by wage satisfaction: if differences in social statuses can explain differences in misdating behavior, we can confirm satisfaction is one of the causes of telescoping effects. For the justification of our instrument, we refer to section 4.3.

We estimate the model by 2-stage least squares, both with (IV-FGLS) and without (robust 2SLS) assumptions on the structure of the conditional variance of the residuals. In both procedures, instead of using wage satisfaction as a predictor of the recall error, we use the projection of *rank* on *wage satisfaction*. This step singles out the component of wage satisfaction which is explained by social comparisons. The predictive capacity of this component on the recall error has a causal interpretation, since the reverse causal channel does not hold (under the null that $E[\epsilon|rank] = 0$). The second step estimates the following model:

$$RE_{ij} = \gamma_1 r_{ij} + \gamma_2 s_{ij} + \gamma_{31}(\widehat{h}_i \times v_{ij}) + \gamma_{32}(\widehat{h}_i \times (1 - v_{ij})) + x_i' \gamma_4 + u_{ij} \quad (7)$$

where \widehat{h}_i is the expectation of wage satisfaction conditional on the exogenous variables and u is a heteroskedastic normally distributed error term.

²⁵To check for the possibility that the effects of saliency and recency also depend on the level of satisfaction, we interact these variables, yet no dependent effect seems to be at stake.

Table 5 presents the estimation results of the second step (see table 4 for the first step). The estimated coefficient $\widehat{\gamma}_{31}$ is not significantly different from zero, regardless of the estimation method or the specification. On the other hand, $\widehat{\gamma}_{32}$ is significant and holds the expected sign ($\widehat{\gamma}_{32} > 0$ at 5%) except in the second specification (due to an increase in the standard errors, but without any change in the coefficient). How can we explain these asymmetric results for wage cuts and wage raises? We suggest a simple answer: because wage cuts and wage raises are not symmetric events for our memory. Wage raises are more frequent and often unrelated to a substantial change in the worker's situation. Conversely, wage cuts are rare events, usually either due to a transition to part-time work or changing employer. Therefore, the latter should be more sensitive to biases of the episodic memory, up to a level which is detectable in our sample.

The magnitude of $\widehat{\gamma}_{32}$ is considerable: everything else being equal, increasing wage satisfaction by one standard deviation causes wage cuts to be recalled 1.7 years earlier. Therefore, two people who experienced a wage change at the same date may recall this date quite differently according to their level of current satisfaction. The direction of these telescoping effects is consistent with a *self-serving memory*: more satisfied people seem to manipulate the events of their past wage history in a more self-supportive way. If you think of memory as a telescope, well-being determines which side of the telescope you use to see the event: this, in a nutshell, is hedonic telescoping.

We think that this piece of evidence can contribute to understanding the hedonic adaptation phenomenon. According to the latter, people tend to adapt to income changes, so that the negative effect of a wage cut depends on its relative temporal distance. Hedonic telescoping shows that the perceived closeness of the event is, in part, endogenously determined so that people's well-being not only depends on backward references passively, but also actively affects the reconstruction of those backward references.

Table 2: Regression of wage satisfaction.

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Dependent variable: wage satisfaction				
log(wage)	0.348*** (5.46)	0.476*** (6.81)	0.172** (2.15)	0.263*** (3.16)
rank			0.484*** (3.43)	0.622*** (4.34)
recalled recency (wage cut)	0.106** (2.13)	0.127** (2.55)	0.0872* (1.75)	0.107** (2.16)
recalled recency (wage raise)	-0.233** (-2.08)	-0.199* (-1.77)	-0.257** (-2.30)	-0.217* (-1.95)
saliency	-0.000796 (-0.79)	-0.000881 (-0.85)	-0.000514 (-0.51)	-0.000544 (-0.53)
cut?	-0.426** (-2.56)	-0.461*** (-2.79)	-0.416** (-2.50)	-0.446*** (-2.72)
age	-0.0435* (-1.65)	-0.0316 (-1.19)	-0.0520** (-1.98)	-0.0426 (-1.62)
age ²	0.000511* (1.67)	0.000392 (1.28)	0.000609** (2.00)	0.000521* (1.72)
French?	-0.386** (-2.06)	-0.362* (-1.96)	-0.457** (-2.45)	-0.438** (-2.39)
male?	-0.0170 (-0.28)	0.0365 (0.56)	-0.0194 (-0.32)	0.0345 (0.53)
Job-related controls	no	yes	no	yes
N	597	584	591	578

t statistics in parentheses

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

Note: All regressions include a constant and dummy variables for the education level. Where specified, they also include controls for job-related characteristics: long-term contract?, tenure, part-time?, working sector, private sector?.

Table 3: Regression of the recall error.

