

Economic Impact of COVID-19: Evidence from Electricity Use in Tehran

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Abstract

The COVID-19 pandemic triggered unprecedented global disruptions, yet measuring its economic cost in real time remains especially challenging in developing economies with scarce official data. This paper quantifies the short-term economic impact of COVID-19 in Tehran, Iran, using a novel high-frequency dataset of electricity billing records from over 4,500 commercial units. I construct a balanced weekly panel by regularizing irregular billing cycles and apply a Difference-in-Differences and event-study framework to estimate the dynamic effects of the pandemic shock. Results show a sharp 13% decline in commercial electricity consumption immediately after the outbreak, with effects persisting for roughly 15 weeks before convergence to pre-pandemic levels. The contraction is most pronounced during mid-peak and peak hours, consistent with reductions in operating-hour activity. Robustness checks—including placebo interventions, extended estimation windows, alternative counterfactuals, and location-level heterogeneity—confirm the validity of the identification strategy. By demonstrating how electricity consumption data can be transformed into a timely proxy for economic activity, this study makes both substantive and methodological contributions. The approach provides a scalable framework for crisis monitoring in data-scarce environments, highlighting the policy value of administrative energy data for rapid and reliable economic assessment.

Keywords: COVID-19; electricity demand; difference-in-differences; event study; Tehran; economic activity

JEL codes: Q41; Q43; C23; E01

1 Introduction

The COVID-19 pandemic created severe disruptions in both health and economic systems worldwide. While advanced economies often rely on high-frequency indicators such as card transactions, labor market flows, or mobility indices, developing economies face persistent data constraints. Traditional measures like GDP are typically reported with long delays and often fail to capture rapid or localized fluctuations, particularly in contexts with large informal sectors and weaker statistical infrastructures. This raises a fundamental challenge: how can crisis-induced economic shocks be measured in real time in data-scarce environments?

One promising approach is to use electricity consumption as a proxy for economic activity. Electricity demand is tightly linked to business operations and industrial intensity, and billing records are routinely collected even where national accounts are limited. Previous literature has documented the long-run association between electricity use and growth, and recent COVID-19 studies have examined electricity market disruptions in Europe, North America, and Asia. However, relatively little is known about how electricity data can be systematically leveraged to construct high-frequency measures of economic activity in developing-country contexts, where timely monitoring is most urgently needed.

This paper addresses that gap by analyzing administrative billing records from 4,550 commercial electricity subscribers across all 22 power grid locations of Tehran, Iran, over the years 2014–2021. The dataset is unique but characterized by irregular billing cycles ranging from 15 to 60 days, requiring substantial preprocessing. To make the data suitable for econometric analysis, I develop a seasonality-adjusted disaggregation method that converts irregular billing intervals into a balanced weekly panel. This methodological step demonstrates how administrative utility data—rarely designed for research purposes—can be transformed into reliable high-frequency indicators of economic activity, offering a contribution that extends beyond the specific case of Tehran.

The empirical strategy employs a Difference-in-Differences (DiD) design, defining 2020 observations as treated and 2019 observations for the same commercial units as controls, aligned by calendar week. An event-study specification further captures the dynamic adjustment path. The results reveal a sharp decline of approximately 13% in total commercial electricity consumption following the onset of the pandemic, with effects persisting for around 15 weeks before converging toward pre-pandemic levels. The reductions are most pronounced during mid-peak and peak hours, consistent with contractions in operating-hour

activity, while off-peak consumption remains relatively stable, reflecting baseline electricity needs.

To test the credibility of these findings, I perform a wide range of robustness checks. Placebo analyses with pre-pandemic treatment dates show no significant effects, reinforcing the causal interpretation. Extended event windows and alternative counterfactuals (using multiple pre- and post-years) confirm the persistence and magnitude of the results. Location-specific event studies demonstrate that all districts of Tehran experienced a contraction, though the intensity varied somewhat across regions. Importantly, stratified DiD results based on baseline consumption intensity and variance show that the sharpest declines occurred among high-consumption and high-variance units. These heterogeneity patterns are consistent with the interpretation that energy-intensive and operationally volatile establishments were disproportionately affected, lending further support to the main findings.

The central contribution of this study is twofold. Substantively, it provides the first causal estimate of the short-term economic costs of COVID-19 in a major Middle Eastern urban economy, complementing evidence from advanced countries. Methodologically, it develops a scalable approach to regularizing irregular utility billing data, demonstrating how such data can serve as a reliable real-time proxy for economic activity in crisis settings. Together, these contributions highlight the broader value of integrating administrative energy data into policy analysis for rapid crisis detection and response in data-scarce environments.

Related Literature. This study is situated at the intersection of two significant research domains. Firstly, it explores the dynamic relationship between economic performance and electricity consumption during the COVID-19 pandemic, a topic that has seen extensive scholarly attention since the onset of the pandemic. A substantial body of literature has emerged, focusing on the pandemic's multifaceted economic impacts. [Altig et al. \(2020\)](#) have delved into the measurement of economic uncertainty in the US and UK during the pandemic period. Similarly, [Kong and Prinz \(2020\)](#) utilized Google search data to analyze the effects of non-pharmaceutical interventions in the US. Research has also targeted specific market and sector shocks, including crude oil ([Salisu & Adediran, 2020](#)), financial markets ([Zhang, Hu, & Ji, 2020](#)), commodities ([H. Chen, Qian, & Wen, 2021](#)), international trade ([Njindan Iyke, 2020](#); [Vidya & Prabheesh, 2020](#)), tourism ([Gössling, Scott, & Hall, 2020](#)), and environmental protection ([He, Pan, & Tanaka, 2020](#); [Magazzino, Mele, & Schneider, 2020](#); [Ming, Zhou, Ai, Bi, & Zhong, 2020](#)).

Particularly pertinent to this study is the body of work examining electricity market per-

formance during the pandemic. [Bahmanyar, Estebarsari, and Ernst \(2020\)](#) constructed a Demand Variation Index to analyze electricity consumption changes in Europe, finding a direct correlation with the severity of restrictive measures. A reduction of up to 37% in electricity consumption compared to the previous year was reported in Italy ([Ghiani, Galici, Mureddu, & Pilo, 2020](#)). Similarly, [Abu-Rayash and Dincer \(2020\)](#) noted a 14% decrease in Ontario, Canada, while [Carvalho et al. \(2021\)](#) used a joinpoint model to assess regional impacts in Brazil. In Spain, a 13.49% reduction was observed during a specific period ([Santiago, Moreno-Munoz, Quintero-Jiménez, Garcia-Torres, & Gonzalez-Redondo, 2021](#)). The approach of [Elavarasan et al. \(2020\)](#) and [García et al. \(2021\)](#) also highlights significant consumption decreases, particularly in commerce and manufacturing.

A smaller but critical segment of this literature posits the use of electricity consumption decrease as a means to evaluate the economic costs of COVID-19 ([Beyer, Franco-Bedoya, & Galdo, 2021](#); [Fezzi & Fanghella, 2020](#)). However, these studies lack a counterfactual framework, potentially underestimating economic costs. This study aims to address this gap by describing a methodology within a counterfactual framework, thereby making a significant contribution to ongoing research.

The second research domain relevant to this study is the long-established relationship between electricity consumption and economic growth. This line of inquiry, initiated by [Kraft and Kraft \(1978\)](#), has grown in relevance with technological advances and the burgeoning electronics industry. Numerous studies have focused on the link between electricity consumption and GDP, demonstrating a close correlation in many countries ([Ferguson, Wilkinson, & Hill, 2000](#); [Narayan & Singh, 2007](#); [Shiu & Lam, 2004](#); [Tang & Tan, 2013](#); [Yoo, 2005](#)). Concurrently, the role of electricity consumption in measuring the shadow economy has garnered attention, with [Kaufmann and Kaliberda \(2016\)](#) and [Lackó \(2000\)](#) demonstrating its efficacy as a yardstick for economic activity. The integration of remote sensing technology and night landscape lighting data to correct GDP estimates further underscores this relationship ([X. Chen & Nordhaus, 2011](#); [Egger, Loumeau, & Püschel, 2017](#); [Henderson, Storeygard, & Weil, 2012](#)).

This study contributes to both strands of the literature in several ways. First, it brings new evidence from a developing-country context, complementing existing studies that have largely focused on advanced economies with more abundant data. By using proprietary billing records from over 4,500 commercial units in Tehran, the analysis provides the first high-frequency, firm-level evidence on the economic consequences of COVID-19 in a major

Middle Eastern urban economy. Second, the paper advances the methodological toolkit by demonstrating how irregular administrative billing data can be transformed into a balanced weekly panel, enabling rigorous application of Difference-in-Differences and event-study designs. This contributes to a broader agenda of developing scalable approaches for crisis monitoring in data-scarce environments. Third, the analysis provides extensive robustness checks—including placebo interventions, extended event windows, alternative counterfactuals, and location-level heterogeneity—that strengthen the credibility of the results. Stratified estimates by baseline consumption intensity and variance further reinforce the main findings, showing that energy-intensive and operationally volatile establishments were disproportionately affected. Taken together, these contributions extend the literature on electricity demand and economic shocks by showing not only the magnitude of COVID-19’s short-term economic impact, but also how electricity consumption data can be systematically leveraged as a real-time proxy for economic activity in developing countries.

Outline. The remainder of this paper is structured as follows. Section 2 provides institutional context and background on the COVID-19 shock and electricity consumption in Iran. Section 3 describes the data sources, outlines the steps for converting irregular billing records into a regular weekly panel, and presents summary statistics. Section 4 details the empirical strategy, including the difference-in-differences and Event-Study frameworks. Section 5 presents the main estimation results, robustness checks, including placebo tests and heterogeneity analyses, as well as an estimate of the aggregate economic costs of the pandemic. Finally, Section 6 concludes with a discussion of the findings and their broader implications.

2 Background

The outbreak of COVID-19 in late 2019 rapidly escalated into a global health and economic crisis. By September 2021, the virus had spread to nearly every country, with more than 230 million confirmed cases and 4.7 million deaths worldwide (WHO, 2021). The pandemic’s complexity was magnified by the emergence of highly transmissible variants such as delta and lambda, which surpassed earlier epidemics like SARS and MERS in terms of infectivity and severity. Beyond the public health emergency, the economic repercussions were profound. The International Monetary Fund projected global growth of 5.5% in 2021, followed by 4.2% in 2022, while the World Trade Organization forecast a 9.2% decline in merchandise trade—the sharpest contraction since the Great Depression (WTO, 2020). The International

Labour Organization likewise reported an additional 33 million unemployed in 2020, raising the global unemployment rate to 6.5% (ILO, 2020). These figures underscore the urgency of understanding how the pandemic affected economic activity across different contexts.

Iran became one of the early hotspots outside China, officially reporting its first cases in February 2020. The government responded with a set of restrictive public health measures, including a third-level quarantine, which curtailed economic activity and mobility. Tehran, the country’s capital and economic hub, was at the center of this disruption. With a population of 8.7 million according to the 2016 census, the city accounted for 22.1% of national GDP in 2019. Its electricity consumption was the highest in the country in 2021, reflecting the intensity of commercial and industrial activity across its 22 power grid regions. These features make Tehran an especially relevant setting for analyzing the short-term economic costs of the pandemic.

The policy interventions introduced in early 2020 created a quasi-experimental environment, enabling the use of a Difference-in-Differences (DiD) framework. By comparing electricity consumption in 2020 (treated period) with the same firms’ consumption in 2019 (control period), it becomes possible to isolate the causal impact of COVID-19 on commercial electricity demand. This design leverages the sudden nature of the pandemic shock and the strict timing of restrictions, providing a credible basis for identifying the economic damages incurred during the initial months of the outbreak.

3 Data

3.1 Data Source

This study draws on proprietary administrative electricity consumption data obtained from the Tehran Electricity Distribution Company. The dataset consists of billing records for approximately 4,550 unique commercial electricity subscribers, distributed across all 22 power grid locations within Tehran. These records span from early 2014 to late 2021, covering a wide temporal range that enables both trend analysis and counterfactual construction.

Each observation in the dataset corresponds to a billing event for a commercial unit. These records capture the total, peak, mid-peak, and off-peak electricity consumption over irregular billing cycles, which range from as short as 15 days to as long as 90 days. Due to the

non-standardized nature of billing intervals across units and time, the dataset exhibits considerable temporal irregularity. There are two distinct sets of meters in the system: one operational from 2014 to 2018, and another from 2018 to 2021. Both sets were used to construct seasonality-adjusted weights as part of the regularization process described later.

The classification of commercial units is provided directly by the electricity authority, ensuring that the sample strictly includes non-residential, non-industrial subscribers engaged in commercial activity. No filtering or stratification was applied beyond standard data cleaning procedures. All units with valid identifiers and non-missing consumption values were retained, allowing for a comprehensive and representative analysis of commercial electricity usage across Tehran.

3.2 Seasonality Adjustment via Weekly Fixed Effects

To address seasonal variation in electricity demand, I estimate weekly consumption weights using a regression framework applied to the pre-pandemic period. The objective is to isolate calendar-related consumption patterns, such as increased demand during warmer weeks, which would otherwise confound the interpretation of time-series variation in electricity usage.

The dependent variable in this specification is defined as:

$$y_{lWt} = \log \left(\frac{\text{total consumption}_{lWt}}{\text{days}_{lWt}} \right),$$

where l indexes the power grid location, W denotes the set of weeks spanned by each billing record, and t indicates the year. I normalize total consumption by the number of days in the billing period to construct a daily average and apply a log transformation to stabilize variance and interpret coefficients in log-points.

The estimated regression model is specified as:

$$y_{iWt} = \sum_{w=1}^{52} \alpha_w D_w + \delta_l + \gamma_t + \epsilon_{iWt}, \quad (1)$$

where y_{iWt} denotes the log of average daily electricity consumption for unit i over a billing period spanning the set of weeks W in year t . The term D_w represents week-of-year dummy variables that capture seasonal variation. The fixed effect δ_l controls for time-invariant differ-

ences across power grid locations l , and γ_t absorbs common year-specific shocks. The error term ϵ_{iWt} captures unit-specific idiosyncratic variation not explained by the model.

The coefficients α_w measure the average deviation of log daily consumption from the annual mean in each calendar week. These estimates are subsequently used to construct seasonality weights for disaggregating billing periods into weekly values. As expected, Figure 1 reveals higher consumption intensities during the summer months, reflecting increased demand for cooling.

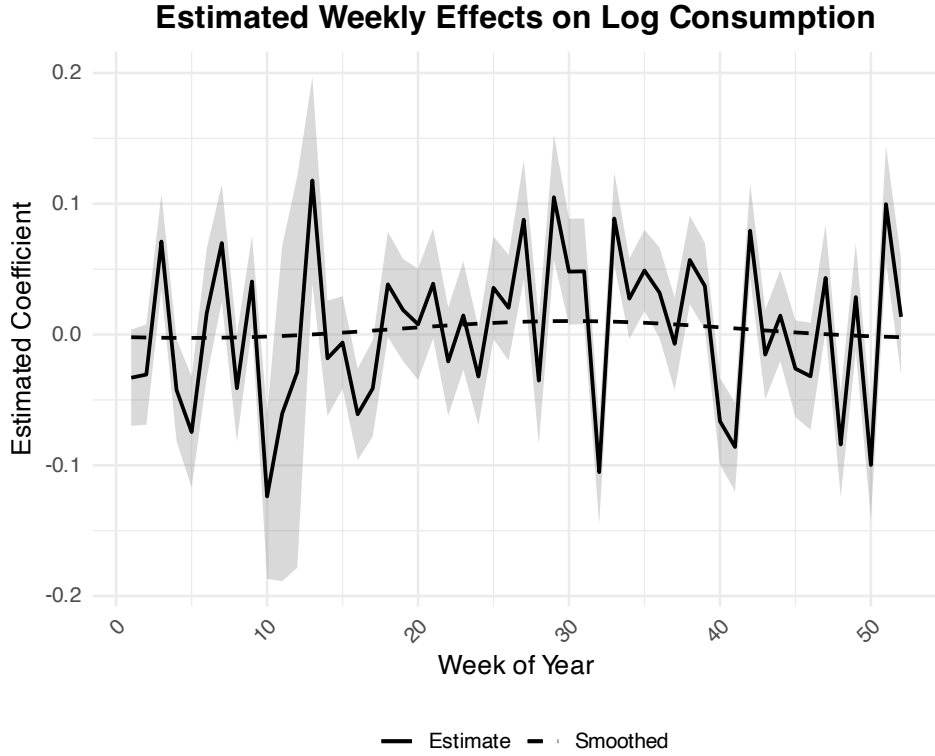


Figure 1: Weekly seasonal effects in commercial electricity demand (pre-pandemic). Coefficients are from a regression of $\log(kWh)$ on week-of-year dummies with location and year fixed effects using pre-COVID data. The solid line shows point estimates; the shaded band shows 95% confidence intervals.

