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

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Abstract

The COVID-19 pandemic has caused severe and widespread economic disruptions; yet, quantifying its magnitude remains challenging in developing countries, where real-time economic indicators are limited. This paper estimates the short-term economic impact of COVID-19 in Tehran, Iran, using high-frequency panel data on electricity consumption from over 4,500 commercial establishments. An Event-Study-based Difference-in-Differences (DID) framework is employed to identify the dynamic treatment effects of the pandemic shock. The results show that total commercial electricity consumption declined by approximately 13% during the early phase of the outbreak, indicating a sharp contraction in economic activity. Consumption began to recover gradually once the spread of the virus was brought under control. These findings highlight the value of electricity consumption data as a timely and reliable proxy for real economic activity, especially in data-scarce environments, and demonstrate a scalable approach for rapid economic monitoring during crises.

Keywords: *COVID-19, Electricity Consumption, Economic Costs, Difference-in-Differences.*

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1 Introduction

In early 2020, the COVID-19 pandemic introduced unprecedented global disruptions in both public health and economic activity. Iran, already contending with structural vulnerabilities, implemented strict containment measures, including regional lockdowns and widespread home quarantines. These interventions had immediate and significant economic repercussions. Key sectors, including commerce and manufacturing, experienced production halts and operational slowdowns. On June 18, 2020, Iran's Minister of Economy, Farhad Dezhpasand, reported to the Islamic Consultative Assembly that the pandemic had reduced the national GDP by 15%. Nevertheless, aggregate measures such as GDP often fail to fully capture rapid or granular fluctuations in economic activity, especially in developing economies where informal sectors and data limitations are prevalent (Chen and Nordhaus, 2011; Henderson, Storeygard, and Weil, 2012). This study addresses that gap by employing high-frequency electricity consumption data from the city of Tehran as a proxy to assess the immediate economic impacts of COVID-19.

Electricity consumption serves as a timely and observable proxy for economic performance. Variations in commercial electricity use can reflect shifts in operational intensity, business closures, and broader economic stress. While not a direct substitute for national accounts data, electricity consumption provides high-frequency insights into economic fluctuations, particularly in contexts where real-time official statistics are limited. Previous literature has explored the long-run association between electricity use and economic development, but fewer studies have applied electricity data to identify and quantify short-term economic shocks like COVID-19.

The empirical analysis is based on a dataset of billing records from 4,550 commercial units sampled across all 22 power grid locations of Tehran, covering the years 2014 to 2021. These billing records are characterized by irregular intervals—ranging from 15 to 60 days—which necessitated significant preprocessing. To construct a balanced panel suitable for econometric analysis, I transformed the raw billing data into a regular weekly format. This was achieved by distributing each bill's consumption over its active days using seasonal weights derived from a regression model estimated on pre-pandemic data with week-of-year and location fixed effects.

The primary identification strategy relies on a Difference-in-Differences (DID) approach. I define the 2020 consumption of each unit as the treated observation and use the same unit's

2019 consumption from the corresponding calendar week as its control. The treatment is marked by the onset of the pandemic in Iran, dated to March 1, 2020. The outcome variable is the logarithm of weekly electricity consumption. I complement the DiD estimation with an Event-Study design to capture the temporal dynamics of the treatment effect. Both methods are implemented across four consumption categories: total, peak, mid-peak, and off-peak.

To test the credibility of the identification strategy, I perform multiple robustness checks. First, a test for parallel trends in the pre-treatment period yields no significant differences between treated and control units, supporting the validity of the DiD framework. Second, I perform a placebo analysis, artificially assigning the treatment six weeks before the actual shock. The absence of significant effects in this placebo window reinforces the causal interpretation of the main results. Third, I estimate location-specific Event-Studies to assess spatial heterogeneity. Although the magnitude of the shock varies across regions, all areas exhibit a consistent pattern: a steep post-shock decline followed by partial recovery.

The central finding is that commercial electricity consumption in Tehran experienced a marked decline following the outbreak of COVID-19, consistent with a substantial reduction in economic activity. The largest drop occurred immediately after the shock, with partial rebounds observed in subsequent weeks. These findings suggest that electricity data can serve as a reliable, near-real-time indicator of economic disruptions in crisis settings, particularly where official data may be delayed, incomplete, or less granular.

