Environ Resource Econ (2018) 69:217–246
https://doi.org/10.1007/s10640-016-0075-6

Endogeneity of Risk Perceptions in Averting Behavior Models

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Accepted: 15 October 2016 / Published online: 5 November 2016

Abstract This paper examines the relationship between averting expenditures / choices and perceived health risks. Models in the literature often employ risk perceptions as explanatory variables without addressing the potential endogeneity of the perceived risk. We examine the implications of ignoring endogeneity in this context, using an application to both drinking water choices and expenditures and perceived health risks. Our data are from an Internet-based cross-Canada survey that employs a novel *interactive* risk ladder to elicit mortality risk perceptions relating to water. We employ two fundamentally different methods to assess the impact of risk perceptions on behavior: an analysis of expenditures on alternate water sources and a model of proportional choice of water sources. Results suggest the presence of averting behavior with respect to perceived mortality risks and that the estimated effect of water risks is greater than 3 times higher when using approaches that correct for endogeneity compared to models that do not.

Keywords Averting behavior · Risk perceptions · Water quality · Human health · Latent class models · Expenditure model · Endogeneity

JEL Classification Q510 · Q530 · I120

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10640-016-0075-6) contains supplementary material, which is available to authorized users.

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1 Introduction

Many analyses of averting behavior to reduce health or environmental risks include the decision-maker's perception of risks. Perceptions are thought to better reflect behavior than expert-elicited or objective measures of risk and empirical evidence suggests significant differences between perceived and objective risk levels.[1] While the use of risk perceptions may be preferred from a behavioral standpoint, they present two (at least) challenges to empirical work. First, the elicitation of these risk perceptions is nontrivial and, second, their use in econometric models raises potential issues of endogeneity. In this paper, we illustrate these issues by examining a case study of drinking water choices, expenditures, and perceived health risks. The three main contributions of this paper are that risk perceptions are elicited through the use of a novel online *interactive* risk ladder tool, effects are examined within two fundamentally different estimation approaches: choice models and expenditure models, and the endogeneity of these risk perceptions is accounted for in ways appropriate to each of the methods (specifically, control function and two-stage least squares instrumental variable (2SLS-IV) approaches).

This paper employs data from a 2009 cross-Canada Internet-based survey that solicits drinking water choices (proportions of consumption that are either direct from the tap, filtered tap, and/or bottled) and expenditures on different drinking water sources, along with perceived mortality risks from the different drinking water sources using the risk ladder tool. For Canadians, these mortality risks are well understood due to some highly publicized contamination events in the early 2000s including an *E. coli* outbreak resulting in the death of seven people and over 4000 people becoming sick.[2] The costs and gravity of these contamination events have not only increased public awareness of the potential health risks from drinking water, but may also have had impacts on the choices and expenditures that individuals make with regard to their drinking water alternatives. Thus health concerns relating to tap water can translate directly into observable averting behaviors, where individuals are trading off quality characteristics, health risks, and costs in their water choices. Using this averting behavior framework, tradeoffs and expenditures can suggest values that individuals place on quality improvement and therefore can be used as a measure of public benefit or loss from quality changes.

Instead of focusing on absolute objective levels of contamination, or rating scales of risk perception, as is common in the averting behavior literature, this paper incorporates self-reported probabilistic perceived risk levels for each of the three choices: tap water, home filtered tap water, and bottled water. These are obtained through the use of a novel Internet-interactive risk ladder tool in our survey.[3] While this method provides us with data on risk perceptions to help explain choices/expenditures, we also recognize that this risk perception measure may be endogenous in the explanation of water choices or expenditures.

[1] For example, laboratory experiments find that individuals place a higher weight on small-risk events and a lower weight on high-risk events compared to objective measures (Shaw and Woodward 2008; Ridell 2012).

[2] This event took place in the year 2000 in Walkerton, Ontario where *E. coli* contamination in local drinking water supplies led to total costs of nearly $65 million (Livernois 2001). Other notable water contamination events took place in 2001 in North Battleford, Saskatchewan where the presence of cryptosporidium, a parasitic organism, led to an estimated 4–7 thousand illnesses in the region (Stirling et al. 2001), and in the aboriginal community of Kashechewan, Ontario where *E. coli* resulted in the evacuation of the community and a total cost of over $16 million (CBC 2006). Between 1993 and 2008, at least 48 water-borne disease events were reported by public health officials in Canada (Wilson et al. 2009).

[3] An illustrative video of the risk ladder in use is provided in the online supplementary material.

There are two potential sources of endogeneity of risk perceptions: simultaneity and omitted variable bias. Simultaneity bias may be present because while risk perceptions may affect the decision of which source of drinking water to choose, these choices may in turn affect perceptions regarding the relative safety of the water sources. For example, an individual may consume bottled water because it is initially perceived to be safer and this perception is reinforced overtime if the individual does not incur any adverse health impacts. Thus there is good reason to believe that there are important feedback effects between water choices and risk perceptions. In addition, unobserved factors affecting water choices may be correlated with risk perceptions leading to omitted variable bias.

Given these two potential sources of endogeneity, it is difficult to know ex ante the direction of the endogeneity bias on the risk coefficient in either a choice or expenditure model but there are two reasons to think that ignoring endogeneity of perceptions would underestimate risk effects in our context. First, the simultaneity bias is most likely negative because of the negative feedback effect from water choices/expenditures to health risks. This negative relationship may arise because risk perceptions are likely lower for drinking water sources people are most familiar with given the rarity of mortality events from drinking water. This negative relationship leads to an underestimation of risk effects in models that do not address endogeneity. Second, there is some prior evidence that the magnitude of water quality perception coefficients increase once methods to address endogeneity are employed (Whitehead 2006; Orgill et al. 2013).

We illustrate how endogeneity associated with risk perceptions may be incorporated into two different averting behaviour models: a multinomial drinking water choice model and a drinking water averting expenditure models. We use a control function approach (Petrin and Train 2010) for the first and two different two-stage-least-squares instrument variable (2SLS-IV) approaches (Wooldridge 2010; Schwiebert 2012) for the second. A key decision factor for the researcher is the choice of instrument. Our main instrument is the respondent's perception of skin cancer mortality risks, which is also collected using the same risk ladder approach in a part of the survey. While we can never be 100% sure that an instrument completely satisfies the exogeneity assumption required for a valid instrument, we believe that this variable represents an improvement over previously applied instruments such as socio-demographic characteristics or satisfaction with drinking water.

Our results suggest the presence of averting behavior with respect to water in Canada and that perceived mortality is a significant predictor of water consumption choices for a large number of respondents in the survey. Furthermore, the impact of risk on expenditures and choices is significantly affected by endogeneity. The estimates of the economic value of risk reductions are similar between the choice and expenditure models and a set of robustness tests shows that these measures are relatively stable over methods to address endogeneity, representations of risk, and model specifications. Specifically, if we do not account for endogeneity we find a substantial underestimation of the value of risk reductions; this value is estimated to be 3 times higher when we correct for endogeneity. Using parameter estimates from these models we calculate a value of statistical life (VSL) estimate pertaining to reductions in the risk of death from drinking water. The VSL estimate is \$3.4 million (\$CAD) using the choice models and between \$3.0 and \$5.4 million using the expenditure models. Note that these value estimates are based on averting expenditures and thus likely represent a lower bound estimate of the actual willingness to pay. These findings suggest that caution is required when estimating econometric models that include individual perception variables and illustrate the importance of properly testing and controlling for endogeneity.

2 Literature Survey

Subjective or perceived risks are often included in a wide variety of empirical models under different contexts that involve decision making under risk or uncertainty. Decisions about the water one chooses to drink are dependent not only on the perceived quality of a baseline such as tap water, but on the perceived quality of other water options, as well. Perceived quality, in turn, is based on the quality characteristics of a good, some of which may be health related, and some of which are not. In addition, to the extent that there may be a non-zero risk of adverse health effects arising from one's choice, then one's assessment of these risks may also come into play. In this section we review the literature on averting behavior models, risk communication and elicitation strategies, and endogeneity of risk perceptions with a focus on drinking water health perceptions.[4]

Averting behavior models are used to analyze an individual's aversion to some negative characteristic associated with the state of his/her environment and are typically framed in terms of improvements to one's personal environmental quality (Courant and Porter 1981; Bartik 1988). Typically, the measure of environmental quality is a variable indicative of a level of contamination, as opposed to the risk level that one would note in a model of expected utility. Again, in the case of water contamination, one would be motivated to drink less of the contaminated water to avoid ingestion of contaminants. This approach has been used in a drinking water context in a number of different ways. Actual expenditures have been used to study unique contamination events ex post (Abdalla et al. 1992) and to obtain WTP for improvements in publicly supplied water quality (Jordan and Elnagheeb 1993; Hagihara et al. 2004; Zerah 2000). On the other hand, discrete choice models have been adopted to determine which factors are most likely to result in spending on "safer" water substitutes (Larson and Gnedenko 1999; McConnell and Rosado 2000; Abrahams et al. 2000; Um et al. 2002; Wu and Huang 2001; Rosado et al. 2006; Lee and Kwak 2007).

