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RESEARCH ARTICLE

On Extreme Perception Bias

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This note investigates perception bias: To what extent do individual opinions confound reality? We estimated the relative gap between self-declared estimates and real data. With a sample of respondents from Laguna, Philippines, we asked about the prevalence of diabetes and smartphone usage. We observed a trend of judgment miscalibration. Responses exhibit significant deviation from facts; for example, inaccuracies can go as high as seven times the real value. Especially for estimates on smartphone ownership, bootstrapped quantile regression models showed that perception bias is associated with age.

Keywords: bootstrapping, overestimation, perception, quantile regression

JEL Classifications: D90, D91, Z10

Perception is an active process of interpretation—involving intention, attention, or expectation that can lead to simplification of strategies and biases (Wu, Swait, & Chen, 2019). Human views provide the foundation of decision-making on issues ranging from the mundane to the critical. These views are constructed from personal experiences and observations, as well as inputs coming from others. Through technological advances, humans have become more exposed to diverse sources of information and external influence. For instance, 75% of the population in 39 countries use the Internet (Poushter, Bishop, & Chwe, 2018). In relation to this, a growing concern over the recent years is the proliferation of misinformation. Past evidence indicates that false beliefs distorted public opinion and behavior (Flynn, Nyhan, & Reifler, 2017). In the ongoing discourse about climate change, for example, many Americans reject supporting scientific explanations (McCright & Dunlap, 2011). During the 2016 U.S. Presidential elections, one fake news article may have been as persuasive as one TV campaign ad (Allcott & Gentzkow, 2017). Even in the job market, when employers read a name like "Tyrone" or "Latoya," they do not care at all about race but are discriminating only against the social background conveyed by the names (Bertrand & Mullainathan, 2004). There is also much evidence of consumers' "perception bias" towards marketing information either due to selective attention or inattention, distortion of information to support their prior belief or preference, or skepticism about the claimed value of product attributes (Wu et al., 2019). There also those who believe that vaccines can cause autism in children (Freed, Clark, Butchart, Singer, & Davis, 2010) and that generic drugs are not safe and less effective (Qian, Mishuk, & Hansen, 2018). Such cases put into the spotlight the ability of individuals to accurately judge information. This is supported by a Reuters Institute's transnational report, where 55% of the respondents indicated concern about their ability to discern between real and fake information on the Internet (Newman, Fletcher, Kalogeropoulos, & Nielsen, 2019).

Based on the principle of homophily, people tend to associate with sentiments that are closer to their own (McPherson, Smith-Lovin, & Cook, 2001). Those with perceptions that deviate from facts are more likely to accept false information and promote misperceptions themselves. A contributing factor that leads to inaccurate views is overconfidence. Psychological research has shown that people sometimes overestimate the precision of their own judgment (Moore, Tenney, & Haran, 2015). This form of judgment miscalibration induces people to rely heavily on their own opinion and consequently induces biased decision-making (Bazerman & Moore, 2013).

But, how far do people's views deviate from real data? Are facts as pessimistic as what people conjecture? To understand these questions, this research note proposes a quantitative indicator, "perception bias." It measures the relative inaccuracy by which respondents' answers differ from real-life statistics. We attempted to estimate perception bias using data from a sample of Philippine participants. Respondents were asked to estimate the rates of diabetes and smartphone ownership in their country. Overall, statistical evidence implies exaggerated responses far from real values. The main contribution of our work is that we provide a concrete quantitative analysis of this bias. Besides constructing an indicator, we also conducted robust statistical analyses like t-tests. To ensure accurate estimates from our small sample, we employed non-parametric modeling in the form of bootstrapped quantile regressions.

Our paper consists of two pen-and-paper surveys. In our first study, we elicited exact numerical answers. Using our proposed indicator on perception bias, we find that respondents give values as high as seven times the factual data. For the prevalence of diabetes, older and more risk-tolerant respondents report more pessimistic and biased estimates. For smartphone usage, age is the most significant determinant of perception bias. On the other hand, younger respondents give more biased answers. These results are supplemented by a second study where only the minimum and maximum estimates are asked. Persistent overestimation remains: even the lower bound estimates of respondents are higher than actual statistics. Overall, our findings differ from those past statistical studies on sample survey methods. In Belyaev and Kristrom's (2015) study, respondents were also asked about their lower and upper bound estimates. Unlike our survey, their method was not tested with real-world respondents. They only conducted computer-generated simulations in order to identify the unknown statistical distribution of self-selected intervals. Our work fills these gaps with a two-pronged strategy. First, we separately investigate point estimation and bounds estimation. Study 1 asks for point estimates, whereas Study 2 demands for bound estimates only. The first study will allow a precise measurement of how respondents' exact point answers differ from real values. The second study may measure uncertainty, that is, the smaller the distance between the bounds, the less uncertain the respondent is. Second, we use surveys with adult respondents instead of simulations. This allows reliable estimation of how individual opinions deviate from factual statistics.