	(1)	(2)	(3)	(4)
	OLS	OLS	FGLS	FGLS
Dependent variable: recall error				
$h \times cut?$	0.636** (1.98)	0.662** (2.04)	0.598** (2.29)	0.623** (2.27)
$h \times raise$	-0.915*** (-4.05)	-0.865*** (-3.32)	-0.792** (-2.34)	-0.777** (-2.18)
recency	-3.284*** (-9.73)	-3.364*** (-9.68)	-2.556*** (-8.09)	-2.710*** (-8.07)
saliency	-0.000622 (-0.11)	-0.000870 (-0.14)	0.00334 (0.63)	0.00461 (0.80)
cut?	-0.334 (-0.34)	-0.174 (-0.17)	-0.335 (-0.31)	-0.168 (-0.15)
age	0.434*** (3.23)	0.392*** (2.76)	0.453*** (3.48)	0.433*** (3.16)
age ²	-0.00373** (-2.28)	-0.00336* (-1.94)	-0.00418*** (-2.71)	-0.00407** (-2.51)
male?	-0.138 (-0.41)	-0.181 (-0.47)	0.00942 (0.03)	0.0258 (0.07)
log(wage)		0.113 (0.26)		0.0622 (0.17)
Job-related controls	no	yes	no	yes
N	597	584	597	584

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

Note: h = wage satisfaction; $raise?$ = wage raise; $cut?$ = wage cut. All regressions include a constant and dummy variables for nationality and the education level. Where specified, they also include controls for job-related characteristics: long-term contract?, tenure, part-time?, working sector, private sector?.

Table 4: IV estimations, first step.

	(1)	(2)
	OLS	OLS
Dependent variable: wage satisfaction		
rank	0.666*** (5.79)	0.635*** (4.42)
recency	0.0418 (0.95)	0.0531 (1.18)
saliency	-0.000908 (-0.89)	-0.000857 (-0.82)
age	-0.0497* (-1.89)	-0.0403 (-1.53)
age ²	0.000590* (1.93)	0.000498 (1.64)
French?	-0.467** (-2.48)	-0.423** (-2.30)
male?	0.0203 (0.34)	0.0341 (0.52)
log(wage)		0.255*** (3.06)
Job-related controls	no	yes
N	591	578

t statistics in parentheses

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

Note: Regressions include a constant and dummy variables for the education level. Column 2 also includes job-related controls.

Table 5: Instrumental variable regressions of the recall error.

	(1)	(2)	(3)	(4)
	2SLS	2SLS	IV-FGLS	IV-FGLS
Dependent variable: recall error				
$\hat{h} \times cut?$	2.407*	2.407	2.354**	2.469*
	(1.86)	(1.56)	(2.28)	(1.89)
$\hat{h} \times raise?$	-0.271	0.825	0.0877	0.984
	(-0.25)	(0.56)	(0.07)	(0.72)
recency	-3.400***	-3.464***	-2.662***	-2.815***
	(-9.89)	(-9.81)	(-8.15)	(-8.09)
saliency	0.00345	0.00257	0.00781	0.00810
	(0.59)	(0.40)	(1.39)	(1.36)
cut?	-3.091	-0.338	-2.489	-0.424
	(-0.94)	(-0.13)	(-0.74)	(-0.16)
age	0.483***	0.449***	0.499***	0.495***
	(3.43)	(2.99)	(3.73)	(3.49)
age ²	-0.00443**	-0.00419**	-0.00484***	-0.00495***
	(-2.56)	(-2.28)	(-3.04)	(-2.94)
male?	-0.285	-0.195	-0.177	-0.0206
	(-0.79)	(-0.49)	(-0.56)	(-0.06)
log(wage)		-0.772		-0.800
		(-0.96)		(-1.23)
Job-related controls	no	yes	no	yes
N	593	580	593	580

t statistics in parentheses

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

Note: \hat{h} = predicted wage satisfaction; *raise?* = wage raise; *cut?* = wage cut. Instrument: wage rank. All regressions include a constant and dummy variables for nationality and the education level. Where specified, they also include controls for job-related characteristics: long-term contract?, tenure, part-time?, working sector, private sector?.

6. Discussion

What is the rationale behind hedonic telescoping? We think that the most convincing interpretation is in terms of *egocentric recall bias* (Schacter et al., 2003), where the past is recalled in a self-enhancing manner (in line with the economic concept of *self-serving beliefs* (Babcock et al., 1995)). According to this explanation, people who are more satisfied tend to selectively attribute positive characteristics to their past experience, which in turn, contributes to their current well-being, concurring to a virtuous simultaneous effect. This explanation goes along with Zimbardo and Boyd’s analysis of heterogeneous time perspectives (Zimbardo and Boyd, 2008), which may be more past-positive or past-negative oriented. Time perspective reflects the way past information is processed, so that two people going through the same experience will recall it differently. Zimbardo and Boyd claim that people displaying strong past-positive perspectives are more satisfied with their lives than people with high past-negative ones. Hedonic telescoping offers supportive evidence for this finding.

Nonetheless, we can conjecture different explanations and interpret this effect in terms of *self-signaling*. Given that temporal judgments are cognitively demanding and quite fallacious tasks, people may exploit the readily available information on current wage satisfaction to adjust their temporal judgment. A similar interpretation suggests that hedonic recall minimizes one’s cognitive dissonance between being satisfied (or unsatisfied) with one’s wage and recalling a recent negative experience (or a recent positive experience). This explanation is in line with the *consistency bias* (Schacter et al., 2003), according to which past is recollected in a way which is consistent with our current knowledge and beliefs.

We cannot but acknowledge that our analysis neglects some important psychological factors. We do not look at the encoding specificity, meaning that we have disregarded how information is learnt and stored (for a neuroeconomic model of optimal encoding see Brocas and Carrillo, 2016). Furthermore, we can only induce the emotional characteristics that respondents attach to wage changes nor we are able to control for their current mood. Finally, expectations are left out of our study, essentially because of measurement issues (for an economic model of subjective time for future events see Geoffard and Luchini, 2010).

