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1 To test or not to test? Risk attitudes and prescribing by
2 French GPs

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5 **Abstract**

6 Risk is a key dimension of economic decisions, but whether risk attitudes can
7 predict real economic behaviour is still subject to investigation. We measure gen-
8 eral practitioners' (GPs) risk attitudes and check for a relationship with variations in
9 prescribing practices. Individual-level risk attitudes are elicited from simple survey
10 choices on a representative national panel of 939 French GPs, and are linked to their
11 volume of lab-test prescriptions through administrative records. Specifically, we esti-
12 mate individual components of a flexible decision model under risk (rank-dependent
13 utility) using random-coefficient estimations, and then treat these components as

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1 predictors of observed lab-test prescribing. We find that (1) GPs exhibit the usual
2 patterns of risk attitudes: risk aversion and inverse S-shaped probability weighting
3 prevails (2) risk aversion captured by the utility function is positively correlated
4 with lab-test prescribing.

5 Keywords: *General practitioners; risk attitudes; rank-dependent utility; lab-test*
6 *prescribing; practice variation.*

7 *JEL Classifications:* C93, D81, I11.

8 *Word count:* 5916

1 Introduction

2 Medical decisions involve many sources of uncertainty, one of the chief being diagnosis.
3 General practitioners (GPs) have to decide whether to base their judgment on information
4 from clinical examination or to reduce uncertainty by prescribing tests. Deciding to
5 search for further information entails a time and monetary cost for both the patient and
6 the health system that may be counterbalanced by increased diagnostic accuracy. A risk-
7 seeking GP may therefore avoid this cost by doing without the tests and relying on his
8 clinical judgment, whereas a risk-averse GP may prefer to have the back-up of biological
9 testing. Lab-test prescribing may therefore be related to the GP's attitude towards risk.
10 We investigate this assumption on a representative sample of French GPs, for whom risk
11 attitudes were measured and matched with observed test prescription behaviour obtained
12 through data linkage with the French social security database.

13 Economists consider risk as a key dimension of many economic situations. Theoretically
14 sound economic models linking risk attitudes to real-life decisions allow for quantitative
15 measurement of risk attitudes from choices. Many elicitation methods have been de-
16 veloped in experimental economics for either laboratory or field use (Binswanger, 1980;
17 Gneezy & Potters, 1997; Holt & Laury, 2002; Tanaka et al., 2010; Wakker, 2010).¹

18 In a lab setting, they have been extensively used on student populations to explain
19 the strategic or economic behaviours observed in experiments. In the field, they have
20 been used to elicit risk attitudes of specific groups such as farmers (Binswanger, 1980),
21 entrepreneurs and managers (Koudstaal et al., 2016), sex workers (Lépine & Treibich,
22 2020) or adolescents (Sutter et al., 2013), as well as in general population studies (An-
23 derson & Mellor, 2008; Tanaka et al., 2010; Falk et al., 2018). The latest elicitation
24 experiments provide evidence on the cognitive and demographic factors explaining risk
25 attitudes (Dohmen et al., 2018; Falk et al., 2018; l'Haridon & Vieider, 2019).

26 In terms of psychometric properties, choice-based measures of risk attitudes appear less

¹There are many other methods in the experimental literature but here we limit ourselves to the main methods used outside the lab.

1 satisfactory than a qualitative measure based on a Likert scale of willingness to take risks
2 ([Dohmen et al., 2011](#); [Pedroni et al., 2017](#); [Mata et al., 2018](#)). Particularly regarding
3 external validity, most of the empirical evidence linking risk attitudes and economic
4 behaviours uses a qualitative measure (see for example, ([Beauchamp et al., 2017](#)) for
5 health behaviour, ([Dohmen et al., 2011](#)) for financial management at the household
6 level or ([Fouarge et al., 2014](#); [Skriabikova et al., 2014](#)) for career orientation). This is
7 because a Likert scale is less costly to apply in large-scale studies and easier for the
8 general population to understand than choice-based methods. The latter require longer
9 instructions and response time and were not originally designed for lab-experiments with
10 convenient samples rather than large scale surveys ([Vieider et al., 2015](#); [Galizzi et al.,](#)
11 [2016](#)).

12 Our paper contributes to this literature by implementing a parsimonious choice-based
13 measure of risk attitudes, specifically developed for the investigated population (i.e.
14 French GPs) and the interview mode (telephone interviews), on a large representative
15 sample (N=1206). The method relies on binary choices between a lottery and sure gain to
16 measure risk attitudes both under the expected utility (EU) framework (utility function
17 curvature) and the rank-dependent expected utility (RDU) framework (utility function
18 curvature and shape of the probability function), rapidly and with minimal cognitive
19 effort. In Microeconomics, this incorporation of risk attitude measures in models of
20 individual decision-making offers vital support for the theoretical literature.

21 Just as choice-based measures of risk attitudes should be preferred to self-reported ones,
22 real observed behaviour should be preferred to stated/declared behaviour. A recent line
23 of research aims at linking data sourced from behavioural experiments with adminis-
24 trative records or large commercial data-sets ([Galizzi & Wiesen, 2018](#)). We contribute
25 to this literature by linking GPs' risk attitudes with one common clinical practice: the
26 prescription of lab-tests. This enables us to provide the first analysis connecting choice-
27 based risk attitudes with a professional behaviour observed through the French Social
28 Security database.

1 In addition to the implications of our work for the study of risk attitudes in general and
2 their predictive power, understanding GPs' behaviour and preferences under uncertainty
3 is critical for health economics and medicine (Gigerenzer & Gray, 2014; Verma et al.,
4 2014). While medical decisions primarily impact the health of the patient, they also have
5 a financial impact on the healthcare system, on patients and on the doctors themselves.
6 Medical decision-making thus offers a genuine setting for exploring risk attitudes and
7 their effect on professional practices. GPs' preferences may have direct implications
8 for their professional behaviour in terms of medical decisions and the quality of their
9 medical services (Simpkin & Schwartzstein, 2016). Understanding the factors impacting
10 the medical decisions of GPs is particularly important, as they are first-line health-
11 care professionals. They represent the patient's first contact with the health system,
12 and their examination and diagnosis are the first steps in the treatment process. They
13 have to make decisions not only regarding curative care, like specialists, but also on
14 hospitalisation, long-term care, or prescription of further medical tests. These decisions
15 have direct micro-economic consequences on a patient's well-being, as well as macro-
16 economic consequences on the health care system. Their effect is amplified in the case
17 of epidemics such as COVID 19, where testing and hospitalisation decisions are key to
18 managing the contamination level and death rate.

19 Prior research on lab-test prescription has focused on the analysis of unwarranted practice
20 variations (Wennberg & Gittelsohn, 1973), repeatedly showing GPs' responsibility in
21 these variations (Vinker et al., 2007; Sá et al., 2017). A related line of research focuses
22 on ways of controlling over-prescribing; various experiments show how the number of
23 lab-test prescriptions can be significantly reduced through actions addressing doctors
24 ((Eisenberg et al., 1977; Axt-Adam et al., 1993; Bates et al., 1999; Attali et al., 2006)).
25 However, there has been little investigation of the underlying factors that may explain
26 variations in volume of prescriptions.

27 In the present study, we investigate a behavioural explanation of GPs' lab-test prescrib-
28 ing, specifically exploring the economic psychology of decision-making under risk. In
29 fact, risk aversion may well increase GPs' willingness to gather as much information as

1 possible before making a diagnosis and taking a prescription decision (see (Michel-Lepage
2 et al., 2013) for a similar result on GPs' use of rapid-antigen diagnostic tests in tonsil-
3 litis in children²). Risk attitudes may also be intrinsic characteristics that impact the
4 trade-off doctors make when choosing between treatments (see (Bories et al., 2018) for
5 the decision hematologists make between using chemotherapy or less intensive care to
6 treat acute myeloid leukemia) or when deciding on preventive care methods (see (Massin
7 et al., 2015) for pandemic influenza vaccination).

8 We measured the risk attitudes of the French primary caregivers, general practitioners,
9 and related these attitudes to their lab-test prescribing as recorded in the social security
10 database. To do so, we developed a simple choice-based procedure for elicitation of risk
11 attitudes, and implemented it on a representative national panel survey of 1206 French
12 GPs (the final analysis covers 939 of them). Then, using a record-linkage process involving
13 the Social Security reimbursement data-files, we obtained risk-attitude estimations that
14 can be considered as potential predictors of one aspect of these GPs' real clinical practice:
15 prescribing lab tests.

