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Water in the time of corona(virus): The effect of stay-at-home orders on water demand in the desert

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ABSTRACT

In response to COVID-19, many U.S. states implemented stay-at-home orders to mitigate disease spread, causing radical changes across all facets of consumer behavior. In this paper, we explore how a stay-at-home (SAH) order impacted one aspect of behavior: the demand for water. Using a unique panel dataset of property-level water usage in Henderson, Nevada, we analyze changes in water usage from the SAH order, finding an initial and continuous decline in average daily usage for commercial and school users. In contrast, we find an initial increase in consumption by residential users with this effect increasing over time. Aggregated across all users, the SAH order led to an increase in net water usage between 32 and 59 million gallons over the first 30 days.

1. Introduction

In response to the outbreak of the global COVID-19 pandemic, society dramatically shifted the way in which people consume, educate, and work. Urged to stay-at-home (SAH) and practice social distancing by political and public health officials, consumer spending radically changed with a shift toward necessities and a substantial decline in luxury items (Baker et al., 2020). The economy shifted toward embracing remote work, with an estimated half of workers employed pre-pandemic operating from home (Brynjolfsson et al., 2020) with substantial increases in unemployment filings for those unable to do so (Beland et al., 2020). When combined, these myriad factors point to a new reality: more people are in their homes for more hours than ever before. This means that household resource utilization – electricity, natural gas, and water usage – are likely affected by this societal change. At the same time, these same factors may lead one to expect, a priori, a fall in resource utilization by non-residential users. These observations raise several important empirical questions: firstly, how is the COVID-19 pandemic re-shaping resource utilization for residential and non-residential users? Second, if there exists an asymmetric pandemic response across users, what is the aggregate utilization change?

In this paper, we seek to understand household utilization of one key resource subsequent to COVID-19: water. To mitigate the possibility that water consumption patterns are driven by geography – specifically the relative abundance/scarcity of water – we study water usage in Henderson, Nevada, a large desert city with existing societal preferences for conservation. Nevada enacted a SAH order on March 17, 2020 with a gradual reopening starting May 9, 2020.

While there is a rich literature on estimating water demand (Howe and Lineweaver, 1967; Foster and Beattie, 1979; Chicoine et al., 1986; Hewitt and Hanemann, 1995; among others) and a burgeoning literature on responses to pricing and conservation efforts (Michelsen et al., 1999; Olmstead et al., 2007; Ferraro and Price, 2013; Brent et al., 2015; Wichman et al., 2016), less work exists studying the responsiveness of water demand to a crisis like COVID-19. It is natural to hypothesize there may be a response, as...
psychology research suggests a strong linkage between mood and consumer decision-making (Gardner, 1985) in addition to research suggesting significant behavioral changes following crises or disasters (Nordløkken et al., 2016; Ito and Kuriyama, 2017). Our major contribution is in uncovering how water demand changes in response to the pandemic and providing econometrically sound estimates of the heterogenous effects to the SAH order that has important water conservation implications.

We exploit the panel nature of our data and model average daily water usage at the property-by-water-billing level before and after the SAH order was implemented compared against the typical water usage from the same periods in previous years. We use property-specific and year fixed effects to control for as many household or temporal drivers of water consumption as feasible possible. We find water usage by residential users initially increased by 11.7–13.1% during the first month following the stay-at-home period, which we attribute to behavioral changes induced by the pandemic. Commercial usage decreased by 34.1–35.7% while schools fell by 55.8–66.2%, consistent with the effects of the SAH closure on these user types. Aggregating across all users, we find the SAH order led to an increase in net water usage between 32 and 59 million gallons over the first 30 days. To put these effects in context, this equates to a 1.8–3.3% increase in monthly per capita water usage, respectively.

These findings have important policy implications across two distinct fronts. First, as remote work becomes increasingly commonplace, policymakers may need to renew their efforts at promoting conservation, especially amongst users in higher-income areas who are not as water price sensitive. Secondly, the locational re-sorting motivated by COVID-19 is likely to see continued migration from coastal cities to inland areas, especially cities in the Western United States, which already face significant water constraints. Developing the appropriate policies to educate new residents on sustainable water usage will be of paramount importance especially in an uncertain climatic future with potentially dire water scarcity in the future.

We proceed as follows: we describe our study area and data in Section II, our empirical model and results in Sections III and IV, respectively before discussing the overall findings in Section V and conclude in Section VI.

2. Study area and data

Our study area is Henderson, Nevada, one of the principal cities of the Las Vegas Metropolitan Statistical Area. After the city of Las Vegas, Henderson is the second largest city in Nevada, with an estimated population of over 340,000 (U.S. Census Bureau, 2020a). The entire Las Vegas Valley (LVV) has undergone tremendous population growth since the early 1990s and, due to its location in the Mojave Desert, water usage is a critical concern. Nearly 90% of the water used is drawn from Nevada’s partition of Colorado River water rights, which entitles the state to 300,000 acre-feet (97.76 billion gallons) per year (SNWA, 2020). This water allocation was assigned in 1922 when the state had three percent of its current population. Thanks to extensive water conservation efforts in the LVV, the state has yet to use its full allowance; however, the unprecedented state-wide responses to the COVID-19 pandemic may change this fact.

