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ABSTRACT

Preferences and COVID-19 Vaccination Intentions*

This paper shows that prospect theory, extended to account for differences across individuals in their patience and their valuation of the vaccination as a common good can explain why more than 40% of the population has intent to reject the Covid-19 vaccination, as well as the differences in vaccination intentions across population subgroups. Indeed, prospect theory by over-weighting the side effect explains the reject of vaccination. This can be partially compensated by a high patience and/or a large valuation of the collective immunity. The calibrated version of our model, based on an original survey carried out on a representative sample of the adult population living in France allowing us to identify curvatures of their value function, their discount rates and their willingness to cooperate, can predict the evolution of the vaccination intentions between November 2020 an March 2021. We also show that the international differences in the vaccination intentions are closely related to the valuation of the vaccination as a common good.

JEL Classification: D81, I12

Keywords: behavioral economics, COVID-19, prospect theory, vaccination choice

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1 Introduction

Vaccination is an individual decision where risk, time and social interactions are crucial. Decision theory can therefore shed light on the determinants of this choice. The vaccination against the Covid-19 is interesting because we observe in some countries a large amount of people having not intention to vaccine.[1] Given the risk of fatal disease, albeit low for younger adults, and the availability of highly efficacious vaccines with excellent safety profile, the expected utility (EU) model will always predict that vaccination is preferred, even though vaccination may have side effects whose expected cost remains lower than the expected cost of the disease.

How to explain this paradox? In this paper, we use prospect theory of Kahneman and Tversky (1979) to solve it. Nevertheless, other arguments than risk may explain vaccination: a high valuation of the long run well-being, or a positive valuation of the participating to herd immunity may argue in favor to vaccine. Therefore, we propose a model integrating risk, time and external effects of social interactions for predicting vaccination intentions. Thereafter, we compare model implications to their empirical counterparts reported in an original survey. Our empirical approach is based on a survey recorded at the end of November 2020 (before the first vaccinations) on a representative sample, that regroups information on Covid-19 vaccination intentions as well as on agents' preferences identified through experimental methods. More precisely, our survey contains results of hypothetical financial decisions asked to each respondent allowing to identify their preferences with regard to risk using Holt and Laury (2002)'s lotteries, time perception (Frederick et al. (2002)), and the propensity to cooperate.[2] Therefore, we can use the results of these experiments to calibrate the model and then to test its ability to predict the observed vaccination intentions.

The decision under risk has been the subject of many developments. In particular, Kahneman and Tversky (1979) and Tversky and Kahneman (1981) have shown that people systematically violate the predictions of EU.[3] Their constructive approach leads them to propose an alternative

[1] For example, at the end of November 2020 (We retain this date because our original survey has been recorded at the end of November 2020), the French who are very strongly affected by the pandemic with 787 deaths per million of inhabitants (compared to 873 in the United Kingdom and 200 in Germany, the two other biggest countries in Europe), are also those having the lowest intentions to vaccine with only 47% of people (compared, at the same time, to 77% for the British and 65% for the Germans). See IPSOS (2020).

[2] Individuals' intrinsic motivations for contributing to a public good can be manifold. Three types of motives can be put forward to rationalize people's to sustain cooperation: *(i)* reciprocity motives (see e.g. Rabin (1993)), *(ii)* social image motives (see e.g. Benabou and Tirole (2006)) and *(iii)* altruistic motives (see e.g. Andreoni (1989)).

[3] See e.g. Barberisis (2013) for a survey on prospect theory.

framework that better fit experimental data: the prospect theory, characterizing by *(i)* a reference dependence (individuals are more attuned to changes in values than they are to their absolute magnitudes), *(ii)* a loss aversion (individuals are more sensitive to losses than to equivalent gains), *(iii)* diminishing sensitivity (the value function is concave for gains but convex for losses), and *(iv)* probability weighting (a weight function transforms probabilities by over-weighting low probabilities and under-weighting high probabilities).[4] Our first contribution consists to apply the Kahneman and Tversky (1979)'s model to vaccination choices, by taking into account side effects[5] as well as the valuation of the vaccination as a common goods. We then show that the impact of the diminishing sensitivity (assumption *(iii)*) is crucial in our vaccination intention analysis: in a context where the reference point (assumption *(i)*) is the good health, the low losses induced by the side effects can have a very important impact compared to the high losses induced by the disease, even death. This can be magnified by probability weighting (assumption *(iv)*) that over-weights in the region of the objective probability of side effects. Since illness and side effects are both losses, the trade-off between accepting or rejecting vaccination may be independent of loss aversion (assumption *(ii)*). However, by introducing a valuation of vaccination as a common good, the effect of loss aversion (assumption *(ii)*) does not disappear because this propensity to cooperate is present whether the individual is a victim or not of side effects. Finally, the impact of time perception is modeled as discounting effect on the health capital valuation: the most impatient individuals under-value this health capital, thus reducing the perception of its loss in case of disease.

We show that our model makes it possible to explain why some individual does not vaccinate, thus opening the door to an explanation of the data. An individual who does not valuate vaccination as a common good may not be vaccinated because the very small losses induced by side effects are very heavily weighted, and are moreover perceived as having very high occurrences. Impatience

[4]For monetary gains, L'Haridon and Vieider (2019) show that individuals in a large number of countries tend to overestimate the small probabilities of gain and underestimate the large probabilities of gain. For health outcomes, Fischhoff et al. (2000) show that the perception of risks to catch flu in the coming year reaches 50%, whereas its objective probability is only 31%. The pessimism is more marked with regard to the mortality rate, since it is perceived to be 0.19 whereas its objective probability is 0.00009. Carman and Kooreman (2014) obtain similar results: the subjective probabilities of dying from influenza are perceived to be 11% (13%) with (without) the vaccine, whereas the objective the objective probabilities are 0.006% and 0.03%, respectively in their experiments.

[5]Mild to severe reactions after Covid-19 vaccination are more frequently observed than with other vaccines, for example against flu. For example, Moderna Laboratory provides probabilities of local and systemic reactions: they are equal to 30% for persons aged for less than 65 years and to 20.9% for more than 65 years old (side effects probabilities for two doses). Severe side effects such as anaphylactic reaction are rare and without threat to health and life with simple treatment. See the website of the Center of Diseases Control and Prevention:
`https://www.cdc.gov/vaccines/covid-19/info-by-product/moderna/reactogenicity.html`

reinforces this choice by devaluing the positive long-term effects of the vaccine. A strong valuation of vaccination as a common good may lead to opting for vaccination.

With these analytical lessons, we turn in a second step to data analysis. We first use our survey to identify preference heterogeneity among the population. The answers to hypothetical financial decisions allows us to estimate *(i)* 5 possible curvatures of the value function, *(ii)* 4 possible discount rates and *(iii)* 6 possible levels of cooperation. Using these information on heterogeneity of preferences, we estimate in order to replicate the distribution of vaccination intentions. Beyond to well predict the vaccination rate by sub-groups of population (gender and age)[6], it also predict the behaviors of more than 60% of individuals. Thereafter, we show that the model can explain 85% of the evolution of the vaccination intentions between November 2020 to March 2021 in France. Finally, by assuming that preferences are the same across OECD countries, we show that the valuation of the vaccination as a common good can explain the large gaps in vaccination intentions observed between France, Germany, Italy, Spain, UK, Canada, Japan and the US. This last results suggests that public health information plays an crucial role in the roll-out of the vaccine.

Scientific evidence strongly supports vaccination programs as well as their safety (see e.g. Stern and Markel (2005)). Nevertheless, the vaccination rejection is mounting in OECD countries and becomes a major challenge for public health (see e.g. Shetty (2010)). Thus, the understanding of the behaviors leading to vaccination rejection is of crucial importance in order to increase coverage rates and thus to fight the Covid-19 epidemic. The paper contributes to the analysis of vaccination intentions by defining preferences that explain the observed individual decisions (perception for infection risks and side effects, valuation of the vaccination as a common goods, patience). There were already some papers explaining the risky behaviors in face of influenza epidemic Ritov and Baron (1990)[7], the AIDS epidemic (Kremer (1996)) or analyzing the altruistic dimension of the

[6]It is well known that gender and age lead to significant gaps in the vaccination intention. Other characteristics, such as education, geographic characteristic as well as health risks induced by co-morbid factors are also significant (see Volpp et al. (2020)). Nevertheless, we cannot use these dimension because we have not the mortality rate, as well as the probability of side effects, for each these characteristics.

