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**Are Views of Water Bodies Related to Water Consumption?
An Empirical Analysis from New Zealand**

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Abstract

Freshwater scarcity is worsening as we quickly approach the freshwater planetary boundary. There has been extensive research and policy development in the space of water scarcity, pollution and accessibility, centered around the Sustainable Development Goals (SDGs). A large body of literature examines household and climate characteristics predictive of water consumption by households. However, there does not appear to be any research on the role of views of and proximity to water bodies in household water consumption. While researchers have long recognised the relationship between “water views” and property prices, the relationships between water views and water consumption have been all but ignored. In this paper, we develop a simple model of water consumption which depends on the perceptions of water scarcity and the perceptions of whether water scarcity is an issue. Using geographic information systems (GIS) viewshed analysis, we model whether properties in Tauranga, New Zealand, have views of lakes and the coast. We then use these variables in a fixed effects model of water consumption. We find that views of lakes are associated with higher water consumption and views of the coast are associated with lower water consumption. We suggest that these effects are driven by psychological biases which alter the perceptions of water scarcity and concern for water scarcity. We deploy a range of robustness checks and argue that our results are likely causal. However, there is still plenty of research required to comprehensively unpack the relationship between views of water bodies and water consumption.

Keywords

Water consumption

Viewshed analysis

Water scarcity

Fixed effects

Water demand

JEL Classification

D12, D91, Q21, Q25

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1. Introduction

Freshwater scarcity is a prominent issue globally and we are fast approaching the freshwater consumption planetary boundary (Kummu et al., 2016; Rockström et al., 2009). Much research and policymaking have focussed on reducing water scarcity, pollution and making water accessible for all. These foci are clearly evident in the United Nation's Sustainable Development Goals (SDGs) which provide the foundations of research and initiatives around the world (United Nations, 2015). Moreover, water accounting methodologies have become popularised as a means of tracking the extraction, use and return of water across regions and countries (United Nations, 2012). These approaches aim to improve the management of water resources at a regional level. In Aotearoa New Zealand, towns, cities and regions are facing more intense and frequent droughts (worsening with climate change), which are adding stress to water resources (Sood & Mullan, 2020). These threats, along with declining water quality and a historic underinvestment in water management infrastructure, have led to the proposal of the controversial Three Waters Reforms (Department of Internal Affairs, 2017). In light of these global and local issues, understanding water demand and household water consumption behaviour is more critical than ever for designing effective water management policy and infrastructure.

There is a large body of literature that demonstrates clear associations between household characteristics (demographics) and water demand (for a review, see Worthington & Hoffman, 2008). Research shows that higher incomes and higher property values are associated with greater water consumption across a range of contexts (Fielding et al., 2012; Ghavidelfar et al., 2017, 2018; Lyman, 1992; Worthington & Hoffman, 2008). Moreover, Worthington & Hoffman (2008) describe a range of other demographic factors that affect water consumption, like household size (which also operates through the property value and income channels), age, interest in gardening, and education level (Worthington & Hoffman 2008). These types of findings are important to policymakers as they allow water policy and demand interventions to be more targeted and thus more efficient. Indeed, there is a burgeoning literature which assesses how and where policy interventions reduce water consumption and encourage pro-environmental behaviours (for a review of field experiments in environmental economics, see Brent et al., 2017). There is also a large field of research that looks into the role of nudges - altering choice architecture without changing incentives or using coercion - in reducing water consumption (Schubert, 2017; Thaler & Sunstein, 2009).

One household characteristic that may influence water consumption but has received relatively little attention is the views of nearby water bodies. Could living near the coast or a lake impact water consumption? If so, what does that mean for future policy work around reducing water consumption and addressing water scarcity?

In this paper, we use water consumption data for Tauranga, New Zealand, to investigate whether the relationship between views of water bodies and water consumption. We first use Geographic Information Systems (GIS) viewshed analysis to calculate whether properties have views of water bodies and how far they are from these water bodies. We distinguish between

views of lakes and views of the coast, as these two types of water bodies are quite distinct in Tauranga and views of them may have differential impacts on water consumption. We then use these variables in standard econometric models of water consumption to examine whether household views of water bodies are related to water consumption.

There is an extensive literature that uses viewshed analysis (and variations of viewshed analysis) to determine if properties have views of the sea and of lakes. A substantial proportion of this literature uses viewshed output as a regressor in hedonic models for property valuations and find positive relationships between views of the sea or lakes and property value (Brown & Brabyn, 2012; Hindsley et al., 2013; Sander & Polasky, 2009; Shultz & Schmitz, 2008). Brabyn (2009) uses viewshed analysis in developing the New Zealand Landscape Classification (NZLC), which depends on the views and perceptions of landforms from a particular location. Bourassa et al. (2004) uses viewshed analysis to find that the effects of views of water bodies on property value diminishes with distance from the water body. Shultz & Schmitz, (2008) find views of small man-made lakes have significant positive effects on property value. This is particularly relevant for the Tauranga region, which mostly contains small lakes.

Views of water affect perceptions of landscape character (Brabyn, 2009; Brown & Brabyn, 2012). We propose that views of water also affect the perceptions of water scarcity and the perceptions of the intrinsic value of water (in line with the literature on pro-environmental attitudes and behaviours - see Rosa & Collado, 2019). These perceptions may subsequently affect water consumption and undermine public water conservation campaigns run during warm periods and droughts (usually, in Summer). As far as we are aware, there are no studies econometrically linking water consumption and views of water.

We develop a simple theoretical model of water consumption, building on the literature on the relationship between perceived water scarcity and water consumption. Some studies have shown negative associations between awareness of water scarcity issues and water consumption (Dolnicar et al., 2012; Gregory & Leo, 2003; Tang et al., 2013). In our model, if views of water bodies increase (decrease) the perceptions of water scarcity or the concern for water scarcity issues, water consumption will decrease (increase). We then run fixed effects regression models regressing views of water bodies on water consumption, controlling for seasonality and time-invariant unobservables. We propose possible interpretations of results, in line with our theoretical model, using insights from behavioural economics and psychology. Our results are robust to changes in the specification of the independent variable, adding controls, using more conservative modelling approaches and selection on unobservables (which we test using the methods described by Oster, 2019). This leads us to conclude that the relationships we find are likely causal.

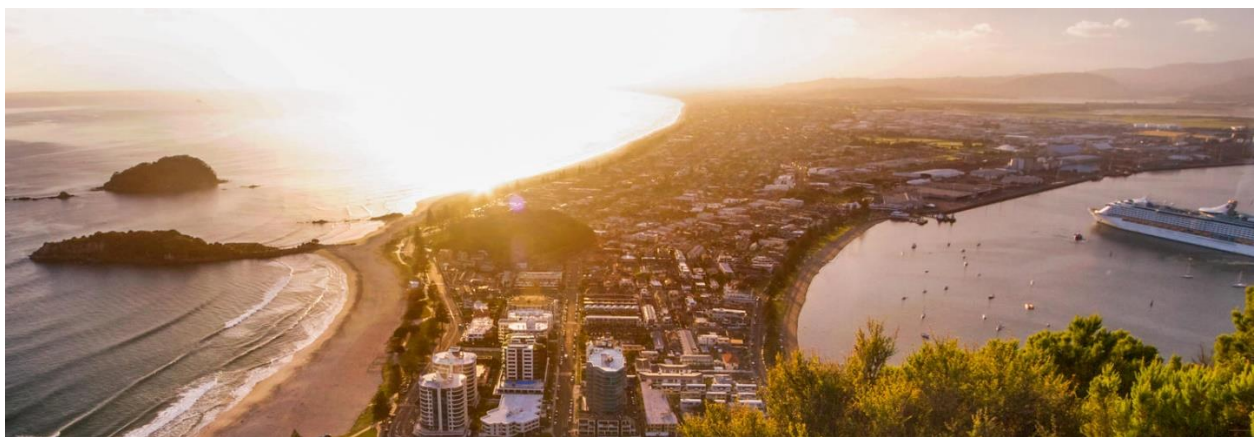
Our contribution to the literature is three-fold. First, we empirically estimate the relationship between views of water bodies (lakes and the coast) and water consumption, which hasn't been done as far as we are aware. Second, we develop a novel theoretical model describing the relationship between views of water bodies and water consumption. Third, we link this model to the behavioural economics and psychology literature to suggest why the

effects of views of water bodies may differ depending on the type of water body. While we cannot directly test our theoretical model and proposed mechanisms, they provide a strong foundation for future research in this area.