16 This analysis enables us to make two original contributions. First, we describe the risk
17 attitudes of a large sample of French GPs under rank-dependent utility (RDU), a flexible
18 descriptive model that encompasses the rational model (EU) as a particular case. Our
19 results show that GPs exhibit the patterns generally observed in convenience samples:
20 risk aversion prevails, but more risk seeking is observed for small probabilities. Second,
21 when we study the relationship between risk attitudes and recorded lab-test prescription
22 volume, we observe a significant impact of risk attitudes (described by the curvature
23 of the utility function), showing that choice-based measurement does have explanatory
24 power for real-life behaviour.

25 The paper is organised as follows: section 2 describes the role of GPs within the French
26 healthcare system, the French GP panel survey used for data collection and the adminis-
27 trative database we linked with our survey data-set. Section 3 describes the choice-based

²In this study, risk aversion is measured using a Likert scale of willingness to take risks and the test decision is revealed through vignettes presenting clinical cases.

1 procedure for elicitation of risk attitude that was implemented with the panel and the
2 econometric model developed to study risk attitudes and their correlation with lab-test
3 prescriptions. Section 4 shows the results, which are further discussed in section 5.

1 **2 Material**

2 **2.1 GPs in the French healthcare system**

3 In France, GPs are the main primary care providers for more than 98% of the population
4 ([Massin et al., 2018](#)). They are self-employed and generally remunerated using a fee-
5 for-service system. There is no ex-ante assignment of patients to primary care services:
6 patients self-select into the GP's practice and change at will. French GPs are independent
7 of the health insurer (the French Social Security and complementary health insurances)
8 and barriers exist against the intervention of any insurers (private or public) in doctors'
9 medical decisions. It is medical professional unions or health authorities (Ordre des
10 Médecins, Haute Autorité de Santé) that regulate the quality of medical practice. The
11 French primary care system was constructed so as to ensure a high level of professional
12 autonomy, although it exposes GPs to some financial risks (market uncertainty) and legal
13 risks. This makes the judgments and decisions of French GPs key to the efficiency of the
14 French healthcare system, and to its evaluation.

15 In terms of incentives, French GPs are not concerned by the financial implications for the
16 Social Security of their medical decisions. In other words, their "gatekeeper" role has not
17 been associated with significant incentives ([Dourgnon & Naiditch, 2010](#)). One constraint
18 is that GPs have to accept the terms of a national agreement making it possible for their
19 patients to be reimbursed by the public insurer for their consultations; however, this does
20 not greatly limit medical practices. In 2012, a Pay for Performance system was set up,
21 but with limited impact on practices ([Michel-Lepage & Ventelou, 2016](#)).

22 **2.2 Survey data**

23 The panel survey of French GPs used to test our risk-attitude elicitation procedure
24 was set up in June 2010 through a partnership between the research department of
25 the Ministry of Health, the regional health observatories and the representatives of self-

1 employed GPs. Its aim is to collect data regularly about medical activity and practices.
2 It consists of a national sample and three regional over-samples (Burgundy, Pays de la
3 Loire and Provence-Alpes-Cote d'Azur). The sampling frame³ was obtained from the
4 Ministry of Health's exhaustive database of health professionals in France. Sampling
5 was stratified by location (urban, peri-urban, or rural areas), gender, age⁴ and volume
6 of activity⁵ in 2008. Of the 6,304 GPs who were contacted and eligible, 2,496 (39.6%)
7 agreed to participate in the panel survey and to respond to five consecutive waves on
8 different topics every 6 months. Professional investigators operated using computer-
9 assisted telephone interview (CATI) software and standardised questionnaires. Each GP
10 received a monetary compensation equivalent to one consultation fee for each survey
11 wave. To limit the selection bias that might have resulted from particular opinions or
12 attitudes, the specific survey topics were not mentioned to GPs before they were asked to
13 participate in the panel. The National Data Protection Authority (Commission Nationale
14 Informatique et Libertés), responsible for ethical issues and protection of individual data
15 in France, approved the panel survey and its procedures. Information was collected on
16 the GP panel through successive waves starting in 2010. The 5th and last wave was
17 completed in early 2013; it collected opinion on several policy issues and contained our
18 risk-attitude choice-based elicitation procedure. For this study, we focus on the 939 GPs
19 who answered all the questions of the risk-attitude elicitation module and whose data
20 could be linked to the national database containing all the GPs' expenditures, presented
21 in the next section. All these GPs also participated in the first four cross-sectional
22 survey waves. The sampling scheme and response rates at different stages of the survey
23 are presented in appendix [A](#).

³GPs who had not received a fee of at least one euro during the year were excluded from the sampling frame, as well as those planning to cease practising or to move within one year and those with a full-time practice in alternative medicine (e.g., acupuncture or homeopathy.)

⁴Three classes : <49 [Q1], 49-56, >56 years old [Q3]

⁵Annual workload is defined by number of consultations and home visits: <2,849 [Q1], 2,849-5,494, >5,494 [Q3].

1 **2.3 Administrative data: Lab-test prescriptions**

2 To the information obtained from the panel survey, we linked annual data from the In-
3 dividual Record of Activity and Prescriptions (RIAP in French) for most of the panel.
4 It gives each GP's total workload (total number of consultations and home visits, short-
5 ened in the following to 'volume of activity') and the characteristics of their patients
6 (proportion of patients under 16, proportion of patients over 60, proportion of patients
7 covered by the universal healthcare program (CMU in French, i.e. patients with totally
8 free health-care because of their low income) and patients exempt from payment because
9 of long-term illness). It also records all reimbursed expenditure for insured patients, es-
10 pecially the volume/quantity of biological tests prescribed by the GP (measured as the
11 sum of coefficients defined in the classification of medical procedures). In the analysis,
12 we use the patients' characteristics as control variables (see Figure 1) and the quantity
13 of biological tests prescribed as our main medical practice variable to be explained. By
14 linking this administrative electronic database managed by the French national health
15 insurance system (CPAM in French) to our GP survey, we obtain a measurement of
16 medical practice (lab-test prescribing) which is not self-reported like most of the survey
17 items, but is an objectively observed characteristic of the GPs' professional activity.

1 **3 Method**

2 **3.1 Measuring risk attitudes**

3 We developed a choice-based risk preference elicitation method, inspired by those used in
4 lab experiments (Abdellaoui et al., 2011), and incorporated it within the 5th wave of the
5 GP panel survey. The method and its practical implementation are described hereunder.

6 **3.1.1 Notation**

7 We consider binary lotteries x_py that give outcome x with probability p and y with
8 probability $1-p$. A lottery giving outcome x with certainty ($p = 1$) will be denoted x . We
9 study GPs' preferences over lotteries using the standard notation \succ for strict preference
10 and \sim for indifference. Outcomes are expressed in numerical units, so that the expected
11 value (EV) of x_py can be defined as $px + (1 - p)y$. The certainty equivalent (CE) c of
12 a lottery x_py is the outcome that makes a decision-maker indifferent between receiving
13 a sure c and receiving the lottery: $c \sim x_py$. By definition, a GP exhibits risk aversion
14 (seeking) for a lottery if the CE is lower (higher) than the EV. The difference between
15 the CE and the EV is the risk premium and quantifies the degree of risk preference. The
16 CE therefore allows for simple quantitative measurement of risk attitudes.

17 For a given lottery x_py , we measure the CE using the bisection method. This consists in
18 an iterative series of binary choices between a sure outcome c_j and the lottery, with c_j
19 varying in $]y, x[$ according to the bisection algorithm (see appendix B.1). CEs measured
20 using the bisection method allow risk attitudes to be quantified from a few simple choices
21 between a sure outcome and a lottery.

22 **3.1.2 Experimental design**

23 Table 1 presents the parameters of the lotteries used to elicit risk attitudes. For each
24 lottery, CE was measured through a 3-step bisection algorithm (presented in more detail

1 in appendix B.1).

k	x_k	p_k	y_k
1	100	0.5	0
2	100	0.2	0
3	100	0.8	0
4	100	0.5	50
5	50	0.5	10

Table 1: Lotteries used for the elicitation of risk attitudes (Gains are in euros)

2 The first three lotteries have a fixed maximum outcome, a null minimum outcome and
3 involve various probabilities over the probability interval. Lotteries 4 or 5 involve the
4 same probability and various maximum and minimum outcomes. These two types of
5 stimulus aim at disentangling the role of outcomes and the role of probabilities in risk
6 attitudes (see Sect 3.2.1).