[7]Ritov and Baron (1990) have shown that some people are reluctant to vaccinate a child when the vaccination can cause side effects, even though vaccination reduces the overall illness risk. This first bias then favors omissions (such as letting someone die) over commissions (such as killing someone actively). Indeed, omissions may result from ignorance whereas commissions involve more malicious intentions or more effort, itself a sign of stronger intentions. A second bias discussed in Ritov and Baron (1990) is the tendency to reject vaccine when there is a lack of information about probabilities for child to be victim of side effects. (these missing information being not obtained). Therefore, Ritov and Baron (1990) shows that vaccine rejection is much greater when the ambiguity relates to side effects of vaccination than to the risks of death from influenza. In our study, we restrict ourself to an analysis under risky environment but not in uncertainty, needing to use decision theory à la Gilboa and Schmeidler (1989) and Gilboa

vaccine decision in a public good context (Talamas and Vohra (2020), Bohm et al. (2016)). This behavioral dimension has led many authors to advocate the use of nudges (Thaler and Sunstein (2008)) for encouraging vaccination, as described in Chen and Ryan (2017) for the flu vaccination. It also complement previous studies that identified others factors explaining vaccination intentions such as religion, ideology, social pressure, misinformation and the concept of psychological antecedents of vaccine hesitancy (Tickner et al. (2006), Grabenstein (2013), Larson et al. (2016), Anderberg et al. (2011), Chang (2018), Hansen and Schmidtblaicher (2021), Qian et al. (2020) and Betsch et al. (2018)). Beyond preferences, the social interactions and free-riding behaviors also suggest that when a large population share is vaccinated, the incentives to vaccine are reduced for those without vaccinations, thus leading to difficulties in reaching full coverage (see e.g. Geoffard and Philipson (1997)). Nevertheless, it seems that the reluctance is a leading cause for vaccination rejection (see e.g. Lau and Hirani (2021)), then putting the individual preferences to the forefront.[8]

The plan of the rest of the paper is as follows. In the section 2, we first present the model. Having derived empirical predictions from the theoretical model, we undertake a quantitative analysis in the section 3. The section 4 is devoted to model predictions, on French and international data. Finally, section 5 concludes.

2 The vaccination decision

The choice of vaccination is modeled as a trade-off between two lotteries, the rejection of vaccination leading to opt for an option where the risk is the loss of one's health capital, while acceptance introduces the risk of getting vaccine-related side effects (VRSE). Following Grossman (1972), we assume hat health is an asset than provides utility and the arguments of the two options are:

- Without vaccine, the health stocks of an individual can take two values: T_d if she contracts the disease and T if she stays healthy, with $T_d < T$. The associated probabilities of these two states (T_d, T) are $(p, 1-p)$.

- With Covid-19 vaccine, the health outcomes are $(T - t + X, T + X)$ where t is the health loss induced by VRSE and X measured the health gains (psychological health) associated to

and Schmeidler (1995). We let these extensions for future researches.

[8] See e.g Bos and Postma (2010) or Cheny and Toxvaerd (2014) for survey on vaccination and economics.

the individual participation to the collective immunity, i.e. the individual valuation of the vaccination as a common good.[9] The probability of developing VRSE is noted q.

In order to maintain this trade-off inside reasonable option values, we assume that the VRSE are of second order in comparison with disease:

Assumption 1 ($A1$): The expected damage linked to VRSE is significantly lower than the expected losses induced by disease: $qt < p(T - T_d)$.

EU theory. The vaccination decision depends on the valuation of each health outcomes, given by the utility function $u(\cdot)$, with $u' > 0$ and $u'' < 0$. Individual accepts vaccine iff

$$qu(T - t + X) + (1 - q)u(T + X) > pu(T_d) + (1 - p)u(T) \tag{1}$$

The minimum value of the left-hand-side (LHS) of (1) with respect to X is obtained when $X = 0$ (no valuation of vaccination as a common good). Therefore, a sufficient condition to accept vaccination is $q[u(T) - u(T - t)] < p[u(T) - u(T_d)]$, which is always satisfied with $u(\cdot)$ linear and $A1$, but also when t is small with respect to T.[10] The vaccination intention is reinforced when $X > 0$, as well as with the concavity of the utility function. However, this decision theory on vaccination intentions is not consistent with the observed large fraction of the people rejecting the vaccination.

Prospect theory. Prospect theory introduces two modifications of EU: *(i)* value function replaces utility function, and *(ii)* decision weights replace probabilities. The value function, denoted $v(x)$, introduces a reference point, which is defined as the status quo (Kahneman and Tversky (1979), p. 274), and loss aversion . Decision weighting, denoted $w(p)$, models how a probability is transformed in a perceived risk. It assumes an over-weighting of small probabilities and an under-weighting of large probabilities. In our study, we will use the value function and the weighting function suggested by Tversky and Kahneman (1992), without differentiating the parameters for gains and losses, since we focus essentially on losses.

[9]More generally, X can be interpreted as the effect on welfare of contributing to disease eradication, which may generate positive utility as shown experimentally by Godinot et al. (2021). In the Grossman (1972)'s model, as utility is a function of health, it makes no difference to assume that X has a direct effect on health, or on the utility of choosing to be vaccinated.

[10]In this case, the approximation of (1) around T and for t close to zero, leads to $qu'(T)t < pu'(T)(T - T_d) + pu''(T)(T - T_d)^2 \Rightarrow qt < p(T - T_d) + p\frac{u''(T)}{u'(T)}(T - T_d)^2$ and is also satisfied under $A1$.

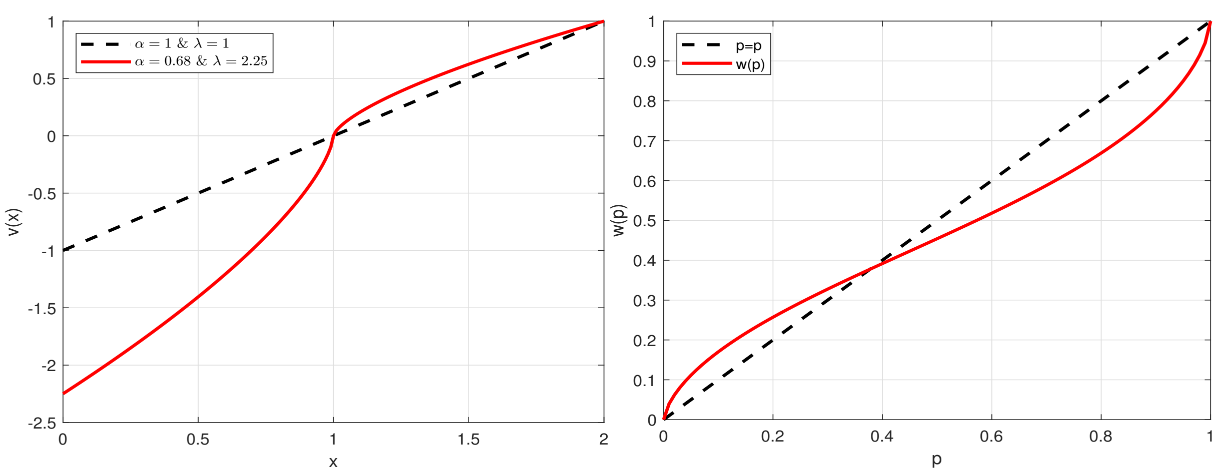
Assumption 2 ($A2$)**:** Preferences are given by, for all outcome x and probability y

$$v(x) = \begin{cases} (x-T)^{\alpha} & \text{if } x \geq T \\ -\lambda(T-x)^{\alpha} & \text{if } x < T \end{cases} \tag{2}$$

$$w(y) = \frac{y^{\delta}}{(y^{\delta}+(1-y)^{\delta})^{\frac{1}{\delta}}} \quad \text{for } 0 \leq y \leq 1 \tag{3}$$

with $0 < \alpha \leq 1$, $\lambda > 1$ and $0 < \delta \leq 1$.

First, we assume that the reference point is the initial stock of health T: a bad health episode (disease or VRSE) will be perceived as losses, and only cooperative agents can obtain a gain when they are vaccinated and healthy. Loss aversion is measured by $\lambda > 1$ that controls for the larger valuation of a one unit loss than a unit gain around the reference point, whereas α controls the curvature of the value function. The panel (a) of the Figure 1 shows that the value function gives more weight to a loss than for a gain of the same size, because $\lambda > 1$. The panel (b) of the Figure 1 shows that individual gives more weight to low probability than their objective values.[11] It is important to remark than given that $q > p$, this over-weighting of the objective probability is larger for VRSE risks than for the death risks.



(a) Value function $v(x)$

(b) Decision weight $w(p)$

Figure 1: **Prospect theory and preferences (assumption 2).** For the value function (Equation (2)), we normalize T to unity, and we set $\lambda = 2.25$ and $\alpha = 0.68$ as in our experimental data. For the weight function (Equation (3)), we set $\delta = 0.69$ as in Tversky and Kahneman (1992).

[11]When $\delta = 1$, we have $w(y) = y$ implying that individual does not transform probabilities.

The Covid-19 vaccination. Noting V and NV the options of the vaccination and non-vaccination respectively, the decision leading to the Covid-19 vaccination must then satisfy:

$$\mathcal{V}(NV) \equiv w(p)v(T_d) + w(1-p)v(T) \quad < \quad \mathcal{V}(V) \equiv w(q)v(T-t+X) + w(1-q)v(T+X) \quad (4)$$

Let us notice that higher values for t increase the probability to reject of vaccination.