2. Empirical Context

Tauranga (Figure 1) is a coastal city in New Zealand which is well-suited for analysing the effects of water views because it has both a coastline and freshwater lakes. The beaches and sea are highly regarded internationally. The lakes are relatively small and arguably less appealing. Indeed, there are no "major" lakes in Tauranga (Elisha Sawe, 2017).¹ This study uses quarterly household-level water consumption data for approximately 39,224 single-unit residential properties in Tauranga for the year 2020-21.

Figure 1. A picture of Mount Maunganui beach and the Tauranga coastline. (Source: 100% Pure New Zealand, 2022).



3. Theory

3.1 Model Overview

We adapt the approaches taken in Chan and Kotchen (2014) and Dorner (2019) to theorise a simple utility function:

$$u = U(Y, -\theta k) \tag{1}$$

where utility u is a function increasing in water consumption Y , decreasing in the perceived contribution to water scarcity k and quasi-concave. θ is an indicator of whether the consumer cares about water scarcity $\theta \in [0,1]$. In reality, θ could take on many values between zero and one, but for simplicity, we could assume there are two types of consumers: those who care ($\theta = 1$) and those who do not care ($\theta = 0$) about water scarcity.

¹ Major refers to the top twenty lakes in New Zealand by surface area.

The perceived contribution to water scarcity k can be written as a function of water consumption itself (as higher water consumption reduces the availability of water for others) and the perceived extent of the water scarcity issue.

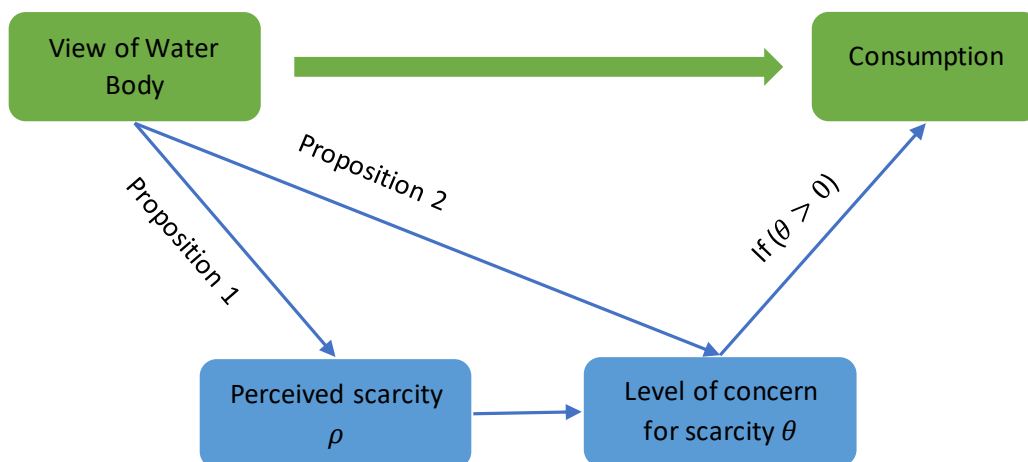
$$k = \rho Y \tag{2}$$

where ρ is the perception of the extent of the water scarcity issue and is a real number between 0 and 1 [$\rho \in \mathbb{R} \mid 0 \leq \rho \leq 1$]. We can see that if $\rho = 0$ - that is, the individual doesn't believe there are any water scarcity issues - the perceived contribution to water scarcity k will be equal to zero and the utility function will contract to only be increasing in the consumption of water Y . We can re-write (1) by integrating (2):

$$u = U(Y, -\theta\rho Y) = U[Y(1 - \theta\rho)] \tag{3}$$

From (3), our model shows that if consumers perceive greater water scarcity *and* care about water scarcity, utility from water consumption will decline at all levels of consumption and *ceteris paribus*, we expect individuals to consume less water. We propose that views of water bodies affect parameters ρ and θ and thus affects water consumption. We diagrammatically illustrate this in Figure 2. This model would lend itself to structural estimation (if you could measure perceived scarcity and concern for scarcity), which is out of the scope for this paper.

Figure 2. Theoretical model of water scarcity effect (blue boxes and lines represent the proposed unobservable mechanism through which the observed relationship - in green - occurs).



3.2 Model background and research propositions

Our simple framework is consistent with the literature on the relationship between perceived water scarcity and water consumption. Several studies show negative associations between awareness of water scarcity or water conservation issues and water consumption (Dolnicar et al., 2012; Gregory & Leo, 2003; Jorgensen et al., 2009). For example, Tang et al. (2013), in the context of agricultural water use, posits that, “farmers' water use strongly relates to their

awareness and perception of water shortage". Tang et al. (2013) develops a structural model to examine the determinants of farmers' perceptions of water scarcity and find that age, time spent farming and social networks significantly influence these perceptions. However, the authors do not consider views of water bodies as determinants of the perceptions of water scarcity and do not empirically link perceptions of water scarcity to water consumption.

In line with Singh et al. (2018), we argue that persistent views of water bodies are part of peoples' experiences and interactions with water and this in turn influences their perceptions of water scarcity issues and the degree to which they care about such issues. Hence, in our theoretical framework, we propose that views of and proximity to water affects consumption by influencing ρ and θ . However, views and proximity to water will only influence water consumption if people care about water scarcity in the first place ($\theta > 0$). We show the proposed effect on perceived water scarcity of having views of water bodies in Figure 2. In Figure 2, the blue lines represent the proposed mechanism for the effect of views of water bodies on water consumption (the observable effect shown by the green arrow). We note that in our later analysis, we cannot directly observe perceptions of water scarcity and the extent to which consumers care about water scarcity (and we therefore cannot show whether our proposed mechanisms are true). Nonetheless, the model in Figure 2 provides a useful foundation for future research that may couple structural estimation (in line with Tang et al., 2013) and the empirical analysis of water consumption data.

Concerning the differential impact of views of lakes and views of the coast on water consumption, we state two propositions that are in-line with our theoretical conceptualisation of water demand, the local context and the economics and psychology literature.

We suggest that consistent views of and interactions with lakes may lead to downward-bias estimates of the severity of water scarcity issues and thus lead to higher water consumption. Individuals who are frequently exposed to freshwater may be prone to the Baader–Meinhof phenomenon (frequency bias) where they believe there is more freshwater than there actually is (Fiedler & Armbruster, 1994). Tversky & Kahneman (1973) describe a similar notion of availability bias, where an individual's perceptions of a group are based on readily available information. Hence, we may expect individuals to form their views of the state of water assets and scarcity in-part by their immediate surroundings.

Proposition 1: individuals with lake views will have a lower perception of water scarcity ρ and *ceteris paribus* consume more water

On the other hand, we suggest that consistent views of the "beautiful" Tauranga coastline may garner a higher level of intrinsic value for water and thus reduce water consumption (100% Pure New Zealand, 2022). In the study area (Tauranga), the beaches and coast are of high-quality nationally and internationally. For example, 100% Pure New Zealand (2022) describes Mount Maunganui Beach (in Tauranga) as one of the most stunning beaches in New Zealand (Figure 1). Moreover, in 2019, Mount Maunganui Beach was ranked as the top beach on TripAdvisor for the sixth year running. We hypothesise that views of such

“stunning” beaches and coastline may generate a greater appreciation and concern for water scarcity. Analogous to beauty premiums in the labour market (Hamermesh & Biddle, 1994), being exposed to beautiful bodies of water may increase the value placed on water and result in a greater concern for water scarcity issues (affecting parameter θ instead of p). Indeed, there are many studies linking positive interactions with nature to a higher perceived values of nature (Rosa & Collado, 2019; Soga & Gaston, 2016; Wolsko & Lindberg, 2013).