Two natural extensions of our paper concern the study of different objects of recall and different satisfaction domains. On the one hand, we focused on a particular object of recall: the date of a wage change. Testing hedonic recall on the recalled past level of wage is the next fundamental step on the way to rationalize income adaptation through imperfect memory. On the other hand, we focused on wage history and wage satisfaction, but extension to other domains, such as health satisfaction or job satisfaction, certainly represents an interesting development. Aware that retrospective temporal judgments are an unusual topic in economics, we would also like to suggest possible applications of hedonic telescoping to more standard domains of the discipline. Below we offer two examples.

Firstly, temporal judgments affect the perceived evolution of economic outcomes. Let us take the case

of a major economic phenomenon: inflation. Insofar as perceived inflation depends on consumers' ability to recall price changes during the last 12 months, temporal judgments do matter. We are not the first noticing the relationship between telescoping effects and perceived inflation (see Kemp, 1999) and hedonic telescoping can add a piece to this puzzle. If we consider price raises as the real analog of a nominal wage cut, more satisfied people may tend to backward telescope the date of the price increment. Therefore, for some goods, they could recall the price raise as taking place more than 12 months before the interview, i.e. outside the reference period for inflation. As a result, the stronger the backward telescoping is, the lower the perceived inflation is.

Secondly, temporal judgments can affect public policy accountability, thus influencing political behavior. A common fiscal strategy consists in collecting higher taxes at the beginning of the political cycle and lowering them at the end of the term, to increase consensus before the elections. At the beginning of the term, citizens experience a drop in their disposable income; at the end of the term, they are likely to benefit from higher financial satisfaction. According to hedonic telescoping, current enhanced satisfaction contributes to backward telescoping the date of the initial income drop. As a consequence, the previous government may be unduly held accountable for the income drop decided by the current government.

Of course, it would be naive to think that this is the full story. Perceived inflation and taxation are complex subjects and many elements affect them. Yet, hedonic recall may help to understand some empirical patterns.

7. Conclusion

Although backward reference points are known to determine current well-being, the role of well-being in shaping memories has been poorly explored in economics. Thanks to the unique opportunity of a matched dataset with self-reported and observed information on wage history, we are able to corroborate some previous findings from the psychology literature and empirically support the existence of a novel recall bias for temporal judgments. In particular, we show that people treat retrospective information about their wage cuts differently according to their current wage satisfaction: more satisfied people recall wage raises as more recent and wage cuts as more remote than they actually were. We also show that, at least for wage cuts, current satisfaction is an actual driver of misdating behaviors.

We denote this pattern in imperfect recall as “hedonic telescoping”, with explicit reference to the related study on “hedonic recall bias” (Prati, 2017), which shows similar effects when the recalled information is the *amount* of wage instead of the *date* of a wage change. The pattern is the same: more satisfied people distort information in a more satisfying manner and vice versa less satisfied people. Indeed, the core idea behind the hedonic recall hypothesis is that people are, to a certain extent, architects of their own memories.

References

- Babcock, L., Loewenstein, G., Issacharoff, S. and Camerer, C. (1995). Biased judgments of fairness in bargaining, *The American Economic Review* **85**(5): 1337–1343.
- Bartlett, F. C. (1932). Remembering: An experimental and social study, *Cambridge University Press* .
- Baudelot, C., Cartron, D., Gautié, J., Godechot, O., Gollac, M., Senik, C. and Cohen, D. (2014). *Bien ou mal payés?*, Éditions rue d’Ulm.
- Baumeister, R. F., Bratslavsky, E., Finkenauer, C. and Vohs, K. D. (2001). Bad is stronger than good., *Review of General Psychology* **5**(4): 323.
- Bayer, C. and Juessen, F. (2015). Happiness and the persistence of income shocks, *American Economic Journal: Macroeconomics* **7**(4): 160–87.
- Belli, R. F. (2014). Autobiographical memory dynamics in survey research, in T. J. Perfect and D. S. Lindsay (eds), *SAGE Handbook of Applied Memory*, Sage, pp. 366–384.
- Bénabou, R. and Tirole, J. (2002). Self-confidence and personal motivation, *The Quarterly Journal of Economics* **117**(3): 871–915.
- Bernheim, B. D. and Thomsen, R. (2005). Memory and anticipation, *The Economic Journal* **115**(503): 271–304.
- Betz, A. L. and Skowronski, J. J. (1997). Self-events and other-events: Temporal dating and event memory, *Memory & Cognition* **25**(5): 701–714.
- Blaney, P. H. (1986). Affect and memory: a review, *Psychological Bulletin* **99**(2): 229.
- Bluck, S. and Habermas, T. (2001). Extending the study of autobiographical memory: Thinking back about life across the life span., *Review of General Psychology* **5**(2): 135.
- Bodoh-Creed, A. L. (2019). Mood, Memory, and the Evaluation of Asset Prices, *Review of Finance* .
URL: <https://doi.org/10.1093/rof/rfz001>
- Brocas, I. and Carrillo, J. D. (2016). A neuroeconomic theory of memory retrieval, *Journal of Economic Behavior & Organization* **130**: 198–205.
- Brown, G. D., Gardner, J., Oswald, A. J. and Qian, J. (2008). Does wage rank affect employees’ well-being?, *Industrial Relations: A Journal of Economy and Society* **47**(3): 355–389.
- Brown, N. R. (1990). Organization of public events in long-term memory., *Journal of Experimental Psychology: General* **119**(3): 297.