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, Baker, Barrero, Bloom, Bunn, Chen, Davis, Leather, Meyer, Mihaylov, 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 and Adediran, 2020), financial markets (Zhang, Hu, and Ji, 2020), commodities (Chen, Qian, and Wen, 2021), international trade (Njindan Iyke, 2020; Vidya and Prabheesh, 2020), tourism (Gössling, Scott, and Hall, 2020), and environmental protection (He, Pan, and Tanaka, 2020; Magazzino, Mele, and Schneider, 2020; Ming, Zhou, Ai, Bi, and Zhong, 2020).

Particularly pertinent to this study is the body of work examining electricity market performance during the pandemic. Bahmanyar, Estebsari, 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, and Pilo, 2020). Similarly, Abu-Rayash and Dincer (2020) noted a 14% decrease in Ontario, Canada, while Carvalho, Bandeira de Mello Delgado, de Lima, de Camargo Cancela, dos Siqueira, and de Souza (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, and Gonzalez-Redondo, 2021). The approach of Elavarasan, Shafiullah, Raju, Mudgal, Arif, Jamal, Subramanian, Balaguru, Reddy, and Subramaniam (2020) and García, Parejo, Personal, Guerrero, Biscarri, and León (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, and Galdo, 2021; Fezzi and 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, and Hill, 2000; Narayan and Singh, 2007; Shiu and Lam, 2004; Tang and 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 (Chen and Nordhaus, 2011; Egger, Loumeau, and Püschel, 2017; Henderson et al., 2012).

This study contributes to the literature by employing a counterfactual framework to quantify the economic impact of COVID-19 through high-frequency electricity consumption data from over 4,500 commercial units in Tehran. Compared to Ai, Zhong, and Zhou (2022), which examines 322 firms in Hunan Province, this paper offers a broader empirical scope and reveals a more protracted recovery trajectory, lasting 16 weeks rather than 12. By leveraging a dense urban dataset and applying robust identification strategies, the analysis advances our understanding of how localized shocks manifest in electricity demand, providing a scalable method for assessing economic disruptions in data-constrained, developing country settings.

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 as well as robustness checks, including placebo tests and heterogeneity analyses. Section 6 presents an estimate of the aggregate economic costs of the pandemic. Finally, Section 7 concludes with a discussion of the findings and their broader implications.

2 Institutional Background

In early 2020, the outbreak of the COVID-19 pandemic in China marked the beginning of a global health crisis with extensive socio-economic repercussions. This unprecedented epidemic rapidly spread worldwide, impacting public health and economies on a massive scale. By September 2021, COVID-19 had reached almost every corner of the globe, with over 230 million confirmed cases and 4.7 million deaths, sparing only a dozen countries and territories (WTO, 2020a). The pandemic's complexity was further compounded by the emergence of highly transmissible and virulent mutant strains like delta and lambda, surpassing previous epidemics like SARS and MERS in terms of infectivity and mutation rate.

The economic impact of the pandemic has been profound. The International Monetary Fund projected a 5.5% global economic growth in 2021, followed by 4.2% in 2022, while the World Trade Organization anticipated a 9.2% decline in global merchandise trade, signaling the worst recession since the Great Depression (WTO, 2020b). The International Labor Organization reported a significant rise in global unemployment, with an additional 33 million people unemployed in 2020, raising the unemployment rate to 6.5% (ILO, 2020). These statistics underscore the necessity of in-depth analyses to understand the full socio-economic impacts of COVID-19.

The virus was initially reported in Wuhan, China, in late 2019 (Zhu, Zhang, Wang, Li, Yang, Song, Zhao, Huang, Shi, Lu, et al., 2020), and quickly spread to other countries, including Iran. Iran officially confirmed its first cases in February 2020, quickly becoming a global hotspot for the virus. In response, the Iranian government implemented various public health measures, including a third-level quarantine. Despite these measures, the restrictions led to reduced economic activities and travel, particularly impacting Tehran, Iran's capital and economic hub. According to 2016 census data, Tehran had a population of approximately 8.7 million and contributed 22.1% to Iran's GDP in 2019. In 2021, Tehran's electricity consumption, a key economic indicator, was the highest in the country, with significant usage across various sectors.

