Energy Strategy Reviews 49 (2023) 101119

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Work-from-home, electricity, and water: Evidence from COVID-19 in Qatar[☆]

David H. Bernstein [a], Alecia Cassidy [b,c,*], Ahmed A. Khalifa [d]

[a] University of Miami, United States of America
[b] University of Alabama, United States of America
[c] RWI, Germany
[d] Qatar University, Qatar

ARTICLE INFO

Dataset link: Replication Materials for: Work-from-home, electricity, and water: Evidence from COVID-19 in Qatar (Original data)

JEL classification:
C1
Q4
Q25

Keywords:
COVID-19
SARS-CoV-2
Work-from-home
Energy
Water

ABSTRACT

Working from home will be key to mitigating harms from future pandemics and has also been proposed as a way to curtail emissions from commuting. This paper exploits a work-from-home order in Qatar to investigate the impacts of working from home on both electricity and water usage. We deploy quantile methods to analyze the distribution of consumption before and during the COVID-19 pandemic, and find evidence that use was shifted from work to home for both electricity and water. For residential use, increases are largest in percentage terms for the lowest deciles of both the electricity and water distributions. For commercial use, reductions are largest in percentage terms for the lowest deciles of both distributions. Our results have implications for which types of customers policymakers might want to target for governmental aid in future pandemics. Our estimates imply that the overall net impact of the shift from commercial to residential usage was a decrease in carbon emissions of 0.160 million metric tons over the period 2019–2020.

1. Introduction

As of November 9, 2022, there have been at least 633.5 million cases of COVID-19, resulting in 6.6 million direct deaths.[1] Governments responded to this public health threat by enacting policies that encouraged residents to work from home. These restrictions decreased global energy demand by 11 percent [10]. Motivated by this fact, our paper delves deeper into the implications of work-from-home on a micro scale for both electricity and water use.

Understanding how electricity and water use respond to work-from-home orders is vital for two reasons. First, pandemics are projected to become more frequent in the future.[2] Work-from-home policies are a key policy lever to mitigate harms of pandemics as vaccine development and deployment can be a slow process. Our estimates of the effects on electricity and water use can help to inform policymakers on how to prepare for energy and water impacts and how government aid can be best deployed in times of crisis.

Second, work-from-home has been proposed as a way to cut global emissions from commuting to work [11].[3] Shorter workweeks have been considered by policymakers or have already been implemented in France, Spain, and England.[4] Given that under the status quo, annual

☆ This research was made possible by the National Priorities Research Program (NPRP) grants NPRP9-232-5-026, NPRP12C-0821-190017, and NPRP10-0131-170-300 from the Qatar National Research Fund (a member of the Qatar Foundation). The statements made herein are solely the responsibility of the authors and not necessarily those of the Federal Energy Regulatory Commission or the U.S. Government. We thank the Conservation and Energy Efficiency Department at KAHRAMAA, Qatar, for their support. This paper was presented at the 2022 Allied Social Sciences Association (ASSA) Annual Meeting, Advances in Energy Economics Research on January 8, 2022 and at the Association of Environmental and Resource Economist (AERE) Summer Conference on June 3, 2022. We thank our ASSA discussant, Todd Gerarden, for the detailed feedback. In addition, we are grateful for the comments and suggestions by conference participants, as well as: Dylan Brewer, Massimiliano Caporin, Traviss Cassidy, Shawkat Hammoudeh, Mark Howells, Chris Parmeter, Sonia Yeh, and anonymous referees.

* Corresponding author at: University of Alabama, United States of America.
E-mail addresses: dbernstein@bus.miami.edu (D.H. Bernstein), awcassidy1@ua.edu (A. Cassidy), aliabdelkh@qu.edu.qa (A.A. Khalifa).

1 See the COVID-19 Dashboard by the Center for Systems Science and Engineering at Johns Hopkins University.

2 See: Jones et al. [1], Hilsenrath [2], and Pike et al. [3].

3 Haxhimusa and Liebensteiner [4] show that emissions fell by 18.4% in the first year of the pandemic.

4 It is worth noting that working from home also presents a host of new societal challenges, including introducing new occupational health problems and disruptions to productivity [5,6]. These challenges vary across countries and contexts [7,8]. For a broad overview, see [9].

https://doi.org/10.1016/j.esr.2023.101119
Received 30 January 2023; Received in revised form 16 May 2023; Accepted 28 June 2023
Available online 5 July 2023

global energy consumption is predicted to increase 25% by 2040 [12],[5] this policy trend is likely to continue as policymakers scramble to deploy every feasible tool in their arsenal to reduce emissions.

This work focuses on the impact of a work-from-home order in Qatar due to COVID-19. We exploit a large and up-to-date dataset of confidential monthly electricity and water readings from the Qatar General Electricity & Water Corporation (KAHRAMAA) from March 2019 to October 2020. We estimate effects for both commercial and residential customers, establishing separate estimates for residential customers by residence type and whether the account-holders are Qatari nationals. The findings suggest that the work-from-home order substantially shifted consumption from work to home, where low usage groups tended to have the largest percentage impact.

We build on several recent studies that provide statistical evidence that electricity and water consumption has changed during the COVID-19 pandemic. Our work complements recent work by Abulibdeh et al. [13] that characterizes the electricity response to COVID-19 in Qatar using a machine-learning framework. The focus of Abulibdeh et al. [13] is to understand how the difference between actual and simulated electricity consumption can be explained by COVID-19 case counts. Irwin et al. [14] use customer-level data from Nevada to study water use, and find that commercial users decrease water consumption by up to 44%, school users decrease usage by up to 109%, and residential users increase their usage by up to 31%.[6] Eastman et al. [15] additionally finds that there are signs of increasing consumption in the residential sector but not for commercial customers in the US. In Europe, Roidt et al. [16] shows that the water footprint and the consumption of electricity decreased in several European countries during the pandemic. Abu-Bakar et al. [17] finds evidence that residential water consumption in England increased as a result of the pandemic. Rizvi et al. [18] finds that water consumption increased by more than 30% in Dubai during Ramadan and during the pandemic. Santiago et al. [19] find a 13% reduction in Spain's power demand due to lockdown measures. Similarly, Cheshmehzangi [20] finds a 67% increase in electricity bills in China.[7] Moreover, Cicala [24] finds that residential energy consumption increased by 10% and commercial and industrial energy consumption fell by 12% and 14% respectively during the pandemic. Brewer [25] finds that rises in residential energy consumption offset reductions in industrial energy consumption.

With the exceptions of Abulibdeh et al. [13], Irwin et al. [14], Rizvi et al. [18], Abu-Bakar et al. [17], and Cheshmehzangi [20], the above studies use data aggregated to the utility, region, or national level. Our study benefits from rich microdata to characterize responses for both water and electricity, and for both commercial and residential sectors.[8]

While the literature has focused on average effects, we are interested in both average and quantile effects[9] of work-from-home so that we can assess the distributional effect of work-from-home policies and pandemics on energy and water use. Distributional impacts are important because of their crucial policy implications. If the poorest residents bear the burden of energy and water use because they disproportionately shift use from their place of work to their residence while working from home, then additional governmental aid such as electricity or water discounts/subsidies might be best targeted at the lowest quintile of the electricity and water distribution in future pandemics.[10]

Similarly, our finding that the smallest businesses reduce energy and water use more than the largest ones might indicate that the smallest businesses are more likely to temporarily shut down and thus might experience economic hardship due to the pandemic. The government could target commercial customers in the lower percentiles of the energy and water use distribution for additional support in future pandemics. Moreover, a special concern arises in the case of water: steep reductions or elimination of water use in commercial buildings is problematic because pipes are generally designed to have continuous water flow. Thus, there is the possibility of a deterioration of the existing capital stock due to lack of usage. The government could implement measures in future pandemics to protect against infrastructure deterioration in a highly targeted way — by focusing on the commercial users in the lower deciles.

Targeting utility usage subsidies is a relevant policy lever for pandemics and other emergencies because utilities typically have vast amounts of frequently updated usage data that can be used to quickly identify those in need. Subsidies can also be immediately applied to bills, expediting deployment of aid to those who need it most. Our results imply that governments could even deploy subsidies based on quintile of use pre-emergency, so as to preempt the negative consequences of emergencies to people and infrastructure. It is worth mentioning that in Qatar and other Gulf states, this is arguably the most socially feasible solution given the history of subsidization and that utility distributors, such as KAHRAMAA in Qatar, are usually national entities.

Lastly, we see our results as complementing existing literature by helping policymakers understand a context in which the stakes are high.[11] With the highest per-capita energy consumption and the highest per-capita emissions in the world, understanding energy use in Qatar can help us to understand the behavior of high users in a way that studies based in countries such as the United States and developing countries are not able to.[12] Energy demand management is particularly important in the Qatari context seeing as the load profile tends to be relatively flat across the course of a day– a fact which suggests that high disposable income impedes conservation [37].

2. Background

Here we review background information on Qatar and the broader literature on energy use and COVID-19.

2.1. The Qatari context

Qatar suffered a large outbreak of SARS-CoV-2 from April to July 2020, but has since stabilized; see Fig. 1, where we produce the trajectory of cases, deaths, and recoveries over time.[13] The outbreak

[5] The U.S. Energy Information Administration projects a 50% increase by 2050 (EIA, 2019).

[6] They are able to determine time-varying effects using daily data, and impacts are dampened over time for commercial and residential users and intensified over time for residential users.

[7] Several other papers on the Chinese context incorporate more dimensions into the discussion of the impacts of COVID-19 on carbon emissions, including thinking about renewable energy growth [21], supply chain and industrial impacts [22], and green finance and economic growth [23].

[8] Irwin et al. [14], Rizvi et al. [18] and Abu-Bakar et al. [17] focus on water only. Cheshmehzangi [20] studies energy use exclusively.

[9] For recent examples of quantile methods applied to energy use, see [26–31]. See [32, Table 1] for a summary of the recent literature for household energy efficiency.

[10] With respect to distributional impacts, an important caveat is presented in Section 7: we can only study patterns across households with our billing data, and will be unable to detect potentially more important distributional impacts, such as shifting of work within households or differential impacts across demographic groups. Novel work by Navas-Martın et al. [33] suggests these could be sizeable.

[11] In fact, the stakes are ever-rising. Gurriaran et al. [34] model the evolution of Qatari energy use as global warming proceeds. Qatar can benefit from a reduction in emissions, carbon capture, and renewable energy systems that require peaking natural gas plants during intermittent periods for photovoltaics (PV) and wind. Furthermore, given Qatar's growing population (pre-COVID-19), it may benefit from more efficient energy [35] and water usage.

[12] It is also worth noting that nearly 99% of water in Gulf states is produced from desalination, a very energy-intensive process; see [36] for more details.

[13] The source of the data is the: COVID-19 Dashboard by the Center for Systems Science and Engineering at Johns Hopkins University which we obtain via [38].