7 Because of survey constraints, it was not possible to use these 5 stimuli on each respon-
8 dent. For each respondent, we elicited the CEs of a total of 3 lotteries only. One group
9 (two third) of respondents was assigned lotteries 1, 2 and 3 (the fixed outcome lotteries).
10 The other group (one third of respondents) was assigned lotteries 1, 4 and 5 (the fixed
11 probability lotteries).

12 A specific procedure was designed to implement the risk attitude elicitation task. CATI
13 (computer-assisted telephone interview) software was developed to deal with the con-
14 straints of the GP survey, i.e. bisection algorithm, limited amount of time for the in-
15 terview, standardised phrasing of questions for each professional interviewer, cognitive
16 complexity of the tasks⁶.

17 We used standard wording where GPs had to choose between a sure monetary gain and
18 a lottery with monetary consequences. An example of a binary choice is:

⁶A pilot study was conducted on 50 doctors to evaluate the feasibility of binary lottery choices through telephone interviews. Acceptability and feasibility was tested on the interviewer side too. This pilot study was also intended to optimise the wording of the interviews and limit their length to between 5 and 10 minutes. At the beginning of the survey, the team of interviewers received personal training for this specific section.

1 Between the following two options, do you prefer: option A that gives you
2 a 50% chance of winning 100 euros and 0 otherwise, or option B that gives
3 you 40 euros for sure?

4 According to the bisection, option B changed from one iteration to the other. In addi-
5 tion, a graphical aid presenting the choice tasks was mailed to each GP, to support the
6 telephone interview process (see appendix B.2).

7 **3.2 Econometric model**

8 **3.2.1 Modelling risk preferences**

9 Our econometric estimations aim at interpreting our measure of risk attitudes (CE) under
10 risky choice models. We consider expected utility (EU), the classical model of decision
11 under risk (von Neumann & Morgenstern, 1947). We also consider rank-dependent util-
12 ity (RDU), arguably the most descriptively powerful model of risky choice (Tversky &
13 Kahneman, 1992). Risk attitudes are measured through certainty equivalents $c_{i,k}$ elicited
14 for each respondent i and for each of the lotteries k . We now present the formula for
15 RDU that encompasses the standard EU model as a particular case.

16 Under RDU, the theoretical certainty equivalent $c_{i,k}^{\hat{}}$ of a lottery (x_k, p_k, y_k) is given by
17 Eq. 1

$$c_{i,k}^{\hat{}} = u_i^{-1}[[w_i(p_k)(u_i(x_k) - u_i(y_k)) + u_i(y_k)] \tag{1}$$

18 The formula introduces a strictly increasing utility function u_i , and a strictly increasing
19 probability weighting function w_i is specified. Under EU, there is no probability weighting
20 and $w_i(p) = p$.

21 Under EU, risk attitudes are captured by the shape of the utility function only. Under
22 RDU, risk attitudes depend on both utility and probability weighting.

1 Our analysis allows for model components (and thereby risk attitudes) to vary across
 2 respondents, hence the index i .

3 We now present the parametric specifications considered for utility and probability weight-
 4 ing. For the utility function, two specifications are considered and compared. The first
 5 assumes constant absolute risk aversion (CARA) and is specified by equation $u_{\alpha_i}(x) =$
 6 $1 - e^{-\alpha_i x}$. The second assumes constant relative risk aversion (CRRA) and is specified
 7 by equation $u_{\alpha_i}(x) = x^{\alpha_i}$.

8 For the probability weighting function, the Prelec (1998) specification is assumed $w_{\gamma_i}(p) =$
 9 $e^{-(-\log(p))^{\gamma_i}}$. When $\gamma_i = 1$ the probability weighting function is linear and the model
 10 simplifies to EU. Values $\gamma < 1$ characterise the commonly observed inverse-S shaped
 11 probability weighting.

12 Regarding the error structure, we assume that theoretical CEs ($c_{i,k}^{\hat{}}$) and observed CEs
 13 ($c_{i,k}$) differ by a Fechner error (Eq. 2).

$$c_{i,k} = c_{i,k}^{\hat{}} + \epsilon_{i,k}, \text{ with } \epsilon_{i,k} \sim N(0, \sigma_i^2) \quad (2)$$

14 The variance of errors σ_i^2 can differ across individuals and allows for between-individual
 15 heteroscedasticity.

16 To capture heterogeneity in attitudes, we assume that risk parameters $\alpha_{i,a}$ and $\gamma_{i,a}$
 17 are randomly distributed across individuals. Specifically, (non-negative) parameters are
 18 assumed to follow (log)normal distributions. We denote $\bar{\alpha}$ and σ_{α} the mean and standard
 19 deviation of individual parameters α_i and $\bar{\gamma}$ and σ_{γ} the mean and standard deviation of
 20 individual parameters γ_i

21 This model specification enables us to derive the likelihood function associated with our
 22 measurements.

For each lottery, the bisection procedure produces two bounds $c_{i,k}^-$ and $c_{i,k}^+$ such that
 $c_{i,k}^- < c_{i,k} < c_{i,k}^+$. Therefore, each observation consists in an interval $(c_{i,k}^-, c_{i,k}^+)$, and the

likelihood of a given interval writes:

$$\begin{aligned}
l(c_{i,k}^-, c_{i,k}^+) &= p(c_{i,k}^- < c_{i,k} < c_{i,k}^+) \\
&= p(c_{i,k}^- - \hat{c}_{i,k} < \epsilon_{i,k} < c_{i,k}^+ - \hat{c}_{i,k}) \\
&= \Phi\left(\frac{c_{i,k}^+ - \hat{c}_{i,k}}{\sigma_i}\right) - \Phi\left(\frac{c_{i,k}^- - \hat{c}_{i,k}}{\sigma_i}\right)
\end{aligned} \tag{3}$$

1 where Φ is the cumulative function of the normal distribution.

2

3 Our econometric specification defines a non-linear random-parameter interval regres-
4 sion model where parameters vary across respondents according to a given distribution.

5 The objective of the estimation is to measure the characteristics of these distributions
6 $(\bar{\gamma}, \sigma_\gamma, \bar{\alpha}, \sigma_\alpha)$ and to recover individual parameters α_i and γ_i . The model is estimated

7 by simulated maximum likelihood⁷, and individual parameters are derived, using the

8 Bayes rule, from the estimated distributions as priors, updated from observed individ-

9 ual choices (see [Train \(2009\)](#)). Random coefficient estimation is increasingly popular in

10 the literature. [Murphy & ten Brincke \(2018\)](#) show that it yields more stable individual

11 estimates than individual-level estimation. Its main advantage is that each respondent

12 benefits from information about the group, which optimises the use of information and

13 shrinks individual outlying values. The individual parameters α_i and γ_i characterising

14 the risk attitudes of each GP will be used as explanatory variables in the model of lab-test

15 prescribing as dependent variable, as presented hereunder.

16 3.2.2 Modelling lab-test prescribing

17 The second step of our econometric analysis consists in measuring the impact of risk

18 attitudes on prescriptions. We explain the volume of prescriptions per visit, y_i , for year

19 2012, using the log-linear model in Eq. 4:

⁷1000 Halton draws are taken for each respondents. The likelihood is estimated using the BFGS algorithm. Robust and clustered standard errors are computed using the sandwich estimator with individual clustering taken into account in the meat component

$$\log(y_i) = c + \beta\alpha_i + \mu\gamma_i + X_i'\theta + \nu_i \quad (4)$$

- 1 With $\nu_i, \sim N(0, \rho)$
- 2 Eq. 4 is the regression equation of (the log of) prescriptions on the utility curvature (α)
- 3 and the shape of the probability weighting function (γ) for money, and a set of control
- 4 variables X_i related to the GPs and their patients (see Fig.1) .

The vector of control variables X_i is composed of GP characteristics that were also used as the four stratification variables for the sampling:

- Gender
- Age: categorical variable with three classes i.e. <49, 49-56, >56 years old.
- Location of general practice: categorical variable with three classes i.e. rural, peri-urban and urban areas.
- Annual volume of activity defined by number of consultations and home visits: categorical variable with three classes i.e. <2,849, 2,849-5,494, >5,494.

The other set of control variables is composed of characteristics of the GP's patients, obtained through the RIAP:

- Age <16 is the proportion of patients under 16.
- Age >70 is the proportion of patients over 70.
- CMU is the proportion of patients covered by the CMU (free health-care because of low income)
- EXO is the proportion of patients exempt from payment because of long-term illness.