Study 1: Point Estimation

Methodology

Study 1 focuses on the following research question: *To what extent do respondents' point estimates deviate from real data?* To investigate this, we recruited Tagalog respondents from Laguna, a first-class province in the Philippines, for a preliminary study on decision-making. Invitations were sent to potential respondents. Those who registered were informed beforehand that they are going to participate in a research activity, and their identities were anonymized. Everyone gave consent to the use of their data. All 32 participants received P120 (approximately 2.5 USD) for completing this study and additional compensation for an unrelated study. Participants (62% women and 38% men) lived in the province of Laguna for an average of 14 years, and are from 19 to 61 years in age.

Everyone was given questionnaires in the Filipino language. In relation to this study, Question 1 below pertains to an issue that has a serious connotation, that is, the prevalence of diabetes in the country. In contrast, Question 2 tackles a less serious topic related to people's lifestyle of smartphone usage.

Based on a survey done in 2017:

> *QUESTION 1: For every 100 Filipinos aged 20 to 79, how many do you think have diabetes? What is your final estimate?* _______
>
> *QUESTION 2: For every 100 Filipinos, how many owns a smartphone? What is your final estimate?* _______

Results

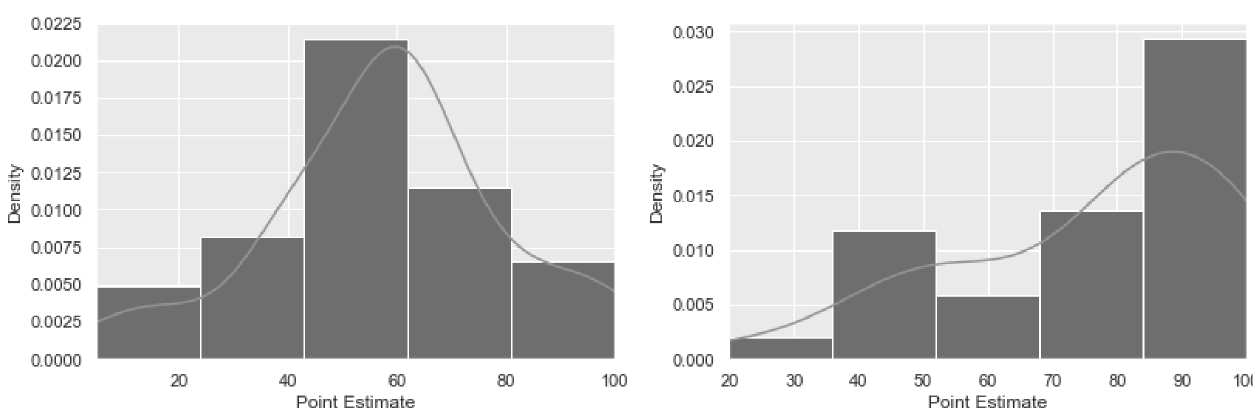
Gaps in perception refer to the difference between real statistical data and the estimates of our respondents. Factual values for Questions 1 and 2 were compiled by IPSOS from the World Bank and NewZoo, respectively. For Question 1, real data indicates a 7% prevalence of diabetes in the Philippines (IPSOS, 2018). When asked for an exact numerical answer, extreme overestimation was observed in our study. Participants had an average answer of 57.8 (Figure 1a). Using one sample t-test, we provide statistical support for this. The null hypothesis is that the observed average is equal to the real value, 7. When this is rejected, it implies that respondents' perception significantly differs from factual data. Our results indicate a p-value of 0.00. There is evidence that the mean is statistically different from the hypothesized value of 7.

Patterns for Question 2 also exhibit overestimation (Figure 1b). The average estimate of respondents in our study is 76.3 out of 100. The difference is striking when compared to factual data that indicates a 23% usage of the smartphone (IPSOS, 2018). Similar to Question 1, t-tests (p-value= 0.00) for Question 2 reject the null hypothesis that the average of participants' answers is equal to 23.

To further understand the gap between perception and reality, we construct the following indicator. We define perception bias (PB) as:

$$\mathrm{PB} = \frac{|Real\ value - Estimate|}{Real\ value} \times 100 \tag{1}$$

PB describes the relative inaccuracy by which respondents' answers deviate from real values. Point estimates in Question 1, on the average, are 728% larger than factual data. This extreme bias is also



(a) Prevalence of diabetes (b) Smartphone usage

Figure 1. Distribution of point estimates.

observed in Question 2. Given the real value of 23, observations from our study have an aggregate PB of 232%. For Questions 1 and 2, t-tests indicate that PB is significantly different from 0, that is, p-value = 0.00.