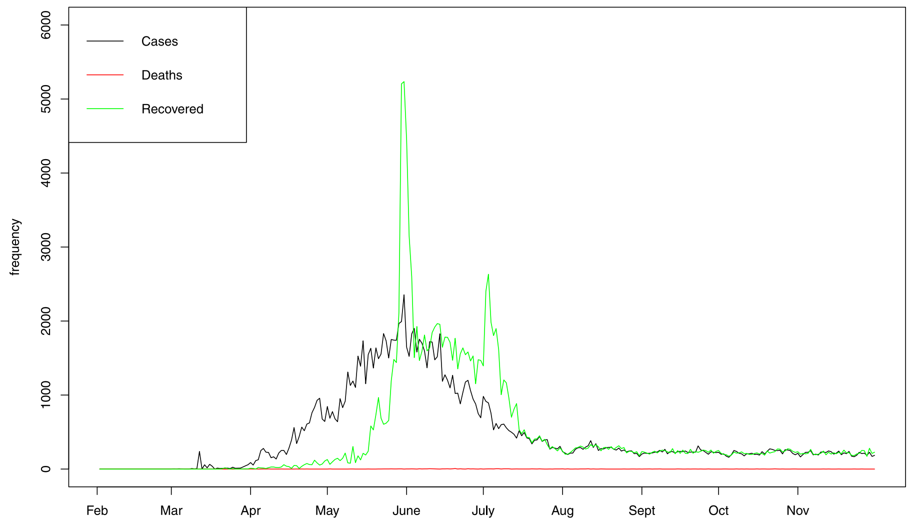


Fig. 1. Daily COVID-19: Deaths, cases and recoveries in Qatar in 2020.

had far-reaching impacts: the population decreased from 2,795,484 in March 2020 to 2,735,707 in August 2020, representing a 2.2 percent decline.[14] The iShares MSCI Qatar ETF plunged from $17.79 on December 31, 2019 to $14.57 on March 31, 2020. To control the pandemic, the State of Qatar took austere measures to physically distance its inhabitants. One of these measures was the enforcement of work-from-home for the government and private sectors.

Qatar's climate is characterized by a long, scorching summer (May to September) and a relatively mild winter (December to February). Temperatures during the peak summer months can soar to an average of 42° and occasionally cross 50°. Conversely, during winter, temperatures can drop to an average of around 15°.

In light of the hot climate, cooling homes and buildings is crucial in Qatar. Air conditioning accounts for approximately 60%–70% of electricity consumption in Qatar[15] Qatar has little geographical variation, so demand for cooling does not vary across different parts of Qatar. Additionally, Qatar relies on energy-intensive desalination processes for its potable water needs, further contributing to its high per-capita energy consumption.[16]

Electricity use is highly subsidized in Qatar, as in most Gulf states. Electricity is provided for free to Qatari nationals and at reduced cost to non-Qatari nationals. Therefore, we are careful to analyze effects separately by citizenship to capture the fact that non-Qatari citizens have a pecuniary incentive to conserve.[17]

Utility subsidies are also useful to consider when it comes to policy recommendations. The government of Qatar has vast resources at its disposal to handle pandemics — government profits stemming from oil and natural gas are large enough to fully fund many amenities for Qatari citizens, such as electricity, water, and health care. The question in policymakers' eyes is how to swiftly deploy funds in emergencies like the COVID-19 pandemic.

Our paper offers a candidate solution. The fact that utility subsidies have been historically popular means that the government has a policy lever at its disposal that can be quickly deployed in times of crisis such as COVID-19. Targeting electricity and water subsidies to the most at-need is administratively advantageous in Qatar and other gulf states, since utility distributors are typically national entities and collect vast amounts of data on usage. This allows the government to quickly identify at-risk customers. By contrast, collecting income data to determine how to distribute government aid would take months.

2.2. COVID-19, energy, and emissions

Our paper contributes to a nascent but growing literature on the impact of COVID-19 on energy and emissions more broadly. Loschel et al. [39] examine the relationship between working from home and energy-conserving actions, and find evidence that individuals develop conservation behaviors. Aruga et al. [40] deploy an autoregressive distributed lag (ARDL) model to measure the link between COVID-19 cases and energy consumption before and after the lockdown in India. The authors find that, "richer regions were quicker to recover their energy consumption to the level before the lockdown" and that a "long-run relationship holds between the COVID-19 cases and energy consumption". Aruga et al. [40] also find that a relaxation of lockdown restrictions allowed for energy consumption to increase, but that the effect was less pronounced in poorer regions. Belbute and Pereira [41] find that the pandemic will cause, "significant structural change that need to be considered in the development of future reference forecasts". In contrast, Smith et al. [42] find that consumption and emissions are likely to return to their pre-pandemic levels within two years.

3. Data

The primary data source for this work is the Qatar General Electricity & Water Company (KAHRAMAA), which we obtain directly from the company. The KAHRAMAA data includes the monthly consumption of water and electricity for residents of Qatar. We utilize the data from March 2019 to October 2020 because this period allows us to compare consumption before and during the pandemic.

The panel consists of the water consumption levels in kWh of electricity and m^3 of water. Fig. 2 displays the average consumption for water and electricity for both consumers and businesses over time.[18] These plots suggest that commercial energy and water usage dip during the pandemic, whereas residential energy and water usage spike.

[14] We are careful to exclude those who left Qatar from our analysis; see the Data section.

[15] See: https://time.com/6236839/qatar-world-cup-outdoor-air-conditioning-environment/.

[16] This also means that water demand is relatively uniform across the country.

[17] Khalifa et al. [35] stresses the importance of treating these groups differently.

[18] As we analyze two 8-month time periods ($T = 16$), we cannot reliably test for non-stationarity in the data [43, Table 4].

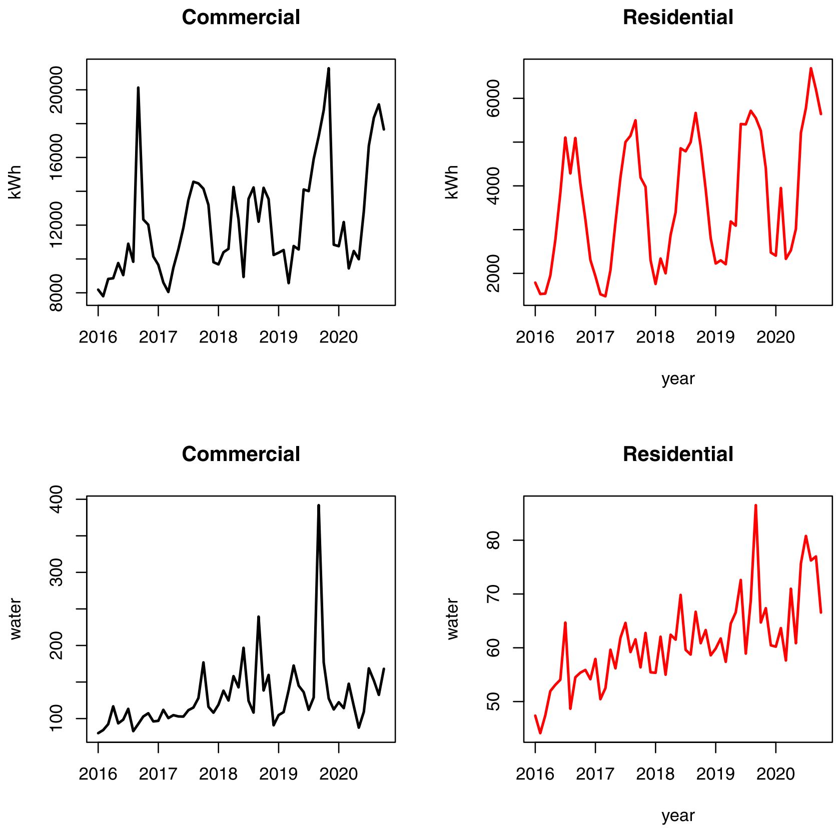


Fig. 2. Electricity and water in Qatar, all data.

For our analysis, we use a balanced panel dataset from March–October 2019 and March–October 2020. As the dataset does not distinguish between a zero value and a missing value (coded as 0, rather than *NA*), we omit individuals that have one or more zero values.[19] We selected this dataset to avoid removing individuals in the relevant COVID-19 time horizon, and to limit the temporal effects on consumption outside of the pandemic (such as changes in income, number of family members, etc.). Our sample selection is further justified as we are interested in understanding the behavior of individuals and firms that remain in Qatar during the pandemic rather than individuals and firms that may have left the country. We find that parameter estimates from leaving these missing observations in the analysis, as well as imputing the missing values with averages using adjacent readings are similar at the mean.[20] Table 1 presents the summary statistics for the dependent variables in this work.

From Table 1 we divide the data by year, and by group. We are able to distinguish between the residential and commercial sectors. Within the residential sector, we can distinguish between Qatari and non-Qatari customers, as well as the type of residence. Flats have $1-5$ bedrooms, while villas have $3-10$ bedrooms. Qataris in villas use more electricity and water than non-Qataris in villas. This difference in levels can be partially explained by the fact that non-Qataris pay for water and electricity, while Qataris generally do not.[21,22] Thus, Qataris presumably have less of an incentive to save.

We see immediately that the difference in means from 2020 to 2019 ($\mu_{20}-\mu_{19}$) are relatively large and significant for sufficiently large samples.[23] Qatari villa residents increased their electricity and water consumption by over 3%, while non-Qatari villa residents increased their electricity consumption by nearly 4% and water usage by over 6%. Similarly, non-Qatari flat residents increased their electricity consumption by over 5% and water usage by over 10%. The commercial electricity and water sectors had a reduction in usage of over 8% overall.

Our stringency data are provided by Guidotti and Ardia [38]. The stringency index is developed by Hale et al. [44], who "introduce the Oxford COVID-19 Government Response Tracker (OxCGRT), providing a systematic way to track the stringency of government responses to COVID-19 across countries and time". The stringency index is the simple average of nine response sub-indices which are rescaled to a value from 0 to 100 where 100 indicates the strictest policy mix. The variables for the sub-indices include: public information campaigns, school closing, workplace closing, canceled public events, gathering restrictions, closed public transportation, stay at home requirements, restrictions on internal movements and international travel restrictions.

As seen in Fig. 3, the State of Qatar started with a stringency index of 8.33 in the beginning of February 2020, which increased to 41.67 by the middle of March, peaked at 86.11 in late March, and subsequently declined to 64.81 in November. The index helps to explain the initial spread of SARS-CoV-2 in Qatar, and subsequent curtailment of the virus. We provide stringency indices over time for the United States, France, India, and Afghanistan for comparison. The trajectory looks most similar to that of the United States, but is very different from

[19] Individuals with zero values in February are also removed because a zero value in February could imply that March contained February's reading.

[20] However, standard errors are larger.

[21] The fact that the response is more similar across deciles for Qataris than non-Qataris is also consistent with a dampened elasticity of demand for non-Qataris.

[22] Qataris do not pay for water and electricity for their primary residence, but may pay for water and electricity in secondary residences or other owned properties that they are renting out.

[23] It is very uncommon for Qataris to live in flats. In our dataset, there were 40 observations, over sixteen months, that are coded as Qataris living in flats. We do not analyze this customer category because it is too small of a sample size to make meaningful conclusions.