Figure 1: Set of control variables, X_i

- 5 Regressors related to risk attitudes come from individual estimations from the risk model
- 6 presented in the previous section. The model is a standard cross-section regression and
- 7 is estimated by OLS. Several variations of the model with subsets of regressors are also
- 8 considered:

- 9 • With and without the set of control variables X_i .

1 • Only with the utility curvature parameter (EU specification) and with both utility
2 and probability weighting parameters (RDU specification).

3 • For robustness, two parametric specifications of the utility functions were used:
4 CARA and CRRA. Regressions with the CARA parameter offer the best fit and
5 are presented in the results section. Regressions with CRRA utility are similar and
6 reported in appendix.

7 In order to avoid the impact of outlying values, individuals with prescription values
8 corresponding to the 1% of highest or lowest values are removed from the analysis.
9 After removing 2% of observations (20 respondents), a Shapiro test fails to reject that
10 prescription volumes follow a log-normal distribution ($p = 0.69$).

1 4 Results

2 4.1 Raw data analysis

3 All subsequent statistical analyses were run on a sample of 939 GPs who completed the
4 risk attitudes elicitation module and for whom administrative data (with prescription
5 information) were available. The sample scheme is available in Figure 4 of appendix A as
6 well as comparison between this sample and the target population and other subsamples
7 (Table 6). Of the 939 respondents, 644 were assigned lotteries 1, 2 and 3 and 295 lotteries
8 1, 4 and 5.

9 Table 2 reports descriptive statistics for certainty equivalents $c_{i,k}$ with $k = 1, \dots, 5$. %RA
10 represents the percentage of certainty equivalents that are below the expected value of
11 the evaluated lottery, and therefore represents the percentage of risk-averse GPs for this
12 specific lottery.

k	x	p	y	EV	Mean	Median	Sd	% RA
1	100	0.5	0	50	31.4	25.0	20.5	82.5
2	100	0.2	0	20	24.5	17.5	22.7	67.5
3	100	0.8	0	80	48.9	55.0	22.2	92.1
4	100	0.5	50	75	63.4	57.5	11.5	85.4
5	50	0.5	10	30	26.2	27.5	10.0	76.3

Table 2: Descriptive statistics on CEs

13 Lottery 1 was assigned to all the respondents, whereas lotteries 2 and 3 were assigned
14 to one group of respondents and lotteries 4 and 5 were assigned to the other group. The
15 CEs provided for lottery 1 show whether the two groups had similar risk attitudes. This
16 assumption was not rejected by a t-test comparing mean CEs ($p = 0.93$), nor by a χ^2
17 test comparing risk attitudes ($p > 0.99$). Overall, risk aversion prevails in our data.
18 For all the lotteries, median CEs are below the EV and more than 60% of respondents
19 exhibit risk aversion. However, despite this overall pattern, both the degree of risk
20 aversion as measured by the risk premium and the share of respondents exhibiting risk

1 aversion vary significantly depending on the characteristics of the lotteries. In fact, RAs
2 change systematically with lottery probabilities: the lower the probability, the less risk
3 aversion is observed. Variations of RA with probabilities are significant, according to
4 χ^2 tests comparing RA for $p=0.2$ versus $p=0.5$ ($p < 0.001$) and for $p=0.5$ versus $p=0.8$
5 ($p < 0.001$). This pattern is a component of the fourfold pattern of risk attitudes and
6 can be accounted for by RDU (Tversky & Kahneman, 1992).

7 The standard deviations of the CEs show that preferences are highly heterogeneous in our
8 sample. This justifies the use of a random-coefficient model for the econometric estima-
9 tions. Overall, these descriptive statistics convey a model-free picture of our main results
10 concerning risk attitudes. Risk attitudes are heterogeneous and probability-dependent.
11 The next section refines the analysis through econometric estimations of risky choice
12 models.

13 4.2 Model parameters

14 Table 3 reports the results of the random-coefficient estimations. The first columns
15 assume linear probability weighting ($\gamma_i = 1$), a case in which our RDU model (Eq.1)
16 simplifies to EU.

		EU				RDU			
		CARA		CRRA		CARA		CRRA	
		Estimate	Stde	Estimate	Stde	Estimate	Stde	Estimate	Stde
Mean	$\bar{\alpha}$	0.026	0.001	0.634	0.020	0.016	0.001	0.815	0.019
	$\bar{\gamma}_o$					0.589	0.019	0.473	0.014
	$\bar{\sigma}$	11.454	0.307	14.246	0.258	9.134	0.243	9.461	0.254
Standard deviations	σ_α	0.025	0.001	0.518	0.036	0.021	0.001	0.455	0.031
	σ_γ					0.303	0.033	0.257	0.024
	σ_σ	4.615	0.460	2.153	0.655	3.018	0.334	3.026	0.397
LL		-5707.68		-6138.51		-5435.14		-5517.05	

Table 3: Results of the risk-attitudes model

17 The CARA exponential utility function provides a better goodness of fit under both EU
18 and RDU. More precisely, under EU, CARA utility provides a better individual likelihood
19 for 711 out of 939 respondents (binomial test $p < 0.001$). Under RDU, CARA utility
20 provides a better individual likelihood for 517 out of 939 respondents (binomial test $p =$

1 0.002). We will therefore focus on this specification, given that similar patterns appear
2 under the CRRA utility specification. We also observe that accounting for probability
3 weighting dramatically increases the likelihood, which leads us to focus on results under
4 RDU. The increase in likelihood is statistically significant according to log-likelihood
5 ratio tests ($p < 0.001$ for the CRRA and the CARA utility specifications).

6 Risk attitudes, as captured by the distribution of model parameters, are consistent with
7 the patterns reported in the literature. The mean utility function is concave, which con-
8 tributes to risk aversion, and the mean probability weighting function is inverse-S-shaped.
9 In particular, the mean CARA utility parameter is 0.016 and is significantly larger than
10 0 (Wald test, $p < 0.001$). Regarding probability weighting, the mean of the Prelec pa-
11 rameter is significantly lower than 1 (Wald test, $p < 0.001$), which is consistent with
12 inverse-S-shaped probability weighting: respondents tend to overweight small probabili-
13 ties (which implies more risk seeking) and underweight medium and large ones (which
14 implies more risk aversion). Strong heterogeneity across respondents is also captured,
15 with a standard deviation of 0.021 for the CARA parameter and 0.30 for the probability
16 weighting parameter. The estimations of standard deviations are statistically significant
17 and justify the use of a random-coefficient model to capture preference heterogeneity.

18 The distributions corresponding to these estimated values are plotted in Fig 3. On the
19 left-hand panel, dotted lines plot the distribution of CARA parameters obtained under
20 EU. We can see that omitting probability weighting results in larger (i.e. more risk-
21 averse) utility parameter values. This observation is consistent with the analysis reported
22 by [Abdellaoui et al. \(2008\)](#). The distribution of PWF parameters shows that not only the
23 mean, but a large majority, of individual parameters are lower than 1, suggesting that
24 inverse-S-shaped probability weighting largely prevails in our sample. Fig 2 illustrates
25 the heterogeneity captured by the random-coefficient estimations, plotting utility and
26 weighting functions for the median and quartile parameters.

27 Overall, our econometric analysis shows that the risk attitudes of our panel of GPs
28 are similar to those generally observed in the literature on other types of subjects. They

- 1 exhibit a concave utility function and an inverse-S-shaped probability weighting function.
- 2 Our random coefficient estimations capture sizeable heterogeneity in risk parameters.
- 3 This is in line with our hypothesis that this heterogeneity explains heterogeneity in
- 4 volume of lab-test prescriptions.