This study focuses on Tehran to understand the economic costs of COVID-19, considering the city's importance in Iran's economy, particularly in the secondary industries sector. The experiences of Tehran in combating the pandemic offer valuable insights for other cities facing similar challenges. A comparative analysis is essential to estimate the pandemic's economic impact. The quarantine policy in Iran created a quasi-experimental setting, allowing for the use of a Difference-in-Differences (DID) model. This model compares electricity consumption in 2020 (the treatment group) with the same lunar calendar dates in 2019 (the control group), thus estimating the economic damages caused by COVID-19 post-quarantine implementation.

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:

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

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 differences 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.

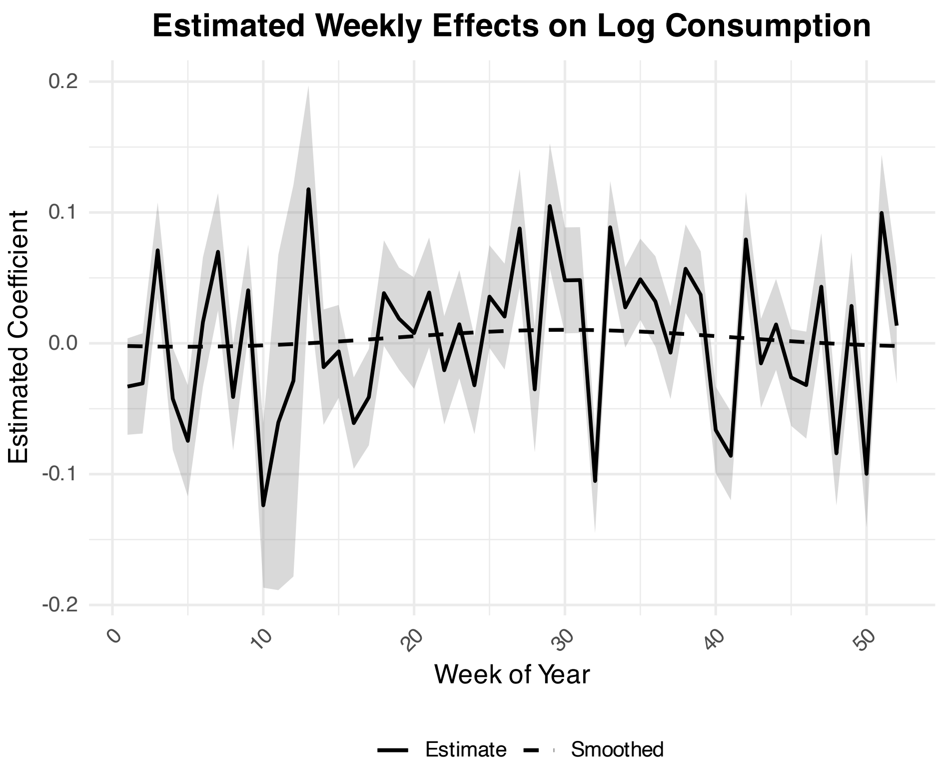

Figure 1: Estimated weekly seasonal effects from pre-pandemic commercial electricity consumption. The figure plots estimated coefficients from a regression of daily electricity use on week-of-year dummies, controlling for location and year fixed effects. The solid line shows point estimates and the shaded area 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.