Table 1
Summary statistics.

	March–October 2019				March–October 2020				N	$\mu_{20}-\mu_{19}$	p
	1st Qu	Med	μ_{19}	3rd Qu	1st Qu	Med	μ_{20}	3rd Qu			
Residential sector											
Villa, kWh											
Qatari	6013	11 356	12 851	17 910	6553	11 834	13 247	18 211	376 848	396	(0.00)
Non-Qatari	2071	4 288	5 939	7 872	2289	4 553	6 171	8 108	639 232	232	(0.00)
Flat, kWh											
Non-Qatari	605	1 427	2 040	2 675	675	1 577	2 146	2 790	969 904	106	(0.00)
Villa, Water m^3											
Qatari	86	139	192	225	92	146	198	233	364 960	6	(0.00)
Non-Qatari	25	50	89	104	28	54	96	112	614 352	6	(0.00)
Flat, Water m^3											
Non-Qatari	9	18	27	31	12	20	30	34	616 784	3	(0.00)
Commercial sector											
kWh	1032	2 507	8 194	5 908	816	2 174	7 516	5 373	317 488	−678	(0.00)
Water m^3	8	22	91	70	8	21	83	63	128 512	−8	(0.00)

Notes: Summary statistics are calculated from the sample used for our main regressions, found in Tables 2 and 3.

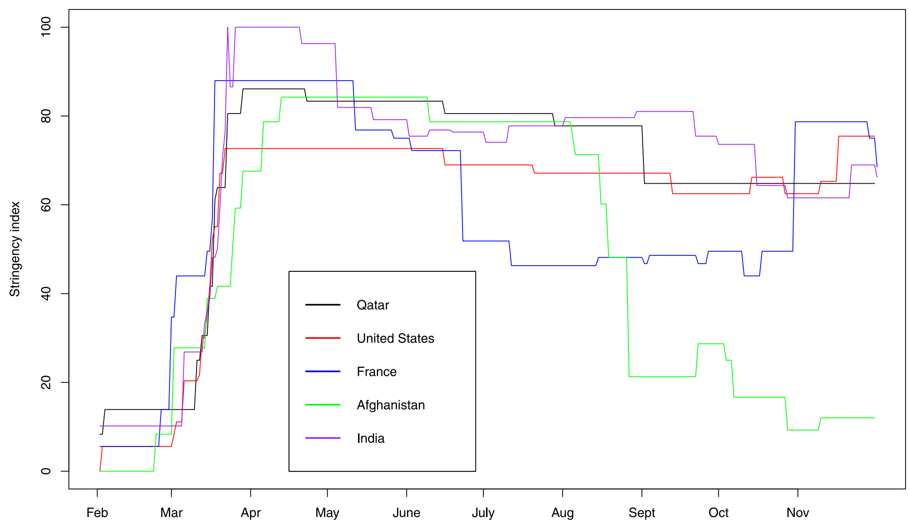


Fig. 3. Daily stringency index in 2020.

that of Aghanistan. We expect our results using the stringency index to generalize to most well-off countries, while they may not be applicable to developing countries because the stringency pattern was so different.

4. Econometric methodology

To understand the distributional impacts of the COVID-19 pandemic and subsequent work-from-home order on electricity and water consumption, we utilize the Quantile Regression (QR) framework [45, 46] in addition to standard panel methods. Quantiles are arguably the most important parameters in our study because of our focus on understanding which groups could benefit from utility subsidies.

Moreover, QR is particularly suited to our data and theoretically sound. While standard methods, such as ordinary least squares (OLS), estimate the conditional mean of the dependent variable, the QR estimates the conditional quantiles. In the case where the conditional mean coincides with the conditional median, there may be little benefit to the additional computational cost of the QR.[24] However, in the presence of influential data points, as we have in the present setting, the computational costs of QR are justified. The skewness in the distribution of electricity use apparent in Table 1 underscores this additional advantage of estimating quantiles rather than averages. Given the nature of our dataset and existing empirical evidence that electricity consumption is not normally distributed, we favor the QR results.[25]

For the purpose of estimation, we begin with the pooled linear model:

$$y_{it} = x_{it}'\beta + \epsilon_{it},\ i = 1,\dots,n,\ t = 1,\dots,T \tag{1}$$

where x_{it} is a $k \times 1$ vector of explanatory variables and y_{it} is the response. The $k\times1$ vector, β, contains the parameters, and ϵ_{it} is a mean-zero and symmetric residual. The quantile estimator is obtained from the minimization of:

$$\min_{\beta(\tau)} \sum_{i,t} \rho_\tau \left(y_{it} - x_{it}'\beta(\tau)\right), \tag{2}$$

for any $\tau \in (0,1)$, where $\rho_\tau(z) = z(\tau - \mathbb{I}\{z<0\})$.[26]

The primary equation we use in the estimation is:

$$\log(C_{it}) = \delta_0 + \alpha^{\text{COVID}} \cdot \mathrm{D}_t + x_t'\beta + \epsilon_{it}, \tag{3}$$

where C_{it} is either kWh of electricity, or m^3 of water, and D_t is a dummy variable that is equal to 1 for dates after and including March 2020, and

[24] In the situation where the OLS residuals are normally distributed, the QR estimator in Eq. (2) is less efficient than OLS [45].

[25] Furthermore, we reject the null hypothesis that each month-year-subset of the data is normally distributed with a Jarque–Bera test of our response as in [31, Table 1].

[26] To estimate this model for our dataset, we use the `rq` call in the `quantreg` (version 5.83) package [47] within R.

Table 2
Summary of α^{COVID} for regressions of electric subsets.

	Dependent variable:			
	log(Electricity Consumption)			
	(Villa Qatari)	(Villa non-Qatari)	(Flat non-Qatari)	(Commercial)
$\tau = 0.25$	0.049*** (0.003)	0.075*** (0.003)	0.118*** (0.003)	−0.220*** (0.007)
Mean FE	0.043*** (0.002)	0.070*** (0.002)	0.072*** (0.002)	−0.162*** (0.004)
$\tau = 0.50$	0.044*** (0.002)	0.048*** (0.002)	0.080*** (0.002)	−0.143*** (0.006)
$\tau = 0.75$	0.038*** (0.002)	0.043*** (0.002)	0.047*** (0.002)	−0.087*** (0.006)
Observations	376,848	639,232	969,904	317,488

Notes: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors following Koenker [47] are in parentheses below quantile estimates. Cluster-robust standard errors clustered at the customer level are in parentheses below fixed effects estimates.

Table 3
Summary of α^{COVID} for regressions of water subsets.

	Dependent variable:			
	log(Water Consumption)			
	(Villa Qatari)	(Villa non-Qatari)	(Flat non-Qatari)	(Commercial)
$\tau = 0.25$	0.069*** (0.003)	0.113*** (0.003)	0.200*** (0.017)	−0.117*** (0.034)
Mean FE	0.054*** (0.002)	0.094*** (0.002)	0.149*** (0.002)	−0.099*** (0.006)
$\tau = 0.50$	0.050*** (0.003)	0.077*** (0.004)	0.134*** (0.002)	−0.047*** (0.011)
$\tau = 0.75$	0.034*** (0.003)	0.070*** (0.004)	0.090*** (0.003)	−0.101*** (0.012)
Observations	364,960	614,352	616,784	128,512

Notes: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors following Koenker [47] are in parentheses below quantile estimates. Cluster-robust standard errors clustered at the customer level are in parentheses below fixed effects estimates.

zero otherwise. In x_t, we have a dummy variable for each month to control for seasonality. The intercept is given by δ_0. A time-invariant fixed effects term is present in the fixed effects (FE) regressions, but not in the QRs. The regressions are log-level, so the interpretation is that during the work-from-home order, there is a $100 \times \alpha^{\mathrm{COVID}}$ percent change in consumption.[27]

We also estimate the model using the stringency index of Hale et al. [44] divided by 100 in place of D_t (and coded to zero prior to its existence), in which case we have:

$$\log(C_{it}) = \delta_0 + \alpha^{\mathrm{STR}} \cdot \mathrm{StringencyIndex}_t + x_t'\beta + \epsilon_{it}, \tag{4}$$

where $\mathrm{StringencyIndex}_t$ is the index which is contained to the unit interval.

5. Empirical findings

Here we present our empirical findings both in tables and graphically. In Tables 2–3, we present the interquartile range for the QRs. For contrast and comparison, we also present the results for OLS and fixed effects panel regressions.[28] In Figs. 4–6, we plot the QRs for all deciles to illustrate our findings.

As seen in Table 2, during the pandemic, there was a 4.4 percent increase in median electricity consumption for Qataris in villas, a 4.8 percent increase in median electricity consumption for non-Qataris villa residents, and an 8% increase for non-Qataris in flats at the median. There was a 14.3 percent decrease in median commercial electricity consumption. All of these estimates are in line with a substantial shift of electricity consumption from work to home. All of these are statistically significant.[29] Mean estimates from a model with customer fixed effects are substantively similar and statistically significant, and significance holds up to clustering at the customer level.

In Table 3, we see that the pandemic was associated with a 5 percent increase in median water consumption for Qataris in villas, a 7.7 percent increase in median water consumption for non-Qataris villa residents, and a 13.4% increase for non-Qataris in flats at the median. There was a 4.7 percent decrease in median commercial water consumption. As with the electricity case, all of these estimates are statistically significant and mean estimates from the fixed effects model are qualitatively similar.[30]

The fact that the effects appear to be larger in magnitude for the 25th quantile than for the 75th quantile in Tables 2 and 3 merits further investigation into heterogeneous impacts by quantile. In Figs. 4–6, we plot the nine connected deciles of all QRs in black, with the OLS (mean) results given in red, and bands for the 95% confidence intervals in gray and dashed red, respectively.[31] For commercial water usage, the 10th percentile estimates were unavailable due to a lack of sufficient variation in the data, so we have substituted the 11th percentile estimate in the figure as it was the closest available percentile for which we were able to produce estimates.[32]

As seen in Fig. 4, the commercial sector's use of electricity is monotonically increasing in decile, indicating that the smallest businesses have the largest proportional decrease in consumption (−35% for $\tau = 0.1$), while the largest firms are least impacted (−5% for $\tau = 0.9$). The same cannot be said for water usage, which exhibits some non-monotonicity in higher deciles. However, the lower deciles still are the most impacted in percentage terms.

In Fig. 5, we see that work-from-home increased electricity consumption from 3% to 11% depending on the decile. Higher electricity users had the lowest overall percentage increase, while the lowest electricity users had the highest percentage increase.

In Fig. 6, we see that work-from-home increased water consumption from 2% to 25% depending on the decile. Similarly to electricity consumers, higher water users had the lowest overall percentage increase, while the lowest electricity users had the highest percentage increase.