We obtain water billing and usage from the Henderson Water District covering all users from 2017 through bills ending September 30, 2020. Water bills are generated at the property level and include information on user type and address, bill generation date, days in the billing cycle, and the water consumed in gallons. We restrict attention to three user types: Residential, Commercial, and Schools, which comprise the three largest consumers. There are approximately 98,099 distinct users in the District, with residential users comprising 98% of the total user base. Henderson is heavily residential, as shown in Figure A1, with other land uses spatially dispersed throughout the city.

For each water bill, we calculate average daily water usage (in gallons) for residential, commercial, and school users based on the gallons consumed and number of days in the billing cycle. The average commercial user consumes 6,459 gallons per day (gpd) with residential users consuming 502.3 gpd while school users consume 10,557.7 gpd over our study period.

3. Empirical implementation

To estimate the impact of the SAH order on water usage, we exploit the arguably exogenous nature of the SAH order date coupled with the panel nature of the data. We use data spanning the first billing cycle that starts and completes before the March 17, 2020 SAH order began, and data spanning the first four billing cycles that start and complete after the SAH order. To control for the seasonal and cyclical nature of water usage, we also include data on water usage around the SAH for the three previous years. Thus, the final data set is comprised of five water bills per year per property. Equation (1) is the main estimating equation.

$$
\ln(gallons/day)_{i0} = \sum_{\omega=1}^{4} \sum_{k=1}^{2020} \beta_{k}(1(k_0) \times I(Post j = \omega March 17)) + \eta_i + \lambda_i + \epsilon_i
$$

1 In related literature, Tanaka and Ida (2013) and Cho et al. (2016) study the effect of earthquakes on electricity demand while Pourfarzad (2016) studies the impact of floods on transportation networks. Related to COVID-19, Cicala (2020) finds a decrease in European electricity demand in the early pandemic.

2 We focus on Henderson due to the availability of high-frequency water data.

3 A user is synonymous with a property and is the level of water bill generation.
The variable \( \ln(gallons/day)_{t,k} \) measures the log of gpd consumed by property \( i \) in billing cycle \( j = (1, 2, 3, 4) \) in year \( t \). \(^4\) \( I(k) \), is equal to one for all bills in year \( k \), \( \{2017, 2018, 2019\} \), zero otherwise. \( I(\text{Post } j = \omega \text{ March } 17) \) is equal to one for property \( i \) if the start day and month of billing cycle \( j \) for bill \( \omega \) occurs after March 17 and zero otherwise where \( \omega = \{1, 2, 3, 4\} \). Lastly, \( \eta_i \) and \( \delta_j \) are exhaustive sets of property and year fixed effects, respectively, and \( \epsilon_{it} \) is an idiosyncratic error term.

Of interest are the coefficient estimates of \( \beta^\omega \) which capture the average change in water consumption over the billing cycle occurring immediately before and the \( \omega \) billing cycles after the SAH date in year \( k \). For example, \( \beta^\omega_{2020} \) captures the average change in water consumption comparing the billing cycle immediately before and \( \omega \) billing cycles after the actual COVID-19 SAH order of March 17, 2020 while \( \beta^\omega_{2019} \) captures the same average change in water consumption in the period around March 17, 2019. The first difference effect over the billing cycles before and after March 17, 2020 is of primary interest.

One may be concerned that seasonality in water usage, e.g., landscaping, may confound the estimated effect in 2020 as summer months correspond to a greater water need not attributable to the SAH order. As shown in Fig. 1, there is evidence of seasonality in the data with water use increasing from January to August with a decline thereafter, which is attributable to regional water authority regulations on allowable watering days. Estimating the direct effect of the SAH order thus requires a property-level water usage counterfactual, or the change in water usage that would have occurred without the order. Estimating this counterfactual is challenging since there does not exist a group of control properties located in the city not subject to the SAH. To overcome this issue, we use properties as their own counterfactuals. Specifically, we roll back the March 17 SAH order and estimate the first difference effects over the billing cycles, that we uniformly fail to reject the null of coefficient equality at the 5% level. While not a definitive test, using variation and school properties we can see in Table 1 from the

4. Results

We report estimates of equation (1) in Table 1 separately for the three user types. Turning attention first to residential properties in column 1, we show that the coefficient estimates on \( I(2020) \times I(\text{Post } j = \omega \text{ March } 17) \) reflect an increase of water consumption by approximately 30.5%, 60.0%, 75.8%, and 89.3% over the first four billing cycles after the SAH order relative to the immediate billing cycle before the SAH order was issued.\(^5\) All estimated effects are statistically significant at the one percent level.

