

Article

The Responsiveness of Urban Water Demand to Working from Home Intensity

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Abstract: Working from home (WFH) is now widespread around the world. Sustainability benefits can arise from WFH, but there remains limited evidence on resource use and its full sustainability implications. To provide some answers on this issue, we analyse water use data from Sydney, Australia, mapped against mobility changes during the natural experiment that COVID-19-related lockdowns represented. We use an auto-regressive distributed lag model to evaluate how variations in WFH influence the demand for water, after accounting for factors like temperature, rainfall, water restrictions, and so on. We find that in response to a 10% increase in WFH, single residential demand does not significantly change, whilst multi-dwelling demand increases 1%, industrial demand decreases 2%, commercial demand increases 3%, and miscellaneous demand increases 3%. Overall, sectoral changes balance each other out, leaving no significant change in aggregate demand. Our contribution is two-fold. First, we operationalise WFH by looking at the intensity of workplace mobility during the pandemic. Second, we establish disaggregated sectoral water consumption elasticities to WFH and show that aggregate water consumption patterns disguise sectoral changes that relate to where and when water is consumed. These results need to inform infrastructure and water supply–demand planning.

Keywords: telework; urban water consumption; water infrastructure; infrastructure resilience; climate change

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1. Introduction

This article analyses the impact of changes in working from home (WFH) on the aggregate urban water demand and per-property water demand across five urban consumption sectors. During the height of the COVID-19 pandemic (March 2020 to May 2021), office occupancy rates and office-based work were greatly reduced, leading to less motorised travel within cities and reductions in air and noise pollution [1,2]. This highlighted some of the many potential environmental benefits that WFH practices may provide, especially in terms of reduced greenhouse gas emissions [3–6]. Beyond environmental benefits, WFH practices also offer a range of social and economic benefits, including economic productivity and more equitable access to employment, improved community resilience, and improved work–life balance [7]. Conversely, WFH may also lead to environmental rebound by potentially promoting more urban sprawl, living in larger houses, increased resource use, and greater dependence on car use [8–11]. In this article, we analyse how the intensity of WFH is associated with changes in urban water consumption across two residential sectors urban form types, as well industrial, commercial, and miscellaneous uses. The two residential sectors, single dwellings and multi-unit dwellings, proxy for the implications of WFH for water consumption under compact and low-density urban development forms.

1.1. Implications for Urban Infrastructure Planning and Resilience

WFH needs to be accounted for in planning, including for urban water systems. The extent and longevity of the shift in work practices were so extensive that it has created a persistent change in the social acceptance and frequency of WFH practices and other related modes of working away from a fixed place of work, especially when considering psychological factors [12,13]. Employees frequently choose to WFH when they can and are allowed to do so and also tend to report higher job satisfaction than those who do not [13].

A priori, WFH may have a volumetric impact on water demand, as well as an impact on its spatial and temporal distribution. This is important for two key reasons. Firstly, the current water infrastructure (i.e., pumps and pipelines) was built based on assumptions about how much water is needed in different locations at different times. Pipe dimensions were designed to accommodate expected peak demands, and therefore assumptions of peak demand have strong implications for the design of water infrastructure systems, which are costly to refurbish [14]. A temporal-spatial change in water demand leaves some pipelines over-dimensioned and others under-dimensioned. Adapting water supplies to new water demand patterns in a large city may require upgrading pipe networks, wastewater infrastructure, and/or demand management [15–17]. Secondly, if the total volume of water use changes, this has implications for whether further supply augmentations are needed, i.e., investments in increasing water supply, such as the expansion of catchments and dams or investments in desalination plants. This is especially important in the context of water stress. Improving the resilience of water supplies, however, comes at monetary cost [18–20], as well as environmental and social costs [19,21]. For this and other reasons, planning for a resilient water supply requires careful analysis and calibration [22,23].

1.2. What Is Already Known?

So far, the evidence on how water consumption is influenced by WFH practices is incomplete. The handful of studies that exist mostly focus on residential sectors and relatively simplistically compare water demand patterns before, during, and/or after a disruption (usually applying crude measures such as COVID-19-related work-from-home orders) without adequately accounting for confounding factors, nor measuring the elasticity of water consumption with respect to the intensity of WFH.

Several studies have explored the impact of COVID-19 on urban water use. Vizanko et al. [24] found, using an Agent-based simulation model, that social distancing in itself leads to an increase in residential water demand. Shu et al. [25] showed that in the context of China, commercial water use was significantly reduced as a result of COVID-19-related indicators such as reduced mobility. Sabzchi-Dehkharghani et al. [26], analysing water demand data from Tabriz, Iran, found that residential water demand increased during the pandemic but decreased again after the pandemic, with socio-economic factors and population density having a considerable impact on the size of the demand changes. Ribas et al. [27], analysing residential water use data from during the most intense parts of the COVID-19 pandemic in Northeast Spain, found that indoor water use increased significantly during the pandemic and argued that this was linked to a greater prevalence of WFH behaviours. Hackbarth et al. [28] analysed water use data in commercial buildings in southern Brazil and found that certain types of businesses, like law and accounting firms, saw a 28% reduction in water using during COVID-19, whilst engineering offices had an increase in water use of about 15%, showing the influence of the type of economic activity on commercial water demand. Almulhim and Aina [29] undertook a household survey in Saudi Arabia and found that 50–86% of respondents self-reported increases in water bills, which impacted their household budgets. As an interesting data point, Gholami et al. [30] reported an overall increase in water use of 10–15% in different cities across Iran during the COVID-19 pandemic. Buurman et al. [31] reviewed the overall

evidence of water use changes during COVID-19 and identified changes in daily water demand patterns and that residential water use increased between 6% and 13%, with some changes in the commercial and industrial sectors unclear (although the indications are it was somewhat reduced).

Other authors have explored the impact of WFH directly on water use. Nemati and Tran [32] found based on analysing the water consumption data (using time-series analysis) from six water utilities across the United States that there was a small overall increase in water demand (3–14%) during stay-at-home orders, with increases in residential water demand (12–14%), and reductions in non-residential water demand (23–45%). Similarly, Bakchan et al. [33] analysed daily time-series data representing water consumption in Austin, Texas, during COVID-19-related lockdowns. Using a time-series model incorporating climatic variables, seasonality variables, variables associated with social distancing restrictions, and area variables, they found that the aggregate daily water demand was reduced by up to 9%. Kalbusch et al. [34] studied the impact of COVID-19-related lockdowns on urban water demand in Brazil and found a reduction in water demand in the commercial, industrial, and government sectors but an increase in the residential sector. Similar to the study by Kalbusch et al. [34], Balacco et al. [35] studied the impact of the COVID-19 pandemic and its lockdowns (in Italy) on water demand during different stages of restrictions as a result of the pandemic. They found a change in the temporal pattern of water use and reduced water demand peaks and highlighted the importance of social phenomena and behaviours in water demand. At the micro-scale, i.e., in a study of water use in an office building in Jakarta, Indonesia, Kurniawan and colleagues [36] found that there was a 31% increase in water use during a COVID-19 outbreak in the city, but this was due to the changed behaviour of the remaining workforce in the building (about half kept working) and a supposed increase in washing behaviours.