- Burt, C. D. (1992). Retrieval characteristics of autobiographical memories: Event and date information, *Applied Cognitive Psychology* **6**(5): 389–404.
- Burt, C. D., Kemp, S. and Conway, M. A. (2003). Themes, events, and episodes in autobiographical memory, *Memory & Cognition* **31**(2): 317–325.
- Bygren, M. (2004). Pay reference standards and pay satisfaction: what do workers evaluate their pay against?, *Social Science Research* **33**(2): 206–224.
- Carlson, N. R., Heth, D., Miller, H., Donahoe, J. and Martin, G. N. (2009). *Psychology: the Science of Behavior*, Pearson.
- Clark, A. E. (1999). Are wages habit-forming? Evidence from micro data, *Journal of Economic Behavior & Organization* **39**(2): 179–200.
- Clark, A. E., Diener, E., Georgellis, Y. and Lucas, R. E. (2008). Lags and leads in life satisfaction: A test of the baseline hypothesis, *The Economic Journal* **118**(529): F222–F243.
- Clark, A. E., Frijters, P. and Shields, M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles, *Journal of Economic literature* **46**(1): 95–144.
- Clark, A. E. and Oswald, A. J. (1996). Satisfaction and comparison income, *Journal of Public Economics* **61**(3): 359–381.
- Clark, A. E. and Senik, C. (2010). Who compares to whom? The anatomy of income comparisons in Europe, *The Economic Journal* **120**(544): 573–594.
- Deaton, A. and Stone, A. A. (2013). Two happiness puzzles, *American Economic Review* **103**(3): 591–97.
- Di Tella, R., Haisken-De New, J. and MacCulloch, R. (2010). Happiness adaptation to income and to status in an individual panel, *Journal of Economic Behavior & Organization* **76**(3): 834–852.
- Emmerling, J. and Qari, S. (2017). Car ownership and hedonic adaptation, *Journal of Economic Psychology* **61**: 29–38.
- Ferrer-i Carbonell, A. and Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness?, *The Economic Journal* **114**(497): 641–659.
- Frey, B. S. and Stutzer, A. (2002). What can economists learn from happiness research?, *Journal of Economic Literature* **40**(2): 402–435.
- Friedman, W. J. (1993). Memory for the time of past events., *Psychological Bulletin* **113**(1): 44.

- Friedman, W. J. and Huttenlocher, J. (1997). Memory for the time of "60 minutes" stories and news events., *Journal of Experimental Psychology: Learning, Memory, and Cognition* **23**(3): 560.
- Geoffard, P.-Y. and Luchini, S. (2010). Changing time and emotions, *Philosophical Transactions: Biological Sciences* **365**(1538): 271–280.
- Gibbons, J. A. and Thompson, C. P. (2001). Using a calendar in event dating, *Applied Cognitive Psychology* **15**(1): 33–44.
- Godechot, O. and Senik, C. (2015). Wage comparisons in and out of the firm. Evidence from a matched employer–employee French database, *Journal of Economic Behavior & Organization* **117**: 395–410.
- Gottlieb, D. (2014). Imperfect memory and choice under risk, *Games and Economic Behavior* **85**: 127–158.
- Graham, C. (2016). Subjective well-being in economics, in M. D. Adler and M. Fleurbaey (eds), *The Oxford Handbook of Well-Being and Public Policy*, Oxford University Press, pp. 424–452.
- Greene, W. H. (2008). *Econometric analysis*, Pearson Education.
- Grund, C. and Sliwka, D. (2007). Reference-dependent preferences and the impact of wage increases on job satisfaction: Theory and evidence, *Journal of Institutional and Theoretical Economics JITE* **163**(2): 313–335.
- Hinrichs, J. V. (1970). A two-process memory-strength theory for judgment of recency, *Psychological Review* **77**(3): 223.
- Huttenlocher, J., Hedges, L. and Prohaska, V. (1988). Hierarchical organization in ordered domains: Estimating the dates of events., *Psychological Review* **95**(4): 471.
- Janssen, S. M., Chessa, A. G. and Murre, J. M. (2006). Memory for time: How people date events, *Memory & Cognition* **34**(1): 138–147.
- Kemp, S. (1999). An associative theory of estimating past dates and past prices, *Psychonomic Bulletin & Review* **6**(1): 41–56.
- Kennedy, Q., Mather, M. and Carstensen, L. L. (2004). The role of motivation in the age-related positivity effect in autobiographical memory, *Psychological Science* **15**(3): 208–214.
- Li, K. K. (2013). Asymmetric memory recall of positive and negative events in social interactions, *Experimental Economics* **16**(3): 248–262.
- Linton, M. (1975). Memory for real-world events, *Explorations in Cognition* pp. 376–404.