Proposition 1. *High valuation of the common good dimension of the vaccination favors the vaccination strategy.*

Proof. If $X > t$, then all outcomes when the vaccination is chosen are perceived as gains with respect to the reference point: the vaccination is a dominant strategy as in the EU case or in a case without VRSE. This is not the case if $0 < X < t$. □

The valuation of the common good dimension of the vaccination strategy is thus crucial.
If $0 < X < t$, the decisions rule (4) becomes

$$-w(p)\lambda(T-T_d)^\alpha \quad < \quad w(1-q)X^\alpha - w(q)\lambda(t-X)^\alpha. \quad (5)$$

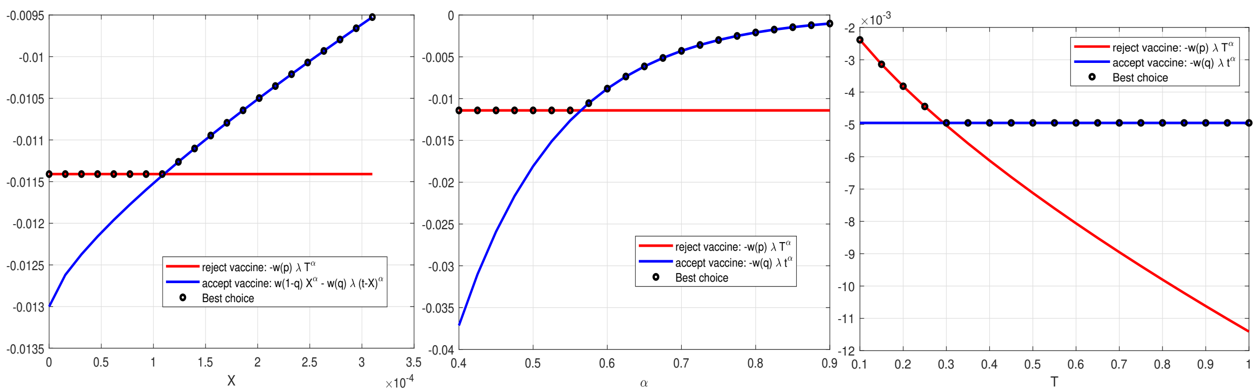
Proposition 2. *The vaccination will be a dominated strategy for individuals with a low valuation of the vaccination as a common good ($X < t$).*

Proof. Remark that $\min_{X\geq 0}\{w(1-q)X^\alpha - w(q)\lambda(t-X)^\alpha\} = -w(q)\lambda t^\alpha$ is reached at $X = 0$. We thus retain this lower bound for the RHS of (5) for the proof. A simple example where this inequality is not satisfied can be found by assuming $T_d = 0$, $T = 1$ and since t is of second order in relation with T, $0 < t < 1$. Therefore, the inequality (5) becomes simply $w(p) > w(q)t^\alpha$. It is obvious that for an ad hoc calibration such that $w(p) = tw(q)$ this inequality becomes $t > t^\alpha$ and is never satisfied with $0 < \alpha < 1$, then showing that it exists preferences such that vaccination is a dominated strategy. □

What about agent's impatience? Assume that T represents the actualized sum of days in good health h from today and until an horizon L, i.e. $T = \sum_{\tau=0}^{L} \beta^\tau h$ where $\beta \in [0;1]$ is the discount factor. For myopic agents (Strotz (1956)), $\beta \to 0$, and their impatience acts as if they have a short horizon: the perceived value of their health stock is then very small, i.e. of the same order of magnitude than the number of healthy days lost due to VRSE of the vaccine ($T \to t$).

Proposition 3. *Impatient agents (Myopic behaviors) reject more easily vaccination.*

Proof. For simplicity, assume that the valuation of vaccination as a common good is at its lower bond (i.e. $X = 0$). Impatient agents, characterized by a short horizon ($T \to t$), accept vaccination (Equation (4)) iff $u(t) - w(p)[u(t) - u(T_d)] < u(t) - w(q)[u(t) - u(T_d)] \Leftrightarrow (w(p) - w(q))[u(t) - u(T_d)] > 0$. Since $q > p$, this condition is not satisfied: impatience can lead to reject vaccination. $\square$



(a) Impact of X

(b) Impact of α

(c) Impact of T

Figure 2: **Rejection or acceptance of vaccination: Equation (3).** For these numerical examples, we set $T_d = 0$ and $w(q) = 0.2935$ and $w(p) = 0.0051$. In panels (a) and (b), we have $T = 1$ and $t = 0.00075$. In panels (a) and (c), we set $\alpha = 0.68$. In panels (b) and (c), we set $X = 0$. In panel (c), we have $t = 0.0031$.

The Figure 2 shows how the best option can be modified by the valuation of the vaccination as a common good (impact of X in panel (a)), the curvature of the value function (impact of α in panel (b)) and the myopic behaviors (impact of T in panel (c)). Proposition 1 indicates, the greater the evaluation of vaccination as a common good (X) the higher the option value of vaccination (see Panel (a) of the Figure 2). The panel (b) of the Figure 2 shows that low values for α the best strategy is to reject the vaccine. Indeed, using the equation (5) which is simply $w(p) > w(q)t^\alpha$ when $X = T_d = 0$ and T normalized to unity (implying $t < 1$), we deduce that large values for α allows this restriction (the vaccination acceptance) to be more likely satisfied. Finally, the panel (c) of the Figure 2 shows that only the option of vaccination rejection depends on T: the greater the T, the greater the chance of satisfying this inequality, and therefore the greater the rate of acceptance of the vaccination.[12]

Our model can be viewed as a decision threshold framework, where the decision maker switches from the no treatment to the treatment decision, in our case the vaccination decision, if the probability of disease is higher than a threshold. This notion has been initially defined for curative treatment by Pauker and Kassirer (1975), then extended in various directions as a tool to help making curative treatment decisions by considering a diagnostic risk (Pauker and Kassirer (1980)), a therapeutic risk (Eeckhoudt (2002)), and both a diagnostic and a therapeutic risk (Felder and Mayrhofer (2018) and Felder (2020)).

3 Empirical Analysis

3.1 Calibration and Estimation Methods

The numerical solution of our discrete choice model is based on two set of parameters: a first set is based on external information, and the second is estimated using the model restrictions and the observed data.

Calibration based on external information: Ψ. A first set of calibrated parameters is common to each agent:

$$\Psi_1 = \{T_d, \lambda, \delta\} \text{ with } dim(\Psi_1) = 3.$$

For simplicity, we normalize $T_d = 0$ by assuming that it corresponds to death. For the parameter values of preferences, we retain the values of Tversky and Kahneman (1992), i.e. $\lambda = 2.25$ and $\delta = 0.69$.[13]

The probability of death after a Covid-19 infection (p_i) is age and gender specific. In our sample, we can identify $67 \times 2 = 134$ states with respect to (w.r.t.) these dimensions ($\max(Age) - \min(Age) + 1 = 67$). The Figure 3 shows that this probability increase very strongly after 60 years and is significantly highest for men. Finally, let us remark that the decision weights magnify the objective probability of death after a Covid-19 by multiplying the risk of death by 80 for those

[12] Obviously, there are interactions between the impacts of parameter (X, α, T) on the vaccination intentions. See the Figure 4 or the Figures in the Appendix A that illustrate these interactions.

[13] These parameters, in particular the loss aversion (λ) cannot be deduced from our data.

younger than 25 years (those with the lowest probability of death) and by only 10 for those older than 70 years (those with the highest probability of death).

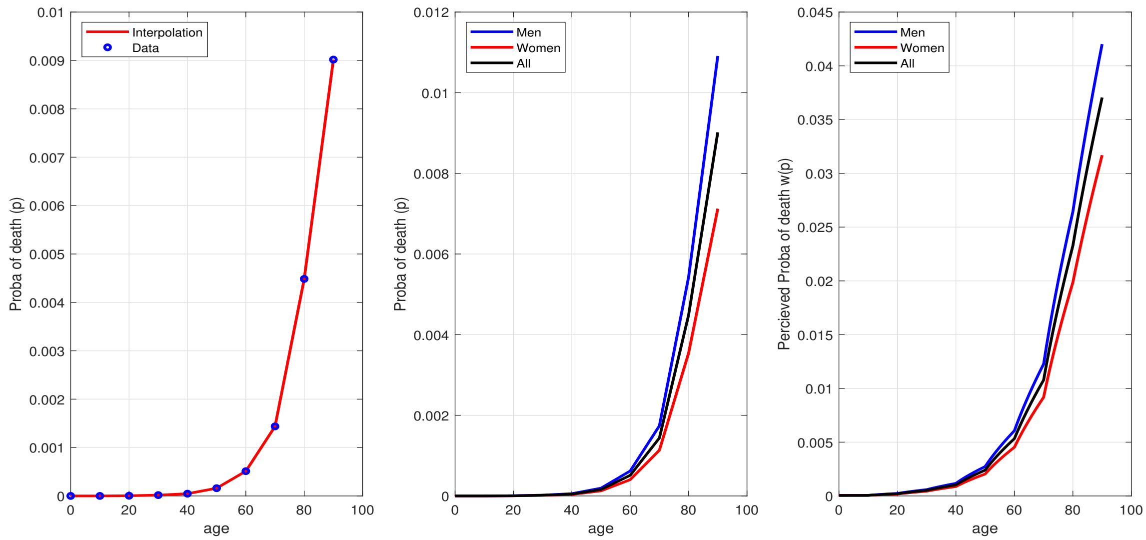


Figure 3: **Probability of fatal Sars-Cov2 infection over 8 months by Age and Gender in France (November 2020).** Data: Santé Publique France

Moderna provides probabilities of VRSE (local and systemic reactions) for each of the two doses by sub-groups of population by age, the persons aged for less than 65 years, the young (Y) and for more than 65 years, the old (O).[14,15] We add the two probabilities for each dose in order to have the global risk for VRSE of vaccination. We then obtain $q_i \in \{q_Y, q_O\}$ with $q_Y = 30\%$ and $q_O = 20.9\%$.

