

# The Short and long run dynamics

of household response to water demand management

By Yvonne Matthews

Climate, Freshwater & Ocean Science



**NIWA**

Taihoro Nukurangi

# Tauranga water supply hite

Water restrictions  
possibility as Dan  
woes continue



Taurar  
litres a



# Nelson-Tasman region drought of 2019 worse than 2001, says MP Nick Smith

Cherie Sivignon · 14:45, Feb 14 2019



and tomorrow! This region. In fact, it was the Airport (37 days), in 60 port record was 38 days eed "cluster" ^GG

# It's official - Southland drought' is a r

Rachael Kelly · 18:05, Mar 30 2022



A warning was made last week about a looming water crisis in Tasman district.

**A Airport** has just ended its longest dry spell on record - s ending 23 January 2022

rd at the Airport is 38 days, rded in January 2020)

uckland Airport.  
rainfall, 9am to 9am total



cli

Anita Erskine, of Papatotara, has been feeding baleage out to her cows for about a month to keep condition on them, because there is not enough grass for them to eat during Southland's dry season.





# Motivation

Urban water supplies are under stress by population growth and worsening summer droughts

Research questions:

1. How do households respond to drought
2. How do households respond to water demand management?
3. How does response vary in the short versus long term?

# What does the literature say?

- There is a large body of literature concerned with residential water demand and elasticities
- Common explanatory variables include climate, season, household characteristics, and urban configuration
- Price elasticity typically around -0.25 to -0.75
- More price sensitive: small households, high consumption, low income
- Few studies use household-level data
- Researchers assumed LR elasticity was higher without actually testing the relationship
- AR1, PAM, and ECM models impose restrictions (Cuddington & Dagher, 2015)
- A recent time-series study about Auckland water found the LR was smaller but they thought it was sampling error.



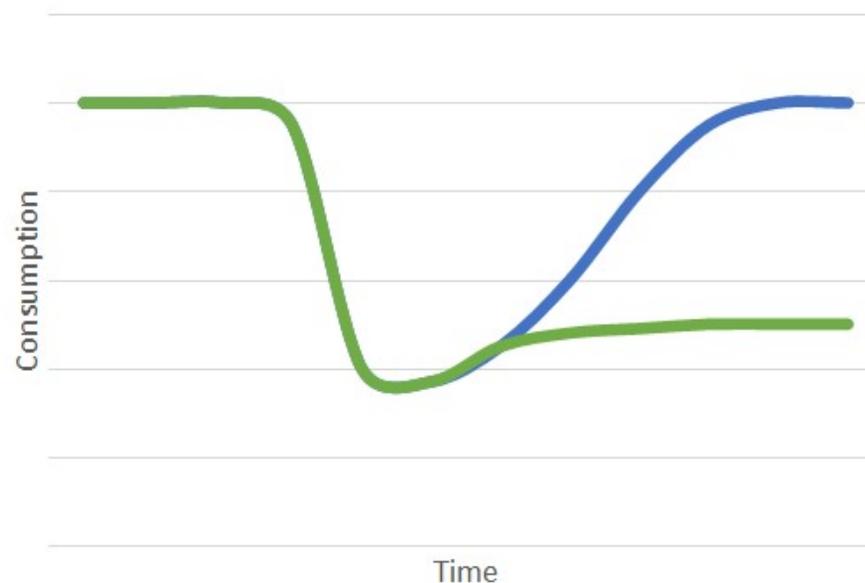
# Are there long-term effects of drought or demand management?

Economic theory suggests:

- Long-run elasticity may be higher if people can invest in water conservation technology

or

- it may be lower because there are no substitutes and water conservation is hard to maintain