By adjusting for week-specific seasonal fluctuations, the resulting panel more accurately captures temporal variation in electricity usage, thereby enabling valid causal inference in the subsequent empirical analysis. The full weekly consumption trends are presented in Figure B.1, Figure B.2, Figure B.3, and Figure B.4.

3.3 Descriptive Statistics and Trends

Figure 2 illustrates the weekly electricity consumption for the treatment group (2020) and the control group (2019), aligned by lunar calendar weeks to ensure comparability. The external

shock of interest is the emergence of COVID-19 and the lockdown implemented in Tehran. A critical assumption in the Difference-in-Differences (DID) framework is that both groups followed parallel trends before the shock. As seen in the figure, electricity consumption in 2020 closely mirrors that of 2019 in the pre-shock period (weeks -6 to -1), supporting the validity of the parallel trends assumption.

Immediately after the shock, electricity consumption in 2020 fell sharply below that of 2019. Although both groups display a brief surge in consumption just before Nowruz—likely driven by pre-holiday commercial activity—the divergence persists well beyond the holiday period. It takes approximately fifteen weeks for 2020 consumption to converge back to 2019 levels. This sustained gap reflects a delayed recovery in commercial operations, attributable to the economic disruptions caused by COVID-19 containment measures.

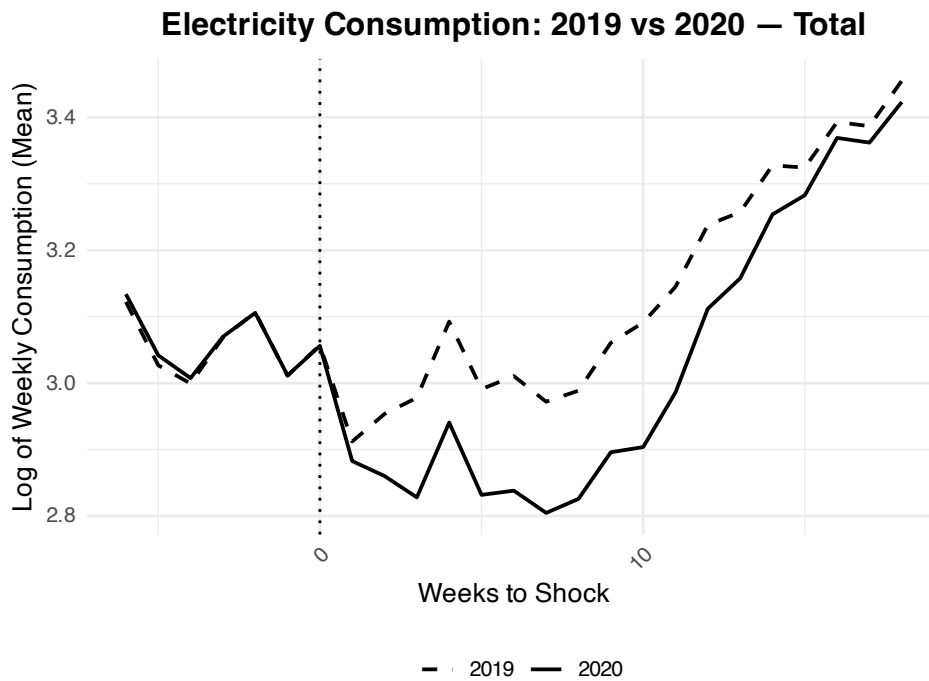


Figure 2: Weekly total commercial electricity consumption, 2019 vs 2020 (Tehran). Series plot $\log(kWh \text{ per week})$ for the same 4,550 commercial subscribers aligned by calendar week; dashed line is 2019 (control), solid line is 2020 (treated). Week 0 marks the COVID-19 onset in March 2020.

The trends in mid-peak and peak consumption follow a similar pattern, reinforcing the overall shock response. In contrast, off-peak consumption remains relatively stable, likely reflecting baseline power demand for essential infrastructure and equipment that must remain active regardless of operational scale. These disaggregated patterns are presented in Figure B.5, Figure B.6, and Figure B.7.

Table 1 presents the descriptive statistics for the full sample used in this analysis. The

dataset comprises 209,300 weekly electricity consumption observations, encompassing 4,550 unique commercial units spread across 22 power grid regions in Tehran. The sample is structured as a balanced panel, consisting of two matched groups.

Table 1: Summary Statistics for Weekly Electricity Consumption

Statistics	N	Mean	Std. Dev.	Min	Median	Max
Panel A. Full sample						
Log Total Consumption	209,300	3.05	1.81	0	3.41	11.22
Log Mid-Peak Consumption	209,300	2.86	1.72	0	3.21	10.59
Log Peak Consumption	209,300	1.06	1.40	0	0	9.93
Log Off-Peak Consumption	209,300	1.00	1.45	0	0	10.15
Treated (2020 = 1)	209,300	0.50	0.50	0	0.50	1
Week of Year	209,300	14	6.63	3	14	25
Year	209,300	2,019.50	0.50	2,019	2,019.50	2,020
Panel B. 2019 sample						
Log Total Consumption	104,650	3.09	1.82	0	3.48	11.22
Log Mid-Peak Consumption	104,650	2.90	1.73	0	3.28	10.59
Log Peak Consumption	104,650	1.07	1.41	0	0	9.93
Log Off-Peak Consumption	104,650	1.00	1.45	0	0	10.15
Treated (2020 = 1)	104,650	0	0	0	0	0
Week of Year	104,650	14	6.63	3	14	25
Year	104,650	2,019	0	2,019	2,019	2,019
Panel C. 2020 sample						
Log Total Consumption	104,650	3.01	1.80	0	3.35	11.07
Log Mid-Peak Consumption	104,650	2.81	1.70	0	3.15	10.59
Log Peak Consumption	104,650	1.04	1.38	0	0	9.83
Log Off-Peak Consumption	104,650	1.00	1.45	0	0	10.01
Treated (2020 = 1)	104,650	1	0	1	1	1
Week of Year	104,650	14	6.63	3	14	25
Year	104,650	2,020	0	2,020	2,020	2,020

Notes: N is the number of unit-week observations (balanced panel: $4,550 \text{ units} \times 46 \text{ weeks} = 209,300$). Consumption variables are logs of weekly kWh. “Treated” equals 1 for 2020 observations.

The treatment group consists of observations from the year 2020, spanning six weeks before to fifteen weeks after the shock (January 11 to June 21), reflecting firm-level electricity usage during the pandemic period. The control group consists of the same firms and the same lunar calendar weeks in 2019, enabling a clean counterfactual comparison under the difference-in-differences design. The average log total consumption is 3.05 (approximately 23 kWh), with substantial cross-sectional and temporal variation (standard deviation of 1.81). The data also exhibit balanced distribution across years (mean year = 2019.5) and treatment

status (mean treated = 0.5), supporting the internal validity of the empirical strategy.

4 Empirical Model

To identify the causal impact of the COVID-19 shock on commercial electricity consumption, I employ a Difference-in-Differences (DiD) design that exploits the temporal variation between the pre- and post-shock periods, combined with cross-sectional variation across commercial units. Specifically, I compare the trajectory of each unit's electricity usage in 2020 (the treated year) to its consumption in 2019 (the control year), aligning observations by calendar week. This approach leverages within-unit variation over time, thereby controlling for all time-invariant heterogeneity in consumption levels and structural characteristics across units. The treatment period begins in the first week of March 2020, coinciding with the official onset of the pandemic in Iran and the introduction of containment measures.

The key identifying assumption is that, in the absence of the COVID-19 shock, commercial electricity consumption in 2020 would have followed the same path as in 2019. In other words, the Difference-in-Differences estimator is unbiased under the *parallel trends assumption*. Evidence supporting this assumption comes from the graphical comparison in Figure 2, which shows that pre-treatment trends in 2019 and 2020 are nearly parallel. Furthermore, formal pre-trend tests using the Event-Study specification confirm that pre-treatment coefficients are statistically indistinguishable from zero. These diagnostics provide reassurance that the observed divergence after March 2020 can be attributed to the pandemic shock rather than pre-existing differential trends.

A second assumption is that no other shocks or policies differentially affected electricity consumption in 2020 relative to 2019. Given the absence of major structural or regulatory changes to the electricity sector during this period, and the fact that COVID-19 represented the dominant macroeconomic and social shock, this assumption appears reasonable. Nevertheless, I address potential concerns by conducting a series of robustness exercises (described below), including placebo interventions, extended windows, and alternative control years.

Finally, the design assumes that the treatment is homogeneous in timing across all units, with the shock beginning simultaneously in March 2020. While the intensity of the effect may vary across firms depending on baseline consumption profiles or resilience, the timing assumption is plausible given the national scope of COVID-19 restrictions. Importantly, I

explore heterogeneity in treatment effects by stratifying units according to baseline consumption intensity and the stability (variance) of their pre-COVID consumption. These stratified analyses reinforce the main findings and support the credibility of the identification strategy: the largest reductions are concentrated among high-consumption and high-variance units, which are more likely to represent commercial establishments highly exposed to the shock.

To quantify the average effect of the COVID-19 shock, I estimate the following baseline DiD specification:

$$y_{iw} = \beta_0 + \beta_1 \cdot \text{Treated}_i + \beta_2 \cdot \text{Post}_w + \beta_3 \cdot (\text{Treated}_i \times \text{Post}_w) + \theta \cdot \text{Week}_w + \delta_i + \varepsilon_{iw} \quad (2)$$

Here, y_{iw} is the logarithm of weekly electricity consumption for commercial unit i in week w . The dummy variable Treated_i equals one for all observations from 2020, while Post_w equals one for all weeks after the onset of the pandemic. The coefficient of interest, β_3 , is the DiD estimator capturing the average causal impact of COVID-19 on electricity consumption. Unit fixed effects δ_i absorb time-invariant differences across units, while $\theta \cdot \text{Week}_w$ controls flexibly for common time shocks. Standard errors are clustered at the unit level to allow for arbitrary serial correlation in electricity consumption within units.

To examine the dynamic path of treatment effects, I extend the specification to an Event-Study framework:

$$y_{iw} = \sum_{k \neq k_0} \beta_k \cdot \mathbf{1}(\text{Period}_w = k \wedge \text{Treated}_i = 1) + \lambda_w + \delta_i + \varepsilon_{iw} \quad (3)$$

This model replaces the post-shock dummy with a series of binary indicators for each period k , defined as weeks relative to the intervention. One pre-treatment week k_0 is omitted as the reference period. The resulting coefficients β_k trace the trajectory of the treatment effect before and after the pandemic shock. Pre-shock estimates ($k < 0$) provide a test of the parallel trends assumption, while post-shock estimates ($k > 0$) capture the timing, magnitude, and persistence of the consumption decline.

Beyond the pooled DiD specification, I exploit variation in baseline characteristics to test the robustness of the results. First, I stratify commercial units by baseline consumption intensity (low, medium, high). Results show that high-consumption units experience the largest

and most persistent declines, while low-consumption units display much smaller reductions. This pattern is consistent with the interpretation that more energy-intensive businesses (e.g., retail, offices, and services) were more severely affected by the restrictions. In contrast, small or marginal consumers were less impacted.

Second, I classify units by the variance of their pre-COVID consumption (stable vs. volatile users). Units with higher variance—likely representing firms with irregular demand patterns or seasonal fluctuations—exhibit stronger declines during the COVID-19 period. By contrast, stable users experience smaller and shorter-lived effects. These results provide external validation of the main specification: if the pandemic shock disproportionately constrained economic activity in the more dynamic segments of the commercial sector, then the observed heterogeneity by variance is consistent with economic intuition.

Together, the baseline DiD, Event-Study dynamics, and heterogeneity analyses present a coherent picture. The COVID-19 shock led to a sharp contraction in commercial electricity consumption, with the effects concentrated in the high-intensity and high-variance segments of the market. These patterns strengthen the credibility of the identification strategy, reduce concerns about spurious correlation, and provide a richer understanding of the mechanisms through which the pandemic affected economic activity as proxied by electricity use.

5 Results

5.1 Main Results

I begin by examining the dynamic impact of the COVID-19 shock using the Event-Study specification. Figure 3 presents the estimated weekly treatment effects for total electricity consumption. Each point corresponds to the coefficient β_k relative to the week immediately preceding the shock ($t = -1$), with 95 percent confidence intervals.

The pre-treatment coefficients are tightly clustered around zero and statistically indistinguishable from it, providing strong evidence in favor of the parallel trends assumption that underpins the Difference-in-Differences design. In the post-treatment period, however, a sharp and immediate decline is observed. Total commercial electricity consumption falls by roughly 13–19 percent in the first weeks following the onset of restrictions, reflecting the sudden contraction in business activity. The negative effects persist for more than fifteen weeks

before gradually narrowing, indicating a slow and uneven recovery. This dynamic profile is consistent with the notion that the COVID-19 shock caused not only an immediate disruption but also lingering economic weakness due to prolonged demand suppression, mobility restrictions, and heightened uncertainty.

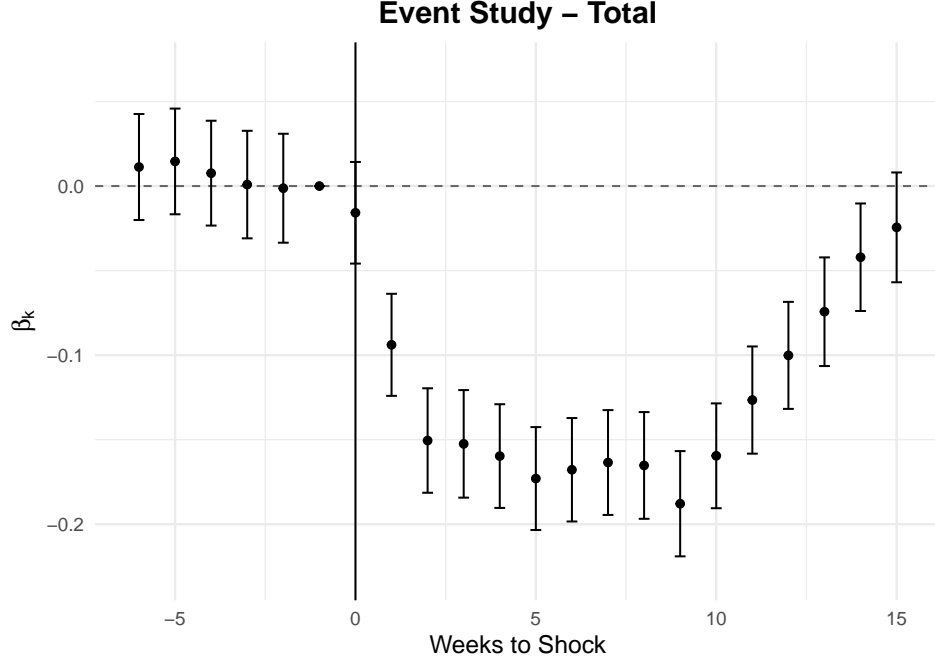


Figure 3: Dynamic effects of COVID-19 on total commercial electricity consumption. Event-Study coefficients (β_k) from the specification in Section 4, measured relative to the week immediately before the shock ($t = -1$). Outcome is $\log(kWh \text{ per week})$; points show estimates and bands 95% confidence intervals. Pre-treatment coefficients cluster near zero; post-treatment weeks show a 13–19% decline and gradual recovery.

Event-Study plots for mid-peak, peak, and off-peak consumption are reported in Appendix Figures B.8, B.9, and B.10, with the corresponding coefficient tables provided in Appendix Table A.1. These disaggregated dynamics reveal important heterogeneity: mid-peak consumption exhibits even larger and more prolonged reductions, peak-hour consumption shows a smaller but still statistically significant decline, and off-peak consumption remains relatively stable with modest and short-lived decreases. Taken together, the Event-Study results indicate that the brunt of the contraction occurred during mid-day and evening hours, when commercial activity is typically at its highest, while background nighttime consumption proved more resilient.