Finally, we use bootstrapped quantile regression to model the dynamics between a set of variables and specific percentiles of our perception bias measure, PB. The following socioeconomic factors are used as explanatory variables for this study. *Age* is the age of the participant. *Female* is a binary variable equal to 1 if female, 0 if male. *Resident* refers to the number of years the respondent has lived in Laguna province. Lastly, *Risk* measures self-declared risk-taking. An answer of 0 means the participant is extremely risk-averse, whereas 10 implies the highest risk-loving

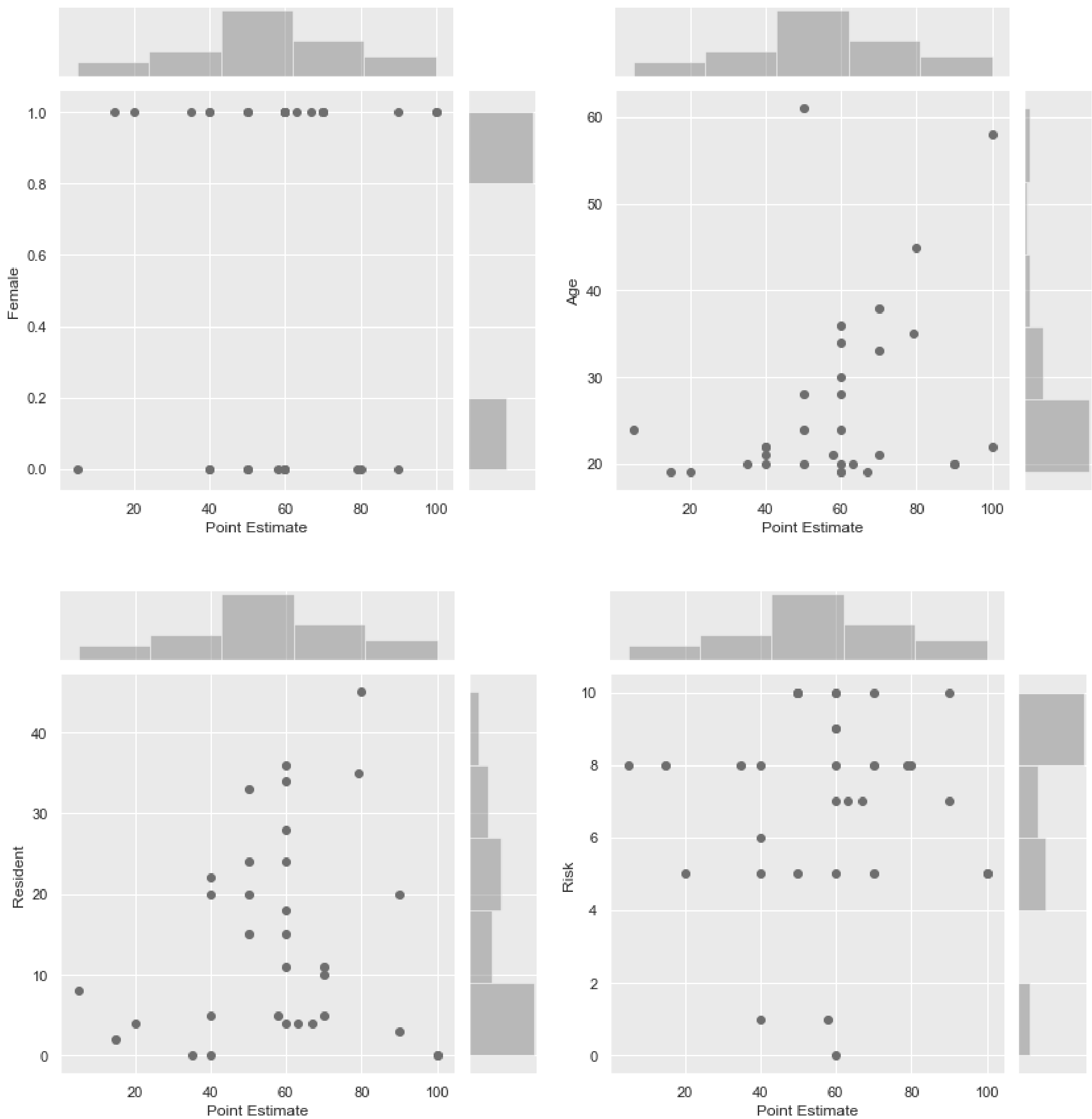


Figure 2. Joint plots of point estimates and explanatory variables.

tendency. They were asked the following "wise man" question translated in the Filipino language:

> As the proverb says, "Nothing ventured, nothing gained," there is a way of thinking that in order to achieve results, you need to take risks. On the other hand, as another proverb says, "A wise man never courts danger," meaning that you should avoid risks as much as possible. Which way of thinking is closest to the way you think? On a scale from 0-10, with 10 being completely in agreement with the thinking, "Nothing ventured, nothing gained," and 0 being completely in agreement with the thinking. "A wise man never courts danger."

