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Revisiting the primary bias: the role of innumeracy in the misperception of prevalence of chronic illnesses

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Abstract:

Although people have been repeatedly found to underestimate frequencies of common illnesses and overestimate those of rare illnesses, not much is known about this consistent bias in risk perception, termed “primary bias” in the literature, as well as the origin of its variations among different subpopulations. To fill this gap, we conducted a national survey among a representative sample of the French population ($n=3,245$) to compare the perceived and actual prevalence of chronic illnesses, and to test the hypothesis that numeracy may play an important role in the accuracy of judgments of risk frequencies. The participants were asked to complete a 10-items numeracy scale and to estimate the prevalence of a variety of social conditions and chronic illnesses such as cancers or heart diseases by using a percentage scale. The analyses show that (1) participants tend to greatly overestimate the prevalence of conditions affecting small percentages of people, and underestimate those affecting a large percentage of them, (2) the Tversky and Kahneman’s probability weighting function provides an adequate model to represent the discrepancy between the perceived and actual prevalence of these illnesses or occupations, and (3) the magnitude of the primary bias varies principally as a function of the respondents’ numeracy. These results suggest that the primary bias that affects perceptions of prevalence of chronic diseases is not fundamentally different from those characterizing other types of probabilistic judgments. They also confirm that numeracy plays a considerable role in people’s ability to transform epidemiological observations from their social environment into more accurate estimates.

Introduction

The current pandemic of COVID-19, and the prospect of further major epidemics in the future, has highlighted the importance to better understand how people perceive risk for their health (Dryhurst et al., 2020; McColl et al., 2022). In this article, we will focus on one specific dimension of risk perception which have been relatively neglected in the recent psychological literature, the judgements of frequencies in the field of chronic illnesses. Since the early stages of research on risk perception, scientists have shown through a number of famous surveys and laboratory experiments that people seem to display a range of recurrent and substantial biases when asked to think about the probability or frequency of health-related events (e.g., conjunction fallacy or unrealistic optimism (Baron, 2006)). Notably, since the pioneering experimental research conducted by Attneave (Attneave, 1953) in the fifties then by Lichtenstein and her colleagues in the late seventies (Lichtenstein et al., 1978), it has been consistently found that people tend to underestimate the number of high-frequency events, and conversely, to overestimate that of low-frequency ones. In particular, it has been shown that the absolute frequencies of fatalities attributable to common chronic diseases (cancers, heart diseases, diabetes, etc.) were systematically underestimated, while those attributable to rare diseases or disasters – such as botulism or tornadoes – were greatly overestimated. This typical phenomenon of distortion in the perception of risk, which is characterized by the flatness of the best-fit curve of the relationship between perceived and observed risks, has been called “primary bias” in the psychological literature (Gigerenzer et al., 2012; Johnson & Tversky, 1983; Lichtenstein et al., 1978). For Lichtenstein et al (1978, p. 551), the primary bias refers to the common tendency “to overestimate small frequencies and overestimate larger ones”. Nevertheless, it should be noted that at this stage the tendency to overestimate the low-frequency events and to underestimate the high-frequency events was not replicated in the study when their subjects had to rate the occurrence of events unrelated to health and illness such as the frequency of words or occupations.

Since the discovery of the ‘primary bias’ in risk perception, different psychological mechanisms have been offered to explain why people are likely to estimate the frequency of some events more accurately than some others. In their seminal article, Lichtenstein and her colleagues suggested that the availability heuristic – i.e., a mental shortcut through which one estimates the frequency or the probability of an event based on how easy some instances or occurrences can be brought to mind and recalled, might account for the primary bias in judgments of risk frequency. Therefore, people would be more likely to overestimate the frequency of “sensational” events which trigger intensive media coverage than that of “undramatic” events. Though Lichtenstein, Slovic and their colleagues have not directly tested the explanation of the primary bias by the availability heuristic (Hertwig et al. 2005), this interpretation is rather consistent with the results of subsequent researches showing that probability estimates for undesirable events can be biased by their severity or vividness. For example, (Harris et al., 2009) found that people judge rare events as more likely to occur when their value is particularly negative than when it is more neutral. Similarly, Vosgerau (Vosgerau, 2010) showed in a series of experiments that participants estimate the likelihood of desirable and undesirable events to be higher than comparable neutral events. The author attributed the overestimation of these specific events to the misattribution of the arousal related to the outcome. To sum, people would be more likely to overestimate small probabilities or frequencies for an affect-laden than for a neutral event. As noted by Slovic et al (Slovic et al., 2007): “Perhaps the biases in probability and frequency judgment that have been attributed to the availability heuristic may be due, at least in part, to affect.”

During the same period, Tversky & Kahneman conducted a number of famous studies of decision-making under risk in the field of economics and finance (Gilovich et al., 2002). In particular, they investigated probabilistic judgments by using more indirect elicitation methods based on choices between lotteries to infer potential distortions in the human perception of probability (for instance, the participants are asked to choose between pairs of gambles such as A_1 (5%, \$240) or B_1 (7%, \$200)). The advantage of the indirect methods is that they generally rely on more natural and less cognitively demanding tasks. This research has shown that subjective

probabilities, or relative frequencies, are typically characterized by several remarkable mathematical properties, which are consistent with the existence of a primary bias in probabilistic judgments (Budescu et al., 2011; Prelec, 1998; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Firstly, these judgments can be represented as a regressive function, i.e., there is an inflexion value above which the subjective frequencies are lower than the objective frequencies of negative or positive events, (and conversely). Secondly, probabilistic judgments can be represented by an asymmetrical curve, i.e., there exists a given value different from 50% at which the subjective frequencies equal the objective frequencies of events. As a consequence, the graphical representation of probabilistic judgments is represented as a sigmoid, or reverse S-shaped curve, i.e., the perceived risk frequencies are concave until the above-mentioned inflexion point, after which it is then convex (see Figure 1). These empirical works have conducted to develop a model for the judgments related to probability in psychological and behavioral sciences using non-linear functions of transformation of objective probabilities, which show that the smaller frequencies tend to be overestimated and the larger frequencies are underestimated by subjects. According to Prelec (1998: 497), these sub-proportional probability weighting functions are generally “regressive, s-shaped and with a fixed point and invariant inflection point at $1/e = .37$.” Furthermore, it was recently found in an experimental study of decision-making under risk that undergraduate students with higher numeracy were significantly less prone to this distortion of objective probabilities than those with lower numeracy (Petrova et al., 2014).