Having established the dynamic adjustment patterns, I now turn to the average treatment effects from the Difference-in-Differences (DiD) framework. Table 2 reports the baseline estimates for total, mid-peak, peak, and off-peak consumption. The coefficient on the interaction term $Treated \times Post$ is negative and statistically significant across all categories. On average,

total electricity consumption declined by 12.8 percent relative to the pre-COVID period, after controlling for calendar week trends and unit fixed effects. Mid-peak consumption experienced an equally sharp 12.8 percent reduction, while peak consumption fell by 6.5 percent. Off-peak usage declined by about 3 percent, a smaller but still statistically significant effect. These results corroborate the Event-Study evidence, showing that the onset of COVID-19 led to a substantial and immediate contraction in commercial electricity use.

Table 2: DiD Estimates of the Impact of COVID-19 on Electricity Consumption

	Total	Mid-Peak	Peak	Off-Peak
Treated	0.005 (0.016)	-0.001 (0.015)	0.020* (0.009)	0.024** (0.009)
Post	-0.276*** (0.008)	-0.285*** (0.007)	-0.101*** (0.005)	-0.057*** (0.005)
week	0.029*** (0.001)	0.030*** (0.001)	0.010*** (0.000)	0.007*** (0.000)
Treated × Post	-0.128*** (0.010)	-0.128*** (0.010)	-0.065*** (0.006)	-0.026*** (0.006)
Num.Obs.	209300	209300	209300	209300
R2	0.880	0.874	0.930	0.938

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Difference-in-Differences estimates of the impact of COVID-19 on weekly electricity consumption. Dependent variable is log(kWh) per commercial unit. Treated = 2020, Control = 2019. All regressions include unit fixed effects and week-of-year controls. Standard errors are clustered at the unit level.

To investigate whether these average effects conceal systematic heterogeneity, I stratify establishments along two key dimensions: baseline consumption intensity and pre-COVID demand volatility. Tables 3 and 4 report the DiD estimates for these subsamples.

The results reveal clear patterns. Units in the top tercile of baseline consumption intensity experienced disproportionately larger and more persistent declines compared to those in the bottom tercile. This suggests that the most electricity-intensive businesses—likely larger retail outlets, offices, and service establishments—were more severely disrupted by the restrictions. Likewise, establishments with higher pre-COVID variance in electricity demand exhibited sharper drops than their more stable counterparts. This heterogeneity is consistent with the interpretation that volatile users, whose demand already fluctuates substantially, are particularly sensitive to adverse shocks and operational disruptions.

These stratified results reinforce the main conclusion: the contraction in electricity use

was not homogeneous but concentrated among the more energy-intensive and less stable segments of the commercial sector. By aligning with the patterns documented in the Event-Study, the heterogeneity analyses strengthen confidence in the validity and interpretation of the empirical findings.

Table 3: DiD Estimates by Baseline Consumption Intensity

	Low	Medium	High
Treated	0.020 (0.036)	-0.008 (0.025)	0.003 (0.018)
Post	-0.212*** (0.015)	-0.341*** (0.013)	-0.276*** (0.011)
week	0.015*** (0.001)	0.038*** (0.001)	0.033*** (0.001)
Treated × Post	0.054** (0.020)	-0.225*** (0.017)	-0.213*** (0.016)
Num.Obs.	69782	69782	69736
R2	0.651	0.413	0.766

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: Heterogeneous Difference-in-Differences estimates by baseline consumption terciles (low, medium, high). Baseline consumption is defined using pre-COVID (2019) weekly averages. Dependent variable is log(kWh) per unit. All regressions include unit fixed effects and week-of-year controls. Standard errors clustered at the unit level.

Table 4: DiD Estimates by Pre-COVID Consumption Stability (Variance Terciles)

	Low	Medium	High
Treated	-0.029*** (0.007)	-0.017 (0.012)	0.061 (0.045)
Post	-0.140*** (0.008)	-0.302*** (0.011)	-0.387*** (0.018)
week	0.009*** (0.001)	0.030*** (0.001)	0.046*** (0.002)
Treated × Post	-0.063*** (0.011)	-0.166*** (0.013)	-0.154*** (0.026)
Num.Obs.	69782	69782	69736
R2	0.985	0.926	0.634

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: Heterogeneous Difference-in-Differences estimates by terciles of pre-COVID consumption variance. Variance calculated from 2019 weekly consumption for each unit. Dependent variable is log(kWh) per unit. All regressions include unit fixed effects and week-of-year controls. Standard errors clustered at the unit level.

While the Event-Study and DiD results collectively provide compelling evidence of the pandemic’s economic impact, potential concerns such as anticipatory behavior or unobserved confounders cannot be entirely ruled out. These issues are examined further through a series of robustness checks presented in the following section.

5.2 Robustness Check

A critical assumption underlying the Difference-in-Differences and Event-Study frameworks is that treated and control units followed parallel trends before the intervention. To formally assess this assumption, I conduct a joint significance test on the six lead coefficients in the Event-Study regression. The null hypothesis posits that all pre-treatment coefficients are jointly equal to zero. The test strongly rejects the null ($\chi^2(6) = 22.586, p < 0.001$), indicating statistical evidence of deviations from perfect pre-trends. However, these estimated lead coefficients are economically small in magnitude and display no systematic upward or downward pattern. Moreover, as shown in Figure 3, the pre-treatment coefficients are tightly centered around zero with confidence intervals generally overlapping it. Together with the placebo and extended-window exercises presented below, this evidence supports the view that the observed post-treatment effects are not driven by spurious pre-trends or arbitrary timing.

To assess whether the estimated effects could be driven by spurious time patterns unrelated to COVID-19, I implement a placebo test by artificially shifting the treatment date six weeks earlier than the actual onset of the pandemic. This creates a pseudo-treatment period beginning in mid-January 2020, when no COVID-related restrictions or demand shocks were present. The Event-Study framework is then re-estimated using this placebo shock date.

Figure 4 presents the placebo Event-Study results for total commercial electricity consumption. The coefficients fluctuate narrowly around zero in both the pre- and post-placebo periods, and none are statistically distinguishable from zero at conventional levels. The absence of systematic post-placebo effects supports the conclusion that the main estimates are not confounded by unobserved factors unrelated to the pandemic. In particular, it reinforces that the sharp drop observed in the actual Event-Study is specific to the timing of the COVID-19 shock.

Placebo tests for mid-peak, peak, and off-peak consumption categories yield similarly null results. These are reported in Appendix Figures B.11–B.13, with the corresponding coefficient

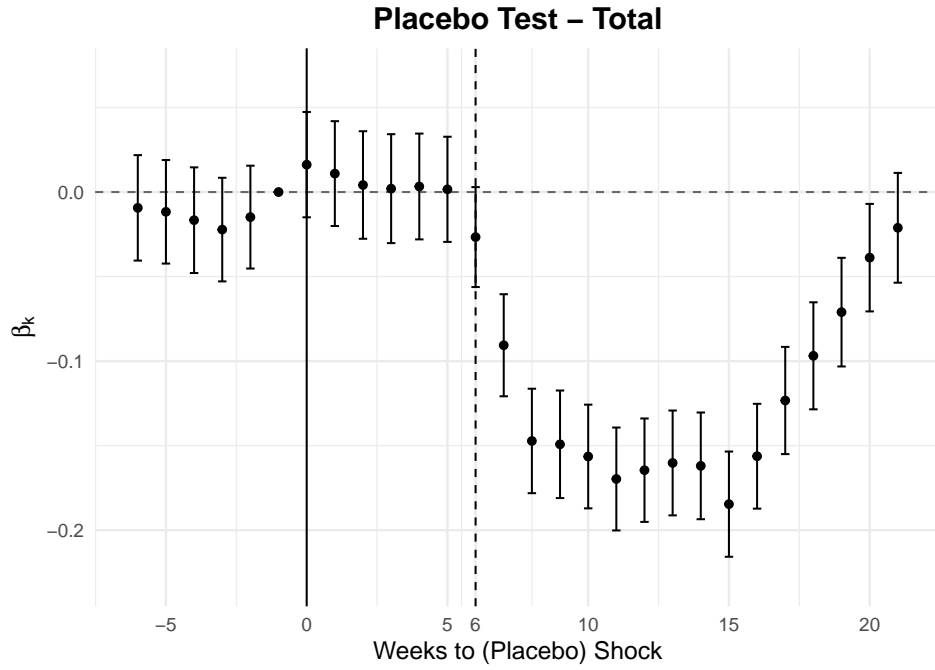


Figure 4: Placebo Event-Study for total commercial electricity consumption. The pseudo-treatment date is shifted 6 weeks earlier than the actual COVID-19 onset. Event-Study coefficients fluctuate around zero before and after the placebo, with no systematic deviations (outcome: $\log(\text{kWh per week})$; 95% confidence intervals shown).

estimates presented in Appendix Table A.2. Taken together, the placebo exercises strengthen the causal interpretation of the main findings by demonstrating that the estimated effects do not arise from pre-existing seasonal trends or arbitrary treatment timing.

As an additional robustness check, I re-estimate the Event-Study specification by extending the analysis window from the original $[-6, 15]$ weeks to a broader range of $[-20, 28]$ weeks around the shock date. This expansion serves two purposes. First, it tests whether the estimated treatment effects are sensitive to the choice of time window. Second, it allows for the inspection of longer-term dynamics both before and after the intervention.

The results, shown in Figure 5 for total consumption (with corresponding plots for mid-peak, peak, and off-peak consumption reported in Appendix Figures B.14–B.16, and the coefficient estimates summarized in Appendix Table A.3), indicate that the extended pre-treatment period continues to exhibit coefficients that are statistically indistinguishable from zero. This reinforces the validity of the parallel trends assumption over a wider pre-shock horizon. Post-treatment effects are consistent in magnitude and timing with those obtained in the baseline window: a sharp decline in consumption immediately after the shock, followed by a gradual recovery toward pre-pandemic levels. The shape, statistical significance, and persistence of the effects remain largely unchanged, confirming that the baseline estimates are not an artifact

of the initial time-window selection.

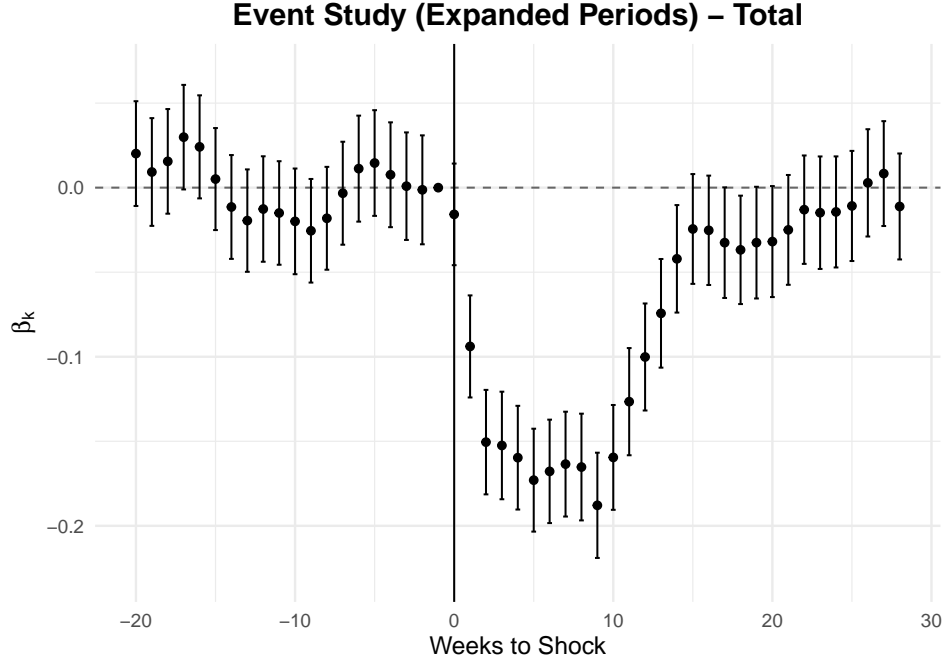


Figure 5: Event-Study with extended window for total commercial electricity consumption. Horizon is $[-20, +28]$ weeks around week 0 (COVID-19 onset). Pre-treatment coefficients remain near zero; post-treatment shows a sharp decline followed by gradual recovery (outcome: $\log(\text{kWh per week})$; 95% confidence intervals).

As an additional robustness exercise, I replace the 2019 control group with the average consumption from 2018, 2019, and 2021, excluding 2020. This approach assumes that the COVID-19 shock was transitory and had no persistent effect on commercial electricity demand by 2021. Using this multi-year average as the counterfactual smooths idiosyncratic fluctuations from any single year and provides a more stable benchmark for assessing the pandemic's impact.

The resulting Event-Study plot in Figure 6 confirms the robustness of the baseline findings. Pre-treatment coefficients remain statistically indistinguishable from zero, reinforcing the validity of the parallel trends assumption. Post-treatment dynamics mirror those of the main specification, with a sharp and statistically significant decline in total consumption immediately after the shock, followed by a gradual recovery toward baseline. The magnitude and persistence of the estimated effects are nearly identical to the original results, indicating that the main conclusions are not sensitive to the choice of a single-year control group. Results for mid-peak, peak, and off-peak consumption categories are reported in Appendix Figures B.17–B.19, with the corresponding coefficient estimates provided in Appendix Table A.4.

A final robustness exercise examines whether the baseline results are driven by particular

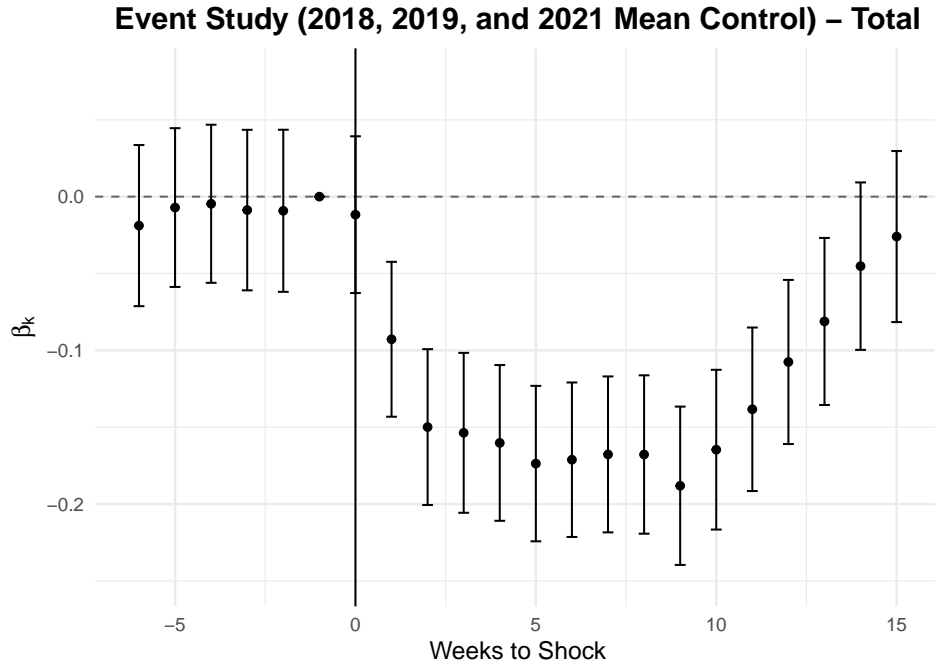


Figure 6: Event-Study using an alternative counterfactual for total consumption. The control is the mean of 2018, 2019, and 2021 (excluding 2020). Results mirror the baseline: pre-treatment near zero and a sharp post-treatment decline with recovery (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

geographic areas within the city of Tehran. To investigate this, I re-estimate the Event-Study model separately for each of the power grid locations, sorted by their average total consumption from highest to lowest.

The results in Figure 7 show that the post-shock decline in electricity consumption is evident across all locations, though the magnitude and recovery speed vary somewhat. In nearly every case, the initial drop occurs immediately after the shock, and consumption remains below pre-shock levels for several weeks before converging back toward baseline. These patterns suggest that the pandemic’s economic impact was pervasive across different parts of the city rather than being concentrated in a few high-consumption areas.

Event-Study plots for mid-peak, peak, and off-peak consumption by location are presented in Appendix B.20–B.22, which display qualitatively similar dynamics. The consistency of results across geographic areas further supports the conclusion that the documented effects are not artifacts of locally specific shocks or measurement anomalies.