The last set of calibrated parameters is based on experimental data and thus being individual specific

$$\Psi_{2,i} = \{T_i, X_i, \alpha_i\} \text{ with } dim(\Psi_{2,i}) = 3.$$

The survey allows us to identify 4 values for T, 5 values for α and 6 values for X thus leading to 120 deterministic characteristic in our sample (120 states for preferences).

Estimated parameters: θ. Firstly, we assume that the size of VRSE in term health losses is age-specific: $t_i \in \{t_Y, t_O\}$. Secondly, we assume that measurement errors can affect the values of

[14] See the website of the Center of Diseases Control and Prevention:
`https://www.cdc.gov/vaccines/covid-19/info-by-product/moderna/reactogenicity.html`

[15] It also exist information on trials conducted by Pfizer and Astra Zeneca, but the subgroups of population are not homogeneous, thus not allowing us to compute the average probabilities for side effects over all population and by age. We then arbitrary use only the Moderna statistics. In addition, our empirical analysis being carried out in November 2020, it is not relevant to integrate the risks of side effects differentiated according to the vaccine's type, information which will be known later.

α_i and T_i: their possible values, denoted $\widetilde{\alpha}_i$ and $\widetilde{T}_i$, are lower than α_i and T_i. They can differ from the values for the vaccine decision since it is for hypothetical monetary decisions. Finally, the size of X (the warm glow effect of the vaccination) is indeterminate: here, we simply introduce a multiplicative coefficient. Therefore, we introduce the following set of parameters:

$$\widetilde{\alpha}_i = a_1 \alpha_i + (1 - a_1), \qquad \widetilde{T}_i = a_2 T_i + (1 - a_2), \qquad \widetilde{X}_i = \quad a_3 X_i.$$

Therefore, the vector of estimated parameters is

$$\theta = \{a_1, a_2, a_3, t_Y, t_O\}$$

Targeted Moments. A first set of moments regroups the prevalences of vaccine acceptance by subgroup of population, abusively denoted VR as "vaccination rates":

$$VR_\omega = \frac{\sum_{i \in \omega} \mathcal{P}_i}{T_\omega} \quad \forall \omega \in \{F, M, Y, O\} \text{ and } T_\omega = dim(\omega)$$

where, for each individual i, $\mathcal{P}_i = 1$ if $\mathcal{V}_i(V) > \mathcal{V}_i(NV)$ and $\mathcal{P}_i = 0$ otherwise.

A second set of moments measures the consistency between the model predictions and the vaccination intentions registered in our survey for each individuals i. For each subgroup ω, we compute the fraction of individuals that the model correctly predicts: the number of person for which the model predicts correctly they accept vaccine among all individuals that accept vaccine (CY) as well as the fraction of individuals that the model correctly predicts that they reject vaccine among all individuals that reject vaccine (CN). These consistency rates are:

$$CY_\omega = \frac{\sum_{i \in \omega} \mathbb{I}(\mathcal{P}_i = 1 \ \& \ \mathcal{D}_i = 1)}{\sum_{i \in \omega} \mathcal{P}_i} \quad \text{and} \quad CN_\omega = \frac{\sum_{i \in \omega} \mathbb{I}(\mathcal{P}_i = 0 \ \& \ \mathcal{D}_i = 0)}{\sum_{i \in \omega} (1 - \mathcal{P}_i)}$$

where $\mathcal{D}_i$ are the vaccination intentions registered in our survey, i.e. $\mathcal{D}_i = 1$ if the respondent accepts the vaccine and $\mathcal{D}_i = 0$ otherwise. Therefore, the targeted moments are

$$m_T = \{VR_F, VR_M, VR_Y, VR_O, 1, 1, 1, 1, 1, 1, 1, 1\} \text{ with } dim(m_T) = 12$$

where the 8 last moments are set to one, meaning that the target is a consistency of 100%.

Estimation. Using $\Psi \equiv \{\Psi_1, \{p_i, q_i, \Psi_{2,i}\}_{i=1}^T\}$ and θ, we evaluate for each of the T individuals in our sample

$$\mathcal{V}_i(NV) \equiv -w(p_i)\lambda \widetilde{T}_i^{\widetilde{\alpha}_i} \qquad \text{and} \qquad \mathcal{V}_i(V) \equiv w(1-q_i)\widetilde{X}_i^{\widetilde{\alpha}_i} - w(q_i)\lambda(t_i - \widetilde{X}_i)^{\widetilde{\alpha}_i}$$

The model parameters θ is found by solving the following problem[16]

$$\min_\theta g_T(\theta) = \min_\theta [m_S(\theta) - m_T]'[m_S(\theta) - m_T]$$

where $m_S(\theta)$ are the simulated moments corresponding to empirical targets m_T:

$$m_S(\theta) = \{VR_F^S, VR_M^S, VR_Y^S, VR_O^S, CY_F, CN_F, CY_M, CN_M, CY_Y, CN_Y, CY_O, CN_O\}.$$

These moments depend on individual behaviors, but also to how many agents have preferences that lead them to prefer the vaccination option. The mass of each agent-type is thus determined by her age and gender but also by her preference characteristics.[17] By aggregation, the model predicts the acceptance probability of vaccination over all population or over each sub-groups using the distribution of characteristics observed in our sample. Beyond these aggregate rate, the predicted vaccination acceptance can then be compared to the vaccination intention registered in our survey for each individual: these results are summarized by the statistics of consistency CY and CN.

3.2 Data

The data collection was conducted online over 908 people from November 26 to December 1, 2020, applying the quota method throughout metropolitan France. The questionnaire did not take more than 20 minutes to complete (we only use part of it here) and was paid €3. The questionnaire was composed of three parts: *(i)* one investigating socio-economic, health and attitudes towards Covid-

[16] In our objective function, we implicitly use a weight matrix with 1s on the diagonal, and hence, we give the same weight at all moments in the estimation process. This restriction is motivated by the fact that consistency measures (CY and CN) are not statistics but theoretical restrictions. Without uncertainty measure for all targeted moments, we are then forced to use this diagonal matrix.

[17] Using our experiments, we identify a discrete space of preference characteristics of dimension $N = 6 \times 5 \times 4 = 120$.

19 vaccination, *(ii)* the second included a choice experiment on preferences for epidemic control measures (not used here), and *(iii)* the third part was 8 decisions in order to measure economic preferences (risk, time, and warm-glow).[18] Our experimental had been collected at the end of the second French lockdown.[19]

		share	*std*			share	*std*
Gender	Female	51.21	1.60		Total	47.13	1.65
Age	65+ years	13.76	1.14	Vaccination	Female	38.27	2.25
				intentions	Male	56.43	2.35
					<65 years	44.82	1.77
					65+ years	61.60	4.35

Table 1: **Descriptive statistics.** Lecture: there are *(i)* 51.21% of Females in the sample and thus 48.79% of Males to complete for the "Gender", *(ii)* 13.76% of 15-64 years and thus 86.24% of 65 years to complete for "Age". The vaccination intentions, 47.13% of individuals answer "Yes, maybe" or "Yes, absolutely" to the question "Would you accept the vaccination against Covid-19, if it were recommended to you by your physician?", and therefore 53% answer "No, definitely not", "No, probably" or "I don't know".

The Table 1 provides the shares of female (51.21%) and elderly (more than 65 years old, 13.76%) in our data. It also give the intention to vaccine against the Covid-19, by age and gender: among the respondents of our survey, only 47.13% of individuals have the intention to vaccine (41.3% have no intention to vaccine: "No, definitely not" "No, probably"; 11.56% do not know), vaccination being the majority among men and those over 65 years of age.

Risk and decisions. To analyze decision making under risk, we use a simple version of Holt and Laury (2002)'s grid. In the 4 choices, A offers a probability p of winning €5,000, and €4,000 otherwise, while B offers a probability p of winning €10,000, and €500 otherwise. The probability p is successively 80, 60, 40 and 20%. For each p, the individual indicates his choice: the level of p from which he switches from B to A gives an indication of his aversion to risk.[20] The smaller p, the

[18] The decisions are stated by indicating that a benefactor was giving money to the respondent when she asks her to make decisions.

[19] During this second lockdown, the French population could move freely to go at work. French citizens have strong views on this crisis, which had been undergone for nearly nine months. Intensive care admissions and deaths had just passed their peak in mid-November, but uncertainties for the future were high. The closure of so-called nonessential retailers raised questions, as did the non-reopening of cultural venues. French people were moving from lockdown to an equally tight curfew.