Looking at the results in Table 1 for commercial (column 2), we see an initial decrease then subsequent increase in water consumption relative to the period immediately preceding the SAH order that correspond to changes in water consumption of approximately –19.6%, 16.1%, 43.6%, and 55.6% over the first four billing cycles with these effects statistically significant at a high level. For schools (column 3), we find negative estimated coefficients on \( I(2020) \times I(\text{Post } j = \omega \text{ March } 17) \) for the first three billing cycles after the stay-at-home order with a positive effect in the fourth billing cycle of approximately –39.0%, –27.4%, –31.8%, and 24.7%, respectively. All estimated effects continue to be statistically significant at a high level.

While the SAH order is plausibly exogenous, the date of the order nonetheless coincides with a billing month where water usage typically rises. As such, first difference estimates captured by the coefficient on \( I(2020) \times I(\text{Post } j = \omega \text{ March } 17) \) not only reflect the direct effect of the SAH order, but also a seasonal component of water usage. As estimates on 2020 water usage captures both components, separating the direct SAH effect from the seasonal component requires counterfactual estimates of water usage in 2020 that plausibly reflects the state of the world for which the SAH order was not enacted. To do this, we leverage variation in water usage in years prior to 2020. In doing such we are inherently assuming that average changes in water usage for the billing cycles before and after the March 17 SAH order in previous years are proportional to what would have happened in 2020 in the absence of the order. Although this key identifying assumption of common trends is not directly testable, we can inspect the stability of the estimated first difference effects around March 17 in the years leading up to 2020, i.e., testing for joint significance in the effects leading up to 2020. Finding stability in the first difference effects around March 17 in the years leading up to 2020 would provide some confidence in the untestable common trends assumption needed to adjust the first difference effects in water usage given the SAH order. For commercial and school properties we can see in Table 1 from the \( p \)-values associated with joint F-tests on coefficient estimates over previous years billing cycles, that we uniformly fail to reject the null of coefficient equality at the 5% level. While not a definitive test, using variation in water usage over prior years to adjust the current first difference estimates for water usage by commercial and school properties seems reasonable.

Unlike commercial and school properties, constructing counterfactuals for residential properties raises some concerns. The \( p \)-values associated with the joint F-tests of equality on previous years usage indicates that the estimated effects are statistically different from

\(^4\) For example, \( \ln(gallons/day)_{t,1} \) represents the log of gpd consumed by property \( i \) over the first complete billing cycle after March 17 in a given year \( t \), while \( \ln(gallons/day)_{t,1} \) represents the consumption by that property over the first complete billing cycle immediately before March 17 in the same year.

\(^5\) These reported percent changes are calculated using the standard Halvorsen and Palmquist (1980) correction (\( \exp(\beta^\omega \times 100) \)) on the estimated coefficients reported in Table 1.
one another (i.e., rejecting the null hypothesis of joint equality in all billing cycles). Again, while not a definitive test, this is perhaps suggestive of common trends being an unreasonable assumption for these properties. To mitigate this concern, we create a subsample of residential properties that have a pre-SAH order average absolute differences in water usage growth rates between 2017 and 2018 and between 2018 and 2019 around some threshold value $\delta$.\footnote{See the appendix for a technical breakdown of how these growth rates were derived. Note, this approach formalizes how we arrive at a subsample where the common trends assumption is more credible. This is in the spirit of prior work using geography (e.g., bordering vs. non-bordering regions), as opposed to growth rate differences, to obtain a subsample of data to bolster the credibility of common trends (e.g., Black et al., 2018).} We iterate through values of $\delta$ to find the largest, in absolute value, average difference in water usage growth rates that yields the largest subsample of residential properties with statistically similar first difference estimates across the various billing cycles in the periods prior to the SAH order; the largest value of $\delta$ satisfying this criteria is $\delta = 0.0275 \pm 2.75$ percentage points resulting in a subsample of 2,308 residential properties that provide statistically similar first difference estimates in years prior to the SAH order. Using this subsample, we re-estimate equation (1) for residential properties and report the results in Table 2.

Column 2 of Table 2 presents results from re-estimating (1) for residential properties with the sample while comparison estimates for all residential properties from Table 1 provided in column 1. The sample’s first difference effects are now noticeably smaller for each of the coefficient estimates on $I(2020) \times I(\text{Post } j = \omega \text{ March 17})$ relative to those obtained using the full sample with the estimated effects, on average, 22% smaller. The F-statistic from the joint test of equality on the coefficient estimates over the counterfactual years fails to reject the null of equality at all levels, increasing confidence in the common trends assumption for residential properties.\footnote{We note that caution is warranted as it relates to broad applicability of these results due to the reduction of residential properties in the estimating sample. Regardless of the concerns related to external validity, we believe these estimates still have important economic and policy significance.}

### 4.1. Difference-in-differences effects

Using the estimated first difference effects in the counterfactual years for commercial and school properties in Table 1 and the first difference effects for residential properties in Table 2, column 2, we adjust our 2020 estimates to net out the average pre vs. post-SAH change in water usage in prior years, or $\frac{1}{4} \sum_{k=2017}^{2019} I(k) \times I(\text{Post } \omega \text{ March 17}), \omega = \{1, 2, 3, 4\}$. We report the difference-in-differences effects...
...declines in water usage, which is expected because all schools were closed while some grocery stores, pharmacies, etc. remained open after the order. The average DID decline in water usage for commercial properties remained open after the order. The average DID decline in water usage for commercial properties was 12.2% (first billing cycle) to 35.9% in the last post-SAH billing cycle. Both the minimum and maximum estimates over the four billing cycles show a similar range, indicating estimation stability. All results are statistically significant at a high level.

