Are People Averse to Acknowledging their Ignorance in Opinion Polls?

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Abstract

People often express an opinion about a policy although they are not fully informed about it. One explanation for this is that people think they are informed about the policy. That is, they are unaware of their ignorance about the policy. An alternative and relatively unexplored explanation is that people are aware of their ignorance about the policy but are averse to acknowledging it. We analyze data from a randomized field experiment that elicits opinions on issues with policy relevance to study aversion to acknowledging ignorance. We find that people are averse to acknowledging their ignorance. We also find evidence that respondents who have depleted the resources available to exercise self-control are more likely to be averse to acknowledging their ignorance. Our results suggest that policymakers should be careful when interpreting opinion polls in which respondents could be motivated to appear informed about policies. Our results also suggest that survey designers should prompt people to use the "don't know" option to reduce their aversion to acknowledging their ignorance.

1 Introduction

Public opinion is known to have a direct effect on policies of governments (Page & Shapiro, 1983; Lax & Phillips, 2012). For example, in 2016, the United Kingdom decided to leave the European Union based on the opinion of the public elicited through a referendum. Public opinion is also known to influence the decisions of the Supreme Court in the United States (Collins & Cooper, 2016).

There are several ways in which public opinion is expressed. People may express their opinion via protests. The strength and clarity of the message signalled through the protest can determine the influence of the message on policy changes (Fassiotto & Soule, 2017). Public opinion is typically elicited through surveys or opinion polls. The topics of these surveys range from policies about the environment (Morrison & Hatfield-Dodds, 2011) to those about the legalization of drugs (Palamar, 2014). In addition to surveys, social media has made it increasingly easy to elicit public opinion since people do not have to be explicitly asked for an opinion. For example, there were over 70 million tweets in just one year about the gun control laws in the United States that were analyzed to identify public opinion on the topic. Opinions from social media are comparable to opinions from standard surveys, and thus form an important source of eliciting public opinion (O'Connor, Balasubramanyan, Routledge, & Smith, 2010). Given the ease of obtaining public opinion and its relevance in policy, it is important to study how people form opinions.

Sears, Lau, Tyler, and Allen (1980) find that a person's opinion on a policy is not guided by his personal interests. It is instead guided by his perception on the role of the policy. In such a case, he would need enough information about how a policy works to form an opinion about it. However, previous studies suggest that people usually know very little about the policies of the government (e.g., Carpini & Keeter, 1997; Fernbach, Rogers, Fox, & Sloman, 2013; Mondak & Davis, 2001).

Although people usually know very little about policies, they often express an opinion about them (Carpini & Keeter, 1997; Fernbach et al., 2013). Most of the literature explains the finding that people express an opinion about a policy in the absence of full information by suggesting that people incorrectly think that they are informed about the policy (e.g., Fernbach et al., 2013; Dunning, 2011). That is, they are unaware of how much they do not know about the policy. An alternative explanation is that people are aware of how much they do not know about the policy but are averse to acknowledging their lack of knowledge about it (Ziller & Long, 1965; Sturgis, Roberts, & Smith, 2014).

The literature on aversion to acknowledging ignorance is scarce. This motivates us to contribute to this literature in several respects. First, we analyze if people are averse to acknowledging their ignorance. Second, we allow for population heterogeneity by distinguishing between different classes of people that differ in the degree to which they acknowledge their ignorance and test if these different classes are averse to acknowledging their ignorance. Third, we allow for population heterogeneity by distinguishing between a class of people who is able to acknowledge their ignorance and a class of people who is unable to do so, and test if aversion to acknowledging ignorance in the former class. Both classes of people may be unaware of their ignorance in some questions of a survey and may be aware but averse to acknowledging their ignorance in some other questions. However, people who are able to acknowledge their ignorance would acknowledge their ignorance on one or more questions in a survey. While it may interesting to test if the class of people who is unable to acknowledge their ignorance is averse to acknowledging their ignorance, the methodology that we use does not allow us to test this. Finally, we test one factor that may generate an aversion to acknowledging ignorance. Previous studies suggest that if people exercise self-control in a task, they deplete the resources available to exercise self-control in subsequent tasks (Baumeister, Bratslavsky, Muraven, & Tice, 1998). This is known as ego-depletion. We test if a state of ego-depletion makes people more averse to acknowledging their ignorance. Having answered these questions, we explore some consequences of the existence of an aversion to acknowledging ignorance.

Consistent with the findings in the literature (e.g., Sturgis et al., 2014; Ziller & Long, 1965), we find that people are averse to acknowledging their ignorance. We identify a class of people constituting 8-19% of the population, characterized by lower levels of education, who may be less averse to acknowledging their ignorance. We distinguish between those who are able to acknowledge their ignorance and those who are unable to acknowledge their ignorance and find that aversion exists among the former. Finally, we find some evidence that ego-depletion increases aversion to acknowledging ignorance.

The rest of the paper is organized as follows. Section 2 reviews the literature on ignorance in opinion polls and motivates the research questions. Section 3 describes the data and the survey design. Section 4 explains the empirical approach. Section 5 presents the results. Section 6 concludes the paper.

2 Ignorance in opinion polls

People are often uninformed (Bartels, 1996; Mondak & Davis, 2001), partially informed (Mondak & Davis, 2001), and sometimes misinformed (Kuklinski, Quirk, Jerit, Schwieder, & Rich, 2000) about policies. However, they often express an opinion about a policy when asked to do so (Carpini & Keeter, 1997; Fernbach et al., 2013; Schuman & Presser, 1980). People are often willing to express an opinion on obscure policies (Schuman & Presser, 1980), complex policies (Fernbach et al., 2013), and on fictitious policies invented by the researchers (Bishop, Tuchfarber, & Oldendick, 1986; Sturgis & Smith, 2010). People may express an opinion about a policy in the absence of full information because they may think that they have enough information (although this is inadequate) to form an opinion (Dunning, 2011; Lord, Ross, & Lepper, 1979; Fernbach et al., 2013). That is, they may be unaware of how little they know about the policy. An alternative explanation is that people are often aware of how little they know about the policy but are averse to acknowledging their lack of knowledge of the policy (Ziller & Long, 1965; Sturgis et al., 2014).

Dunning (2011) suggests that if people retrieve enough knowledge (although this is inadequate) about a topic from their memory, they will claim to know something about the topic. That is, a threshold of knowledge has to be reached for people to claim that they know something. People are often unsure of whether they know something or not. They may feel like they know (Koriat, 1995). This is perhaps the motivation for using a threshold. Dunning also suggests that if people do not cross the threshold, they will not claim that they know something about the topic. We build on the existing research and propose that if people do not cross this threshold, they will still sometimes claim that they know something about the topic. This is, although people know that they do not have enough knowledge on a topic, they will still claim that they are knowledgeable about the topic because they are averse to acknowledging their ignorance.

The knowledge retrieved from memory possibly determines the confidence of people. If people retrieve enough knowledge to express an opinion, then they are confident enough to express an opinion. Thus, analogous to the threshold of knowledge is a threshold of confidence. Crossing (not crossing) the threshold of confidence is a state characterized by high (low) confidence.

2.1 Awareness of ignorance

This subsection discusses the reasons for why people are often unaware of their ignorance on policies. Subsection 2.2 discusses the reasons that explain why people are often aware of their ignorance on policies but are averse to acknowledging their ignorance. We then present our research questions.

Dunning (2011) identifies 3 broad categorizations of reasons that explain why people may be unaware of their ignorance. We discuss them below.

Unknown unknowns

Often, people are unaware of their ignorance because they do not have information that is required to form an opinion and do not know that they lack this information. This information is referred to as "Unknown unknowns." We discuss four explanations of why people are unable to identify what they do not know (unknowns) about a policy.

First, the "Illusion of Explanatory Depth" (IOED) explains why people are unable to identify the unknowns. The IOED can be described as the phenomenon where people feel they understand the world with far greater detail than they actually do (Rozenblit & Keil, 2002; Keil, 2003). If people think they understand a policy better than they do, they may miss the unknowns. When people miss the unknowns, they may even be more likely to express a polarized opinion on policies (Fernbach et al., 2013)[1].

Second, the "Illusion of Knowledge" explains why people are unable to identify the unknowns. The "Illusion of Knowledge" leads people to believe that they have comprehended something, when in fact they have not (Glenberg, Wilkinson, & Epstein, 1982; Epstein, Glenberg, & Bradley, 1984). It differs from the IOED as it tests comprehension about knowledge provided to respondents during the experiment rather than testing their pre-existing knowledge (Rozenblit & Keil, 2002). An illusion of knowledge could play a role in opinion formation in contexts where people form opinions immediately after obtaining information about a policy. They would be more likely to miss the unknowns if they incorrectly believe to have comprehended how the policy works.

Third, overconfidence may make people more likely to miss the unknowns. Overconfidence can result from the fact that people are poor at recognizing how much knowledge they have (Eva, Cunnington, Reiter, Keane, & Norman, 2004). The IOED is different from overconfidence, as the former does not hold for all types of knowledge. In particular, the IOED holds for knowledge that involves complex causal patterns while the latter holds for knowledge that involves procedures or narratives (Mills & Keil, 2004). For example, IOED may explain why a person thinks he understands a complex policy while overconfidence may explain why a person thinks he knows how to bake a cake. Walters, Fernbach, Fox, and Sloman (2016) find that when respondents are asked to list the unknowns, their confidence reduces in areas where they were overconfident. Thus, a general overconfidence in addition to the IOED may lead people to miss the unknowns on complex policies.

Fourth, a person's epistemic belief or his belief about the nature of knowledge may determine his likelihood of missing the unknowns[2]. Schommer (1990) finds that the more people believe that learning is quick, the more likely they are to make oversimplified conclusions and the more likely they are to overestimate their understanding of a text provided to them.

[1] One explanation for this relates to people's construal style, or how they interpret the world. When people focus on the "why" of the task rather than the "how" and "in what order", they experience a diminished IOED (Alter, Oppenheimer, & Zemla, 2010).

[2] Schommer (1990) suggests five categories of epistemic beliefs. These are: (a) Knowledge is simple rather than complex, (b) Knowledge is handed down by authority rather than derived from reason, (c) Knowledge is certain rather than tentative, (d) The ability to learn is innate rather than acquired, (e) Learning is quick or not at all.

Furthermore, people who believe that knowledge is certain, as opposed to being tentative, are more likely to provide a certain conclusion after reading a passage that did not have an explicit conclusion. Given these findings, we can expect that people's epistemic beliefs are likely to play a role in their comprehension of a policy. It is likely that those who believe that knowledge is certain and those who believe that learning is quick are more likely to miss the unknowns about a policy.

Misinformation

If people miss the unknowns, then they are less likely to be aware of their ignorance about policies. A second reason why people may be unaware of their ignorance about policies is that people may be misinformed about policies. People often believe that they have accurate knowledge on a topic when in fact they are misinformed (Kuklinski et al., 2000). The presence of misinformation hinders a person from being aware of his ignorance. Furthermore, studies suggest that it is often difficult to correct people of their misinformation (Lord et al., 1979; Prasad et al., 2009).

Reach-around knowledge

A third reason why people may be unaware of their ignorance about policies is that they may reach back or reach around to any knowledge (although not directly relevant) in their memory that they think is relevant and use this to form an opinion (Dunning, 2011). People are also found to use heuristics, or mental shortcuts, to form opinions (Prasad et al., 2009; Kuklinski & Quirk, 2000). This may explain why a significant proportion of people claim to be familiar with fictitious concepts invented by researchers (see e.g., Atir, Rosenzweig, & Dunning, 2015; Paulhus, Harms, Bruce, & Lysy, 2003; Sturgis & Smith, 2010; Bishop et al., 1986). For example, Graeff (2003) finds that respondents are more likely to claim to be familiar with non-existent consumer brands, for which there was broad knowledge to refer to. He finds that people are likely to be familiar with a fictitious product named Yamijitsu stereos since they relied on their general impression of Japanese stereo equipment. Thus, if people reach back to related knowledge about a policy (that is not directly related) from their memory, they are more likely to be unaware of their ignorance about the policy.

2.2 Aversion to acknowledging ignorance

People often express an opinion about a policy although they do not have full information about it. The first reason for this is that they may be unaware of their ignorance about the policy. This was discussed in the previous subsection. The second reason for this is that people may be aware of their ignorance about the policy but may be averse to acknowledging it.

Factors leading to aversion

There are three possible reasons that could explain why people are averse to acknowledging their ignorance.