[20] For example, with an individual with EU preferences, the expected gains $\mathcal{U}_A \in \{4800; 4600; 4400; 4200\}$ for the option A and $\mathcal{U}_B \in \{8100; 6200; 4300; 2400\}$ for the option B. For $p \leq 0.4$ option A becomes preferable ($\mathcal{U}_A > \mathcal{U}_B$) for a risk neutral agent. If option A is preferred for $p > 0.4$, then the agent is risk averse, whereas if B continues to be the preferred option for $p < 0.4$ the agent is risk lover. For $p \leq 0.4$ option A becomes preferable for a risk neutral agent. If option A is preferred for $p > 0.4$, then the agent is risk averse, whereas if B continues to be the preferred option for $p < 0.4$ the agent is risk lover.

greater the risk aversion. The Table 2 reports the results of this experiment in our survey.

Using lotteries experiments to calibrate model. For vaccination choice, preferences are given by $A2$. In order to estimate the value of α, we choose as reference point for the Holt and Laury (2002)'s lotteries the max min of both lotteries, in other words the minimum outcome that could be insured: the reference point is assumed to be 4000. Therefore, we compare the two following alternatives:

$$A: \ w(p)1000^{\alpha} \ \text{ with } \ B: \ w(p)6000^{\alpha} - w(1-p)\lambda 3500^{\alpha}.$$

For each individual, we can deduce the threshold parameter α such that $A \sim B$:

$$w(p)1000^{\alpha} = w(p)6000^{\alpha} - w(1-p)\lambda 3500^{\alpha} \quad \Leftrightarrow \quad w(p)(6^{\alpha} - 1) = w(1-p)\lambda 3.5^{\alpha}$$

This restriction provides a link between each individual data p and three parameters $\{\alpha, \lambda, \delta\}$. Therefore, we calibrate two of them, and estimate the last one with the "moment" p. Following Tversky and Kahneman (1992), we retain the values $\delta = 0.69$ (weighting function for losses) and $\lambda = 2.25$ for loss aversion. Hence, the weight of the probabilities are $w(p) \in \{0.17; 0.328; 0.454; 0.588; 0.775\}$ for $p \in \{0.1; 0.3; 0.5; 0.7; 0.9\}$. For each value of $p \in \{0.1; 0.3; 0.5; 0.7; 0.9\}$, we then deduce the following estimated values for α, which are $\widehat{\alpha} \in \{0.56, 0.47, 0.39, 0.31, 0.18\}$. The higher the value of p, the higher the risk aversion, i.e. the lower the value for α. Loss aversion causes premature rejection of B (the riskiest option) over EU preferences, resulting in a lower α parameter.

Warm glow and public good game. The first experiment reproduces a sample public good game (Samuelson (1954)), played at 4 players. They are each given an endowment of €5,000 and can choose to invest 0, 1,000, 2,000, 3,000, 4,000 or €5,000 in a group project, then divided equally between the 4 players, regardless of the amount paid. It is specified that the amount of this group project is multiplied by 2 before the transfer.[21] This experiment simply measures the degree of

[21] Here, we assume that an individual cares nothing at all for the public good, but gives only for the warm glow, ie. she maximizes an utility function that characterizes an egoistic individual valuating the warm glow (see Andreoni (1989)). Indeed the evaluation of public good requires a repeated game where individual can learn about the type of the other game participants and then play strategies.

Intensity in choices		0	1	2	3	4	5
Risky choices	share	8.04	8.04	24.66	24.33	33.92	–
	std	0.90	0.90	1.43	1.44	1.57	–
Patience	share	50.77	11.12	16.41	21.69	–	–
	std	0	1	2	3	–	–
Cooperation	share	11.01	32.26	25.88	13.21	4.40	13.21
	std	1.03	1.55	1.45	1.12	0.68	1.12

Table 2: **Descriptive statistics.** For risky choices, individuals are faced with 4 different lotteries where they must choose between a risky option and a safe option. The variable takes the value 0 if the individual always chooses the safe option, and 4 if she always chooses the risky option. For time decisions, individuals are faced with 3 different binary choices where they have to choose a sum of money today or a larger sum in a year. The variable takes the value 0 if the individual always chooses to take money immediately, and the value 3 if she always wait one year to take money. For measuring propensity to cooperate, the variable takes the value 0 if the individual puts €0 in a common pot and 5 if she puts €5000.

warm glow (see Andreoni (1989)) which is maximum by transferring all its initial endowment into the common pot for warm glow motives. Fifty years of experiments have shown that participants contribute to the public good between 40 and 60% of their initial stake (Zelmer (2003)). Results of our experiment (see Table 2) are in this range: our average transfer is equal 41.5%.

Using the public good game experiments to calibrate model. In our model, we assume that the valuation of the public good is a warm glow: hence, we simply have $X = -x + F(x)$ where $F(x)$ corresponds to the welfare gains to public goods, $F(x) = \frac{1}{a}\Psi x^a$ with $0 < a < 1$, net of the voluntary contribution, x. The optimal solution is $x^* = \Psi^{\frac{1}{1-a}}$ and thus $X = \frac{1-a}{a}\Psi^{\frac{1}{1-a}} = \frac{1-a}{a}x^*$. If we normalize to unity the endowment, the value of the contribution to the public good is proportional to $X = \{0; 0.2; 0.4; 0.6; 0.8; 1\}$, but its level remains undetermined.

Time preferences. For the time preferences, 3 choices were proposed between amounts today and in one year: choice A gives 5,300, 5,600 or €5,900 immediately whereas the choice B provides €6,000 in one year. The larger the preference for the present, the lower the choice in option A. The decision-maker is impatient in this last case, neutral for 2 choices in A, and patient otherwise. The impatient agents have a very high discount rate, 13.20%, usually observed in experimental studies with immediate option available (Frederick et al. (2002)), the patient and the very patient have a discount rate of 7.14% and 1.69% respectively. In our experiment (see Table 2), half of the subjects chooses the first option of A.

Using time experiments to calibrate model. We have normalized $T = 1$. With an average distance to death equal to 37 years in our sample, this means that we normalize to unity $T = 37 \times h$. Then, we account for a high discount rate by reducing $T = 1$, in accordance with the discounting of the agents. For $\widehat{\beta} \in \{0.87; 0.93; 0.98; 1\}$ deduced from our experimental data, we obtain $\widehat{T} = \{0.22; 0.36; 0.71; 1\}$ for time horizon of 37 years, leading to $T = \frac{1-\beta^{37}}{1-\beta} \times h/(37 \times h)$.

Selection of the individuals. Obviously, not all of the individuals in our survey make consistent choices. We have therefore chosen to exclude all those who were not consistent[22] in their responses because our calibration is based under the assumption that individuals use decision theory to make choices: the statistics are therefore made on 67% of consistent individuals, i.e. 608 people among the 908 questioned. Among the 300 non-consistent (i.e. 33%), 30 were not consistent only for time decisions, 231 only for risky decisions and 39 for both.

3.3 Results

The results of the estimations are reported in Tables 3 and 4. The model fit all the average rates

Groups (ω)		All	< 65 (Y)	65+ (O)	Female (F)	Male (M)
Prevalence of	VR_ω model	48%	47%	55%	41%	55%
vaccine acceptance	VR_ω data	47%	38%	55%	41%	55%
Consistency	CY	59%	56%	61%	52%	61%
	CN	57%	60%	54%	65%	51%

Table 3: **Targeted Moments**. Predicted and observed population proportions that accept vaccine (prevalence rates) and consistency rates.

of vaccination intention, even if it slightly over-estimate the one of the youngest individuals (see Table 3).[23] It is also important to notice that the consistency between the individual vaccination

[22] An individual is considered as non-consistent if she prefer a safe lottery to a moderate risk one but prefer a highly risky lottery to the safe one. The same reasoning applies for choice in time.

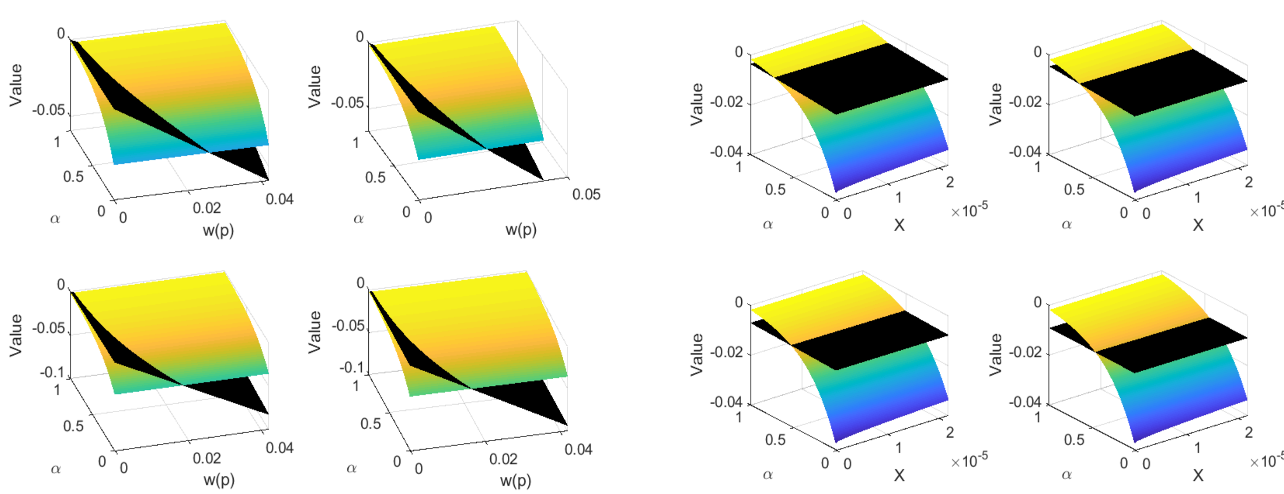
[23] The results are better for the over 65s who are most concerned by the vaccination at this period, but also because the under 65s include two age groups that certainly do not have the same risks, the under 50 years and 50-64 years. However, Moderna having only communicated on the VRSE risks for two age groups (under 65 and over 65), it was not possible to estimate the 50-64 age group in order to improve the fit for the young. Let us notice that if we assume that the VRSE risk is $q_{50-64} = \varpi q_Y + (1-\varpi) q_O$ with $\varpi = 25\%$ for the 50-64 years old, then an estimation of $\widehat{t}_{50-64}$ =7e-04 leads to reproduce the vaccination intentions of the 50-64 years old (52%) and to improve the model's fit for the under 65 that would become $VR_Y = 33\%$.

intentions reported in the survey and the model's predictions for each agent are quite high, with the model predicting approximately 60% (between 52% and 61%) and of vaccination intentions for all groups of agents, as well as 60% (between 51% and 65%) of the intentions to reject the vaccine.