- Loftus, E. F., Klinger, M. R., Smith, K. D. and Fiedler, J. (1990). A tale of two questions: Benefits of asking more than one question, *Public Opinion Quarterly* **54**(3): 330–345.
- Martin, J. M., Lejarraga, T. and Gonzalez, C. (2018). The effects of motivation and memory on the weighting of reference prices, *Journal of Economic Psychology* **65**: 16–25.
- Mullainathan, S. (2002). A memory-based model of bounded rationality, *The Quarterly Journal of Economics* **117**(3): 735–774.
- OECD (2013). OECD guidelines on measuring subjective well-being.
- Oswald, A. J. and Powdthavee, N. (2008). Does happiness adapt? A longitudinal study of disability with implications for economists and judges, *Journal of Public Economics* **92**(5-6): 1061–1077.
- Piccione, M. and Rubinstein, A. (1997). On the interpretation of decision problems with imperfect recall, *Games and Economic Behavior* **20**(1): 3–24.
- Prati, A. (2017). Hedonic recall bias. Why you should not ask people how much they earn, *Journal of Economic Behavior & Organization* **143**: 78–97.
- Prohaska, V., Brown, N. R. and Belli, R. F. (1998). Forward telescoping: The question matters, *Memory* **6**(4): 455–465.
- Reed, A. E. and Carstensen, L. L. (2012). The theory behind the age-related positivity effect, *Frontiers in Psychology* **3**.
- Ross, M. (1989). Relation of implicit theories to the construction of personal histories, *Psychological Review* **96**(2): 341.
- Ross, M., Eyman, A. and Kishchuk, N. (1986). Determinants of subjective well-being, *Relative deprivation and social comparison: The Ontario symposium*, Vol. 4, Lawrence Erlbaum Associates Hillsdale, pp. 79–93.
- Rubin, D. C. and Baddeley, A. D. (1989). Telescoping is not time compression: A model, *Memory & Cognition* **17**(6): 653–661.
- Saucet, C. and Villeval, M. C. (2018). Motivated memory in dictator games, *GATE - WP 1804* .
- Schacter, D. L. (2001). *The seven sins of memory: How the mind forgets and remembers*, Boston: Houghton Mifflin.
- Schacter, D. L., Chiao, J. Y. and Mitchell, J. P. (2003). The seven sins of memory: implications for self, *Annals of the New York Academy of Sciences* **1001**: 226–239.

- Senik, C. (2004). When information dominates comparison: Learning from russian subjective panel data, *Journal of Public Economics* **88**(9): 2099–2123.
- Senik, C. (2014a). The french unhappiness puzzle: The cultural dimension of happiness, *Journal of Economic Behavior & Organization* **106**: 379–401.
- Senik, C. (2014b). *L'économie du bonheur*, Le Seuil.
- Shimojima, Y. (2002). Memory of elapsed time and feeling of time discrepancy, *Perceptual and Motor Skills* **94**(2): 559–565.
- Skowronski, J., Walker, W. R. and Betz, A. (2003). Ordering our world: An examination of time in autobiographical memory, *Memory* **11**(3): 247–260.
- Steffel, M. and Oppenheimer, D. M. (2009). Happy by what standard? The role of interpersonal and intrapersonal comparisons in ratings of happiness, *Social Indicators Research* **92**(1): 69–79.
- Stutzer, A. (2004). The role of income aspirations in individual happiness, *Journal of Economic Behavior & Organization* **54**(1): 89–109.
- Sudman, S. and Bradburn, N. M. (1973). Effects of time and memory factors on response in surveys, *Journal of the American Statistical Association* **68**(344): 805–815.
- Talarico, J. M., LaBar, K. S. and Rubin, D. C. (2004). Emotional intensity predicts autobiographical memory experience, *Memory & Cognition* **32**(7): 1118–1132.
- Thompson, C. P., Skowronski, J. J. and Lee, D. J. (1988). Telescoping in dating naturally occurring events, *Memory & Cognition* **16**(5): 461–468.
- Van Praag, B. M. and Ferrer-i Carbonell, A. (2004). The impact of past and future on present satisfaction, *Happiness quantified: A satisfaction calculus approach*, Oxford University Press, pp. 138–159.
- Veenhoven, R. (1991). Questions on happiness: Classical topics, modern answers blind spot, in F. E. Strack, M. E. Argyle and N. E. Schwarz (eds), *Subjective Well-Being: an interdisciplinary perspective*, Pergamon Press, pp. 7–26.
- Wagenaar, W. A. (1986). My memory: A study of autobiographical memory over six years, *Cognitive Psychology* **18**(2): 225–252.
- Wang, Q., Peterson, C. and Hou, Y. (2010). Children dating childhood memories, *Memory* **18**(7): 754–762.
- Waters, R. and Leeper, R. (1936). The relation of affective tone to the retention of experiences of daily life., *Journal of Experimental Psychology* **19**(2): 203.

- White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica* pp. 817–838.
- Wilson, A. (2014). Bounded memory and biases in information processing, *Econometrica* **82**(6): 2257–2294.
- Zimbardo, P. and Boyd, J. (2008). *The time paradox: The new psychology of time that will change your life*, Simon and Schuster.
- Zimmermann, F. (2019). The dynamics of motivated beliefs, *CRC Discussion Paper Series n.073* .

Appendix

Questionnaire

To elicit the recalled dates of the last wage raise and wage cut, we use the following questions from the SalSa survey:

I) - Have your wages or your bonuses increased since last year?

Ia) - [If not]: In which year was the amount of your wage or your bonuses raised for the last time? ("never" or "year")

II) - During your professional life, have you ever experienced a wage cut, including bonuses?

IIa) - [If yes]: In which year did it happen for the last time?²⁶

Questions (I) and (II) have an assertive structure ("yes"/"no") and question (I) is framed in relative time ("...since last year?"), while (Ia) and (IIa) are in absolute time ("In which year...?"). For consistency, we only consider the answers to questions (Ia) and (IIa) in our analysis, which are actual RTJs in absolute time.