First, people are averse to acknowledging their ignorance because appearing uninformed is not socially desirable (Mondak & Davis, 2001; Zaller, 1992). In the previous subsection, we noted that people often express an opinion on fictitious issues because they think they are familiar with them. Some studies find that people are willing to give their opinions on fictitious issues because of an increased pressure to respond (e.g., Bishop et al., 1986; Graeff, 2002). People may be pressurized to respond if they think that having an opinion is socially desirable. Furthermore, people with lower education and lower political knowledge are more likely to give an opinion on fictitious issues (Bishop et al., 1986). This could indicate that they do not want to appear uninformed. Studies have found that encouraging people to use the DK option increases their likelihood of using it (e.g., Mondak & Davis, 2001; Scoboria & Fisico, 2013). Mondak and Davis (2001) uses the following prompt in each question "Many people don't know the answers to these questions, so if there are some you don't know, just tell me and we'll go on". It is likely that the prompt makes it less socially desirable to have an opinion.

Second, people may be averse to acknowledging their ignorance because doing so disconfirms their status or reputation. Studies disagree on whether actual knowledge leads to an increase (Atir et al., 2015; Dunning, 2011) or a decrease (Bishop et al., 1986; Sturgis & Smith, 2010) in the willingness to provide an opinion. However, when people report being knowledgeable about a topic, they are more likely to express an opinion (Bradley, 1981; Atir et al., 2015; Jee, Wiley, & Griffin, 2006). Studies also find that when people report being interested in a topic, they are more likely to express an opinion (Sturgis & Smith, 2010). The fact that people who report being knowledgeable about or interested in a topic are more likely to express an opinion in itself does not mean that they are averse to acknowledging their ignorance, as it could be that they actually have more information about the topic. However, studies also find that when questions eliciting a person's knowledge about or interest in a topic are asked before the questions eliciting an opinion on the topic, the willingness to provide an opinion is higher than if the order is reversed (Bishop, Oldendick, & Tuchfarber, 1984; Sturgis & Smith, 2010; Atir et al., 2015). This finding supports the idea that in addition to a person's perception of his knowledge and interest on a topic, making this salient or noticeable, by asking them to explicitly state it, may lead to an increase in his aversion to acknowledging his ignorance. Thus, if people have claimed to be knowledgeable about or interested in a topic, then they are less likely to acknowledge their ignorance on a particular question that they do not know enough about, as doing so would disconfirm their status or reputation of being an "expert" on the topic. Sturgis et al. (2014) finds that in a survey, people who state being interested in a topic are more likely to choose the middle option (neither/nor) rather than the "don't know" (DK) option to "save-face".

The above discussion suggests that a person's status of being an expert is made salient when he is explicitly asked to report his knowledge or interest on a topic. In some situations, the status of a person may be determined based on the social situation. For example, Ziller and Long (1965) find that professionals in clinical psychology, as compared to technicians, are more likely to give an opinion on questions when the hierarchy in status is made salient. In this case, the social situation determines that the status of professionals is higher than the status of technicians. Similarly, older students (teachers) may also be more likely to provide an opinion if they think that their status is higher than the status of younger students (teachers) (Ziller & Long, 1965).

The literature suggests that people are more likely to express an opinion when they feel that their status requires them to have an opinion. In such situations, people are aware of their ignorance on a topic but are averse to acknowledge their ignorance. However, there could be another explanation. People may search their memory with the objective of finding something relevant to the question (confirmation-biased memory search) and they may reach a state where they think they have enough knowledge about the question and may be more likely to provide an opinion (Kunda, 1990). We can link this explanation to the threshold of knowledge that was discussed earlier. If a person thinks that he is supposed to have an opinion about a question and has not crossed the threshold of knowledge required for him to think that he is knowledgeable about the question, then he may be averse to acknowledging his ignorance. Alternatively, he may engage in a confirmation-biased memory search and collect enough information in his mind for him to cross the threshold and think that he is informed about the particular question. In this case, he would be unaware of his ignorance.

Third, people may be averse to acknowledging their ignorance if they have depleted the self-control resources available to refrain from expressing an opinion. The two previous factors can explain why expressing an opinion is the norm or the status-quo. Refraining from expressing an opinion in favor of acknowledging ignorance might require self-control. Studies suggest that all acts of self-control draw from a common yet finite pool of resources (Baumeister et al., 1998; Baumeister & Heatherton, 1996). If people exercise self-control on a task, they are less likely to exercise self-control in subsequent tasks. This is referred to as ego-depletion. A person with a depleted ego is less likely to exercise self-control and is more likely to follow the norm (Pocheptsova, Amir, Dhar, & Baumeister, 2009). Thus, a person with a depleted ego is less likely to exercise self-control to refrain from expressing an opinion and is more likely to express an opinion (the norm). That is, a person with a depleted ego is less likely to acknowledge his ignorance and is thus more averse to acknowledging his ignorance. This idea is consistent with the research that suggests that an ego-depletion leads to a decreased use of deliberate thinking and a high reliance on the status-quo options (Pocheptsova et al., 2009). Morrison and Hatfield-Dodds (2011) suggest that ego-depletion is a possible reason for respondents choosing the status-quo "not-sure" option on questions eliciting views on environmental when there is an increase in the volume and complexity of information about climate change. Mead, Baumeister, Gino, Schweitzer, and Ariely (2009) find that depleted respondents are less likely to cheat since being honest is the norm.

Although expressing an opinion is usually the norm, we do not exclude the idea that for a class of people, acknowledging ignorance may be the norm if they know beforehand that they are unfamiliar with the topic. In such a case, an ego-depletion may make people less likely to express an opinion.

Unexplored research questions

There are only a few studies in the literature that test if people are averse to acknowledging their ignorance. Few papers explore possible mechanisms that may lead to an aversion to acknowledging ignorance. The scarce literature motivates us to study aversion to acknowledging ignorance. We now present the research questions that we intend to answer in this study.

Question 1: Are people averse to acknowledging their ignorance? There are some studies in the literature that test if people are averse to acknowledging their ignorance (e.g., Sturgis et al., 2014; Ziller & Long, 1965). Some studies follow a procedure that leads to the conclusion that people are averse to acknowledging their ignorance (Sturgis & Smith, 2010; Mondak & Davis, 2001; Bishop et al., 1984). However, the authors refer to it as an "unexpected finding" and do not explore it further. We contribute to this literature by testing if people are averse to acknowledging their ignorance. We use a procedure that has not been used before to answer this question.

Question 2: The previous question assumes that the population is homogeneous. An extension to the previous question involves allowing for population heterogeneity by distinguishing between different classes of people. It may be important to distinguish between different classes of people to allow for the fact people may vary in their degree of aversion to acknowledging their ignorance. Some papers in the literature allow for population heterogeneity as it may be restrictive to assume that the population is homogeneous (e.g., Bagozzi, Mukherjee, & Alvarez, 2012; Bagozzi & Marchetti, 2015). We can distinguish between two or more classes of people that differ based on observed and unobserved characteristics. We then test the following question: Does aversion to acknowledging ignorance exist among different classes of people?

Question 3: The previous question distinguishes between classes of people that differ in their degree of aversion to acknowledging ignorance. We can also distinguish between two classes of people that differ in their ability to acknowledge their ignorance. Both classes may be unaware of their ignorance in some questions of a survey or may be aware and averse to acknowledging their ignorance in other questions of a survey. However, one class is able to acknowledge their ignorance in one or more questions while the other class is unable to acknowledge their ignorance on any question. Having identified these two classes, we can test the following question: Does aversion to acknowledging ignorance exist among the class that is able to acknowledge their ignorance? While it may also be interesting to check if those who are unable to acknowledge their ignorance are also averse to acknowledging their ignorance, the methodology that we use cannot test this.

Question 4: The first three questions explored the existence of aversion to acknowledging ignorance. The next step is to test a possible factor that may generate an aversion to acknowledging ignorance by answering the following question: Does a state of ego-depletion increase people's aversion to acknowledging ignorance? When people exercise self-control on a task, they are less likely to exercise self-control in subsequent tasks (Baumeister et al., 1998; Baumeister & Heatherton, 1996). This is known as ego-depletion. As discussed above, people are more likely to follow the norm when they have depleted the self-control resources available to refrain from following the norm (Baumeister et al., 1998; Pocheptsova et al., 2009). Given that participants rarely acknowledge their ignorance, we assume that expressing an opinion is the norm. Refraining from expressing an opinion requires self-control. Thus, a state of ego-depletion makes people more likely to express an opinion (less likely to refrain from expressing an opinion) and makes them more averse to acknowledging their ignorance.

3 Data and survey design

3.1 Data

The dataset used in this study is from a survey fielded in 2012 in the LISS panel (Longitudinal Internet Studies for the Social Sciences) administered by CentERdata at Tilburg University in The Netherlands[3]. The panel is based on a true probability sample of households drawn from the population register and hence is representative of the population. It consists of 5000 households comprising 8000 individuals who participate in monthly Internet surveys of about 15 to 30 minutes in total and are paid for each completed survey. One member of the household provides the household data and updates this information at regular time intervals. Households that could not otherwise participate are provided with a computer and Internet connection. A longitudinal survey is fielded in the panel every year, covering a large variety of domains including work, education, income, housing, time use, political views, values, and personality.

The survey that we use contains opinions of respondents on 14 questions[4]. Of the 7517 respondents in the survey, there was no response by 1790 respondents (23.8%). Of the remaining 5727 responses, there were only 3 incomplete responses. Respondents were randomly assigned to 4 treatment groups. In the first treatment group, respondents were forced to answer all the questions. In the second treatment group, respondents were allowed to skip a question if they wished. In the third treatment group, respondents were not allowed to skip questions but were offered an explicit "don't know" (DK)/"no opinion" option. In the fourth treatment group, respondents were not allowed to skip questions, were offered an explicit DK/"no-opinion" option, and were also prompted to use the DK/"no-opinion" option[5]. The randomization into the 4 treatment groups is summarized in Table 1.

Table 1: Summary of dataset

	Group				Total
	1	2	3	4	
Skip questions		yes			
DK/"no opinion" option			yes	yes	
Prompted				yes	
Respondents	1,420	1,375	1,463	1,466	5724
Percent	24.81	24.02	25.56	25.61	100

Since this study focuses on people's choice of acknowledging their ignorance, we do not include respondents who were forced to answer all questions. Including respondents who were allowed to skip questions requires us to check if the choice of skipping a question means

[3]More information about the LISS panel can be found at www.lissdata.nl or in Scherpenzeel, Das, Ester, and Kaczmirek (2010)

[4]The dataset is titled: The "Dont Know" Option and the Outcomes of Opinion Polls.

[5]The prompt can be translated from Dutch as follows: If you really don't know where you would position yourself, feel free to say so.

the same as choosing the DK/"no opinion" option. Since this is difficult to check, we do not include respondents who were allowed to skip questions. This leaves us with the two groups who were offered an explicit DK/"no opinion" option. One group was prompted to use the DK/"no opinion" option and the other group was not prompted. As a notional shorthand, we refer to the two groups as PY (Prompted-yes) and PN (Prompted-no), respectively. These groups have 2929 observations that correspond to 51.2% of the total completed responses.

The 14 questions of the survey ask people their opinion about issues with policy relevance. They are presented in Appendix A.

Descriptive statistics

Table 2 presents descriptive statistics. There were 1466 respondents in the PY treatment group and 1463 in the PN treatment group. 46% of the sample is male. The age of respondents ranges from 16 to 92 years and the mean age is 50. 51% of the sample is working, and 21 % of the sample is retired; these form the largest categories. Other categories form a small proportion of the sample. 10% of the sample has completed only primary school, 37% of the sample has completed only high school, and 53% of the sample has completed college. The majority of the population is educated and old. From the variables indicating people's perception about the survey, we find that on average, people found the survey to be clear and not so difficult. They also found it moderately thought-provoking, interesting and enjoyable.

3.2 Survey design considerations

We restrict our sample to the two groups that include a "don't know" (DK)/"no opinion" option. The survey design literature does not have a consensus about the inclusion of a DK or the "no opinion" option[6]. There are several arguments for and against the inclusion of a DK option. First, the choice of a DK option could indicate survey satisficing or a lack of interest for a respondent who wants to finish the survey with less effort (Krosnick et al., 2002). Second, a DK response could indicate a respondent's unwillingness to reveal his true opinion because the nature of the question is sensitive (Berinsky, 1999; Rubin, Stern, & Vehovar, 1995). However, if respondents are ensured anonymity, they are more likely to give their true opinion (Lax, Phillips, & Stollwerk, 2016). Finally, if a respondent chooses the DK option, it could mean that the respondent acknowledges that he does not have enough knowledge or information to express an opinion (Converse, 1976).