$\widehat{a}_1$	$\widehat{a}_2$	$\widehat{a}_3$	$\widehat{t}_Y$	$\widehat{t}_O$
0.7879	0.5154	2.1920e-05	1.5835e-04	2.2634e-03

Table 4: **Estimated parameters.** Solution for $\theta \equiv \{a_1, a_2, a_3, t_Y, t_O\}$.

The parameters that allow the model to reach this good fit are in Table 4. With respect to the evaluations of $\{T, \alpha\}$ deduced from our experimental data, it appears that both are slightly increased when we use our health data because $\widehat{a}_1 < 1$ and $\widehat{a}_2 < 1$. For the time discounting, T is increased from $T \in \{0.22; 0.36; 0.71; 1\}$ to $\widetilde{T} \in \{0.3854; 0.4957; 0.7715; 1\}$. This implies estimated values for $\beta \in \{0.936; 0.9555; 0.985; 1\}$, i.e. discount rates in $\{6.83; 4.65; 1.52; 0\}$, which are reasonable values. The same is true for α, our estimation shifting its estimate from $\alpha \in \{0.56; 0.47; 0.39; 0.31; 0.18\}$ to $\widetilde{\alpha} \in \{0.7732; 0.7268; 0.6856; 0.6443; 0.5773\}$. This upward adjustment of α leads it to more usual values, its population mean now being 0.7, closer to the value reported in Tversky and Kahneman (1992).

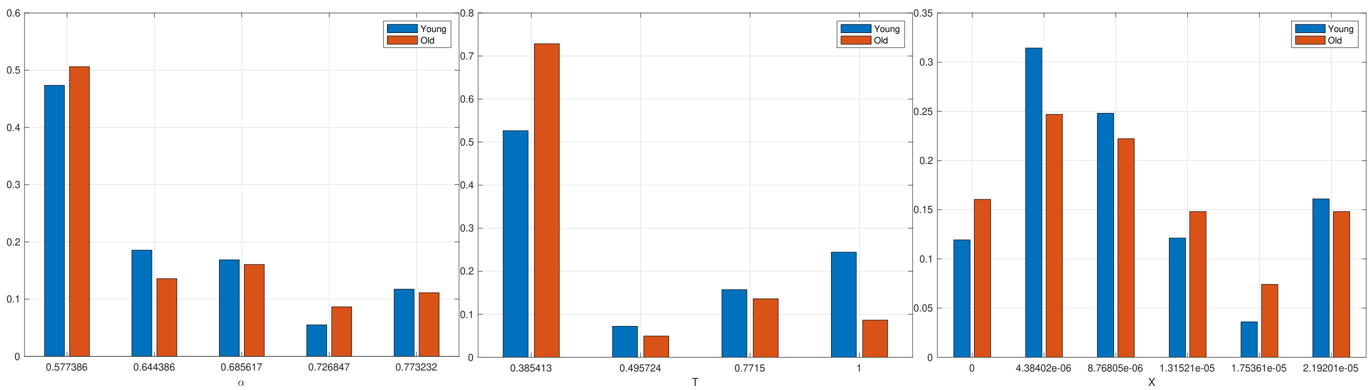


(a) Impact of T, α and aging

(b) Impact of T, α and X

Figure 4: **Vaccination intentions.** In panels (a) and (b), the NW graphic represent decisions with $T = 0.22$, the NE graphic those with $T = 0.36$, the SW graphic those with $T = 0.71$ and the SE graphic those with $T = 1$. The black value functions represent the option of the vaccination rejection, and the value functions in color represent the option of the vaccination acceptance. When the value function in color is higher than the black value function, the individual choose to be vaccinated.

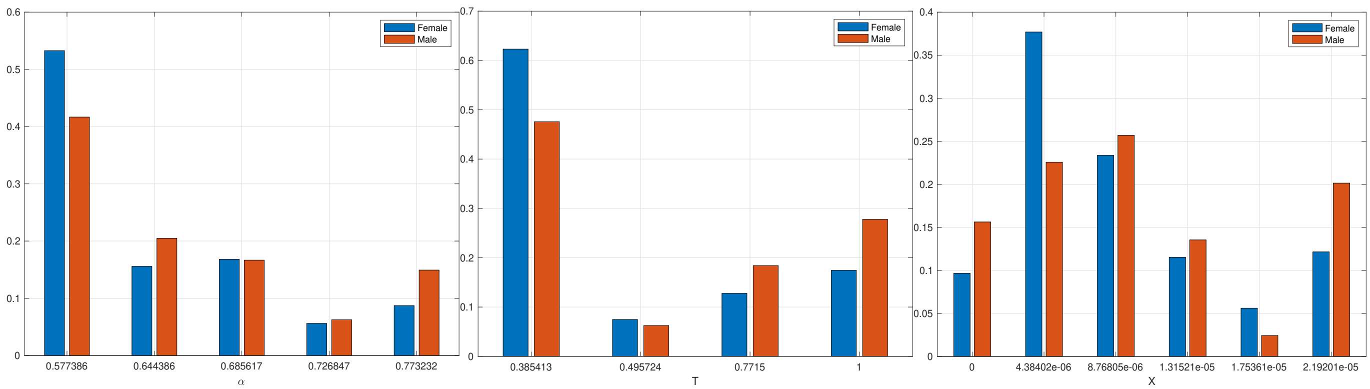
The damages to the health stock of individuals caused by the VRSE $\{\widehat{t}_Y; \widehat{t}_O\}$ are modest. This is consistent with their transitory effects which must be compared to a health stock available over a lifetime. If we consider that those under 65 have an average life expectancy of 30 and those over 65 have 10 years, then our estimates of t_Y and t_O correspond respectively to 1.72 days and 8.22 days of good health lost. These magnitudes of VRSE damages seem reasonable insofar as the secondary effects are felt between 3 and 5 days. It also seems reasonable that older people have a harder time recovering if they are victims of these VRSE. The valuation of vaccination as a common good may seem low, or even very low ($\widehat{a}_3$ is very low). However, it must be compared to the value of the loss of health induced by the VRSE, which leads it to represent 2% of the cost of VRSE, i.e. approximately 2 hours and 23 minutes of healthy life lost.



(a) α by age (b) T by age (c) X by age

Figure 5: **Distributions of Preferences' Characteristics by Age.** Each panel gives the fraction of individuals of each type within her age class ('young' being those aged less than 65 years).

The Figure 4 displays the value functions that lead to these results. The panel (a) shows that decision is sensitive to the risk of illness: an increase in the decision weight $w(p)$ rises the acceptance rate for vaccination. This significant sensitivity of the model to the death rate explains why it can reproduce the differences between the young and old agents as well as between women and men. The panel (b) provides a generalization of the discussion of the section 2: larger values for T, α and X lead to favor the acceptance of vaccine. Beyond these differences in death risks, there are also differences in preferences, revealed by our survey, which also induce different attitudes towards the vaccine. If we segment the population according to age, the Figure 5 shows that two characteristics tend to favor more vaccine acceptance in the elderly than in the young: the elderly have a slightly greater curvature of their value function and are more cooperative. These two characteristics can be partially compensated by the greater impatience of the elderly, that damps their acceptance of vaccination. If the population is segmented by gender, the Figure 6 shows that a larger fraction of males have the characteristics that tend to favor vaccine acceptance: males are more patient, more cooperative and have a value function with greater curvature than females. Thus, the differences in preference between subgroups of the population tend to amplify the differences in risk.



(a) α by gender (b) T by gender (c) X by gender

Figure 6: **Distributions of Preferences' Characteristics by Gender.** Each panel gives the fraction of individuals of each type within her gender group.