Turning to the DID results for commercial and school properties, the estimated effects are unambiguously negative, showing evidence of a uniform decline in water usage relative to the bill preceding the SAH order in both the initial period and all subsequent billing cycles. For commercial properties (panel B, Table 3), the average DID effects range from −34.7% in the first billing cycle to −11.0% in the fourth billing cycle after the SAH order. As with the residential estimates, the minimum and maximum estimates are within the same range and all results are uniformly statistically significant at a high level.

The estimated DID effects for school properties (panel C, Table 3) follow a similar pattern as commercial properties with the estimated declines in water usage being larger in absolute value, which is expected because all schools were closed while some commercial properties – grocery stores, pharmacies, etc. – remained open after the order. The average DID decline in water usage for commercial properties is estimated to be 11.0% in the fourth billing cycle after the SAH order.
Table 2
First difference estimates with and without the Pre-SAH order trends restriction.

| Property Type: | (1) | (2) |
|----------------|-----|-----|
| Dependent Variable: | ln(gallons/day) | ln(gallons/day) |
| Sample: | Full Sample | Restricted Sample (δ = 0.0275) |
| I(2020) X I(Post 1 March 17) | 0.266*** (0.00171) | 0.193*** (0.0113) |
| I(2019) X I(Post 1 March 17) | 0.319*** (0.00202) | 0.0858*** (0.00583) |
| I(2018) X I(Post 1 March 17) | 0.232*** (0.00187) | 0.0734*** (0.00608) |
| I(2017) X I(Post 1 March 17) | 0.299*** (0.00200) | 0.0755*** (0.00548) |
| P(β₁2019 = β₁2018 = β₁2017) > F | 0.000 | 0.121 |
| Observations | 1,834,986 | 40,874 |
| Number of Properties | 96,303 | 3,289 |
| I(2020) X I(Post 2 March 17) | 0.470*** (0.00204) | 0.352*** (0.0133) |
| I(2019) X I(Post 2 March 17) | 0.411*** (0.00222) | 0.116*** (0.00843) |
| I(2018) X I(Post 2 March 17) | 0.378*** (0.00211) | 0.122*** (0.00877) |
| I(2017) X I(Post 2 March 17) | 0.445*** (0.00224) | 0.123*** (0.00885) |
| P(β₂2019 = β₂2018 = β₂2017) > F | 0.000 | 0.559 |
| Observations | 1,834,986 | 33,474 |
| Number of Properties | 96,303 | 2,983 |
| I(2020) X I(Post 3 March 17) | 0.564*** (0.00221) | 0.429*** (0.0161) |
| I(2019) X I(Post 3 March 17) | 0.538*** (0.00244) | 0.201*** (0.0128) |
| I(2018) X I(Post 3 March 17) | 0.504*** (0.00233) | 0.208*** (0.0148) |
| I(2017) X I(Post 3 March 17) | 0.592*** (0.00246) | 0.218*** (0.0149) |
| P(β₃2019 = β₃2018 = β₃2017) > F | 0.000 | 0.200 |
| Observations | 1,834,986 | 25,945 |
| Number of Properties | 96,303 | 2,581 |
| I(2020) X I(Post 4 March 17) | 0.638*** (0.00231) | 0.573*** (0.0181) |
| I(2019) X I(Post 4 March 17) | 0.626*** (0.00258) | 0.264*** (0.0174) |
| I(2018) X I(Post 4 March 17) | 0.543*** (0.00244) | 0.266*** (0.0196) |
| I(2017) X I(Post 4 March 17) | 0.652*** (0.00259) | 0.268*** (0.0200) |
| P(β₄2019 = β₄2018 = β₄2017) > F | 0.000 | 0.948 |
| Observations | 1,834,986 | 20,868 |
| Number of Properties | 96,303 | 2,308 |

Year Fixed Effects: y
Property Fixed Effects: y

Notes: ***p < 0.01, **p < 0.05, *p < 0.10. Robust standard errors shown in parenthesis are clustered at the property level. Column (1) reports estimates of equation (1). Each panel of column (2) (which presents results for separate billing cycles) shows estimates of equation (1) after restricting attention to residential properties with a 2017 to 2019 average absolute difference in water usage growth rates of less than 0.0275. See text for more details.
school properties ranges from 61.0% to 29.7% relative to the billing cycle immediately prior to the order for the first and fourth billing cycle, respectively. As with the other user types, we find evidence of estimation result stability in the minimum and maximum estimates and continued statistical significance at a high level.