Figure 2 presents the joint plots of point estimates and the explanatory variables.

Unlike linear regression, which can only estimate the average effect of the explanatory variables, quantile regression allows us to compare the impact of the explanatory variables on low and high values of the response variable. For each quantile , quantile regression minimizes the objective function

$$\sum_{i=1}^{n} q|e_i| + (1-q)|e_i| \tag{2}$$

where e_i is the error term of the *ith* observation and is defined as

$$e_i = y_i - \left(\beta_0 + \sum\nolimits_{j=1}^{k} \beta_j x_{ji}\right). \tag{3}$$

Here, y_i is the response variable and $x_{1i}, x_{2i}, \ldots, x_{ki}$ are the explanatory variables for the *ith* observation. The parameter β_0 is the intercept, and each $\beta_{j>0}$ is a coefficient that represents the effect in quantile q of the response variable after a one-unit change in the *jth* explanatory variable. For brevity, our analysis will merely focus on the median regression (50th quantile) and extreme quantiles (20th and 80th percentile).

Compared to linear regression, quantile regression analysis is non-parametric. It does not assume a particular parametric distribution for the dependent variable. It is, thus, more robust against outliers (Koenker & Hallock, 2001). It will help understand relationships between variables outside the mean of our data. Given that we are dealing with small sample size, we also apply bootstrapping for robust estimates (Nikitina, Paidi, & Furuoka, 2019). Bootstrapping for quantile regression can be described as follows. Set a large number that defines the number of iterations, that is, how many times bootstrapping will be repeated. We set the number of repetitions to 1,000 in this study. Then, for every iteration, create the bootstrap sample by randomly drawing with replacement from the original dataset. This means that an observation from the dataset can be selected more than once. In our study, the size of the bootstrap sample is set to the size of our dataset. Using the bootstrap sample, quantile regression is performed to compute the regression coefficients for the current iteration. After all the iterations have been completed, the result is a bootstrap distribution of the regression coefficients, which approximates their sampling distribution. The expected values of the coefficients are the coefficients of the bootstrapped quantile regression.

For the question on the prevalence of diabetes, coefficient estimates from the regressions are presented in Table 1.[1] Those for Question 2 are shown in Table 2. Again, coefficients are estimated with the perception bias measure, PB, as the dependent variable. Our quantile regressions estimate the change in a specific quantile of the dependent variable (PB) produced by a one-unit change in an explanatory variable. For comparison, we include bootstrapped linear regressions that estimate the average value of the dependent variable.

In the analysis that follows, what is most relevant is the change in the magnitude of coefficient estimates across percentiles. We comment on a few trends, especially the consistently observed effects of age and risk tolerance. The magnitude of the coefficient for *Risk* is positive. It is increasing in magnitude across percentiles. Self-reported risk-taking has a larger impact on the higher quantiles of PB; for example, the coefficient is higher in magnitude in the median than the 20th quantile. The more risk-tolerant the respondent is, the higher his perception bias is.

Coefficients for Question 1 imply that *Age*'s coefficient is positive for the median and 80th percentiles. Those at the upper quantile of PB, the positive coefficient, show that older respondents have a more pessimistic perception of the prevalence of diabetes. Older participants overestimate diabetes prevalence greater than the rest of the sample. Our results from this study are supported, as shown in Figure 3. It shows the prevalence of diabetes in the

Table 1. *Bootstrapped Quantile Regression Models: PB for Question 1*

Explanatory variable	Linear regression	20th	50th	80th
Age	9.96	-2.18	16.77	13.03
Female	-8.40	96.86	-88.46	-5.58
Resident	-1.20	8.99	-3.27	-4.39
Risk	2.47	3.59	16.12	25.28
Intercept	465.70	318.10	306.42	451.40
R^2	0.106	0.106	0.079	0.163

Table 2. *Bootstrapped Quantile Regression Models: PB for Question 2*

Explanatory variable	Linear regression	20th	50th	80th
Age	-3.88*	-2.53	-3.63	-5.34**
Female	13.81	-34.19	43.87	27.21
Resident	1.52	2.69	1.81	2.32
Risk	9.31	11.5	7.62	1.90
Intercept	241.32***	145.86	245.99***	389.92***
R^2	0.237	0.199	0.178	0.201