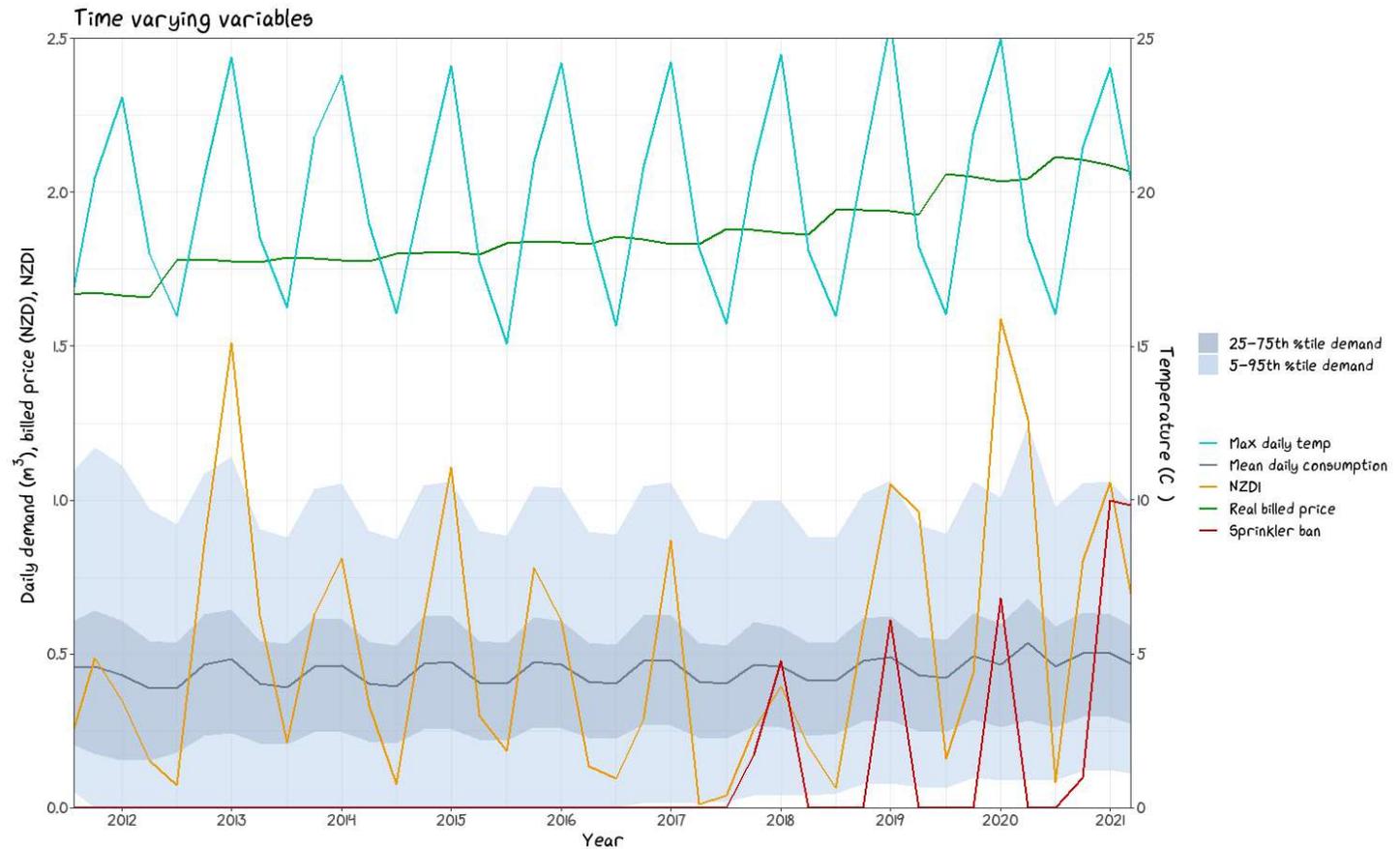
## Study area

- Tauranga is a fast-growing coastal city population ~132,000
- Water is supplied by two streams
- In 1998 it was projected that demand would exceed supply within 5 years
- Council introduced meters and volumetric charging by 2002 and peak demand reduced 25 per cent
- No water restrictions until 2017
- New treatment plant was able to be deferred by 15 years, saving ratepayers millions?