Proposition 2: individuals with sea views will have greater concern for water scarcity and *ceteris paribus* consume less water.

In our econometric model of water demand, we estimate the relationship between views of lakes and views of the coast and water consumption, controlling for important property level characteristics, seasonality and regional heterogeneity. Again, we cannot elicit the exact mechanism through which this relationship is operating. However, if the relationships are significant and in-line with our propositions, it implies some support for the mechanisms proposed above.

4. GIS Data and Methods

All necessary data to determine views of and proximity to the coast and lakes for Tauranga City properties are publicly available. The full set of publicly available GIS data used in this paper are described in Table 1.

Table 1. Description of publicly available GIS layers used for analysis.

Layer	Description	Source
Statistical Area 1 Units	Definitive set of statistical area 1 (SA1) 2018 boundaries. SA1 units are a relatively new aggregation that combines meshblock units to present a greater level of detail on population characteristics. SA1 units usually contain 100-200 residents and are capped at 500 residents.	StatsNZ (2018)
NZ Territorial Authorities	Definitive set of New Zealand territorial authorities' boundaries. Territorial authorities are officially (Local Government Act 2002) defined as a city or district council.	StatsNZ (2019)
NZ Coastlines	This layer spatially delineates the coastline of New Zealand, defined as the line forming the boundary between land and sea at mean high water. This is part of the Topo50 map series for New Zealand.	LINZ (2022a)
NZ Lake Polygons	This layer digitises any standing bodies of fresh inland water (denoted here as lakes). This is part of the Topo50 map series for New Zealand.	LINZ (2022b)
NZ Property Parcels	Provides boundaries and title information for the full set of property titles registered in New Zealand.	LINZ (2022c)

	This data does not contain information on ownership or characteristics of any buildings.	
DEM (24 m resolution)	Global elevation data from Airbus Defence and Space's World DEM dataset. The resolution is 24 m and is the most consistent and accurate satellite-based DEM on a global scale.	Airbus Defence and Space (2022)

The following steps are used in ArcGIS Pro to operationalise the layers in Table 1 to produce variables for views of the coast and lakes and distance to the coast and lakes. These steps produce a series of points on the coast and around lakes that represent the locations we are calculating the viewsheds for.

ArcGIS Pro Step by Step Methods:

- 1) Select the Tauranga City polygon in the Territorial Authorities layer and create a new layer with only this polygon.
- 2) Clip the NZ Coastlines, NZ Lakes and NZ Property Parcels layers to the new Tauranga City polygon.²
- 3) Use the *Near* ArcGIS Pro function to calculate the shortest distance from each Tauranga property parcel to the coastline and the nearest lake. These are our proximity to the coast and lakes variables.
- 4) Use the *Generate Points Along Lines* ArcGIS Pro function to generate a series of points (N = 999) in close proximity around the perimeter of all Tauranga lakes, which are relatively small.³
- 5) Use the *Generate Points Along Lines* ArcGIS Pro function to generate a series of points along the Tauranga coastline (N = 750).
- 6) Generate a 3 km buffer around the coastline and then only select the buffer area that is in the Ocean (not on land).²
- 7) Select only ocean areas within the buffer by running a *Union* between the buffer layer and the Tauranga territorial authority boundary layer and selecting for areas outside Tauranga City's boundary (which doesn't cover the coastal marine area).
- 8) Use the *Generate Random Points* ArcGIS Pro function to generate random points (N = 250) in the 3 km sea buffer region.⁴
- 9) Merge the random points in the sea buffer with the points along the coastline.

² To clip the coastline layer, we digitised a new polygon which encompasses some of the Pacific Ocean because the Tauranga City territorial authority boundary does not include some relevant parts of the coast.

³ The number of points is somewhat arbitrary. We had to keep the number of points beneath 1000 for the viewshed tool and we selected as close to the maximum as possible to give us greater accuracy.

⁴ Properties may not be able to view the coast (or beach) but may have views of the sea just beyond the coastline. Hence, we create additional points in the sea to calculate viewsheds for. We do not do this for lakes because the lakes in Tauranga are relatively small and are fully enclosed polygons. Hence, the points on the opposite side of the lake will have the same effect as the additional random points we generate for the coast (which is not an enclosed polygon).

- 10) Use the *Viewshed (Ready to Use)* ArcGIS Pro function to calculate a raster for all locations (cells) within a 5 km radius that have views of any of the points around the lakes. This uses a 24 m DEM (Airbus Defence and Space, 2022).
- 11) Use the *Viewshed (Ready to Use)* ArcGIS Pro function to calculate a raster for all locations (cells) within a 5 km radius that have views of any of the points on the coast or in the sea buffer. This uses a 24 m DEM (Airbus Defence and Space, 2022).
- 12) Run a *Spatial Join* between the Tauranga properties layer and each viewshed (lakes and coast, respectively) using the match option “*have their centre in*”. This returns a value of one if the geometric centre of the property is in a location with views of the lake or sea (depending on which viewshed was used).
- 13) Finally, to clean the coast viewshed output, we intersect the resulting layer with the Tauranga City boundary to only include locations on land within the Tauranga City boundaries.

The DEM with a 24 m resolution obtains a good balance between achieving a sufficient level of detail and processing capability. A 24 m DEM is well within the range of DEM resolutions used in the academic literature and is manageable with standard computing hardware (Hindsley et al., 2013; Mason et al., 2021; Sander & Polasky, 2009). Moreover, the source of our DEM data (WorldDEM Dataset - Airbus Defence and Space, 2022) is widely used in academic research (for recent examples, see Farooq et al., 2019; Mason et al., 2021; Puliti et al., 2017).

Another option was to use Lidar data (1 m resolution DEM), which is available for most of New Zealand. However, as our viewshed analysis uses the entire Tauranga city territory, the computational requirements were excessive and unnecessarily precise for computing a “view” variable to be used in later econometric models. Hindsley et al., (2013) developed an adaptation of the typical viewshed analysis for assessing the impact of water views on property values. They generate a unique DEM for each property to ensure that individual properties don’t block their own view of amenities and so that a full 360-degree view can be accounted for. This approach was necessary for our analysis as we are only interested in views of specific water bodies, which are in a pre-defined direction from each property.

Our distance to water bodies variables are relatively simple planar Euclidian distance to the nearest water body (in line with work by Kummur et al., 2011). This is because visual distance, not travel distance (which could be estimated using network analysis - for example, see Guo et al., 2019), is the variable of interest. The distance to water bodies variable is a useful alternative independent variable because distance to water bodies and views of water bodies are closely related. If our results are robust to using the view and distance variables, we can be confident that our viewshed analysis is performing well (not including areas that shouldn’t be and vice versa). Moreover, the distance to water bodies variable can help us investigate whether the strength of the relationship between views of water bodies and water consumption declines with distance (as the effects of views of water bodies on property prices do - a natural extension of work by Bourassa et al., 2004).

5. Econometric Data and Methods

Water demand at the household level is influenced by various socio-demographic factors such as household size, age, income, interest in gardening, and education level (Worthington & Hoffman 2008). As with most water demand studies, socio-demographic information is not available at the household level (Worthington & Hoffman, 2008). Like other studies, we therefore use property characteristics as proxy variables. House area is a proxy for household size, site area for outdoor water needs, building age as a proxy for water-efficiency of fixtures, and capital value as a measure of wealth.