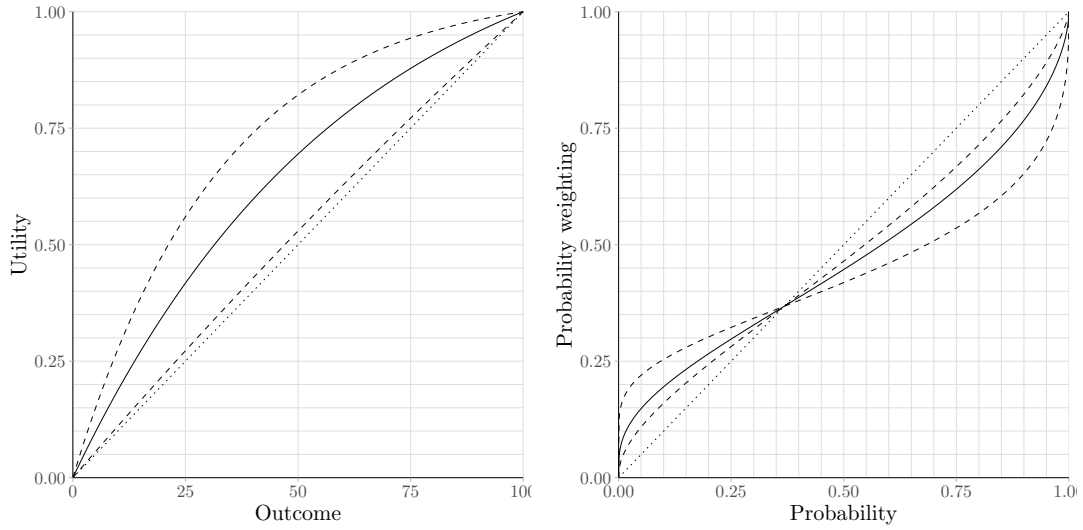


Figure 2: Utility and probability weighting for median and inter-quartile interval parameters

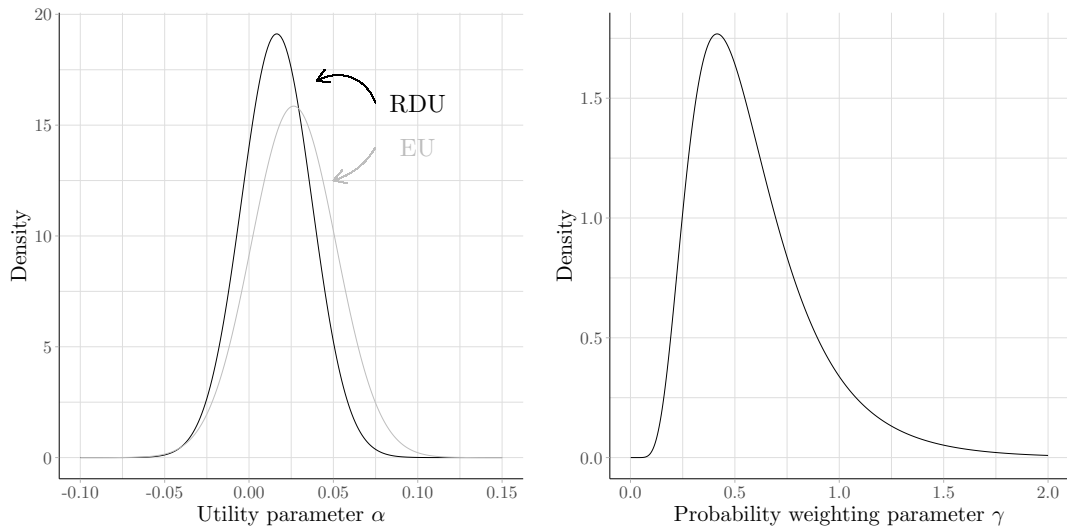


Figure 3: Distributions of individual parameters

1 4.3 Lab-test prescriptions

2 The dependent variable measuring GPs’ test-prescribing behaviour is the volume of bio-
3 logical tests prescribed per visit for 2011. Table 4 reports Spearman correlations between
4 this variable and estimated risk parameters. Correlations between prescriptions and util-
5 ity parameters measured under RDU are statistically significant. Other correlations are
6 not. Interestingly, utility parameters measured under EU have the expected sign and
7 similar magnitude to those measured under RDU, but are not significant. This may
8 be because the former are biased or more noisy when probability weighting is ignored.
9 [Wakker \(1994\)](#) argues that utility measured under expected utility can be too distorted
10 by risk perception to be useful in other contexts. However, if probability weighting is
11 corrected for, the estimated utility function can be useful in other contexts. Our data
12 support this claim. Utility parameters measured under RDU have more explanatory
13 power than utility parameters measured under EU.

	Spearman correlation with Prescription	
	utility (p value)	probability weighting (p value)
EU with CARA	0.06 (0.07)	
EU with CRRA	-0.06 (0.08)	
RDU with CARA	0.07 (0.04)	-0.02 (0.52)
RDU with CRRA	-0.07 (0.03)	-0.03 (0.39)

Table 4: Spearman correlations between prescriptions and risk parameters

14 Table 5 reports the results of a series of linear regressions of (the log of) prescriptions on
15 CARA parameters (under EU and under RDU) and controls.

16 Whether considered alone or with controls, under EU or under RDU, the CARA param-
17 eter is found to impact prescriptions. The magnitude of the parameters varies from 1.05
18 when the CARA parameter measured under EU is considered alone, to 1.2 when the
19 CARA parameter measured under RDU is considered along with controls.

20 The probability distortion parameter is not statistically significant at the 5% level. Sim-
21 ilar results are observed for the CRRA utility (presented in Table 7 in appendix 7).

1 Results from the control parameters are as expected. Lab-test prescribing increases with
2 the volume of activity (consultations) and the share of patients with chronic diseases
3 (EXO), and decreases with the share of young patients and the share of patients with
4 universal health coverage (CMU). Regarding GP characteristics, males prescribe 12%
5 fewer lab-tests than females, and younger GPs prescribe fewer tests than older ones.
6 Location does not significantly impact lab-test prescriptions.

Variable	Modality	CARA & EU		CARA & RDU	
		No control	with control	No control	with control
Patients's characteristic	Intercept	3.422*** (0.019)	3.324*** (0.108)	3.433*** (0.033)	3.331*** (0.112)
	Fee exemption	Ex		1.880*** (0.342)	1.880*** (0.342)
		Cmu		-2.653*** (0.420)	-2.657*** (0.420)
	Patients' age	Age < 16		-0.960*** (0.261)	-0.963*** (0.261)
		Age > 70		0.022 (0.320)	0.016 (0.321)
	Gender	Women			
	Men		-0.120*** (0.027)	-0.120*** (0.027)	
GP's characteristic	Age	<49 yo			
		49-56 yo		-0.083** (0.027)	-0.082** (0.027)
		>56 yo		-0.117*** (0.031)	-0.116*** (0.031)
	Location	urban			
		peri-urban		-0.058 (0.035)	-0.058 (0.035)
		rural		0.009 (0.031)	0.010 (0.031)
Volume of activity	consults		0.0001*** (0.00002)	0.0001*** (0.00002)	
Risk attitudes	Utility curvature	1.047 (0.561)	1.045* (0.501)	1.325 (0.678)	1.231* (0.607)
	Shape of Pwf			0.007 (0.048)	-0.002 (0.043)
	Observations	919	919	919	919
	R ²	0.004	0.217	0.004	0.217
	Adjusted R ²	0.003	0.207	0.002	0.206
	Residual Std. Error	0.365 (df = 917)	0.325 (df = 907)	0.365 (df = 916)	0.325 (df = 906)
	F Statistic	3.483 (df = 1; 917)	22.805*** (df = 11; 907)	1.945 (df = 2; 916)	20.882*** (df = 12; 906)

Note: . corresponds to p<0.1; * to p<0.05; ** to p<0.01; *** to p<0.001

Table 5: Impact of risk attitudes on lab-test prescriptions

7 The results show that the shape of the utility function explains a small but statistically
8 significant share of variance in lab-test prescribing among GPs. The relationship is
9 stronger when the utility function is estimated under RDU, (i.e. corrected for probability
10 weighting). Our analysis does not detect a significant impact of the probability weighting
11 in lab-test prescribing. Accounting for probability weighting can therefore be considered
12 as a way to refine the measurement of the utility function.

1 Overall, the results support the assumption investigated in this paper. They show that
2 variations in risk attitudes among GPs are related to variations in a specific medical
3 practice: volume of lab-test prescriptions.

1 5 Discussion

2 5.1 Main contribution

3 This paper investigated the explanatory power of choice-based elicitation of risk atti-
4 tudes by exporting advanced elicitation techniques outside the lab. We surveyed a spe-
5 cific population: general medical practitioners. This population is very hard to reach
6 but particularly relevant for the research field, given the decisions they have to make
7 daily under uncertainty and their consequences for patients. We provide a description of
8 French GPs' risk attitudes using an original and parsimonious elicitation method. Doc-
9 tors were surveyed through telephone interviews and risk attitudes were elicited using
10 binary choices between a lottery and a sure gain, for several levels of probabilities and
11 gains.