In our analysis, we take a DK response to mean that the respondent acknowledges that he does not have enough knowledge to express an opinion. This is the standard practice in the literature (e.g., Mondak & Davis, 2001; Kleinberg & Fordham, 2017). If a person chooses the DK option, then it means that he is acknowledging his ignorance. However, if he does not use the DK option, it could indicate that either he is unaware of his ignorance or that he is aware but averse to acknowledging his ignorance. We think that survey satisficing is less

[6]The literature treats these two options to be the same. For brevity, we refer to either of the two options as the DK option.

Table 2: Descriptive statistics

Variable	Count	Mean	SD	Minimum	Maximum
Demographics					
Male	2929	0.46	0.50	0	1
Age	2929	50.00	17.33	16	92
Net income	2790	1420.07	1031.53	0	10000
Urban	2929	0.84	0.36	0	1
Labor market status					
Working	2929	0.51	0.50	0	1
Retired	2929	0.21	0.41	0	1
Other	2929	0.09	0.29	0	1
Inactive	2929	0.09	0.29	0	1
Student	2929	0.09	0.29	0	1
Education					
Primary	2929	0.10	0.31	0	1
High school	2929	0.37	0.48	0	1
College	2929	0.53	0.50	0	1
Survey behavior					
Response time	2929	11.92	6.38	2	65
Survey after 20:00	2929	0.19	0.39	0	1
Survey perception					
Difficult	2929	2.14	1.23	1	5
Clear	2929	4.11	0.94	1	5
Think	2929	3.15	1.10	1	5
Interest	2929	3.61	0.96	1	5
Enjoy	2929	3.70	0.94	1	5

of a problem in the survey. We check this in the next section and indeed find that survey satisficing is not problematic. In the survey, respondents are ensured of anonymity and are thus less likely to use the DK option to hide their true opinion.

3.3 Treatment effect

Standard economic theory suggests that people know their true preferences (Simon, 1955; Freeman III, Herriges, & Kling, 2014; March, 1978). If people know their preferences and state their true preferences, then prompting them to use the DK option should have no effect. If this is the case, we would expect the number of DK responses to be identical in the PY treatment group that prompts people to use the DK option and in the PN treatment group that does not prompt people to use the DK option. However, recent evidence from Behavioral Economics suggests that for a variety of reasons, people may not always state their true preferences (see e.g., Loomis, 2014; Carlsson, 2010). If the number of DK responses is lower in the PN treatment group (higher in the PY group when prompted), then this indicates that respondents in the PN treatment group were less likely to reveal their true preferences than respondents in the PY treatment group. In particular, this would indicate that people in the PN treatment group are more averse to using the DK option than respondents in the PY treatment group. The difference in the aversion levels of the two treatment groups helps us identify that in general, respondents are averse to acknowledging their ignorance. If the number of DK responses is not lower in the PN treatment group (higher in the PY treatment group), then it could mean either that respondents are not averse to acknowledging their ignorance or that prompting people to use the DK option was ineffective to identify if people are averse to acknowledging their ignorance.

A similar methodology is used in the literature to test if people claim to know more than they actually do (see e.g., Rozenblit & Keil, 2002; Alter et al., 2010; Mills & Keil, 2004; Fernbach et al., 2013). In these studies, participants are asked to rate their understanding of a device (e.g. can opener). A higher rating indicates a better understanding of the device. They are then asked to give an explanation of how the device works and then re-rate their understanding of the device. In all cases, the rating after the explanation is lower than the rating before the explanation, indicating that before the explanation, people overestimated their understanding of the device. The difference in the pre-explanation and post-explanation ratings helps to identify that in general, people tend to overestimate their understanding of the device[7]. If the two ratings were the same, it could indicate either that people do not exhibit the IOED or that the treatment (asking people to give an explanation) was ineffective in identifying the IOED. This methodology is similar to the one we use, in that, it relies on a difference between two ratings to identify if people claim to know more than they actually do.

There could be two alternative explanations for a difference in the number of DKs across the PY and PN groups. First, it is possible that prompting people to use the DK option makes people who are unaware of their ignorance to become aware of it. However, this is unlikely given that people are unlikely to become aware of their ignorance by merely thinking about the topic (Zeveney & Marsh, 2016). Second, a higher DK response rate in the PY treatment group could indicate that the prompt encourages people to use the DK option as a way to finish the survey early (Mondak & Davis, 2001; Young, 2012; Krosnick, 1991). However, we expect that survey satisficers form a very small fraction of our sample. We check for this in the next section and indeed find that survey satisficing is not problematic in our sample.

In the survey, respondents in the PY group are prompted to use the DK option. Whether to encourage or discourage the use of a DK option is widely debated in the survey design literature. Some studies argue that the DK option should be discouraged (e.g., Brown, 1983; Cronbach, 1946; Schreiber et al., 2006) because encouraging it can lead to an understatement of knowledge (Sherriffs & Boomer, 1954). Encouraging the use of the DK option has been found to increase the number of DK responses with an additional increase in the accuracy of

[7]This is termed as the Illusion of Explanatory Depth (IOED). The IOED also explains people's overestimation of their understanding of policies (e.g., Alter et al., 2010; Fernbach et al., 2013).

responses (Scoboria & Fisico, 2013; Nesbitt & Markham, 1999). Mondak and Davis (2001) randomly assign two versions of a question to respondents. The first version is: "Many people don't know the answers to these questions, so if there are some you don't know, just tell me and we'll go on." The second version is: "Many people don't know the answers to these questions, but even if you're not sure I'd like you to tell me your best guess." They find that the DK responses are lower in the latter condition. The studies that look at the effect of encouraging people to use the DK option are mainly from the survey design literature and do not explore the reason for the increase in DKs when people are encouraged[8]. One explanation that they do give is that prompting people to use the DK option encourages people to use it as a way to finish the survey early. However, they overlook the fact that people might be averse to acknowledging their ignorance.

[8] Throughout the paper, we use the term "prompting" instead of "encouraging"

4 Empirical Approach

Subsection 4.1 describes the approach along with a description of the models used. Subsection 4.2 describes the explanatory variables used in the models.

4.1 Approach

Existence of aversion to acknowledging ignorance

To test if people are averse to acknowledging their ignorance, we consider a linear regression model. The dependent variable is the number of DK responses of each respondent. The count of DKs can range from 0 to 14 since there are 14 questions on the survey. The independent variable of interest is a dummy variable that takes a value of 1 if a person was in the PY treatment group, and a value of 0 if the person was in the PN treatment group. The PY treatment group prompts people to use the DK option while the PN treatment group does not prompt. If the treatment dummy is positive and significant, then this indicates that people are averse to acknowledging their ignorance. We estimate another specification in which we include control variables. We would expect that the addition of the control variables should not affect the coefficient of the treatment dummy since respondents are randomly assigned to one of two treatment groups. A discussion of the control variables used is provided in section 4.2.

We extend our analysis by estimating Count-data models with and without control variables. This is done with the motivation that they may provide a better fit to the data. The starting point for Count-data models is the Poisson regression. Let y_i represent the count of DKs. Let x_i represent the set of independent variables. It includes the treatment dummy as well as other control variables. Let n denote the number of observations. The Poisson regression assumes that the dependent variable follows a Poisson distribution with its distribution specified as

$$f(y_i|x_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \qquad y_i = 0, 1, 2, .., 14 \tag{1}$$

where λ_i is the intensity or rate parameter. The relationship between the parameter λ and the covariates x_i is parameterized as

$$\lambda_i = \exp(x_i'\beta). \tag{2}$$

Combining Equations (1) and (2) leads to the following conditional probability function

$$f(y_i|x_i) = \frac{\exp(-\exp(x_i'\beta))\exp(y_i x_i'\beta)}{y_i!} \tag{3}$$

and the following conditional expectation and conditional variance functions

$$E(y_i|x_i) = \exp(x_i'\beta) = Var(y_i|x_i). \tag{4}$$

The equality of the conditional mean and variance is referred to as the Equidispersion property. Given Equations (1) and (2) and the assumption that the observations $y_i|x_i$ are independent, we can estimate the Poisson regression using the maximum likelihood (ML) principle. The log-likelihood function takes the form

$$lnL(\beta) = \sum_{i=1}^{n}\{y_i x_i'\beta - exp(x_i'\beta) - lny_i!\}. \tag{5}$$

We can obtain parameter estimates using the Gauss-Newton or Newton-Raphson iterative algorithms.

One important limitation of the Poisson regression is that it does not account for unobserved heterogeneity. Furthermore, the Equidispersion property may not hold if the data is overdispersed or underdispersed. That is, the conditional variance is greater than or less than the conditional expectation. An extension to the Poisson model involves modelling the unobserved heterogeneity by introducing a multiplicative random term. We allow λ to be random rather than to be completely determined by the regressors. In particular, $\lambda = \mu v$, where $\mu_i = \exp(x_i'\beta)$ and $v \sim gamma(1, \alpha)$, where α is the variance parameter of the gamma distribution. α is also referred to as the overdispersion parameter. The marginal distribution of y is a Poisson-gamma mixture referred to as the negative binomial (NB) distribution whose density function is given by

$$f(y_i|x_i) = \frac{\Gamma(y_i + \psi_i)}{\Gamma(y_i + 1)\Gamma(\psi_i)}\left(\frac{\lambda_i}{\lambda_i + \psi_i}\right)^{y_i}\left(\frac{\psi_i}{\lambda_i + \psi_i}\right)^{\psi_i} \tag{6}$$

where $\Gamma()$ is the Gamma distribution. The precision parameter ψ_i^{-1} is specified as

$$\psi_i = (1/\alpha)\lambda_i^k \tag{7}$$

where $\alpha > 0$ is an overdispersion parameter and k is an arbitrary constant. The conditional expectation of the NB model is the same as that in the Poisson model and is given by

$$E(y_i|x_i) = \lambda_i = exp(x_i'\beta). \tag{8}$$

The conditional variance is given by

$$Var(y_i|x_i) = \lambda_i + \alpha\lambda_i^{2-k}. \tag{9}$$

If $\alpha = 0$, we obtain the Poisson model. If we specify $k = 1$, then we obtain the negative binomial-1 (NB1) model. If we specify $k = 0$, then we obtain the negative binomial-2 (NB2) model. This variance function implies that the NB regression can account for overdispersion as it is larger than the conditional expectation. It is more general than the Poisson regression in this regard. Parameter estimates can be obtained using the maximum likelihood principle based on the density given in Equation (6). To choose between the NB1 and NB2 model, we can choose the model with the lower Bayesian Information Criteria (BIC) (Cameron & Trivedi, 2013)[9].

To test if the Poisson regression is overdispersed, a simple regression-based test as proposed by Cameron and Trivedi (1990) can be implemented based on Equation (9). We can test $H_0 : \alpha = 0$ against $H_1 : \alpha > 0$ using an auxiliary regression. If $\alpha = 0$ in Equation (9), then the conditional variance function equals the conditional mean, as in the case of the Poisson model. If $\alpha > 0$ in Equation (9), then the conditional variance is larger than the conditional mean and is specified as in the case for the NB2 model. We generate the variable z_i as

$$z_i = \frac{(y_i - \hat{\lambda}_i)^2 - y_i}{\hat{\lambda}_i}$$

and then regress z_i on $\hat{\lambda}_i$ without an intercept term. We can then use a t-test to test if the coefficient of $\hat{\lambda}_i$ is significantly different from zero. If it is, then there is an indication of overdispersion in the Poisson regression. A number of alternative methods exist to test if the Poisson regression is overdispersed (see Cameron & Trivedi, 1990). If the Poisson regression is overdispersed, we can use the NB1 regression, NB2 regression, or an alternative Count-data model. We can also use the Poisson regression to obtain the point estimates and compute robust standard errors. This procedure is referred to as the quasi-maximum likelihood (QML) estimation. This has an advantage over using the negative binomial regression, although the latter is more efficient, as the latter is not consistent if the unobserved heterogeneity term is not gamma distributed (Cameron & Trivedi, 2010).

Aversion among classes of the population

The analysis in the previous question assumed that the population is homogeneous. We now relax the assumption that the population is homogeneous and test if aversion to acknowledging ignorance exists among different classes of the population. We estimate finite mixture models (FMM) following the methodology of Deb, Trivedi, et al. (1997). The dependent variable is the count of DKs of each respondent, as was the case in the previous question. Some studies in the literature have used a mixture model to account for population heterogeneity (e.g., Bagozzi & Marchetti, 2015; Bagozzi et al., 2012; Bagozzi, Brawner, Mukherjee, & Yadav, 2014). Hill and Kriesi (2001) use a FMM to analyze opinion change on pollution reduction policies for different classes of people. To our knowledge, no other study has used a FMM to model the count of DKs. Studies that model the count of DKs use a linear regression assuming that all respondents behave in the same way (e.g., Mondak & Davis, 2001; Scoboria & Fisico, 2013).