We also include Statistical Area 1 (SA1) census unit socio-demographic variables which capture some of the variation between small communities.⁵ These variables include median income, median age, homeownership rate, and proportion of residents with post-secondary-school education. Property-level variables are hereafter referred to as group 1 variables, while the census-area variables are referred to as group 2 (contextual) variables.

There are four water meter readings for each property (group 1 unit) representing the quarters between 1 July 2020 and 30 June 2021.

We elect to pool the four quarters together and include time fixed effects (dummies for each time period) to account for period-specific or seasonal shocks. As Oaxaca & Geisler (2003) show, pooled ordinary least squares (OLS) enables us to consistently estimate the coefficients on time-invariant variables (views of water bodies). As we have a large number of properties ($N = 39,224$), a small number time periods ($N = 4$) and we include time fixed effects in our modelling, estimates will still be consistent if there is serial correlation (Mundlak, 1978; Wooldridge, 2010, 2013). In our modelling, we apply log transformations to our dependent variable and continuous predictor variables. This is in line with the extensive water demand and water consumption modelling literature and has the advantage the estimates can be interpreted as elasticities (for example, see Donkor et al., 2014; Ghavidelfar et al., 2018; Schleich & Hillenbrand, 2009).

For panel data clustered by level 2 groups (SA1 units in our case), the literature suggests using fixed effects or mixed models with random effects for the level 2 groups (also known as within-between, hierarchical, Mundlak or correlated random effects models) (Bell et al., 2019; McNeish & Kelley, 2019; Mundlak, 1978). Fixed effects models are more popular in the economics literature while mixed models are more commonly used in other social science disciplines. McNeish and Kelley (2019) suggests this is because endogeneity is considered more of a problem in economics, while psychology traditionally focussed on controlled experiments. We start with a properly defined fixed effects model and then use a within-between mixed model specification which allows for random slopes as a robustness check.

⁵ SA1 units usually contain 100-200 residents and are capped at 500 residents. See Table 1 for more information on the SA1 units.

The fixed effects model is desirable because it accounts for all time-invariant level 2 variables and ensures these variables do not bias the within estimates of level 1 variables (Wooldridge, 2010). Hence, we account for all demographic factors at the Statistical Area 1 level (the demographics are time-invariant over the four quarters). The fixed effects model is as follows:

$$y_{ijt} = \beta_0 + \beta_1 n_t + \beta_2 x_{it} + \beta_3 p_{it} + c_j + \epsilon_{it} \quad (4)$$

where y_{it} is logged daily water consumption for property i in SA1 area j at time t , n_t is a vector of time period dummies, x_{it} is a column vector of our regressors of interest (views of water bodies - lakes and sea), p_{it} is a column vector of control variables (logged if appropriate) that vary at level 1, c_j is a vector of intercepts for each level 2 group and ϵ_{it} is an idiosyncratic error term. Under (4), β_2 are the coefficients of interest on our independent variables and they represent *within* SA-1 effects (as *between* SA-1 effects are removed by the SA-1 fixed effects). For example, if x_{it} is a dummy variable (0,1) for views of the sea, β_2 reflects the average change in water consumption between properties in the same SA-1 unit who have and don't have views of the sea. Evidently, this is a useful model because we only compare properties in the same SA-1 unit and SA-1 units are relatively fine spatial aggregations (in terms of population statistics).

To obtain unbiased estimates of the effect of x_{ijt} on water consumption, we assume contemporaneous exogeneity:

$$E[\epsilon_{ijt} | x_{ijt}, p_{ijt}, c_j] = 0 \quad (5)$$

For this assumption to be valid, variables that may affect x_{it} and y_{it} causing omitted variable bias must be time-invariant and appropriately defined at level 2. To test for the appropriateness of the SA-1 fixed effects, we use a Mundlak approach to test whether the means of our level 1 variables by level 2 groups are jointly zero in a random effects model (Mundlak, 1978). Unlike the Hausman test, we are able to include a robust variance-covariance matrix when we perform this diagnostic test. We find strong evidence (p-value $\ll 0.01$) that the time-invariant SA-1 level variables are related to our predictors and outcome variable and that SA-1 level fixed effects are appropriate. Moreover, we provide supplementary within-between (Mundlak) modelling to include between SA-1 associations where we control for a set of SA-1 level covariates. For the between SA1 estimates, we are less worried about non-classical measurement error that may arise from assuming SA-1 demographics appropriately control for property demographics that influence water consumption (Hausman, 2001).

The within-between or Mundlak models are random-effects type models that relax some of the restrictive assumptions in typical random effects models (Bell et al., 2019; Mundlak, 1978; Wooldridge, 2013). In a typical random effects model, we would model random intercepts c_j for each SA-1 unit and assume that these intercepts are uncorrelated with x_{ijt} :

$$Cov[c_j, x_{ijt}] = 0 \quad (6)$$

In our fixed effects model, we were not required to assume a relationship between the SA-1 intercepts and our level 1 varying regressors. In a correlated random effects model (Mundlak model), we relax the random effects assumption and explicitly model the relationship between the SA-1 intercepts and the level 1 regressors x_{ijt} and p_{ijt} . Usually, the modelled relationship (developed by Chamberlain, 1980; and Mundlak, 1978) is as follows:

$$E[c_j | \bar{x}_j] = \varphi + \delta_1 \bar{x}_j + \delta_2 \bar{p}_j \quad (7)$$

where \bar{x}_j and \bar{p}_j are vectors of averages across each SA-1 unit and φ is random variation. We can thus decompose c_j into:

$$c_j = \varphi + \delta_1 \bar{x}_j + \delta_2 \bar{p}_j + a_j \quad (8)$$

where a_j are the random intercepts for each SA-1 unit, with an expectation of zero. By substituting (8) into the fixed effects model (4), we get the final correlated random effects model:

$$y_{ijt} = \beta_0 + \beta_1 n_t + \beta_2 x_{ijt} + \beta_3 p_{ijt} + \beta_3 H_j + \varphi + \delta_1 \bar{x}_j + \delta_1 \bar{p}_j + a_j + \epsilon_{ijt} \quad (9)$$

It is well-documented that the estimate of β_2 in (9) is identical to the estimate from the fixed effects model in (4) (for further discussion, see McNeish & Kelley, 2019). However, in (9), we can now include SA-1 level variables H_j and we can estimate the contextual (essentially, the between) effects δ_1 of our regressors of interest \mathbf{x} . To put it in context, estimates of δ_1 will show the change in average water consumption when moving from an SA-1 unit without views of water bodies to an SA-1 unit with views. Another advantage of (9) is that we can include random slopes on \mathbf{x} for each SA-1 unit (McNeish & Kelley, 2019; Mundlak, 1978). If the random slopes are important, excluding them may generate bias estimates and standard errors. Excluding random slopes, where they are significant, will lead to "anti-conservative" standard errors (Barr et al., 2013; Bell et al., 2019).

In saying that, modelling random effects and slopes (interactions between each SA1 unit and the view of water variables) is not a parsimonious approach and uses up many degrees of freedom. Indeed, our initial fixed effects model (4) minimises the Akaike information criterion (AIC) and Bayesian information criterion (BIC) (compared to the within-between models with and without random slopes - equation 9). In this sense, these models are conservative and a good test of whether results from our preferred fixed effects models are robust.

As a robustness check for our viewshed GIS analysis (which we use to generate x_{ijt}), we run our fixed effects (4) models using a categorical distance to the nearest water body term $\{x \in (\text{within 500 m, between 500 m and 1 km, between 1 and 2 km, greater than 2 km})\}$ as an alternative measure of "view" exposure to types of water bodies. If being close to water bodies has a similar association with water consumption as being able to view water bodies, we can

be confident that our viewshed analysis is performing well. We also run interactions between our views of water variables and time period dummies to check whether certain periods (or seasons) are driving key results. Finally, we run interactions between our categorical distance to water variables and views of water variables. In line with insights from Bourassa et al. (2004), this enables us to observe if the strength of the relationship declines with distance from the water body.