These research findings have nevertheless raised a number of criticisms among psychologists and behavioral scientists. First of all, most of the underlying data has been collected from small, convenient, and non-representative samples of students from advantaged groups, which raises legitimate issues about the representativeness and generalizability of the data collected (Ioannidis & Doucouliagos, 2013; Pashler & Harris, 2012). However, it should be noted that a recent international study conducted in 19 countries successfully replicated most of the experimental findings underlying the prospect theory for decision under risk (Ruggeri et al., 2020). Second, some extensions of research devoted to primary bias in the area of health and

illness have led to the collection of somewhat contradictory evidence (Raude et al., 2018). On one hand, the original finding by Lichtenstein et al (1978) that people tend to underestimate the higher absolute frequencies of deaths related to various biomedical causes (and overestimate the lower ones) has been successfully replicated by Hakes & Viscusi (2004) among a non-representative sample of U.S. citizens, as well as by Hertwig et al. (2005) among a convenience sample of German students. However, other researchers found in larger samples of individuals that they were more likely to greatly overestimate some of the most common health threats, such as those associated with cigarette smoking (Lundborg & Lindgren, 2004; Viscusi, 1990), diabetes or hypertension (Frijling et al., 2004). In other words, asking questions about the relative frequencies of harmful events, rather than their absolute frequencies, seems to lead to inconsistent or even contradictory results in risk perception research. These inconsistencies in the scientific evidence should incite us to develop an experimental design to test whether such biases in judgment of risk frequencies should be attributed to methodological-experimental artefacts or poor cognitive skills, including limited memory and computational capacities (Gigerenzer, Fiedler, & Olsson, 2012). Interestingly, latter research in psychology on how people estimate the frequency of risk showed that some categories of people provide much more accurate judgements than some others. For instance, Hakes & Viscusi (2004) found in a large sample of US citizens that the magnitude of the primary bias varied across sociodemographic factors, with the better educated participants – and to a lesser extent, white and male participants – providing more accurate risk estimates.

Thus, in this article, we took advantage of a large national health survey conducted in France to examine the conditions under which perceived prevalence of a variety of chronic illnesses is more or less biased (or inaccurate). The main research questions we wanted to address include the following: firstly, do the primary bias that has been observed in the aforementioned experiments on judgments of absolute frequency of an array of health-related risks also exist in a more ecologically realistic situation, in which people are asked to estimate the relative frequencies of widespread illnesses, and how reliable is the probability weighting model

developed in the field of judgment and decision-making in predicting the perceived prevalence of these illnesses? Secondly, are the judgments of frequencies related to non-health events prone to the same bias as the judgment about the frequency of health events? Indeed, it seems that people are better at making frequency judgments about events they are more familiar with. For instance, Kahneman and Tversky (1973) found in their seminal research about base rate neglect that U.S. students made fairly accurate judgments when they were asked to estimate the proportion of graduate students in different academic fields. Thirdly, is the primary bias in frequency judgments specific to younger and more educated subjects or are they potentially universal across social groups? Given the extensive body of literature that exists on the socioeconomic and demographic variations in both numerical and non-numerical judgments about health risks (Finucane et al., 2000; Hakes & Viscusi, 2004; Kahan et al., 2007), it seems reasonable to assume that there may be considerable differences among people and groups in the accuracy of their estimates of illness prevalence. Fourthly, can these potential sociodemographic variations in the accuracy of frequency judgment be accounted for by the unequal distribution of numeracy skills within the whole population? Indeed, there is now growing evidence that individuals with higher numerical ability exhibit much less biased perceptions of health risk and benefit than those with poorer numerical ability (for a review, see Reyna et al., 2009).

Subjects and Methods

The data were collected from an online survey of French adults (18 years or older) participating in a large national panel devoted to research on consumer attitudes and behaviors. The panelists consented to participate in surveys on a regular basis in exchange for financial compensation. For the sake of representativeness, the panel included individuals who were recruited in both online and offline populations. However, only online panelists were offered to participate, as telephone interviews were not suitable for the type of questions submitted to the subjects. The survey complied with the recommendations of the National Data Protection Authority (CNIL), which is responsible for the ethic standards and protection of personal data collected in France. All

subjects were informed about the objective of the research and gave electronic informed consent. In total, 6,000 panelists were contacted by email in October of 2014, and 3,245 agreed to respond to the survey (cooperation rate = 54%).

Measures

Observed prevalence of chronic illnesses: For this study, we selected a list of 12 well-known chronic illnesses, i.e. “conditions that last a year or more and require ongoing medical attention and/or limit activities of daily living” (Bernell & Howard, 2016). This includes communicable illnesses (e.g., HIV or hepatitis), non-communicable illnesses (e.g., cancers or heart diseases), and metabolic and endocrine disorders (e.g., diabetes, high blood sugar). Statistics provided by the national public health authorities in their annual report on the state of the population’s health were used to measure the objective prevalence of a variety of chronic diseases in France (DREES, 2015). As shown in Table 1, the actual prevalence of these illnesses in the French population, i.e., the proportion of this population being affected by a particular chronic disease or disorder at a the time of the study, ranged from a rate of 1.1% for genetic disorders to 57.8% for eye diseases such as myopia or astigmatism.

Perceived prevalence of chronic illnesses: To date, there is still a lot of disagreement among scientists on how judgments of risk should be measured in empirical research (Weinstein, 1998). As noted by Viscusi (1990, p. 1256): “Obtaining meaningful survey responses regarding individuals' risk perceptions is not a straightforward task”. This methodological problem can also be attributed to the fact that elicitation methods are more or less natural and often require considerable cognitive efforts from individuals. Furthermore, there exist substantial variations in the definition and measurement of the concept of risk among scientific disciplines (Althaus, 2005). For instance, Slovic (1999) showed that some previous research used to refer to the probability or the frequency that an event will occur when investigating risk perceptions, while others refer instead to the severity of its consequences. Furthermore, even the term of frequency encompasses a variety of concepts, such as absolute frequency, relative frequency, or cumulative

frequency. For chronic diseases, epidemiologists commonly assess health risk by calculating the incidence (rate of new cases within a given time frame) or prevalence (proportion of cumulative cases at a certain time point) of the condition in a given population. This information about the relative frequency of a disease can alternatively be expressed in terms of fractions, odds, or percentages. However, people's comprehension of these various numerical expressions of how common a disease is within a population can be taken for granted since eliciting probabilistic judgments has been repeatedly found to pose a number of difficulties in research on risk perception (Diefenbach et al., 1993; Gigerenzer, 1991; Peters, 2008; Rothman & Kiviniemi, 1999).

To address this issue, participants were asked to estimate the prevalence of the 12 above-mentioned chronic illnesses (see Table 1), by using a percentage scale, i.e., a relative frequency scale based on a reference sample of 100 individuals. Although subjects in laboratory experiments have been shown to have some difficulties using and understanding numerical information, there is sound evidence that using a more succinct percentage format is a better method than using other numeric formats to represent simple probabilities (Woloshin & Schwartz, 2011). In addition, asking people about risk as a percentage in a population (distributional format) rather than asking them about risks to an individual (singular format) proved to reduce significantly some methodological biases, such as the overuse of "50" without intending the associated number of 50% (de Bruin et al., 2000). In our survey, the format and phrasing of the questions were adapted from the item developed by Viscusi (1990): "Among 100 people living in France, how many do you think have (*Disease*)? Please give a value between 0 and 100". Thus, the accuracy of people's judgments of the percentages measured through this method provides insight into the accuracy of people's judgments on the relative frequency of specific illnesses, or the perceived prevalence, by comparing them with the estimates of "objective" prevalence based on epidemiological data (the observed prevalence).

Perceived and actual prevalence of occupational status: In the same vein, the participants were asked to estimate the proportion in the French population of a series of 13

occupational and employment statuses, such as the current unemployment or retirement rates. The format and phrasing of the questions were identical to those employed to estimate the prevalence of specific illnesses: “Among 100 people living in France, how many do you think are (*Occupation*)? Please give a value between 0 and 100”. The data used to determine the objective prevalence of these occupational and employment statuses in the French population were drawn from the annual statistics released in 2015 by the French national institute for statistical and economic studies (INSEE).