Groups (ω)		All	< 65 (Y)	65+ (O)	Female (F)	Male (M)
Benchmark	data	47%	38%	55%	41%	55%
	model	48%	47%	55%	41%	55%
Patience	$\underline{T} = 0.38$	41% (0.42)	41% (0.35)	45% (0.81)	37% (0.32)	46% (0.41)
	$\overline{T} = 1$	60% (0.35)	55% (0.26)	92% (0.66)	55% (0.41)	66% (0.34)
Curvature	$\underline{\alpha} = 0.57$	33% (3.23)	35% (2.63)	23% (6.07)	29% (3.41)	38% (2.84)
	$\overline{\alpha} = 0.77$	80% (3.17)	77% (3.04)	100% (3.87)	75% (3.69)	85% (2.81)
Common good	$\underline{X} = 0$	44% (0.08)	43% (0.08)	55% (0)	36% (0.12)	53% (0.03)
	$\overline{X} = 2.19\ 10^{-5}$	52% (0.06)	51% (0.06)	59% (0.05)	45% (0.06)	61% (0.08)
Side effects	$\underline{t} = 1.58\ 10^{-4}$	54% (-0.14)	-	100% (-0.87)	50% (-0.33)	58% (-0.08)
	$\bar{t} = 2.26\ 10^{-3}$	21% (-0.64)	15% (-0.05)	-	17% (-0.14)	25% (-0.12)

Table 5: **Sensitivity Analysis on Structural Parameters**. The model is simulated with counterfactual values for $\{T, \alpha, X, t_Y, t_O\}$. For example, for the patience, all individuals have the same value for T, set at its minimal value ($\underline{T} = 0.38$) or its maximal value ($\overline{T} = 1$), and transformed by the formula $\widetilde{T} = a_2 T + (1 - a_2)$. Elasticities (in %) are reported in parenthesis.

The Table 5 provides a sensitivity analysis of the model to agents preferences. It appears that those are the changes in the curvature of the value function (α) that modify the most the model's implications (the elasticities w.r.t. α are the highest). This first result puts to the spotlight the key role of the prospect theory for fitting of vaccination intentions, through the heterogeneity in curvature of the individuals' value functions, allowing the model to account for the differences identified by our survey in the valuation of the loses. If we consider the 65 years and over for example, a high value of α, therefore implying a quasi-linearity of the value function, leads all these individuals to accept vaccination because the loses induced by the VRSE become negligible for them, given their largest risks. The patience (T) seems to play a larger role for the seniors than for the other sub-population groups, because this population is the most impatient (see Figure 5): by changing this parameter for all people in the age group, it is thus among the elderly than the counterfactual simulation modifies the behaviors of the largest number of individuals. Changes in the valuation of vaccination as a common good (X), as well as those in the valuation of the VRSE induced by the vaccine (t), do not strongly modify decisions, even if, for the 65 years and over, smaller size of VRSE than those perceived by the individuals of our survey makes it possible to achieve the objective of a voluntary vaccination rate of 100%.

4 Model Predictions

4.1 To Predict the Evolution of the French Vaccination Intentions

Between November 2020 and March 2021, the second wave in France increased the risk of mortality: the Figure 7 gives the gaps of the deaths rate between these two periods. We simply re-simulate our estimated model after integrating this new information concerning the evolution of the deaths risks. Given that this death risk has increased, our model predicts an increase in vaccination intentions as well as the intentions to vaccine recorded by an other survey (Oxada and Ifop surveys (2021)). Does our model able to predict the evolution of the vaccination intentions? By answering to this question, we provide a test of our with respect to its elasticity of the mortality rate.

Table 6 reports results. First of all, we can notice that the model well predict the large increase of the vaccination intentions (+14pp in the data and +12pp in the model, thus explaining 85% of the increase). This underlines that the elasticity of the aggregate vaccination demand w.r.t. the decease risk is well estimated. But, this encouraging result on the average rate of vaccination should not lead us to forget that behind a common average, it could exist significant differences among

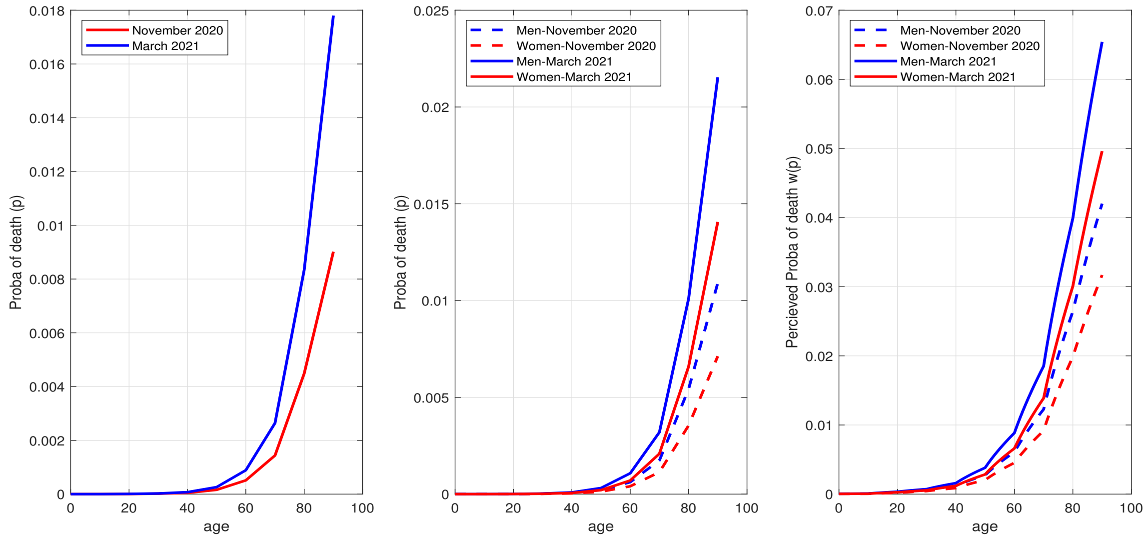


Figure 7: **Death Probability by Age and Gender in France (November 2020 & March 2021).** Data: Santé Publique France

population groups. Table 5 shows that the changes in the vaccination acceptation are different across sub-groups and also that the model reproduces quite well the changes in the distribution of the vaccination intentions for all population groups between the two dates. In particular, it fits exactly the one of women and men, relatively well those of youngest individuals, but slightly over-estimates the vaccination intentions of the elderly. Hence, this large contribution of the death risks on the vaccination intentions suggests that the communication on risks is a first order component for the success of the rollout of vaccination.

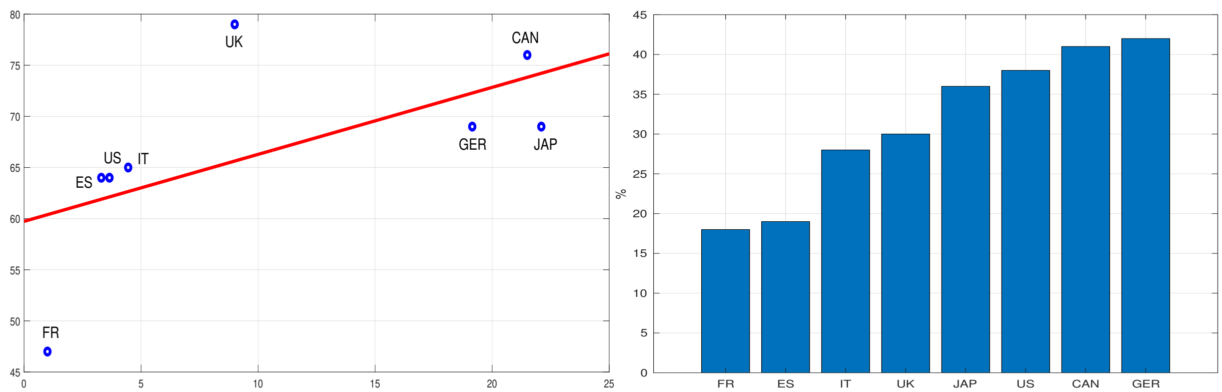
Group	(ω)	All	< 65 (Y)	65+ (O)	Female (F)	Male (M)
VR_ω	model	59% (+11pp)	54% (+7pp)	89% (+34pp)	53% (+12pp)	65% (+10pp)
	data	61% (+14pp)	48% (+10pp)	78% (+23pp)	56% (+15pp)	65% (+10pp)
	forecast error	2% (+3pp)	-6% (+3pp)	-11% (-11pp)	3% (+3pp)	0% (0pp)

Table 6: **Predicted Vaccination Rates (VR) for Mars 2020 to Mars 2021**. The forecast error is the difference between data and model predictions. The variations (in percentage points, ppt) between November 2020 and March 2021 are reported in parentheses. Data for mortality rates: France, March 2020 to March 2021. All model's parameters are the same than in the benchmark (see Table 4). The data on the intention to vaccine in March 2021 comes from Oxada and Ifop surveys (2021).

In this forecast, we keep at their November 2020 levels the probability of VRSE by age. However, in November, a uncertainty about the safety of vaccines could still exist in the absence of long-term observations, the knowledge improvement in March about the safety of vaccines had significantly improved. Perhaps that these information on the evolution of VRSE risks could help the model to reach a better fit. The valuation of the vaccination as a public good may have also change with the large diffusion of information on collective benefits of vaccination.