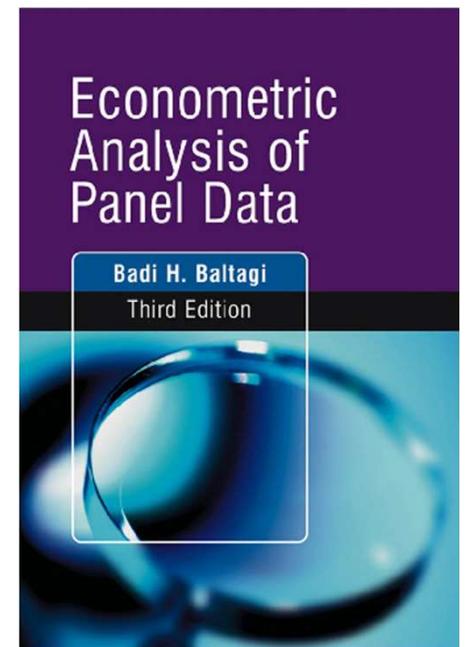
# Data

- Panel time series
- Billed consumption data from 56,000 single unit residential properties from 2011-2021
- Integrated property, census and climate variables
- Some data limitations



# The benefits of using panel data?

- As far as an individual household is concerned, supply is perfectly elastic. Therefore, we can model water demand as a single equation and assume regressors are at least weakly exogeneous
- Panel data are able to identify and measure effects that are not detectable in cross-section or time series models
- Large disaggregated samples provide more reliable estimates
- A lack of household level data is a “fundamental limitation” in water research

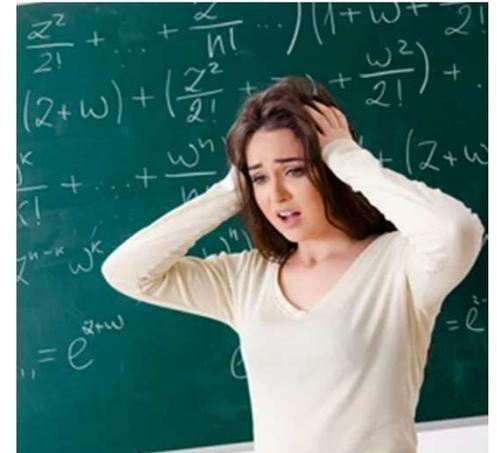


# Modelling approach

- Used a dynamic ADL model in order to distinguish between SR and LR effects
- Used 2SLS - first-differenced and used the second lag as an instrument for the first lag to eliminate the effect of serial correlation

$$\Delta q_{it} = \gamma_q \Delta \widehat{q}_{it-1} + \sum_l^L (\gamma_{pl} \Delta p_{t-l} + \gamma_{ban,l} \Delta ban_{t-l} + \gamma_{NZDI,l} \Delta NZDI_{t-l} + \gamma_{temp,l} \Delta temp_{t-l}) + v_{it}$$

- Two time subscripts, t-1 quarter and t-4 quarters
- The t-4 represents the SR impact, while t-4 is the residual impact after a year or more



# Model 1 results

Variable	Coefficient (SE)
Intercept	-0.013 (0.001)
$\Delta\hat{y}_{-1 \text{ quarter}}$	0.492 (0.003)
$\Delta\text{Log price}_{-1 \text{ quarter}}$	-0.439 (0.030)
$\Delta\text{Log price}_{-1 \text{ year}}$	0.383 (0.021)
$\Delta\text{Sprinkler ban}_{-1 \text{ quarter}}$	-0.162 (0.002)
$\Delta\text{Sprinkler ban}_{-1 \text{ year}}$	-0.056 (0.002)
$\Delta\text{Temp}_{-1 \text{ quarter}}$	0.011 (<0.001)
$\Delta\text{Temp}_{-1 \text{ year}}$	0.041 (<0.001)
$\Delta\text{NZDI}_{-1 \text{ quarter}}$	0.079 (0.001)
$\Delta\text{NZDI}_{-1 \text{ year}}$	-0.102 (0.001)

SR price elasticity = -0.439  
 LR price elasticity  
 =  $(-0.439 + 0.383) / (1 - 0.492)$   
 = -0.11

LR sprinkler ban response  
 = -0.43

Adjusted  $r^2 = 0.087$

## Potential reasons for these results?

- Water pricing has been in place for 20 years. Anyone who might be motivated to install water-efficient appliances probably already did so
- Response to pricing may be mostly behavioural, which is hard to maintain
- Prices must be continually raised to maintain the impact
- In response to outdoor restrictions, people can always put in more rainwater storage or replace plants with drought-tolerant species. These are long-term adaptations
- Unfortunately outdoor restrictions have a limited total impact