5. Discussion

As the results indicate a substantial change in water usage across types, it is natural to wonder about the mechanisms driving such divergent results. Here, we discuss three factors that are consistent with our empirical results. First, while all users in Henderson face the same tiered pricing schedule – i.e., first tier of usage faces the lowest per-gallon price with higher tiers billed at higher rates – users enter into the tiers at different consumption points and face different fixed pricing components. The entry points and fixed pricing components differ based on meter sizes and user type.

This leads to each user type facing differing marginal and average prices, especially amongst the highest volume users – commercial and schools. This provides an incentive for these users to adopt water saving technologies not typically found in residential settings such as automatic shut-off facets and automatic low-flow toilets. Additionally, commercial and school users are likely to have dedicated building maintenance personal to spot potential leaks within the water system.

Second, our empirical results are consistent with the nature of the SAH order. It closed most businesses (commercial) and schools, leading to substantial decreases in water usage among these types. With this closure and encouragement to stay home, residents were in their houses for more hours per day than ever before and, as residential users comprise 98% of the total user base within Henderson, even a small per residence increase will have outsized effects on the aggregated total. This is especially relevant if newly-remote workers brought home their in-office consumption patterns, leading to possible overuse.

Lastly, our empirical results may also reflect behavioral responses to the pandemic. During the early stages of the pandemic and

\[ \beta_{\text{2020}}^\omega - \sum_{k=2017}^{2019} \beta_k^\omega. \]

In column (2), the DID estimates are computed using the expression

\[ \beta_{\text{2020}}^\omega - \max_k \beta_k^\omega. \]

In column (3), the DID estimates are computed using the expression

\[ \beta_{\text{2020}}^\omega - \min_k \beta_k^\omega. \]

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One may be concerned that weather-related differences between the counterfactual years may be driving the results. In Appendix Table A1, we include weather controls in equation (1) with the results being qualitatively similar.

The entry points and fixed pricing components differ based on meter sizes and user type.

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Table 3
Difference-in-differences estimates of the impact of the COVID-19 SAH order.

| Panel | (1) DID | (2) DID (Min) | (3) DID (Max) |
|-------|---------|---------------|---------------|
| (A) Residential Restricted (δ = 0.0275) | | | |
| Bill 1 | 0.115*** (0.012) | 0.108*** (0.012) | 0.120*** (0.012) |
| Bill 2 | 0.232*** (0.014) | 0.230*** (0.015) | 0.236*** (0.015) |
| Bill 3 | 0.220*** (0.018) | 0.211*** (0.019) | 0.230*** (0.018) |
| Bill 4 | 0.307*** (0.022) | 0.305*** (0.024) | 0.309*** (0.022) |
| (B) Commercial Properties | | | |
| Bill 1 | -0.426*** (0.027) | -0.441*** (0.031) | -0.417*** (0.032) |
| Bill 2 | -0.200*** (0.025) | -0.223*** (0.030) | -0.161*** (0.030) |
| Bill 3 | -0.130*** (0.025) | -0.149*** (0.031) | -0.102*** (0.029) |
| Bill 4 | -0.117*** (0.025) | -0.151*** (0.032) | -0.097*** (0.029) |
| (C) School Properties | | | |
| Bill 1 | -0.942*** (0.173) | -1.084*** (0.206) | -0.816*** (0.180) |
| Bill 2 | -0.987*** (0.205) | -1.088*** (0.232) | -0.924*** (0.227) |
| Bill 3 | -0.899*** (0.261) | -1.114*** (0.273) | -0.763*** (0.263) |
| Bill 4 | -0.353*** (0.152) | -0.586*** (0.204) | -0.173 (0.180) |

Notes: ***p < 0.01, **p < 0.05, *p < 0.10. This table presents a range of DID estimates obtained after estimating equation (1). For commercial and school properties, all estimates are derived from the model estimates reported in columns (2) and (3) of Table 1, respectively. For residential properties, all estimates are derived from model estimates reported in column (2) of Table 2. In all cases, for any billing cycle, j = ω, the DID estimates reported in column (1) are computed using the expression: \( \hat{\beta}_\omega^{2020} - \sum_{k=2017}^{2019} \hat{\beta}_k^\omega. \) In column (2), the DID estimates are computed using the expression \( \hat{\beta}_\omega^{2020} - \max_k \hat{\beta}_k^\omega. \) In column (3), the DID estimates are computed using the expression \( \hat{\beta}_\omega^{2020} - \min_k \hat{\beta}_k^\omega. \)
with little other protective guidance aside from social distancing, people were encouraged to frequently wash to mitigate risk (CDC, 2020) with some going as far as washing packages and groceries (Godoy, 2020; Fernstrom, 2020). Additionally, with a significant closure of restaurants, there was a shift toward eating in the home, leading to an increase in dishes to be washed. With the closure of schools, households with young children experienced a recently child-vacated bathroom or kitchen with a dripping tap multiple times. This is not surprising since children view water usage in the context of recreation and have an incomplete understanding of water as an integrated system making it difficult to internalize the idea of water conservation (Covitt et al., 2009; Havu-Nuutinen et al., 2011). Anyone of these behavioral responses could contribute to the estimated increase in residential usage and it is likely some combination therein provides a likely explanation though further research on these behavioral responses is likely warranted.