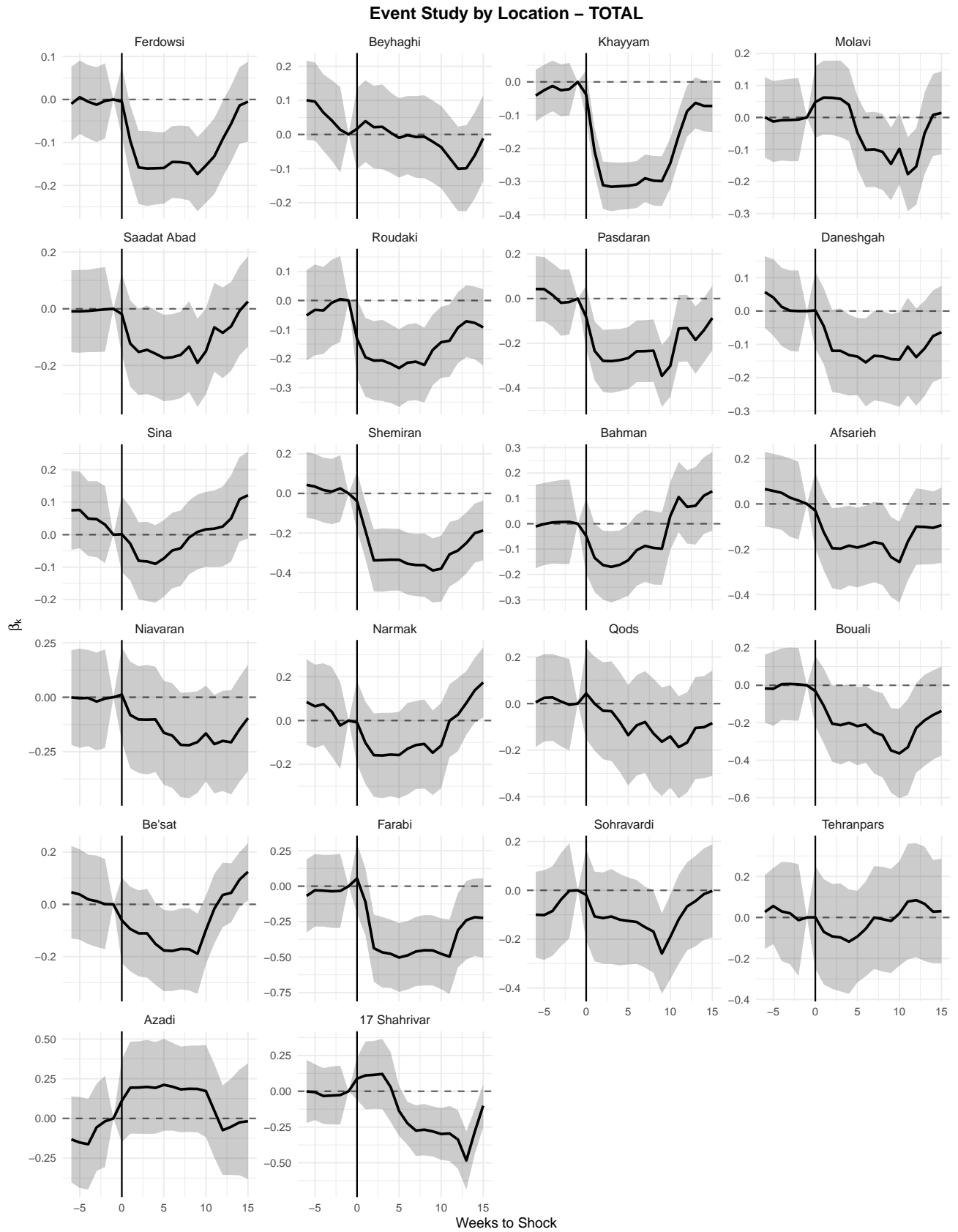


Figure 7: Event-Study for total commercial electricity consumption by location. Panels (locations) are ordered by baseline total consumption. Across locations, consumption drops immediately after week 0 and recovers gradually (outcome: $\log(kWh \text{ per week})$).

5.3 Economic Costs of COVID-19

To quantify the economic cost of COVID-19 for Tehran, I rely on the common practice of mapping electricity consumption to economic output. Electricity is widely used as a proxy for GDP when higher-frequency output data are missing, since nearly all productive activities depend on energy. My estimates identify commercial electricity consumption losses in Tehran during the first wave of COVID-19. To translate these losses into GDP terms, I construct a simple proportionality benchmark: GDP per kilowatt-hour (kWh).

Because GDP data are available only at the provincial level, I use Tehran province's GDP in 1397 (2018/19) — 5,700,934 billion rials — together with province-level commercial electricity consumption in 1397 (2018/19) — 5,936,571,000 kWh — to calculate a baseline ratio of roughly 960,000 rials of GDP per kWh. I take 1397 (2018/19) as the reference year, since it is the last year unaffected by COVID-19 (1398/2019–20 already contains the pandemic shock). The GDP figures come from the National Accounts Yearbook (Statistical Center of Iran), and the electricity statistics from the Annual Report of the Ministry of Energy, Electricity Distribution Sector (2018/19).

Assumption. This back-of-the-envelope translation assumes a *unit elasticity* of GDP with respect to electricity in the relevant margin for the commercial sector (i.e., a 1% fall in electricity implies a 1% fall in output). This is a strong proportionality assumption and provides an order-of-magnitude estimate rather than a structural counterfactual. Related work has used electricity to proxy short-run economic activity under data scarcity and crisis conditions (e.g., [Ai, Zhong, and Zhou \(2022\)](#) and [Fezzi and Fanghella \(2020\)](#)), but the elasticity can vary across sectors, technologies, and time horizons.

Multiplying the baseline GDP–electricity ratio by the estimated commercial electricity loss in Tehran city yields an approximate GDP loss of 57 trillion rials during the initial months of the pandemic. This figure should be interpreted with caution. It assumes that the province-level GDP–electricity proportionality applies within Tehran city's commercial sector and that electricity scales directly with output in the short run; it also ignores heterogeneity in electricity intensity across activities and potential spillovers to other sectors. With these caveats, the calculation offers a transparent, scalable yardstick for assessing the short-run economic costs of COVID-19 when high-frequency GDP measures are unavailable.

6 Conclusion

This paper estimates the short-term economic impact of the COVID-19 pandemic in Tehran, Iran, using high-frequency electricity consumption data from over 4,500 commercial units. Employing a Difference-in-Differences framework and an Event-Study design, the results reveal a sharp decline of nearly 13% in total commercial electricity consumption immediately after the onset of the pandemic, with the effect persisting for roughly fifteen weeks before converging toward pre-pandemic levels. The reductions were most pronounced during mid-peak and peak periods, indicating substantial contractions in operating-hour activity. Robustness checks—including placebo tests, expanded event windows, and location-specific analyses—confirm that pre-existing trends, arbitrary treatment timing, or localized shocks do not drive these findings.

Beyond providing evidence on the economic consequences of COVID-19 in a major urban economy, the study demonstrates the utility of high-frequency electricity data as a timely and reliable proxy for real economic activity in data-scarce environments. The methodology of regularizing irregular billing data into a balanced weekly panel within a counterfactual framework offers a scalable approach for rapid economic monitoring during crises. These results underscore the importance of integrating administrative utility data into policy analysis, enabling faster detection of economic shocks and more targeted policy responses.

Declarations

Funding. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability. The proprietary administrative electricity data were obtained from the Tehran Electricity Distribution Company and cannot be made publicly available due to confidentiality restrictions. Replication code supporting the findings of this study is available from the author upon reasonable request.

Competing interests. The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions. The author solely undertook all stages of the research, including con-

ceptualization, data curation, methodology design, empirical analysis, and manuscript preparation.

Appendix

A Supplementary Tables

This section reports additional Event-Study coefficient tables that complement the main text results. Each table presents the dynamic treatment effects of COVID-19 on electricity consumption under different specifications or control definitions.

Event-Study Coefficients (Main Specification)

Table [A.1](#) reports the baseline Event-Study coefficients for Total, Mid-Peak, Peak, and Off-Peak electricity consumption, relative to the counterfactual constructed from previous years. The dynamics differ across categories. For *Total consumption*, the coefficients reveal a sharp and persistent decline beginning immediately after the onset of COVID-19 restrictions, with losses of roughly 18 to 19 percent at the trough. The trajectory of *Mid-Peak consumption* closely mirrors total use but with somewhat larger magnitudes, indicating that mid-day and early-evening commercial activity—particularly in retail and services—was disproportionately affected. In contrast, the decline in *Peak consumption* is smaller, on the order of 3 to 7 percent, suggesting that electricity demand during the busiest hours of the day, partly driven by essential activities, was more stable. Finally, the coefficients for *Off-Peak consumption* are modest and often imprecisely estimated, consistent with the interpretation that background electricity demand at night—such as refrigeration or security systems—remained relatively resilient. Overall, the evidence underscores that the bulk of the adjustment in electricity use occurred during commercial hours.

Table A.1: Event-Study Coefficients by Relative Week (Treated vs. Counterfactual)

Rel. Week	Total	Mid-Peak	Peak	Off-Peak
-6	0.012 (0.016)	0.007 (0.015)	0.022* (0.009)	0.023* (0.009)
-5	0.015 (0.016)	0.010 (0.015)	0.025** (0.009)	0.027** (0.009)
-4	0.008 (0.016)	0.001 (0.015)	0.025** (0.009)	0.029** (0.009)
-3	0.001 (0.016)	-0.006 (0.016)	0.023* (0.009)	0.028** (0.009)
-2	-0.001 (0.016)	-0.008 (0.016)	0.019* (0.009)	0.025* (0.010)
0	-0.015 (0.015)	-0.021 (0.015)	0.005 (0.009)	0.017+ (0.009)
1	-0.093*** (0.015)	-0.102*** (0.015)	-0.027** (0.009)	0.011 (0.009)
2	-0.150*** (0.016)	-0.158*** (0.015)	-0.051*** (0.009)	0.003 (0.009)
3	-0.152*** (0.016)	-0.160*** (0.016)	-0.051*** (0.009)	0.003 (0.009)
4	-0.159*** (0.016)	-0.168*** (0.015)	-0.054*** (0.009)	0.002 (0.009)
5	-0.173*** (0.016)	-0.181*** (0.015)	-0.066*** (0.009)	-0.003 (0.009)
6	-0.167*** (0.016)	-0.174*** (0.015)	-0.071*** (0.009)	-0.007 (0.009)
7	-0.163*** (0.016)	-0.169*** (0.015)	-0.073*** (0.009)	-0.010 (0.009)
8	-0.165*** (0.016)	-0.170*** (0.016)	-0.075*** (0.009)	-0.010 (0.009)
9	-0.187*** (0.016)	-0.194*** (0.015)	-0.081*** (0.009)	-0.016+ (0.009)
10	-0.159*** (0.016)	-0.165*** (0.015)	-0.065*** (0.009)	-0.012 (0.009)
11	-0.126*** (0.016)	-0.132*** (0.016)	-0.046*** (0.010)	-0.006 (0.009)
12	-0.100*** (0.016)	-0.106*** (0.016)	-0.031** (0.009)	-0.006 (0.009)
13	-0.074*** (0.016)	-0.080*** (0.016)	-0.018+ (0.010)	-0.004 (0.010)
14	-0.042* (0.016)	-0.046** (0.016)	-0.007 (0.009)	0.003 (0.009)
15	-0.024 (0.017)	-0.028+ (0.016)	0.003 (0.010)	0.007 (0.010)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Event-Study estimates of the dynamic impact of COVID-19 on weekly electricity consumption. Dependent variable is log(kWh) per commercial unit. Treated = 2020, Control = 2019. All regressions include unit fixed effects and week-of-year controls. Standard errors are clustered at the unit level. Coefficients are reported relative to the week immediately preceding the COVID-19 outbreak ($t = -1$).

Placebo Event-Study (Treatment Shifted by 6 Weeks)

Table A.2 presents a placebo Event-Study where the treatment date is artificially shifted forward by six weeks. As expected, the estimated coefficients are close to zero in most periods,

supporting the validity of the identification strategy and showing that spurious dynamics do not drive the main results.

Table A.2: Placebo Event-Study Coefficients by Relative Week (Treatment shifted by 6 weeks)

Rel. Week	Total	Mid-Peak	Peak	Off-Peak
-6	-0.012 (0.016)	-0.013 (0.015)	0.003 (0.009)	0.008 (0.009)
-5	-0.015 (0.016)	-0.016 (0.015)	0.003 (0.009)	0.008 (0.009)
-4	-0.019 (0.016)	-0.021 (0.015)	0.004 (0.009)	0.010 (0.009)
-3	-0.025 (0.016)	-0.027+ (0.015)	0.004 (0.009)	0.012 (0.009)
-2	-0.018 (0.016)	-0.021 (0.015)	0.006 (0.009)	0.012 (0.009)
0	0.013 (0.016)	0.008 (0.015)	0.024** (0.009)	0.025** (0.009)
1	0.008 (0.016)	0.001 (0.015)	0.025** (0.009)	0.029** (0.009)
2	0.001 (0.016)	-0.006 (0.016)	0.023* (0.009)	0.028** (0.009)
3	-0.001 (0.016)	-0.008 (0.016)	0.019* (0.009)	0.025* (0.010)
4	0.000 (0.016)	-0.005 (0.015)	0.014 (0.009)	0.019* (0.009)
5	-0.001 (0.016)	-0.006 (0.015)	0.013 (0.009)	0.019* (0.009)
6	-0.029+ (0.015)	-0.036* (0.014)	-0.003 (0.009)	0.015+ (0.009)
7	-0.093*** (0.015)	-0.102*** (0.015)	-0.027** (0.009)	0.011 (0.009)
8	-0.150*** (0.016)	-0.158*** (0.015)	-0.051*** (0.009)	0.003 (0.009)
9	-0.152*** (0.016)	-0.160*** (0.016)	-0.051*** (0.009)	0.003 (0.009)
10	-0.159*** (0.016)	-0.168*** (0.015)	-0.054*** (0.009)	0.002 (0.009)
11	-0.173*** (0.016)	-0.181*** (0.015)	-0.066*** (0.009)	-0.003 (0.009)
12	-0.167*** (0.016)	-0.174*** (0.015)	-0.071*** (0.009)	-0.007 (0.009)
13	-0.163*** (0.016)	-0.169*** (0.015)	-0.073*** (0.009)	-0.010 (0.009)
14	-0.165*** (0.016)	-0.170*** (0.016)	-0.075*** (0.009)	-0.010 (0.009)
15	-0.187*** (0.016)	-0.194*** (0.015)	-0.081*** (0.009)	-0.016+ (0.009)
16	-0.159*** (0.016)	-0.165*** (0.015)	-0.065*** (0.009)	-0.012 (0.009)
17	-0.126*** (0.016)	-0.132*** (0.016)	-0.046*** (0.010)	-0.006 (0.009)
18	-0.100*** (0.016)	-0.106*** (0.016)	-0.031** (0.009)	-0.006 (0.009)
19	-0.074*** (0.016)	-0.080*** (0.016)	-0.018+ (0.010)	-0.004 (0.010)
20	-0.042* (0.016)	-0.046** (0.016)	-0.007 (0.009)	0.003 (0.009)
21	-0.024 (0.017)	-0.028+ (0.016)	0.003 (0.010)	0.007 (0.010)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Placebo Event-Study results, shifting the treatment six weeks earlier than the actual COVID-19 onset. Dependent variable is log(kWh) per unit. Estimates include unit fixed effects and week-of-year controls. Standard errors clustered at the unit level. No systematic effects are detected, supporting the validity of the identification strategy.

Event-Study with Extended Window

Table [A.3](#) extends the estimation window to include a longer set of pre- and post-treatment periods. The results remain consistent with the baseline estimates, confirming that the observed treatment effects are not sensitive to the choice of event window.