Numeracy: Numeracy is generally defined as the ability to comprehend and use simple mathematical and probabilistic concepts (Peters, 2008). To date, numerous numeracy scales have been proposed in the literature to test the objective ability of individuals to understand and/or compute numbers (Reyna et al, 2009). Here, the participants were asked to complete a 10-items numeracy scale developed by Lipkus et al. (2001) to measure each subject’s ability to deal with numeric information about risks and benefits, e.g., “Imagine that we flip a fair coin 1,000 times. What is your best guess about how many times the coin would come up heads in 1,000 flips?”, and “Which of the following represents the biggest risk of getting a disease? 1%, 10%, 5%?”. This scale showed a relatively high internal consistency (Cronbach’s $\alpha = .77$). Thus, a numeracy score could be calculated for each participant by summing the total number of correct responses for these 10 items.

Socioeconomic and demographic characteristics: A variety of sociodemographic and health characteristics were systematically collected among the participants at the beginning of the survey. These included gender, sex, age, level of education, occupation, household income, location, housing conditions, family and marital status, as well as perceived health status. The characteristics of the sample are shown in Table 1.

Statistical Analysis

We calculated arithmetic means and 95% confidence intervals for the perceived relative frequencies of each socioeconomic and illness-related variables. We used t-tests to compare statistical differences in means among various categories of respondents. We examined the relationship between the perceived and observed prevalence of diseases or socio-occupational status by using a two-parameter probability weighting model developed in the field of behavioral decision-making (Prelec, 1998). Behavioral studies of judgment and decision-making under risk have demonstrated through a series of laboratory experiments that the relationship between subjective and objective probabilities of events can be adequately described by a nonlinear transformation of the relative frequencies defined as:

$w(p) = \exp(-\beta(-\ln(p))^\alpha)$ where α and $\beta \in [0,1]$ and p is the actual probability or frequency.

This weighting function translates the observed prevalence (p) into the perceived one [$w(p)$]. It also implies that there exists an inflection point under which the deviation between the perceived and observed prevalence gets smaller as the observed prevalence increases (and vice versa). A simple analysis of this function shows that the size of the deviance is controlled by α and the position of the inflexion point by β . Hence, we can estimate α on subgroups of the population to measure how a specific characteristic impacts the curvature of the perception curve, i.e, the magnitude of the primary bias (see Figure 1).

Our estimation procedure relies on the box-constrained version of the Broyden-Fletcher-Goldfarb-Shanno (commonly referred to as BFGS) optimization method (Byrd et al., 1995), as implemented in the package 'optimx', to estimate α and β by minimizing the mean squared error (MSE) of $w(p)$. Other optimization methods have been tested and gave similar or higher MSE. All the analyses were performed using R 3.6.1 (with R Studio 1.2).

We also wanted to perform multivariate analysis of the potential factors associated with the deviation between a perceived and an observed prevalence. To that purpose we considered the following equation for α :

$$\alpha = \frac{1}{1 + \exp(-\gamma)}$$

so that $\alpha \in [0,1]$ and where we define γ has

$$\gamma = \sum \delta_i X_i + \epsilon$$

where X_i are the studied cofactors and δ_i their estimated coefficients.

We used the same estimation procedure to estimate δ_i and β . We computed the determination coefficient R^2 as a measure of fitness quality, and produced 95% confidence intervals of the estimates from the numerically estimated Hessian matrix.

To quantify the impact of cofactor i on the perception curve, we defined the Mean Error Increase (MEI_{*i*}) as:

$$MEI_i = \frac{E(|P - w(p, X_i = 1, X_{j \neq i} = 0)|) - E(|P - w(p, X = 0)|)}{E(|P - w(p, X = 0)|)}$$

where P is the observed prevalence and X are defined as dichotomous variables whose reference value is 0. MEI_i measures the proportion of increase (or decrease) in the perception error depending solely on X_i when all other cofactors are at their reference value. In other terms, an MEI_i of 10%, means that individuals with characteristic X_i will have, on average, a perception bias increased by 10% compared to individuals who do not have this characteristic. We also define the Mean Absolute Error (MAE_{*i*}) and the Mean Relative Error (MRE_{*i*}) as:

$$MAE_i = E(|P - w(p, X_i = 1, X_{j \neq i} = 0)|)$$

and

$$MRE_i = E(|P - w(p, X_i = 1, X_{j \neq i} = 0)|/P)$$

MAE_i and MRE_i measure the average absolute or relative difference (respectively) between the perceived and observed prevalence for each covariate included in the analysis when all others are at their reference value. For example, an MAE_i of 5% could mean that on average the perceived prevalence of individuals with X_i characteristic is 15% when the observed prevalence is 10%, while the MRE_i in the same context would be 50%.

Results

Are the perceived prevalence of chronic illnesses biased and how?

As shown in Table 1, the participants tend to significantly overestimate a large majority of the most common chronic illnesses in France ($t < 4.4$, $df < 3,245$, $p < .001$). However, the nature and magnitude of this bias in the perception of the prevalence of these illnesses showed substantial differences, which depend to a large extent on their actual prevalence. First, the discrepancy between the perceived and actual prevalence calculated for each illness was considerably higher for the less prevalent illnesses than for the more prevalent illnesses in the population (e.g., the prevalence of communicable diseases and genetic disorders are overestimated by about a factor of 10 and 12, respectively, while that of metabolic disorders was only overestimated by 20%). Second, the overestimation bias observed in the prevalence of these illnesses tends to decrease until a certain threshold, which represents the correct estimation, then switches into an underestimation that increases as the magnitude of the prevalence increases. In other words, there exists a phenomenon of overestimation when prevalence is low, while there is one of underestimation when prevalence is high. In addition, it should be noted that contrary to the results obtained by Lichtenstein and her colleagues, the same pattern was found in our study for the estimates of the rate of a variety of occupational and employment statuses in the French population.

Overall, participants tended to provide more accurate or unbiased estimates when the actual prevalence rate of the status was closer to the inflection point ($1/e$) defined by Prelec. This suggests that the primary bias that affects perceptions of prevalence of chronic diseases may not be fundamentally different from those characterizing other types of frequency or probability judgments. Last but not least, we found that the Tversky and Kahneman's probability weighting function provided a suitable mathematical model for this primary bias in the perceived prevalence of chronic illnesses.

Does the 'primary' bias vary in magnitude as a function of individual characteristics?

In line with the results of previous studies, the magnitude of the primary bias in the perceived prevalence of chronic illnesses appears to vary as a function of the participants' sex, level of education and numeracy. As shown in Figures 2 and 3 (for the details, see Table 2), the calculated alpha coefficients, which represents as outcome variable the slope of the reversed S-shaped curve at the inflection point, were 0.56 for males versus 0.37 for females, and 0.54 for the more educated versus 0.30 for the less educated participants. Furthermore, the discrepancy between the perceived and the actual prevalence of chronic diseases was found to vary to a lesser extent by age group, occupation and health status, and to a larger extent according to the individual's level of numeracy. As shown in Figure 4, the alpha coefficient was 0.63 for the more numerate versus 0.28 for the less numerate. However, as shown in Figure 5, there exists significant variations in the participants' numeracy score depending on their sex ($t(3,243) = 7.9, p <.001$) and level of education ($F(3,244) = 219.1, p <.001$).