Models of averting behavior may benefit from exploration of the use of probabilistic risk estimates in place of absolute contamination levels. Whereas individuals may be unfamiliar with technical names and effects of specific contaminants, it may be the case that they are familiar with risk, which can provide more depth to statistical implementation of the theoretical model. Risk perceptions play a very important role in determining the behavior of individuals. The perceptions of risk are the foundation of consumption decisions where risk is a characteristic of the good. The use of risk perceptions, as opposed to objective risk information, may be best for the valuation of risk reduction particularly in relation to health risk studies (Jones-Lee 1974; Freeman 1993; Hammitt and Graham 1999).

To gather perceptions of risk, some studies use a direct and discrete approach by asking survey respondents to identify a personal risk level from amongst a stated set of discrete values (Johannesson et al. 1991) or on a Likert-scale basis (Abdalla et al. 1992) or to note whether a personal risk is higher or lower than that for an "average" person or situation (Johannesson et al. 1996; Hagihara et al. 2004). Lee et al. (1998) use a more continuous approach for the elicitation of risk values. While these risk perception solicitation methods have had some success, much effort has been put into the development of devices that can gather risk perceptions more precisely (quantitatively explicit perceptions). Grid-like representations appear to be the most popular method to communicate risks and to elicit risk perceptions (Jones-Lee et al. 1985; Bhattacharya et al. 2007; Tsuge et al. 2005; Adamowicz et al. 2004, 2012; Carlsson et al. 2004).

[4] A much more detailed discussion of this literature is presented in Schram (2009).

An alternative is the use of a risk-ladder which facilitates the interpretation and placement of personal risks by including relative risk information. The literature finds support for the use of the risk ladder in order to communicate continuous risk perceptions relating to health (Ancker et al. 2006; Corso et al. 2001). However, there have been few uses of risk ladders as an elicitation tool. Konishi and Adachi (2011) use a risk ladder to help inform respondents to a stated preference survey about the health risks from arsenic, but they use a 10 point Likert scale to solicit the risk. Jakus et al. (2009) use a risk ladder method similar to that used in the present study but use a static representation with tick marks in a mailed brochure and elicit responses through a telephone call. Since their study was targeted at the impact of current water consumption risk perceptions associated with arsenic exposure on bottled water expenditures, they did not elicit risk perceptions for different types of drinking water sources nor ask questions about filtered water expenditures. Data were gathered from communities with known exposure to arsenic levels that were higher than the legal standard and the sample size used in the analysis (n = 201) is substantially smaller than our study. Perceived risk values were modeled as a function of perceived exposure to arsenic, among other demographics, and were included in a Heckman selection model to investigate expenditures. Results from the study suggested that perceived risks were not a significant variable in the choice to buy bottled water, but were a significant predictor of expenditures on bottled water although. Most importantly in the context of our study, no methods to address potential endogeneity of perceptions were employed.

Most studies of water risks and averting behavior do not control for the possible endogeneity of the water quality or risk perception variable. Using a qualitative water quality perception variable, Whitehead (2006) estimates the willingness to pay for water quality improvements by full information maximum likelihood in a two equation set up. To control for possible endogeneity of perceived water quality, socio-economic variables including race, gender, age, and whether the respondent is a farmer are used as instruments. Orgill et al. (2013) use whether the individual is satisfied with the current drinking water taste and smell as an instrument for perceived water quality although they note that this factor is probably not a suitable instrument as it is likely not purely exogenous. They employ Wooldridge's 'forbidden regression' by directly applying 2SLS to a nonlinear model (Wooldridge 2010). Nauges and van den Berg (2009) use the average water risk perception in the municipality where the household lives as a proxy for individual risk perceptions to avoid the endogeneity issue. Konishi and Adachi (2011) address endogeneity in their analysis of water quality risks but this analysis is based on a contingent valuation analysis rather than averting behavior.

3 Survey Data

The survey was fielded online to a national sample during the months of February and March 2009.[5] Members of the Ipsos-Reid online panel aged 18 and older were recruited for the survey via email. Recruits were chosen at random from the internet panel. A suitable distribution, comparable to the Canadian population, in terms of age, income, region, and gender was requested for the sample. Beyond these criteria, participation was at the discretion of the respondent. A comparison of survey data to the 2006 Canadian census reveals similar values,

[5] The survey was developed using the aid of 7 focus groups, and a pretest with follow-up calls. The pretest was implemented by Ipsos-Reid, and resulted in 128 completed surveys. Particular consideration was given to the design of the risk ladder for gathering risk perception information. The goal for the survey was 1000 respondents. In order to achieve this, 5556 invites were sent out to the Ipsos-Reid online panel. 1304 individuals completed the survey, which would indicate a response rate of 23.5%. The 4252 non-responders include those who quit the survey partway through, as well as those that did not choose to activate their survey link.

e.g., mean household income in the survey sample is \$66,899.41 and estimated at \$69,548.00 in Census sample. The median age in the survey sample is 45, in comparison with a census median age of 39.5.[6] The mean household size in the survey sample is 2.95 persons, whereas the census indicates a mean household size of 2.50 persons. The regional distribution of respondents in the survey sample was also compared to the regional population distribution from the Census. With the exception of Quebec,[7] differences in regional population between data sources are within 1% and the 1304 completed surveys appear to be a statistically representative sample of the Canadian population.

The survey collected data on the composition of drinking water consumption, costs for filtration and bottled water, quality perceptions, mortality risk perceptions, attitudes and experience with water quality issues, and demographics. To gather consumption information, the respondent indicated the proportions of each type of water that they drink in an average month (Bottled, Filtered Tap, or Regular Tap water). Following these questions, information on the cost incurred for purchased or filtered water was gathered.[8]

For filtration systems, the respondents were asked to indicate the initial cost of the system in use, the amount of money they would spend on replacement filters, and the frequency of replacement. The monthly cost of filtration is the sum of costs associated with the purchase or rental of the filtration system itself, and those associated with filters and filter replacements. The cost for purchased systems (container style, or tap attachment) was amortized over the useful life of the product.[9] The respondent's internal discount rate was used for the amortization calculation and calculated from responses to a series of debriefing questions designed to determine individual rates of time preference.[10] Depending on responses, a respondent's internal discount rate was assigned one of the following annual rates: 10, 20, 45, or 65%.[11] The equivalent monthly rate was used in an amortization calculation to produce a monthly cost. Costs for refrigerator filtration systems were assumed to be zero since we assume that individuals do not purchase the appliance directly for its ability to filter water.[12] In order to calculate monthly costs associated with maintenance or filter replacement, the reported cost of a replacement filter was amortized over the number of periods indicated by the individual as a replacement frequency. In most cases, this value was between two and three months. The monthly filtration cost is then the sum of both maintenance costs, and system

[6] The reason the census median age is lower than our sample is that it includes all Canadians whereas our sample includes only adults.

[7] When compared, for Quebec the difference in regional population between data sources is 1.45% and is overrepresented in the survey sample.

[8] In this study, the cost of tap water is treated as zero, as was done by Abrahams et al. (2000). This zero cost assumption for tap water is fairly innocuous as the marginal cost of tap water in Canada has been estimated to be around 11 cents per person per month (Dupont and Jahan 2012).

[9] Following Abdalla et al. (1992) we used 10 years or 120 months for tap attachment filters. For container style filters, which are likely to see much more wear and tear, 5 years or equivalently 60 months was considered the useful life of the product.

[10] A double-bounded binary choice scenario was presented to respondents where they chose between a receiving \$100 in 1 month from now or \$116 in 7 months. A follow-up question with a higher (\$128) or lower (\$105) monetary amount received in seven months was presented to respondents depending how they answered the first question.

[11] These rates are slightly high, however they are consistent with responses in the survey, and on average only a small decrease (less than \$1.00) was noted when the same calculations were done using 10% rates for all respondents.

[12] Although there may be an implicit cost associated with this feature of a refrigerator, the cost of the appliance was not gathered in the survey. A total of 82 individuals reported themselves to be refrigerator water filter users.

rental or purchase costs.[13] Costs were inflated to represent 100% monthly consumption of filtered water.[14] The average filtration cost for respondents in the survey is \$13.53 per month. The standard deviation around the mean, \$80.85, is quite large and indicates significant variability in this value.

The monthly cost for 100% consumption of bottled water was calculated by using information on the current cost, and the current proportion of consumption reported by each individual. The average monthly cost for 100% consumption of bottled water was calculated to be approximately \$108.04 per month.[15] Again, this value has a relatively large standard deviation of approximately \$166.45 indicating significant variability.

Water quality characteristics were elicited from respondents for each drinking water type on four dimensions -taste, odor, appearance, and convenience—using a 7-point Likert scale defined as 1 is poor and 7 is excellent. These values are converted into three level dummy variables (low, medium, and high).