12 Our approach constitutes a key improvement from existing research measuring risk at-
13 titudes in surveys using psychometric scales (Dohmen et al., 2011; Falk et al., 2018) or
14 multiple price lists (Andersen et al., 2008; Galizzi et al., 2016; Falk et al., 2018). Our
15 methodology offers two main advantages. First, binary choices are arguably the simplest
16 task individuals can perform regarding decisions under risk, and therefore reveal pref-
17 erences with minimal noise. Second, the method provides enough richness to estimate
18 the components of the two main models of decision under risk, Expected Utility and
19 Rank Dependent Utility. The advantage of eliciting the latter is to "de-bias" the mea-
20 sure of utility, by accounting for probability weighting (Wakker, 2010). In this paper, we
21 used a random coefficient model to estimate the utility function as well as the probability
22 weighting function from a limited number of binary choices. In fact, thanks to these mod-
23 els' efficient use of the available information, individual-level parameters of sophisticated
24 models were derived despite the limited number of observations per individual.

25 We then exploited these individual parameters as predictors of an important medical
26 practice by GPs: lab-test prescribing. We find a positive correlation between risk aver-
27 sion and number of tests prescribed, which points to the relevance of risk attitudes in

1 explaining medical practice variation. What’s more, the explained behaviour is not self-
2 declared or stated, as in the majority of the studies in medicine or economics, but comes
3 directly from the individual administrative record of each GP’s prescriptions. To the best
4 of our knowledge, our study is the first to investigate the external validity of risk attitude
5 measures with a real, objectively measured professional behaviour, thereby eliminating
6 the potential desirability bias associated with most survey studies.

7 **5.2 Robustness of the findings**

8 Our results on the utility functions hold whatever decision model is considered: EU or
9 RDU. To that end, our methodological innovation consists in relying on a two-stage es-
10 timation of the underlying structural-equation models. The first stage is a non-linear
11 random-coefficient model aimed at eliciting risk preferences and their individual hetero-
12 geneity from observed choices. The second stage is a linear model explaining revealed
13 prescribing behaviour by (first-stage estimated) risk preferences and control variables.
14 The first stage is estimated using a likelihood maximisation procedure, and the second
15 by OLS. This fast approach enabled us to explore the robustness of the results to several
16 specifications (CARA vs CRRA utility, EU vs RDU, control or not).

17 A possible limitation of this approach is that in the second stage, risk preferences are
18 considered as regressors, even though, in practice, they are not observed directly but
19 rather estimated from the first stage, thus being captured with estimation errors. This
20 may create an error-in-measurement bias that can lead to under-estimations of the effect
21 in the second stage. An alternative approach consists in estimating the two structural
22 equations simultaneously. We implement it, as a robustness check. The results are
23 presented in appendix C.2. Both coefficients and inferences are consistent with the
24 results of the two-stage estimations.

25 **5.3 Main results**

26 We obtain two main results concerning the specific population investigated.

1 First, on average, French GPs overweight small probabilities and underweight interme-
2 diate and high probabilities, consistent with the inverse-S-shaped probability weighting
3 commonly observed in experimental and behavioural economics in a laboratory setting
4 ([Wakker, 2010](#)). We thus add to the existing evidence showing that the descriptive rel-
5 evance of Prospect Theory for students' or convenience samples in the lab also holds in
6 the field ([Tanaka et al., 2010](#)).

7 This behavioural investigation of GPs' prescribing practice addresses an important re-
8 search question in public health and health economics: the existence of significant prac-
9 tice variations in the prescribing and medical behaviour of health professionals. This
10 literature generally provides evidence on the existence -and extent- of variations in prac-
11 tices; for example in the prescribing of laboratory tests ([Busby et al., 2013](#); [Verstappen
12 et al., 2004](#)), in the use of certain surgical procedures ([Weeks et al., 2015](#)), or in drug
13 prescriptions ([Molitor, 2018](#)). These small-area variations cost the American health care
14 system several billions ([Sirovich et al., 2008](#); [Weeks et al., 2016](#)) and could be potentially
15 associated with unnecessary care ([Fisher et al., 2003](#); [Emanuel & Fuchs, 2008](#)). However,
16 the literature generally has little to say about the psychological and economic causes
17 of these variations, although several papers stress the need to study the mechanisms of
18 medical decision-making, rather than its consequences ([Kristiansen & Hjortdahl, 1992](#);
19 [Diefenbach et al., 2016](#)).

20 One contribution of this paper is to provide new evidence on non-biological factors, i.e.
21 GPs' behavioural characteristics, that explain variations in family-medicine practices
22 and may affect patients' outcomes. We show that when it comes to prescribing lab tests,
23 GPs' risk attitudes may lie behind a limited but non-negligible proportion of (over-)
24 prescribing. From a public policy perspective, our results suggest that interventions
25 targeting highly risk-averse practitioners and providing personalised recommendations
26 on lab-test use might help reduce unnecessary healthcare provision.

1 **6 Conclusion**

2 In this paper, we find that risk attitudes elicited using a choice-based method have
3 significant external explanatory power for real health-related medical decisions. Estab-
4 lishing this link between doctors' psychological traits and medical behaviours constitutes
5 a promising break-through towards better understanding practice variation. It should
6 encourage further measurements of health professionals' characteristics in the field or in
7 surveys.

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1 Appendix

2 **A Sampling scheme and comparison of the sample with the** 3 **target population**

4 Of the 1904 GPs who participated in all five waves of the survey, 1568 (82.4%) were
5 offered the risk attitude elicitation questions during the fifth wave. Of the 1206 (76.9%)
6 who agreed to answer these questions, 966 (80.1%) performed all 18 binary choices. The
7 survey data was linked to RIAP records for 939 GPs (97.2%). A summary of the sampling
8 scheme and response rates is presented in Figure 4.

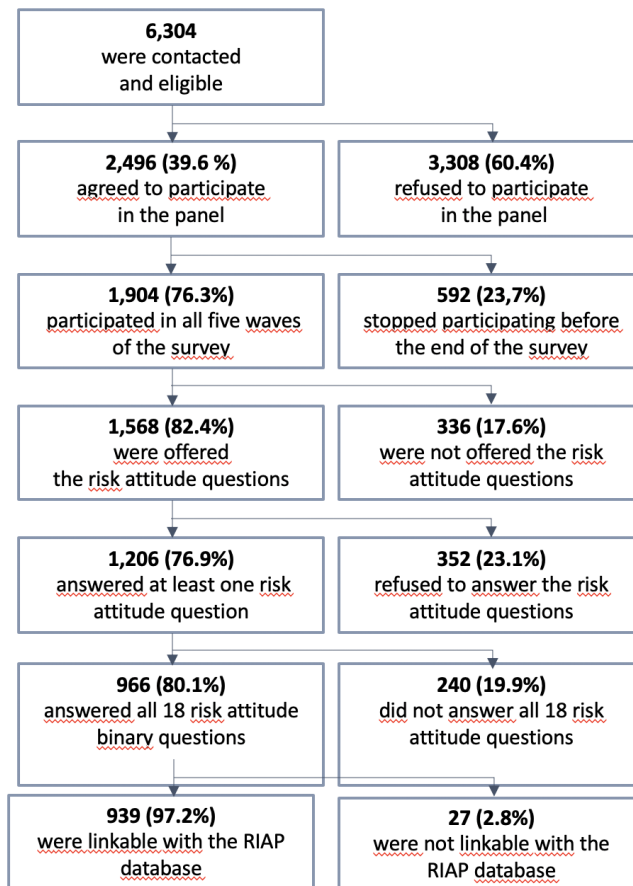


Figure 4: Sampling scheme and response rates at the different stages of the survey process

		% in the target population (N=50,898)	% in the first survey sample of the panel (N=2496)	% GPs surveyed in the fifth wave of the panel (N=1568)	Final sample used for the statistical analysis (N=939)
Gender	Male	73.3	72.2	71.7	72.0
	Female	26.9	27.8	28.3	28.0
Age	<49 yo	31.3	34.3***	33.6	34.7
	49-56 yo	34.9	37.5***	39.0	38.1
	>56	33.8	28.2***	27.4	27.2
location	rural	18.0	23.9***	22.8	21.8
	peri-urban	17.2	18.9**	19.1	20.1
	urban	64.7	57.2***	58.0	58.0
Volume of activity	<2849	25.0	22.1***	22.3	21.6
	2849-5494	50.0	49.5	49.3	50.2
	>5494	25.0	28.4***	28.4	28.2

Table 6: Sample comparisons throughout the selection process

Two-sample tests of proportion were conducted to compare the sample of each column sequentially (1) with (2), (2) with (3) and (3) with (4) . ***, ** or * denote significantly different proportions between samples with χ^2 test p value at the 1, 5, and 10% levels .