FMM is a semiparametric approach that characterizes the count of DKs as an additive mixture of two or more distributions. This allows the identification of two or more classes of people. These classes are constructed based on observed variables as well as unobservables. In this regard, the classes are latent in nature and do not have labels. The effect of the

[9]Since the NB1 and NB2 have the same degrees of freedom, we can use the fitted log-likelihood value or the BIC

treatment dummy and demographic variables can vary between the classes[10]. The FMM has several advantages over other parametric models. They are less restrictive than related parametric models, as they assume that the dependent variable can arise from more than one distribution of the same family. The FMM may provide a good numerical approximation even if the underlying mixing distribution is continuous (Deb et al., 1997).

In a FMM, the dependent variable y_i is postulated as an additive mixture of C distinct populations with component densities $f_1(y_i|\theta_1), ..., f_C(y_i|\theta_1)$, in proportions $\pi_1, ..., \pi_C$, where $\sum_{j=1}^{C} \pi_j = 1$, $\pi_C = (1 - \sum_{j=1}^{C-1} \pi_j)$, and $\pi_j > 0$ for $j = 1, ..., C$. The mixture density is given by

$$f(y_i|\Theta) = \sum_{j=1}^{C-1} \pi_j f_j(y_i|\theta_j) + \pi_C f_C(y_i|\theta_C) \tag{10}$$

where the mixing parameters π_j are estimated along with other parameters denoted as Θ. The component distributions can be Poisson, NB1 or NB2. For the Poisson, the distribution is similar to Equation (1). For the NB1 and NB2, the distribution is similar to Equation (6) for the cases where $k = 1$ and $k = 0$ respectively. We follow Deb et al. (1997) and maximize the following log-likelihood function using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.

$$lnL(\pi, \theta) = \sum_{i=1}^{n} ln\Bigg((\sum_{j=1}^{C} \pi_j f_j(y|\theta_j) \Bigg). \tag{11}$$

We start by estimating a 2-component FMM mixing with two Poisson distributions. The two components in the model correspond to two classes of people in the population. Similarly, we estimate a 2-component FMM mixing with two NB1 distributions and a 2-component FMM mixing with two NB2 distributions. This leads to a total of three FMMs. We follow a similar procedure to estimate three 3-component FMMs. In practice, a few number of classes is a good approximation of the underlying data (Deb et al., 1997). Thus, we do not extend beyond three components. A positive and significant coefficient of the treatment dummy in either class indicates the existence of aversion among people in that class.

To choose between any two models with the same number of components or with different number of components, we can use the Bayesian Information Criteria (BIC) (Cameron & Trivedi, 2013)[11]. A likelihood ratio (LR) test can be used to choose between models with different number of components. The systematic use of the LR test may lead to the choice of a model with a small number of components since the null hypothesis is on the boundary of the parameter space (Deb et al., 1997). However, Cameron and Trivedi (2013) suggest that the likelihood ratio test may have sufficient power. Cameron and Trivedi also suggest a possibility of bootstrapping the critical values for the LR test. We do not pursue this since

[10]This is referred to as parameter heterogeneity.

[11]$BIC = -lnL + (lnn)k$, where L is the fitted log-likelihood, n is the number of observations, and k is the number of parameters to be estimated

it is computationally expensive in terms of time. The existence of classes can also be found by plotting the directional gradient function, although this is only a heuristic approach (Deb et al., 1997).

Aversion and ability to acknowledge ignorance

With the motivation to allow for population heterogeneity, we distinguish between two classes of people based on their ability to acknowledge their ignorance. The first class is able to acknowledge their ignorance while the second is unable to acknowledge their ignorance. For brevity, we refer to these two classes as the Able-DK class and the Unable-DK class. While both classes may be unaware of their ignorance on some questions and averse to acknowledging their ignorance on some questions, the Able-DK class has the ability to acknowledge their ignorance while the Unable-DK class does not have the ability to acknowledge their ignorance.

In a survey, some people never use the "don't know" (DK) option while others use it one or more times. Those who report zero DKs are likely to not have the ability to acknowledge their ignorance and are likely to be categorized into the Unable-DK class. However, there could be some who are able to acknowledge their ignorance but happen to report zero DKs by chance. The zero-inflated model helps to distinguish between those who are unable to acknowledge their ignorance (zero DKs) and those who are able to acknowledge their ignorance (zero DKs by chance). Respondents who report a positive number of DKs are classified into the Able-DK class.

Distinguishing between zeros and positives in the outcome of interest is not uncommon in the literature. For example, in the domain of voting choice, Bagozzi and Marchetti (2015) distinguish between occasional abstention and routine abstention. The zero-inflated model is very similar to a hurdle model. The hurdle model is estimated with the assumption that the zeros in the data are qualitatively different from the positive counts. It assumes that the decision-making process of an individual is a two step approach. In the first step, an individual decides whether to choose the DK option at all and in the second step decides how many times to choose the DK option. However, this is not a realistic representation of the actual decision making process (Kleinberg & Fordham, 2017).

Let y_i be the count of DKs and x_i be the set of explanatory variables including the treatment dummy and additional control variables. The zero-inflated model distinguishes between two types of people, one for whom y_i is always zero, and the other for whom y_i is positive but can sometimes be zero. Essentially, the excess of zeros can come from two sources, and the zero-inflated model tries to model the inflation of the zeros. Suppose the count density is $f_2(y)$. We can add a separate component that inflates the probability of a zero by π. Then

$$Pr[y=j] = \begin{cases} \pi + (1-\pi)f_2(0) & \text{if} \quad j=0, \\ (1-\pi)f_2(j) & \text{if} \quad j>0. \end{cases}$$

We can define a binary variable as follows

$$d_i = \begin{cases} 1 & \text{if} \quad y_i > 0, \\ 0 & \text{if} \quad y_i = 0 \end{cases}$$

where $d_i = 0$ with probability π_i and $d_i = 1$ with probability $(1 - \pi_i)$. The density of an observation is given by

$$f(y) = [\pi + (1 - \pi) f_2(0)]^{1-d} \times [(1 - \pi) f_2(j)]^d. \tag{12}$$

We can let $\pi = \pi(x, \theta_1)$ by introducing regressors. Let the base density be $f_2(y|x, \theta_2)$. Then we can use maximum likelihood method to estimate the following log-likelihood function

$$\begin{aligned} lnL(\theta_1, \theta_2) = \sum_{i=1}^{n} (1 - d_i) ln[\pi(x_i, \theta_1) + (1 - \pi(x_i, \theta_1))\ f_2(0|x_i, \theta_2)] \\ + \sum_{i=1}^{n} d_i ln[(1 - \pi(x_i, \theta_1))\ f_2(y_i|x_i, \theta_2)]^d. \end{aligned} \tag{13}$$

We can estimate $\pi(x, \theta_1)$ using the logit as $\pi(x, \theta_1) = exp(x_i'\beta_1)/[1 + exp(x_i'\beta_1)]$. If $f_2(y|x, \theta_2)$ uses a Poisson density, then the model is called zero-inflated Poisson (ZIP), and if it uses a NB2 density, then the model is called zero-inflated negative binomial (ZINB).

A statistic proposed in Vuong (1989) is often used to compare non-nested models. We can use this statistic to choose between Poisson model and ZIP model, since neither model is nested in the other. We can also use it choose between NB2 model and ZINB model. Let $f_j(y_i|x_i)$ denote the predicted probability that the random variable Y equals y_i, under the assumption that the distribution is $f_j(y_i|x_i)$ for $j = 1, 2$. Let

$$m_i = ln\left(\frac{f_1(y_i|x_i)}{f_2(y_i|x_i)}\right).$$

Vuong's statistic tests the non-nested hypothesis of model 1 versus model 2. To test the hypothesis that $E[m_i] = 0$, the statistic is given by

$$\nu = \frac{\sqrt{n}[\frac{1}{n}\sum_{i=1}^{n} m_i]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - \bar{m})^2}} = \frac{\sqrt{n}\bar{m}}{s_m} \tag{14}$$

where ν has a limiting standard normal distribution. We can use the likelihood ration (LR) test to compare the ZIP and ZINB models since the former is nested in the latter.

The zero-inflated model can be considered as a special case of the FMM with two components. The mixture weights for the two components are π and 1 - π. One component is a degenerate probability mass function $f_1(y)$ with $f_1(j) = 1$ if $j = 0$ and $f_1(j) = 0$ if $j > 0$. The other component is the untruncated probability mass function $f_2(y)$ (Cameron & Trivedi, 2013).

Possible aversion generation mechanism

To test if ego-depletion generates an aversion to acknowledging ignorance, we test if acknowledging ignorance early in the survey causes people to be less likely to acknowledge their ignorance later in the survey. If a person acknowledges his ignorance early in the survey, then doing so may require self-control and may lead to an ego-depletion. An ego-depletion might make him less willing to acknowledge his ignorance later in the survey because he has depleted the resources required to refrain from expressing an opinion. If we find that acknowledging ignorance early in the survey causes people to be less likely to acknowledge their ignorance later in the survey, then this indicates that ego-depletion increases aversion to acknowledging ignorance. However, it could also be the case that respondents who acknowledge their ignorance in the start, are less likely to acknowledge their ignorance later in the survey because they have more of an incentive to appear informed. Future research can distinguish which of the two explanations is more likely.

To test if acknowledging ignorance early in the survey causes a reduction in the likelihood of acknowledging ignorance later in the survey, we divide the analysis into two cases. In the first case, we define a dummy variable that takes the value of 1 if a person stated a DK response in the first question, and 0 otherwise. The dependent variable is the number of DKs in questions 2 through 14. In the second case, the dummy takes the value of 1 if a respondent stated a DK in the first 2 questions, and 0 otherwise. The dependent variable is the number of DKs in questions 3 through 14. We estimate the Poisson regression, NB1 regression, and the NB2 regression for the two cases. We choose between the models based on the criteria defined in the first question. The effect of the dummy variable represents a correlation rather than a causation as the choice of a DK response early in the survey is not random. A person who stated a DK response early in the survey has the underlying characteristics that make him more likely to state a DK response later in the survey than someone who did not report a DK early in the survey. We could account for this self-selection using a control-function estimator, which assumes that after controlling for observed variables, the choice of DK is as good as random. However, there might be some unobservables that affect the choice of DK responses. To account for this self-selection problem, we estimate the Poisson regression with endogenous treatment effects as proposed by Terza (1998). Using this model, we can estimate the average treatment effect (ATE), or the causal effect of stating a DK early in the survey on the count of DKs later in the survey.

We let x_i be the set of covariates used to model the count outcome y_i, where y_i is the count of DKs later in the survey. Let w_i be the set of covariates used to model the choice of a DK response early in the survey. In the analysis, we choose the same set of variables for x_i and w_i as variables that effect the choice of DK early in the survey are possibly the same as those that affect the count of DKs later in the survey. We discuss the control variables in the next subsection. We can define $z_i = (x_i, w_i)$ as the set of exogenous variables in the model. Given that the control variables should be exogenous, we estimate specifications that use a slightly different set of control variables to check if the ATE is similar across specifications.

The outcome y_i has the following conditional expectation function

$$E(y_i|x_i, t_i, \epsilon_i) = exp(x_i\beta + \delta t_i + \epsilon_i) \tag{15}$$

where ϵ_i is an error term. The probability density function for y_i, conditional on the covariates, is given by

$$f(y_i|z_i, t_i, \epsilon_i) = \frac{exp\{-exp(x_i\beta + \delta t_i + \epsilon_i)\}\{exp(x_i\beta + \delta t_i + \epsilon_i)\}^{y_i}}{y_i!}. \tag{16}$$

The choice of DK early in the survey (treatment) t_i can be modeled as

$$t_i = \begin{cases} 1, & \text{if } w_i\gamma + \mu_i > 0 \\ 0, & otherwise \end{cases}$$

where the error terms ϵ_i, μ_j are bivariate normal with mean zero. For simplicity, we omit details of the derivation of the conditional distribution function. The log-likelihood function is given by

$$lnL = \sum_{i=1}^{n} ln\{f(y_i, t_i|z_i)\}. \tag{17}$$

This procedure is computationally expensive since it involves numerical approximation using the Gauss-Hermite quadrature.