Respondents were then asked to indicate their perceived personal annual risk of death for their current composition of water consumption, as well as for situations in which they drank only one type of water (e.g. 100% bottled water or 100% filtered water or 100% tap water). The risk ladder employed a "semi-logarithmic" scale since logarithmic scales do not allow for the adequate display of other death risk information.[16] Semi-logarithmic scales are reported as being effective at eliciting the predicted theoretical properties for risk valuations (Corso et al. 2001). In order to assist respondents with putting water-related death risks into context, the risk ladder showed respondents a variety of annual death risks based on Canadian data. Prior to eliciting these risk perceptions, each respondent was asked to identify his/her personal risk of mortality from skin cancer on the risk ladder for use as an instrument. The risk ladder was an interactive graphic by which the individual could use a sliding mechanism to choose and lock in their perceived risk level for each water source. See Fig. 1 for the risk ladder .

Table 1 provides a set of summary statistics on water quality characteristics, monthly cost and other variables used in the modeling. The descriptive statistics and summary data presented in this section reveal that Canadians have a minor to moderate concern with drinking water quality in Canada, thereby, supporting the view that averting behavior is taking place. Alternatives to tap water, on average, seem to provide improvements on most quality dimensions listed, as well as a small perceived risk reduction. The paper turns next to a description of the econometric methods and empirical strategies used in the analysis.

Table 2 details the average perceived risk of death for each respondent's current drinking water consumption profile, the perceived risks for 100% consumption of each water type, as

[13] In some cases, individuals indicated a positive consumption amount, but did not know the costs they incurred for that consumption. These cases mostly arose in filtering expenditures, as there are many components to expenditures on filtration for which "don't know" was a possible answer (e.g. replacement cost, replacement frequency, system cost). In the case where an individual indicated positive consumption, but did not know a specific expenditure, the average cost specific to each water alternative was used.

[14] For example, if an individual reported spending approximately \$1.00 for 1% of their monthly consumption, 100% consumption would cost them approximately \$100.00.

[15] We removed two observations with very high monthly bottled water costs of \$5000 and \$10,000. Including these two outliers, the mean and standard deviation is \$119.38 and \$347.85 and we used 10 standard deviations of the mean ($\sim$\$3600) as the outlier cut-off threshold. The 1302 remaining observations have bottled water costs within 10 standard deviations of the mean.

[16] That is, each exponential decrease (ex. 10^{-5} to 10^{-6}) in the level of risk was given its own linear section in the risk ladder, in which the appropriate decreases (ex. 0.00045–0.00040%, a decrease of 0.00005%) were represented in a linear fashion. The "semi-logarithmic" property of the risk ladder describes the appearance of the change between each exponential section.

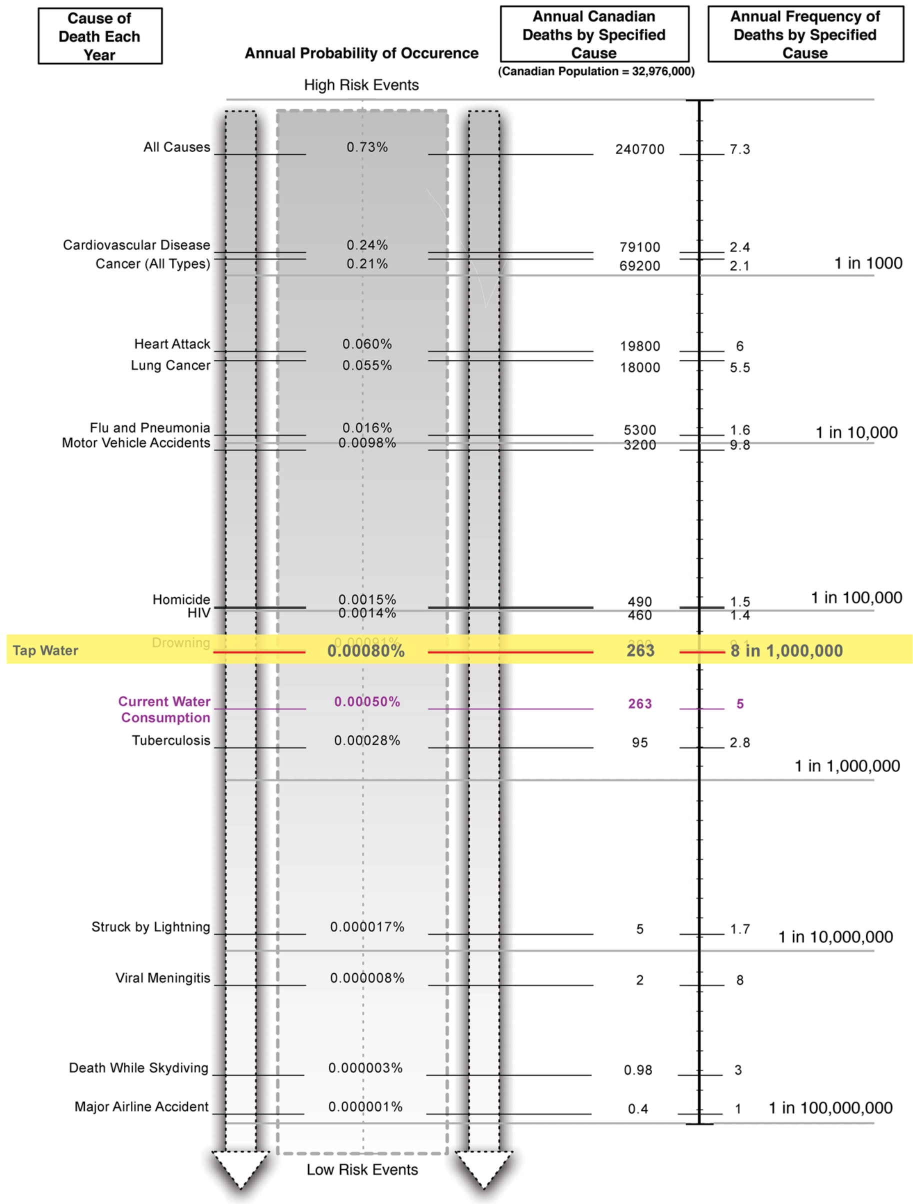

Fig. 1 Risk ladder

well as the current skin cancer risk perceptions. Tap water was generally perceived to be the most risky drinking water source followed by filtered water, and bottled water being reported as the least risky. Ideally, these perceived risk levels would be compared to objective risk levels but reliable estimates of the number of deaths caused by drinking water in Canada is unavailable. Using extrapolated numbers based on United States data, Canadian researchers have estimated that drinking water causes roughly 90 deaths and 90,000 cases of illness annually due to waterborne infections in Canada (Edge et al. 2001).[17] Another objective estimate based on the number of bladder cancer cases attributable to water consumption is around 192 deaths per year.[18] Although the reliability of these numbers should be interpreted cautiously, the mean perceived risk levels elicited in this study are higher than these objective estimates, but the median elicited risk levels are lower.

There is more robust data on objective risk levels for skin cancer in Canada and comparing the perceived levels elicited through the ladder shows a similar story as the drinking water risks: the mean perceived risks are higher than objective risks but median perceived risk levels are lower.[19] Skin cancer risk perceptions are higher than drinking water risk perceptions. In fact, the ratio of the average skin cancer risk perceptions to current drinking water risk perceptions is 3.3 which is quite close to the objective risk ratio of 2.7 for these risk sources.[20]

4 Empirical Methods

This section outlines the methods used in the empirical analysis. After presenting the basic choice and expenditure models that do not incorporate endogeneity of risk perceptions, we discuss the endogenous risk perception variable and the instrumental variable in more detail. The final section describes the techniques used to correct for endogeneity concerns in both modeling frameworks.

4.1 Water Choice Model

Following Abrahams et al. (2000)'s adaptation of Courant and Porter's (1981) model of averting behavior, a respondent's utility is assumed to depend upon the consumption of each water source, W_i, a perceived health production variable, H^*, the quality characteristics of each water source, q_i, and a numeraire good, X. This formulation assumes that individuals gain utility both directly through the consumption of water, and indirectly through the production of health. Health production is analogous to the production of cleanliness in the treatment of the original averting behavior model of Courant and Porter (1981). Joint production from other "services" provided by the averting behavior is accounted for by separating standard quality characteristics out from those that produce health. The perceived expected health variable, H^* is then produced based on exposure (consumption) to each water alternative. Actual expected health, H, is related to the perceived variable through the use of risk perceptions. Actual expected health uses objective risk measures, π_j. Whereas for expected health, actual risk values are replaced with perceived risk values, π_j^*. Following Dickie and Gerking (1996), perceived risk is assumed to be a function of the objective risk, as well as attitudes, α, and experiences, β, with water safety:

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[17] The 90 deaths per year figure is confirmed cases based on extrapolated data from the United States and may underestimate actual numbers due to under-reporting (Edge et al. 2001).

[18] The 192 deaths are derived from a mortality rate of 20 bladder cancer deaths per 100,000 people over a 35-year period reported in the survey used by Adamowicz et al. (2011). This rate was multiplied by the 33.6 million people in Canada in 2009. The mortality rate information is based on studies by Wigle (1998) and Canadian Cancer Society's Advisory Committee on Cancer Statistics (2015).