In summary, the previous studies on this topic:

- Estimated water demand change in response to WFH in a binary sense (WFH vs. not WFH) rather than identifying the elasticity of water consumption to WFH patterns. Other papers have estimated the impact of COVID-19 in a more or less binary sense. Some articles have highlighted the important role of WFH in the impact on water demand during COVID-19. We argue therefore that estimating elasticities to WFH enables the extrapolation of water demand responses beyond the COVID-19 period.
- Relate to a mix of geographies and contexts and with some level of consistency but also variability in their outcomes. This indicates the need for a broader range of studies to allow for the variability to be better explained. Importantly, such studies require an empirical and analytical basis that allows for understanding which factors shape the differences in the results.
- Suggest, somewhat inconsistently across different studies, that residential water demand increases with WFH but large and relatively inconsistent decreases are seen in commercial water use. Further evidence is required to establish this finding more firmly.
- Inconsistent results regarding the overall change in water demand, with some studies indicating no change and others indicating a significant increase.

Further evidence is therefore needed to allow water planners to better understand the likely changes in urban water demand in the future under different WFH scenarios.

1.3. Research Question Addressed

To improve the knowledge on how WFH shapes water use, as an example of key resource uses, we therefore explore the link between a measure of the intensity of WFH practices and sectoral water demand. To this end, we, as a first study, establish elasticities, i.e., to answer the question:

Research Question. How much will an x% increase or reduction in the prevalence of WFH behaviours change sectoral water demands?

We answer this question based on a case study in Sydney, Australia, using an econometric regression model and a combination of water demand data from Sydney Water corporation, weather data from the Bureau of Meteorology, and insights on events like lockdowns and water restrictions from publicly available government sources, as well as mobility data from Google as a proxy for aggregate WFH intensity. The pandemic and variation in the intensity of WFH over time provide a natural experiment for testing the impact and elasticity of water consumption to WFH.

2. Case Study

Sydney, Australia, is a large metropolitan region with approximately 5.2 million people. Sydney Water Corporation is the water service provider, and the data in this study relate to Sydney Water's entire delivery area, which, in addition to Sydney, also includes some of the hinterlands and an estimated population of 5.3 million people across an area of 12,879 km², with a population density of 428 persons per square kilometre. When accounting for all sectors, Sydney used 524,802 ML of water in 2020–2021, which is approximately 272 L per person per day [37]. The water supply in Sydney comes from two main sources, i.e., from dams and a desalination plant [37].

There was a significant drop in per capita water use during what was referred to as the Millennium drought, which peaked during 2001–2008, with the pre-drought per capita water demand at around 425 L per day and a post-drought demand which did not return to pre-drought levels. This was at least in part due to the widespread adoption and consistency of water conservation behaviours [38]. The dataset used in our study captured a sharp decline in dam levels from mid-2017 to January 2020, which prompted restrictions on water use.

3. Methodology

To analyse the impact of WFH practices on water consumption, we model the aggregate water consumption for Sydney, as well as the per-property monthly water consumption across 5 sub-sectors, in an auto-regressive distributed lag (ARDL) framework. This time-series model incorporates a distributed lag model, as well as explanatory variables in a multivariate manner, with the parameters estimated according to regression. This is applicable both to stationary and non-stationary time series [39]. It allows us to estimate the elasticity of water demand to mobility after controlling for a range of other factors.

3.1. Data

We used the following data, sourced variously from Sydney Water, the Bureau of Meteorology [40], and Google [41], as well as publicly available data on major events [37,42]:

- Property counts per sector, postcode, and month.
- Water demand data, per sector, postcode, and month.
- Weather data, per postcode and month.
- Mobility data, per type and month.
- Data on the timing of water restrictions, changes in billing system, mobility restrictions, etc.

3.1.1. Water Demand Data

Data on water consumption and property counts were provided by Sydney Water. Sectors were defined as per the codes in Sydney Water's database (shown in brackets—explained further in Supplementary Materials):

- Single-dwelling residential homes (70),
- Multi-dwelling properties (2, 71, 73, 193, 212, 223, 225, 238, 245),
- Industrial businesses (1),
- Commercial businesses (146, 171),

- Miscellaneous (all other codes).

The multi-dwelling property category incorporates multi-residential and a small number of industrial and commercial strata units (i.e., for which there is shared ownership of a property title) because it was impossible due to the new billing system and accounting to separate these in a sensible manner. Properties that were denoted as “occupied land”, “vacant land”, and “lot for development” (i.e., that would normally be in the residential category) were categorised as Miscellaneous. The details on how this was carried out are shown in Table S1 in the Supplementary Materials. Overall, residential sectors (single and multi-unit dwellings) typically constitute 75 per cent of overall water consumption in Sydney. The other sectors are individually quite small: commercial (9 per cent), miscellaneous (8 per cent), and industrial (6 per cent).

3.1.2. Unit of Analysis

To remove the trends and impacts associated with changes in population and business activity, we calculated the water consumption on a per-property basis by dividing the aggregate monthly water use by the number of metered dwellings/properties in a given year and month for the same set of codes. The way that the number of dwellings/properties was counted changed in July 2019 because of a change in billing system (see Figure 1). We also note that per capita water demand is common practice amongst water planners. Our choice of instead analysing the per-property demand, which is contrary to this standard, is justified based on two observations:

1. The elasticities we estimate are equally applicable on a per capita basis, regardless of the method of estimation.
2. This makes more sense for non-residential sectors.

We also removed any data from unmetered properties. To capture any potential changes in how water consumption was recorded associated with the change in billing system, a dummy variable was constructed (Old/New) indicating which system was in place (New = 1).