If the ATE of t_i is negative and significant, then it implies that a choice of DK early in the survey causes a person to state fewer DKs later in the survey. Although we present the results for only two cases, we estimate regressions for eight cases. In the eighth case, we look at the effect of a DK response in the first eight questions on the count of DKs in the last 6 questions. We plot the results of the eight specifications and draw inferences from it.

4.2 Explanatory variables

The literature suggests that people with different demographics characteristics may differ in the extent to which they use the DK option. In addition, there are other factors that may determine the use of DKs.

Higher DK responses are found for respondents with lower education (Bishop, Oldendick, Tuchfarber, & Bennett, 1980; Schuman & Presser, 1980). In this regard, we include dummy variables to indicate a respondent's highest level of education. We define a dummy variable to indicate if a respondent's highest level of education is high school and one to indicate if it is college. The base category is primary school[12].

[12]The dataset defines education categories based on the guideline from CBS (Statistics Netherlands). *vmbo* (intermediate secondary education, US: junior high school) and *havo/vwo* (higher secondary education/preparatory university education, US: senior high school) were combined to form High School. *mbo* (intermediate vocational education, US: junior college), *hbo* (higher vocational education, US: college), and *wo* (university) were combined to form College.

The dataset that we use allows us to control for the labor market status of respondents. We define a dummy variable that takes the value of 1 if a respondent is retired, and 0 otherwise. Similarly, we define a dummy variable for students and for those who are inactive[13]. Finally, we define a dummy to take the value of 1 if a respondent is a homemaker or does something else, and 0 otherwise. A respondent is working if he is employed, self-employed, or works in a family business. They form the base group.

Income can play a role in people's opinion about policy (Berinsky, 2004). We take the natural log of the net-income per month and use this variable in our models[14].

Those with less interest in a topic are more likely to report a DK (Rapoport, 1982). The dataset that we use asks respondents whether they found the survey difficult, clear, thought-provoking, interesting, and enjoyable. Their responses were measured on a scale of 5: a value of 1 indicates "certainly no" and a value 5 indicates "certainly yes". These questions are presented in Appendix A.

Men are found to be less likely to use the DK option than women (Rapoport, 1982). We include a dummy variable that takes a value of 1 if the individual is male, and 0 otherwise.

As people grow older, they are less likely to use the DK option since they are more likely to be knowledgeable (Rapoport, 1985). It could also be that older people are more likely to know the extent of their ignorance (Dunning, 2011). In our models, we control for the age of respondents. We also experiment with a squared age term to check if the effect of our variable of interest is robust to a flexible functional form of age.

We define a dummy variable that takes the value of 1 if a respondent lives in a locality whose population density per kilometer-square is greater than 500, and 0 otherwise[15]. Whether a person lives in an urban area could influence his opinion on policies (Bagozzi et al., 2012).

We include a dummy variable that takes a value of 1 if the respondent filled the survey before 03:00 or after 20:00 hours, and 0 otherwise. This was done to control for the tiredness of respondents. We vary the definition of the dummy to check if the effect of the dummy is robust to the definition of the dummy variable.

Finally, we control for response time on the survey. This is the logarithm of the mean response time for individuals in the 14 questions[16].

[13] This category includes job seekers following job loss, first-time job seekers, job seekers exempted from job seeking following job loss, those who have (partial) work disability, those who perform unpaid work while retaining unemployment benefit, and those who perform voluntary work.

[14] Income above or below thrice the standard deviation from the mean were removed as outliers. If the self-reported net-income was missing in the survey, this value was imputed from gross income. The LISS panel provides imputed income data from July 2008. For more information about the calculation of imputed income see https://www.dataarchive.lissdata.nl/study_units/view/322

[15] The codebook of the dataset defines a locality with a population less than 500 as "not-urban"

[16] The dataset contains response time of each individual on each of the 14 questions. 21 observations with negative durations were removed. For each individual, if the response time on a given question exceeds 1.5 times his 75th percentile response, then we consider it as an outlier. This leads to the removal of 3187 values. We retry our analysis without removing outliers and with removing observations that exceed 2 time the 75th percentile. Both of these do not lead to large changes in the coefficient of the variable.

5 Results

We do not expect background characteristics of respondents to differ between the PN and the PY treatment groups since respondents were randomly assigned to one of two groups. We conduct a number of tests to check if background characteristics differ between the two groups. This is sometimes referred to as the test for balancedness of covariates. Results from the independent samples t-test suggest that there is no significant difference in age ($t = 0.85, p = 0.39$) or income ($t = 0.81, p = 0.41$) between the two groups. Results from a Chi-square test reveals no significant association between gender and the treatment groups ($\chi^2 = 0.28, p = 0.59$). We estimate a Chi-square test, similarly, and find that the labor market status categories ($\chi^2 = 5.41, p = 0.24$) and the education categories ($\chi^2 = 0.05, p = 0.97$) are equally distributed across the treatment groups[17]. Overall, we find that the demographics of respondents are similar across the two groups.

Existence of aversion to acknowledging ignorance

To test if people are averse to acknowledging their ignorance, we estimate a number of regressions, where the dependent variable is the number of DKs reported by each respondent. The value of the dependent variable can range from 0 to 14. Table 3 presents the frequencies of the number of DKs. We observe that 27% never choose the DK option and 0.4% choose the DK option on every question. The mean number of DKs is 2.10. Although the dependent variable is clustered towards zero, there appears to be a considerable amount of dispersion.

Table 4 presents the results from the various specifications that we estimate. Specification (1) is a linear regression model estimated using the OLS method. In this specification, we only include the treatment dummy. We also estimate Count-data models with the motivation that these might provide a better fit to the data. We start with the estimation of the Poisson regression (estimates not shown here). It is often the case that the Poisson regression is overdispersed. This means that the conditional expectation is greater than the conditional variance (see Section 4 for details). To test if this is indeed the case, we estimate an auxiliary regression after the Poisson regression and find that the Poisson regression is overdispersed. Since the Poisson regression is overdispersed, we estimate the NB1 and the NB2 regressions. The NB1 specification is preferred to the NB2 specifications since it provides a slightly better fit[18]. In Table 4, Specification (2) is the NB1 regression. The marginal effect of the treatment dummy represents the treatment effect and this is similar in magnitude, sign, and statistical significance across all specifications, including the Poisson and the NB2 specifications. Indeed, different models may produce similar coefficients regardless of their fit (Cameron & Trivedi, 2013). In Specification (2), which is the NB1 specification without other controls, the marginal effect of the treatment dummy is 0.26 and this is sig-

[17] There is no significant association between the education categories defined by CBS ($\chi^2 = 2.99, p = 0.70$) and the full set of labor market status categories ($\chi^2 = 11.81, p = 0.46$) provided in the dataset, with the treatment groups.

[18] The log-likelihood of the NB2 (-5676.387) specification is lower than the log-likelihood from the corresponding NB1 specification (-5675.373).

Table 3: Frequencies of count of DKs

DK	Count	%	Cumm %
0	799	27.3	27.3
1	667	22.8	50.1
2	518	17.7	67.7
3	321	11.0	78.7
4	244	8.3	87.0
5	143	4.9	91.9
6	93	3.2	95.1
7	61	2.1	97.2
8	30	1.0	98.2
9	12	0.4	98.6
10	18	0.6	99.2
11	7	0.2	99.5
12	3	0.1	99.6
13	2	0.1	99.6
14	11	0.4	100.0
Total	2929	100	
Mean	2.10		
SD	2.25		

nificant at the 1 % level. This suggests that, on average, a person in the PY condition states 0.26 more DKs than a person in the PN condition. In other words, prompting the use of DKs increases the use of DKs. This is consistent with the findings in the literature (e.g., Scoboria & Fisico, 2013; Mondak & Davis, 2001). As discussed in Subsection 3.3, a positive and significant treatment dummy indicates that people are averse to acknowledging their ignorance. Since people were randomly assigned to one of the two treatment groups (PY or PN), we can attribute a causal interpretation to the effect of the treatment dummy.

Since respondents are randomly assigned to one of the two treatment groups, we would not expect the inclusion of control variables to affect the magnitude of the treatment dummy. We check if this is the case. Specification (3) is a linear regression with other control variables. Specification (4) is the NB1 regression with control variables[19]. The coefficients of the treatment dummy in both specifications are similar to the coefficients from the specifications without the control variables. In specification (4), these control variables are jointly significant in the model, as evidenced by the Wald test ($\chi^2(18) = 391.03, p = 0.00$) and the likelihood ratio test ($\chi^2(18) = 930.20, p = 0.00$)[20]. We take this as an indication that none of

[19]The Poisson regression for this case is overdispersed. The log-likelihood of the NB2 (-5223.405) specification is lower than the log-likelihood from the NB1 (-5210.271) specification and so we prefer the latter model.

[20]In specification (4), our treatment variable is significant, as evidenced by the Wald test ($\chi^2(1) = 11.46, p = 0.00$) and the likelihood ratio test ($\chi^2(1) = 11.55, p = 0.00$).

the control variables mediate the relationship between the treatment and the count of DKs although they are good predictors of the count of DKs.

A difference in the DK responses between the PY and PN treatment groups could also arise because respondents who want to finish the survey early use the DK option more often when prompted to do so. However, we think that survey satisficing is less of a problem in the survey for several reasons. First, since the survey contains only 14 questions, people spend less time on the survey and are thus less likely to want to finish the survey early. Second, about 27% of the respondents in our sample never use the DK option and less than 5% of the sample chooses the DK option more than 6 times out of the 14 questions. The low number of DKs is some indication that respondents do not use the DK option as a way to finish the survey early. Third, from the descriptive statistics reported in Section 3, we observe that on average, respondents found the survey to be clear, not difficult, thought provoking, interesting, and enjoyable. This indicates that people are more likely to take the survey seriously. Fourth, in Specification (4), we observe that a 1% increase in a respondent's response time leads, on average, to 0.22 more DKs and this is significant at the 1 % level. This indicates that response time is a measure of survey difficulty rather than a measure of survey-satisficing. Fifth, in Specification (4), we find that the dummy indicating if people filled the survey late at night is not significant[21]. This is another indication that people do not choose the DK option (when tired) as a means to finish the survey early.

Aversion among classes of the population

With the motivation to allow for population heterogeneity, we test if aversion to acknowledging ignorance exists among different classes of people who differ in the degree to which they can acknowledge their ignorance. We estimate finite mixture models (FMM) to test this. Table 5 presents several information criteria of the various models we estimate. We estimate FMMs that differ in the underlying distribution and in the number of components. We estimate three 3-component FMMs mixing with Poisson, NB1, and NB2 distributions. We refer to these models as FMMP(3), FMMNB1(3), and FMMNB2(3), where the numbers in parenthesis represent the number of components in the model. Similarly, we fit three 2-component FMMs. We also present the information criteria of the Poisson, NB1, and NB2 regressions (unicomponent models).

If we use the BIC to compare models with the same number of components, we find that NB1 is the best unicomponent model, FMMNB1(2) is the best 2-component model, and FMMNB1(3) is the best 3-component model. If we use the BIC to compare between these three models with different components, then NB1 is the best model. If we use the likelihood ratio (LR) test to compare between these three models with different components, FMMNB1(3) is the best model[22]. The LR test in this setting is likely to choose a model

[21]We vary the definition of this variable by checking if people are more likely to state a DK after 19:00, 21:00 or 22:00, but find no significant effect for any of these.

[22]LR test rejects the FMMNB1(2) in favor of FMMNB1(3) ($\chi^2(22) = 51.96, p = 0.0003$) and rejects the NB1 specification in favor of the FMMNB1(2) ($\chi^2(22) = 98.94, p = 0.00$); The use of the likelihood ratio test in this non-standard setting means that we have used conservative critical values.