Table A.3: Event-Study Coefficients by Relative Week (Expanded Sample)

Rel. Week	Total	Mid-Peak	Peak	Off-Peak
-13	-0.019 (0.015)	-0.020 (0.015)	-0.001 (0.009)	0.004 (0.009)
-12	-0.012 (0.016)	-0.013 (0.015)	0.003 (0.009)	0.008 (0.009)
-11	-0.015 (0.016)	-0.016 (0.015)	0.003 (0.009)	0.008 (0.009)
-10	-0.019 (0.016)	-0.021 (0.015)	0.004 (0.009)	0.010 (0.009)
-9	-0.025 (0.016)	-0.027+ (0.015)	0.004 (0.009)	0.012 (0.009)
-8	-0.018 (0.016)	-0.021 (0.015)	0.006 (0.009)	0.012 (0.009)
-7	-0.003 (0.016)	-0.007 (0.015)	0.014 (0.009)	0.016+ (0.009)
-6	0.012 (0.016)	0.007 (0.015)	0.022* (0.009)	0.023* (0.009)
-5	0.015 (0.016)	0.010 (0.015)	0.025** (0.009)	0.027** (0.009)
-4	0.008 (0.016)	0.001 (0.015)	0.025** (0.009)	0.029** (0.009)
-3	0.001 (0.016)	-0.006 (0.016)	0.023* (0.009)	0.028** (0.009)
-2	-0.001 (0.016)	-0.008 (0.016)	0.019* (0.009)	0.025* (0.010)
0	-0.015 (0.015)	-0.021 (0.015)	0.005 (0.009)	0.017+ (0.009)
1	-0.093*** (0.015)	-0.102*** (0.015)	-0.027** (0.009)	0.011 (0.009)
2	-0.150*** (0.016)	-0.158*** (0.015)	-0.051*** (0.009)	0.003 (0.009)
3	-0.152*** (0.016)	-0.160*** (0.016)	-0.051*** (0.009)	0.003 (0.009)
4	-0.159*** (0.016)	-0.168*** (0.015)	-0.054*** (0.009)	0.002 (0.009)
5	-0.173*** (0.016)	-0.181*** (0.015)	-0.066*** (0.009)	-0.003 (0.009)
6	-0.167*** (0.016)	-0.174*** (0.015)	-0.071*** (0.009)	-0.007 (0.009)
7	-0.163*** (0.016)	-0.169*** (0.015)	-0.073*** (0.009)	-0.010 (0.009)
8	-0.165*** (0.016)	-0.170*** (0.016)	-0.075*** (0.009)	-0.010 (0.009)
9	-0.187*** (0.016)	-0.194*** (0.015)	-0.081*** (0.009)	-0.016+ (0.009)
10	-0.159*** (0.016)	-0.165*** (0.015)	-0.065*** (0.009)	-0.012 (0.009)
11	-0.126*** (0.016)	-0.132*** (0.016)	-0.046*** (0.010)	-0.006 (0.009)
12	-0.100*** (0.016)	-0.106*** (0.016)	-0.031** (0.009)	-0.006 (0.009)
13	-0.074*** (0.016)	-0.080*** (0.016)	-0.018+ (0.010)	-0.004 (0.010)
14	-0.042* (0.016)	-0.046** (0.016)	-0.007 (0.009)	0.003 (0.009)
15	-0.024 (0.017)	-0.028+ (0.016)	0.003 (0.010)	0.007 (0.010)
16	-0.025 (0.016)	-0.028+ (0.016)	0.003 (0.010)	0.008 (0.010)
17	-0.032+ (0.017)	-0.036* (0.016)	0.001 (0.010)	0.008 (0.010)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Event-Study results with an extended time window ($[-20, +28]$ weeks around the shock). Dependent variable is log(kWh) per unit. All regressions include unit fixed effects and week-of-year controls. Standard errors clustered at the unit level. Pre-treatment coefficients remain indistinguishable from zero, reinforcing the parallel trends assumption.

Event-Study with Alternative Control (Mean of 2018, 2019, and 2021)

Table A.4 shows the Event-Study coefficients when the counterfactual is constructed as the mean of 2018, 2019, and 2021 consumption. The results are very similar to the main specification, indicating that the findings are robust to alternative definitions of the control group.

Table A.4: Event-Study Coefficients by Relative Week (Control: Mean of 2018, 2019, and 2021)

Rel. Week	Total	Mid-Peak	Peak	Off-Peak
-6	-0.024 (0.027)	-0.027 (0.025)	0.014 (0.021)	-0.013 (0.022)
-5	-0.012 (0.026)	-0.016 (0.025)	0.023 (0.021)	-0.002 (0.021)
-4	-0.009 (0.026)	-0.015 (0.025)	0.028 (0.020)	0.006 (0.021)
-3	-0.013 (0.027)	-0.020 (0.025)	0.022 (0.021)	0.006 (0.022)
-2	-0.014 (0.027)	-0.022 (0.025)	0.025 (0.021)	0.015 (0.022)
0	-0.016 (0.026)	-0.023 (0.025)	0.016 (0.020)	0.015 (0.021)
1	-0.097*** (0.026)	-0.106*** (0.024)	-0.019 (0.020)	0.004 (0.021)
2	-0.155*** (0.026)	-0.163*** (0.024)	-0.043* (0.020)	-0.004 (0.021)
3	-0.158*** (0.027)	-0.167*** (0.025)	-0.044* (0.020)	-0.004 (0.022)
4	-0.165*** (0.026)	-0.174*** (0.024)	-0.046* (0.020)	-0.004 (0.021)
5	-0.178*** (0.026)	-0.188*** (0.024)	-0.057** (0.019)	-0.006 (0.021)
6	-0.176*** (0.026)	-0.184*** (0.024)	-0.064*** (0.019)	-0.011 (0.021)
7	-0.172*** (0.026)	-0.179*** (0.024)	-0.067*** (0.019)	-0.015 (0.021)
8	-0.172*** (0.026)	-0.179*** (0.025)	-0.068*** (0.020)	-0.016 (0.021)
9	-0.193*** (0.026)	-0.200*** (0.025)	-0.075*** (0.020)	-0.022 (0.021)
10	-0.169*** (0.027)	-0.175*** (0.025)	-0.064** (0.020)	-0.020 (0.021)
11	-0.143*** (0.027)	-0.149*** (0.026)	-0.049* (0.021)	-0.017 (0.022)
12	-0.112*** (0.027)	-0.119*** (0.026)	-0.032 (0.021)	-0.016 (0.022)
13	-0.086** (0.028)	-0.092*** (0.027)	-0.019 (0.022)	-0.014 (0.022)
14	-0.050+ (0.028)	-0.055* (0.027)	-0.005 (0.022)	-0.007 (0.022)
15	-0.031 (0.028)	-0.035 (0.027)	0.005 (0.022)	-0.001 (0.023)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Event-Study results using an alternative counterfactual constructed from the mean of 2018, 2019, and 2021 consumption (excluding 2020). Dependent variable is log(kWh) per unit. All regressions include unit fixed effects and week-of-year controls. Standard errors clustered at the unit level. Results are robust to this alternative control definition.

B Supplementary Figures

This section provides additional graphical evidence that complements the main results. The figures document weekly electricity consumption patterns, dynamic Event-Study effects, placebo checks, extended estimation windows, alternative counterfactuals, and heterogeneity by location. Together, they demonstrate that the core findings reported in the main text are robust to alternative specifications and consistent across different settings.

Weekly Consumption Trends

Figures B.1–B.4 plot the weekly electricity consumption of commercial units in Tehran from 2018 through 2021, separately for total, mid-peak, peak, and off-peak categories. These long-run series highlight the strong seasonality in electricity demand: consumption rises in the summer months (driven by cooling needs) and falls during the winter. The vertical dashed line marks the onset of the COVID-19 shock in March 2020. In each series, a pronounced dip is visible in 2020, interrupting the usual seasonal cycle and signaling the magnitude of the pandemic’s economic disruption.

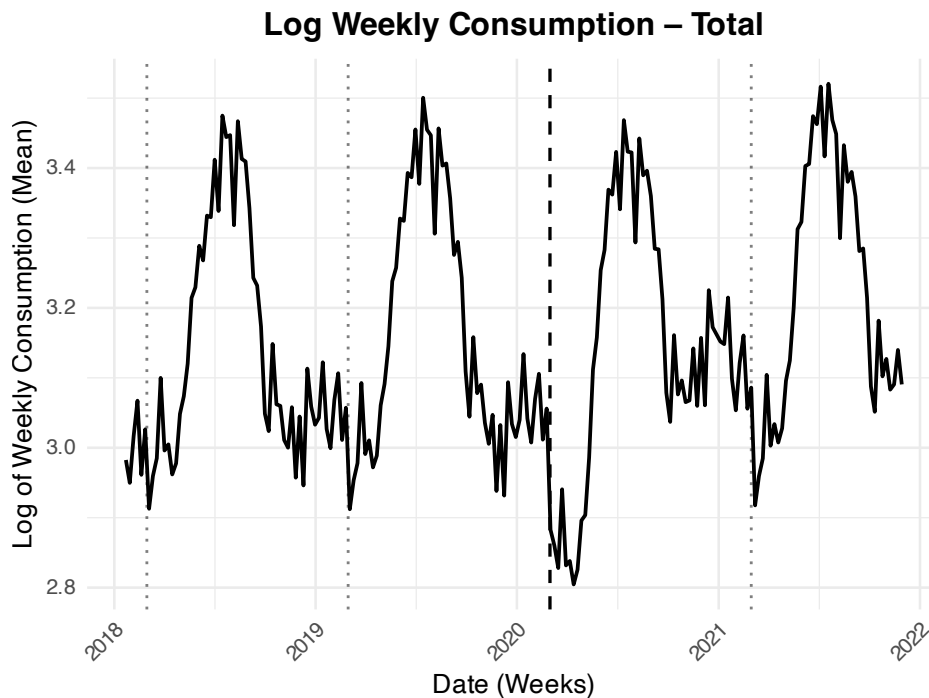


Figure B.1: Weekly total commercial electricity consumption, 2018–2021 (Tehran). Series show $\log(kWh \text{ per week})$; seasonal peaks occur in summer and troughs in winter. The vertical dashed line marks March 2020 (COVID-19 onset).

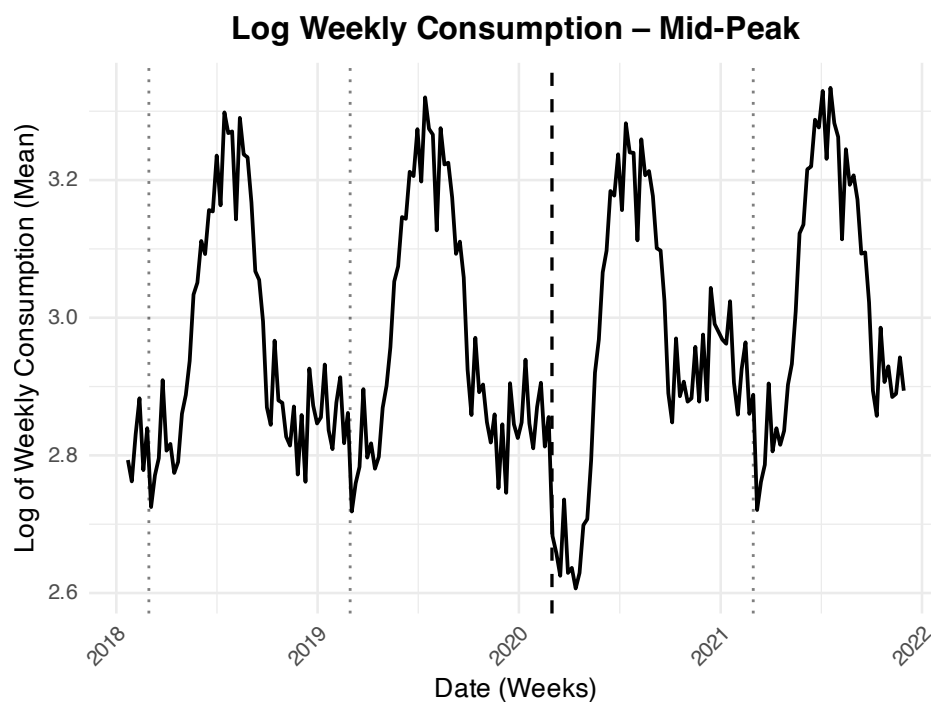


Figure B.2: Weekly mid-peak commercial electricity consumption, 2018–2021. Series show $\log(kWh \text{ per week})$; mid-day /early-evening demand contracts most in 2020 relative to seasonal norms. Vertical dashed line: March 2020 (COVID-19 onset).

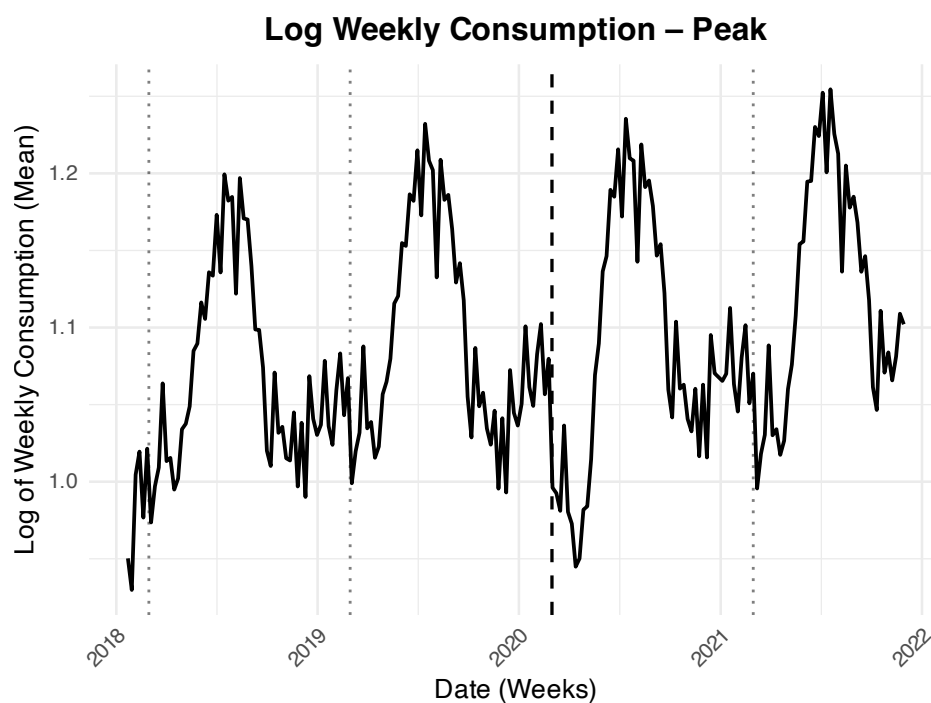


Figure B.3: Weekly peak-hour commercial electricity consumption, 2018–2021. Series show $\log(kWh \text{ per week})$; peak demand falls in 2020, though less than mid-peak. Vertical dashed line: March 2020 (COVID-19 onset).

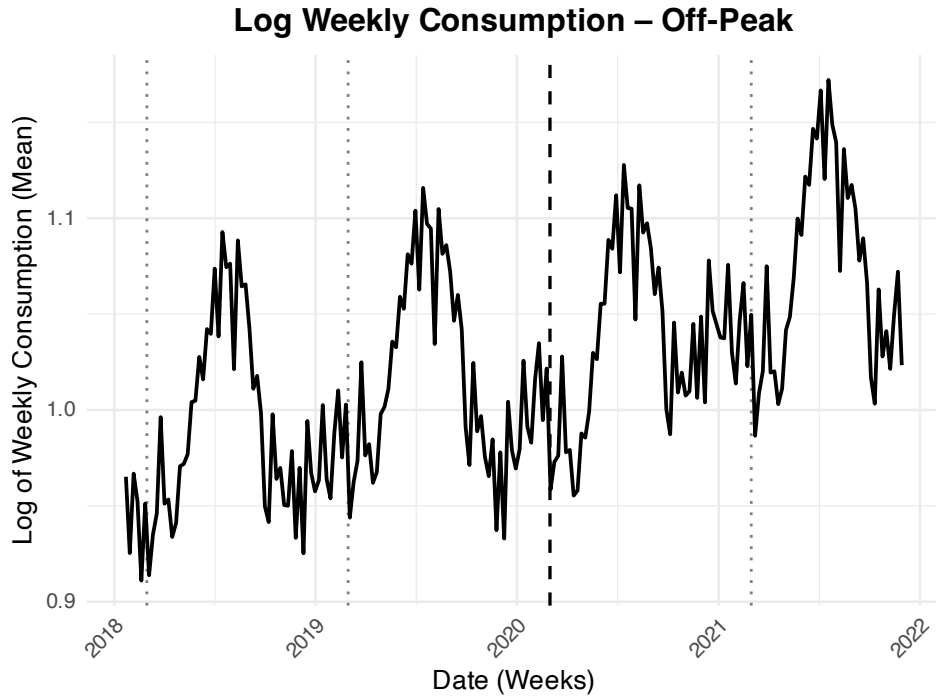


Figure B.4: Weekly off-peak commercial electricity consumption, 2018–2021. Series show $\log(kWh \text{ per week})$; night-time demand is comparatively stable, with a modest dip in early 2020. Vertical dashed line: March 2020 (COVID-19 onset).