In Table 4, we segment the commercial data by reported premises names for the three largest categories of water and electric usage. We find a similar pattern for shops, offices, and commercial buildings (CB) as for the aggregated data. Shops reduced their electricity consumption by the largest share of the three categories. For water, offices generally reduced their consumption by the largest share of the three categories. Shops reduced their median electricity usage by 22.1%, while CBs and offices reduced their usage from 10.8 to 13.7%, respectively. Offices

[27] We present the estimates in percentage terms since we want to understand the effects relative to pre-COVID usage. This is especially important because villas use so much more than other customer categories.

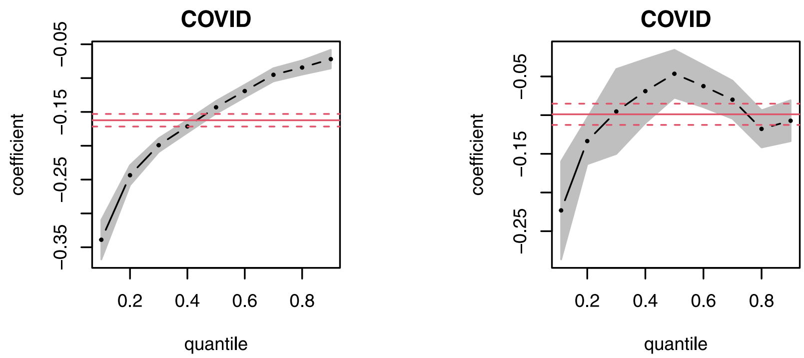
[28] A Hausman Test rejects the null hypothesis of the random effects specification, in favor of the fixed effects estimator.

[29] For the tables, we deploy a Huber sandwich estimate for the standard errors which is the default option in `quantreg`, Koenker [47].

[30] We note that the water outcome variable is more sensitive to the number of household members than the electricity outcome variable. This is partially explained by the fact that showering increases linearly with the household size, while air conditioning does not.

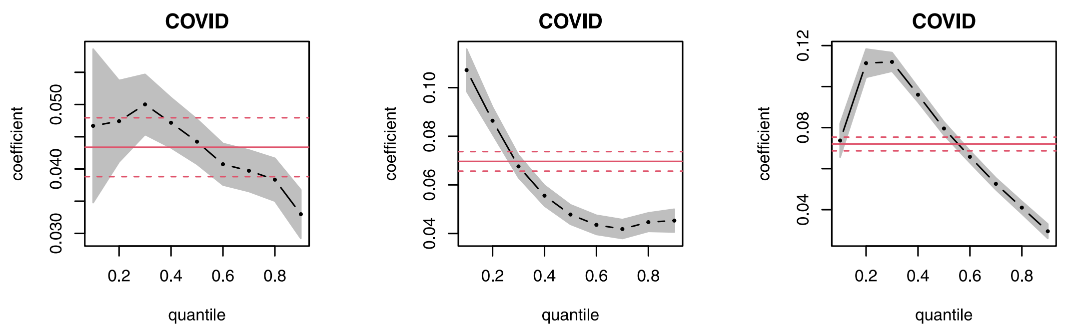
[31] For faster compute time, the standard errors for the plots use an estimate of the asymptotic covariance matrix where the errors are assumed to be independent and identically distributed (iid) as in [45].

[32] The 9th percentile estimate is also unavailable; estimates for the 8th and 12th percentiles are substantively similar to the 11th. When the commercial water regression for $\tau = .10$ is run without any month controls, we find that the coefficient on COVID is −0.287 (0.011) and STR is −0.341 (0.695).



(a) Electricity (b) Water

Fig. 4. Quantile plots for commercial users.



(a) Villas for Qatari Citizens (b) Villas for Non-Qatari Citizens (c) Flats for Non-Qatari Citizens

Fig. 5. Electricity quantile plots for residential users.

Table 4
Summary of α^{COVID} for commercial subsets of water and electric.

	Dependent variable:					
	log(Consumption)					
	Electric			Water		
	(Shop)	(Office)	(CB)	(Shop)	(Office)	(CB)
$\tau = 0.25$	−0.308***	−0.163***	−0.211***	−0.134***	−0.182***	−0.182***
	(0.008)	(0.015)	(0.036)	(0.013)	(0.024)	(0.039)
$\tau = 0.50$	−0.221***	−0.137***	−0.108***	−0.118***	−0.167***	−0.087**
	(0.008)	(0.013)	(0.024)	(0.016)	(0.023)	(0.036)
Mean FE	−0.271***	−0.189***	−0.138***	−0.154***	−0.158***	−0.119***
	(0.006)	(0.012)	(0.029)	(0.009)	(0.017)	(0.029)
$\tau = 0.75$	−0.136***	−0.110***	−0.042	−0.154***	−0.113***	−0.123***
	(0.009)	(0.014)	(0.029)	(0.018)	(0.031)	(0.045)
Observations	127,664	51,632	14,880	58,048	15,984	6624

Notes: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors following Koenker [47] are in parentheses below quantile estimates. Cluster-robust standard errors clustered at the customer level are in parentheses below fixed effects estimates.CB stands for commercial buildings.

Table 5
Summary of α^{STR} for regressions of electric subsets.

	Dependent variable:			
	log(Electricity Consumption)			
	(Villa Qatari)	(Villa non-Qatari)	(Flat non-Qatari)	(Commercial)
$\tau = 0.25$	0.068***	0.107***	0.171***	−0.333***
	(0.004)	(0.004)	(0.004)	(0.010)
Mean FE	0.059***	0.097***	0.102***	−0.247***
	(0.002)	(0.003)	(0.003)	(0.005)
$\tau = 0.50$	0.061***	0.067***	0.113***	−0.218***
	(0.003)	(0.003)	(0.003)	(0.008)
$\tau = 0.75$	0.050***	0.060***	0.067***	−0.133***
	(0.003)	(0.003)	(0.002)	(0.008)
Observations	376,848	639,232	969,904	317,488

Notes: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors following Koenker [47] are in parentheses below quantile estimates. Cluster-robust standard errors clustered at the customer level are in parentheses below fixed effects estimates.

reduced their median water usage by 16.7%, while CBs and shops reduced their usage from 8.7 to 11.8%, respectively.

For completeness, we also produce the plots where the dependent variable is specified in levels in Figs. A.1 through A.3 of the Appendix. The results indicate that the largest users are most impacted in absolute terms. This is unsurprising given that the scale of use varies so much within all four customer groups. Effects in percentage terms are arguably the more policy-relevant parameter, insofar as inequity and energy insecurity are a concern [48].

Next, we present results using the stringency index as the primary independent variable. In Table 5 we see that at the median, commercial electricity consumption could have decreased by 21.8% under full stringency, while households may have increased between 6.1%–11.3%. For the upper (lower) quartile, commercial electricity consumption could have decreased by 13.3% (33.3%) and households may have had an increase between 5.0% – 6.7% (6.8%–17.1%).

In Table 6, we present the water estimates with the model using the stringency index divided by 100 of Hale et al. [44] in place of D_t. We see that at the median, commercial electricity consumption could have decreased by 10.3% under full stringency, while households may have increased between 6.9% – 17.4%. For the upper (lower) quartile, commercial electricity consumption could have decreased by 14.6% (18.5%) and households had an increase between 4.5% – 12.4% (9.8%–26.1%).

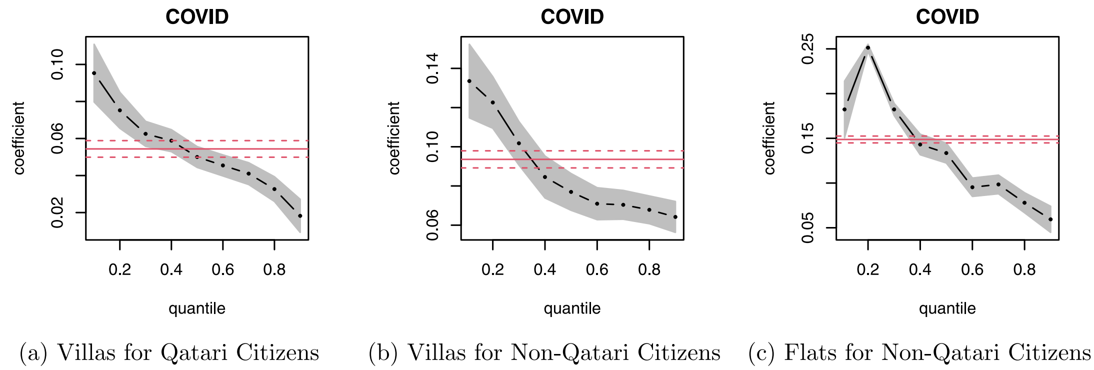


Fig. 6. Water quantile plots for residential users.

Table 6
Summary of α^{STR} for regressions of water subsets.

	Dependent variable:			
	log(Water Consumption)			
	(Villa Qatari)	(Villa non-Qatari)	(Flat non-Qatari)	(Commercial)
$\tau = 0.25$	0.098***	0.143***	0.261***	−0.185***
	(0.005)	(0.005)	(0.006)	(0.013)
Mean FE	0.075***	0.132***	0.209***	−0.154***
	(0.003)	(0.003)	(0.003)	(0.008)
$\tau = 0.50$	0.069***	0.097***	0.174***	−0.103***
	(0.004)	(0.005)	(0.005)	(0.015)
$\tau = 0.75$	0.045***	0.095***	0.124***	−0.146***
	(0.004)	(0.005)	(0.004)	(0.017)
Observations	364,960	614,352	616,784	128,512

Notes: *p < 0.1; **p < 0.05; ***p < 0.01. Standard errors following Koenker [47] are in parentheses below quantile estimates. Cluster-robust standard errors clustered at the customer level are in parentheses below fixed effects estimates.

For illustration, Figs. A.4–A.6 in the Appendix show the deciles for STR. These results are very similar to Figs. 4–6.

6. Threats to identification

Because we do not have a counterfactual for how quantiles of the electricity and water use distributions would have behaved post March-2019 in the absence of COVID, a reasonable concern is that our results are driven by pre-existing trends in water and electricity use. We want to address two distinct possible threats to identification. The first potential threat is that *overall* electricity and water use were trending up over time in the residential sector and trending up over time in the commercial sector, and were bound to continue on these paths. This would invalidate our *overall* findings that residential consumers increased use during COVID and commercial customers decreased use during COVID. Nota bene this would not necessarily invalidate our findings on the impacts being different for the different quantiles. That is, even if pre-existing overall trends persisted, a finding that impacts were heterogeneous by quantile could still be valid as long as the distribution of consumption was not becoming more dispersed over time (more on this latter possibility below).

Fig. 2 shows that we might be concerned about a preexisting trend in the residential sector, though not necessarily in the commercial sector.[33] To allay concerns over pre-existing trends driving the overall results, we use data from all available years and months in a more traditional panel setting.[34]

We specify the panel regression as follows:

$$\log(C_{it}) = \delta_0 + \alpha^{\mathrm{COVID}} \cdot \mathrm{D}_t + x_t'\beta + y_t'\sigma + \delta_i + \epsilon_{it}, \tag{5}$$

Here, we include month (x_t) and year (y_t) effects and use data from Jan 2016 through October 2020, as well as customer fixed effects (δ_i). Roughly speaking, this specification behaves more like a difference-in-differences regression, where one difference is between years before 2019 and 2020 and the other difference is COVID months vs non-COVID months in a given year. Assuming any time trend in consumption affects all months equally, including the "baseline" non-COVID months of January and February in 2020 along with year effects could net out the extra consumption that would have occurred in 2020 in the absence of COVID.