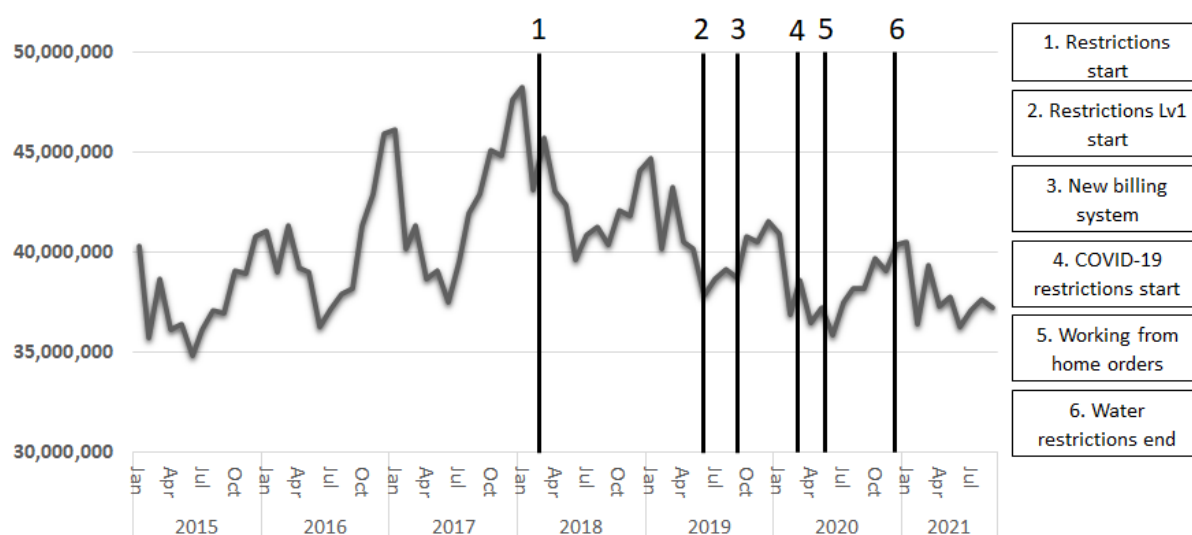


Figure 1. Aggregate water demand and key events. Y-axis unit is liters used in a month for the entire Sydney Water area. For clarity of the graphics, we did not include all the events in Table 1.

3.1.3. Emergence of COVID-19 and WFH Orders

The institutional restrictions on mobility during the study period likely impacted water use behaviours and the prevalence of WFH. Table 1 provides a chronology of the key events related to such restrictions across Sydney.

Table 1. Restrictions on mobility during the study period. Sources: NSW Parliamentary Research Office [43], Wikipedia, and the Audit Office of NSW [44].

Date	Key Events and Official Changes in COVID-19 Restrictions Across Sydney
30 March 2020	Restrictions were introduced that dictated that “a person must not, without reasonable excuse, leave the place of residence”.
1 July 2020	The level of restriction was eased to allow freer mobility.
17 July 2020	A tightening of restrictions again, reducing mobility.
30 September 2020	Almost all community outbreaks of COVID-19 in New South Wales contained.
19 December 2020	Stay-at-home orders were issued for the Northern Beaches due to an increase in cases.
6 May 2021	Public Health Order requiring wearing masks on public transport and in airports issued.
26 June 2021	“Lockdown” of Greater Sydney. Stay-at-home restrictions, along with closure of certain premises and limit on outdoor gatherings to ten people in certain areas. Work-from-home and stay-at-home restrictions, closure of premises, limits on outdoor gatherings to ten people.
23 August 2021	Additional restrictions in a small number of local government areas, including a night-time curfew.
21 September 2021	An easing of restrictions on mobility allowing some limited mobility.
11 October 2021	Stay-at-home orders were removed for those who were vaccinated.
16 October 2021	Removal of nearly all restrictions on mobility for those who were vaccinated.

3.1.4. Water Restrictions

Water demand is affected by water restrictions [38]. Sydney Water staff therefore provided information on the restriction levels at different times, and the details of these determinants are shown in Table 2. Figure 1 shows the aggregate water consumption in Sydney over the study period, as well as the timing of selected institutional events (water restrictions and COVID-19 events).

Table 2. Water restrictions at different times during the time series.

Restriction Level	Time Period	Description
Baseline restrictions in place	Until 31 August 2018	Waterwise guidelines [42]
Voluntary restrictions	1 September 2018–31 May 2019	Education/advertising campaign to reduce water use
Level 1 restrictions	1 June 2019–9 December 2019	Sydney Water staff and water conservation report [45]
Level 2 restrictions	10 December 2019–31 February 2020	
Level 1 restrictions	1 March 2020–30 November 2020	
Baseline restrictions	From 1 December 2020 onwards	Waterwise guidelines [42]

3.1.5. Weather and Climate

Variations in season, weather, and climatic conditions significantly affect water consumption [46–50]. Therefore, to control for such variations we consider the influence of the following variables based on data from the Bureau of Meteorology in Australia [40]: maximum temperature (in °C), average temperature (in °C), total rainfall in a month (in mms), and number of days with rainfall (i.e., number of days in the series with rainfall > 0 mm). Including these variables allows us to separate out the effects on water demand that relate to variations in weather conditions, and this then allows us to more clearly see the impact of WFH patterns.

To explain the context of the time series, Figure 2 shows the patterns of temperature and rainfall over the period of the analysis.

Data from the Bureau of Meteorology [40] include observations from all weather stations across the city. For analysis relating to all of Sydney, we utilised the mean monthly values across all stations. For analysis relating to specific postcodes across the metropolitan areas, we used the weather station data closest to the geographical midpoint of the postcode.