To translate the estimated DID effects into more easily understood terms, we estimate the change in water consumption – in gallons – over a 30-day billing cycle. We do this for all billings cycles to derive the net effect considering the increase from residential properties and the potential offsetting decrease from commercial and school properties, reporting this in Table 4. Looking first at the first billing cycle in panel A of Table 4, we see that average net effect of water consumption over the three property types is an increase in water usage of approximately 47.8 million gallons. This net increase in water usage continues over subsequent cycles (panels B–D) with the

Table 4
Difference-in-difference estimates expressed in terms of the aggregate change in water consumption by billing cycle.

| (A) Bill 1 | (1) DID | (2) DID (Min) | (3) DID (Max) |
|------------|---------|--------------|--------------|
| **Estimated %Change in average daily consumption** | | | |
| Residential | 12.19% | 11.40% | 12.75% |
| Commercial | −34.69% | −35.66% | −34.10% |
| Schools | −61.02% | −66.18% | −55.78% |
| **Estimated change in water consumption over 30 days (in gallons)** | | | |
| Residential | 176,872,066 | 165,514,822 | 185,033,195 |
| Commercial | −116,286,309 | −119,545,977 | −114,308,909 |
| Schools | −12,754,793 | −13,833,610 | −11,660,464 |
| Net Effect | 47,830,964 | 32,135,235 | 59,065,822 |
| (B) Bill 2 | DID | (Min) | (Max) |
| **Estimated %Change in average daily consumption** | | | |
| Residential | 26.11% | 25.86% | 26.62% |
| Commercial | −18.13% | −19.99% | −14.87% |
| Schools | −62.73% | −66.31% | −60.31% |
| **Estimated change in water consumption over 30 days (in gallons)** | | | |
| Residential | 378,956,947 | 375,303,138 | 386,292,542 |
| Commercial | −60,767,151 | −67,007,787 | −49,851,573 |
| Schools | −13,113,390 | −13,861,836 | −12,606,774 |
| Net Effect | 305,076,406 | 294,430,515 | 323,834,195 |
| (C) Bill 3 | DID | (Min) | (Max) |
| **Estimated %Change in average daily consumption** | | | |
| Residential | 24.61% | 23.49% | 25.86% |
| Commercial | −12.19% | −13.84% | −9.70% |
| Schools | −59.30% | −67.18% | −53.37% |
| **Estimated change in water consumption over 30 days (in gallons)** | | | |
| Residential | 357,125,396 | 340,922,799 | 375,300,138 |
| Commercial | −40,866,244 | −46,406,385 | −32,507,543 |
| Schools | −12,396,722 | −14,042,579 | −11,157,327 |
| Net Effect | 303,862,429 | 280,473,835 | 331,635,267 |
| (C) Bill 4 | DID | (Min) | (Max) |
| **Estimated %Change in average daily consumption** | | | |
| Residential | 35.93% | 35.66% | 36.21% |
| Commercial | −11.04% | −11.24% | −9.24% |
| Schools | −29.74% | −44.35% | −15.89% |
| **Estimated change in water consumption over 30 days (in gallons)** | | | |
| Residential | 521,503,131 | 517,561,515 | 525,452,639 |
| Commercial | −37,014,630 | −46,983,604 | −30,990,229 |
| Schools | −6,217,576 | −9,270,271 | −13,861,836 |
| Net Effect | 478,270,925 | 461,307,640 | 491,141,417 |

Notes: In each sub-panel labeled “Estimated %Change in average daily consumption” we re-produce the DID estimates reported in Table 3 (approximate %Change in the outcome variable) after taking the transformation, [exp(x)−1] × 100, which allows us here to interpret model estimates in terms of the actual %Change in the outcome variable. In the corresponding sub-panel labeled “Estimated change in water consumption over 30 days (in gallons)” we take each DID estimate and multiply it by the product of: (a) the total number of known properties across each user type; (b) the average number of gallons of water consumed per day over the course of the billing cycle averaged over all properties within each user type; (c) 30 days. This allows us to convert the DID estimates we report into an estimate of the aggregate change in water consumption (in gallons) over the course of 30 days (which is the approximate length of a billing cycle) for each of the four billing cycles following the COVID-19 SAH order.
average net increase in usage jumping to approximately 305.1 million gallons, 303.9 million gallons, and 478.3 million gallons, respectively. Minimum and maximum estimates are also reported in Table 4. Though we find a sizable increase in overall water consumption across our three user classes, we are careful to note that there are ten additional user classes that are not part of our empirical study as these groups are smaller and consume less water than the three analyzed. While these include groups with more consistent and weather invariant usages – golf courses, parks, and landscaping – it does include other groups like governmental buildings, churches, and industry, which may well have decreased water usage due to the SAH but unlikely to offset the overall rise in usage.