The results are presented in Tables A.1 and A.2 in the Appendix.[35] For electricity use, we find an overall increase of 6.5% for Qataris in villas, 3.2% for non-Qataris in villas, 1.1% for non-Qataris in flats, and a 16.4% reduction for commercial customers. Recall the magnitudes of the main average fixed effects results (from the second row of Table 2) were increases of 4.3%, 7%, 7.2% and a reduction of 16.2%, respectively. The 95% confidence intervals constructed from cluster-robust standard errors overlap with the main results for the commercial estimates but not the residential estimates. However, the results are substantively similar.[36] The fact that the magnitude of estimates is higher than the main results in two of the groups and lower in the other two groups casts doubt on the idea that pre-existing trends could be entirely driving our effects.

For water use, we find an overall increase of 6.8% for Qataris in villas, 11.7% for non-Qataris in villas, 15.1% for non-Qataris in flats, and a 13.2% reduction for commercial customers. Recall the magnitudes of the main average fixed effects results (from the second row of Table 2) were increases of 5.4%, 9.4%, 14.9% and a reduction of 9.9%, respectively. 95% confidence intervals constructed from cluster-robust standard errors overlap for all but the non-Qatari in villa case. We do not find compelling evidence that our results are merely the product of pre-existing trends in usage.

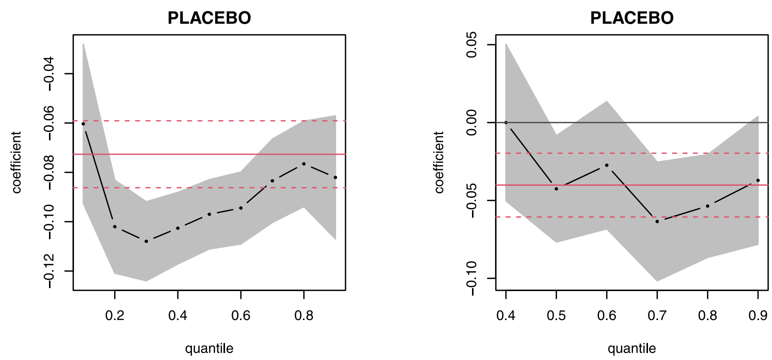
The second possible threat to identification is that the *distribution* of consumption would have become more dispersed over time in the

[33] The commercial sector exhibits some evidence of an upward trend over time, but an upward trend would tend to bias the results us towards finding a positive effect on consumption. We find a negative effect, indicating that this pretrend is unlikely to explain the results. To the extent that there is a positive pretrend, we can interpret our main commercial sector results as a lower bound on the magnitude of the effect of COVID.

[34] This has the advantage of being computationally practical, unlike the quantile regression with all observations.

[35] Table A.3 aggregates the data from the main analysis with interaction terms, as suggested by a referee. The parameter estimates are identical (up to three decimal places) to the fixed effects parameter estimates in Tables 2 and 3.

[36] In one out of 8 cases, the test that the confidence interval overlap is greater than 50% is statistically significant [49]. The test is rejected for the commercial electricity sector, with 63.5% overlap.



(a) Electric (b) Water

Fig. 7. Placebo quantile plots for commercial users.

absence of COVID. To tackle this possibility, we employ a placebo test where we repeat our main quantile analysis using only non-COVID months. Recall that our main quantile analysis compares Mar–Oct in 2019 to Mar–Oct in 2020. Our placebo instead compares Jan–Feb in 2019 to Jan–Feb in 2020. If the distribution of consumption becoming more dispersed over time is driving our results on the comparison of quantiles over time, we should find heterogeneous effects by quantile in this placebo test in a pattern that mirrors our main results.

The placebo results are presented graphically in Figs. 7–9. Six out of eight placebo tests do not indicate the same pattern of quantile effects as we find in our main results, suggesting that our results are not merely a reflection of diverging consumption between quantiles between the years 2019 and 2020. Specifically, the placebo test appears to fail for electricity use in villas for non-Qatari citizens as well as electricity use in flats for non-Qatari citizens when looking at the pattern of change in use across quantiles. However, it is worth mentioning that the overall sign of the effects is the opposite of what it is in the main results for electricity use for both of these groups, calling into question the idea that our results for these two customer group are completely driven by changes between 2019 and 2020 consumption that would have occurred in the absence of COVID.[37]

Moreover, the magnitude of effects for the placebo tests of these two groups is much smaller than the magnitude of our main effects for electricity use in non-Qataris in flats and non-Qataris in villas. Estimates from the placebo test are small enough that if we were to treat the impacts found in Fig. 8(c) as a counterfactual for percentage change that would have occurred in the absence of COVID, and subtract them off of the impacts in Fig. 5(c), the resulting differenced impacts would still support our conclusion that the lowest deciles experienced a larger reduction in use than higher deciles did for non-Qataris living in flats. A similar argument pertains to non-Qataris in villas.

7. Discussion

Using our estimates, we calculated a back-of-the-envelope net effect on the COVID-induced shift in utility usage from work to home on carbon emissions. Our calculations are summarized in Table 7. First, we obtained carbon intensity numbers for both electricity and water from Kharaama for the commercial and residential sectors.[38] Note that water is produced using desalination in Qatar, which is a carbon-intensive process. Then, we multiplied each of these with the sub-sector weighted average estimates of residential electricity use from our paper, as well as the average commercial estimate.[39] We then multiplied these weighted averages by the total units of households and firms in Qatar respectively, for both electricity and water.[40] We find that the overall net impact of the shift from commercial to residential usage was a decrease in consumption of 0.160 Million Metric Tons annually. For context, the average passenger vehicle emits about 4.6 metric tons of carbon dioxide per year.[41] So, 0.16 Million Metric Tons of CO_2 emissions is equivalent to the annual emissions of about 34,782 cars.

In addition to the overall finding that utility usage was shifted from work to home, and the finding of an overall net negative carbon emissions due to the shift, three findings stand out in our study. First, our study suggests impacts of COVID are strongest for the lowest deciles of the use distribution of both electricity and water. This implies subsidies could be targeted to address negative impacts of the pandemic; we explain why these subsidies are both administratively advantageous and socially feasible in Section 2.

Second, increases in use for both water and electricity are higher in percentage terms for non-Qataris than for Qataris. This larger response by non-Qataris might be because they have more elastic demand for electricity.[42] The fact that Qataris do not generally pay for utilities might explain why their electricity usage would not respond as strongly as that of non-Qataris.[43] One mechanism could be that Qataris have less of an incentive to take actions like turning off lights during the day and raising their thermostats when they are away. A lower elasticity of demand in any given period would result in Qataris changing their behavior less than non-Qataris in response to the work-from-home policy. This has important implications for Gulf states, where subsidies for nationals are common (and increasingly controversial in light of the need to conserve).

[37] For the placebo tests, there were data limitations for water usage in two groups. For non-Qatari citizens in flats, effects at deciles 1, 2, 5 and 6 were not identified. For deciles 1 and 2, there were no nearby identified quantile effects, so we omit them from the plot. For the 5th and 6th decile effects, we have substituted the 51st and 61st percentile. For companies, effects were not identified at deciles 1–3, and there were no nearby quantiles that were identified to substitute, so we omit deciles 1–3 from the plot.

[38] These numbers were obtained via direct email correspondence between the authors and Kharaama. We can provide documentation of these emails upon request.

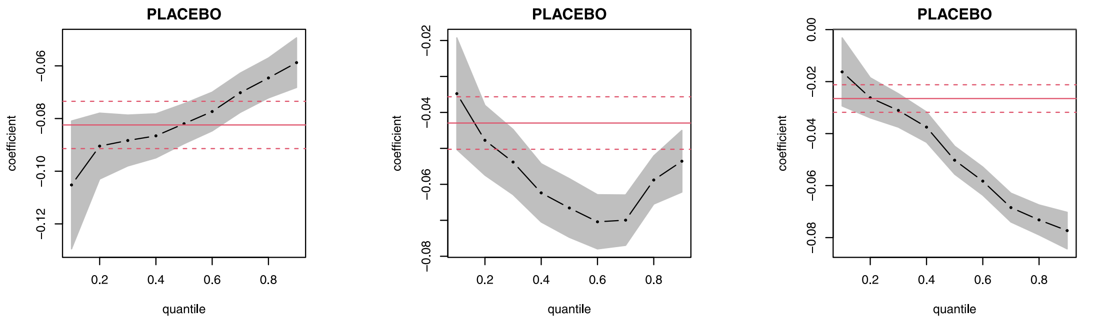
[39] We are assuming that the fractions of customers in each sub-sector for residential customers is roughly reflective of the national fractions.

[40] We use figures for the number of total households from [50], and the number of total firms from [51].

[41] This statistic is from [52], and was last updated in 2022.

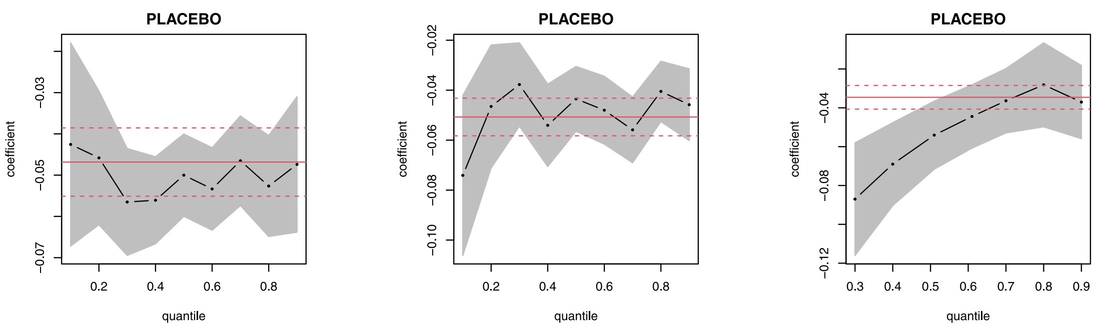
[42] The fact that the response is more similar across deciles for Qataris than non-Qataris is also consistent with a dampened elasticity of demand for non-Qataris.

[43] Qataris do not pay for water and electricity for their primary residence, but may pay for water and electricity in secondary residences or other owned properties that they are renting out.



(a) Villas for Qatari Citizens (b) Villas for Non-Qatari Citizens (c) Flats for Non-Qatari Citizens

Fig. 8. Placebo electricity quantile plots for residential users.



(a) Villas for Qatari Citizens (b) Villas for Non-Qatari Citizens (c) Flats for Non-Qatari Citizens

Fig. 9. Placebo water quantile plots for residential users.

Table 7
Back-of-the-envelope carbon emissions calculations.