4.2 International Gaps of the Valuation of the Vaccination as a Common Good

The previous section has shown that the model's elasticity to the death risk cannot be rejected. Therefore, we can use our estimated model to purge individual behaviors from the significant international gaps in death risk. Therefore, at the same time that we purge from international differences of risks, our model can be used to estimate how a structural factor must change to explain the international differences in the vaccination intentions. In this section we test the assumption that, in combination with risk heterogeneity, the valuation of the vaccination as a common good is different across countries.



(a) Common Good Valuation and Vaccination (b) Share of People with Interpersonal Trust

Figure 8: **Evaluation of the Vaccination as a Common Good.** Lecture Panel (a): 79% of English people intended to be vaccinated in October 2020, which is consistent with a evaluation of the vaccination as a common good 9 times bigger than that of the French. Panel (b): World Values Survey. The survey question was "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?". Possible answers were "Most people can be trusted", "Don't know" and "Can't be too careful"

To conduct this test, we make the strong assumption that the preferences are the same across countries, as well as the distribution of agent types. Therefore, the model can predicts the vaccination intentions for each country given the death probabilities for each countries and its specific valuation of its inhabitant of the vaccination as a common good. Figures 8 provide results. Obviously, a high valuation of the vaccination as a common good lead to more vaccination intentions (panel (a)). If we consider that the propensity to cooperate is closely related to interpersonal trust (panel (b)), then Figure 8 shows that the differences in the propensity to cooperate deduced from our model are highly correlated with the measures of interpersonal trust, therefore validating of our approach. The interesting point is the large difference among countries, this valuation being 23 times larger for Canadian and Japanese than for a French (The valuation of the vaccination as a common good is equivalent to only 2h30 of a healthy day for a French, but this reaches 2 days and 9h and 30 minutes for a Canadian of a Japanese). Let us notice that France and the U.K. seems to be particular because these two countries are far from the line of best fit, then suggesting that other factors would be important to explain the specificities in the vaccination intentions in these countries. One may mention a gap in the perception of the risk of VRSE, thus leading population to strongly support vaccination in the U.K. and the opposite in France.

5 Conclusion

This article shows that the prospect theory solves the paradox of the low vaccination intentions observed in France while the mortality linked to Covid-19 is one of the highest in OECD countries. Our model allows to understand why communication on positive benefit-risk balance, though scientifically correct, may not be sufficient to convince vaccine hesitant individuals. Indeed, it is implicitly based on the expected utility assumption where the decision depends on a comparison of the expected benefits and costs (here, the VRSE) of the vaccine. Prospect theory, by overweighting costs, i.e. by valuating more highly a rise in small losses (here the extent of VRSE on health capital) than in very large ones (the impact of a severe form of Covid-19) and by overweighting their likelihood may explain vaccination refusal.[24] In this sense, our model predictions are consistent with previous experimental findings on the impact of vaccine effectiveness and VRSE on decisions. First, when explaining choices among hypothetical vaccines, the literature consistently find that risks of VRSE are more weighted than vaccination benefits, measured by the effectiveness of protection (see e.g. Godinot et al. (2021) and Verelst et al. (2018)). Second, results obtained from stated preferences surveys regarding HPV vaccination (Chyderiotis et al. (2021)) or Covid-19 vaccination among health

[24]The usual convexity of the value function over losses in prospect theory, which is linked with the reflection effect. Since Camerer (2000), many applications have shown that prospect theory is useful for predicting apparently irrational behaviors.

care workers (Diaz Luevano et al. (2021)) show that statements such as "the benefits are higher than the risks" generates disutility and significantly decreases vaccination intentions compared to neutral statements about VRSE.[25] The detrimental effects of such statements are higher than the positive effects generated by statements on either vaccine effectiveness. Beyond this argument based on decision under risk, we also show that individuals who valuate vaccination as a common good will then be more likely to opt for vaccination, as will patient individuals who value the long-term effects of a disease on their health. These results are consistent with those showing that the willingness to avoid transmitting the virus to others or to contribute to disease eradication significantly increase vaccination intention, when compared to a vaccine providing individual protection only (Godinot et al. (2021) and Chyderiotis et al. (2021)).

Quantitative analysis of the model show that all these channels are important to explain the vaccination intentions in France, by age and gender. This model predicts 85% of the rise in vaccination intentions observed between November 2020 and March 2021, showing the high sensitivity of these decisions to the evolution of the death risk (the only change between the two date). Finally, counterfactual simulations suggest that the gaps in the valuation of vaccination as a common good may explain the differences in the vaccination intentions across OECD countries. The gaps in vaccination intentions across countries unexplained by differences in the common good valuation introduced in our model can be linked to other components of the polarization of the political opinions, exacerbating distrust against experts. In France, those who had voted for a far left or far right candidate in the 2017 Presidential election were 67% to state that they would refuse the vaccine, as compared to 19% for those voting to governmental parties (see COCONEL-Group (2020)). In the U.S., 44% of Republicans, as compared with 81% of Democrats will accept the Covid-19 vaccination (see SteelFisher et al. (2021)). These radical political views are less present in Canada, German and Japan.

[25] Forty years ago, Tversky and Kahneman (1981) showed that the framing of decision strongly influences the risky behavior. Talking about lives saved (gains relative to a reference point) or deaths (losses in this case) was not neutral: people were strongly more risk averse in the first framing, with positive consequences. Chen and Ryan (2017) also emphasizes that talking about risk reduction with vaccine or increased risk without has an impact is not neutral: loss aversion leads to more vaccine intentions in the second presentation. This suggests that decision-makers of public health should take into account the behavior of agents and test their massages in order to maximize vaccine intentions.

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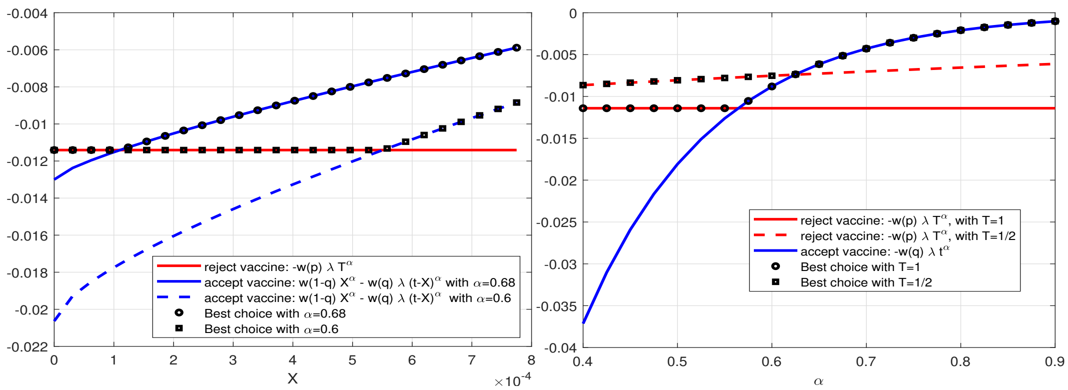
Appendix

A Interaction Between Preferences' Parameters and Vaccination Intentions



(a) Interactions between X and α (b) Interactions between T and α

Figure 9: **Rejection or acceptance of vaccination: Equation (3).** For these numerical examples, we set $T_d = 0$ and $w(q) = 0.2935$ and $w(p) = 0.0051$. In panels (a) and (b), we have $T = 1$ and $t = 0.00075$. In panels (a) and (c), we set $\alpha = 0.68$. In panels (b) and (c), we set $X = 0$. In panel (c), we have $t = 0.0031$.

Panel (a) of the Figure 9 shows that when the curvature of the value function (α) is low, the threshold value of cooperation from which the individual accepts the vaccination (the value of X from which "accept" dominates "reject") is higher. Indeed, as shown in the Figure 10, lower curvature indicates greater sensitivity to low losses: it is therefore necessary to be more cooperative to compensate for the high valuation of losses induced by side effects.

Panel (b) of the Figure 9 shows that a high patience (large value of T) leads to a lowest threshold value of α (the value of α from which "accept" dominates "reject"): it is therefore necessary to be more patient to compensate for the high valuation of losses induced by side effects (low values of α, see Figure 10).

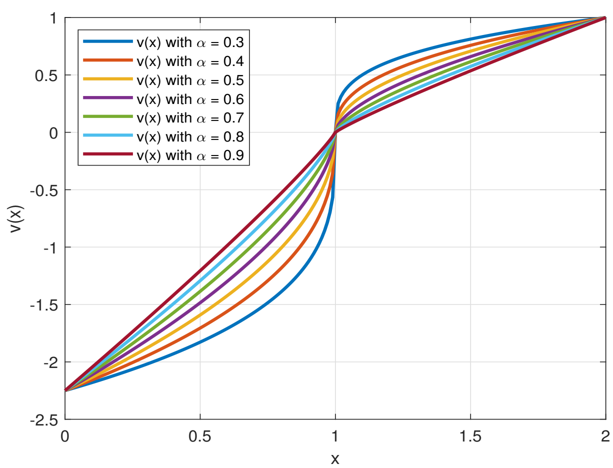


Figure 10: **Value Function $v(x)$: Impact of α.** $v(x)$, $\forall x \in [0, 2]$, with 1 as reference point and $\lambda = 2.25$.