[19] The estimated age-standardized mortality rate for skin cancer in Canada is 2.3 per 100,000 (Canadian Cancer Society's Advisory Committee on Cancer Statistics 2015). Applied to the 2009 Canadian population of 33.6 million, this mortality rate implies approximately 773 deaths per year from skin cancer in Canada.

[20] The ratio of the objective risk levels between skin cancer and drinking water risks is calculated using the 773 annual deaths from skin cancer and 282 estimated deaths from drinking water (192 from bladder cancer and 90 from microbial infections).

Table 1 Descriptive statistics: means (SD) of selected variables

Variable	Level	Variable type	Mean	SD
Use bottled water (treatb = 1)		Dummy	0.723	0.448
Water quality characteristics				
Bottled_Taste	Medium	Dummy	0.418	0.493
	High	Dummy	0.551	0.498
Bottled_Odor	Medium	Dummy	0.412	0.492
	High	Dummy	0.573	0.495
Bottled_ Appearance	Medium	Dummy	0.315	0.465
	High	Dummy	0.678	0.467
Bottled_ Convenience	Medium	Dummy	0.467	0.499
	High	Dummy	0.412	0.492
Tap_Taste	Medium	Dummy	0.498	0.500
	High	Dummy	0.303	0.460
Tap_Odor	Medium	Dummy	0.510	0.500
	High	Dummy	0.307	0.462
Tap_Appearance	Medium	Dummy	0.483	0.500
	High	Dummy	0.415	0.493
Tap_Convenience	Medium	Dummy	0.250	0.433
	High	Dummy	0.725	0.447
Filtered_Taste	Medium	Dummy	0.598	0.491
	High	Dummy	0.353	0.478
Filtered_Odor	Medium	Dummy	0.584	0.493
	High	Dummy	0.369	0.483
Filtered_ Appearance	Medium	Dummy	0.500	0.500
	High	Dummy	0.471	0.499
Filtered _Convenience	Medium	Dummy	0.520	0.500
	High	Dummy	0.408	0.492
Monthly costs				
100% Bottled water		Continuous	108.04	166.453
100% Filtered water		Continuous	13.53	80.849
Socio-demographic characteristics				
Child		Dummy	0.368	0.482
Age index		Continuous	1.000	0.337
Income		Dummy	0.412	0.492
College		Dummy	0.185	0.389
Gender (female = 1)		Dummy	0.495	0.500
Household size		Continuous	2.948	1.352
Language (English = 1)		Dummy	0.783	0.413
Wrong		Dummy	0.150	0.357
Skin cancer risk		Dummy	0.672	0.470
Number of observations		1302		

Age index is calculated as the age of each respondent divided by the mean, producing a variable with a range of approximately 0.5–1.5. The College variable indicates whether an individual had attended any college. Income variable is indicative of annual household income greater than $70,000.
Wrong indicates an incorrect response when tasked with the assessment of a probability

Table 2 Perceived annual risk of death from drinking water and skin cancer

Perceptions	Mean (%)	Median (%)	SD (%)
Drinking water			
Current consumption	0.0087928	0.000001	0.075363
100% Consumption by water type			
Tap	0.0132576	0.000002	0.095876
Filtered	0.0101038	0.000001	0.086510
Bottled	0.0074549	0.000001	0.007455
Skin cancer			
Current risk levels	0.0289521	0.000006	0.114573

Current consumption risks measures the respondent's perceived personal annual risk of death for their current composition of water consumption which is a mix of the three water types

$$\pi_j^* = \pi_j^* \left(\pi_j, \alpha, \beta\right) \tag{1}$$

In Eq. (1) and in what follows, j = 1,2,3 for tap, filtered and bottled water, respectively. This approach assumes that water quality and health risk are weakly complementary to water consumption, thus, a respondent maximizes utility over X, and W_{j} subject to, non-negativity constraints on W_{j} and X, as well as the budget constraint:

$$Y = W_1 p_1 + W_2 p_2 + W_3 p_3 + X \tag{2}$$

This budget constraint differs slightly from Abrahams et al. (2000). In that study the budget constraint included the average cost of a filter, and specified the same "price" for both tap water and filtered water. In this paper, following from a better data set, it is assumed that the price associated with each alternative corresponds to the monthly cost associated with adopting that alternative, as described in the previous section. The conditional demand for each water source is then a function of price, income, perceived risk, quality characteristics, and attitudes and experience about water safety. The associated conditional indirect utility function is:

$$\mathrm{V_i} = \mathrm{V_i}(\mathrm{p_i}, \mathrm{Y}, \pi_{\mathrm{i}}^*, \mathrm{q_i}, \alpha, \beta) \tag{3}$$

where the price of tap water is equal to zero ($\mathrm{p}_1 = 0$). Our model involves explaining a respondent's choice among three water alternatives. Respondents choose a water alternative if the utility of that choice is greater than that of each other alternative (i.e. choose k if $\mathrm{V_k} > \mathrm{V_i}$ for all $i \neq k$). We append an error term (ε) to account for the fact that while the respondent knows his/her indirect utility, the researcher does not. If the error terms are independent and identically distributed with a type I extreme value distribution, the researcher estimates the probability of i choosing option j (Pr_{ij}) with a conditional logit model.

Recall, however, the data on water consumption choices gathered in our survey are proportional in nature. That is, for each individual, the proportion of each type of water consumed in an ordinary month is specified. We treat these proportions data as if they reflect individuals' repeated choices over the time period. Equation (4) shows the likelihood function we use. It is a modification of Guimaraes and Lindrooth (2007)'s grouped data approach.

$$L = \prod_{i=1}^{N} \prod_{j=1}^{J} Pr_{ij}^{n_{ij}} \tag{4}$$

In Eq. (4), Pr_{ij} is the probability of individual i choosing option j, n_{ij} is the number of times individual i chose option j in the specified number of choice replications ρ. Specifically, n_{ij} is the product of the number of replications, ρ, and the corresponding proportion of choice of option j for individual i, $\alpha(n_{ij} = \rho\,\alpha_{ij})$.[21]

Estimation of Eq. (4) requires that we make three reasonable assumptions about choices. First, at each choice occasion within an ordinary month, all three water options are available to the individual. Second, using a variable to indicate the number of replications imposes a predetermined number of replications on each individual (i.e. ρ is constant across individuals). Third, each individual consumes the same amount of water in each month.

Another matter of concern with estimation of the utility parameters in models of choice is the imposition of homogeneous preferences. That is, each individual is assumed to have the same marginal utility associated with various alternative specific characteristics. While the inclusion of individual specific variables (demographics) may condition the individuals' choice probability and produce a type of measure of predisposition towards certain options, it does not completely account for heterogeneity in value of choice characteristics across the sample. Following Swait (2006), latent class models are also estimated to allow for unobserved heterogeneity and as extensions to basic multinomial logit models.

4.2 Water Expenditures Model

An alternative approach to assessing the impact of risk perceptions on choices is to examine the impact on expenditures directly. Expenditures on bottled water, for example, reflect a form of averting behavior. We examine averting expenditures directly using expenditures on bottled water as the dependent variable. We examine this in a selection framework to account for the zero versus non-zero expenditures on bottled water as well as the magnitude of expenditures. In addition to a number of demographic variables we explain averting expenditures with our risk perception variable as well as the water quality characteristics variables.

4.2.1 Risk Perception Variable

If we include the risk perception variable directly as collected (that is, as a continuous probability value), this imposes the assumption that risk reductions have a proportional effect on drinking water behavior (Hammitt and Graham 1999).[22] To relax this assumption, we recode it as a dummy variable corresponding to low and high levels of risk.[23] We examiner four different high risk cut-off levels: Drisk0 considers any individual with a positive risk perception level as high risk, Drisk1 uses a high risk cut-off level of 1 in 100,000,000 chance

[21] The empirical model does not specify a particular value of ρ, but rather the proportions represent the average drinking water consumption shares over the month. Without the reproduction of such occasions in an experimental fashion, knowledge of the number of choice occasions for drinking water that one faces in a month is difficult to obtain in a survey format. Most individuals are not likely to know how many times they drink water in each month.

[22] For example, reducing risk from 1 in 100,000,000 chance of death in a year to zero has the same effect on behavior as reducing risk from 101 in 100,000,000 to 100 in 100,000,000.

[23] Preliminary analysis using the continuous risk probability variable yields no statistically significant relationship between risks and water source choices. This can be interpreted in two ways. Either, there is no relationship or risk reductions do not have linear effects on behaviour (but may have nonlinear effects depending on the base level of risk). The advantage of using the dummy variable approach is that the nonlinearity of the effect of risk reductions can be modelled quite flexibly. One disadvantage of the dummy variable approach is choosing the appropriate threshold level between low and high levels of risk. In order to illustrate this we employ four different specifications in the paper.