We estimate variance-covariance matrices that are robust to unknown forms of heteroscedasticity and serial correlation. We also ensure our standard errors are clustered at the property level (and, in the supplementary within-between modelling, clustered at the more conservative SA1 unit level). Finally, we use well-cited methods described by Oster (2019) to assess the possibility that omitted variable bias is driving our results. Using tools developed by Oster (2019), we can estimate the coefficients of our view variables if selection on unobservables is equally as strong as selection on observables. We also compute Oster’s delta values to determine how strong selection on unobservables would need to be to reduce our coefficients to zero.

6. Results

6.1 Descriptive results

Viewshed results show that large areas of Tauranga City have views of the harbour and ocean (Figure 2). Properties with lake views tend to be further inland but are spread across most areas of the city (Figure 3).

Figure 2. Map of viewshed for Tauranga City Coast and Sea.

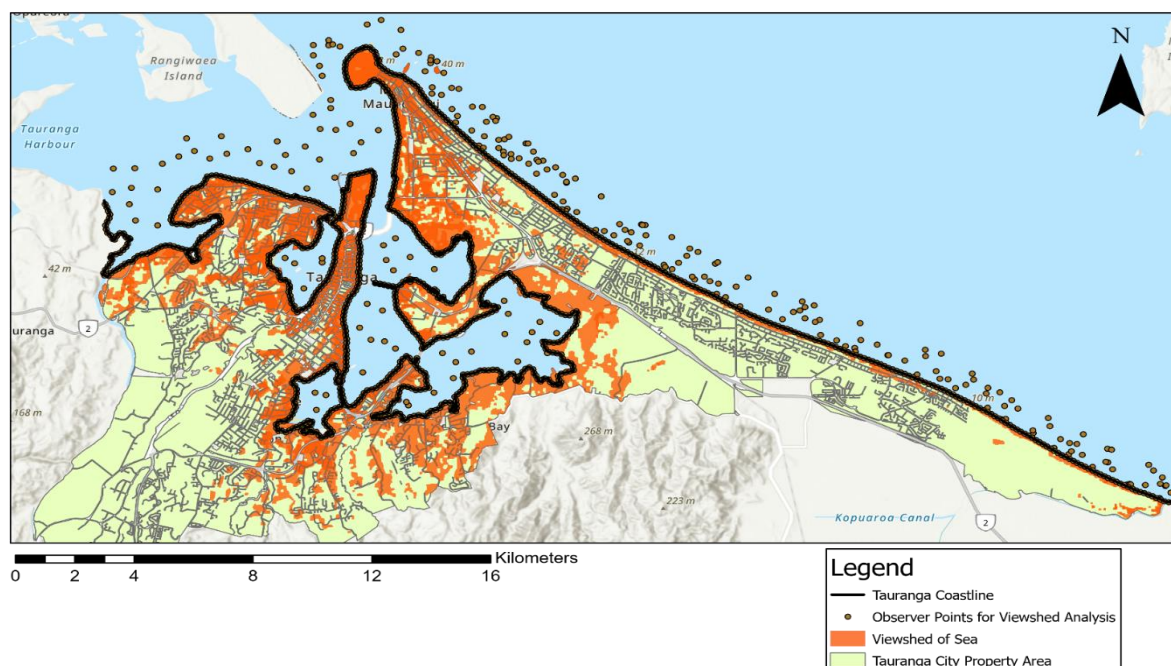
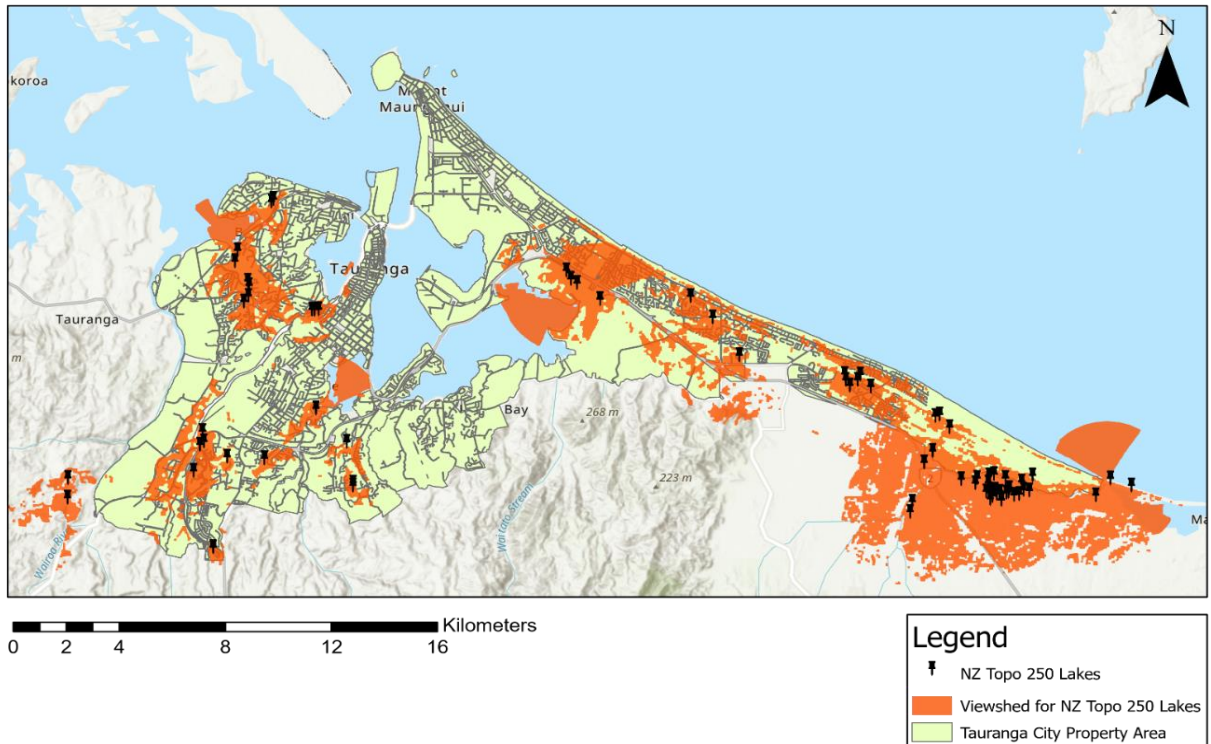


Figure 3. Map of locations that have views of lakes in Tauranga City.



We present summary statistics for the variables used in the fixed effects models (Table 2). In column one, we show statistics for the whole sample while in columns two and three we show statistics for the sub-sample with views of lakes and views of the coast, respectively. There is a reasonably high proportion of properties that have some view of a lake or the coast (31.7% and 30.4% respectively). The average water consumption per property per day is 0.47 m³, equivalent to 171.55 m³ or 171.55 thousand litres per property per year. The average building age is 29 years old, the average Capital Value (CV) is NZD 781,446, the average built area is 111 m² and median personal income per year is NZD 34,224. Overall, the summary statistics are similar between the overall sample and the two sub-samples with views. However, properties with views of lakes appear newer and properties with views of the coast appear older on average. Moreover, properties with views of the coast have higher values (CVs) on average. These differences highlight the importance of controlling for property-level and SA1 level characteristics when we look at the relationship between views of water bodies and water consumption.