****significant at the 1%, **5%, *10% level, seed(1), 1000 replications*

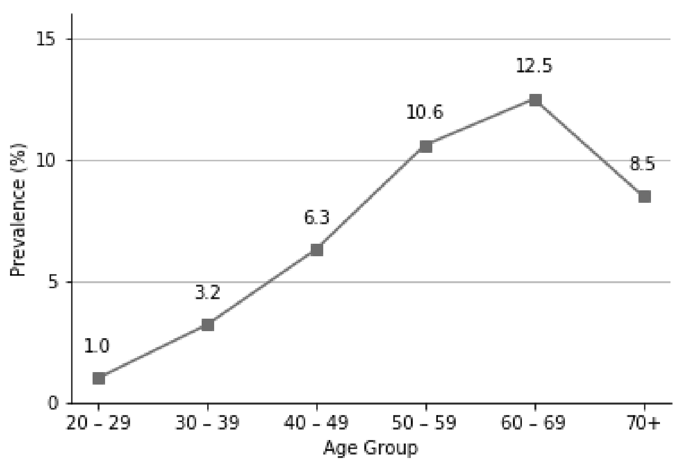


Figure 3. Prevalence of diabetes in the Philippines among adults, 20 years and above (based on fasting blood glucose level of ≥ 126mg/dL).

Philippines per age group in 2013[2] (Food and Nutrition Research Institute, 2015). It indicates that diabetes prevalence tends to be significantly higher in older age groups. Intuitively, older participants have a higher probability to experience diabetes themselves, especially those in the 60–69 age group (Tan, 2015). Another potential reason is that they are more likely exposed to other people with diabetes. This could be a rational deviation of older respondents from the irrational average overestimation of the sample.

Results are also interesting when we look at coefficients for Question 2. We focus on the linear regression and the 80th quantile. *Risk* has a positive coefficient. The higher is a respondent's taste for risk, the higher is the gap between his answer and factual data.[3] Note, however, that this coefficient is decreasing in magnitude as the percentile for PB goes up. In contrast, on average, we find that PB decreases with age. For those with extreme perception bias, that is, 80th quantile, the variable *Age* has a statistically significant and negative impact on PB estimates related to smartphone use. Compared to older participants, younger respondents tend to overestimate smartphone use in the Philippines. A potential reason is that, in the Philippines, 88% of the total mobile Internet population is under the age of 34 (Fintechnews Singapore, 2016). Those 34 and under are 47% more likely to own a smartphone than those who are 50 years old and above. Younger people also tend to be more familiar with the latest technological innovations (Silver, 2019).

Study 2: Bounds Estimation

Methodology

A second study was conducted to complement Study 1. Study 2 has a different research question from the first study. It attempts to investigate: *Do real values fall within the lower and upper bound estimates of respondents?* Participants were again recruited in Laguna. All 36 participants received a fixed participation fee of PhP120 (US$2.5) for this study and an additional payment for an unrelated study. Their age ranged from 20 to 80. The sample is 53% female and 47%, male.

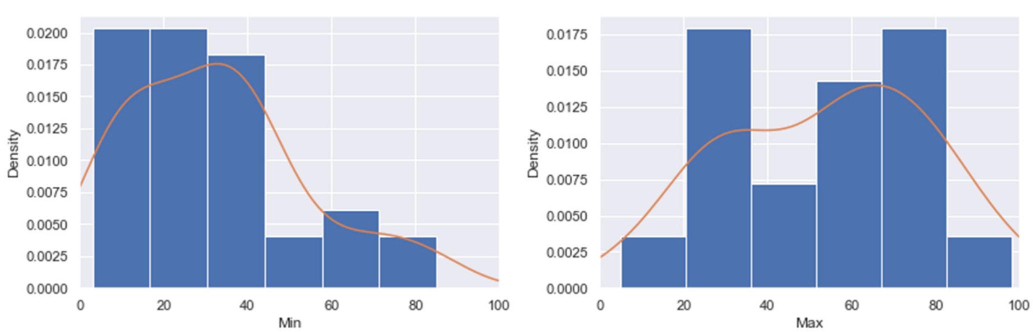
Study 2 has the same design as Study 1, except that exact point estimates were not elicited. Instead, 36 participants were asked for their minimum and maximum estimates. The questionnaire contains the same questions regarding diabetes and smartphone, but with the following modifications:

What is your minimum estimate? _______
What is your maximum estimate? _______
Where do you think your answer is nearer? Is it nearer your MINIMUM estimate or your MAXIMUM estimate? Write either MINIMUM or MAXIMUM in the blank: _________