# Model 2: adding interaction effects

Combined effectiveness lower

Demand is more price elastic in summer

Negligible

Sprinkler bans less effective the higher the temperature

Sprinkler bans more effective with drought

Climate change double whammy

Interaction variables	Coefficient (SE)
$\Delta \text{Log price} \times \Delta \text{sprinkler ban}_{-1 \text{ quarter}}$	-0.418 (0.883)
$\Delta \text{Log price} \times \Delta \text{sprinkler ban}_{-1 \text{ year}}$	1.002 (0.054)
$\Delta \text{Log price} \times \Delta \text{temp}_{-1 \text{ quarter}}$	-0.752 (0.028)
$\Delta \text{Log price} \times \Delta \text{temp}_{-1 \text{ year}}$	-1.485 (0.027)
$\Delta \text{Log price} \times \Delta \text{NZDI}_{-1 \text{ quarter}}$	-0.656 (0.068)
$\Delta \text{Log price} \times \Delta \text{NZDI}_{-1 \text{ year}}$	0.522 (0.059)
$\Delta \text{Sprinkler ban} \times \Delta \text{temp}_{-1 \text{ quarter}}$	0.161 (0.003)
$\Delta \text{Sprinkler ban} \times \Delta \text{temp}_{-1 \text{ year}}$	1.165 (0.046)
$\Delta \text{Sprinkler ban} \times \Delta \text{NZDI}_{-1 \text{ quarter}}$	-1.353 (0.027)
$\Delta \text{Sprinkler ban} \times \Delta \text{NZDI}_{-1 \text{ year}}$	-3.708 (0.165)
$\Delta \text{Temp} * \Delta \text{NZDI}_{-1 \text{ quarter}}$	0.038 (0.000)
$\Delta \text{Temp} * \Delta \text{NZDI}_{-1 \text{ year}}$	-0.006 (0.002)

## Model 3: Property & sociodemographic interactions

Property or census variable	Δ Log price		ΔSprinkler ban	
	-1 quarter	-1 year	-1 quarter	-1 year
Log property mean demand	0.240**	0.131**	-0.037**	0.036**
Log site area	0.131**	-1.542**	0.036**	0.110**
Log house area	-1.542**	0.399**	0.110**	-0.174**
Modernised dummy	0.399**	0.528**	-0.174**	-0.035**
Log capital intensity	0.528**	-0.022	-0.035**	0.046**
Pool dummy	-0.022	1.976	0.046**	-0.380*
Good landscaping dummy	1.976	-0.052	-0.380*	0.327
Log pop density	-0.052	-0.059	0.327	0.021**
Log income	-0.059	-0.022	0.021**	-0.017*
Homeownership %	-0.022	-1.626**	-0.017*	0.104**
Postgrad education %	-1.626**	0.394**	0.104**	-0.162**
Pop under 20 years %	0.394**	-0.286*	-0.162**	0.074**
Pop over 64 years %	-0.286*	0.241**	0.074**	-0.090**



## Policy implications

- Using price to reduce demand requires continually increasing the price to maintain the effect
- Incentivizing household water storage may make households conserve water in a drought but costs more than municipal water storage, by volume
- Real-time metering combined with temporary “drought pricing” might be a more efficient and equitable way to manage demand

---

# High resolution drought forecasting

---



Published: 28 July 2022

**NIWA and the Ministry for Primary Industries (MPI) are working together to develop a new drought forecasting tool, with each organisation investing \$100,000 in the project.**

The tool uses innovative climate modelling, the latest in machine learning and other data-driven techniques. It will help farmers and growers better prepare for periods of dryness and drought.

The tool updates daily to provide forecasts at a much higher spatial resolution than previously available. This will enable the provision of district-level predictions of dryness and drought.



“Having a tool that draws on the best available science each day to provide advance warning of future dry spells will make a big difference to farmers' planning and decision making. This will not only contribute to the bottom line, but also to their own wellbeing and animal welfare.”

Nick Story, Director Rural Communities and Farming Support, MPI

Thank you

Climate, Freshwater & Ocean Science