Table 3 Drinking water risk dummy variables

High risk cut-off level (%)	>0	>0.000001	>0.000002	>0.00001
Choice models				
Dummy variable	Drisk0c	Drisk1c	Drisk2c	Drisk10c
Percentage high risk (=1)	71.2%	46.3%	33.7%	13.4%
Mean risk reduction (%)*	0.0001427	0.0002119	0.0002785	0.0005902
Expenditure Models				
Dummy variable	Drisk0e	Drisk1e	Drisk2e	Drisk10e
Percentage high risk (=1)	41.3%	30.2%	25.6%	16.9%
Mean risk reduction (%)*	0.0002063	0.0002814	0.0003321	0.0005027

* The mean risk reduction is calculated as the difference between the average risk levels in the high and low risk categories

of death in a year, Drisk2 uses the high-risk cut-off level of 2 in 100,000,000, and Drisk10 uses 10 in 100,000,000. These different risk level dummies are summarized in Table 3. We also present the relevant risk reductions levels relevant for the choice models and the expenditure models. For the expenditure models, the relevant risk reduction quantity is the difference in risk perceptions between 100% tap water and the current risk level. These reductions are calculated as the difference in mean risk levels for high and low risk individuals implied by the dummy variable cut-off levels. As the high risk cut-off level increases, the percentage of respondents in the high risk category decreases while the mean risk reduction associated with the dummy variable increases.

4.3 Instrumental Variable

For an instrumental variable strategy approach to adequately control for risk perception endogeneity, a valid instrument is required. Essentially, we require an instrument that is strongly correlated with water risk perceptions (a strong instrument), but uncorrelated with unobservables affecting water type choice (satisfies the exogeneity restriction). As an instrument, we use individual perceptions of skin cancer mortality risk which was elicited from respondents using the same risk ladder approach as water risks. This probabilistic skin cancer risk variable is converted to a dummy variable using the same cut-off value as the water risk variable. Our choice to use skin cancer risk perceptions is supported by the expectation that this risk is correlated with water risk perceptions due to common beliefs and attitudes towards risks in general. To the extent that this instrumental variable is not completely exogenous, the focus of this paper is to provide an illustration of methods to both elicit risk perceptions and then appropriately model these perceptions rather than the specific results.

To test instrument strength, we can conduct an F-test of the skin cancer variable using the first stage regression results. The exogeneity restriction cannot be directly tested because we do not observe the error term of the outcome equation. For the instrument to satisfy the exogeneity restriction, we assume that there are no direct effects of skin cancer risk perceptions on the water choice/expenditure variables or any effect running though omitted variables, nor any reverse effects of water choices/expenditures on skin cancer risk perceptions. The skin cancer risk variable captures the respondent's current annual perceived risk of dying from skin cancer, net of any behavioral adjustments. A person with a low skin cancer risk perception could think there is a low initial risk of skin cancer mortality or that there was initially a high risk, but they have taken actions to reduce this risk (i.e. apply sunscreen), and thus do not perceive the current risk to be high. Conversely, respondents who state a high skin cancer risk may be less likely to undertake additional averting behavior because they could also be less likely to take any risk reduction actions and hence the high skin cancer risk perception in the first place. To the degree there is a relationship between skin cancer risk perceptions and preventative action to mitigate drinking water risks, the mechanism for this effect is most likely through the drinking water risk perception channel. Besides these factors, skin cancer risk perceptions are unlikely to be correlated with many other external unobserved factors determining water choices such as the state of local municipal drinking water infrastructure or water quality issues in the past (e.g. historical *E. coli* outbreaks). Furthermore, there are no clear reverse feedback effects of water choices/expenditures on forming skin cancer risk perceptions. However, we can never be completely certain of the validity of the instrument and recognize that using responses to a question from the same individual as an instrument for responses to another question can lead to concerns about correlations between water choices/expenditures and skin cancer risk perceptions that are not fully captured by the drinking water risk perceptions.

4.4 Modeling Techniques for Incorporating Endogeneity of Risk Perceptions

In the choice models a control function approach is used to address potential endogeneity (Petrin and Train 2010). The first step of the control function approach is to estimate risk perception models for each of the three water choices. The estimated residuals from this first stage equation can then be included in the choice models to control for endogeneity. Because there are three water choices, we interact the skin cancer instrument with three socio-demographic variables (gender, age, and language) to create three instruments.[24] While we have three first stage equations, there is only one estimated endogenous variable in the second stage. Risk perception is a dummy variable and we use a probit model of risk perceptions as a function of the quality characteristics, the alternative specific constants, cost, as well as the three interacted instruments.[25] As suggested by Wooldridge (2014), the three generalized residuals from the probit models are then included in the choice model.[26] We consider alternative instrument interactions as well as different functional forms of the first stage equation as part of the robustness analysis.[27]

[24] We chose gender, age, and language as they are the most plausible exogenous socio-demographic variables available, but cannot be assured these variables are completely endogenous. To check the robustness of the results to different socio-demographic variables, Table 9 also summarizes models using alternative socio-demographic variables. Results are similar across the different specifications.

[25] Lewbel et al. (2013) highlight that the control function approach is less robust than IV methods when the endogenous variable is not continuous and the model is nonlinear. Wooldridge (2014) provides a more in-depth theoretical explanation of the control function approach and binary endogenous variables and argues that the control function approach can be applied.

[26] The generalized residual can be computed as the derivative of the log likelihood with respect to the constant term and is equal to the inverse mills ratio for a probit model.

[27] One potential issue with the control function approach is accounting for the new distribution of errors that is induced by the residuals included in the second stage equation. One solution is to apply the log-odds transformation and estimate the model in linear form as opposed to as a logit (Blass et al. 2010). The dependent variable is now $\ln[\alpha_{ij}/(1-\alpha_{\mathrm{ij}})]$ where α_{ij} is the share of consumption for individual i of alternative j. The benefit of this procedure is that the distribution of the errors around the mean doesn't affect consistency as long as the errors have zero conditional mean. However, this approach does not work if the shares for each alternative are not strictly positive. This is, in fact, the case with our data since almost 65% of respondents do not consume any filtered water and 18% drinking tap water only.

For the expenditure models we employ modeling strategies that address endogeneity within the selection model framework. Wooldridge (2010) and Schwiebert (2012) both outline approaches for handling endogeneity in selection models. The Wooldridge (2010) approach consists of first running a probit model for the selection equation and including the calculated inverse mills ratio in a 2SLS-IV model with the instrument. The other approach presented in Schwiebert (2012) starts by estimating the first stage of a 2SLS-IV model and then includes the estimated residual in the selection and expenditure equation of a Heckman selection model. This second approach can be considered as an application of the control function method. The key difference between these two approaches is that the Wooldridge approach corrects for endogeneity only in the expenditure equation, whereas the Schwiebert approach controls for endogeneity in both the selection and expenditure equation of the selection model.

5 Results

5.1 Water Choice Model Results

We estimate four models to illustrate potential impacts of endogeneity in the estimation of water choices. Model 1 is a multinomial logit model that does not control for endogeneity. Model 2 uses the same multinomial framework as Model 1with the control function approach to correct for endogeneity. Models 3 and 4 are similar to Models 1 and 2 but use the latent class model framework in place of the multinomial logit in order to capture preference heterogeneity. In each model, three alternative choices are included: tap water, bottled water and filtered water. The equation for each alternative includes a constant (for bottled and filtered water), a set of water quality characteristics measured by self-reported perceptions (taste, odor, appearance and convenience), the risk measure and price. The price variables only enter the equations for filtered and bottled water. The “price” for tap water is assumed to be zero.

Table 4 presents the multinomial logit models without controlling for endogeneity (Model 1) and using the control function approach (Model 2). The estimated coefficients in Model 1 without correcting for endogeneity are all significant with signs that one would expect, with the exception of appearance. In terms of quality characteristics, water taste appears to be the most important and relevant to choices. The alternative specific constants for filtered and bottled water are negative and significant at the 1% level; suggesting that individuals prefer tap water, all other variables held constant, and that unobserved characteristics of water sources are important for water choices. The estimated coefficient on monthly cost is negative and significant suggesting that individuals are price sensitive. In terms of water risk perceptions, the estimated coefficient for the risk dummy variable, Drisk1, is −0.92 and significant at the 1% level suggesting that water sources with high perceived health risk levels are less likely to be chosen.