The multivariate analysis, including all studied cofactors (numeracy, sex, age, education, socioeconomic status, and type of estimate (chronic illnesses versus occupations)), allowed us to account for all covariates at the same time, hence removing potential confounding effects (Table 3). The determination coefficient (R^2) of the multivariate model was 18% and covariates whose MEI 95% confidence interval including 0% were considered non-statistically significant. In this analysis, a low numeracy index accounted for 59.3% (MEI, 95% CI [43.6%; 74.2%]) of the primary bias estimated by the model, which may lead to a relative deviation of the perceived prevalence of 105.4% (MRE, 95%CI [75.4% ; 146.3%]). The sociodemographic factors were also found to play an important role in the misperception of the prevalence as the sex of the participants accounted for 47.9% (95%CI [32.7%; 68.1%]) of the primary bias, and a low education level (limited to middle school) and being young (18 to 39 years old) accounted for 18.7% (95%CI [11.5%; 27.0%]) and 11.6% (95%CI [3.0%; 21.9%]), respectively. The other socio-demographic covariates did not significantly affect the magnitude of the primary bias. Moreover, contrary to

our expectation based on the existing literature, we did not find that the type of estimate (chronic illnesses versus occupations) reduce significantly the inaccuracy in frequency judgments when using a percentage scale (MEI = 3.68%, 95%CI [-3.65%; 11.88%]).

Is the effect of sex and education on the primary bias mediated by numeracy?

To determine whether sex and educational differences in the magnitude of the primary bias were due to differences in numerical abilities (see fig. 5), we used methods developed by Preacher and Hayes (2008) which allowed us to estimate path coefficients in simple and multiple mediator models and to provide confidence intervals for both direct and indirect effects. In this mediation model, sex and education were the independent variables; the level of numeracy was the mediator, and the alpha coefficient, which represents the curvature of the probability weighting function at the inflexion point, i.e., the magnitude of the primary bias, was the dependent variable. The Hayes and Preacher's macro (2014) was used to calculate the parameter estimates and bootstrap confidence intervals. The results are shown in Figure 6. Interestingly, sex and education still had both a significant direct effect on the magnitude of the primary bias after adjusting for the indirect effects of numeracy ($p < .001$). The people's numerical ability accounted for 45% of the relationship between the level of formal education and numeracy, but only 21% of the relationship between sex and numeracy. Thus, the gender gap in the accuracy of the perceived prevalence of illnesses was not essentially explained by the sexual differences in the numeracy skill.

Discussion

How accurate are judgments that people make about risk frequencies? Despite the fact that perceptions of risk have been extensively studied since the famous works conducted by Lichtenstein and colleagues, there is still pervasive disagreement among psychologists and behavioral scientists about people's capabilities to estimate frequencies and numbers related to health and illness in an unbiased manner. On one hand, a number of studies consistently showed that people were likely to overestimate rare health risks (and underestimate common health

risks), a psychological effect named ‘primary bias’ in the literature about judgement and decision-making (Baron, 2006). On the other hand, the overestimation or underestimation of certain health risks seems to depend, to a large extent, to the type of elicitation methods solicited by the researchers to examine risk judgements (Weinstein, 1998). According to Fischhoff (2012, p. 188), “systematic research on this question (how accurate are lay perception of risk) has only just begun”. Although Fischhoff’s opinion about the state of current knowledge regarding the perception of health risks may be viewed as overly pessimistic, it nevertheless points out a potential lack of replication and refutation culture in this field. Notably, since the seminal work conducted by Tversky and Kahneman in the seventies, questions about whether some common cognitive biases in risk-related judgment and decision-making persist across a variety of populations and communities has not been seriously considered and reinvestigated until only recently (Ruggeri et al, 2020).

In this study, we tested the hypothesis that the Tversky and Kahneman’s probability weighting function predicts the primary bias in risk judgements and estimates when using a direct elicitation method in ecologically realistic conditions. In line with the results from a previous study of risk judgements related to infectious diseases (Raude et al, 2018), we found that the probability weighting function provided a suitable mathematical model for this bias in the perceived prevalence of well-known chronic illnesses at the level of aggregate judgments. This is a remarkable finding as this function was initially developed by Tversky and Kahneman on the basis of an indirect elicitation method, which led them to infer the reversed S-shape of probabilistic judgments from a series of choices under risk made by the subjects enrolled in experimental studies. Nevertheless, even though the perceptions of risk have long been recognized as an important variable within the leading theories of human behaviors, we still know relatively little about the social and individual variations – and therefore the origins – of some well-known cognitive biases, which shape the way people think about the probability or frequency of negative events. For instance, due to the large utilization of small and convenient samples in the past research, it should be noted that most studies did not investigate the role of

demographic factors such as nationality, gender or education, in the accuracy of risk perceptions (Hakes & Viscusi, 2004; Raude et al., 2005). Therefore, we still do not know whether the primary bias observed in the judgments of probability or frequency are either potentially universal or more specific to certain categories of people.

Moreover, to the best of our knowledge, no study has investigated the effect of numeracy on the magnitude of the primary bias in risk judgements. This is relatively surprising as (1) a number of studies about cognitive biases in risk perception have shown consistent differences among subgroups of population according to their numerical skills, and (2) the level of numeracy was repeatedly found to vary as a function of the respondents' gender, socioeconomic status, or education (Peters, 2008; Reyna et al., 2009). Notably, a large majority of the studies examining the role of innumeracy in the misperception of health-related risks has been conducted in relation to breast cancer. Most of them came to the conclusion that people are likely to overestimate their personal risk of developing the disease when compared to the epidemiological evidence, with the less numerate participants providing more biased risk estimates than the more numerate ones. In other words, the misperception of risks related to breast cancer seems to depend to a large extent on the level of innumeracy. For instance, Schwartz and his colleagues found that women lower in numeracy provided more inaccurate risk estimates than those higher in numeracy (Schwartz et al., 1997). Similarly, Davids et al found that all women were likely to overestimate their risk of dying from breast cancer. More generally, participants exhibiting higher level of numeracy appeared to make significantly less biased risk judgments than those with poor numerical abilities (Davids et al., 2004).

Overall, our study confirms that accuracy of risk perceptions varies largely according to people's numerical skills, which are unequally distributed across sociodemographic groups. Consistent with past research, better educated and male participants have a higher level of numeracy. In the psychological literature, several explanations have been offered to account for the gender gap in numeracy skills among children and adults, ranging from biological and evolutionary factors to

social and cultural factors such as less gender-restricted educational opportunities (Halpern et al., 2007; Yalcin, 2019). However, it seems that the gender inequalities in education cannot fully explain gender differences in adult numeracy as policies favoring women achievement in mathematics and sciences did not eliminate over time the sexual differences in this cognitive ability (Cook, 2018; Weber et al., 2014). More specifically, it appears in our study that individuals lower in numeracy tend to systematically overestimate the prevalence of conditions affecting less than 20-35% of the population and to underestimate that of more common conditions, such as eyes disorders and diseases, when compared to those higher in numeracy. Furthermore, we found that people's numerical skills accounted to a large extent for the variations observed in past research in the magnitude of the primary bias in risk judgements as a function of the socioeconomic and demographic characteristic of the participants (Hakes & Viscusi, 2004, Raude et al, 2018). Nevertheless, the reasons why the more educated and numerate male participants still outperform their female counterparts on the measure of accuracy of risk perception remains largely elusive at this stage.