Table 2. Summary statistics for the variables used in the main analysis and robustness checks

Variable	Full Sample (N = 39,224)		View Lakes Sample (N = 12,422)		Views Coast Sample (N = 11,911)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
View of Lake	31.7%	-	100%	-	21.8%	-
View of Coast	30.4%	-	20.9%	-	100%	-
Within 0.5 km of Lake	22.1%	-	45.9%	-	16.8%	-
0.5 to 1 km from Lake	32.0%	-	34.5%	-	23.5%	-
1 to 2 km from Lake	28.4%	-	19.6%	-	29.1%	-
2+ km from Lake	17.6%	-	0.0%	-	30.6%	-
Within 0.5 km of Coast	37.5%	-	28.4%	-	64.9%	-
0.5 to 1 km from Coast	26.4%	-	30.5%	-	26.2%	-
1 to 2 km from Coast	23.1%	-	29.2%	-	8.9%	-
2+ km from Coast	12.9%	-	11.9%	-	0.0%	-
Post-Secondary Education	43.9%	8.3%	42.7%	7.7%	44.7%	8.2%
Proportion of Homeowners	57.8%	13.1%	62.0%	13.0%	56.9%	12.2%
Daily Water Use (m ³ /day)	0.47	0.28	0.48	0.28	0.46	0.29
Building Age (yrs)	29.25	19.82	22.61	15.98	37.63	19.06
Capital Value (NZD)	\$781,446	\$412,986	\$755,144	\$264,028	\$827,823	\$514,500
Built Area (m ²)	111.16	132.99	93.39	112.64	116.12	131.64
Median Income (NZD)	\$34,223	\$7,203	\$34,024	\$6,552	\$33,623	\$6,680
Median Resident Age (yrs)	41.05	9.42	42.94	9.97	42.13	9.37

6.2 Empirical results

Table 3 presents the fixed effects model estimates with different inclusions with respect to the predictors of interest. The first three columns present results for regressors that relate to lakes and the final three columns relate to the coast. In each set of three, the first column (1 and 4) reports the results for the model with the view of water variable, the second column (2 and 5) shows the results for the model with the categorical distance from water variable and the third column (3 and 6) shows the results for the model with the interaction between the view of water and distance to water variables. In Table 3 (and subsequent tables), care must be taken when interpreting the coefficients. The dependent variable is logged and so are the continuous predictors while the categorical or binary predictors are not. The coefficients on log variables may be interpreted as elasticities. The coefficients on dummy and linear variables are semi-elasticities, which are the percent change in water consumption in response to a unit change in the explanatory variable.

Views and distance to water bodies variables

We find that having views of lakes are associated with 4.52% higher water consumption. Conversely, views of the coast are associated with 4.26% lower water consumption. These results are robust to using a distance to water measure instead. Properties more than 500 m from a lake consume 6.1% more water than properties less than 500 m from a lake. We perform two-tailed t-tests and find that there is no significant further decline associated with living more

than 500 m from a lake. Households living closer to lakes (or with views of lakes) have higher water consumption on average.

Conversely, households more than 500 m from the coast consume 4.5 to 6.1% more water. As with the lakes model, the effect of additional distance is statistically insignificant. These results suggest that people living in close proximity to the coast and people living with views of the coast consume less water on average.

When we include an interaction between views of water bodies and distance to water bodies, we find that the relationship between views of lakes and the coast are stronger for those living within 500 m of the water body itself and the strength of the relationship declines with distance from the water bodies. For example, when living within 500 m of a lake, views of the lake are associated with 7.3% higher water consumption. However, when living 500 m to 1 km or 1 to 2 km from a lake, views of the lake are associated with only 1.1% or 4.4% higher water consumption, respectively. Turning to the coast, when living within 500 m of the coast, properties with views of the coast have 6.8% lower average water consumption. However, when living 500 m to 1 km or 1 to 2 km from the coast, properties with views of the coast have lower water consumption by only 1.1% or 3.3%, respectively. These interactions minimise the AIC and BIC criteria (relative to models with either views of water bodies or distance to water bodies variables alone – this validates the inclusion of the interaction).

Other variables

We also find that a 10% increase in the CV is associated with 5% greater water use (between 4.7 and 5.2% depending on the exact model) and a 10% increase in the building age is associated with approximately 0.75% higher water use. Built area (m²) does not enter our model with any significance and we suspect any relationship is likely incorporated into the CV regressor coefficient.

Interactions with time

In Table 4, we present the results for our preferred fixed effects model with an interaction with time period dummies. Each period (1 to 4) lines up reasonably closely with the four seasons in New Zealand. Hence, in Table 4, we label the periods by the season they correspond to (noting that Winter is the base and starting period). These results show that the relationship between views of lakes and water consumption doesn't vary across the seasons (periods). However, the relationship between views of the coast and water consumption are stronger (more negative) in Spring and Autumn than Winter and Summer.

Table 3. Main fixed effects results using view of water variables, distance to water variables and interactions between view and distance variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log (Daily Water Use)	Lake	Lake	Lake	Coast	Coast	Coast
View of water	0.0442*** (0.0125)		0.0708*** (0.0193)	-0.0435*** (0.0137)		-0.0700*** (0.0201)
0.5 to 1 km from water		-0.0629*** (0.0170)	-0.0280 (0.0211)		0.0437** (0.0189)	0.0186 (0.0212)
1 to 2 km from water		-0.0827*** (0.0256)	-0.0571** (0.0285)		0.0595** (0.0279)	0.0381 (0.0295)
More than 2 km from water		-0.0795* (0.0481)	-0.0530 (0.0494)		0.0429 (0.0457)	0.0211 (0.0465)
Between 0.5 and 1 km*View of water			-0.0597** (0.0242)			0.0593** (0.0257)
Between 1 and 2 km*View of water			-0.0264 (0.0314)			0.0361 (0.0341)
Log (Building Age)	0.0769*** (0.00655)	0.0770*** (0.00656)	0.0765*** (0.00655)	0.0780*** (0.00656)	0.0776*** (0.00656)	0.0782*** (0.00657)
Log (CV)	0.480*** (0.0164)	0.483*** (0.0164)	0.480*** (0.0164)	0.489*** (0.0165)	0.483*** (0.0164)	0.493*** (0.0166)
Log (Built Area)	-0.00157 (0.00276)	-0.00182 (0.00276)	-0.00180 (0.00276)	-0.00161 (0.00276)	-0.00172 (0.00276)	-0.00160 (0.00276)
Constant	-7.655*** (0.224)	-7.616*** (0.224)	-7.621*** (0.224)	-7.753*** (0.226)	-7.714*** (0.225)	-7.813*** (0.227)
Time Controls	YES	YES	YES	YES	YES	YES
SAI Controls	YES	YES	YES	YES	YES	YES
Observations	155,843	155,843	155,843	155,843	155,843	155,843
R-squared	0.085	0.086	0.086	0.085	0.085	0.086

*Note: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; There aren't sufficient observations greater than 2 km from water that can see water*

Table 4. Fixed effects modelling results for view of water bodies variable with a time period interaction

	(1)	(2)
Log (Daily Water Use)	Lakes	Coast
View of Water	0.0438*** (0.0134)	-0.0344** (0.0143)
View of Water*Spring	0.00243 (0.00518)	-0.0166*** (0.00513)
View of Water*Summer	-0.00491 (0.00636)	-0.00364 (0.00633)
View of Water*Autumn	0.00428 (0.00566)	-0.0160*** (0.00541)
Log (Building Age)	0.0769*** (0.00655)	0.0780*** (0.00656)
Log (CV)	0.480*** (0.0164)	0.489*** (0.0165)
Log (Built Area)	-0.00157 (0.00276)	-0.00161 (0.00276)
Constant	-7.719*** (0.224)	-7.820*** (0.226)
Time Controls	YES	YES
SA1 Controls	YES	YES
Observations	155,843	155,843
R-squared	0.086	0.085

*Note: Cluster robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Results for Mixed Model

As a robustness check, we present our within-between model results in Appendix 1. Using a likelihood ratio (LR) test, we found random slopes to be an important addition to the within-between models. We also find the variance of the random effects and random slopes are large and significant, indicating that the relationship between views of water bodies and water consumption vary considerably by SA1 unit.