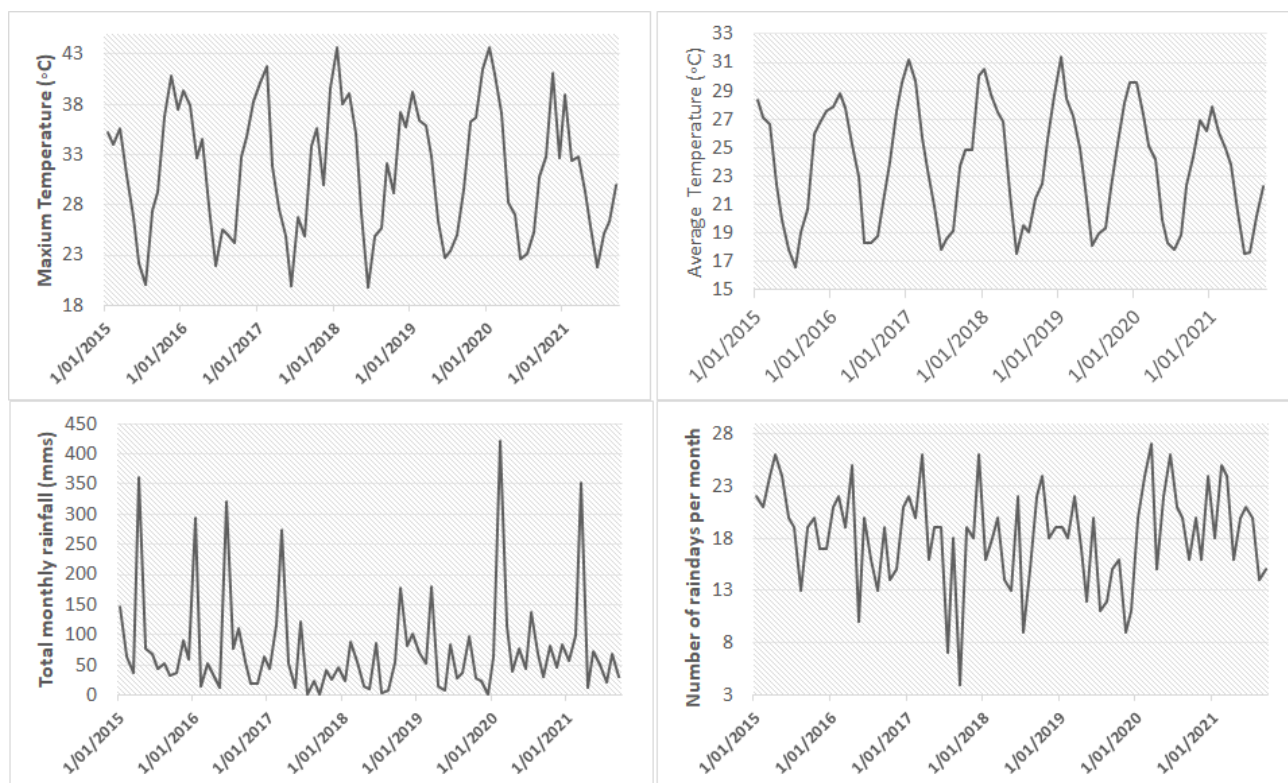


Figure 2. Weather-related variables over the time series (2015–2021). (**Top left**): Maximum temperature in °C. (**Top right**): Average temperature in °C. (**Bottom left**): Total monthly rainfall in mms. (**Bottom right**): Number of rainy days in a month.

3.1.6. Mobility Data as a Proxy for WFH Intensity

To define our variable that describes the extent of WFH and its variability, in this paper, we make use of newly available data (<https://www.google.com/covid19/mobility/> (accessed on 27 September 2023)) [51]. This allows for measuring monthly variations in the actual WFH prevalence rather than formal institutional orders, thereby providing a more practical measure of this key variable. Mobility is measured relative to the baseline period (a five-week baseline period of 3 January to 6 February 2020) and shows the percent difference over time, sourced from mobile phone users who opted in to ‘Location History’ on their Google Account. This information is provided for different categories of zones across regions, as a measure of the number of people spending time in these areas. Here, we only consider residential (i.e., in homes) and workplace mobility data.

We focused on workplace mobility as the closest proxy for WFH practices. Two alternatives, i.e., residential mobility (in homes) and transit mobility (on public transport), are closely correlated with workplace mobility but also capture the population movements of non-working populations. An increase in the workplace mobility variable thus captures an increase in workplace-based work, while a decrease captures an increase in WFH practices.

These types of data have been used in a number of studies for a range of purposes, especially in medical research [52–55]. It has been argued to be an under-utilised but reliable estimate of community mobility [55].

Estimates of the proportion of the community that opts in to sharing location history ranges up to about 95%, and close to 100% of the working population in Sydney has a mobile phone [56]. This means that the Google data represent a very large sample to gauge mobility from.

Figure 3 shows the variation in residential, transit, and workplace mobility over the period from February 2020 to December 2021 for the Sydney metropolitan region. It shows the very large impact on mobility in workplaces during March and April 2020 (−40 per cent) and again from August to September 2021 (−31 per cent). As mobility in workplaces and transit declined, mobility in residential settings increased in a broadly symmetrical manner. The relative difference between workplace and transit mobility is likely explained by a shift in mobility from public transport (i.e., transit) to cars. The near-symmetrical relationship between residential and workplace mobility provides a strong rationale for using mobility data as a proxy for the intensity of WFH. We also note that in addition to official restrictions, mobility was also affected by the spread of COVID-19 in the community.

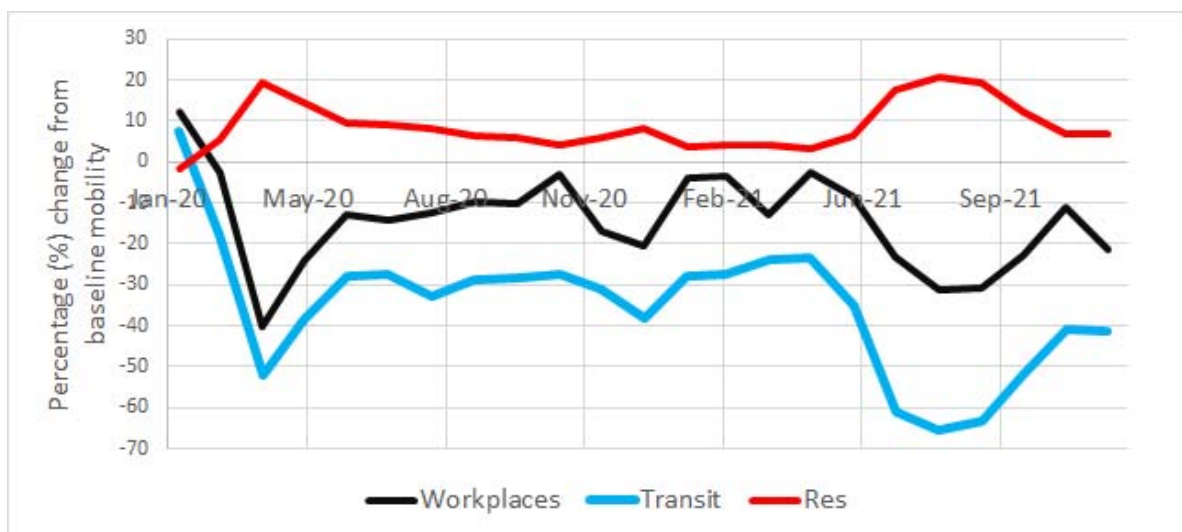


Figure 3. Mobility data during the study period for workplaces, transit, and residential locations. Y-axis in this figure is the percentage change from the baseline, which was established in the months before February 2020. Source: [51].

3.2. Time-Series Characteristics of Weather and Per-Property Water Consumption

We examine the time-series characteristics of key variables. Specifically, we test for the presence of unit roots in the data. Unit roots are stochastic properties in the consumption of water over time that may result in spurious relations due to missing variables or the passing of time. This includes identifying underlying trends that might interfere with the identification of WFH-practice-related variation. We also identify whether discrete events, such as in the introduction of water restrictions and COVID-19 or WFH orders, are associated with structural breaks (average shifts) in the time-series characteristics. For this, we use the Augmented Dicky–Fuller (ADF) test.