Last but not least, we didn't find in this study any significant difference in the magnitude of the primary bias, when comparing the perceived prevalence of medical and non-medical conditions. Their indistinguishable level of inaccuracy is striking given that several studies conducted on convenient samples showed that judgments of frequencies related to undesirable events were more prone to an overestimation bias than those related to more neutral or desirable events. The absence of difference in the magnitude of the primary bias according to the type of condition should lead us to question some of the post-hoc explanations that have offered in the previous research. In particular, one could plausibly hypothesize that the availability heuristic, which have been introduced to explain the primary bias since the seminal study by Lichtenstein et al (1978), play a greater role in the formation of risk judgments when people are asked about absolute frequencies (thinking about risks as a raw number) than when they are asked about relative or cumulative frequencies (thinking about risks as a percentage in a population). Nevertheless, more

research is needed at this stage to determine to what extent the perceived severity of chronic illnesses affect their perceived prevalence in the population.

Of course, this study is not without limitations. First, it is important to underline that the utilization of other elicitation methods might have led to different results. Although the respondents were allowed to use decimals in their responses, only a few individuals actually provided estimates which included numbers after the decimal point. Therefore, the utilization of another response scale, such as the number of cases per 10,000 or 100,000 people, might have generated more or less accurate prevalence estimates. Second, although percent scales proved more reliable than other measurement scales, it cannot be excluded that some people still found them difficult to use and interpret, and responded to the questions with non-opinion. Third, although we investigated a range of chronic illnesses that affect large proportions of the adult population (between 1% and 58%), we were not able to ask people about several medical conditions that a majority (> 50%) of the population may have developed because there is not such a thing in the current developed countries. These methodological considerations should lead us to remain cautious in the interpretations of and extrapolations from the results of this study.

Conclusion

By revisiting the primary bias discovered by Lichtenstein and colleagues in the late seventies, this study contributes significantly, in our opinion, to a better understanding of this phenomenon. First, it shows that the weighting probability function provides an adequate model to account for this well-documented bias in the perceived prevalence of chronic illnesses, as well as other personal conditions or characteristics such as occupations. Second, it shows how this bias varies across populations, with a lack of basic numerical skills playing an essential role in the inaccuracy of the perceived prevalence of chronic illnesses. Indeed, most people did not express unbiased judgments but innumeracy appears to substantially increase the misperception of health-related risks. Third, these results indicate that numeracy not only reflects the people's ability to understand and use statistical information in their decision-making, but also their ability to

transform routine observations and discussions about cases of illness in personal networks and public sources of information, such as television and social media, in more accurate health risk estimates. Last but not least, they suggest that certain common biases in frequency judgments may be considerably reduced by education and practice.

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Table 1. Difference between perceived and observed prevalence of chronic diseases and occupational status in France: actual percentage, mean estimated percentage, difference in percentage points (*standard deviation*), t-value (*p-value*), and ratio.

Variable	Actual prevalence	Mean perceived prevalence [95% CI]	Difference between perceived and actual prevalence (SD)	t-value (p-value)	Ratio perceived / actual prevalence
Chronic diseases					
Genetic diseases	1.1%	13.5% [12.9%;14.1%]	0.12 (0.16)	42.65 (<0.001)	12.26
Transmissible diseases	1.7%	17.0% [16.4%;17.7%]	0.15 (0.18)	46.69 (<0.001)	10.01
Cancer	4.6%	28.3% [27.5%;29.0%]	0.24 (0.21)	59.33 (<0.001)	6.14
Hearing impairments	9.1%	23.2% [22.5%;23.9%]	0.14 (0.19)	39.70 (<0.001)	2.55
Skin diseases	9.7%	24.1% [23.4%;24.9%]	0.14 (0.20)	38.34 (<0.001)	2.49
Neurologic disorder	10.8%	20.4% [19.7%;21.1%]	0.10 (0.19)	27.48 (<0.001)	1.89
Mental illnesses	14.0%	15.1% [14.5%;15.7%]	0.01 (0.16)	3.47 (<0.001)	1.08
Digestive diseases	15.4%	20.9% [20.2%;21.6%]	0.05 (0.19)	15.53 (<0.001)	1.36
Respiratory diseases	20.6%	28.6% [27.8%;29.4%]	0.08 (0.21)	20.44 (<0.001)	1.39
Nutritional & metabolic diseases	25.6%	30.4% [29.6%;31.2%]	0.05 (0.21)	12.17 (<0.001)	1.19
Cardiovascular diseases	28.2%	25.9% [25.2%;26.6%]	-0.02 (0.20)	-6.31 (<0.001)	0.92
Eye diseases	57.8%	42.6% [41.8%;43.5%]	-0.15 (0.24)	-34.40 (<0.001)	0.74
Occupational statuses					
Military employees	1.3%	16.1% [15.5%;16.8%]	0.15 (0.17)	46.23 (<0.001)	12.42
Real estate workers	1.4%	13.8% [13.3%;14.4%]	0.12 (0.15)	43.17 (<0.001)	9.88
Farmworker/Fishermen	3.0%	14.4% [13.9%;14.9%]	0.11 (0.14)	44.00 (<0.001)	4.79
Bank/Insurance workers	3.3%	18.0% [17.4%;18.6%]	0.15 (0.17)	45.96 (<0.001)	5.45
Hospitality workers	3.7%	21.6% [20.9%;22.3%]	0.18 (0.18)	52.77 (<0.001)	5.84
Transportation workers	5.3%	16.8% [16.2%;17.4%]	0.12 (0.17)	36.44 (<0.001)	3.17
Unemployed population	6.2%	24.3% [23.5%;25.0%]	0.18 (0.2)	48.32 (<0.001)	3.91
School attending population	8.1%	29.5% [28.7%;30.3%]	0.21 (0.22)	53.44 (<0.001)	3.65
Sales workers	12.4%	25.3% [24.5%;26.0%]	0.13 (0.19)	35.74 (<0.001)	2.04
Manufacturing workers	13.5%	22.7% [22.1%;23.3%]	0.09 (0.17)	29.80 (<0.001)	1.68
Administration/Teaching/Health workers	30.3%	27.4% [26.8%;28.1%]	-0.03 (0.18)	-8.65 (<0.001)	0.91
Retired population	31.9%	32.1% [31.4%;32.8%]	0.00 (0.18)	0.62 (0.53)	1.01
Working population	51.2%	48.2% [47.5%;48.9%]	-0.03 (0.18)	-8.73 (<0.001)	0.94

Table 2. Results of the univariate analyses estimating the alpha coefficient (measuring the magnitude of the primary bias) according to the sociodemographic characteristics of the participants and type of condition (alpha value and 95% CI).

Variable	Alpha value estimates	95%CI
Male	0.56	[0.52;0.60]
Female	0.37	[0.34;0.41]
Middle School	0.31	[0.28;0.35]
High School	0.41	[0.37;0.45]
Some College and higher	0.54	[0.50;0.58]
18 to 39 years old	0.45	[0.42;0.49]
40 to 54 years old	0.43	[0.39;0.47]
55 years old and older	0.45	[0.42;0.49]
Low Numeracy (<5)	0.25	[0.21;0.28]
Medium Numeracy (>=5 & <8)	0.46	[0.42;0.50]
High Numeracy (>=8)	0.63	[0.59;0.68]
Low SES	0.38	[0.34;0.42]
Jobless	0.42	[0.39;0.46]
Intermediate SES	0.54	[0.49;0.59]
High SES	0.56	[0.50;0.62]
Non-health related condition	0.44	[0.40;0.47]
Health related condition	0.46	[0.42;0.49]

Note. The higher the alpha value, the lower the magnitude of the primary bias

Table 3. Results for the multivariate analyses estimating the alpha coefficient (measuring the magnitude of the primary bias) according to the sociodemographic characteristics of the participants and type of condition (alpha value and 95% CI).