	Electricity:			
	Weighted average (kWh/month)	Carbon intensity factor (kg/kWh)	Units assumed (households or firms)	Total (Mil Metric Tons/month)
Res	310.401	0.628	201,432	0.039
Com	−1327.428	0.628	76,666	−0.064
	Water:			
	Weighted average (m^3/month)	Carbon intensity factor (m^3/kWh)	Units assumed (households or firms)	Total (Mil Metric Tons/month)
Res	7.145	8.2	201,432	0.012
Com	−0.792	8.2	76,666	−0.000
			Total monthly net effect	−0.013
			Total yearly net effect	−0.160

Notes: Number of total households comes from [50]. Number of total firms comes from [51]. Factors for kg/kWh and kg/m^3 come from e-mail correspondence between the authors and Kharaama.

Third, in percentage terms, the effects are higher in magnitude overall for the commercial than for the residential sector for most of our specifications. Though our dataset is not comprehensive, this finding might imply that the work-from-home order was a net positive in terms of electricity and water usage; this contrasts with the finding of Brewer [25] but is in line with Cicala [24].

One reason why work-from-home might reduce consumption overall that has been highlighted by the literature is that people internalize the costs of utility consumption at home but not at work, and thus save more when forced to work from home (see, e.g., [39]). The underlying assumption is that elasticity of demand is higher for residential customers than for commercial customers.

Our context sheds light on another potential explanation for the commercial reduction to outpace the residential increase: a work-at-home arrangement can result in overall conservation if it piggybacks on at-home use that would have happened anyways. People who do not pay for utilities have little incentive to conserve, and would have kept their lights on and appliances running in the absence of working from home. Their demand for electricity and water could be so inelastic that having them work from home adds little to their utility consumption at home (most appliances would be running no matter what), but decreases utility consumption at work substantially.

With a large portion of subsidized residential consumers, this piggybacking phenomenon has the potential to explain behavior in many Gulf states. But, it also should be considered as an explanation in other situations. One example could be a worker whose residential demand is inelastic because they take no steps towards conserving energy, leaving all appliances on constantly, even while at work. Another example could be a situation where a stay-at-home partner watches the kids at home during the day. In either of these cases, shifting work from the office to home could save energy.

There are several important limitations of our study that should be considered when interpreting our findings. First, it is impossible to disentangle the impacts of all family members staying home from the impacts of people who would have otherwise traveled to work and worked at an office staying home, and during much of the COVID segment of our study period, the majority of residents stayed home. A comparison of the results based on the stringency index and the results based on the work-from-home order can somewhat speak to the difference, but only in qualitative terms.

Second, though we do our best to characterize distributional impacts across households, our study cannot differentiate between the impacts of work-from-home on various demographic groups within a household. The work-from-home order may have disproportionately affected women and people with children, and could had differential effects by age group. For example, in the Spanish context, Navas-Martın et al. [33] show nontrivial differential effects driven by within-household shifting of burdens. In particular, they find that household maintenance tasks were disproportionately shouldered by adults aged 35–54 years, with more cohabitants, and that this was especially true for women. Furthermore, Birimoglu Okuyan and Begen [9] highlight the potential for disproportionate mental health and lifestyle impacts on these same groups. In sum, it is plausible in our context that these disproportionate increases in domestic work and psychological vulnerability constitute additional distributional impacts of the work-from-home order that we cannot account for or quantify.

Third, our study did not directly observe energy consumption behaviors at the individual level, and thus cannot speak to behavioral mechanisms. Specifically, we cannot account for energy-saving measures that may have been undertaken while individuals were confined to their houses, schedule changes they may have adopted to cope with confinement, or whether individuals tolerated more discomfort than they would have in an office setting in order to save energy at home. Moreover, Navas-Martın et al. [33] find that routines were changed; one particularly relevant finding is that sleep routines were disrupted for more than a third of their sample. If the same behavior is at play in our context, it would likely increase nighttime electricity usage and contribute to the overall increase in home energy consumption that we find.[44] More generally, as with any study using aggregated observational data resulting from individual decisions, our results should not be extrapolated to predict individual-level behaviors [53].[45] As such, our results should be interpreted with caution.

8. Conclusion and policy implications

In this work, we provide estimates for the effects of COVID on quantiles of electricity and water consumption for both residents and businesses. In line with the literature, we find that Qatari residents have increased their water and electricity consumption by 4.4%–13.4% at home, while businesses have decreased their consumption by 4.7%–14.3% during the pandemic, a result we believe can be attributed to work-from-home. Our estimates can be used by policymakers to understand how future pandemics will shift electricity and water demand from work to home. Furthermore, our study is timely given the recent policy interest in encouraging work-from-home to reduce emissions from commuting [54].

We find that, overall, the net effect of the utility shift from work to home was a decrease in carbon emissions of about 0.160 million metric tons in 2020. This is a sizeable decrease in carbon emissions.

[44] Psychological impacts of these routine could also be consequential; see [5, 9].

[45] In our case, we observe household-level data, but do not observe individual decisions. Our data contains energy and water use at the month level, which is the finest level of granularity we have access to.

One key contribution of our work is that we are able to estimate effects for the entire distribution of electricity and water use. Residents who consumed the most electricity and water prior to the pandemic increased their consumption by the smallest percentage. Residents consuming the least pre-pandemic increased their at-home usage substantially. Hence, to the extent that lower electricity and water users are also lower income, they may benefit from government assistance. In future pandemics, policymakers could target these segments of the population for governmental aid. A congruous policy recommendation to this work is found in [55], who suggest that energy poverty risk during future lockdown events could be mitigated by implementing a flexible discount system on electricity bills. This discount system would vary according to the individual's income and the time of year.

Policy tools like water and energy subsidies are vital given the recent concerns that have arisen over energy insecurity during the COVID-19 crisis [48]. Carfora et al. [56] find an increase in energy poverty in many European Union member countries as a result of lockdown measures, while the lockdowns resulted in new job opportunities in other nations.

We also find that the smallest commercial customers reduced their electricity consumption by the largest percentage of their pre-pandemic level. This implies that these presumably smaller businesses may have suffered the most from the economic downturn that ensued after the work-from-home order was instituted. Analogously to the residential case, they could be targeted for aid or utility subsidies in future times of crisis. For water in particular, because lower flow rates could lead to deterioration of commercial plumbing systems, the government could institute measures to protect infrastructure in future pandemics; efforts to stem infrastructure deterioration could focus on lower deciles of the commercial water use distribution.

From an administrative perspective, targeting electricity and water subsidies is advantageous in Qatar and other Gulf states, where utility companies are national entities and collect vast amounts of data on usage. It is much easier for the government to identify at-risk customers this way than to collect income data. Aid in the form of targeted electricity and water subsidies can be deployed much more quickly to respond to a crisis such as a pandemic. Furthermore, subsidies are arguably more socially acceptable and administratively feasible than other policy levers as they have been in place for decades.

Moreover, we find that increases in use for both water and electricity are higher in percentage terms for Non-Qataris than for Qataris. This might be because subsidies decrease the elasticity of demand for Qatari citizens- they have less of an incentive to take actions like turning off lights during the day and raising their thermostats when they are away. If they have a lower elasticity of demand in any given period, they are bound to change their behavior less than non-Qataris in response to the work-from-home policy. This should be noted by policymakers in Gulf states, where subsidies for nationals are common.

In sum, our findings could help policymakers to anticipate shifts in utility demand during future work-from-home orders and develop effective targeting strategies. We summarize policy takeaways rooted in our findings in a bulleted list in the Appendix (Appendix A.1). An interesting extension of this work could be to compare the reduction in water and electricity consumption at work and the increase in consumption at home for the same workers to determine which types of work produce the largest shifts in use.

CRediT authorship contribution statement

David H. Bernstein: Data curation, Conceptualization, Methodology, Software, Validation, Writing – original draft, Investigation, Original idea generation, Writing – review & editing. **Alecia Cassidy:** Writing – review & editing, Conceptualization, Methodology, Writing – original draft, Investigation, Original idea generation. **Ahmed A. Khalifa:** Writing – review & editing, Supervision, Funding, Networking, Investigation, Original idea generation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The electricity and water data are from KAHRAMAA & Qatar General Electricity & Water, under an NDA, but we provide de-identified data. Stringency data is publicly available. In Dataverse Repo.

Replication Materials for: Work-from-home, electricity, and water: Evidence from COVID-19 in Qatar (Original data) (Dataverse)

Appendix A

In this Appendix, we first provide a list of policy takeaways. Then, we first present the quantile plots, similar to Figs. 4–6, but for the stringency index and results in levels.[46] Next, we present supplementary tables containing fixed effects results. Lastly, we point the reader to our supplemental code and replication files.

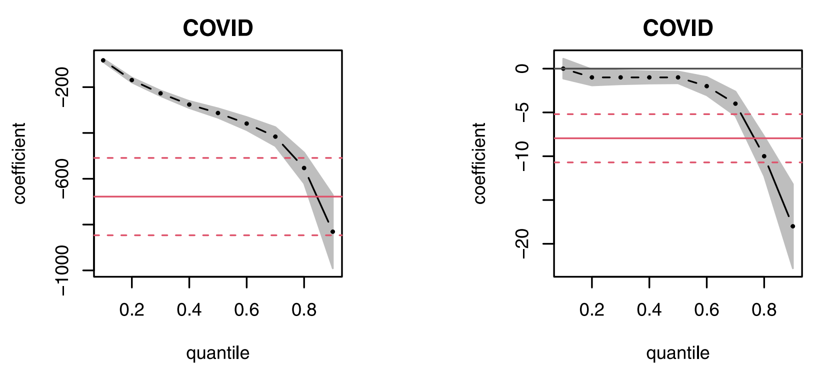
[46] For commercial water usage, the 10th percentile estimates were unavailable due to a lack of sufficient variation in the data, so we have substituted the 11th percentile estimate in the figure as we did in Fig. 4. Estimates for the 8th, 9th, and 12th percentiles are substantively similar to the 11th.

A.1. Policy takeaways

We summarize the policy takeaways below.