This net increase in water usage from the three biggest user classes is somewhat unsurprising as residential users are the largest single class of users and the regional economy shifted more towards remote work with the shutdown of all non-essential businesses that involve individuals interacting in close proximity to each other (restaurants, bars, casinos, entertainment, etc.). While intuitive, these single class of users and the regional economy shifted more towards remote work with the shutdown of all non-essential businesses that usage.

buildings, churches, and industry, which may well have decreased water usage due to the SAH but unlikely to offset the overall rise in consistent and weather invariant usages.

- The authors also wish to thank Roger H. von Haefen and two anonymous reviewers for their helpful comments and suggestions.

A.1 Technical description of the pre-SAH order trends restriction for residential properties

As noted in the manuscript, identification of the causal effect of the stay-at-home (SAH) order in 2020 using a difference-in-differences estimation strategy requires the assumption that on average, changes in water usage that occur between billing cycle \( j = -1 \) and billing cycle \( j = \omega \) in the years 2017, 2018, and 2019 are proportional to average changes in water usage between billing cycle \( j = -1 \) and billing cycle \( j = \omega \) in 2020. Again, while this assumption is untestable, we assess its credibility by investigating the stability of the first difference estimates of \( \beta_{2017}^{\omega} \), \( \beta_{2018}^{\omega} \), \( \beta_{2019}^{\omega} \). We do this by providing p-values associated with tests for joint equality, \( P(\beta_{2019}^{\omega} = \beta_{2018}^{\omega} = \beta_{2017}^{\omega}) > F \). However, for residential users, our baseline model results reported in Table 1 indicate that we reject the null of joint equality for every billing cycle, \( j \); a result which casts doubt on the validity of the model’s underlying identifying assumption.

To address this concern, we use the following procedure. First, for each property in the sample and for each billing cycle, \( j = \omega \), compute the percentage change in water usage from the first billing cycle preceding SAH order to (e.g., \( j = -1 \)) to the \( \omega \)th billing cycle following the SAH order for each year \( t \in \{2017, 2018, 2019\} \) and \( \omega \in \{1, 2, 3, 4\} \):

10 A third of Conference Board surveyed organizations expect 40% or more of their employees will be remote year-round after the pandemic and these organizations are three times more likely to hire remote workers than before the pandemic (Steemers et al., 2020).

11 According to the most recent Census estimates, the top four states with the largest population increases from 2019 to 2020 were located in the West: Idaho, Arizona, Nevada, and Utah (U.S. Census Bureau, 2020b).
Given these computations, we compute the relative growth rates of these differences:
\[ \phi^{\omega}_{2019} = \ln(gallons/day)_{i,2019} - \ln(gallons/day)_{i,2019} - \ln(gallons/day)_{i,2019} - \ln(gallons/day)_{i,2019} \]
\[ \phi^{\omega}_{2018} = \ln(gallons/day)_{i,2018} - \ln(gallons/day)_{i,2018} - \ln(gallons/day)_{i,2018} - \ln(gallons/day)_{i,2018} \]

Third, we compute the average of the absolute value of relative growth rates.
\[ \theta^{\omega} = \frac{|\phi^{\omega}_{2019}| + |\phi^{\omega}_{2018}|}{2}. \]

To help fix ideas, assume that on average, some given property i witnessed an 8% increase in water usage before and after SAH order date in 2017, an 8.25% increase in 2018, and an 8.75% increase in 2019 when we restrict attention to bills j = 1 to j = 4. By choosing the largest threshold value \( \delta^{\omega} \) to be smaller than some threshold value, \( \delta^{\omega} \). Each time we restrict, we: (1) exclude any property, i, from the data such that \( \delta^{\omega} > \delta^{\omega} \); (2) estimate our main econometric model; and (3) compute the p-value, \( P(\beta_{2019}^{\omega} = \beta_{2018}^{\omega} = \beta_{2017}^{\omega}) > F. \)

We repeat this exercise by decreasing the threshold value \( \delta^{\omega} \). With the goal of minimizing data loss, we define \( \delta \) to be the largest value \( \delta^{\omega} \) such that we are unable to reject the null hypothesis that \( \beta_{2019}^{\omega} = \beta_{2018}^{\omega} = \beta_{2017}^{\omega} \). For residential users, we find that \( \delta = 0.0275 \) is the largest threshold value (and thus the least restrictive threshold value) that results in failure to reject the null hypothesis that \( \beta_{2019}^{\omega} = \beta_{2018}^{\omega} = \beta_{2017}^{\omega} \) for each \( \omega = 1, 2, 3, \) and 4. By choosing the largest threshold value \( \delta \), and hence largest subsample of data using the criteria of failing to reject the null of joint significance related to the first difference effects over the years leading up to the SAH order, allows us to only consider properties with limited volatility in water usage over these pre-SAHP time periods making us more confident in historical water usage at the property level serving as a valid counterfactual for that property in the post period. We think this is intuitive in that wide swings in water usage at the property level over the pre-SAHP time periods would cast doubt on the validity of using a property in the pre-SAHP period as its own counterfactual in the post-SAHP period given the seemingly arbitrary nature of water usage associated with these properties exhibiting large growth rate variance in water usage.