Results

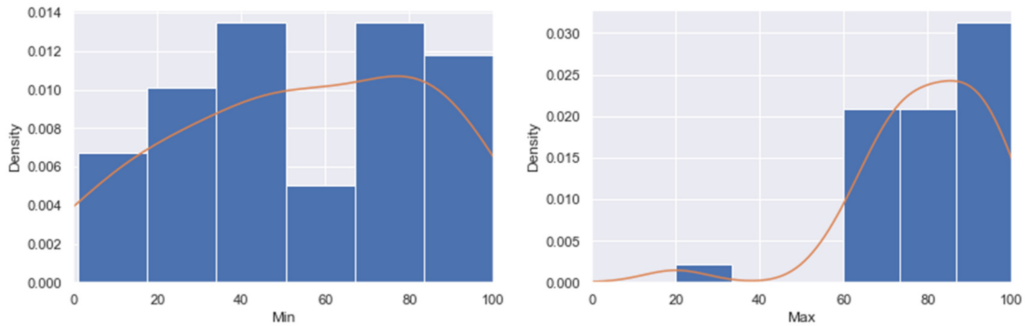
For the first question (the prevalence of diabetes), the minimum estimate of participants is 32.5% on the average (Figure 4a). The mean of their maximum estimate is 53 out of 100 (Figure 4b) The interval length—the difference between the upper and lower bound—is 21.36 units with a standard deviation of 13.42 units. Overall, the beliefs of respondents on the prevalence of disease signal pessimism. Sixty-one percent of respondents stated that their final estimate should be nearer their maximum response.

Observations for the second question, that is, smartphone usage, also suffer from overestimation.



(a) Lower bound (b) Upper bound

Figure 4. Distribution of interval estimates for diabetes prevalence.



(a) Lower bound (b) Upper bound

Figure 5. Distribution of interval estimates for smartphone usage.

Table 3. *Bootstrapped Quantile Regression Models: Interval Length for Question 1*

Explanatory variable	Linear regression	20th	50th	80th
Age	0.094	0.33	0.088	-0.058
Female	5.41	3.79	-1.47	6.90
Resident	0.046	-0.037	0.029	0.058
Risk	0.93**	-0.233	0.152	1.16
Intercept	6.44	-2.15	13.17	21.40*
R^2	0.125	0.144	0.032	0.207

Eighty-six percent of respondents believe that their final estimate is nearer the upper bound. There is a perception that the majority of the population owns a smartphone, that it is something commonly used by everyone. When asked about their minimum estimate, respondents believe 55.4% of the population uses a smartphone (Figure 5a). On average, the maximum estimate is as high as 80 out of 100 people (Figure 5b). The average length of these estimates is 24.83 units, with a standard deviation of 25.7 units.

We find that real data for Questions 1 and 2 rarely fall within the lower and upper bounds of participants' answers. For Question 1, the real value of 7% is beyond the participants' self-reported interval of 32.5 to 53. Merely two respondents had 7% within their lower and upper bound estimates. On average, the real estimate of 23% from Question 2 also fails to fall within the respondents' mean interval from 55.4 and 80. Seven respondents had the factual value in the interval they provided. When employing t-tests as in Study 1, we find that the participants' lower and upper bound estimates are statistically different from real data (that is, all p-values are 0.000, and the null hypothesis is rejected). These show an extreme degree of overestimation by the respondents.

Now, we define *Interval Length* as the difference between respondents' maximum and minimum estimates. It is a potential measure of uncertainty in answers. The higher the interval is, the less certain is the respondent. Tables 3 and 4 shows bootstrapped quantile regression analyses with a replication sample size of 1,000. Figure 6 shows the joint plots of intervals and the explanatory variables. Like before, a particular focus should be on changes in coefficient magnitudes across percentiles. We find again notable observations for *Age* and *Risk*. Findings for Questions 1 and 2 are similar, and we summarize as follows. *Age*'s impact decreases in magnitude as the percentile increases, especially for Question 1. For those with extremely low interval lengths, that is, the 20th percentile, older age is associated with higher values of *Interval Length*. We see the opposite result with those in the 80th percentile. For *Risk,* especially for Question 1 on diabetes, what is interesting are coefficient estimates for the linear regression. On average,

Table 4. *Bootstrapped Quantile Regression Models: Interval Length for Question 2.*

Explanatory variable	Linear regression	20th	50th	80th
Age	0.008	0.075	0.179	-0.462
Female	8.15	4.22	6.92	8.12
Resident	0.044	0.123	0.085	0.23
Risk	0.59	-0.599	0.309	1.23
Intercept	14.89	0.1799	-1.46	38.75
R^2	0.036	0.068	0.082	0.094