3.3. Analysis Approach

We use the outlined datasets in the analysis of the aggregate and sectoral time series of water consumption in Sydney, Australia (January 2015–September 2021). This is carried out to identify the impact of WFH prevalence on water consumption in Sydney. To this end, we use an auto-regressive distributed lag (ARDL) framework. The ARDL framework can contain both stationary and non-stationary variables. The ARDL specification estimated in our analysis is set out in error correction form in Equation (1); all variables in lowercase letters are logs.

$$\begin{aligned}
\Delta wc_{k,t} = & c_0 + c_1 t - \alpha (wc_{k,t-1} - \beta_T Temp_t - \beta_R Rain_t - \beta mob_t) \\
& + \sum_{i=1}^{p-1} \varphi_{wc,k,i} \Delta wc_{k,t-i} + \sum_{i=0}^{q-1} \varphi'_{tempt,i} \cdot \Delta Temp_{t-i} \\
& + \sum_{i=0}^{q-1} \varphi'_{rain,i} \cdot \Delta Rain_{t-i} + \sum_{i=0}^{q-1} \varphi'_{mob,i} \Delta mob_{t-i} + \bar{X}'_t \cdot \bar{\gamma} + u_t
\end{aligned} \tag{1}$$

where:

- c_0 is an intercept parameter.
- c_1 is a trend parameter.
- t is a monthly time index.
- k is the water sector.
- $wc_{k,t}$ is the water consumption for sector k in month t .
- $Rain_t$ is the monthly rainfall in month t .
- $Temp_t$ is the monthly average temperature in month t .
- mob_t is the Google-data-based residential or workplace mobility in month t (Note: there are separate models for this).
- α is the speed of the adjustment coefficient, i.e., how quickly water consumption patterns return to their long-run (equilibrium) trends.
- β_T is the elasticity for average monthly temperature.
- β_R is the elasticity for total monthly rainfall.
- $\bar{X}'_t$ is a vector of dummy variables or time variables associated with the level of restrictions, a new billing system, and COVID-19 and WFH practices.
- $\bar{\gamma}$ is a vector of elasticities associated with each of the dummy variables in $\bar{X}'_t$.
- $\varphi_{wc,k,i}$ are auto-regressive parameters associated with the water use in sector k i months prior to t .
- $\varphi'_{tempt,i}$ are auto-regressive parameters associated with monthly average temperature from i months before t .
- $\varphi'_{rain,i}$ are auto-regressive parameters associated with monthly total rainfall from i months before t .
- The α , β , and γ parameters are elasticities.
- Δ indicates difference, i.e., for example, $\Delta wc_{k,t}$ means the change in water use from month $t - 1$ to month t for sector k or the change in total water consumption for the aggregate analysis.

For modelling purposes, water demand ($wc_{k,t}$) and mobility (mob_t) values are transformed into an index (base period = 100). Mobility- and weather-related variables potentially condition long-run levels of water demand, as well as short-run fluctuations in water demand.

Measures of economic activity, such as GDP, are not included in Equation (1). In the empirical analysis, the monthly GDP index is added to the aggregate regression. GDP expansion in Australia significantly reflects population growth. As the population and economy grow, the aggregate water demand increases. The sectoral regressions are based on the water consumption per property. As the population and economy expand, so does the number of properties in the economy. In both cases, GDP expansion is, for the examined time period, orthogonal to the remaining variables in Equation (1).

Various combinations of variables are tested in the $\bar{X}'_t$ vector, including water restriction in interaction with seasonality capturing above-average rainfall months (December–March each year). In this modelling framework, these variables are only expected to condition short-run variations in water consumption, rather than conditioning any long-run equilibrium relationships.

4. Results

4.1. Stationarity or Trends

Table 3 summarises the Augmented Dicky–Fuller (ADF) test results. Testing for trends and breaks in the data, the Augmented Dicky–Fuller (ADF) test inform us that the:

1. Rainfall and average temperatures are non-zero mean stationary processes. Each of these vary seasonally but exhibit little deviation from seasonal patterns.
2. The weather variables, over this time frame, exhibit no trend; however, their inclusion provides insight into long-run impacts on water consumption associated with climate-related changes in weather patterns.
3. Water consumption in detached homes, industrial, and miscellaneous settings is a non-zero mean stationary process. The absence of a trend in detached home water consumption is likely the result of the much greater share of garden maintenance in these settings.
4. Multi-unit dwelling water consumption and commercial water consumption are non-stationary processes with negative deterministic trends (trend coefficient $\neq 0$). These trends may be the result of increasing awareness and the installation of water-efficient appliances.
5. The first difference in the ADF tests is stationary processes without trends in each case.

The p -values from the ADF MacKinnon values with three lags are reported in Table 3.

Table 3. Stationarity test weather and water consumption trends.

Factor	MacKinnon Approximate p -Value, $Z(t)$	Trend
Rainfall (mms)	0.00	no
Average temperature (°C)	0.00	no
Sydney total, aggregate (ML)	0.03	no
Detached dwelling water consumption, per property (kL)	0.01	no
Multi-dwelling water consumption, per property (kL)	0.63	yes
Industrial water consumption, per property (kL)	0.03	no
Commercial water consumption, per property (kL)	0.04	yes
Miscellaneous water consumption, per property (kL)	0.03	no

Note: The results here are based on Augmented Dicky–Fuller tests performed with three lags.

As per Tables 1 and 2, a series of events took place over the study period that may be reflected in the average water consumption levels. Starting in early 2018, a series of water use instructions and restrictions were put in place. Table 4 summarises the systematic testing of the structural breaks associated with these discrete events, as well a search for structural breaks in the data series over the full period. This search identified that:

- The evidence of structural breaks is clearest in the multi-dwelling and commercial water consumption—the two data series that also exhibit deterministic trends in the above analysis. In both these data series, potential structural breaks are identified and significant at conventional statistical levels ($p < 0.05$).
- For single-dwelling water consumption, there is some evidence of a structural break associated with the introduction of level 1 water restrictions, but only weak evidence of any COVID-19-related events ($p > 0.05$).
- No significant breaks were detected in the per-property industrial water consumption, whereas the per-property miscellaneous water consumption suggests a structural break with the emergence of COVID-19 in February 2020.

From a modelling perspective, the stationarity and structural break results suggests that the time-series characteristics of sub-sectoral water consumption vary between

sectors. For this reason, we employ an ARDL framework that is suitable for stationary and non-stationary combinations, as well as a time (months) since the introduction of restrictions (level 1) as a means of capturing trend/break dynamics.

Table 4. Augmented Dicky–Fuller test and test for structural breaks. What are shown are p -values associated with the statistical tests for structural breaks. $p < 0.05$ is used as a test to indicate statistical significance.

Sector/Variable	March 2018	June 2019	July 2019	February 2020	March 2020	Search
Sydney total, aggregate (ML)	0.42	0.34	0.49	0.07	0.46	0.50
Detached dwelling water consumption (kL per property per month)	0.11	0.04	0.10	0.07	0.38	0.07 (February- 2019)
Multi-dwelling water consumption (kL per property per month)	0.04	0.02	0.28	0.74	0.96	0.06 (February- 2019)
Industrial water consumption (kL per property per month)	0.97	0.41	0.39	0.21	0.39	0.30
Commercial water consumption (kL per property per month)	0.07	0.00	0.00	0.00	0.00	0.00 (February- 2020)
Miscellaneous water consumption, per property (kL per month)	0.63	0.61	0.55	0.01	0.15	0.14

Note: The results in this table are based on structural break tests performed after regressing log total water consumption (Δ) on log total water consumption ($t - 1$) and three lags. Test performed using Stata user-written commands sbknown and sbsingle.