Parameter	Alpha value estimates		Mean error increase		Mean absolute error		Mean relative error	
		95%CI		95%CI		95%CI		95%CI
Intercept	1.50	[1.13;1.86]						
Male	REF		0%		3.01%	[2.12%;4.07%]	61.23%	[41.62%;85.85%]
Female	-0.67	[-0.85;-0.49]	47.9%	[32.7%;68.07%]	4.47%	[2.99%;5.88%]	96.58%	[61.18%;132.04%]
More than high school	REF		0%		3.01%	[2.12%;4.07%]	61.23%	[41.62%;85.85%]
High school diploma	-0.40	[-0.61;-0.19]	11.34%	[6.15%;17.36%]	3.38%	[2.36%;4.55%]	69.75%	[46.97%;97.76%]
Less than high school	-0.64	[-0.87;-0.41]	18.71%	[11.46%;26.96%]	3.56%	[2.38%;4.84%]	74.17%	[47.35%;105.52%]
Older than 55 years old	REF		0%		3.01%	[2.12%;4.07%]	61.23%	[41.62%;85.85%]
40 to 54 years old	-0.20	[-0.43;0.03]	5.39%	[-0.97%;13.78%]	3.26%	[2.26%;4.27%]	66.89%	[44.6%;90.7%]
18 to 39 years old	-0.32	[-0.55;-0.09]	11.61%	[3.04%;21.85%]	3.31%	[2.34%;4.57%]	68.16%	[46.51%;98.07%]
Intermediate SES	REF		0%		3.01%	[2.12%;4.07%]	61.23%	[41.62%;85.85%]
High SES	-0.11	[-0.45;0.23]	1.56%	[-2.13%;4.54%]	3.02%	[2.19%;4.17%]	61.46%	[43.09%;88.24%]
Low SES	-0.26	[-0.54;0.02]	7.58%	[-0.01%;16.06%]	3.28%	[2.21%;4.5%]	67.36%	[43.64%;96.33%]
Jobless	-0.21	[-0.49;0.06]	9.6%	[-2.89%;24.2%]	3.26%	[2.38%;4.51%]	66.9%	[47.2%;96.63%]
Health related condition	REF		0%		3.01%	[2.12%;4.07%]	61.23%	[41.62%;85.85%]
Non-health related condition	-0.08	[-0.25;0.09]	3.68%	[-3.65%;11.88%]	3.15%	[2.13%;4.17%]	64.62%	[42.14%;88.62%]
High Numeracy (>=8)	REF		0%		3.01%	[2.12%;4.07%]	61.23%	[41.62%;85.85%]
Intermediate Numeracy (>=5 & <8)	-0.57	[-0.78;-0.35]	28.3%	[17.88%;39.91%]	3.8%	[2.68%;5.2%]	79.96%	[54.01%;114.24%]
Low Numeracy (<5)	-1.42	[-1.67;-1.17]	59.29%	[43.57%;74.19%]	4.73%	[3.52%;6.27%]	105.43%	[75.44%;146.31%]

Note. The higher the alpha value, the lower the magnitude of the primary bias

Figure 1: Tversky and Kahneman's Weighting function for various α values (adapted from Wu & Gonzalez, 1996).

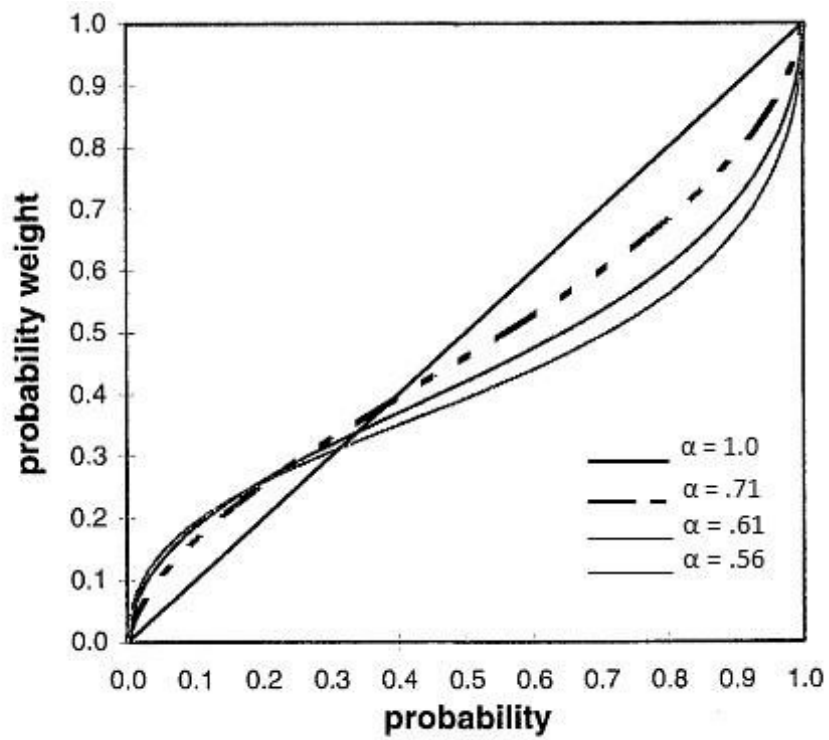


Figure 2: Univariate analysis stratified on gender (mean perceived prevalence and standard deviation).