- 1 We also ran a logit model explaining selection by the stratification variables. A likelihood
- 2 ratio test failed to reject the hypothesis that none of these variable is significant ($p =$
- 3 0.83).

4 B Details on the risk-attitude elicitation module

5 B.1 Algorithm for each certainty equivalent

- 6 In this section, we present the bisection algorithm's parameter for each certainty equivalent
- 7 elicitation procedure. For $k = 1, \dots, 5$, the lottery parameters are presented in Table
- 8 x, and the values in the decision-tree squares are the sure gains in the binary choice.
- 9 Decision A corresponds to the sure gain and B to the lottery. Consistently, if A (B) is
- 10 chosen the next sure gain is lower (Higher).

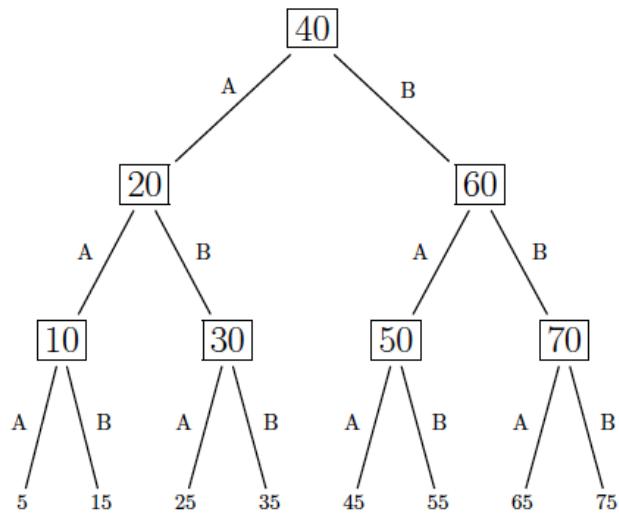


Figure 5: Sequence of binary choices for c_1

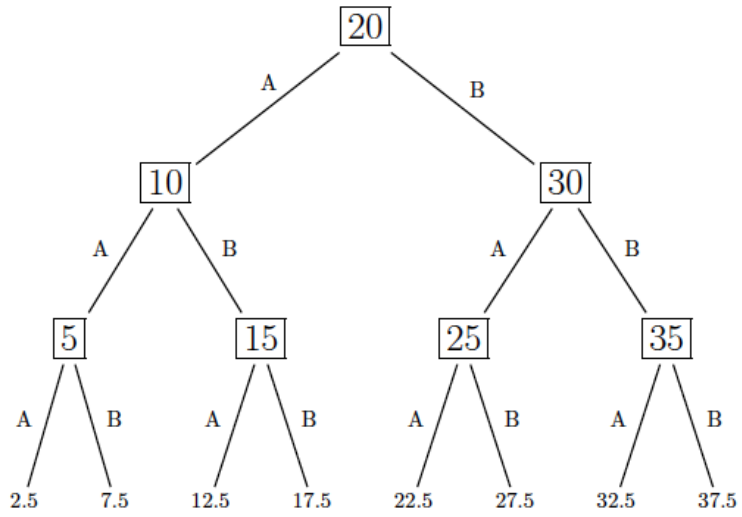


Figure 6: Sequence of binary choices for c_2

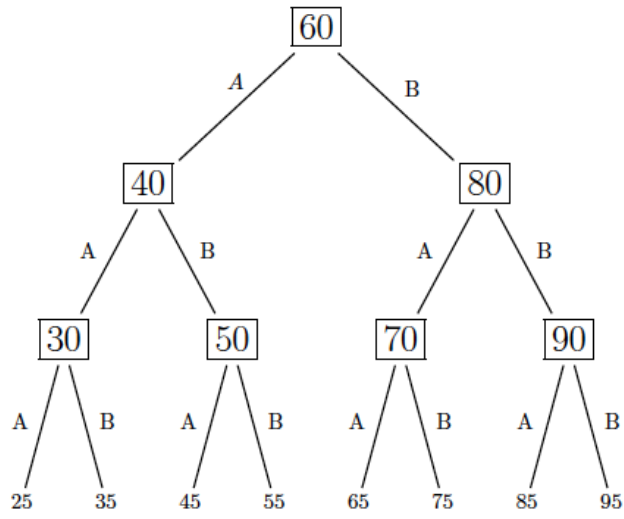


Figure 7: Sequence of binary choices for c_3

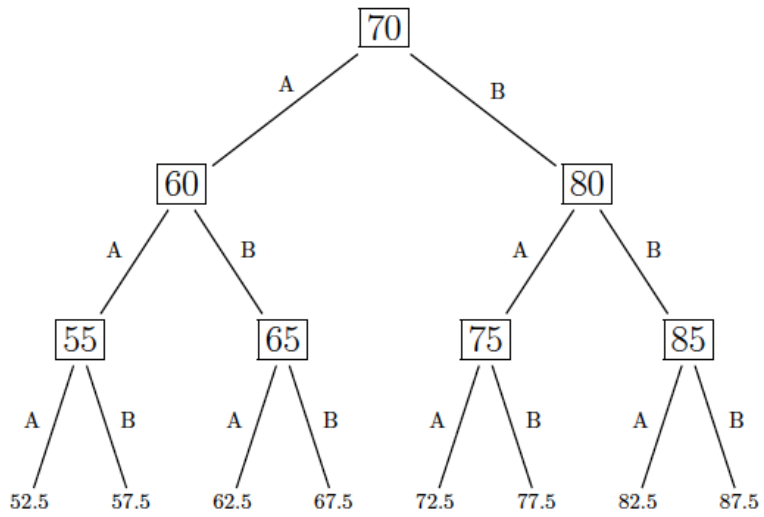


Figure 8: Sequence of binary choices for c_4

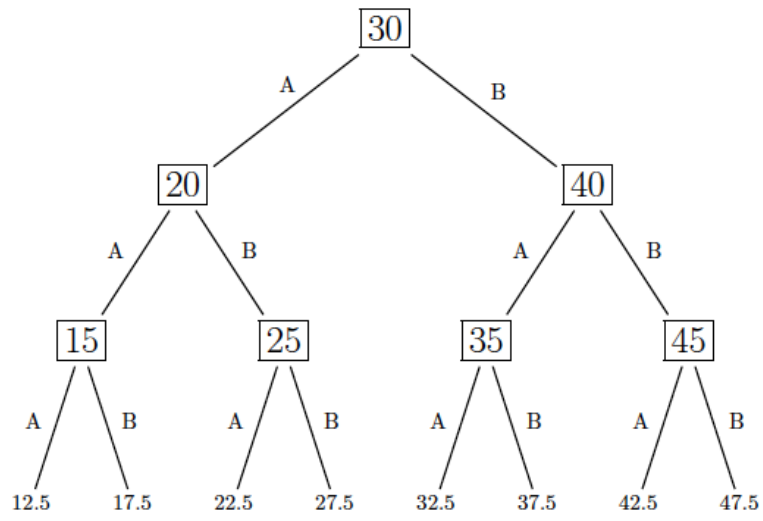


Figure 9: Sequence of binary choices for c_5

1 B.2 Graphical tool

Ce formulaire est à conserver. Indépendant de l'enquête principale, il ne vous sera utile que lors de la toute dernière partie de l'interview.