The estimates for the relationship between views of water bodies and water consumption (without random slopes) in Appendix 1 are significant and identical to the fixed effects results in Table 3 (as we would expect). However, the standard errors are larger and more conservative. When we introduce random slopes, the coefficients decrease slightly in size but retain statistical significance. Given the conservative nature of these results, we find good support for our main fixed effects results. These tables also report “between SA1 effects”, which are really associations rather than effects because they do not control for time-invariant SA1 heterogeneity.

Selection on Unobservables

As the potential for omitted variable bias is a concern, we present results highlighting the likelihood and effects of selection on unobservables (Table 5). As in Oster’s (2019) paper, for our view variables, we report uncontrolled coefficients (first column) and the model R^2 , controlled coefficients (our fixed effects estimates in column three) and the model R^2 and bias-

adjusted coefficients which assume selection on unobservables is equal to selection on observables (column 5). We find that adding controls (SA1 fixed effects, property level characteristics, time dummies) significantly increases the explanatory power of the model and doesn't shift the coefficients on our view variables by much (if anything, adding controls strengthens the observed relationship for views of the coast). Further, the bias-adjusted coefficient on views of lakes is very similar to our main findings and the bias-adjusted coefficient on views of coast is more negative than our main findings. We also report Oster's deltas (in column 6) which shows that selection on unobservables would need to be at least 1.34 and 1.42 times greater than selection on observables to reduce our views of lakes and views of the coast coefficients to zero. Taken together (the stability of our coefficients to controls, the similarity of our coefficients to bias-adjusted coefficients and the relatively Oster's deltas⁶), the results in Table 5 show that omitted variable bias is likely not a major issue for our results.

Table 5. Oster's betas and deltas for our views of lakes and views of coast variables.

View Variable	Uncontrolled Coef.	R ²	Controlled Coef.	R ²	Bias-Adjusted Coef.	Oster's Delta
View of lake	0.04449*** (0.00682)	0.001	0.0442*** (0.0125)	0.085	0.04309	1.339
View of coast	-0.03667*** (0.00705)	0.001	-0.0435*** (0.0137)	0.085	-0.11546	1.417

*Note: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Oster's betas and deltas assume the parameter R_{max} is $= 1.3 * R^2(\text{controlled})$.*

7. Discussion

Our empirical results provide support for our propositions 1 and 2. In Section 2, we described a model of water consumption that depends on the perceived scarcity of water and the concern about water scarcity generally. In short, we postulate that people who believe that water resources are scarce or under pressure and are concerned about water scarcity will consume less water.

In proposition 1, we drew upon notions of frequency and availability bias (Fiedler & Armbruster, 1994; Tversky & Kahneman, 1973) to suggest that people living near lakes may believe there is more freshwater than there actually is. In believing this, these individuals would have a lower perception of water scarcity and thus consume more water than an equivalent person who doesn't live near a lake. Our results support proposition 1 because we find that properties with views of lakes have significantly greater water consumption (4.6% greater) and this relationship is more pronounced for people who live closer to the lakes than people who live further away. Whilst these effects may sound small, they are equivalent to a substantial change in average annual water consumption over the region (and are even larger if the results scale up to the national level). A 4.6% increase in water consumption is equivalent to an

⁶ A common conservative heuristic is that if Oster's deltas are greater than 1 the main results are supported.

additional 7.9 m³ (7,900 litres) of water per property per year. If our suggested mechanism of availability bias is correct, the existence of the lakes may cause 98,134 m³ of additional water consumption (7.9 times number of properties with views) per year.

In proposition 2, we made a distinctive link between beauty premiums in the labour market and beauty premiums in water consumption. We suggest that views and proximity to beautiful bodies of water may increase the value people associate with water. If people value water more, they may have a greater concern for water scarcity and thus consume less water. Our results also support proposition 2 and we find that those with views of the coast consume significantly less water (4.26% less) and that this relationship diminishes with distance from the coast. We also note that the relationship is weaker during winter and summer. One possibility is that warmer weather is associated with higher occupation of coastal holidays homes, and more positive experiences and perceptions of the coast and beaches. However, perhaps during the summer period, overcrowding of beaches and coastal suburbs during peak tourist months (Stats NZ, 2020) may diminish those positive perceptions slightly. As a result, the effects of views of the coast on water use during winter (being the coldest season) and summer (being the season with the highest incidence of overcrowding) are lower. This is one possible interpretation, and it aligns with the “perception” mechanisms we propose in the theory section.

In our framework, the beauty and frequency bias mechanisms might offset each other. However, Tauranga lakes are all relatively small and are not well-known nationally or internationally. Hence, we see less scope for the proposed beauty effects to apply to the lakes (although, they may still exist to a lesser degree for some groups of the population). Indeed, our summary statistics in Table 2 support this notion as on average, properties with views of the sea have higher property values. Conversely, properties with views of the small lakes in Tauranga do not have higher market values on average (suggesting the “quality” of the views are insufficient to generate a market premium). Moreover, we suspect that views of and proximity to the coast wouldn’t result in the proposed frequency bias effects because the frequency bias mechanism operates through perceptions of freshwater availability, not saltwater availability.

We stress that our theory and proposed mechanisms are not the only way our observed results may be operating. While we have built our theory section on previous work in the economics and psychology literature, we are unable to directly test whether the mechanism is correct. We believe this to be an important area for future research (along with studying this phenomenon in different contexts). For example, future work may want to incorporate our theoretical model into a structural equation model to estimate the relationships between views of water bodies and the parameters in our theoretical model (perceptions of scarcity and concern for scarcity).

There are other explanations for our results that lie outside of our proposed model. For example, coastal properties may use less water because their gardens have more salt-resistant plants that need less water. Alternatively, coastal properties may consume less water because

they are more likely to be holiday homes which are occupied less frequently on average. However, in our modelling, we include SA1 unit fixed effects, which should control for local conditions (local climate, visitation patterns etc.). Our approach means we are comparing properties in the same SA1 unit, so we are comparing properties in the same coastal SA1 units. Therefore, factors like more resistant vegetation and the incidence of holiday homes are unlikely to be driving our results (as these factors are likely to be stable across the SA1 geographically scale). Moreover, we find that our results are not sensitive to the addition of controls nor are they sensitive to selection on unobservables.

The results for our control variables align with our expectations, economic theory, and the literature on water demand. Several previous studies have found positive relationships between property value (CV) as a proxy for income and water demand and property value itself and water demand (Dandy et al., 1997; Ghavidelfar et al., 2017; Lyman, 1992; Worthington & Hoffman, 2008). Basic economics informs us that households with higher incomes (proxied by property value) are able to purchase more goods and services (water, in this case). Moreover, property values increase as property and building size increase (*ceteris paribus*) and larger properties tend to use more water on average (Fielding et al., 2012; Ghavidelfar et al., 2017). Older buildings tend to have less efficient household appliances and plumbing and therefore have a higher average water consumption than newer buildings (Worthington & Hoffman, 2008). Indeed, Berhanu et al. (2020) also find a small but significant positive effect of building age on residential water consumption and they propose a similar mechanism. However, in our supplementary within-between models (Appendix 1), we find small negative associations between average building age for an SA1 unit and water consumption. Chang et al. (2010) encountered similar associations and proposed that it may reflect older suburbs having greater tree and foliage cover which means less water is used (particularly, for gardening purposes). If this is the case, our fixed effects estimates will account for this unobserved factor (but the “between” SA1 associations will not).