4.2. WFH Prevalence's Impact on Sectoral Water Demand

The final choice of our model is presented in Table 5 (all variables were included and tested, but only those that are statistically significant with a p -value < 0.05 —except a couple that we have included for the sake of illustration when being close to significant).

The variables that we have included are:

- A measure to account for restrictions, i.e., the number of months since the introduction of the *Waterwise* water restrictions.
- Given the presence of a trend in some of the stationarity statistics, a continuous measure of time (since the start of the dataset).

We modelled discrete events as only having short-run effects. It is feasible that with more data available, social learning effects might be measured as having long-run impacts.

The estimation of Equation (1) was conducted using Stata's *ardl* command [57]; lag lengths are software-determined for each estimation based on the Bayesian Information Criteria.

Table 5. Impact of COVID-19 and WFH practices on sectoral water consumption, Sydney overall, ARDL estimation. p -values are shown in brackets, and values < 0.05 are statistically significant.

	Aggregate	Single Detached Dwelling	Multi-Unit Dwelling	Industrial	Commercial	Miscellaneous
Panel 1. The adjustment speed measures how quickly deviation from equilibrium relationships is corrected each month.						
Ln demand L1	−0.487 * (0.002)	−0.407 * (0.001)	−1.462 * (0.000)	−0.627 * (0.000)	−0.949 * (0.000)	−0.486 * (0.000)
Panel 2. Long-run measures identify changes in equilibrium water demand levels in response to permanent (long-term) changes in weather and mobility patterns.						
Ln rainfall	−0.024 (0.035)	−0.046 (0.004)				
Ln avg temperature	0.210 (0.000)	0.194 (0.012)	0.038 (0.001)	0.155 (0.001)	0.309 (0.000)	0.298 (0.002)
Ln workplace mobility	−0.072	−0.167	−0.084	0.291	0.960	0.314

	(0.500)	(0.278)	(0.001)	(0.000)	(0.000)	(0.035)
Ln GDP index	0.968					
	(0.022)					

Panel 3. Short-run measures, identifying the effects of short-run variations in weather and WFH practices on water consumption. Here you can find the elasticities.

Ln demand LD	−0.372	−0.302				
	(0.001)	(0.005)				
Ln rainfall D1	0.010	0.014				
	(0.006)	(0.001)				
Ln avg temp D1	0.221	0.262				0.294
	(0.000)	(0.000)				(0.000)
Ln avg temp LD						0.163
						(0.020)
Ln workplace mobility D1				−0.395		
				(0.000)		
Ln workplace mobility LD				−0.182		
				(0.041)		

Panel 4. Account for variations not related to changes in long-run relationships.

Months of restrictions	−0.002	−0.001	−0.006		−0.006	−0.008
	(0.030)	(0.029)	(0.000)		(0.001)	(0.000)
Trend			0.001 *		0.002	0.004
			(0.020)		(0.001)	(0.000)
Restrictions (=1)		−0.050 ^	−0.034 *			
		(0.059)	(0.016)			
Constant	6.281	1.339	4.175	2.066	−0.568	1.012
	(0.001)	(0.000)	(0.000)	(0.000)	(0.183)	(0.008)
Months	77	77	77	77	77	77
Adj R ²	0.546	0.490	0.726	0.364	0.604	0.609

Note: The *p*-values are reported in brackets, and the conventional significance measure is (<0.05) used to check the statistical significance of results. L is a lag operator (e.g., L1 is variation in levels at $t-1$, etc.), D is a difference operator (e.g., D1 is t_0-t_1 , D2 is t_0-t_2). ^ indicates following level 1 water restrictions; * indicates following level 1 water restrictions interacting with summer (December–March) months. LnGDP index not significant in any of the sectoral regressions.

Guidance on the results in Table 5:

- The panel 2 results identify the impacts on long-run water consumption associated with ongoing changes in WFH/mobility or weather patterns. The panel 3 and 4 results identify the impacts on short-run water demand associated with fluctuations in weather, mobility, or policy variations.
- The key variable of interest is the long-run effect of changes in WFH prevalence as measured by the workplace mobility variable. Elasticities that indicate increases or reductions in water demand because of more or less WFH are shown in the row labelled “Ln workplace mobility”, i.e., for the long-run relationships, these indicate that a 10% increase in WFH practices leads to a 0.8% increase in multi-dwelling residential water use and no increase in detached housing residential water use, as well as a reduction of 2.9% in industrial water use, 3.1% in miscellaneous water use, and 9.6% in commercial water use. At the aggregate level, whilst not significant, we note that the point estimate is that a 10% increase in workplace mobility leads to a 0.7% reduction in water use; this result is statistically insignificant and therefore consistent with no change in aggregate water use resulting from a change in WFH/workplace mobility prevalence. The implications of these results are discussed in Section 5.
- Elasticities that indicate an increase or decrease in water demand because of higher or lower temperatures are shown in the row labelled “Ln avg temperature”. To translate these numbers, a 1-degree (ongoing/permanent) increase in average temperatures would lead to increases of 0.4% in the multi-residential dwelling sector, 1.6% in the industrial sector, 1.9% in the single detached house residential sector, 2.1% in aggregate water demand, 3% in the miscellaneous sector, and 3.1% in the commercial sector.

- Unsurprisingly, the aggregate water demand is closely associated with economic expansion (GDP). As discussed in Section 3.3, this reflects the association between economic expansion and population growth. Its inclusion does, however, have a negligible impact on the remaining coefficients and is not significant in any of the sectoral regressions (omitted due to non-significance).

We also note that the adjustment speed variable is negative and significant across all sectors. The negative coefficient indicates that consumption patterns quickly return to their long-run trends following seasonal or temporary fluctuations in any of the variables. For water consumption, the aggregate demand and single-home, industrial, miscellaneous, per-property, and series typical water consumption resume to long-run trends within 2–3 months. For multi-unit dwelling and commercial water consumption, the two non-stationary water consumption series adjustments take place within a month. For both, there are temporal trends suggesting additional water consumption determinants not captured in our model.

Other results show a general decline in water consumption following its peak in early 2018 (months of restrictions). For multi-dwelling, commercial, and miscellaneous per-property water consumption, the decline since August 2018 cancels out the positive time trend. An additional average reduction (3.4 per cent) in multi-dwelling water consumption is evident following the introduction of level 1 restrictions in June 2019.