Table 4: Marginal effects explaining the count of DKs using linear regression and negative binomial-1 (NB1) regression

	(1)		(2)		(3)		(4)	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Treatment								
Treatment	0.261***	0.083	0.267***	0.080	0.262***	0.080	0.256***	0.074
Survey perception								
Difficult					0.223***	0.042	0.189***	0.031
Enjoy					0.124	0.076	0.104*	0.060
Clear					−0.062	0.050	−0.060	0.040
Think					0.012	0.037	0.003	0.037
Interest					−0.431***	0.075	−0.369***	0.061
Survey behavior								
Response time					−0.021	0.142	0.227**	0.108
Survey time					0.174	0.106	0.137	0.096
Education								
High school					−0.447***	0.165	−0.380***	0.131
College					−0.975***	0.171	−0.877***	0.111
Labor market status								
Retired					0.173	0.145	0.199	0.148
Inactive					0.056	0.150	0.064	0.139
Student					−0.496*	0.267	−0.363**	0.161
Other					0.131	0.187	0.147	0.159
Demographics								
Male					−0.602***	0.088	−0.641***	0.064
Age					−0.049**	0.019	−0.045***	0.015
Age squared					0.000**	0.000	0.000**	0.000
Log income					−0.034	0.027	−0.012	0.020
Urban					0.009	0.113	−0.000	0.095
Intercept	1.973***	0.058			5.325***	0.709		
Observations	2929		2790		2929		2790	
α					0.80***		0.71***	

Note. (1) and (3) are linear regressions, (2) and (4) are NB1 regressions. Coef refers to coefficients for OLS and marginal effects for NB1 regression. Std.Err refers to robust standard errors. α is the overdispersion parameter.
*p<0.1. **p<0.05. ***p<0.01.

with a lower number of components. Despite this limitation, we observe that it favors the model with a higher number of components (3 components).

We estimate FMMNB1(3) with different starting values for the maximum likelihood iterative algorithm. We find that systematically shifting starting values of the default algorithm

Table 5: Information criteria for Count-data models

Model	LL	DF	AIC	BIC
Poisson	−5656.048	20	11352.100	11470.770
NB1	−5210.271	21	10462.540	10587.150
NB2	−5223.405	21	10488.810	10613.420
FMMP(2)	−5213.812	41	10509.624	10752.910
FMMNB1(2)	−5160.799	43	10407.598	10662.751
FMMNB2(2)	−5166.929	43	10419.859	10675.012
FMMP(3)	−5152.267	62	10428.534	10796.429
FMMNB1(3)	−5140.315	65	10410.629	10796.326
FMMNB2(3)	−5143.060	65	10416.121	10801.818
ZINB	−5194.589	41	10471.180	10714.460

Note. LL denotes fitted log-likelihood. DF denotes degrees of freedom. AIC denotes Akaike Information Criterion. BIC denotes Bayesian Information Criteria. Numbers in parentheses represent the number of components in the model.

by a proportion (0.1, 0.2, and 0.3) leads to very different parameter estimates. This indicates that there are different local optimums. Given the difficulty in identifying the global optimum, we do not present the results of this model. The coefficient of the treatment dummy in the FMMNB1(2) is similar across different starting values.

The marginal effects of FMMNB1(2) are presented in Table 6. The first component constitutes 87% of the population. The confidence interval for the proportion of people in this component is (81-91%). The second component constitutes 13% of the population but could vary to constitute 9-19% of the population. The mean predictions of the two components are 2 and 2.39 respectively, which are not too far apart. This could be because the DK responses of individuals are clustered near zero. While the model requires the mean of DKs to be different in the two components, this difference need not be interpreted. In our case, it is not meaningful to distinguish between a “High” and “Low” DK class. We instead distinguish between the two classes based on their demographics and behavior in the survey (discussed below). The standard deviations of the predictions of the two components are 0.82 and 2.39. Given the high variance of predictions in component 2, we can infer that people in this class vary in the degree to which they state DKs but share some common characteristics.

We find that the treatment dummy is significant in the first component with a marginal effect of 0.2. This indicates that respondents classified in the first component are averse to acknowledging their ignorance. The marginal effect is similar to the marginal effect of the unicomponent NB1 (0.27). The marginal effects of the control variables in this component are roughly similar to those of specification (4) in Table 4. We find that the treatment dummy is not significant in component 2. The insignificant marginal effect of the treatment in this component could mean that this class of people is not averse to acknowledging their ignorance or that the treatment was ineffective in identifying the existence of aversion to acknowledging ignorance.

The FMM can be used to classify a respondent as belonging to component 1 or component 2. We can test if respondent characteristics differ between the two classes. We find that there is no significant difference in age, urban character of a respondent's house, response time or in gender across the two classes. However, we find a higher proportion of respondents who went to college in component 1 (0.57) than in component 2 (0.37), and the difference in proportions is significant at the 5% level ($z = 2.25$). Respondents in component 2 found the survey significantly more difficult ($t = -3.82$) and significantly less clear ($t = 3.36$) than respondents in component 1. The marginal effect of response time in the two components is also informative. In component 2, response time has a significant negative coefficient, while it has a positive coefficient in component 1. In component 2, the more time people take to answer the questions, the less likely they are to state a DK. The above results suggest that respondents in component 2 are less likely to be averse to acknowledging their ignorance than respondents in component 1. A person who can acknowledge that the survey was difficult is possibly more likely to acknowledge his ignorance in the survey. These respondents have lower education and in that regard, it is possible that these people are not under pressure to appear informed. Furthermore, respondents who state fewer DKs when they take more time on a survey are likely to know quickly when they do not know something.

Thus, with the motivation of allowing for population heterogeneity, we distinguished between classes of people. We found evidence for two classes of people and found that a class of people constituting 13% of the population, that could vary to constitute 9-19% of the population, is less likely to be averse to acknowledging their ignorance.

Aversion and ability to acknowledge ignorance

With the motivation to allow for population heterogeneity, we distinguish between two classes of people that differ in their ability to acknowledge their ignorance. We refer to these two classes as the Unable-DK class and the Able-DK class. The Unable-DK class consists of people who are more likely to never use the DK option while the Able-DK class consists of people who are more likely to use the DK option one or more times. We check if respondents in the Able-DK class are averse to acknowledging their ignorance. The methodology that we use does not allow us to check if respondents in the Unable-DK class are averse to acknowledging their ignorance since the model constructs this class of people to have zero DKs and thus respondents in this class cannot reduce the number DK responses they would report if they were prompted to use the DK option.

We estimate the zero-inflated Poisson (ZIP) and the zero-inflated negative binomial (ZINB) model to account for these two classes. The Vuong test for non-nested models rejects the Poisson model in favor of the ZIP model. It also rejects the NB2 model in favor of ZINB model. The LR test rejects the ZIP model in favor of the ZINB model. In this case, there is a clear indication that ZINB is the suitable model and so we only present results for this model.

Table 7 presents the marginal effects for the ZINB model. Each specification has two

Table 6: Marginal Effects explaining the count of DKs using finite mixture model (FMM)

	FMMNB1(2)			
	Component-1		Component-2	
	Coef.	Std.Err.	Coef.	Std.Err.
Treatment				
Treatment	0.207**	0.086	0.439	0.287
Survey perception				
Difficult	0.153***	0.036	0.393***	0.081
Enjoy	0.150**	0.069	−0.536**	0.262
Clear	−0.062	0.049	0.015	0.282
Think	−0.003	0.049	0.090	0.351
Interest	−0.398***	0.075	0.014	0.509
Survey behavior				
Response time	0.732***	0.133	−3.123***	0.501
Survey time	0.167	0.118	−0.071	0.387
Education				
High school	−0.373**	0.149	0.325	0.700
College	−0.928***	0.165	0.296	0.931
Labor market status				
Retired	0.489***	0.171	−3.060*	1.795
Inactive	0.124	0.181	0.075	0.716
Student	−0.256	0.234	−0.636	0.692
Other	0.281	0.204	−0.925	1.320
Demographics				
Male	−0.735***	0.096	−0.176	0.318
Age	−0.057***	0.017	0.183	0.114
Age squared	0.000**	0.000	−0.002	0.001
Log income	0.028	0.025	−0.399***	0.119
Urban	−0.103	0.114	1.151**	0.502
Observations	2790			
Proportion	0.87		0.13	
Predictions	2.00	0.82	2.39	2.54

Note. FMMNB1(2) is the two component FMM mixing with two NB1 distributions. Coef refers to marginal effects and Std.Err refers to robust standard errors. Proportion denotes the proportion of people in each component. Prediction denotes the mean predicted DKs for each component.
*p<0.1. **p<0.05. ***p<0.01.

stages. The first stage is "Inflate". The marginal effects in this stage are analogous to the marginal effects of a logit model where the dependent variable takes the value of 1 if a person said 0 DKs, and 0 otherwise[23]. The Count stage is the NB2 regression that augments the results from the inflation stage. For the Inflation stage, the treatment dummy is not significant at the 10% level. This indicates that prompting people to use the DK option has no effect on the likelihood of a person being classified into the Unable-DK class. Most variables in the inflation stage are insignificant, which indicates that unobservables play a larger role in determining class membership of respondents. For the Count stage, the marginal effect of the treatment dummy is 0.25, and this is significant at the 1% level. This is an indication that respondents in the Able-DK class are averse to acknowledging their ignorance.

As discussed above, the likelihood ratio test rejects the NB2 in favor of the ZINB. Rejection of the null hypothesis in favor of the alternative does not mean that the alternative is correct. From Table 5, we observe that the ZINB provides only a slight improvement over NB1 or NB2 in terms of the fitted log-likelihood. When comparing ZINB to FMMNB(2), we find that FMMNB1(2) may be a better model since it has a lower BIC. It is possible that although those with zero DKs are a distinct class, those with positive DKs could be classified into two or more classes.

To account for population heterogeneity, we distinguish between classes of people on the basis of their ability to acknowledge ignorance. We find that the class that is able to acknowledge their ignorance (Able-DK classes) is found to be averse to acknowledging their ignorance.

Possible aversion generation mechanism

In the previous three questions, we were concerned with the existence of aversion to acknowledging ignorance. We now check if ego-depletion is a factor that may generate an aversion to acknowledging ignorance. We do this by checking if a DK response early in the survey predicts the number of DK responses later in the survey. We divide the analysis into two cases. In the first case, our variable of interest is a dummy variable that takes a value of 1 if a person states a DK on the first question, and 0 otherwise. The dependent variable is the number of DK responses in the last 13 questions. In the second case, we look at the effect of a DK response on the first 2 questions on the number of DK responses in the next 12 questions.

We start by estimating a Poisson regression for the two cases (not presented). An auxiliary regression after the Poisson regression suggests that the Poisson regression is overdispersed. Thus, we estimate NB1 and NB2 regressions for the two cases. We choose the NB1 regression over the NB2 regression for the two cases because it provides a better fit, as evidenced by a higher log-likelihood value. Table 8 presents the marginal effects of the NB1 regressions. From Specification (1), we observe that if a person stated a DK on the first question, then he will state, on average, 2.02 more DKs in the next 13 questions. From

[23] The standard errors are computed differently

Table 7: Marginal Effects explaining the count of DKs using zero-inflated negative binomial (ZINB) model

	Count		Inflate	
	Coef.	Std.Err.	Coef.	Std.Err.
Treatment				
Treatment	0.254***	0.080	−0.019	0.022
Survey perception				
Difficult	0.212***	0.040	−0.026*	0.015
Enjoy	0.095	0.065	0.020	0.017
Clear	−0.067	0.050	0.026	0.021
Think	0.045	0.042	0.010	0.012
Interest	−0.420***	0.066	−0.017	0.024
Survey behavior				
Response time	0.098	0.123	−0.139***	0.028
Survey time	0.171	0.104	0.005	0.037
Education				
High school	−0.380***	0.143	0.008	0.070
College	−0.956***	0.154	0.066	0.060
Labor market status				
Retired	0.233	0.156	−0.021	0.051
Inactive	0.055	0.154	−0.043	0.058
Student	−0.465*	0.247	−0.047	0.096
Other	0.202	0.184	−0.103	0.077
Demographics				
Male	−0.639***	0.092	0.044	0.048
Age	−0.046***	0.017	0.003	0.006
Age squared	0.000**	0.000	0.000	0.000
Log income	−0.026	0.023	−0.015*	0.009
Urban	−0.008	0.118	0.041	0.063
Observations	2790			
ZIP vs Poisson	9.32***			
ZINB vs NB2	3.79***			
ZIP vs ZINB	370.58***			

Note. Inflate denotes the inflation stage and Count denotes the stage where the dependent variable is the count of DKs. Coef refers to marginal effects and Std.Err refers to robust standard errors. ZIP vs Poisson is the Vuong statistic, where ZIP is the zero-inflated Poisson regression. ZINB vs NB2 is the Vuong statistic. ZIP vs ZINB is the likelihood ratio statistic.

*p<0.1. **p<0.05. ***p<0.01.

Specification (2), we observe that if a person stated a DK on the first 2 questions, he will state 1.82 more DKs in next 12 questions. The finding that a DK early in the survey predicts DKs later in the survey is consistent with the findings of Young (2012). However, we should be cautious in interpreting these results. These results suggest only a correlation rather than a causation. The underlying mechanism/characteristics that make a person state a DK early in the survey are the same as those that make him state a DK later in the survey. To control for this self-selection, we estimate a Poisson regression with endogenous treatment effects, that is proposed by Terza (1998), which is often referred to as the ET-Poisson regression.