****significant at the 1%, **5%, *10% level, seed(1), 1000 replications*

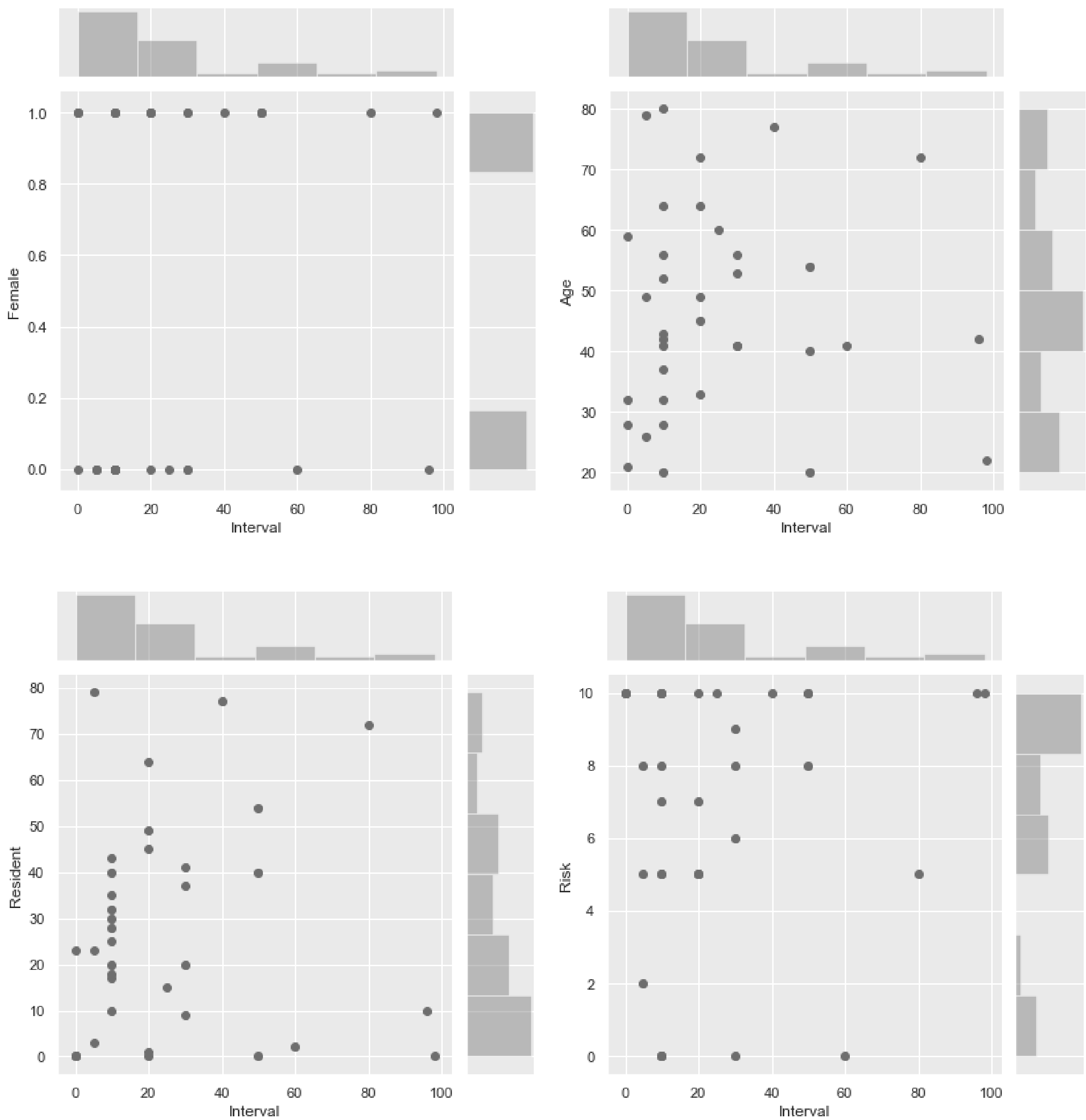


Figure 6. Joint plots of intervals and explanatory variables.

Table 5. *Average Estimates for the Prevalence of Diabetes, Given Different Lower-Upper Bound Weights*

Weight of min response	Weight of max response	Estimate*	Standard deviation	Perception bias, PB (%)
0	1	53.88	23.93	671.42
.10	.90	51.34	23.34	641.07
.25	.75	48.54	22.56	595.53
.5	.5	43.20	21.64	519.64
.75	.25	37.86	21.20	443.75
.90	.10	34.66	21.20	398.21
1	0	32.52	21.30	368.44
Point estimate from Study 1		57.87	22.18	728.57
Real statistical estimate		7		

Table 6. *Average Estimates for Smartphone Usage, Given Different Lower-Upper Bound Weights*

Weight of min response	Weight of max response	Estimate*	Standard deviation	Perception bias, PB (%)
0	1	80.30	15.73	249.87
.10	.90	77.82	15.81	239.32
.25	.75	74.09	16.69	223.49
.5	.5	67.88	19.80	197.10
.75	.25	61.68	24.25	170.71
.90	.10	57.95	27.30	161.78
1	0	55.47	29.44	160.02
Point estimate from Study 1		*76.28*	*21.61*	*232.47*
Real statistical estimate		*23*		

**For all parameters, we reject the null hypothesis that the mean estimate is equal to the true value. p-values are all equal to 0.*

higher self-reported risk tolerance is associated with a greater gap between bound estimates.