²⁶The original questions are:

- *Depuis un an, votre salaire ou vos primes ont-ils été augmentés?*
- *[Si non]: En quelle année le montant de votre salaire ou de vos primes ont-ils augmenté pour la dernière fois ?*
- *Vous est-il arrivé, au cours de votre vie professionnelle, de subir une baisse de votre salaire, primes incluses ?*
- *[Si oui]: En quelle année cela vous est-il arrivé pour la dernière fois ?*

Calculation of the confidence interval for the white noise

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

$$\hat{w} = \exp(\log(w) + n \cdot 0.02 \cdot sd); \quad (\text{A1})$$

$$n \sim \mathcal{N}(0, 1); \quad (\text{A2})$$

where n is a random variable and sd denotes the empirical standard deviation of the logarithms of net wages. Eq. (A1) and (A2) were provided by the National Institute of Statistics and of Economic Studies (INSEE), which manages the DADS.

We do not know the standard deviation sd since we do not have access to the original distribution of wages. However, we can adopt a conservative strategy and compute the standard deviation of the noisy wages \hat{sd} , which is at least as big as the original standard deviation. The average yearly standard deviation of the log-wages is 1.05. In addition, we know that in 95% of the cases n takes values from -1.96 to 1.96. We use this information to set the upper and lower bound of the white noise:

$$\begin{aligned} \hat{w} &= w \cdot \exp(n \cdot 0.02 \cdot sd) \\ &= w \cdot \exp(\pm 1.96 \cdot 0.02 \cdot 1.05) \\ &\Rightarrow \hat{w} \in [w \cdot 0.960; w \cdot 1.042]; \end{aligned} \quad (\text{A3})$$

We slightly round up the lower bound to obtain a more manageable symmetric interval. As a conclusion, we know that, on average, *at least* 95% of the original observations are within the $\pm 4.2\%$ confidence interval.

Description of the FGLS estimation

Let us describe our procedure step by step. Once again, the starting equation is eq.6. Efficient estimation of our coefficients of interest would be achieved if we *knew* the structure of the covariance matrix $\sigma_i^2 j$. Although we do not have this information at our disposal, we can *estimate* $\sigma_i^2 j$. To this purpose, we need to impose a structure which involves a parameter θ and the regressors which cause heteroskedasticity. What are these regressors? Our candidates are recency and saliency, since both are likely to affect the precision of RTJ. We perform Breusch-Pagan/Cook-Weisberg tests on both variables and the null hypothesis of constant variance is rejected at 5% for recency only. Therefore, we include recency in the skedastic function, which we specify according to the standard hypothesis of exponential decay:

$$\sigma_{ij}^2 = \exp(-\theta n_{ij}) \quad (\text{A4})$$

where n_{ij} is the elapsed number of years from the last wage change j for individual i .

We perform FGLS in two steps. In the first step, we estimate eq.7 by OLS, we take the squared residuals and regress them on $\sigma^2(n_{ij}, \theta)$ by non-linear least squares to obtain the predicted covariance matrix $\widehat{\sigma}^2(n_{ij}, \widehat{\theta})$. We do not need to have an efficient estimator of θ , since consistency is enough to achieve asymptotic efficiency of FGLS (Greene, 2008, p.158, theorem 8.5). In the second step, we use $\widehat{\sigma}_{ij}^2$ to weight the OLS regression. We estimate:

$$\frac{RE_{ij}}{\widehat{\sigma}_{ij}^2} = \beta_0 + \beta_1 \frac{r_{ij}}{\widehat{\sigma}_{ij}^2} + \beta_2 \frac{s_{ij}}{\widehat{\sigma}_{ij}^2} + \beta_{31} \frac{(h_i \times v_{ij})}{\widehat{\sigma}_{ij}^2} + \beta_{32} \frac{(h_i \times (1 - v_{ij}))}{\widehat{\sigma}_{ij}^2} + \left(\frac{x_i}{\widehat{\sigma}_{ij}^2} \right)' \beta_4 + \frac{\epsilon_{ij}}{\widehat{\sigma}_{ij}^2} \quad (\text{A5})$$

where $\widehat{\sigma}_{ij}^2 = \exp(-\widehat{\theta} n_{ij})$. The estimated value for the decaying parameter θ is in the 0-to-1 range, in line with the literature (see Van Praag and Ferrer-i Carbonell, 2004, p.144). The estimations of $\widehat{\theta}$ are reported in tables A1 (FGLS) and A2 (IV-FGLS). Column (1) displays estimations without controls, and column (2) with controls.

Table A1: FGLS, first step: non-linear least squares estimation results of the θ parameter.

	(1)	(2)
	NLLS	NLLS
θ	0.160***	0.159***
	(20.71)	(20.31)
N	597	584

t statistics in parentheses

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

Table A2: IV-FGLS, first step: non-linear least squares estimation results of the θ parameter.

	(1)	(2)
	NLLS	NLLS
θ	0.161***	0.159***
	(20.96)	(20.34)
N	591	579

t statistics in parentheses

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

Robustness

In this section, we test the robustness of our results to three restrictions we imposed throughout our study. Firstly, we removed from our analysis recall errors which we suspected to be due to event mismatching (i.e. dating the wrong event) instead of event misdating (i.e. wrongly dating an event). Secondly, we adopted a cardinal interpretation of the subjective well-being variable, instead of an ordinal interpretation. Thirdly, we imposed a logarithmic structure to perceived recency, instead of a linear one.

Outliers

We test a “loose definition” of outliers, where we do not omit from our sample recall errors beyond 15 years and recall errors which seem to be due to event mismatch (i.e. dating the wrong event, instead of wrongly dating an event). This alternative definition changes the identification of the explained variable “recall error” as well as the values of recency and saliency.