To assess comparability across treatment and control years, Figures B.5–B.7 plot consumption in 2019 (the counterfactual) and 2020 (the treated year) for each category. The series track closely in the pre-COVID weeks, lending support to the parallel trends assumption. Following the shock, however, sharp divergences emerge. Mid-peak consumption falls dramatically relative to 2019, peak consumption drops more moderately, and off-peak demand shows only minor differences, underscoring the heterogeneous adjustment across time-of-day categories.

Event-Study Estimates (Main Specification)

Figures B.8–B.10 plot the dynamic Event-Study coefficients for mid-peak, peak, and off-peak consumption. These complement the total consumption Event-Study reported in the main text.

Mid-peak demand shows the sharpest contraction, with coefficients reaching losses of nearly 20% at the trough and recovering only gradually. Peak-hour consumption also falls significantly, but the decline is less severe, suggesting that some essential evening activities persisted despite restrictions. Off-peak demand remains relatively flat, consistent with the idea that baseline electricity usage tied to essential infrastructure is less elastic to shocks. To-

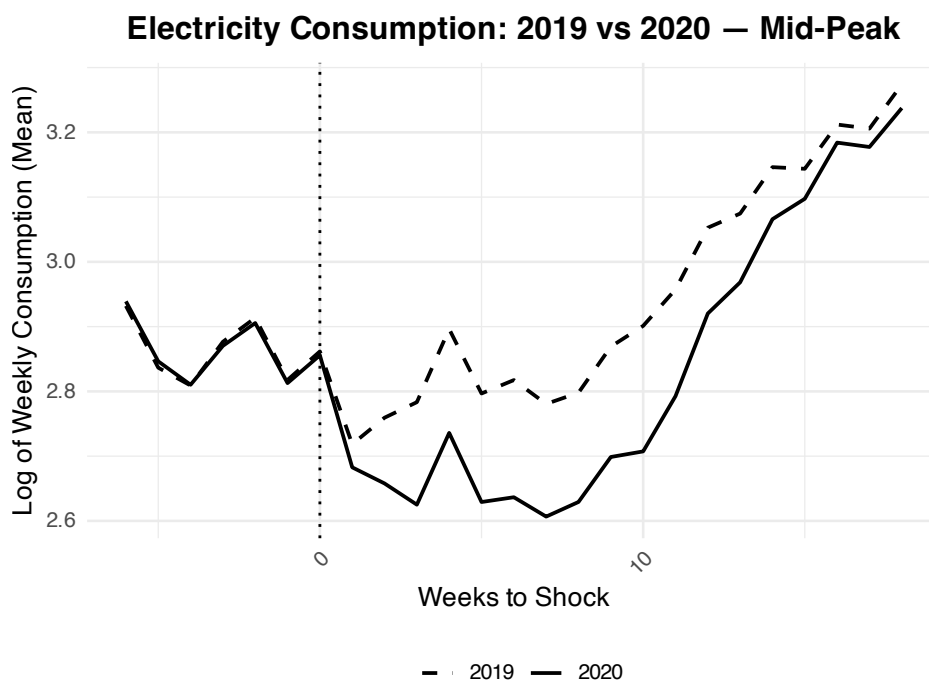


Figure B.5: Weekly mid-peak electricity consumption, 2019 vs 2020. Series show $\log(kWh \text{ per week})$ for the same establishments aligned by calendar week; pre-shock paths overlap, then 2020 drops sharply after week 0 (March 2020).

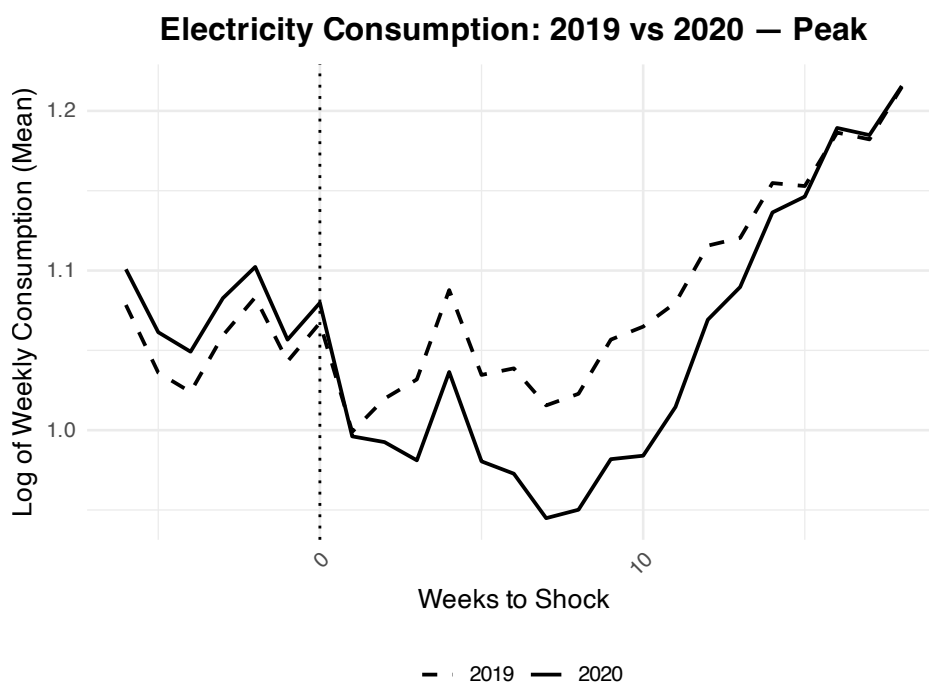


Figure B.6: Weekly peak electricity consumption, 2019 vs 2020. Series show $\log(kWh \text{ per week})$; pre-shock trends are parallel, with a smaller (but clear) post-shock decline in 2020 than at mid-peak hours.

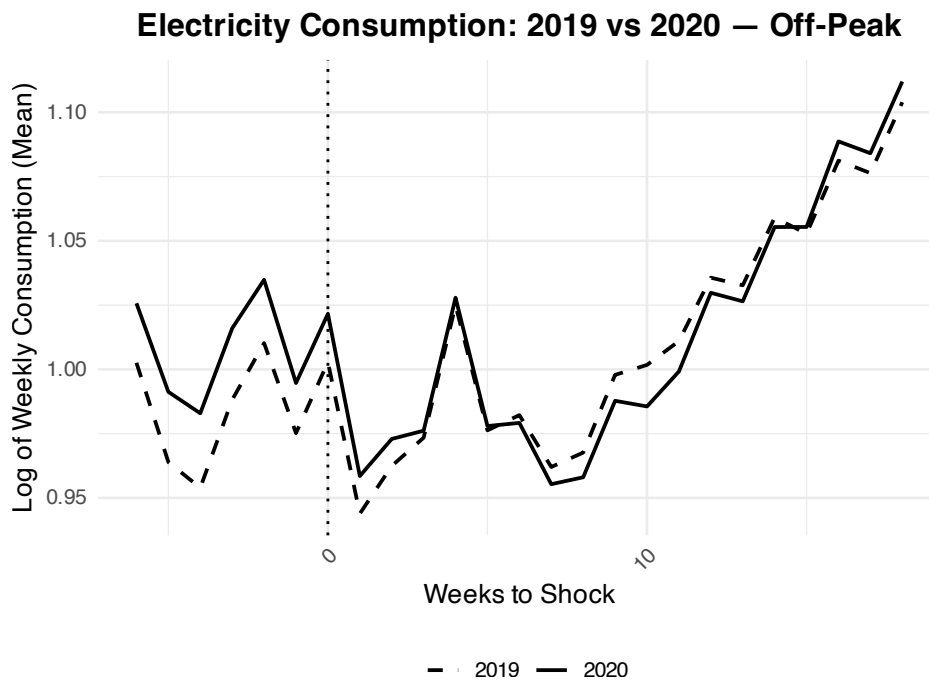


Figure B.7: Weekly off-peak electricity consumption, 2019 vs 2020. Series show $\log(\text{kWh per week})$; differences are modest, reflecting relatively inelastic baseline night-time loads (e.g., refrigeration, security).

gether, these patterns illustrate that the economic contraction was concentrated in commercial operating hours.

Placebo Event-Study

Figures B.11–B.13 conduct placebo tests by shifting the treatment six weeks earlier than the actual shock. The estimated coefficients fluctuate narrowly around zero, with no systematic pattern of post-“placebo” declines. This exercise confirms that the main results are not driven by spurious dynamics or arbitrary timing. It also reinforces the validity of the parallel trends assumption.

Extended Window

Figures B.14–B.16 expand the Event-Study horizon to $[-20, +28]$ weeks. Pre-treatment coefficients remain statistically indistinguishable from zero across categories, bolstering the parallel trends assumption over a longer horizon. Post-treatment trajectories mirror the baseline specification: mid-peak consumption exhibits the largest and most persistent drop, peak con-

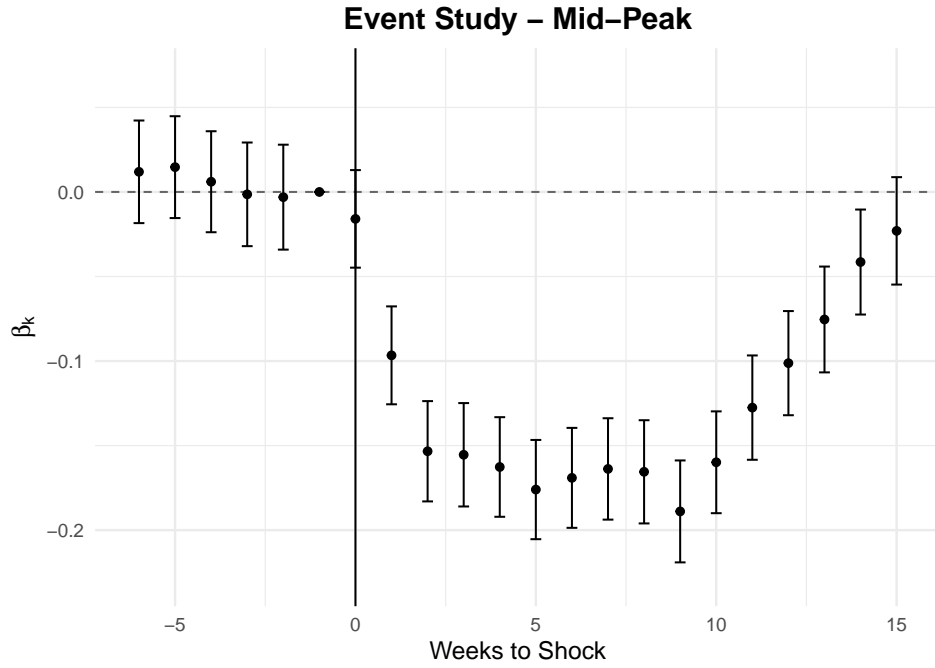


Figure B.8: Event-Study estimates for mid-peak consumption. Coefficients are relative to $t = -1$ (week before COVID-19 onset). Outcome: $\log(kWh \text{ per week})$; 95% confidence intervals shown. Losses approach $\sim 20\%$ at the trough, with gradual recovery.

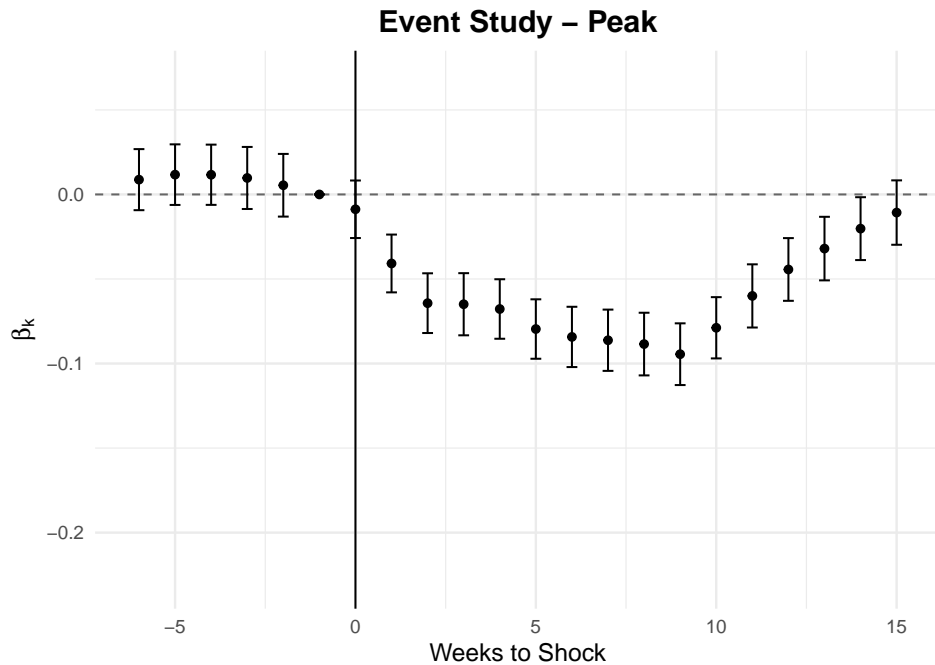


Figure B.9: Event-Study estimates for peak consumption. Coefficients are relative to $t = -1$; outcome is $\log(kWh \text{ per week})$ with 95% confidence intervals. Declines are statistically significant but smaller than mid-peak.

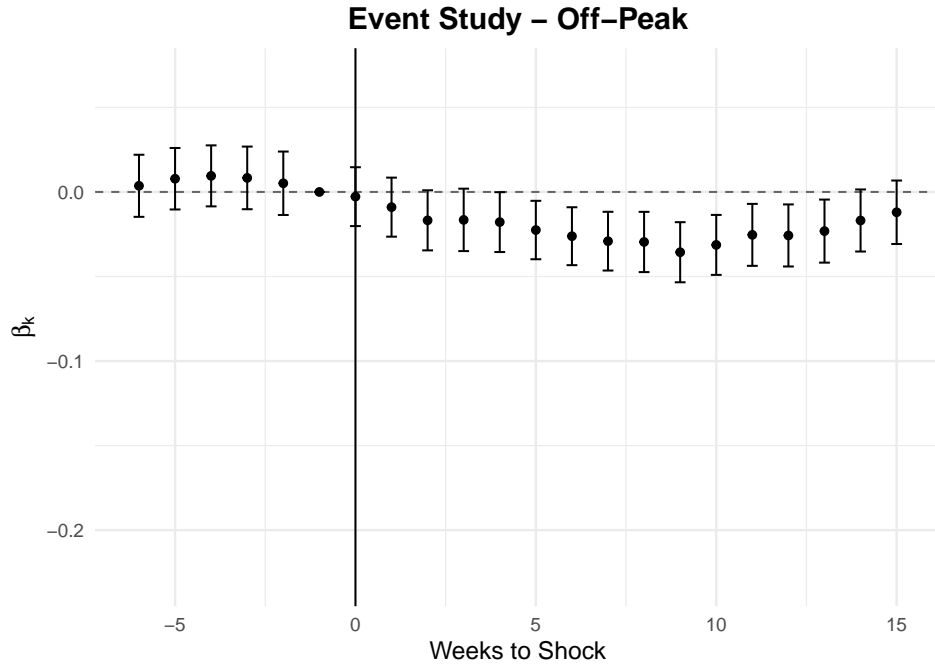


Figure B.10: Event-Study estimates for off-peak consumption. Coefficients are relative to $t = -1$; outcome is $\log(\text{kWh per week})$ with 95% confidence intervals. Effects remain close to zero, indicating resilient baseline night-time demand.