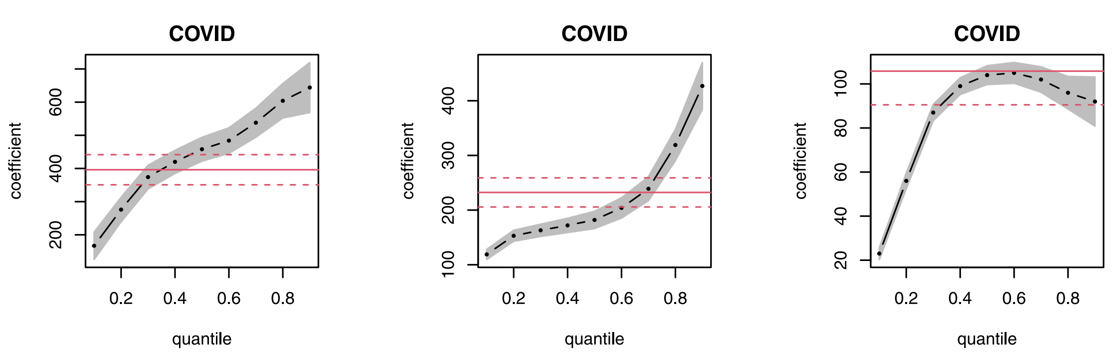
- Policy tools like water and energy subsidies are vital tools to combat energy and/or water insecurity during crises.
- Aid in the form of targeted electricity and water subsidies can be deployed much more quickly to respond to a crisis such as a pandemic.
  - The targeting of subsidies can occur at the utility level in Gulf nations, where vast amounts of use data are collected and utilities are national entities.
  - Our findings indicate that subsidies could go to the lowest users, who are most likely affected by energy and/or water insecurity.
  - Theoretically, implementing subsidies based on usage level could mitigate energy and water inequities resulting from pandemics.
  - This policy recommendation is easier to employ than income-based subsidies, where there is a large administrative burden and taxes are only reported every year; in contrast, monthly utility data is readily available to governments in Gulf nations.
- Demand may be less elastic for users subject to utility subsidies. This means that in a pandemic, they would be less likely to change their behavior than those not subject to utility subsidies. Governments can use this to anticipate the results of confinement mandates for electricity grids and water supply.

A.2. Supplemental figures



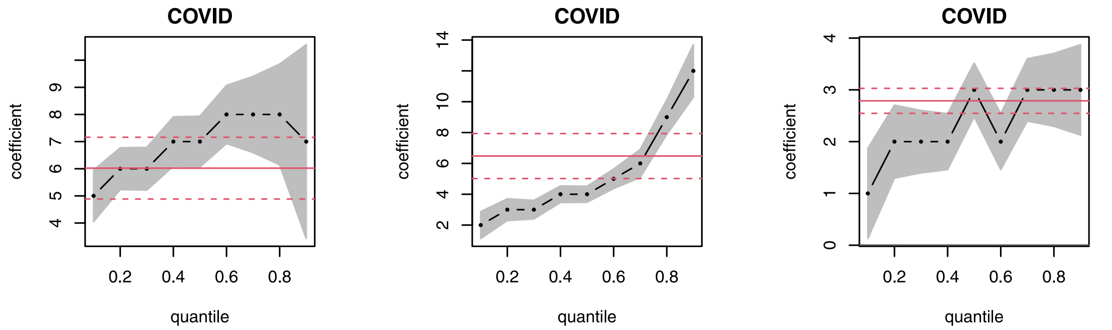
(a) Electric (b) Water

Fig. A.1. Quantile Plots in levels for Commercial Users.



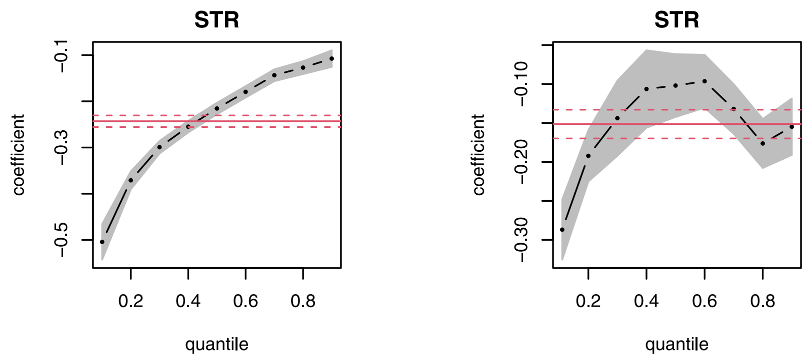
(a) Villas for Qatari Citizens (b) Villas for Non-Qatari Citizens (c) Flats for Non-Qatari Citizens

Fig. A.2. Electricity Quantile Plots in levels for Residential Users.



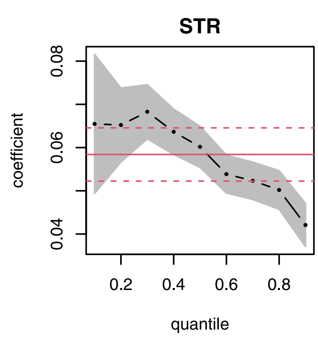
(a) Villas for Qatari Citizens (b) Villas for Non-Qatari Citizens (c) Flats for Non-Qatari Citizens

Fig. A.3. Water Quantile Plots in levels for Residential Users.



(a) Electricity (b) Water

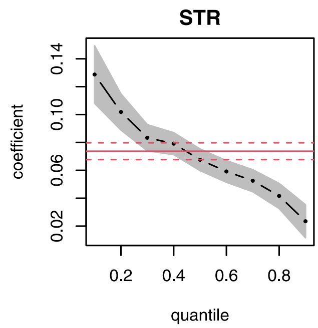
Fig. A.4. Quantile Plots using the stringency index for Commercial Users.



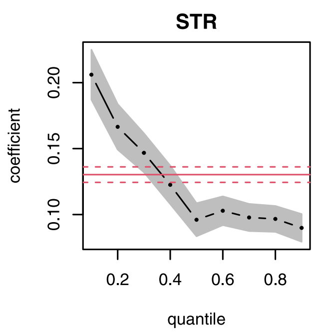
(a) Villas for Qatari Citizens

(b) Villas for Non-Qatari Citizens (c) Flats for Non-Qatari Citizens

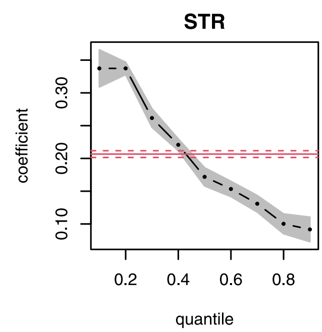
Fig. A.5. Electricity Quantile Plots using the stringency index for Residential Users.



(a) Villas for Qatari Citizens



(b) Villas for Non-Qatari Citizens



(c) Flats for Non-Qatari Citizens

Fig. A.6. Water Quantile Plots using the stringency index for Residential Users.

A.3. Supplemental tables

Table A.1
FE Regressions on full electric sample.

	Dependent variable:			
	log(Electricity Consumption)			
	(Qatari Villa)	(non-Qatari Villa)	(non-Qatari Flat)	(Commercial)
α^{COVID}	0.065***	0.032***	0.011***	−0.164***
	(0.004)	(0.004)	(0.004)	(0.006)
$YEAR_{17}$	0.036***	0.042***	0.043***	0.018***
	(0.003)	(0.003)	(0.002)	(0.004)
$YEAR_{18}$	0.015***	0.022***	0.035***	0.002
	(0.004)	(0.004)	(0.003)	(0.005)
$YEAR_{19}$	−0.024***	−0.018***	0.010***	−0.004
	(0.005)	(0.004)	(0.003)	(0.006)
$YEAR_{20}$	−0.081***	−0.014***	0.023***	−0.065***
	(0.007)	(0.005)	(0.004)	(0.008)
Observations	421,834	624,834	1,097,012	386,280
Month effects	YES	YES	YES	YES
Adjusted R^2	0.564	0.527	0.398	0.214

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Cluster-robust standard errors clustered at the customer level are in parentheses below estimates.

Table A.2
FE Regressions on full water sample.

	Dependent variable:			
	log(Water Consumption)			
	(Qatari Villa)	(non-Qatari Villa)	(non-Qatari Flat)	(Commercial)
α^{COVID}	0.068***	0.117***	0.151***	−0.132***
	(0.006)	(0.005)	(0.006)	(0.016)
$YEAR_{17}$	0.026***	−0.002	0.018***	−0.002
	(0.005)	(0.004)	(0.004)	(0.011)
$YEAR_{18}$	0.053***	−0.001	0.016***	0.017
	(0.007)	(0.005)	(0.006)	(0.014)
$YEAR_{19}$	0.042***	−0.007	0.012*	0.018
	(0.008)	(0.005)	(0.006)	(0.016)
$YEAR_{20}$	0.002	−0.038***	−0.023***	0.006
	(0.010)	(0.007)	(0.008)	(0.021)
Observations	253,924	413,482	315,810	70,702
Month effects	YES	YES	YES	YES
Adjusted R^2	0.033	0.010	0.016	−0.001

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Cluster-robust standard errors clustered at the customer level are in parentheses below estimates.

Table A.3
FE Regression for Mar-Oct 2019 and Mar-Oct 2020 sample of electricity and water subsets.

	Dependent variable:	
	log(Consumption)	
	electricity	water
α^{COVID} ∗non-Qatari Flat	0.072***	0.149***
	(0.002)	(0.002)
α^{COVID} ∗non-Qatari Villa	0.070***	0.094***
	(0.002)	(0.002)
α^{COVID} ∗Qatari villa	0.043***	0.054***
	(0.002)	(0.003)
α^{COVID} ∗Commercial	−0.162***	−0.099***
	(0.004)	(0.006)
Aug	0.951***	−0.015***
	(0.002)	(0.001)
Jul	0.811***	−0.073***
	(0.002)	(0.001)
Jun	0.801***	0.110***
	(0.001)	(0.001)
Mar	−0.364***	−0.145***
	(0.001)	(0.001)
May	0.286***	−0.077***
	(0.001)	(0.001)
Oct	0.754***	−0.090***
	(0.002)	(0.001)
Sep	0.820***	−0.112***
	(0.002)	(0.001)
Observations	2,304,224	1,725,424
R^2	0.427	0.044
Adjusted R^2	0.389	−0.020

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Cluster-robust standard errors clustered at the customer level are in parentheses below estimates.

A.4. Supplemental material

Replication codes and data can be found in the accompanying supplemental material files.

References

[1] K.E. Jones, N.G. Patel, M.A. Levy, A. Storeygard, D. Balk, J.L. Gittleman, P. Daszak, Global trends in emerging infectious diseases, Nature 451 (7181) (2008) URL: https://doi.org/10.1038/s41545-021-00103-8.

[2] J. Hilsenrath, Global viral outbreaks like coronavirus, once rare, will become more common, Wall Street J. (2020).

[3] J. Pike, T. Bogich, S. Elwood, D.C. Finnoff, P. Daszak, Economic optimization of a global strategy to address the pandemic threat, Proc. Natl. Acad. Sci. (2014) URL: https://www.pnas.org/content/early/2014/12/12/1412661112.

[4] A. Haxhimusa, M. Liebensteiner, Effects of electricity demand reductions under a carbon pricing regime on emissions: lessons from COVID-19, Energy Policy 156 (2021) 112392, URL: https://www.sciencedirect.com/science/article/pii/S0301421521002627.

[5] H. Bouziri, D.R.M. Smith, A. Descatha, W. Dab, K. Jean, Working from home in the time of COVID-19: how to best preserve occupational health? Occup. Environ. Med. 77 (7) (2020) 509–510, URL: https://oem.bmj.com/content/77/7/509.

[6] A. Kramer, K.Z. Kramer, The potential impact of the Covid-19 pandemic on occupational status, work from home, and occupational mobility, J. Vocat. Behav. 119 (2020) 103442, URL: https://www.sciencedirect.com/science/article/pii/S0001879120300671.