As we note in the main text, column (1) of Table 2 replicates the first difference estimates shown in column (1) of Table 1. However, column (2) of Table 2 replicates the model estimated in column (1) but with the restriction that \( \delta = 0.0275 \). As noted in the main manuscript, we inspect the sensitivity of the difference-in-differences estimates to choices of \( \delta \); see Figure A2.

### Table A1: Difference-in-Differences Estimates of the Impact of the COVID-19 SAH Order: Sensitivity to the Inclusion of Weather Controls

| Panel          | (1)          | (2)          |
|----------------|--------------|--------------|
| **(A) Residential Restricted (\( \delta = 0.0275 \))** | DID          | DID          |
| Bill 1         | 0.115***     | 0.122***     |
|                | (0.012)      | (0.013)      |
| Bill 2         | 0.232***     | 0.237***     |
|                | (0.014)      | (0.015)      |
| Bill 3         | 0.220***     | 0.246***     |
|                | (0.018)      | (0.019)      |
| Bill 4         | 0.307***     | 0.322***     |
|                | (0.022)      | (0.023)      |
| **(B) Commercial Properties** | DID          | DID          |
| Bill 1         | -0.426***    | -0.457***    |
|                | (0.027)      | (0.029)      |
| Bill 2         | -0.209***    | -0.252***    |
|                | (0.025)      | (0.028)      |
| Bill 3         | -0.130***    | -0.175***    |
|                | (0.025)      | (0.028)      |
| Bill 4         |              |              |

(continued on next page)
Panel (1) (2)

|              | (C) School Properties | Bill 1          | Bill 2          | Bill 3          | Bill 4          |
|--------------|-----------------------|-----------------|-----------------|-----------------|-----------------|
|              | DID                   | -0.117***       | -0.165***       | -0.942***       | -0.987***       |
|              | (0.025)               | (0.028)         | (0.173)         | (0.205)         | (0.261)         |
|              | DID                   | -0.165***       | -0.938***       | -0.970***       | -0.864***       |
|              | (0.028)               | (0.172)         | (0.210)         | (0.272)         |                 |
|              | DID                   | -0.938***       | -0.970***       | -0.864***       |                 |
|              | (0.172)               |                 |                 |                 |                 |
|              | DID                   | -0.987***       | -0.970***       |                 |                 |
|              | (0.210)               |                 |                 |                 |                 |
|              | DID                   | -0.899***       | -0.864***       | -0.353***       |                 |
|              | (0.261)               | (0.272)         | (0.152)         |                 |                 |
|              | DID                   | -0.970***       |                 |                 | -0.340***       |
|              | (0.210)               |                 |                 |                 | (0.157)         |
|              | DID                   | -0.864***       |                 |                 |                 |
|              | (0.272)               |                 |                 |                 |                 |
|              | Did                   | -0.353***       | -0.340***       |                 |                 |
|              | (0.152)               | (0.157)         |                 |                 |                 |

Notes: ***p < 0.01, **p < 0.05, *p < 0.10. This table presents a range of DID estimates obtained after estimating equation (1). For commercial and school properties, all estimates are derived from the model estimates reported in columns (2) and (3) of Table 1, respectively. For residential properties, all estimates are derived from model estimates reported in column (2) of Table 2. In all cases, for any billing cycle, j = ω, the DID estimates reported in column (1) are computed using the expression: \( \hat{\beta}_{ω2020} = \frac{1}{3} \sum_{k=2017}^{2019} \hat{\beta}_{ωk} \). For the sake of reference, the results shown in column (1) are presented as column (1) of Table 3 in the main text. The results presented in column (2) simply replicate the results shown in column (1) after we include average daily precipitation and average temperature over the billing cycle as linear control variables.

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**Fig. A1.** Illustration of the Study Area and Land Use Classifications. Notes: The authors produced this map in ArcMap 10.5.1. The shapefile delineating the Henderson City Boundary was obtained from the City of Henderson GIS Data Portal. The shapefile delineating parcel boundaries and land use classifications was provided courtesy of the Clark County, NV Assessor. Each land use class is based on the state land use code for each parcel. The “other” category includes communication, transportation, and special use properties.
Fig. A2. Sensitivity of Difference-in-Differences Estimates to Choices of $\delta$. Notes: For each of the four billing cycles post the stay-at-home order we present the estimated difference-in-differences effects and corresponding 95% confidence intervals having iterated over values of the average absolute difference in growth rates in water usage, $\delta$; see text and appendix A1 for more details.

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