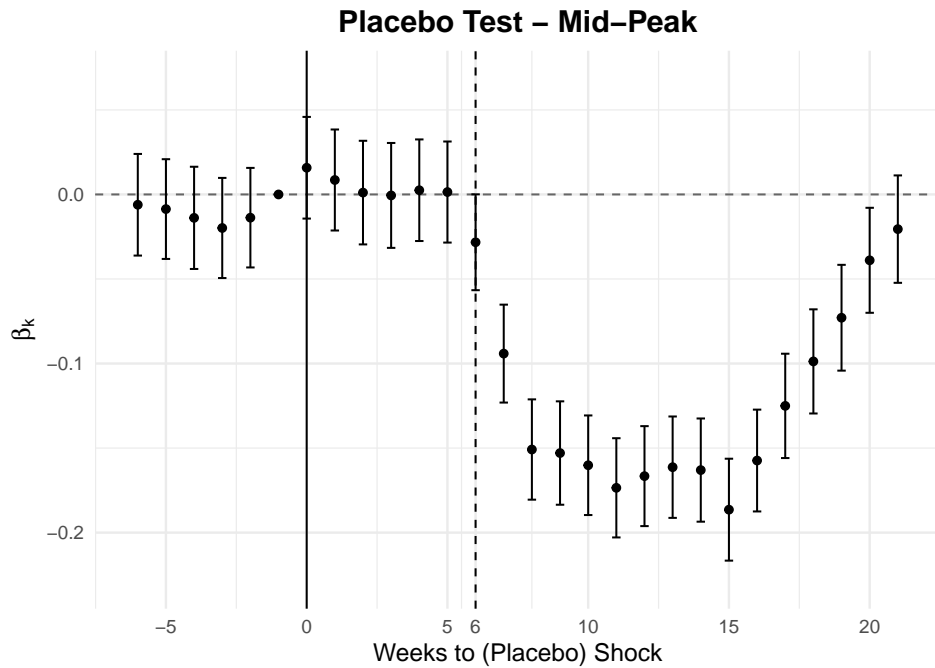


Figure B.11: Placebo test for mid-peak consumption (pseudo-treatment at $t = -6$). Event-Study coefficients are near zero before and after the placebo date (outcome: $\log(\text{kWh per week})$; 95% confidence intervals).

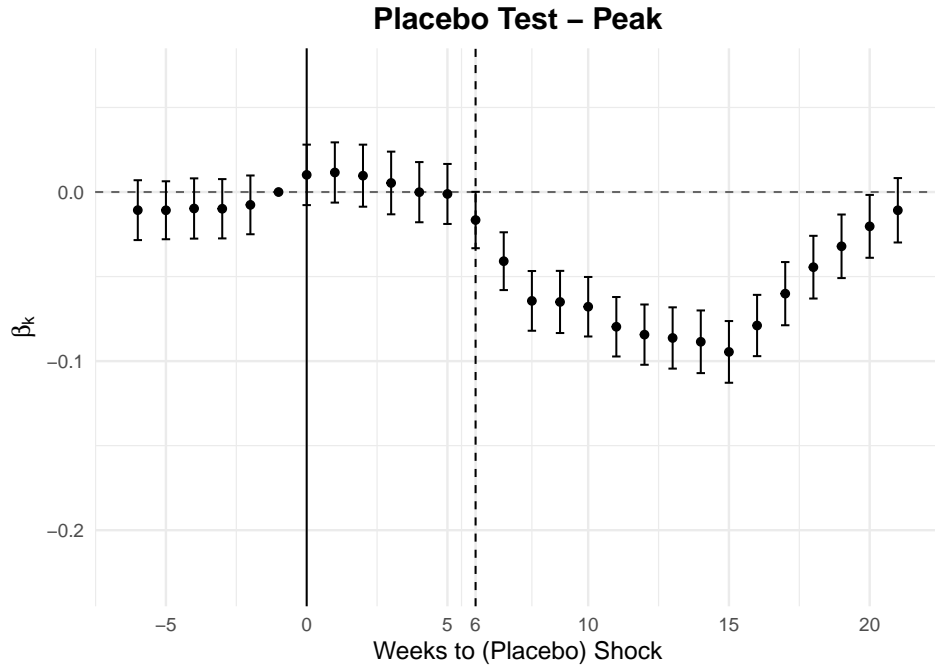


Figure B.12: Placebo test for peak consumption (pseudo-treatment at $t = -6$). No systematic post-placebo effects are detected (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

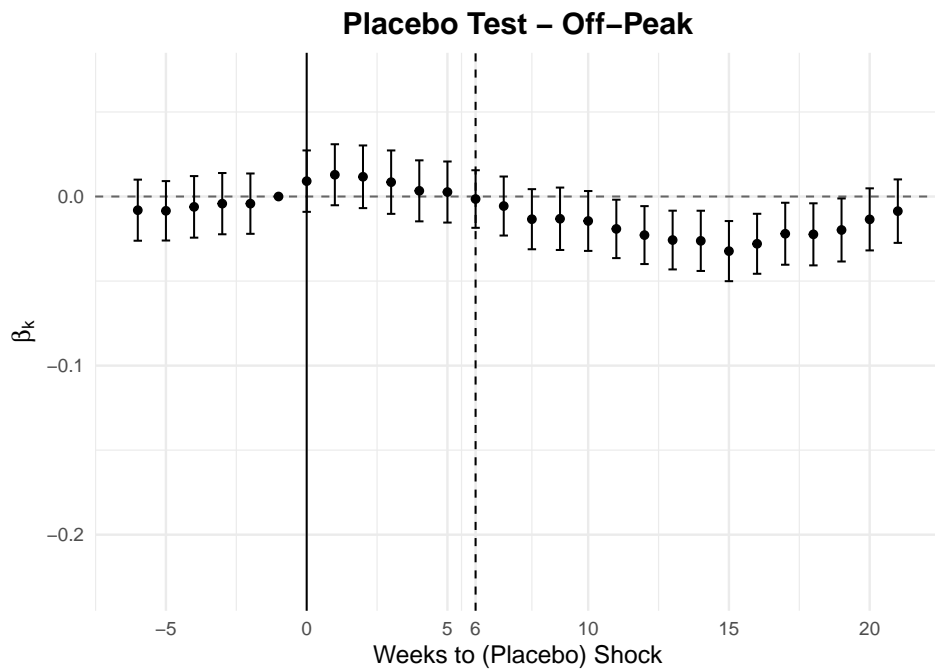


Figure B.13: Placebo test for off-peak consumption (pseudo-treatment at $t = -6$). Coefficients remain close to zero (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

sumption falls moderately, and off-peak demand is largely unaffected. This robustness check shows that the baseline results are not an artifact of the narrower window choice.

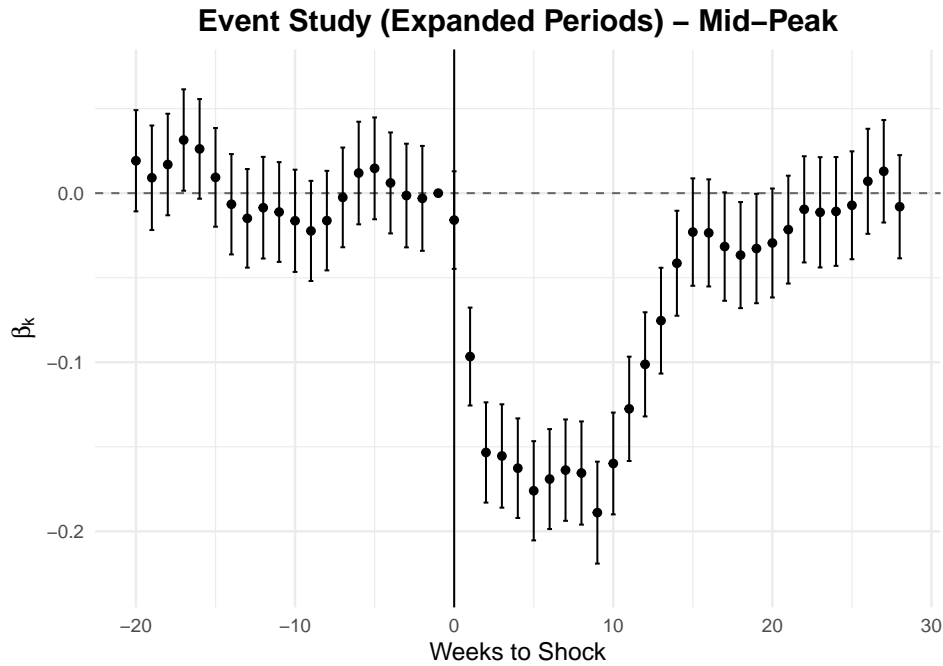


Figure B.14: Event-Study with extended window for mid-peak consumption ($[-20, +28]$). Pre-treatment coefficients are near zero; post-shock dynamics match the baseline (outcome: *log(kWh per week)*; 95% confidence intervals).

Alternative Control

Finally, Figures B.17–B.19 present event studies where the counterfactual is constructed from the average of 2018, 2019, and 2021 consumption. Results are nearly identical to the baseline specification, showing sharp mid-peak declines, moderate peak contractions, and muted off-peak effects. This confirms that the findings are robust to alternative control definitions and not sensitive to reliance on a single pre-COVID year.

Heterogeneity by Location

Figures B.20–B.22 present Event-Study estimates disaggregated by power grid location within Tehran. Each panel reports the dynamic treatment effects for a single location, allowing for the examination of spatial heterogeneity in the pandemic’s impact.

The results reveal that, although the magnitude of declines varies somewhat across locations, the qualitative pattern is remarkably consistent. In nearly all cases, electricity consump-

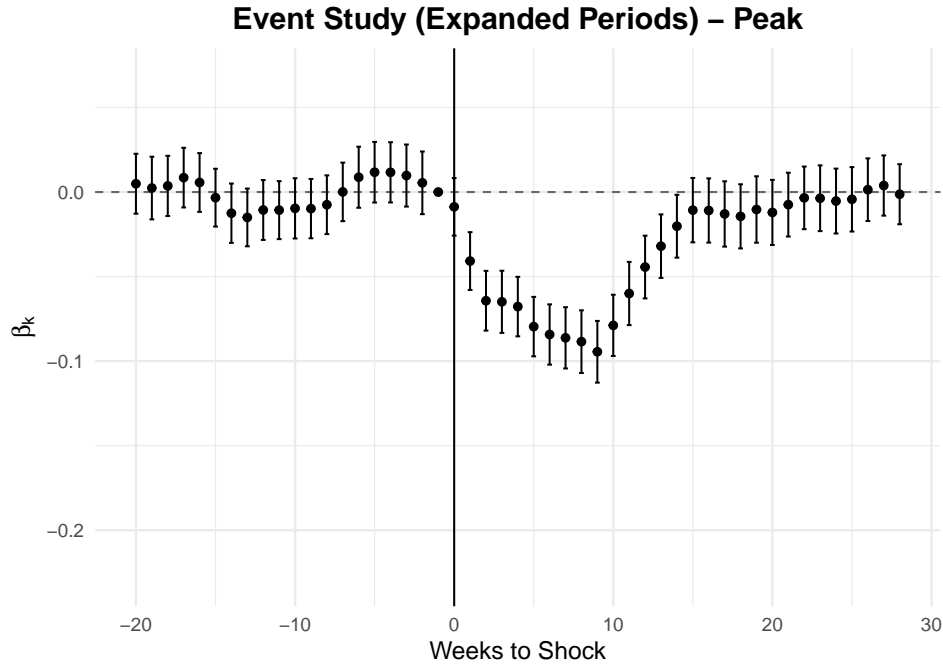


Figure B.15: Event-Study with extended window for peak consumption ($[-20, +28]$). Results are robust across horizons (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

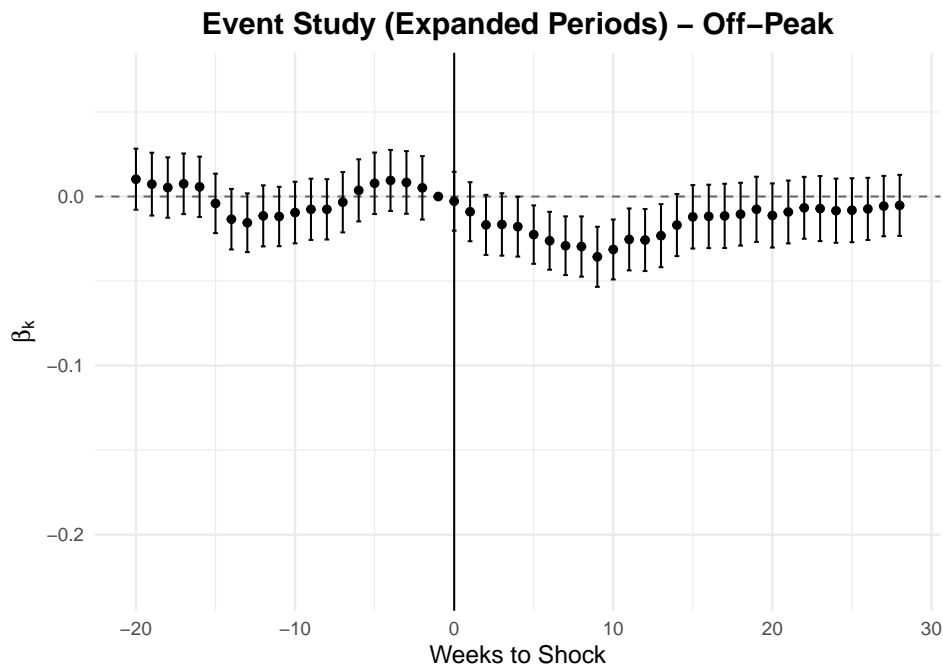


Figure B.16: Event-Study with extended window for off-peak consumption ($[-20, +28]$). Effects remain small and imprecise (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

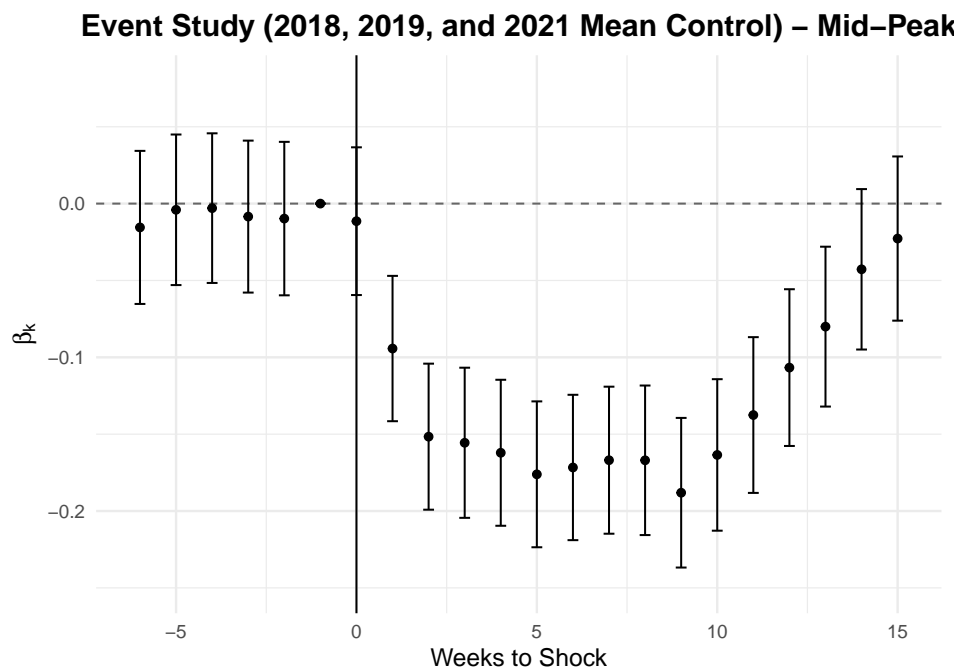


Figure B.17: Event-Study for mid-peak consumption using alternative counterfactual (mean of 2018, 2019, 2021). Results closely track the baseline (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