Lastly, we perform sensitivity analyses using lower and upper bounds information. Sensitivity analysis (Kleijnen, 1995; Pannell, 1997) tackles the parameter uncertainty, for example, the weights that participants give to their lower bound response relative to the upper bound. It allows us to explore changes in estimates, given various combinations of weights. We roughly calculate estimates as follows:

Estimate for Study 2 = (w x lower bound response)
(1 - w) (upper bound response) (4)

where w is the weight for respondents' lower bound response, whereas 1-w is the weight for their upper bound answer. If $w < 0.5$, then it is assumed that respondents put more weight on the upper bound and overestimation maybe more likely. Compared to Press and Tanur (2004) who merely set equal weights of (0.5, 0.5) to lower and upper bounds data, we perform sensitivity tests with arbitrary combinations of weights: (0, 1), (.1, .9), (.25, .75), (.5, .5), (.75, .25), (.9, .1), and (1, 0).

So, how do changes in weights affect our arbitrarily calculated point estimates for Study 2? There is a general tendency for extreme misperception (Tables 5 and 6). This remains valid even under equal weights of (0.5, 0.5). If $w = 0.5$, the estimated values are 43.20 for diabetes prevalence and 67.88 for smartphone use. These are about five times and thrice the value of real data. Even if we assume larger weights for the lower bound response, we still find overestimation. For example, if $w = 0.75$, we get 37.86 for diabetes prevalence and 61.68 for smartphone use. In all cases, the measure for inaccuracy on PB is statistically different from 0.

Comparing sensitivity computations in Study 2 with point estimates from Study 1, it is likely that respondents are biased towards the upper bound. Study 1's mean point estimate of 57.87 for diabetes prevalence is larger than for Study 2's estimate of 53.88 when $w = 0$. Finally, for smartphone usage, the average estimate of 76.28 from Study 1 falls within calculations from Study 2 if w is assumed to be within 0 to 0.25.

Conclusions

In this note, we provide a quantitative analysis of perception bias. We defined perception bias as the relative inaccuracy by which respondents' estimates deviate from factual data. In general, data from Philippine participants reflect significant evidence of overestimation. Respondent estimates are approximately seven times (twice) the real values for the prevalence of diabetes (rate of smartphone use). We supplement these statistical results with evidence from bootstrapped quantile regression models. For the rate of diabetes, older and more risk-tolerant respondents have less accurate estimates. For smartphone usage, we find similar results. Age is the most significant determinant of perception bias. Younger respondents tend to give more extreme estimates of smartphone use. In a supplementary analysis, we also found that real-life statistics rarely fall within the respondents' lower and upper bound estimates.

Overall, the wider implications of our results involve the explicit measurement of judgment bias. We provide stronger evidence on people's susceptibility to misinformation. As already implied in Section 1 of this paper, further applications include issues like fake news (Allcott & Gentzkow, 2017) and discrimination (Bertrand & Mullainathan, 2004). Finally, as the dominant ethnolinguistic group in the Philippines (Minahan, 2012) and Laguna being the third most populated province in the Philippines (Philippine Statistical Authority, 2015), our Tagalog respondents provide a decent representation of the whole population.[4] Our results, nonetheless, cannot be a full generalization. Thus, this study can be extended by having a larger sample size with respondents varying in the region of origin. Future work may also include identifying the relationship between perception bias and other behavioral measures like time orientation (Mello et al., 2009).

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Notes

[1] We use STATA's sqreg command for simultaneous quantile regressions with bootstrapped standard errors.

[2] Food and Nutrition Research Institute's 2013 survey contains the most recent and accessible age-based data on diabetes.

[3] Our result that perception bias increases with risk tolerance is somehow related to the findings of Raheja and Dhiman (2019). There is a relationship between behavioral biases - overconfidence bias and regret bias - and investment decisions, which is mediated by facilitated by risk tolerance.

[4] Food and Nutrition Research Institute (2015) indicates that those from Region IV, where Laguna belongs, have essentially the same prevalence of diabetes as in the whole Philippines. The same, to some extent, may also apply to smartphone usage (Silver, 2019).

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