Overall, our results show that having views of water bodies (or living within a short distance from water bodies) is associated with and may affect water consumption. We suggest that these relationships are driven by perceptions of water scarcity and perceptions of the intrinsic value of water. If our suggested mechanisms are correct, views of lakes may undermine the information campaigns that water authorities run during droughts. Water authorities might want to emphasize in their communications that city water comes from a different source (underground aquifers, in the case of Tauranga), and that small lakes are too shallow or have too poor water quality to be useful sources. Alternatively, water authorities might choose to specifically target people living near freshwater lakes with their water conservation campaigns and interventions. Moreover, our theory suggests that if policymakers can increase the perceptions of scarcity or the concern for scarcity (by increasing the value associated with water), they will see reductions in household water demand. This reinforces suggestions to encourage and enable citizens to have positive experiences in nature as this could generate stronger environmental attitudes and increase the incidence of pro-environmental behaviours (one of which is water conservation).

However, our research has important limitations, one of which is the degree of causality our results imply. We deploy several estimation techniques (SA1 fixed effects, including property-level controls and estimating a set of results with “conservative” random SA1 slopes) and robustness checks (alternative specifications of the independent variable, checking the stability of coefficients to the addition of control and assessing the likelihood of selection on unobservables) to mitigate against omitted variable bias (see Appendix 2 for full discussion). Moreover, while we cannot rule out reverse causality, we find reverse causality arguments to be unconvincing (see Appendix 2 for more discussion). Our results suggest that there is *likely* a causal relationship between views of different water bodies and water consumption. Future work should try to verify this effect using variation in views over time (to avoid potential reverse causality issues). Additionally, more research needs to occur to establish the true mechanism through which these effects may operate. We also only look at this relationship in one regional context and for two types of water bodies.

Nonetheless, we hope our theoretical model, proposed mechanisms and results for the relationship between views of water bodies and water consumption spur more research in this space. Future research could incorporate our theoretical model into existing frameworks for the formation of water scarcity perceptions and test these models empirically using structural estimation. Future researchers may also want to run lab or field experiments to investigate the environmental “beauty premium” hypothesis and the notion of availability bias as it relates to water consumption. Finally, future research could examine the relationship between views of water bodies and water consumption in different geographical and social contexts.

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Appendix 1. Mixed (correlated random effects) model results for views of water bodies with and without random slopes.

	(1)	(2)	(3)	(4)
Log (Daily Water Use, m ³)	Lake	Lake	Coast	Coast
<i>Within SA1 Effects</i>				
View of Water	0.0442** (0.0172)	0.0354** (0.0159)	-0.0435*** (0.0167)	-0.0328* (0.0170)
Log (Building Age)	0.0769*** (0.0153)	0.0761*** (0.0153)	0.0780*** (0.0154)	0.0794*** (0.0154)
Log (CV)	0.480*** (0.0259)	0.483*** (0.0263)	0.489*** (0.0258)	0.515*** (0.0250)
Log (Built Area)	-0.00158 (0.00327)	-0.00155 (0.00324)	-0.00162 (0.00324)	-0.00215 (0.00324)
<i>Between SA1 Effects</i>				
View of Water	-0.0269 (0.0218)	-0.0164 (0.0225)	0.00838 (0.0240)	-0.00345 (0.0250)
Log (Building Age)	-0.115*** (0.0139)	-0.0992*** (0.0180)	-0.109*** (0.0149)	-0.111*** (0.0144)
Log (CV)	-0.367*** (0.0431)	-0.386*** (0.0479)	-0.381*** (0.0427)	-0.341*** (0.0424)
Log (Built Area)	0.0324* (0.0172)	0.0313* (0.0188)	0.0325* (0.0171)	0.0315* (0.0167)
Median Age	-0.00578*** (0.00100)	-0.00544*** (0.00105)	-0.00557*** (0.00101)	-0.00673*** (0.000991)
Proportion of Homeowners	0.321*** (0.0789)	0.362*** (0.0881)	0.333*** (0.0784)	0.321*** (0.0787)
Proportion with Post-Secondary Education	-0.126 (0.0962)	-0.104 (0.116)	-0.111 (0.0946)	-0.0805 (0.103)
Median Income (\$1,000s NZD)	-0.00138 (0.00168)	-0.00193 (0.00208)	-0.00141 (0.00168)	-0.00192 (0.00185)
Constant	-1.485*** (0.386)	-1.857*** (0.0429)	-0.389*** (0.0118)	-1.404*** (0.414)
Time Fixed Effects	YES	YES	YES	YES
SA1 Random Effects	YES	YES	YES	YES
SA1 Random Slopes	NO	YES	NO	YES
Observations	155,843	155,843	155,843	155,843
Number of SA1 Groups	792	792	792	792

Note: Cluster robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Between effects are the coefficients on the group means of the specified regressor.

Appendix 2. Supplementary causality discussion

In empirical economics papers, authors are often arguing whether the relationships they report are causal or correlational. The conditions for true causality are strong and require that the observed coefficients are not subject to:

- 1) Significant omitted variable bias (where an unobservable confounding variable affects both the “treatment” – views of water bodies – and the outcome – water consumption); or
- 2) Simultaneity bias/reverse causality (where the outcome is actually determining the “treatment”, or they are both determined at the same time).

In our paper, we employ estimation techniques and robustness checks that aim to minimise the possibility of omitted variable bias.

We use a fixed effects approach which enables us to control for all time-invariant (over a 1-year period) Statistical Area 1 (SA1) unobservable characteristics which may be affecting both the views of water bodies and water consumption. For example, properties in particular coastal suburbs may be more likely to be holiday homes and consume less water. Our SA1 fixed effects will control for these spatial confounding variables.

- 1) We control for property-level characteristics (like property value, built area and property age) that will undoubtedly be related to both views of water bodies and water consumption. For example, previous work shows that wealthier households (proxied by property value) consume more water and properties with views of water bodies have higher valuations.
- 2) We find that our coefficients of interest are relatively stable to adding property-level controls, seasonal controls and SA1 fixed effects. This suggests that our coefficients are not strongly related to other “potentially” confounding variables.
- 3) Using methods from Oster (2019), we find that selection on unobservables is unlikely to be an issue for our results.
- 4) When we use distance as an alternative specification for the “independent variable”, we find similar results.
- 5) When we run a mixed model which allows for “conservative” random slopes for each SA1 unit, our coefficients decrease slightly but are largely unchanged and still significant.

One major caveat is that our SA1 controls imperfectly control for property socio-demographics (and if we had property level fixed effects, we wouldn't be able to assess the effects of views of water bodies because there is no variation over time). However, given the points made above, we are reasonably confident that our results are not subject to omitted variable bias and selection on unobservables.

Meanwhile, we do have concerns over potential reverse causality because our views of water bodies variables are cross-sectional. This means we cannot track changing individual views for

water users over time and we cannot completely rule out reverse causality arguments. In saying that, it is important to think through the reverse causality argument and what that actually means. In the context of our paper, reverse causality would suggest that water consumption is affecting views of water bodies through some mechanism. This would occur, for example, if environmentally-inclined individuals consume less water and also chose to locate closer to (or further from) water bodies. In this case, one may be concerned that environmentally conscious consumers locate within view of the coast and this drives our observed result. While we cannot rule this out, we would also expect environmentally conscious and aware consumers to locate further from the coast (to minimise their residential impact on coastal ecosystems and as they are more acutely aware of rising sea levels as a result of climate change). Moreover, if environmentally conscious consumers are driving our results, we would not expect people living near lakes to consume more water. The effect should operate in the opposite direction whereby environmentally conscious consumers locate closer to freshwater lakes and biodiversity and also consume less water. Further, environmentally conscious consumers are much less likely to fall prey to the availability bias mechanism we suggest because these individuals are thinking more critically about environmental issues (such as water scarcity). Therefore, overall, we do not find the reverse causality argument convincing (however, we cannot rule it out).