Table A3 displays the outcome from the regression on the new sample of wage satisfaction, according to eq.5. Results are almost unchanged. Table A4 shows the instrumental variable regression of the recall error on wage satisfaction and covariates. Estimated coefficients are consistent with our previous analysis: wage satisfaction is still a significant determinant of the recall error for wage cuts. The effect associated with forward telescoping of wage cuts is 50% bigger, due to the fact that wage cuts happen with a lower frequency than wage raises. Accordingly, the inclusion of mismatched wage cuts tend to boost the related recall errors and, as an outgrowth, the coefficients associated with $\hat{h} \times (1 - v)$. For a similar reason, the coefficients associated with recency are also bigger.

Ordinal satisfaction

Although the least square estimation of subjective well-being is widespread, it implies a cardinal concept of reported satisfaction. The main justification is that the interpretation of the coefficients is straightforward

and that the estimation method does not greatly affect the results (Ferrer-i Carbonell and Frijters, 2004). For the sake of clarity, we relax the restriction on cardinal satisfaction and allow for a more flexible form. Hence, we adopt a non-linear estimator in the regression of wage satisfaction (Ordered Probit) and we use dummy variables for the different satisfaction levels in the regression of the recall error. Columns (1) and (2) in tables A5 and A6 display the results and essentially confirm our previous findings.

Linear recency

Through our analysis, we used a log-transformation of the variable *recency*. That is, we used the logarithm of the difference (in years) between the actual date and the recalled date, instead of the difference itself. To test that this assumption does not undermine our replication of telescoping effects, we run our regressions using $(t_0 - t_{-1})$ instead of $\log(t_0 - t_{-1})$. Columns (3) and (4) in tables A5 and A6 replicate the regressions respectively of wage satisfaction and of the recall error. Results are substantially the same, although the magnitudes of the coefficients associated with recency change, due to the different scale.

Table A3: Regression on wage satisfaction. Alternative definition of the recall error.

	(1)	(2)
	OLS	OLS
Dependent variable: wage satisfaction		
log(wage)	0.509*** (8.20)	0.282*** (3.77)
rank		0.641*** (5.13)
recalled recency (wage cut)	0.102** (2.34)	0.0784* (1.81)
recalled recency (wage raise)	-0.231** (-2.57)	-0.240*** (-2.70)
saliency	-0.00124 (-1.41)	-0.000911 (-1.05)
cut?	-0.447*** (-3.04)	-0.423*** (-2.89)
age	-0.00956 (-0.42)	-0.0225 (-0.99)
age ²	0.000119 (0.45)	0.000265 (1.01)
French?	-0.343** (-2.17)	-0.360** (-2.25)
male?	0.0493 (0.86)	0.0428 (0.75)
Observations	788	779

t statistics in parentheses

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

Note: All regressions include a constant, dummy variables for the education level, long-term contract?, tenure, part-time?, working sector, private sector?.

Table A4: Instrumental variable regressions of the recall error. Alternative definition of the recall error.

	(1)	(2)	(3)	(4)
	2SLS	2SLS	IV-FGLS	IV-FGLS
Dependent variable: recall error				
$\hat{h} \times cut?$	4.016*** (2.82)	4.057** (2.40)	4.928*** (4.75)	5.742*** (4.19)
$\hat{h} \times raise?$	-0.839 (-0.86)	0.599 (0.42)	-0.778 (-0.64)	1.431 (1.04)
recency	-4.719*** (-10.81)	-4.779*** (-10.65)	-3.132*** (-8.42)	-3.286*** (-8.66)
saliency	-0.000396 (-0.05)	0.00266 (0.35)	0.0108* (1.77)	0.0137** (2.15)
cut?	-6.947** (-2.16)	-3.458 (-1.37)	-9.547*** (-2.85)	-6.099** (-2.24)
age	0.370*** (2.65)	0.355** (2.47)	0.228 (1.63)	0.254* (1.77)
age ²	-0.00245 (-1.44)	-0.00269 (-1.54)	-0.000827 (-0.50)	-0.00150 (-0.89)
male?	-0.350 (-0.93)	-0.452 (-1.09)	-0.265 (-0.77)	-0.0604 (-0.16)
log(wage)		-1.259 (-1.45)		-2.024*** (-2.77)
Job-related controls	no	yes	no	yes
Observations	803	786	803	786

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

Note: \hat{h} = predicted wage satisfaction; *raise?* = wage raise; *cut?* = wage cut. Instrument: $rank = 1 - \frac{r-1}{NR-1}$. All regressions include a constant and dummy variables for nationality and the education level. Where specified, they also include controls for job-related characteristics: long-term contract?, tenure, part-time?, working sector, private sector?.

Table A5: Regression of wage satisfaction. Alternative hypothesis on linear effects.

	(1)	(2)	(3)	(4)
	Ord.Probit	Ord.Probit	OLS	OLS
	Dependent variable: wage satisfaction			
log(wage)	0.857*** (6.94)	0.501*** (3.46)	0.469*** (6.70)	0.257*** (3.09)
rank		1.065*** (4.25)		0.620*** (4.32)
recalled recency(wage cut)	0.218** (2.57)	0.187** (2.18)		
recalled recency(wage raise)	-0.348* (-1.84)	-0.383** (-2.01)		
linear recalled recency(wage cut)			0.0149** (2.36)	0.0120* (1.92)
linear recalled recency(wage cut)			-0.0470** (-2.01)	-0.0487** (-2.10)
N	584	577	584	577

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

Note: All regressions include constant term(s), saliency, cut?, sex, age, age², diploma, French?, long-term contract?, tenure, part-time?, working sector, private sector?.