We estimate two ET-Poisson regressions for the two cases mentioned above. We can use this model to estimate the average treatment effect (ATE) of the choice of stating a DK early in the survey. Parameter estimates of the two ET-Poisson regressions can be found in Table 9[24]. The control variables are the same as those used in the previous questions[25]. Numbers in brackets are the ATEs and the corresponding standard errors. Columns labeled "First" are the first stage equations that model the choice of a DK response early in the survey. Columns titled "Outcome" are the outcome stage, that model the count of DKs later in the survey while accounting for the first stage results. The ATE in Specification (1) indicates that if a person stated a DK on the first question, then he will state, on average, 1.29 fewer DKs on the next 13 questions. The ATE in Specification (2) indicates that if a person states a DK on the first 2 questions, then he would state, on average, 1.27 fewer DKs in the next 12 questions. The sign of the dummy in these two specifications are negative while they were positive in the NB1 specification in Table 8. Thus, after controlling for the self-selection, stating a DK early in the survey leads people to state fewer DKs later in the survey. This is inconsistent with the finding of Young (2012) who does not account for the self-selection.

The effect of stating a DK on the count of DKs in the remainder of the survey is negative only if a DK response was stated early in the survey. To check this, we plot the coefficients from eight NB1 and ET-Poisson regressions in Figure 1. In the figure, the x-axis indicates values used to define the dummy. For example, the value of 2 on the x-axis corresponds to the dummy defined as taking a value of 1 if there was a DK on the first 2 questions, and 0 otherwise. The y-axis corresponds to the magnitude of the ATE or of the marginal effect of the treatment dummy. From the line representing the ATE of ET-Poisson specifications, we observe that the ATE becomes positive when the dummy is defined for the first 5 questions. A DK stated on the first 5 questions, a DK stated on the first 6 questions, and so on until a DK stated on the first 8 questions, makes people more likely to state a DK in the remainder of the survey. This suggests that it is a DK early in the survey that generates an aversion to acknowledging ignorance rather than a DK in the middle of the survey.

[24] Age and the squared age term were problematic for convergence of the maximum likelihood estimation. We divided age and the squared age term by 100 and 10000, respectively to rescale it. The ATE does not change if we use only age or if we scale age by subtracting it from its mean and then dividing by its standard deviation.

[25] Given that the explanatory variables should be exogenous, we estimate a specification (not presented) for each of the two cases where we exclude response time on the survey and the measures of survey perception. The ATE for two cases is similar to the corresponding ATE for the two cases without excluding these variables.

Table 8: Marginal effect explaining DKs later in the survey using negative binomial-1 (NB1) regression

	(1)		(2)	
	Coef.	Std.Err.	Coef.	Std.Err.
DK early in the survey	2.022***	0.197	1.827***	0.139
Treatment	0.194***	0.067	0.147**	0.062
Survey perception				
Difficult	0.177***	0.028	0.152***	0.026
Enjoy	0.083*	0.050	0.075	0.049
Clear	−0.053	0.036	−0.067**	0.034
Think	0.017	0.033	0.012	0.031
Interest	−0.312***	0.053	−0.275***	0.052
Survey behavior				
Response time	0.180*	0.099	0.148*	0.088
Survey time	0.125	0.087	0.126	0.084
Education				
High school	−0.356***	0.117	−0.240**	0.111
College	−0.756***	0.104	−0.657***	0.097
Labor market status				
Retired	0.214	0.139	0.105	0.124
Inactive	0.126	0.133	0.082	0.122
Student	−0.242	0.149	−0.331**	0.134
Other	0.091	0.137	0.022	0.123
Demographics				
Male	−0.574***	0.059	−0.538***	0.056
Age	−0.032**	0.013	−0.027**	0.012
Age squared	0.000	0.000	0.000	0.000
Log income	−0.004	0.017	−0.009	0.016
Urban	−0.011	0.087	−0.007	0.082
Observations	2790		2790	
α	0.35***		0.30***	

Note. Coef refers to marginal effects and Std.Err refers to robust standard errors. In (1), the dependent variable is the count of DKs in the last 13 questions, while in (2), the dependent variable is the count of DKs in the last 12 questions.
*p<0.1. **p<0.05. ***p<0.01.

Thus, we find some evidence that acknowledging ignorance early in the survey possibly leads to an ego-depletion and consequently makes people averse to acknowledging their ignorance later in the survey. This gives us some indication that ego-depletion generates an aversion to acknowledging ignorance. Our findings are consistent with research that suggests that people are more likely to follow the status-quo option (expressing an opinion) when they have a depleted ego (e.g., Morrison & Hatfield-Dodds, 2011; Pocheptsova et al., 2009; Mead et al., 2009).

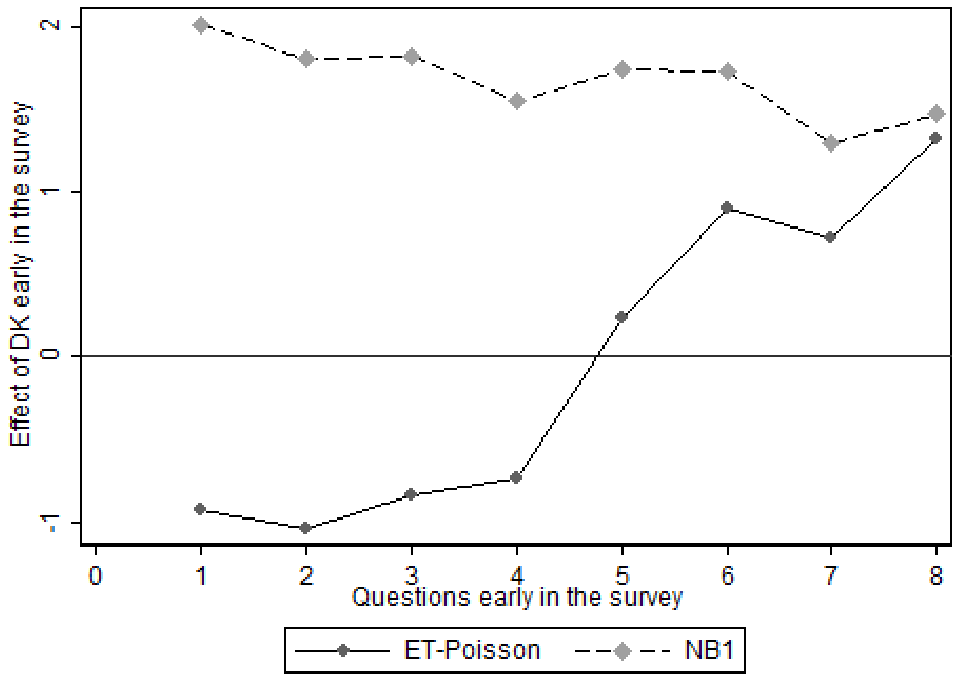

Figure 1: Effect of DK early in the survey. ET-Poisson refers to endogenous treatment effects Poisson regression and NB1 refers to negative binomial-1 regression. Values of the x-axis represent the number of questions early in the survey. Values of the y-axis represent the magnitude of the Average Treatment Effect (ATE) or magnitude of marginal effect of the treatment dummy that takes the value of 1 if there was a DK response early in the survey.

Consequences for respondent behavior in opinion polls

The questions answered above looked at the existence of aversion to acknowledging ignorance and one factor that may generate an aversion to acknowledging ignorance. Given our finding that people are averse to acknowledging their ignorance, it is important to understand the consequences of this. First, respondents who are averse to acknowledging their ignorance may be more likely to use the middle option (neither/nor) than the DK option (Sturgis et al., 2014; Bagozzi et al., 2012). Second, respondents who are averse to acknowledging their ignorance may be more likely to support or oppose an issue than use the DK option. We test this here.

Kleinberg and Fordham (2017) analyzed the proportion of support and opposition for policies among two treatment groups. One group was provided with the DK option while the other group was not provided with the DK option. They find that the proportion of support

Table 9: Parameter estimates of DK early in the survey using endogenous treatment effects Poisson regression (ET-Poisson)

	(1)				(2)			
	Outcome		First		Outcome		First	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Treatments								
DK early	−0.766***	0.065			−0.715***	0.061		
	[−1.290]	[.090]			[−1.278]	[.104]		
Treatment	0.104***	0.036	0.036***	0.000	0.218***	0.036	0.302***	0.000
Survey perception								
Difficult	0.092***	0.016	0.016***	0.000	0.130***	0.015	0.102***	0.000
Enjoy	0.046	0.029	0.013***	0.000	0.059**	0.030	0.017***	0.000
Think	0.005	0.019	−0.030***	0.000	0.027	0.018	0.019***	0.000
Clear	−0.027	0.021	0.012***	0.000	−0.037*	0.020	0.005***	0.000
Interest	−0.211***	0.030	−0.136***	0.000	−0.248***	0.031	−0.175***	0.000
Survey behavior								
Survey time	0.026	0.046	−0.180***	0.000	0.122**	0.047	0.073***	0.000
Response time	0.205***	0.051	0.343***	0.000	0.083*	0.049	0.020***	0.000
Education								
High school	−0.198***	0.056	−0.068***	0.000	−0.252***	0.058	−0.208***	0.000
College	−0.507***	0.063	−0.350***	0.000	−0.580***	0.063	−0.409***	0.000
Labor market status								
Student	−0.303***	0.099	−0.410***	0.000	−0.341***	0.096	−0.309***	0.000
Retired	0.205***	0.070	0.228***	0.000	0.131*	0.070	0.214***	0.000
Inactive	0.048	0.066	−0.063***	0.000	0.190***	0.066	0.323***	0.000
Other	0.120	0.074	0.173***	0.000	0.178**	0.072	0.417***	0.000
Demographics								
Male	−0.384***	0.040	−0.328***	0.000	−0.402***	0.040	−0.292***	0.000
Age	−2.254***	0.731	−1.927***	0.001	−4.083***	0.720	−6.452***	0.001
Age squared	1.017	0.739	0.237***	0.001	3.118***	0.724	5.386***	
Log income	−0.008	0.010	0.004***	0.000	−0.011	0.010	0.006***	0.000
Urban	−0.021	0.050	−0.024***	0.000	−0.001	0.049	−0.009***	0.000
Intercept	1.774***	0.258	−0.655***	0.000	2.360***	0.248	0.803***	0.000
Observations	2790				2790			

Note. First and Outcome denote the first stage and outcome stage equations respectively. Coef refers to parameter estimates and Std.Err refers to robust standard errors. Numbers in brackets are average treatment effects (ATE) with their corresponding standard errors. In (1) and (2), the dependent variable is the count of DKs on the last 13 and last 12 questions respectively. Age and the squared age terms in this model are obtained by dividing age and the square of age by 100 and 10000 respectively.
*p<0.1. **p<0.05. ***p<0.01.

and opposition varies significantly between the two groups. We follow a similar methodology to test if the proportion of support or opposition for issues with policy implications varies between the two groups PY and PN. The PY group was prompted to use the DK option and indeed used the DK option more often than the PN group. In this regard, the PY group is less averse to acknowledging their ignorance.

Table 10 presents the proportion of people supporting an issue, opposing an issue, using the DK option, or using the middle option[26]. In most questions, the proportion of people supporting an issue is lower in the PY group as compared to the PN group. In the sixth question, for example, 30% of the respondents support the policy in the PN group while 26% of the respondents support the policy in the PY group. The difference in the proportions is significant at the 5% level. Similarly, we find that for most questions, the proportion of people opposing an issue is lower in the PY group as compared to the PN group. Our results are consistent with that of Kleinberg and Fordham (2017), in that, when people are allowed to acknowledge their ignorance or prompted to acknowledge their ignorance, they are less likely to support or oppose a policy. We find that the difference between the proportion of support or opposition between the two groups is not statistically significant in most cases. One reason for this could be that the degree of aversion to acknowledging ignorance in the PY group, although lower than in the PN group, is still similar to that in the PN group. In other situations, groups with higher levels of aversion to acknowledging ignorance would be much more likely to support or oppose a policy, in contrast to acknowledging their ignorance.

Policymakers are often interested in knowing the proportion of people that support or oppose a policy. However, if the proportion of support or opposition for a policy is sensitive to the degree of aversion to acknowledging ignorance among people, then policymakers should be cautious in interpreting the proportion of support for or opposition to a policy.

[26]For questions with a seven-point response scale, support was defined as a response of 5,6, or 7. However, defining support as a choice on the response scale below the middle option makes no difference to the interpretation of the proportions.