[7] C. Gottlieb, J. Grobovšek, M. Poschke, F. Saltiel, Working from home in developing countries, Eur. Econ. Rev. 133 (2021) 103679, URL: https://www.sciencedirect.com/science/article/pii/S0014292121000325.

[8] B. Vilhelmson, E. Thulin, Who and where are the flexible workers? Exploring the current diffusion of telework in Sweden, New Technol. Work Employ. 31 (1) (2016) 77–96, URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/ntwe.12060.

[9] C. Birimoglu Okuyan, M.A. Begen, Working from home during the COVID-19 pandemic, its effects on health, and recommendations: The pandemic and beyond, Pers. Psychiatric Care 58 (1) (2022) 173–179, URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/ppc.12847.

[10] S. Shigeru, Impact of Covid-19 on energy demand, 2020, IEEJ Newsletter May 11, 2020.

[11] R. Frost, Could Spain's Four-Day Working Week Save the Planet? Euronews (2021).

[12] IEA, World Energy Outlook 2019, International Energy Agency, Paris, 2019.

[13] A. Abulibdeh, E. Zaidan, R. Jabbar, The impact of COVID-19 pandemic on electricity consumption and electricity demand forecasting accuracy: Empirical evidence from the state of Qatar, Energy Strategy Rev. 44 (2022) 100980, URL: https://www.sciencedirect.com/science/article/pii/S2211467X22001742.

[14] N.B. Irwin, S.J. McCoy, I.K. McDonough, Water in the time of corona(virus): The effect of stay-at-home orders on water demand in the desert, J. Environ. Econ. Manage. 109 (102491) (2021) 1–14.

[15] L. Eastman, E. Smull, L. Patterson, M. Doyle, A shaky recovery driven by residential usage, Raftelis (2020).

[16] M. Roidt, C.M. Chini, A.S. Stillwell, A. Cominola, Unlocking the impacts of COVID-19 lockdowns: Changes in thermal electricity generation water footprint and virtual water trade in Europe, Environ. Sci. Technol. Lett. 7 (2020) 683–689, URL: https://doi.org/10.1021/acs.estlett.0c00381.

[17] H. Abu-Bakar, L. Williams, S.H. Hallett, Quantifying the impact of the COVID-19 lockdown on household water consumption patterns in England, Clean Water 4 (2021) URL: https://doi.org/10.1038/s41545-021-00103-8.

[18] S. Rizvi, R. Rustum, M. Deepak, G.B. Wright, S. Arthur, Identifying and analyzing residential water demand profile; including the impact of COVID-19 and month of ramadan, for selected developments in Dubai, United Arab Emirates, Water Supply (2020) URL: https://doi.org/10.2166/ws.2020.319.

[19] I. Santiago, A. Moreno-Munoz, P. Quintero-Jiménez, F. Garcia-Torres, M. Gonzalez-Redondo, Electricity demand during pandemic times: The case of the COVID-19 in Spain, Energy Policy 148 (2021) 111964, URL: https://www.sciencedirect.com/science/article/pii/S0301421520306753.

[20] A. Cheshmehzangi, COVID-19 and household energy implications: what are the main impacts on energy use? Heliyon 6 (2021) URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7544699/.

[21] S. Li, Q. Wang, X. ting Jiang, R. Li, The negative impact of the COVID-19 on renewable energy growth in developing countries: Underestimated, J. Clean. Prod. 367 (2022) 132996, URL: https://www.sciencedirect.com/science/article/pii/S0959652622025884.

[22] W. Wen, Y. Li, Y. Song, Assessing the "negative effect" and "positive effect" of COVID-19 in China, J. Clean. Prod. 375 (2022) 134080, URL: https://www.sciencedirect.com/science/article/pii/S0959652622036526.

[23] Y. Tian, L. Li, Will COVID-19 affect China's peak CO2 emissions in 2030? An analysis based on the systems dynamics model of green finance, J. Clean. Prod. 356 (2022) 131777, URL: https://www.sciencedirect.com/science/article/pii/S0959652622013890.

[24] S. Cicala, Powering work from home, NBER Work. Pap. Ser. (2020).

[25] D. Brewer, Changes in Electricity Use Following COVID-19 Stay-At-Home Behavior, Working Paper, 2020.

[26] M.-J. Kim, Understanding the determinants on household electricity consumption in Korea: OLS regression and quantile regression, Electr. J. 33 (7) (2020) 106802, URL: https://www.sciencedirect.com/science/article/pii/S1040619020300944.

[27] M. Frondel, S. Sommer, C. Vance, Heterogeneity in german residential electricity consumption: A quantile regression approach, Energy Policy 131 (2019) 370–379, URL: https://www.sciencedirect.com/science/article/pii/S0301421519302186.

[28] I. Kostakis, Socio-demographic determinants of household electricity consumption: evidence from Greece using quantile regression analysis, Curr. Res. Environ. Sustain. 1 (2020) 23–30, URL: https://www.sciencedirect.com/science/article/pii/S2666049020300025.

[29] M. Shahbaz, A. Lahiani, S. Abosedra, S. Hammoudeh, The role of globalization in energy consumption: A quantile cointegrating regression approach, Energy Econom. 71 (2018) (2018) 161–170, URL: https://doi.org/10.1016/j.eneco.2018.02.009.

[30] A. Khalifa, M. Caporin, S. Hammoudeh, The relationship between oil prices and rig counts: the importance of lags, Energy Econom. 63 (2017) (2017) 213–226, URL: https://doi.org/10.1016/j.eneco.2017.01.015.

[31] W.-H. Huang, The determinants of household electricity consumption in Taiwan: Evidence from quantile regression, Energy 87 (2015) 120–133, URL: https://www.sciencedirect.com/science/article/pii/S0360544215005873.

[32] M.A. Andor, D.H. Bernstein, S. Sommer, Determining the efficiency of residential electricity consumption, Empir. Econ. (2020) URL: https://doi.org/10.1007/s00181-020-01967-4.

[33] M.A. Navas-Martın, J.A. López-Bueno, I. Oteiza, T. Cuerdo-Vilches, Routines, time dedication and habit changes in spanish homes during the COVID-19 lockdown. A large cross-sectional survey, Int. J. Environ. Res. Public Health 18 (22) (2021) URL: https://www.mdpi.com/1660-4601/18/22/12176.

[34] L. Gurriaran, K. Tanaka, I.S. Bayram, Y. Proestos, J. Lelieveld, P. Ciais, Warming-induced increase in power demand and CO2 emissions in Qatar and the middle east, J. Clean. Prod. 382 (2023) 135359, URL: https://www.sciencedirect.com/science/article/pii/S0959652622049332.
[35] A. Khalifa, M. Caporin, T. Di Fonzo, Scenario-based forecast for the electricity demand in Qatar and the role of energy efficiency improvements, Energy Policy 127 (2019) 155–164, URL: http://www.sciencedirect.com/science/article/pii/S0301421518307857.
[36] H. Rahman, S.J. Zaidi, Desalination in Qatar: Present status and future prospects, Civ. Eng. Res. J. 6 (5) (2018) 1–7.
[37] I.S. Bayram, F. Saffouri, M. Koc, Generation, analysis, and applications of high resolution electricity load profiles in Qatar, J. Clean. Prod. 183 (2018) 527–543, URL: https://www.sciencedirect.com/science/article/pii/S0959652618303901.
[38] E. Guidotti, D. Ardia, COVID-19 data hub, J. Open Source Softw. 5 (51) (2020) 2376.
[39] A. Loschel, M.K. Price, L. Razzolini, M. Werthschulte, Implications of the COVID-19 Pandemic for Household Energy Consumption: The Stay-At-Home Orders and Energy Conservation Habits, Working Paper, 2021, pp. 1–15.
[40] K. Aruga, M.M. Islam, A. Jannat, Effects of COVID-19 on Indian energy consumption, Sustainability 12 (14) (2020) 5616, URL: http://dx.doi.org/10.3390/su12145616.
[41] J.M. Belbute, A.M. Pereira, Reference forecasts for CO2 emissions from fossil-fuel combustion and cement production in Portugal, Energy Policy 144 (2020) 111642, URL: http://www.sciencedirect.com/science/article/pii/S0301421520303761.
[42] L.V. Smith, N. Tarui, T. Yamagata, Assessing the impact of COVID-19 on global fossil fuel consumption and CO2 emissions, Energy Econ. 97 (2021) 105170, URL: https://www.sciencedirect.com/science/article/pii/S014098832100075X.
[43] C. Kao, Spurious regression and residual-based tests for cointegration in panel data, J. Econometrics 90 (1) (1999) 1–44, URL: https://www.sciencedirect.com/science/article/pii/S0304407698000232.
[44] T. Hale, N. Angrist, B. Kira, A. Petherick, T. Phillips, S. Webster, Variation in government responses to COVID-19, Blavatnik Sschool Working Paper, 2020.
[45] R. Koenker, G. Bassett, Regression quantiles, Econometrica 46 (1) (1978) 33–50.
[46] R. Koenker, Quantile Regression, Cambridge University Press, 2005.
[47] R. Koenker, R Package 'Quantreg', R Foundation for Statistical Computing, Vienna, Austria, 2011, URL: https://cran.r-project.org/web/packages/quantreg/index.html.
[48] M. Graff, S. Carley, COVID-19 assistance needs to target energy insecurity, Nature Energy 5 (2020) 352–354.
[49] G. Cumming, Inference by eye: Reading the overlap of independent confidence intervals, Stat. Med. 28 (2) (2009) 205–220, URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/sim.3471.
[50] Government of Qatar, Web site: Qatar open data portal, distribution of households and household population by average size of household and municipality, Web Site (2022).
[51] Qatar Chamber, Web site: Number of registered firms in Qatar rose 13.4% in 2017, Web Site (2022) https://www.qatarchamber.com/registered-firms-in-qatar/.
[52] United States Environmental Protection Agency, Web site: Greenhouse gas emissions from a typical passenger vehicle, Web Site (2023) URL: https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle.
[53] H. Morgenstern, Ecologic studies in epidemiology: Concepts, principles, and methods, Annu. Rev. Public Health 16 (1) (1995) 61–81, PMID: 7639884. URL: https://doi.org/10.1146/annurev.pu.16.050195.000425.
[54] M. Russo, L. Ruivo, D. Carvalho, N. Martins, A. Monteiro, Decarbonizing the energy supply one pandemic at a time, Energy Policy 159 (2021) 112644, URL: https://www.sciencedirect.com/science/article/pii/S0301421521005097.
[55] D. Bienvenido-Huertas, Do unemployment benefits and economic aids to pay electricity bills remove the energy poverty risk of spanish family units during lockdown? A study of COVID-19-induced lockdown, Energy Policy 150 (2021) 112117, URL: https://www.sciencedirect.com/science/article/pii/S0301421520308284.
[56] A. Carfora, G. Scandurra, A. Thomas, Forecasting the COVID-19 effects on energy poverty across EU member states, Energy Policy 161 (2022) 112597, URL: https://www.sciencedirect.com/science/article/pii/S0301421521004638.