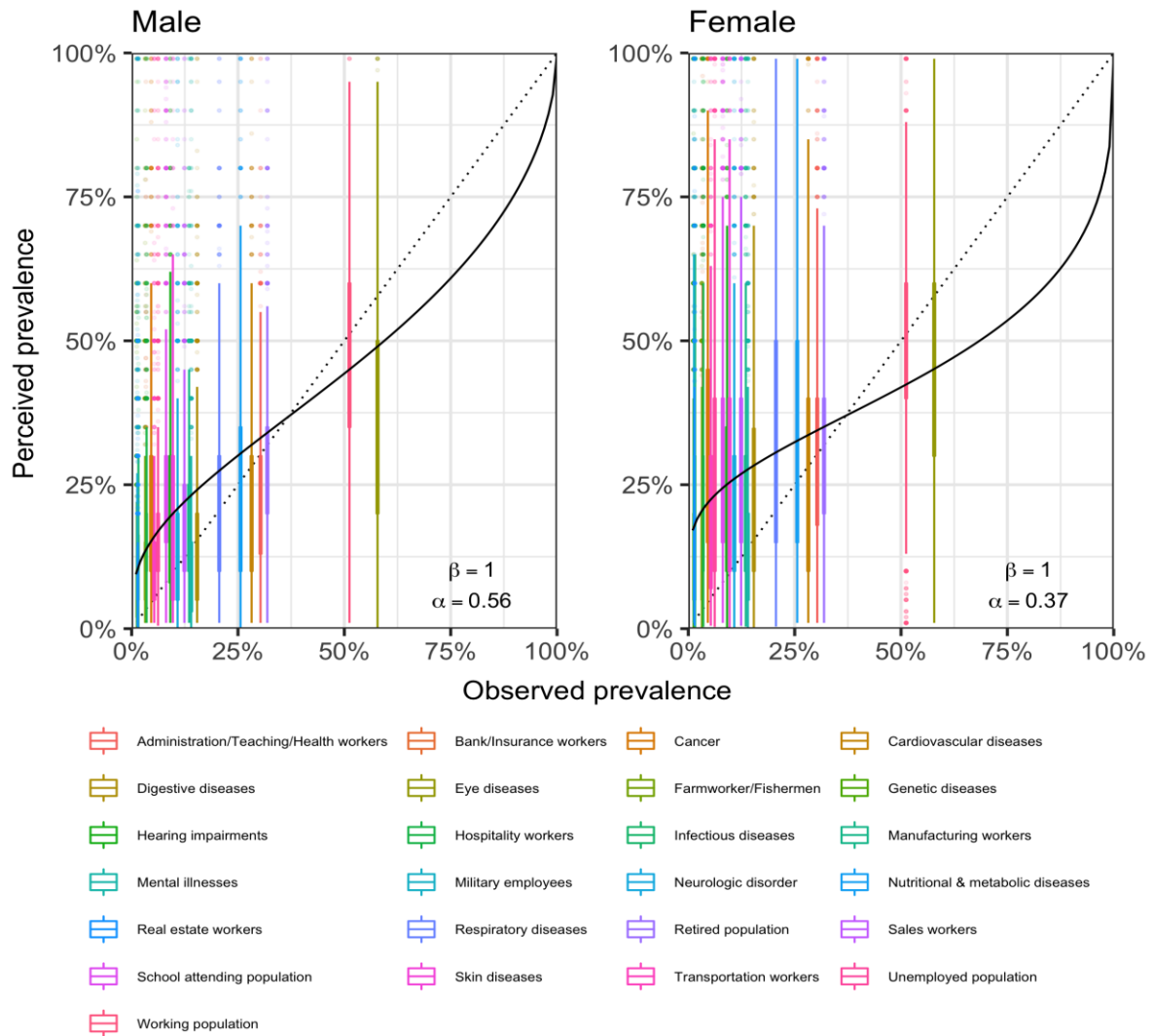


Figure 3: Univariate analysis stratified on level of education (mean perceived prevalence and standard deviation).

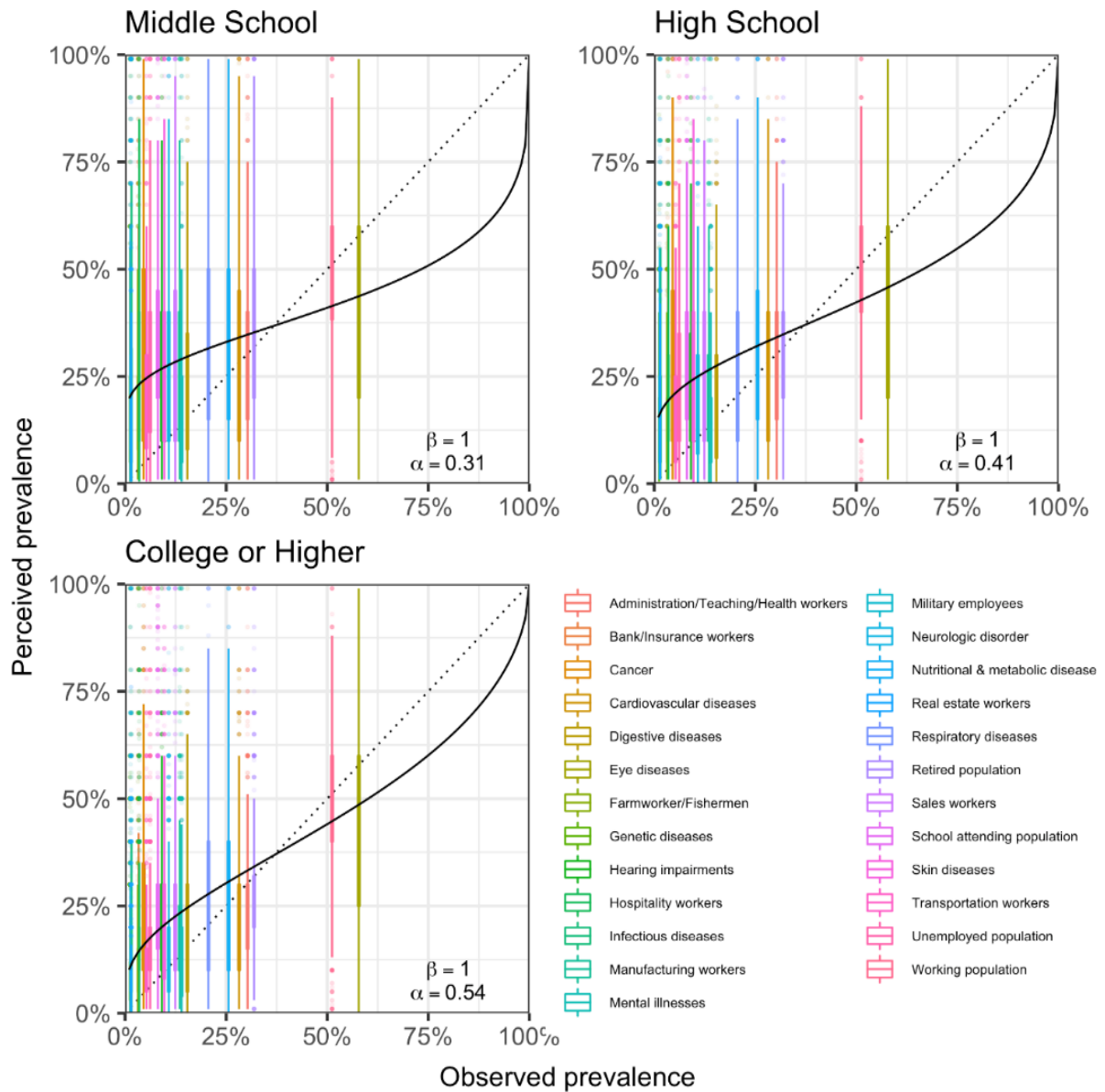


Figure 4. Univariate analysis stratified on numeracy scores (mean perceived prevalence and standard deviation).