Table A6: Instrumental variable regressions of the recall error. Alternative hypothesis on linear effects.

	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
	Dependent variable: recall error			
$\widehat{unsat} \times cut?$	2.862*** (3.72)	3.429*** (4.55)		
$\widehat{sat} \times cut?$	3.764*** (4.56)	3.627*** (3.82)		
$\widehat{verysat} \times cut?$	5.801*** (3.25)	9.230*** (4.72)		
$\widehat{unsat} \times raise?$	-0.0405 (-0.06)	0.0295 (0.05)		
$\widehat{sat} \times raise?$	-0.192 (-0.27)	0.160 (0.19)		
$\widehat{verysat} \times raise$	0.0422 (0.02)	1.196 (0.81)		
$\widehat{h} \times cut?$			3.001** (2.24)	2.855* (1.84)
$\widehat{h} \times raise?$			-0.809 (-0.72)	0.503 (0.34)
recency	-3.394*** (-9.95)	-3.336*** (-9.64)		
linear recency			-0.517*** (-8.56)	-0.524*** (-8.34)
job-related controls	no	yes	no	yes
N	591	579	591	579

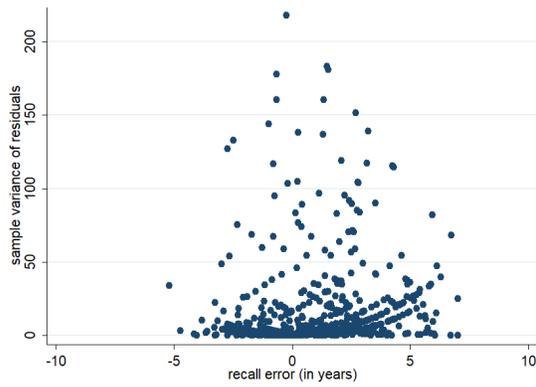
t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: $unsat = 1$ if wage satisfaction = 2, 0 otherwise; $sat = 1$ if wage satisfaction = 3, 0 otherwise; $verysat = 1$ if wage satisfaction = 4, 0 otherwise. All regressions include a constant, saliency, cut? and socio-demographic characteristics: sex, age, age², diploma, French?. Where specified, they also include controls for job-related characteristics: log(wage), long-term contract?, tenure, part-time?, working sector, private sector?.

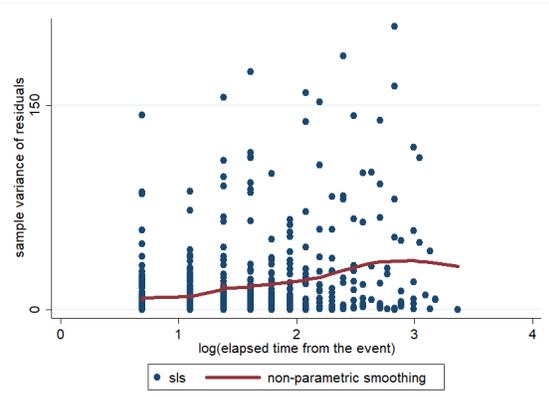
Figures

Figure A1: Visual illustration of heteroskedasticity

(a) Variance of the residuals with respect to the recall error

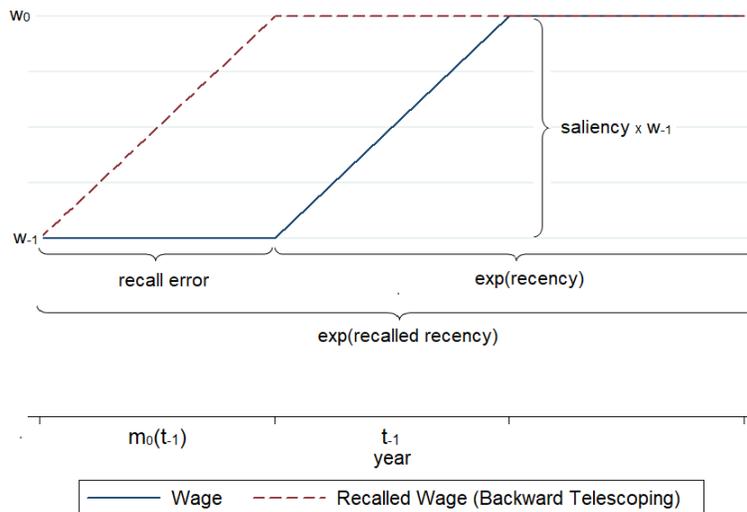


(b) Variance of the residuals with respect to the recency



Reading note: The two figures show the conditional distribution of the variance of residuals from eq.7, with respect to the explained variable “recall error” (fig.(a)) and to the explanatory variable “recency” (fig.(b)). In figure (b), we can see that the variance of the residuals increases as the event happened further in time, according to a relationship which is also illustrated by a locally weighted smoothing (the thick line in the plot).

Figure A3: Graphical illustration of the variables



Reading note: The figure reproduces an example of backward telescoping for a wage raise. The dotted lines and the full lines refer respectively to the recalled wage trajectory and the actual wage trajectory. The temporal distance from the wage change is equal to the exponential of *recency*, while *saliency* is equal to the size of the wage change, weighted by the amount of the initial wage.