Model 2 applies the control function approach to correct for the endogeneity of water risk perceptions and is presented as the second set of results in Table 4. Because we include the constructed variables (i.e. the estimated residuals) in Model 2, the standard errors are computed standard errors using the Krinsky Robb procedure with 10,000 draws. The estimated coefficients in Model 2 are quite similar compared to Model 1 for all quality characteristics,

Table 4 Multinomial logit models of water choices

Variable	Model 1 (non-control)		Model 2 (control function)	
	Coefficient	SE	Coefficient	SE^
Taste				
Medium	1.251***	0.247	1.081***	0.252
High	2.450***	0.279	2.114***	0.304
Odor				
Medium	0.490**	0.247	0.352	0.250
High	0.608**	0.284	0.319	0.303
Appearance				
Medium	−0.029	0.285	−0.241	0.296
High	0.387	0.303	0.053	0.327
Convenience				
Medium	0.510**	0.234	0.526**	0.233
High	1.017***	0.230	0.973***	0.227
ASC				
Filtered	−1.203***	0.097	−1.308***	0.100
Bottled	−0.800***	0.138	−0.802***	0.139
Cost	−0.007***	0.001	−0.006***	0.001
Drisk1c	−0.924***	0.145	−2.875***	0.732
Residual				
Bottled			1.237***	0.456
Tap			1.191***	0.447
Filtered			1.216***	0.451
Log likelihood	−966.6		−962.8	
Likelihood ratio test	739.8		747.4	
Pseudo R^2	0.277		0.280	
AIC	1957.2		1955.6	
Number of Obs.	1302		1302	

^ The standard errors for Model 2 were calculated using the Krinksy–Robb procedure and 10,000 draws. The stars represent significance at 1% (***), 5% (**), and 10% (*) levels. The water quality characteristics (taste, odor, appearance, and convenience) are dummy variables with the low level omitted as the reference group. The Drisk1c dummy variable uses a high risk cut-off level of 1 in 1,000,000 chance of death in a year

the alternative specific constants, and the cost variable.[28] The coefficients for the three residuals are all positive and significant which suggests that Drisk1 is endogenous for all three water sources. The estimated coefficient for the Drisk1 variable decreases from −0.92 to −2.87 when controlling for its endogeneity and remains significant at the 1% level.

Table 5 presents the results of the latent class models (Models 3 and 4) which account for heterogeneity of preferences. Two classes were specified for each estimation.[29] Class

[28] There is some potential for the price coefficient to be also endogenous. While consumers are price takers for each bottle of water or package of bottled water, they may be able to somewhat control the price-per-litre by varying the amount of bulk purchases of water which may carry a lower price per litre.

[29] Models with additional classes were considered but not justified based on the AIC/BIC criteria or had difficulties converging.

membership is determined through a simple constant term to control for unobserved heterogeneity. The latent class models show a marked improvement in the likelihood function over the multinomial logit models. We label the two classes: a price-sensitive group, Class 1, which accounts for approximately 77.4% of the sample, and a price-insensitive group, Class 2, which accounts for the remaining 22.6% of the sample.

Model 3 is the latent class model that does not control for endogeneity and we can see that the estimated coefficients for the quality characteristics are quite similar across the two classes, as are the coefficients for the filtered water alternative specific constant. The estimated coefficients for the risk dummy variable are also quite similar across the two classes. The key differences in preferences between the classes are for bottled water and costs. The estimated coefficient for the bottled water alternative specific constant is −1.35 and statistically significant at the 1% level for Class 2 types and not statistically different from zero for Class 1 types. In terms of costs, the estimated coefficient is −0.001 and statistically significant at the 10% level for Class 2 types and is −0.018 and statistically significant at the 1% level for Class 1 types.

Turning to the control function results (Model 4) for the latent class model, the estimated coefficients for the three additional residual terms are all positive and statistically significant for Class 1 types. While they are of similar magnitude for Class 2 types, the coefficients are not statistically different from zero. By controlling for endogeneity, the estimated coefficient for the water risk perception dummy variable (Drisk1) decreases from −0.86 to −2.68 for Class 1 types.

5.2 Expenditure Model Results

Two models are estimated to illustrate the potential impacts of endogeneity in expenditures models. Model 5 and Model 6, respectively, correspond to the Wooldridge and Schwiebert approaches to handling endogeneity. In each case, three equations are specified: (1) a first stage equation of a 2SLS-IV model of water risk perception; (2) a selection equation that models whether individuals decide to purchase bottled water or not; and (3) an expenditure equation to determine how much bottled water to purchase. Table 6 presents the results for Model 5 and Model 6. Examining the first stage equations of water risk perception in the first two columns of Table 6, we can note that the skin cancer variable is strongly correlated with water risk perceptions. Testing for instrument strength, the F-statistic is 35.0 for the two models suggesting that the skin cancer variable does not suffer from a weak instrument problem.

The third and fourth columns in Table 6 present the results for the selection equation which models the decision of whether to purchase bottled water or not. The key difference is Model 5 includes the estimated residual in the selection equation. As expected, all four high ratings for bottled water characteristic coefficients are estimated to be positive. Bottled water convenience, taste and appearance coefficient estimates are generally statistically significant suggesting that these non-risk characteristics are important determinants of whether to purchase bottled water or not. Conversely, estimated coefficients for high ratings of tap and filtered water quality characteristics are negative suggesting that respondents with higher ratings are less likely to purchase bottled water. For Model 6, the included residual in the selection equation is significant at the 10% level which suggests that the water risk perceptions may be endogenous in the selection equation. The Drisk1 dummy variable coefficient is estimated to be positive and significant for both models suggesting that per-

Table 5 Latent class models of water choices

Variable	Model 3 (non-control)				Model 4 (control function)			
	Class 1: price sensitive (77.4%)		Class 2: price insensitive (22.6%)		Class 1: price sensitive (76.9%)		Class 2: price insensitive (23.1%)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE^	Coefficient	SE^
Taste								
Medium	1.061***	0.317	1.428**	0.665	0.906***	0.326	1.187*	0.687
High	2.221***	0.364	2.642***	0.759	1.900***	0.394	2.245***	0.820
Odor								
Medium	0.515	0.316	0.498	0.646	0.391	0.323	0.326	0.650
High	0.576	0.365	0.751	0.736	0.321	0.391	0.354	0.799
Appearance								
Medium	−0.013	0.361	−0.069	0.794	−0.225	0.374	−0.217	0.786
High	0.422	0.386	0.379	0.864	0.100	0.414	0.085	0.878
Convenience								
Medium	0.452	0.292	0.587	0.693	0.471	0.289	0.601	0.677
High	0.896***	0.286	1.235*	0.677	0.861***	0.284	1.167*	0.662
ASC								
Filtered	−1.119***	0.121	-1.213***	0.273	−1.210***	0.133	-1.351***	0.300
Bottled	−0.059	0.206	−1.354***	0.316	−0.057	0.206	−1.324***	0.311
Cost	−0.018***	0.003	−0.001*	0.001	−0.018***	0.003	−0.001	0.001
Drisk1c	−0.864***	0.190	−1.095**	0.455	−2.678***	0.912	−3.328*	1.897
Residual								
Bottled	–	–	–	–	1.166**	0.573	1.369	1.197
Tap	–	–	–	–	1.108**	0.557	1.419	1.169
Filtered	–	–	–	–	1.117**	0.563	1.432	1.177

Table 5 continued

Variable	Model 3 (non-control)				Model 4 (control function)			
	Class 1: price sensitive (77.4%)		Class 2: price insensitive (22.6%)		Class 1: price sensitive (76.9%)		Class 2: price insensitive (23.1%)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE^	Coefficient	SE^
Log Likelihood	−949.3				−945.6			
Likelihood ratio test	962.2				969.5			
Pseudo R^2	0.336				0.339			
AIC	1948.6				1953.3			
Number of Obs.	1302				1302			

^ The standard errors for Model 4 were calculated using the Krinksy–Robb procedure and 10,000 draws. The stars represent significance at 1% (***), 5% (**), and 10% levels (*). The water quality characteristics (taste, odor, appearance, and convenience) are dummy variables with the low level omitted as the reference group. The Drisk1c dummy variable uses a high risk cut-off level of 1 in 1,000,000 chance of death in a year

Table 6 Expenditure models

Dependent variable	First stage equation		Selection equation		Expenditure equation	
	Model 5 Drisk1e	Model 6	Model 5 treatb	Model 6	Model 5 Monthly bottled water cost	Model 6
Variable			Coefficients (robust standard errors^)			
Constant	0.135***	0.135***	0.565***	0.255	51.3**	−60.0
	(0.039)	(0.039)	(0.194)	(0.264)	(24.9)	(53.3)
Bottled						
Taste	0.104***	0.104***	0.467***	0.343**	−9.65	5.76
	(0.034)	(0.034)	(0.115)	(0.139)	(24.5)	(35.7)
Odor	0.0641*	0.0641*	0.125	0.0603	−27.5	−41.1
	(0.038)	(0.038)	(0.133)	(0.153)	(21.8)	(26.7)
Appearance	−0.003	−0.003	0.319**	0.303*	5.97	2.13
	(0.034)	(0.034)	(0.138)	(0.164)	(18.4)	(30.7)
Convenience	−0.025	−0.025	0.711***	0.749***	13.6	41.0
	(0.028)	(0.028)	(0.096)	(0.117)	(15.5)	(25.2)
Income	−0.077***	−0.077***	0.217**	0.311***	−4.08	4.52
	(0.025)	(0.025)	(0.085)	(0.106)	(12.2)	(19.5)
HH size	0.0057	0.0057	0.051	0.042	14.4**	21.2**
	(0.009)	(0.009)	(0.038)	(0.043)	(6.06)	(8.76)
Skin cancer	0.149***	0.149***	–		–	–
	(0.025)	(0.025)	–		–	–
Inverse mills ratio	−0.008	–	–		15.2***	114.1***
	(0.018)	–	–		(5.64)	(40.5)
Drisk1e	–	–	0.207*	1.43**	135.9*	251.0*
	–	–	(0.109)	(0.672)	(77.9)	(133.5)