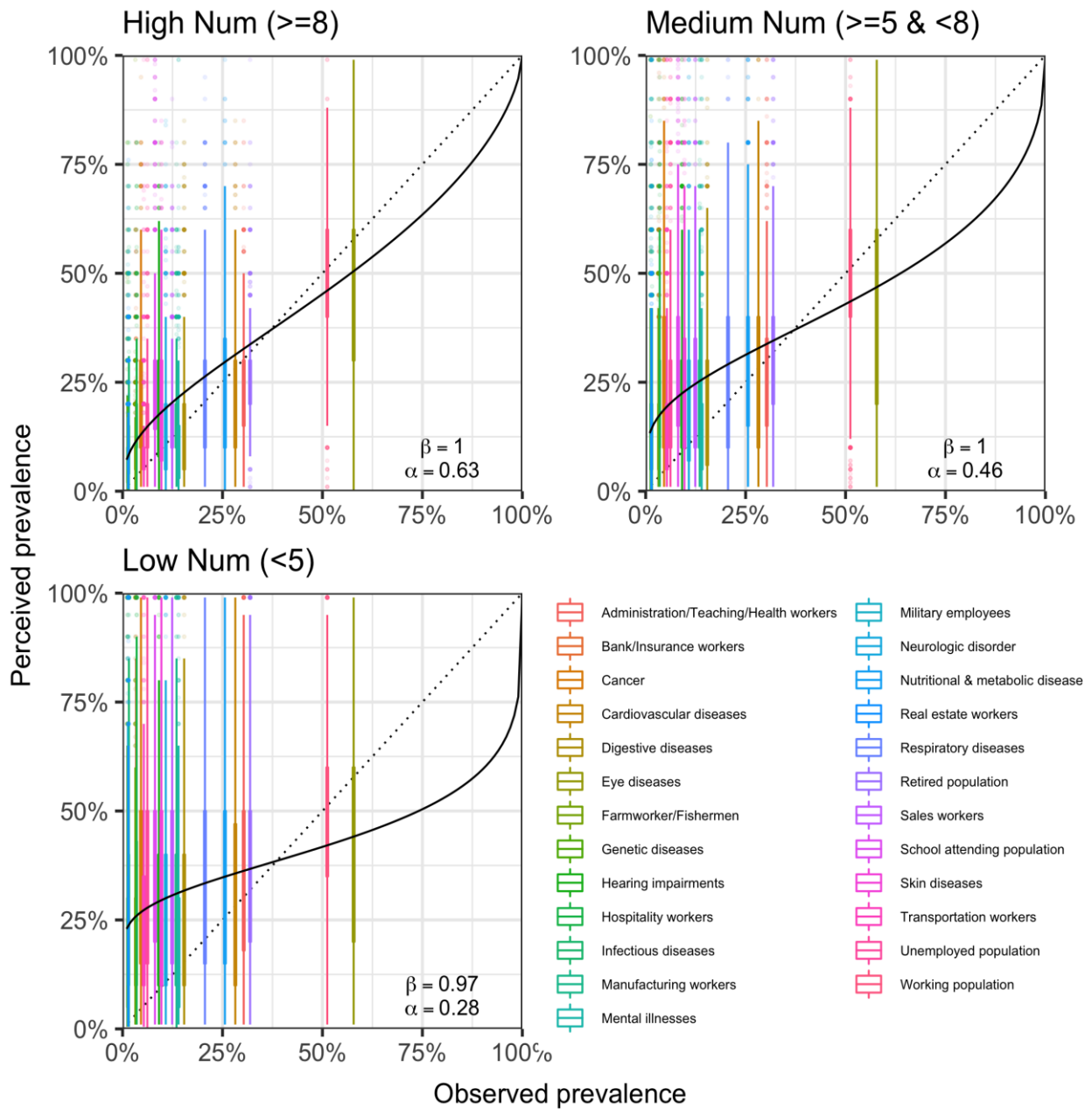


Figure 5. Mean scores across education, and sex on the numeracy scale (0-10)

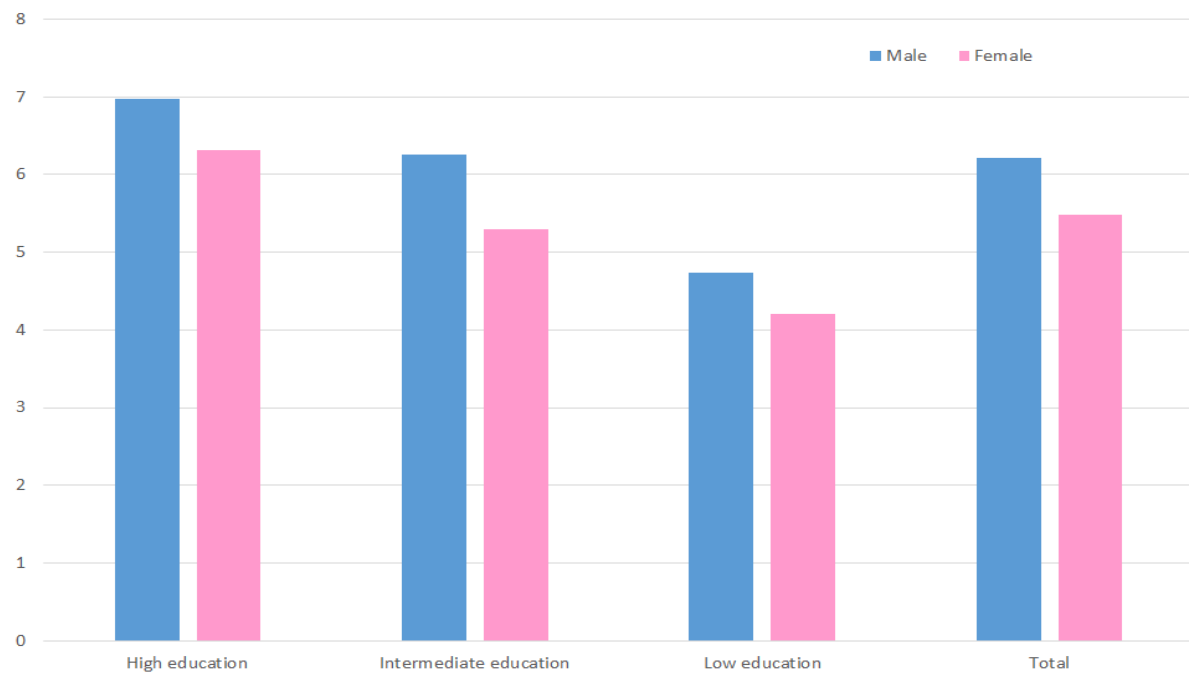
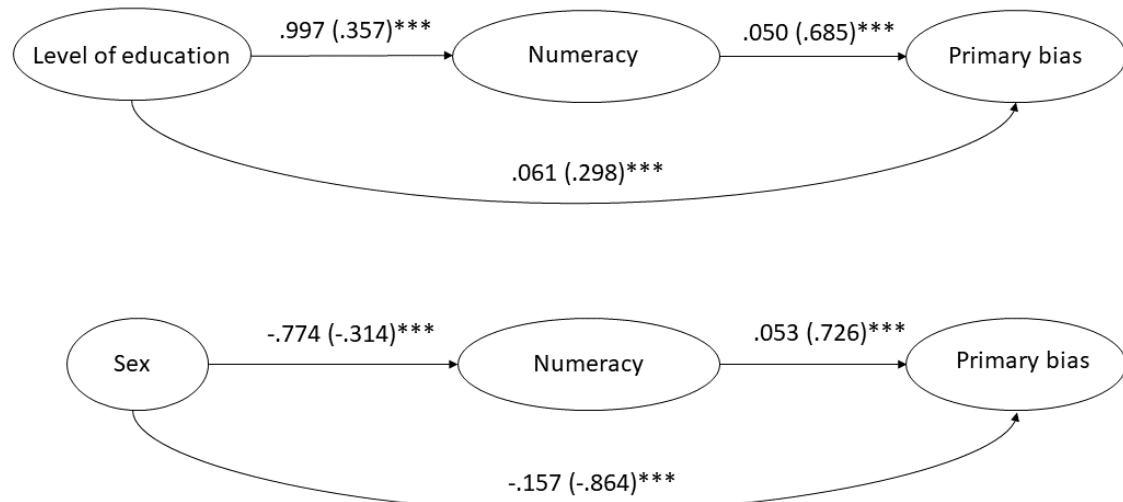


Figure 6. Simple mediation models examining the role of numeracy in sexual and educational differences in the magnitude of the primary bias. Values display unstandardized path coefficients (and standardized path coefficients in parentheses).



*** $p < .001$