5. Discussion

The results of this study show that, for water consumption in Sydney at the aggregate level, permanent changes to where people work—home versus places of employment—are likely to have a very small impact. There are statistically significant increases in multi-unit dwelling residential demand, whilst there is no significant impact for detached homes. There are also expected decreases in water demand for the industrial, commercial, and miscellaneous sectors.

We also note that our result of no statistically significant impact on aggregate water demand is broadly similar to what Nemati and Tran [32] reported, i.e., increases in WFH practices in their study led to a small increase in residential water demand, which was offset by reductions in demand across other sectors. It has previously been reported that WFH unsurprisingly led to an increase in water demand for residential properties, whilst our analysis indicates that the increases in residential water demand are primarily for apartments and units, but surprisingly no statistically significant impact was found on residential water demand in single-home dwellings.

Our results also differ to what was reported by Bakchan et al. [33]. They found an aggregate reduction in demand due to WFH practices. The studies by Nemati and Tran [32] and Bakchan et al. [33] were carried out in the US, and our study was in Australia, so it is possible that there are contextual differences. Furthermore, both those studies used indirect dummy variables to indicate either social distancing policies or WFH orders and therefore did not incorporate any measure of intensity of WFH practices. In addition, and importantly, the results of Bakchan et al. [33] which showed a decline in aggregate water demand of 9% were based on an analysis of data from COVID-19 lockdowns only and therefore other factors may have conflated the results, i.e., the reductions in water demand for the commercial and industrial sectors may be larger than what can be expected outside of lockdowns.

5.1. Residential Dwellings

Surprisingly, the analysis, as summarised in Table 5, indicates that variations in WFH had no statistically significant impact on the water demand in detached single residential properties. In contrast, there was a statistically significant but small increase in water demand for multi-unit dwellings, i.e., for apartments and units.

It is also worth noting the very large number of residential properties, both for multi-dwelling and single-dwelling properties. This explains why, despite a proportionally

relatively small increase in water demand in the residential sector and a proportionally relatively large decrease in water demand in the non-residential sectors, these opposing effects more or less cancel each other out, leaving the aggregate water consumption largely unaffected.

But why do we not see an increase in water use also in single-dwelling residential properties? A priori, the water consumption in detached homes might differ from that in multi-unit dwellings. In Australia, many more detached dwellings have gardens, and this may be part of the explanation. Detached dwellings also tend to house a smaller proportion of residents that are working compared with multi-units, and as the prevalence of WFH practices only affects the working part of the household, this reduces the relative sensitivity of the total household water consumption to variations in WFH intensity. Multi-unit dwellings may relate to different demographics, i.e., a higher percentage of professionals with a capacity to work from home in apartments and units compared to detached dwellings.

5.2. Weather and Water Demand

As perhaps expected, because it is reported in some studies in hotter climates [50,58,59] but not in cooler climates like in Germany [60], temperature was found to be a significant determinant of water consumption. Likewise, as in several other studies in both colder and hotter climates [50,58–60], we found that rainfall was a significant determinant of water use.

In our study, increases in rainfall lead to a reduction in water consumption, primarily driven by a reduction in detached dwelling water consumption. Over the study period, the average temperature in Sydney was 23.7 degrees. With this baseline, a 1.5-degree Celsius increase in average temperature would add an additional 1.3 per cent in climate-related water demand. (At COP25 (the 2015 Paris Agreement), an agreement was made to limit global warming to 1.5 degrees Celsius). This has implications for sustainability in cities.

Permanent changes to average temperatures, for instance, because of climate change and exacerbated by urban patterns that create heat islands (i.e., due to poor urban design), lead to increased water demand across all sectors. This is broadly consistent with a more comprehensive analysis of the impact of future climate change on water demand in Sydney [59], but despite this, as is argued in the article by Barker et al. [59], population is going to remain the dominant driver of future water demand, even in a future of considerable climate change.

5.3. Total Water Use

Unlike some previous studies that found that WFH either increased the overall demand [32] or decreased water demand [33], our study found no significant change in overall water demand as a result of changed WFH prevalence.

Whilst our results show that the impact on aggregate water consumption is not significant, this insight should, however, be qualified by the urban form context of our study. Sydney is a low-density city with a large proportion of single dwellings. In more compact cities or cities/areas with greater proportions of apartments and units, an increase in the prevalence of WFH may also necessitate supply–infrastructure augmentation.

Similarly, if a city or urban area, has more industry or commercial properties as compared with residential properties, this equation may also change, leading to a net increase in water demand. In other words, in denser cities, a higher prevalence of WFH may lead to a net increase in water demand. In highly industrialised cities or cities with very significant commercial zones, a greater prevalence of WFH may lead to a net reduction in water demand.

5.4. Sustainable Resource Use

WFH is by no means a new phenomenon, but its recent popularity is a major shift compared to previous trends. Its potential for sustainability gains are considerable, not just in terms of reduced car travel and associated emission reduction but also across multiple Sustainable Development Goals (SDGs), i.e., SDG 3 Quality Education; SDG 5 Gender Equality; SDG 8 Decent Work And Economic Growth; SDG 9 Building Resilient Infrastructure, Promote Inclusive and Sustainable Industrialisation and Foster Innovation; SDG 10 Reduce Inequality within and among Countries, SDG 11 Sustainable Cities and Communities; SDG 12 Ensure Sustainable Consumption and Production Patterns; and SDG 13 Take Urgent Action to Combat Climate Change and Its Impacts [7]. However, perhaps the most noticeable benefit of WFH is a reduction in pollution and greenhouse gas emissions [6,61,62]. Unfortunately, due in particular to environmental rebound effects, especially associated with a propensity towards relocation for those who WFH to larger homes, towards lower population densities in homes [63], and towards greater car reliance [64], there is, however, remaining uncertainty about whether the reductions in other resource use and greenhouse gas emissions associated with WFH will be offset by increased consumption. This paper has addressed one of the question marks regarding the possibility of increased water use associated with WFH. However, based on the results in this paper, it seems that overall water use does not increase.

5.5. Compact City Agendas

The notion of compact cities (i.e., with a higher density) is widely thought to be a key pathway to achieving sustainable development goals [65]. This is relevant to water consumption too, with multi-unit dwellings typically having smaller per capita water footprints when compared to single dwellings [66]. In our data, the water consumption in single residential dwellings is 56 percent greater than in multi-unit dwellings. However, while the water footprint per property is smaller in compact cities (a potential sustainability gain), our results show that water consumption in multi-unit dwellings (typical of denser urban landscapes) is more responsive to variations in WFH. Changes to WFH practices may thus place additional stress on water distribution and sewage systems within cities and potentially infrastructure resilience. A qualification here is that WFH primarily impacts indoor water use, which is the only (dominant) water use in multi-unit dwellings. In single dwellings, indoor water consumption is a share of the total water consumption, which also includes outdoor water use. WFH therefore has a proportionally higher impact on multi-unit dwellings but possibly causes the same per capita increase in single dwellings as in multi-unit dwellings. Due to the relatively smaller increase in single dwellings, this is not picked up as statistically significant.