Partie "Monnaie"

	Option A	Option B
Question 1	a) +40€ de façon certaine b) ___ € de façon certaine c) ___ € de façon certaine	
Question 2	a) +20€ de façon certaine b) ___ € de façon certaine c) ___ € de façon certaine	
Question 3	a) +60€ de façon certaine b) ___ € de façon certaine c) ___ € de façon certaine	

Le symbole "___" signifie que ces montants vous seront communiqués par l'enquêteur au téléphone

Figure 10: Graphical aid mailed to each GP

1 C Additional results of econometric analysis

2 C.1 Results of second-stage estimations with CRRA regressors

Variable	Modality	CRRA & EU		CRRA & RDU	
		No control	with control	No control	with control
Patients' characteristic	Intercept	3.424*** (0.019)	3.326*** (0.108)	3.433*** (0.039)	3.331*** (0.113)
	Fee exemption	Ex		1.885*** (0.342)	1.877*** (0.342)
		Cmu		-2.663*** (0.420)	-2.655*** (0.420)
	Patients' age	Age < 16		-0.962*** (0.261)	-0.966*** (0.261)
		Age > 70		0.014 (0.320)	0.016 (0.321)
	GP's characteristic	Gender	Women		-0.120*** (0.027)
Men					
Age		<49 yo		-0.084** (0.027)	-0.083** (0.027)
		49-56 yo		-0.117*** (0.031)	-0.116*** (0.031)
		>56 yo			
Location		urban		-0.059 (0.035)	-0.058 (0.035)
		peri-urban		0.009 (0.031)	0.010 (0.031)
		rural		0.0001*** (0.00002)	0.0001*** (0.00002)
Volume of activity	consults				
Risk attitudes	Utility curvature	-0.037 (0.020)	-0.038* (0.018)	-0.055* (0.028)	-0.052* (0.025)
	Shape of Pwf			0.003 (0.043)	-0.005 (0.039)
	Observations	919	919	919	919
	R ²	0.004	0.217	0.004	0.217
	Adjusted R ²	0.002	0.207	0.002	0.207
	Residual Std. Error	0.365 (df = 917)	0.325 (df = 907)	0.365 (df = 916)	0.325 (df = 906)
	F Statistic	3.279 (df = 1; 917)	22.824*** (df = 11; 907)	2.041 (df = 2; 916)	20.923*** (df = 12; 906)

Note: . corresponds to p<0.1,* to p<0.05;** to p<0.01;*** to p<0.001

Table 7: Impact of risk attitudes on lab-test prescriptions

1 C.2 Results of one-stage Maximum Likelihood estimations

2 We report the results of "one stage" estimations where parameters of risk attitudes and
3 parameters explaining prescription are estimated jointly.

4 For these estimation, the likelihood of choice data and the likelihood of prescription data
5 are maximized jointly. The former is conditional on choice characteristics and is expressed
6 as a function taking risk-attitude parameters as arguments; the latter is conditional
7 on risk-attitude parameters and control variables and is expressed as a function taking
8 regression parameters as arguments.

9 Formally, the likelihood of choice data for a respondent writes: $l_i^{risk} = \prod_k l_k$ where l_k
10 is the likelihood of a choice k detailed in Eq. (3). Assuming that individual volumes
11 of lab-test prescription follow a lognormal distribution, the likelihood of an individual
12 prescription volume is $l_i^{prescription} = \phi\left(\frac{\log(y_i) - c + \beta\alpha_i + \mu\gamma_i + X_i'\theta}{\rho}\right)$ (cf Eq. 4). Then, the global
13 likelihood for a given respondent is $l_i = l_i^{choicedata} \times l_i^{prescriptiondata}$. Like in the second
14 stage estimations reported in the core part of the paper, individuals with prescription
15 values corresponding to the 1% of highest or lowest values (i.e. 20 individuals) are re-
16 moved from the analysis. The parameters are estimated using maximization of simulated
17 likelihood with 1000 draws for each respondent. The robust and clustered standard error
18 are computed using the sandwich estimator, with individual clustering taken into account
19 in the mean.

	Variable	Modality	without controls			With control		
			Estimate	Std Error	pvalue	Estimate	Std Error	pvalue
Moments of risk-attitude parameter distributions	$\bar{\sigma}$		9.140	0.238	0.000	9.141	0.247	0.000
	$\bar{\alpha}$		0.016	0.001	0.000	0.016	0.001	0.000
	$\bar{\gamma}$		0.586	0.020	0.000	0.586	0.020	0.000
	σ_{σ}		3.061	0.324	0.000	3.059	0.369	0.000
	σ_{α}		0.021	0.001	0.000	0.021	0.001	0.000
	σ_{γ}		0.301	0.039	0.000	0.302	0.038	0.000
Patients' characteristic	Intercept		3.431	0.034	0.000	3.330	0.139	0.000
	log(sbioc)		-1.010	0.023	0.000	-1.130	0.026	0.000
		Ex				1.880	0.423	0.000
	Fee exemption	Cmu				-2.657	0.503	0.000
	Patients' age	Age < 16				-0.963	0.316	0.002
		Age > 70				0.017	0.377	0.965
	GP's characteristic	Gender	Women					
		Men				-0.120	0.027	0.000
Age		<49 yo						
		49-56 yo				-0.082	0.028	0.003
	>56 yo				-0.116	0.032	0.000	
GP's characteristic	Location	urban						
		peri-urban				-0.058	0.034	0.085
		rural				0.010	0.030	0.744
	Volume of activity	consults				0.000	0.000	0.000
	Risk attitudes	Utility curvature	1.320	0.865	0.127	1.240	0.439	0.005
Shape of Pwf		0.004	0.049	0.929	-0.003	0.043	0.944	
Log-likelihood			-5700.444			-5590.141		

Table 8: One-stage estimations on risk attitudes and prescription (with CRRA and RDU)

	Variable	Modality	without controls			With control		
			Estimate	Std Error	pvalue	Estimate	Std Error	pvalue
Moments of risk-attitude parameter distributions	$\bar{\sigma}$		9.385	0.250	0.000	9.386	0.251	0.000
	$\bar{\alpha}$		0.801	0.018	0.000	0.801	0.018	0.000
	$\bar{\gamma}$		0.472	0.015	0.000	0.472	0.015	0.000
	σ_{σ}		3.115	0.437	0.000	3.114	0.436	0.000
	σ_{α}		0.430	0.027	0.000	0.430	0.027	0.000
	σ_{γ}		0.262	0.025	0.000	0.262	0.025	0.000
Patients' characteristic	Intercept		3.435	0.039	0.000	3.333	0.152	0.000
	log of residual standard deviation		-1.011	0.023	0.000	-1.131	0.026	0.000
		Ex				1.877	0.445	0.000
		Cmu				-2.656	0.550	0.000
		Age < 16				-0.967	0.334	0.004
		Age > 70				0.014	0.348	0.968
		Gender	Women					
			Men			-0.120	0.027	0.000
		Age	<49 yo			-0.082	0.028	0.003
			>56 yo			-0.116	0.032	0.000
GP's characteristic		Location	urban					
			peri-urban			-0.058	0.034	0.084
			rural			0.010	0.031	0.757
		Volume of activity	consults			0.000	0.000	0.000
		Risk attitudes	Utility curvature	-0.057	0.029	0.046	-0.053	0.025
		Shape of Pwf	0.005	0.043	0.906	-0.003	0.040	0.945
Log-likelihood			-5768.825			-5658.500		

Table 9: One-stage estimations on risk attitudes and prescription (with CARA and RDU)

1 C.3 Stats desc on explanatory variables

Variable	Levels	%
Gender (is a social construct)	Feminin	28.0
	Masculin	72.0
tage	1	34.7
	2	38.1
	3	27.2
tau	1	21.8
	2	20.1
	3	58.0
tact	1	21.6
	2	50.2
	3	28.2

	Mean	Sd	min	Q1	Q2 (median)	Q3	Q4
clit	1768.20	728.30	117.00	1267.00	1717.00	2168.00	6862.00
cmu	0.10	0.10	0.00	0.00	0.10	0.10	0.70
c16	0.20	0.10	0.00	0.20	0.20	0.20	0.50
c70	0.10	0.10	0.00	0.10	0.10	0.20	0.80
bioc	34.90	28.70	1.80	24.60	31.40	40.30	783.10

1 C.4 OLS on RA with gender and age

Table 10:

[-1.8ex]	<i>Dependent variable:</i>		
[-1.8ex]	u expo EU	u expo RDU	g expo RDU
[-1.8ex] SexeMasculin	-0.0002 (0.001)	0.00002 (0.001)	0.017 (0.018)
tage2	0.00005 (0.002)	-0.001 (0.001)	-0.056*** (0.018)
tage3	0.002 (0.002)	0.001 (0.001)	-0.062*** (0.020)
Constant	0.028*** (0.001)	0.018*** (0.001)	-0.651*** (0.016)
[-1.8ex] Observations	899	901	902
R ²	0.003	0.002	0.014
Adjusted R ²	-0.0002	-0.001	0.011
Residual Std. Error	0.019 (df = 895)	0.016 (df = 897)	0.225 (df = 898)
F Statistic	0.930 (df = 3; 895)	0.586 (df = 3; 897)	4.202*** (df = 3; 898)

[-1.8ex] *Note:* *p<0.1; **p<0.05; ***p<0.01

	Sick (with probability p)	Not sick (with probability $1 - p$)
Test	u_1	u_2
No test	u_3	u_4

2 Under EU, test is the best decision iif :