Table 10: Proportion choosing different responses

Question	Group	Response type			
		DK	Support	Oppose	Middle
Question 1	PN	0.05*	0.67	0.06*	0.18
	PY	0.07	0.65	0.08	0.20
Question 2	PN	0.06	0.59	0.35	
	PY	0.07	0.59	0.34	
Question 3	PN	0.11*	0.44	0.45	
	PY	0.13	0.43	0.43	
Question 4	PN	0.04	0.84	0.07	0.05
	PY	0.03	0.83	0.08	0.06
Question 5	PN	0.11	0.68	0.21	
	PY	0.12	0.67	0.20	
Question 6	PN	0.17	0.30*	0.53	
	PY	0.18	0.26	0.56	
Question 7	PN	0.02	0.70	0.12	0.16
	PY	0.02	0.69	0.11	0.18
Question 8	PN	0.12*	0.43	0.44*	
	PY	0.16	0.44	0.41	
Question 9	PN	0.13	0.29	0.58	
	PY	0.14	0.28	0.58	
Question 10	PN	0.10	0.51	0.20	0.19
	PY	0.12	0.52	0.19	0.18
Question 11	PN	0.11	0.18	0.71	
	PY	0.13	0.18	0.69	
Question 12	PN	0.35*	0.35	0.30	
	PY	0.38	0.34	0.28	
Question 13	PN	0.29*	0.30*	0.30*	
	PY	0.35	0.27	0.27	
Question 14	PN	0.29*	0.47	0.24*	
	PY	0.33	0.47	0.20	

Note. For questions with a seven-point response scale, support was defined as a choice from 5 through 7 and oppose was defined as a choice from 1 through 3.
* indicates that the proportions in the PN treatment group is significantly different from the proportion in the PY treatment group at the 5% level based on a one sided test.

6 Conclusion

We began this study with the motivation to understand why people often express an opinion about a policy without fully knowing how the policy works. There is a vast literature that suggests that people do so because they are unaware of their ignorance about the policy. A relatively unexplored reason is that people do so because they are aware of their ignorance about a policy but are averse to acknowledging their ignorance. Given that the research on aversion to acknowledging ignorance is relatively scarce, we tried to identify if people are indeed averse to acknowledging their ignorance. We also tested if ego-depletion generates an aversion to acknowledging ignorance. We used an opinion poll administered to a representative Dutch sample in which respondents were randomly assigned to one of two treatment groups. In one group, respondents were prompted to use the "don't know" (DK) option, while in the other group, respondents were not prompted. A difference in the DK responses across the two groups is indicative of the existence of aversion.

In the first question, we tested if people are averse to acknowledging their ignorance. We find that irrespective of the model that we use, people are found to be averse to acknowledging their ignorance. Questions 2 and 3 can be seen as an extended analysis of questions 1. In question 2, we used the finite mixture model (FMM) to test if aversion exists among the different sub-classes of people. We find evidence that there may be two classes of people who differ in their underlying characteristics and in their degree of aversion to acknowledging ignorance. Furthermore, we identified a class of people constituting 13% of the population that is less averse to acknowledging their ignorance than the class constituting 87% of the population. In the third question, we estimated the zero-inflated negative binomial (ZINB) model to test if aversion exists among a class of people who is able to acknowledge their ignorance. We find that this class is indeed averse to acknowledging their ignorance. Having identified the existence of aversion, in Question 4 we tested if ego-depletion is a factor that generates aversion. We find that acknowledging ignorance early in the survey causes people to state fewer DKs later in the survey. This is some indication that ego-depletion plays a role in generating an aversion to acknowledging ignorance.

Our results have implications for the survey design literature. First, we think that the DK option should be included in surveys. While the inclusion of a DK option may induce satisficing to some extent, this is less likely to hold for questions that invite people to think and for shorter surveys. Moreover, since our results suggest the existence of an aversion to acknowledging ignorance, the inclusion of a DK option would not lead to survey satisficing to a large extent. The exclusion of a DK option, however, would lead to an incorrect interpretation of opinions (Kleinberg & Fordham, 2017; Mondak & Davis, 2001). If researchers include the DK option, they can use several methods to account for the DKs in the data (e.g., Manisera & Zuccolotto, 2014; Liao, 1995). Second, we find that prompting people to use the DK option makes them more likely to use it. This result is consistent with the literature (e.g., Scoboria & Fisico, 2013; Mondak & Davis, 2001). Prompting people may lead them to state fewer opinions when they do not actually have one. Third, we find that mixture models are useful in identifying public opinion. These models do not require us to make a restrictive assumption that everyone behaves in the same way. In this study, we used mixture models for a count dependent variable. However, mixture models can also be used for ordered dependent variables (e.g., Bagozzi et al., 2012, 2014).

Our research also has implications for public policy. If public opinion has a direct effect on policy, then it is important to accurately identify public opinion. In the absence of a DK option, the distribution of responses may differ from that in the presence of a DK response (Kleinberg & Fordham, 2017). As discussed in the results, it is likely that in the presence of an aversion to acknowledging ignorance, analyzing the average opinion of people may result in a misleading picture. The literature suggests that people who have identified themselves as experts are more likely to be averse to acknowledging their ignorance (e.g., Atir et al., 2015). Often, these experts play a central role in shaping policy or in shaping views of the common people. If the experts are averse, then they may express an opinion about a policy in the absence of one. Doing so may mislead the general public into supporting or opposing proposed policies.

There are some other advantages of prompting people to use the DK option and thereby trying to encourage them to acknowledge their ignorance. While people may acknowledge their ignorance on a poll, the process of polling may arouse their interests and may encourage them to learn more about the policies (Lang & Lang, 1984). The process of polling has also been found to increase electoral participation (Lang & Lang, 1984).

This study can be extended in many directions. In the second question, we used a FMM to distinguish between classes of people. While we found some evidence for two classes of people, this is not definitive. A richer set of covariates may help to distinguish between the classes more clearly. For example, education has been shown to be a poor proxy for political knowledge (Zaller, 1991; Sturgis & Smith, 2010). Future research can include proxies for political knowledge in the FMM as it may be a better predictor of class membership. In the third question, we used the ZINB to identify if the class of people who is able to acknowledge their ignorance is averse to acknowledging their ignorance. Future research can test if the class of people who is unable to acknowledge their ignorance is also averse to acknowledging their ignorance. We noted that the FMM and ZINB, although better than the NB1 model, may not be the best models. A combination of FMM and ZINB may lead to a better model to account for population heterogeneity. Such a model would account for a class of people who are unable to acknowledge their ignorance and would also account for two or more classes among those who are able to acknowledge their ignorance. Such a model has been proposed by Morgan, Lenzenweger, Rubin, and Levy (2014). In the fourth question, we tested if ego-depletion generates an aversion to acknowledging ignorance. Given that we used observational data for this analysis we cannot conclude for sure if ego-depletion plays a role. Future research can use a randomized control trial to identify if ego-depletion does play a role. On a given question people are either unaware of their ignorance or are aware of their ignorance and are averse to acknowledging it. It could happen that in a survey with several questions, both processes occur simultaneously. Furthermore, drawing on the research of Kunda (1990), we suggested that sometimes there may be an interaction between the two processes. Future research can explore the interaction between the two processes and can explore which of them plays a more important role.

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Appendix

Appendix A Survey questions

There were 4 treatment groups that were randomly assigned to respondents. In the first treatment group, respondents were forced to answer all questions. In the second treatment group, respondents were allowed to skip a question if they wished. In the third treatment group, respondents were not allowed to skip questions but were offered an explicit "don't know" (DK) or "no-opinion" option. In the fourth treatment group, respondents were not allowed to skip questions, were offered an explicit "don't know" (DK) or "no-opinion" option, and were also prompted to use the DK option. Details of the groups was can be found in section 3, about Data and Methodology. As a notational shorthand, we refer to these groups as FC (forced choice), SK (skip), PN (prompted-no), and PY (prompted-yes) respectively.

Some questions were on a seven-point scale (see for example Question 1). Agree/Disagree questions were on a four-point scale (See for example Question 2). Questions 13 and 14 had a binary choice. In addition to the response scale, there was a "don't know"/"No opinion" option. Questions 15 through 19 assessed respondents perception about the survey on a five-point scale. We now present the questions on the survey. Text in brackets is shown only to respondents in certain groups and this is indicated using the "if" logical.

Introduction
This questionnaire contains a number of statements about various topics. Please indicate what you think of these statements by selecting the option that best describes your opinion. [if group=PY:You can also indicate that you have no opinion about a particular statement. / if group=SK:If you can't or don't want to answer a question, then you may skip this question.]

Question 1
Some people and parties think that the differences in income in our country should become bigger. Others think they should become smaller. And of course there are people with an opinion somewhere in between. Where would you position yourself on a line from 1 to 7, where 1 means that differences in income should increase and 7 means that they should decrease? [if group=PY: If you really don't know where you would position yourself, feel free to say so.]
1 The differences in income in our country should increase 1
2 2
3 3
4 4
5 5
6 6
7 The differences in income in our country should decrease 7
8 [if group=PY or group=PN: Don't know]

Question 2

The statutory retirement age should remain at 65 years. [if group=PY: Do you agree with this statement, or disagree, or you don't have an opinion on this / else: Do you agree or disagree with this statement]?
1 Agree entirely
2 Agree
3 Disagree
4 Disagree entirely
5 [if group=PY or group=PN: No opinion]

Question 3
Social welfare benefits should be lowered so that people are stimulated to find a job. [if group=PY: Do you agree with this statement, or disagree, or you don't have an opinion on this / else: Do you agree or disagree with this statement]?

Question 4
Some people think that euthanasia should always be prohibited. Others think that euthanasia should be permitted if the patient makes that request. And of course there are people with an opinion somewhere in between. Where would you position yourself on a line from 1 to 7, where 1 means that euthanasia should be prohibited and 7 means that euthanasia should be permitted? [if group=PY: If you really don't know where you would position yourself, feel free to say so.]

Question 5
Adoption by homosexual couples should be possible. [if group=PY: Do you agree with this statement, or disagree, or you don't have an opinion on this / else: Do you agree or disagree with this statement]?

Question 6
It is a good thing that women can have their egg cells frozen so that they can have children at a later age. [if group=PY: Do you agree with this statement, or disagree, or you don't have an opinion on this / else: Do you agree or disagree with this statement]?

Question 7
In the Netherlands, some feel that ethnic minorities should be able to live here while retaining their own culture. Others feel that they should adapt entirely to Dutch culture. Where would you position yourself on a line from 1 to 7, where 1 means that ethnic Minorities can retain their own culture and 7 means that they should fully adapt? [if group=PY: If you really don't know where you would position yourself, feel free to say so.]

Question 8
There are too many people of another nationality living in the Netherlands. [if group=PY: Do you agree with this statement, or disagree, or you don't have an opinion on this / else:

Do you agree or disagree with this statement]?

Question 9
All people that have lived in the Netherlands illegally for a long time should be permitted to stay here. [if group=PY: Do you agree with this statement, or disagree, or you don't have an opinion on this / else: Do you agree or disagree with this statement]?

Question 10
European unification is progressing steadily. The countries of the European Union have decided to work together increasingly closely. But not everyone agrees with this. Some people and parties feel that European unification should go even further, while others feel that it has already gone too far. Image that all people and parties that feel that European unification should go even further are positioned at the beginning of the line (at number 1), and that all people and parties that feel that unification has already gone too far are positioned at the end of the line (at number 7). Where on this line would you position yourself? [if group=PY: If you really don't know where you would position yourself, feel free to say so.]

Question 11
The Netherlands should spend more money on development aid. [if group=PY:Do you agree with this statement, or disagree, or you don't have an opinion on this / else: Do you agree or disagree with this statement]?

Question 12
The United Nations has too little power. [if group=PY: Do you agree with this statement, or disagree, or you don't have an opinion on this / else: Do you agree or disagree with this statement]?

Question 13
The Queen may only express government policy towards journalists. Do you agree or disagree with this? [if group=PY: You may also indicate that you don't know .]
1 Agree
2 Disagree
3 [if group=PY or group=PN: Don't know]

Question 14
Are you for or against surrogate motherhood? [if group=PY: You may also indicate that you don't know.]
1 For
2 Against
3 [If group=PY or group=PN: Don't know]

Question 15 - Question 19

Finally; what did you think of this questionnaire?
Question 15
Was it difficult to answer the questions?
1 certainly not
2
3
4
5 certainly yes
Question 16
Were the questions sufficiently clear?
Question 17
Did the questionnaire get you thinking about things?
Question 18
Was it an interesting subject?
Question 19
Did you enjoy answering the questions?