5.6. Infrastructure Planning Assumptions

Our results do not challenge the premise that WFH in compact cities tends to reduce resource use, with potential sustainability impacts. However, our results do raise the implication that changes in WFH in compact cities places greater stress on water and sewage infrastructure and, as such, infrastructure resilience.

Achieving a safe and affordable water supply requires continued installation, maintenance, and sometimes refurbishment and upgrade of water infrastructure to ensure that it meets the (changing) needs of a city [67]. The planning of such activities has traditionally relied on age-old assumptions that most workers need to travel from their home to their workplace. Since the advent of COVID-19, urban dynamics has shifted in a significant manner [68], thus challenging previous assumptions. Changed distributions of daytime and night-time population densities lead to opportunities for urban regeneration and a shift in the spatial distribution of commercial services [1]. Specifically, combined with the insights from our study, this makes water infrastructure planning difficult because the existing infrastructure relies on assumptions about when people are in different locations.

As WFH has now become more prevalent, water demand will shift towards areas with denser residential living and away from areas with more commercial/industrial zones. This has implications for infrastructure and the distribution/collection of water/wastewater:

- Residential areas, especially those that include more units and apartments, will experience increases in daytime water use as a result of increases in WFH.
- Areas with more commercial zones or industrial zones, especially with more offices, can expect a significant decrease in daytime water use, i.e., for example, in CBDs.

This shift may require that pipeline networks and water distribution systems are upgraded and refurbished, especially in terms of the sizing of the pipes and the choice of pumps, to make sure that water distribution systems are adequate.

Specifically, in areas with increasing population densities, the piping may be too small, which could lead to issues with pressure (i.e., low pressure). In areas experiencing reductions in demand, the piping will likely be too large, which will lead to increased risks of disease and bacterial growth, as well as odor. Importantly, both under-sized and over-sized infrastructure is not an effective use of resources. Future planning of water infrastructure needs urgently updated assumptions on the requirements in view of changing WFH practices.

5.7. Limitations and Suggestions for Further Study

As with all studies of this kind, the results are by necessity situated in one context and a particular time. Therefore, whilst the results reported in this paper are broadly consistent with some previous findings, further research will be required in order to fully establish the causal mechanisms behind changes in water use as a result of increased WFH prevalence. In other words, we can establish the (consistent) pattern of changes but not the full explanations for the changes.

5.7.1. Longitudinal Study

To address the issue of temporal changes in behaviour, economy, and/or technology, the methodology provided in this paper would first need to be replicated in the same context (i.e., longitudinally) to make sure the patterns of demand responses persist over time. For example, the large decrease in industrial and commercial water demand may rebound as the economy returns to a more normal and steady state after the COVID-19 pandemic.

5.7.2. Multiple Case Studies

There is a need to repeat the study methodology in different cities and contexts around the world (as far as is possible given limitations on data) to better understand the underlying factors that shape water demand responses—for example, different types of residential patterns (i.e., denser cities with larger proportion of units and apartments) with less garden space—and in areas with higher rainfall, the increase in residential water demand may be more pronounced.

5.7.3. Limitations of the Mobility Data

A key innovation in our study is the use of mobility data to capture the variation in WFH intensity. The results thus better identify the impact of WFH, as opposed to the impacts of lockdowns. Nevertheless, the COVID-19 period was unusual (in many ways). For instance, economic activity was also reduced because of measures to restrict the spread of COVID-19. Therefore, as in all previous studies on this topic, COVID-19 remains a potential confounding factor also when using the mobility variable. While separate attempts to capture COVID-19-related impacts—such as including a dummy variable from February 2020 or a specific WFH order dummy variable in parts of 2020 and 2021—were insignificant, this does not preclude the fact that some of the behavioural adjustments that were

observed, and reflected in the consumption data, may still be biased by the COVID-19 experience. Further use of this type of mobility data, well after any impact of COVID-19, is therefore warranted.

5.7.4. Temporal Patterns of Water Use

We have identified in this study that WFH will change the spatiotemporal patterns of water use in cities, which has profound implications for infrastructure planning, and therefore there is an urgent need to better understand this change. Interrogating academic databases (i.e., Scopus, etc.), we only found one article [69] that studied the changes in the spatiotemporal pattern of wastewater catchments or water distribution requirements as a result of WFH behaviours. We conclude therefore that there is a need for more research on this topic.

5.7.5. Resource Use

Finally, the current study focuses on how the prevalence of WFH impacts water use only, whilst the resource implications—from an environmental sustainability perspective—may be more pronounced for other types of resources, such as energy. Therefore, further studies could use our methodology to better understand how WFH prevalence increases or decreases particular energy/electricity use in cities. This topic has been raised by a few studies [70–74], but none have used a method similar to ours, which would provide more robust empirical information.

6. Conclusions

This article has studied how WFH practices influence urban water demand volumetrically and by sector. Since the COVID-19 pandemic and associated mobility restrictions, WFH practices have increased all around the world. These are unlikely to revert to the pre-pandemic levels. This can lead to significant sustainability benefits, but its impacts are also so far unclear in terms of resource use impacts. A small number of studies have studied the impact of increased WFH prevalence on urban water demand, but there remain open questions. Importantly, the current studies focus on the average shifts in water demand during lockdown periods rather than the responsiveness of water demand to the intensity of WFH. The elasticity of water demand is required to project and plan for ongoing changes to the way we work in the future. This is required for infrastructure and water planning.

Therefore, in this study, we employ a study design that combined Google mobility data as a proxy for WFH intensity with sectoral water demand data from Sydney. We analysed the temporal variability by using an ARDL time-series approach. This enables us to account for confounding factors using regressions and to estimate the elasticity in the water demand to changes in the prevalence of WFH practices. After estimating such elasticities, we found that, in the context of and according to the urbanisation patterns of Sydney, there was no statistically significant impact of WFH intensity on the aggregate water demand. However, we also found that whilst apartment blocks and units are likely to see greater increases in water demand, we found no significant increase in single-home (detached) residential dwellings. We also found a significant reduction in water demand in the commercial, miscellaneous, and industrial sectors. As an example, commercial water demand responds strongly to increases in WFH behaviours, with a 1% increase leading to an approximately 1% decrease in commercial water demand, a 0.3% decrease in industrial water demand, etc.

Our study shows that whilst WFH prevalence will in many cases not impact significantly the aggregate water demand, however, it will have implications for the spatiotemporal patterns of water distribution, water and wastewater management, and resilient infrastructure planning. Further research is needed to explore each of these in detail.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su16051867/s1>. Table S1: Method for assigning properties/dwellings to codes.

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