Table 6 continued

Dependent variable	First stage equation		Selection equation		Expenditure equation	
	Model 5 Drisk1e	Model 6	Model 5 treatb	Model6	Model 5 Monthly bottled water cost	Model 6
Variable			Coefficients (robust standard errors^)			
Residual	–	–	–	−1.18*	–	−238.2*
	–	–	–	(0.675)	–	(126.3)
Tap						
Taste	–	–	−0.218	−0.192	–	–
	–	–	(0.136)	(0.139)	–	–
Odor	–	–	−0.042	−0.053	–	–
	–	–	(0.152)	(0.164)	–	–
Appearance	–	–	−0.418***	−0.392***	–	–
	–	–	(0.138)	(0.146)	–	–
Convenience	–	–	−0.238**	−0.243**	–	–
	–	–	(0.117)	(0.118)	–	–
Filtered						
Taste	–	–	−0.297**	−0.301*	–	–
	–	–	(0.138)	(0.157)	–	–
Odor	–	–	−0.169	−0.174	–	–
	–	–	(0.159)	(0.176)	–	–
Appearance	–	–	−0.128	−0.129	–	–
	–	–	(0.157)	(0.151)	–	–
Convenience	–	–	−0.036	−0.039	–	–
	–	–	(0.102)	(0.104)	–	–

Table 6 continued

Dependent variable	First stage equation		Selection equation		Expenditure equation	
	Model 5 Drisk1e	Model 6	Model 5 treatb	Model6	Model 5 Monthly bottled water cost	Model 6
Variable			Coefficients (robust standard errors^)			
Child	–	–	0.080	0.087	–	–
	–	–	(0.109)	(0.109)	–	–
Age index	–	–	−0.339***	−0.327**	–	–
	–	–	(0.129)	(0.136)	–	–
College	–	–	−0.033	−0.037	–	–
	–	–	(0.105)	(0.104)	–	–
Female	–	–	0.077	0.086	–	–
	–	–	(0.083)	(0.089)	–	–
No observations	1302	1302	1302	1302	1302	1302
F test of instrument (skin cancer)	35.0	35.0				

^ The standard errors for Model 6 were calculated using the bootstrap method and 400 draws. The stars represent significance at 1% (***), 5% (**), and 10% (*) levels. The water quality characteristics (taste, odor, appearance, and convenience) are the high level dummy variables and the coefficients can be interpreted relative to the low and medium levels. The Drisk1e dummy variable uses a high risk cut-off level of 1 in 1,000,000 chance of death in a year

Table 7 Bias in risk perception estimates when not controlling for endogeneity

Risk dummy variable	Drisk0 (>0%) (%)	Drisk1 (>0.000001%) (%)	Drisk2 (>0.000002%) (%)
Choice models			
Multinomial logit	−68	−70	−71
Latent class (Class 1)	−73	−68	−71

Drisk0 considers any individual with a positive risk perception level as high risk, Drisk1 uses a high risk cut-off level of 1 in 1,000,000 chance of death in a year, and Drisk2 uses the high-risk cut-off level of 2 in 1,000,000. Drisk10 biases are not presented because most of the naïve estimates are not significant. The estimated bias for the expenditure models cannot be calculated because the coefficients are insignificant when the endogeneity of perceptions is not addressed

ceived tap water risk is an important consideration in whether to purchase bottled water or not.

The fifth and sixth columns of Table 6 present the results for the expenditure equation which models the intensity of averting action.[30] For both models, the estimated coefficient for the Inverse Mills Ratio variable is positive and statistically significant suggesting that it is important to take into account selection effects in modeling bottled water expenditures. The test for endogeneity of water risk perceptions is different under the two modeling approaches, but both tests suggest that water risk perception is endogenous in the expenditure equation. Because the expenditure equation is estimated as part of a 2SLS-IV model in Model 5, we can conduct a Hausman test on water risk perceptions. The Hausman test statistic is 4.18 (p value $= 0.041$) which is statistically significant at the 5% level. For Model 6, we can test endogeneity with a t-test on the estimated residual. The estimated coefficient for the included residual is negative and statistically significant at the 10% level which implies that not controlling for endogeneity would bias the water risk perception coefficient downwards. Turning to the variable of interest, the Drisk1 coefficient is estimated to be positive and significant for both approaches and ranges from \$135.9 in Model 5 to \$251.0 in Model 6. These values can be interpreted as the monthly expenditure on bottled water that can be attributed to avoiding tap water health risks. The difference in coefficient estimates between these two approaches can be partly explained by the fact that Model 5 does not control for endogeneity in the selection equation, while Model 6 controls for endogeneity in the selection and expenditure equations. These expenditure model results corroborate the central result already observed with the choice models: risk perceptions are endogenous and not correcting for this endogeneity will underestimate the value of risk reductions.

5.3 Results for Alternative Specifications of the Risk Perception Variable

While the results presented so far suggest that not controlling for endogeneity in these models leads to a substantial underestimation in the value of risk reductions, we recognize the relative arbitrary choice of the specific dummy variable cut-off level. Therefore, to investigate this, we re-estimate the full set of results using the three other cut-off levels summarized in Table 3. We summarize our findings in Table 7. It presents the bias in the risk coefficient as we change the dummy variable cut-off level specification by comparing estimates from models that do not control for endogeneity (Models 1 and 3) with those that do. For the

[30] Note that similar to Models 2 and 4, Model 6 uses constructed variables in the selection and expenditure equations and the standard errors of the parameter estimates will not be valid (Wooldridge 2010). Therefore, we use nonparametric bootstrap replication to calculate estimates of empirical standard errors.

expenditure models, the risk coefficient is not statistically significant using a simple selection model without controlling for endogeneity. The endogeneity biases are similar across cut-off choices and estimation approaches; they range between −68 and −73%. Across all estimates, the endogeneity bias from using naïve models is −70%. Stated equivalently, the effect of water risks is estimated to be 3 times higher using approaches that control for endogeneity compared to models that do not.

5.4 Welfare Estimates

Using the modeling results presented above, we can derive implied welfare estimates for water risk reductions. We use the risk reduction levels presented in Table 3 as the relevant risk changes.[31] To make our results comparable to previous estimates in the literature, we convert these values to an implied Value of a Statistical Life (VSL) estimate. To arrive at an estimate of an individual VSL, we divide the costs by the average household size in the survey (2.95 individuals), and multiply the monthly costs by 12 to yield annual costs.

The VSL results for all modeling approaches and the four Drisk levels are presented in Table 8.[32] Examining the results using Drisk0 in the first column, the VSL estimates for the multinomial logit model are \$2.6 million for Model 1 (without controlling for endogeneity) and \$8.1 million for Model 2 (that controls for endogeneity). For the latent class models, we present the VSL estimates for Class 1 types (Class 2 types are price insensitive) which are around 77% of the sample. Controlling for endogeneity increases the VSL estimate from \$0.9 million in Model 3 to \$3.4 million in Model 4 for Class 1 types. For the expenditure models, the VSL is estimated to be \$3.0 million using the coefficients from Model 5 and \$5.4 million using Model 6's estimated coefficients. The other columns of Table 8 correspond to VSL estimates using different high risk cut-off values for the water risk dummy. Across most model specifications, as the high risk cut-off values increase, the VSL estimates decrease. These results can perhaps be expected because, as shown in Table 3, the mean risk reductions increase as the risk dummy cut-off values increase. Thus, the lower VSL estimates are associated with higher mean risk reductions. For the choice models, the change in VSL estimates is relatively small across Drisk0, Drisk1, and Drisk2 suggesting a certain degree of proportionality across small changes in low risk levels. For the expenditure models, the substantial decrease between Drisk0 and Drisk1 suggest nonlinearity in valuation of smaller risk changes.

5.5 Robustness Analysis

In addition to our examination of the effects of the choice of the risk dummy variable cut-off level, we conduct three additional robustness checks on our modeling results because the appropriate first-stage model, distribution of the error term, and instrument variable are specification issues. First, we use a linear probability model in the first stage equation instead

31 For the expenditure models, the estimated coefficient for Drisk1e represent the value individuals place on a reduction in tap water mortality risk level of 0.0002814%. For the choice models, we can divide the Drisk1c coefficient by the cost coefficient to derive the implied value for a reduction in general water mortality risk level of 0.0002119%.

32 We also ran the models using a more limited sample which excluded the 5% of individuals with the highest tap water risk perceptions. Welfare measures estimated using models without these extreme individuals were generally higher by 20–40% across the different risk levels. For example, using the Drisk0 risk level and the limited sample, the VSL estimate for the multinomial logit model (Model 2) is estimated to be \$10.7 million (32% higher than the full sample result) while the estimate for the latent class model (Model 4) is estimated to be \$4.8 million (41% higher).