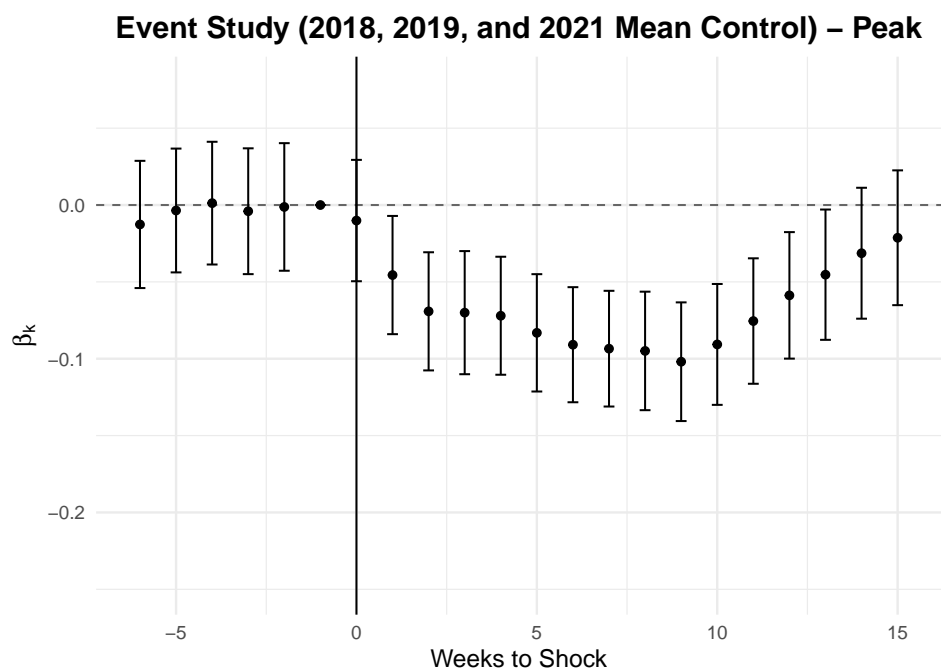


Figure B.18: Event-Study for peak consumption using alternative counterfactual (mean of 2018, 2019, 2021). Timing and magnitudes are consistent with the baseline (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

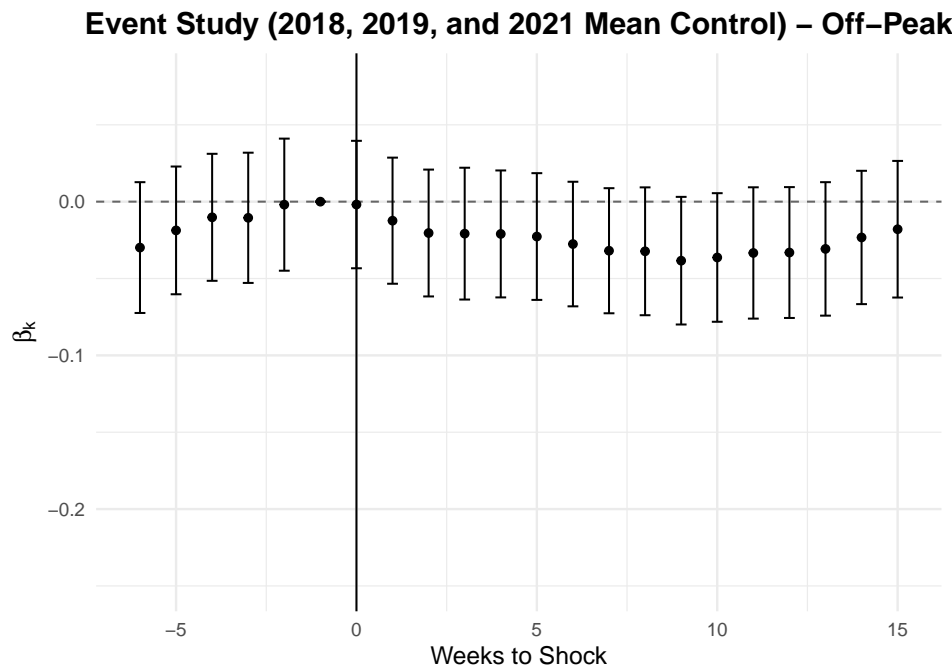


Figure B.19: Event-Study for off-peak consumption using alternative counterfactual (mean of 2018, 2019, 2021). No meaningful deviations from zero are observed (outcome: $\log(kWh \text{ per week})$; 95% confidence intervals).

tion drops sharply in the weeks immediately following the COVID-19 shock, with recovery only occurring gradually over subsequent weeks. Locations with higher baseline commercial activity exhibit somewhat larger percentage declines, consistent with the heterogeneity patterns documented earlier by consumption intensity and variance.

These findings underscore that the economic contraction induced by COVID-19 was not confined to a handful of areas, but rather spread across the city as a whole. The similarity of dynamics across locations strengthens the interpretation of the results as reflecting broad-based economic disruption rather than localized shocks or measurement artifacts. At the same time, the modest variation in magnitudes suggests that some neighborhoods or commercial districts may have been more resilient than others, potentially due to differences in sectoral composition, exposure to restrictions, or reliance on essential services. This dimension of heterogeneity could provide a useful avenue for further research.

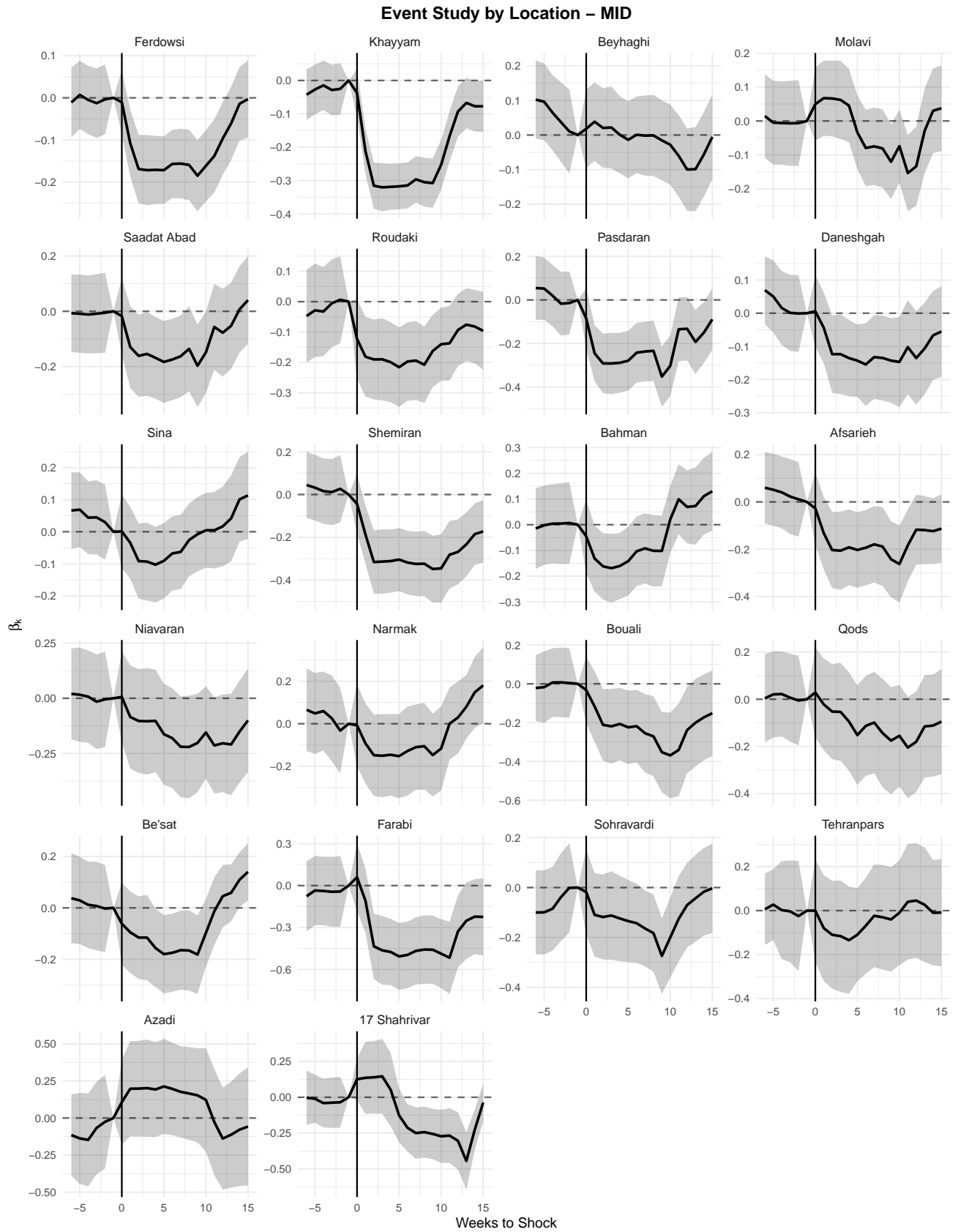


Figure B.20: Event-Study for mid-peak consumption by location. Panels are locations sorted by base-line total consumption. Most locations show an immediate post-shock drop and gradual recovery (outcome: $\log(kWh \text{ per week})$).

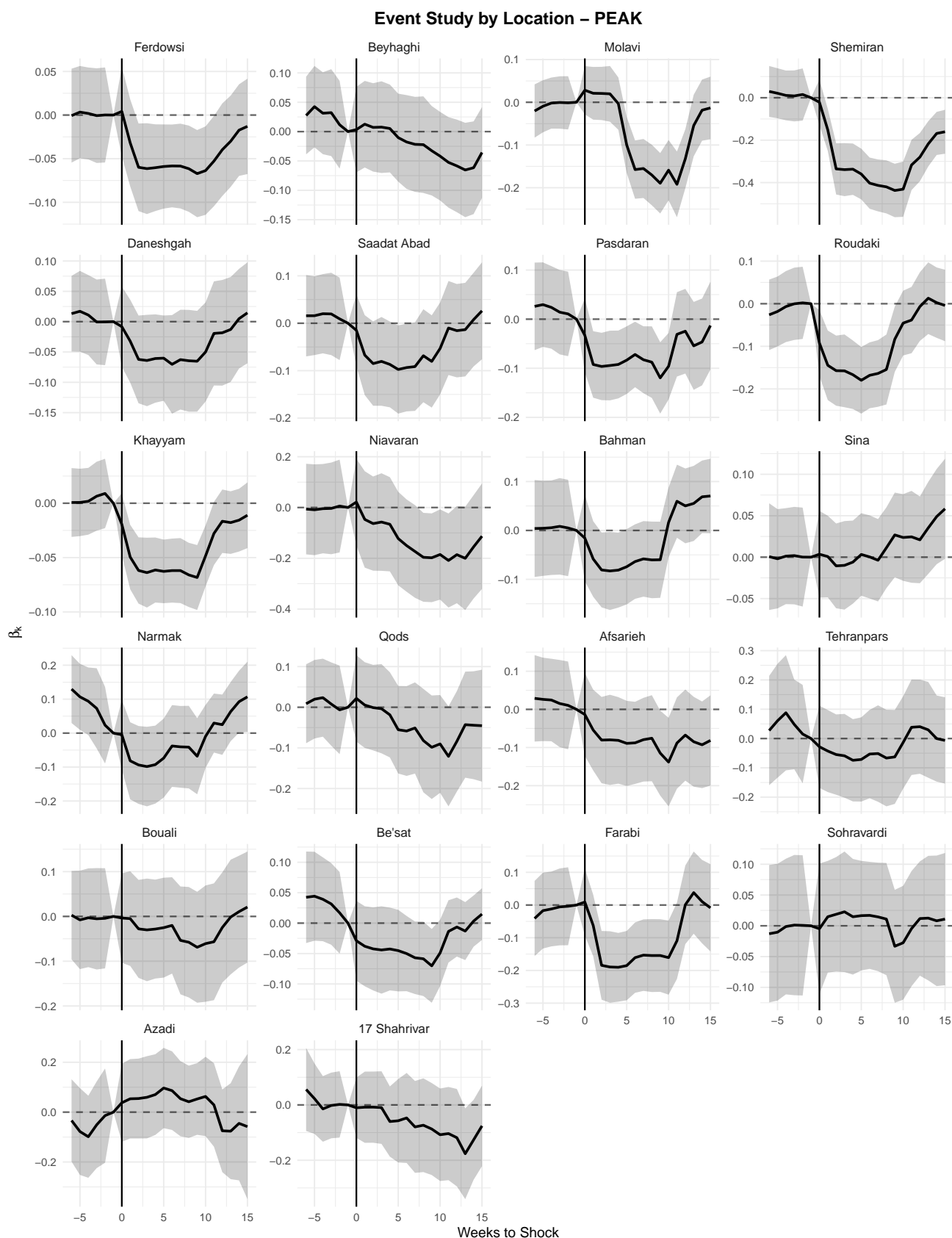


Figure B.21: Event-Study for peak consumption by location. Panels are locations sorted by baseline total consumption; declines are moderate and persistent (outcome: $\log(kWh \text{ per week})$).

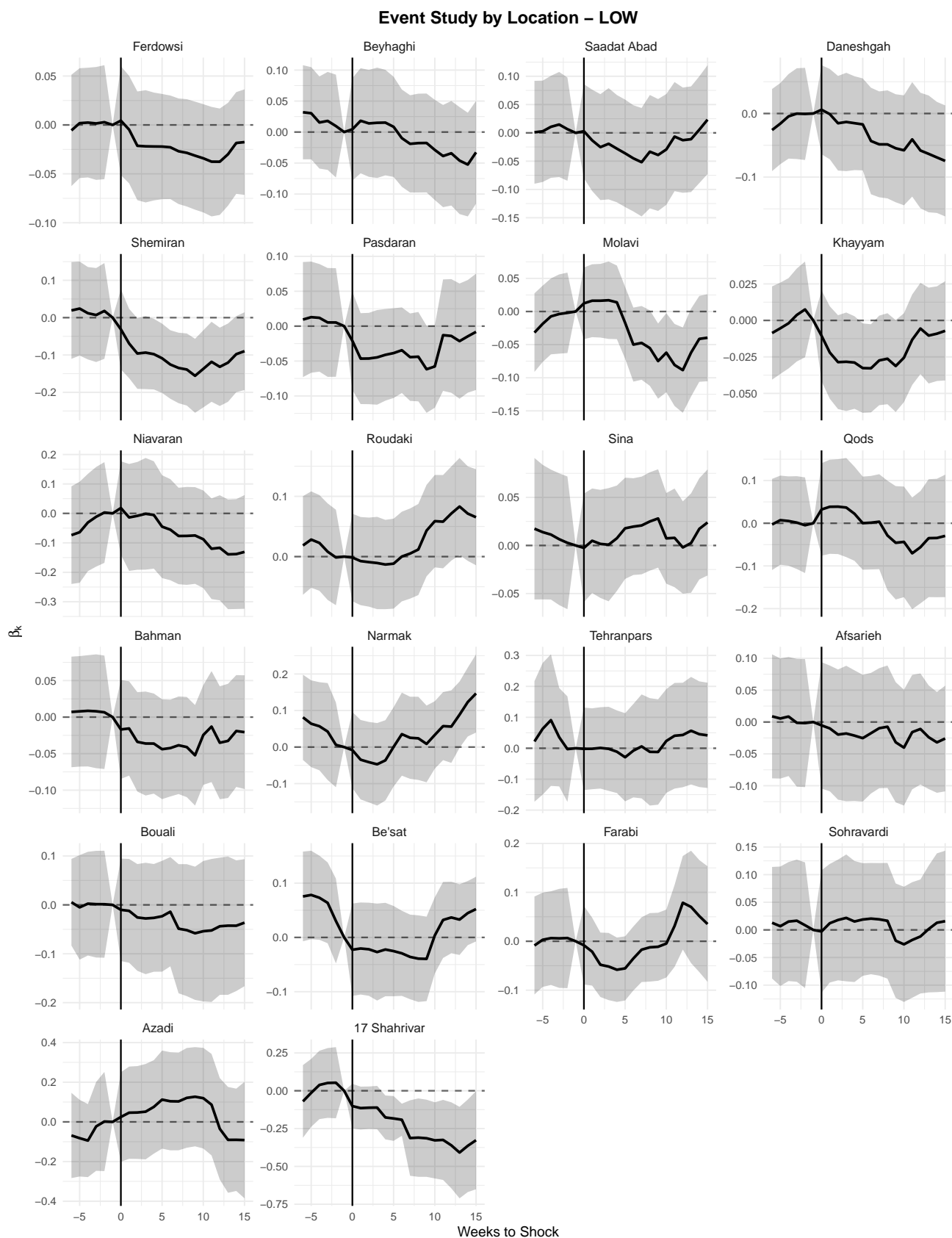


Figure B.22: Event-Study for off-peak consumption by location. Panels are locations sorted by baseline total consumption; effects are small, consistent with resilient night-time loads (outcome: $\log(\text{kWh per week})$).

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