Table 8 Mean value of a statistical life (VSL) welfare estimates (2009 Canadian Dollars, millions)

Model approach	Control for Endogeneity	High risk cut-off value			
		Drisk0 (>0%)	Drisk1 (>0.000001%)	Drisk2 (>0.000002%)	Drisk10 (>0.00001%)
Choice models					
Model 1:	No	\$2.63	\$2.64^	\$2.12^	\$0.37^
Multinomial logit		(0.84)	(0.71)	(0.57)	(0.20)
Model 2:	Yes	\$8.12	\$8.72	\$7.23^	\$2.04
Multinomial Logit		(4.12)	(3.25)	(2.46)	(1.10)
Model 3: Latent	No	\$0.91	\$0.94	\$0.80^	Not sig.
Class (Class 1)		(0.35)	(0.26)	(0.20)	
Model 4: Latent	Yes	\$3.37^	\$2.94	\$2.79^	\$0.84
Class (Class 1)		(1.80)	(1.12)	(0.90)	(0.50)
Expenditure models					
Model 5	Yes	\$2.96	\$1.97	\$1.71	\$1.19
	(Expenditure equation only)	(1.75)	(1.13)	(0.98)	(0.67)
Model 6	Yes	\$5.41	\$3.63	\$3.05	\$2.14
	(Both selection model equations)	(2.96)	(1.93)	(1.58)	(1.05)

Standard errors in parentheses. ^ indicates that the cost variable for these models was divided by 100 for computational reasons. Drisk0 considers any individual with a positive risk perception level as high risk, Drisk1 uses a high risk cut-off level of 1 in 1,000,000 chance of death in a year, Drisk2 uses the high-risk cut-off level of 2 in 1,000,000, and Drisk10 uses 10 in 1,000,000. The estimates for Model 1–4 were calculated as the ratio of the Drisk and cost coefficients using the Krinksy–Robb procedure and 10,000 draws. The standard errors for Model 6 were calculated using the bootstrap method and 400 draws. Not sig. denotes not statistically different from zero at the 10% significance level. For the Latent Class Models, values are presented for Class 1 types (77% of sample for all risk levels) only as Class 2 types' WTP values are not statistically significant. Control function results are presented using the skin cancer variable interacted with age index, gender, language in the first stage probit model

of a probit model. Second, we include higher-order polynomials of the residual terms to relax the assumption that the residuals enter the second stage models as a simple linear term. Third, we use alternative socio-demographic variables interacted with the skin cancer variables to generate the three instruments for use in the first stage. We illustrate these robustness checks with the results from the latent class model using the control function approach (Model 4).

Table 9 presents the VSL estimates for different combinations of these alternative specifications. Comparing estimates between probit and linear first-stage specifications, we note that the linear probability model generally estimates higher welfare measures. However, any differences in results between probit and linear first stage specifications diminish substantially as higher-order residual terms are included. This finding suggests may wish to adopt more flexible control functions in place of a simple linear specification. The results from the probit first stage specification are more sensitive to the inclusion of higher-order residuals which tend to increases the VSL estimates. Polynomial transformations of the residuals from the linear probability model do not lead to substantial changes in VSL estimates. Examining

Table 9 Mean value of a statistical life (VSL) estimates using the latent class Model (Model 4) under alternative specifications (2009 Canadian Dollars, millions)

Risk dummy variable	First-stage specification	Interacted Instrumental variables	First-order residuals	Second-order residuals	Third-order residuals
Drisk0	Probit	Age index, gender, language	\$3.37	\$4.08	\$4.43
			(1.80)	(1.93)	(2.35)
	Linear		\$4.02	\$3.89	\$4.02
			(1.68)	(1.70)	(1.86)
Drisk1	Probit		\$2.94	\$3.09	\$4.09
			(1.12)	(1.13)	(1.54)
	Linear		\$3.67	\$3.70	\$4.12
			(1.24)	(1.30)	(1.40)
Drisk2	Probit		\$2.79	\$3.11	\$3.35
			(0.90)	(0.95)	(1.21)
	Linear		\$3.47	\$3.54	\$3.41
			(1.07)	(1.04)	(1.21)
Drisk10	Probit		\$0.84	\$1.37	\$1.51
			(0.50)	(0.59)	(0.79)
	Linear		\$1.60	\$1.79	\$1.71
			(0.66)	(0.73)	(0.83)
Drisk1	Probit	Age index, gender, college	\$2.48		
			(1.19)		
	Linear		\$3.07		
			(1.35)		
	Probit	Age index, gender, hhsize	\$2.53		
			(1.20)		
	Linear		\$2.96		
			(1.32)		
	Probit	Age index, gender, wrong	\$2.32		
			(1.18)		
	Linear		\$2.88		
			(1.33)		
	Probit	Age index, gender, child	\$2.22		
			(1.15)		
	Linear		\$2.70		
			(1.24)		

Table 9 continued

Risk dummy variable	First-stage specification	Interacted Instrumental variables	First-order residuals	Second-order residuals	Third-order residuals
	Probit	All seven IV dummies (age index, gender, language, college, hhsize, wrong, child)	\$3.22		
			(1.18)		
	Linear		\$3.83		
			(1.23)		

Standard errors in parentheses. Drisk0 considers any individual with a positive risk perception level as high risk, Drisk1 uses a high risk cut-off level of 1 in 1,000,000 chance of death in a year, Drisk2 uses the high-risk cut-off level of 2 in 1,000,000, and Drisk10 uses 10 in 1,000,000. The estimates were calculated as the ratio of the Drisk and cost coefficients using the Krinksy-Robb procedure and 10,000 draws. The values are presented for Class 1 types (~77% of sample for all specifications) as Class 2 types' WTP values are not significant

the second set of results in Table 9, we can note that the results are relatively robust to the different socio-demographic variables interacted with the skin cancer risk variable.

While our study is illustrative of the direction and magnitude of the impact of endogeneity and not on a specific measure of VSL, a comparison with the general VSL literature is instructive. The most comparable results are from a Canadian stated preferences study of cancer and microbial disease risk reductions in municipal drinking water systems that estimated a VSL of \$14 to \$20 million (2004 CAD) (Adamowicz et al. 2011). These VSL estimates are based on willingness to pay to avoid public risk reductions and may include altruistic values in contrast to our VSL estimates that capture only private risk reductions. The Treasury Board of Canada Secretariat's (2007) Cost-Benefit Guide recommends that federal departments use a VSL value of \$6.1 million (2004 CAD) based on an earlier meta-analysis by Chestnut et al. (1999). In their global meta-analysis, Lindhjem et al. (2011) calculate an average VSL of approximately \$6.1 million (2005 USD) across all studies. The VSL estimates in this paper are lower than these measures, but our estimates are based on averting expenditures, and as such can be seen as lower bound estimates. Interestingly, Lindhjem et al. (2011) also present an average VSL for studies with a specific health risk focus and their figure of \$4.0 million (2005 USD) is quite comparable to the range of values estimated in our study.

6 Conclusions

This paper estimates a series of averting behavior models for water alternatives using reported choices and expenditures on drinking water options. In order to account for risk perceptions, the models include a self-reported probability measure of risk of death obtained from the use of a novel interactive risk ladder employed in our Internet-based survey of Canadian respondents. The results suggest the presence of averting behavior with respect to water and that perceived mortality is a significant predictor of water consumption choices. The estimates of the economic value of risk reductions are generally similar between the choice and expenditure modeling frameworks.

Naïve models that ignore endogeneity of risk perceptions underestimate the effect of risk perceptions on water choices/expenditures. For the expenditure models, the risk coefficients are insignificant in a simple selection model that does not account for endogeneity, but they become positive and significant when the endogeneity of risk perceptions is taken into account. Across the choice model specifications, the average bias in the water risk coefficient is −70% compared to models that correct for endogeneity. Accordingly, welfare measures derived from models that control for endogeneity are around 3 times higher compared to naïve model estimates and this result appears to be relatively robust over the different modelling approaches, alternative methods to treat endogeneity, and representations of risk. This finding suggests that caution is required when estimating econometric models that include individual perception variables and highlights the importance of properly testing and controlling for endogeneity. More broadly, the techniques employed in this paper can be applied to other econometric settings where the researcher is interested in including potentially endogenous variables (e.g. individual attitudes, beliefs, opinions, etc.) either because these variables are of interest or the researcher would like to include other potentially endogenous variables as controls.

Using responses to survey questions as instruments to help address issues of endogeneity also has its own limitations. On the one hand, surveys are an ideal setting for working with instrumental variables because the researcher has complete control over survey design and can include specific questions to be used as strong, valid instruments. In this research, the specific question on skin cancer risks was included in the survey in this spirit. On the other hand, completely satisfying the exogeneity criterion of instrumental variables will always be difficult with survey data as long as the same individual is answering all the questions. Respondent mood, attitudes, and other unaccounted for biases may raise concerns about links between the instrumental variable and the dependent variable that bypass the potentially endogenous variable. However, careful design and testing of survey questions can provide useful instrumental variables that help address endogeneity issues in applied work.

Acknowledgements Thanks to Shelby Gerking for comments on an earlier version of this work. We would like to thank the Canadian Water Network for financial support of the survey.

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