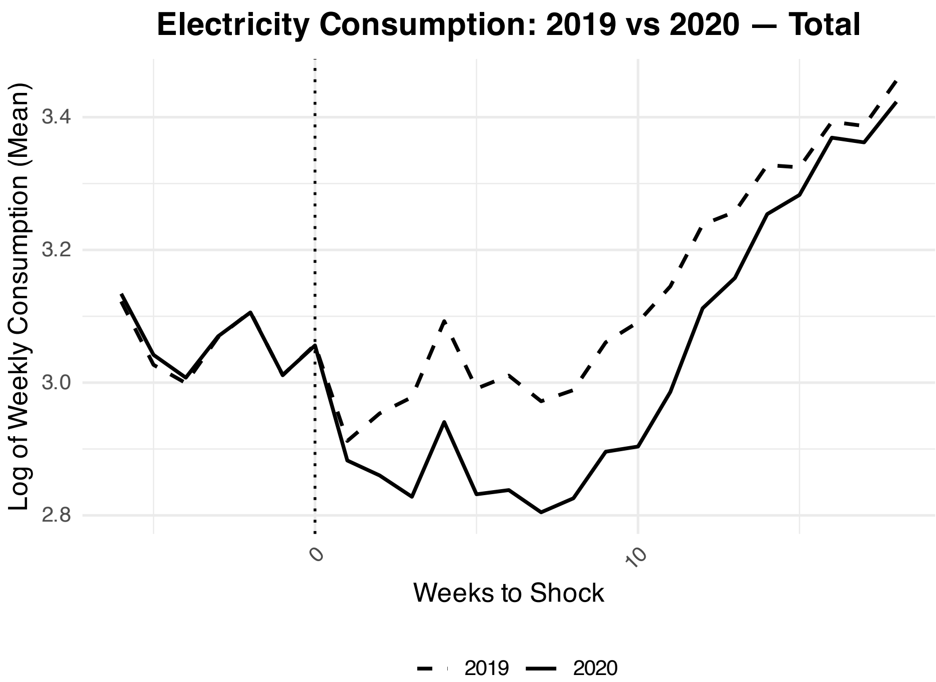

Figure 2: Weekly total electricity consumption in Tehran, 2019 vs. 2020. The figure plots the log of average weekly consumption for commercial units, aligned by calendar week. The dashed line shows 2019 (control) and the solid line 2020 (treated), with week 0 marking the onset of COVID-19 in March 2020.

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.

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

Table 1: Summary Statistics for Weekly Electricity Consumption

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.

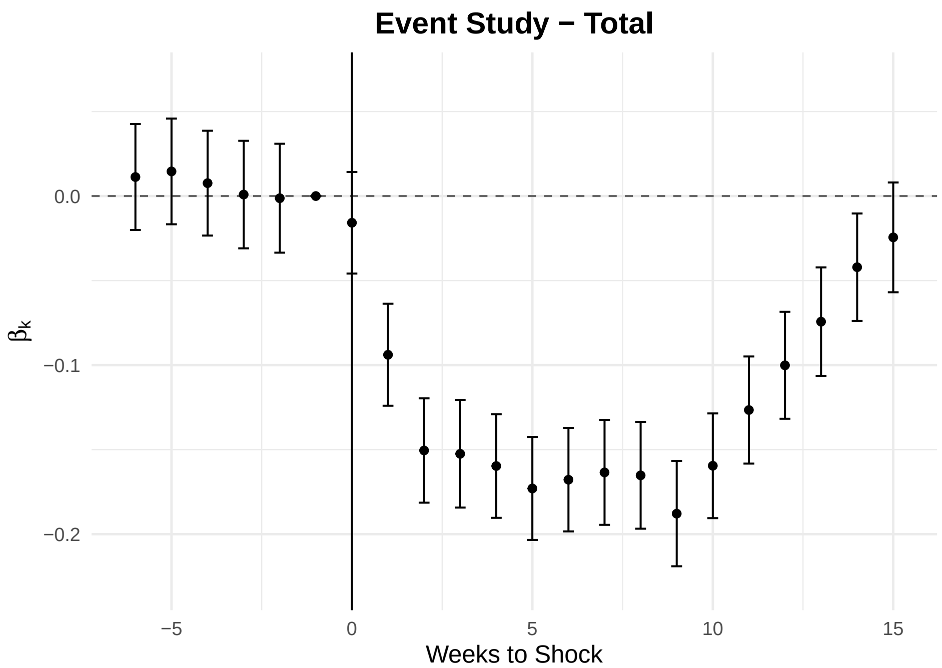

Figure 3: Event-Study estimates of the impact of COVID-19 on total weekly electricity consumption in Tehran. The figure plots coefficients (β_k) from the specification in Section 4, showing deviations in treated units relative to the week immediately preceding the shock ($t = -1$). Pre-treatment coefficients are tightly clustered around zero, supporting the parallel trends assumption. Post-treatment periods show a sharp and persistent decline of roughly 13–19 percent, followed by a slow recovery phase.

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* × *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.

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

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

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

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.

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

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

Table 3: DiD Estimates by Baseline Consumption Intensity

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

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

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

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 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

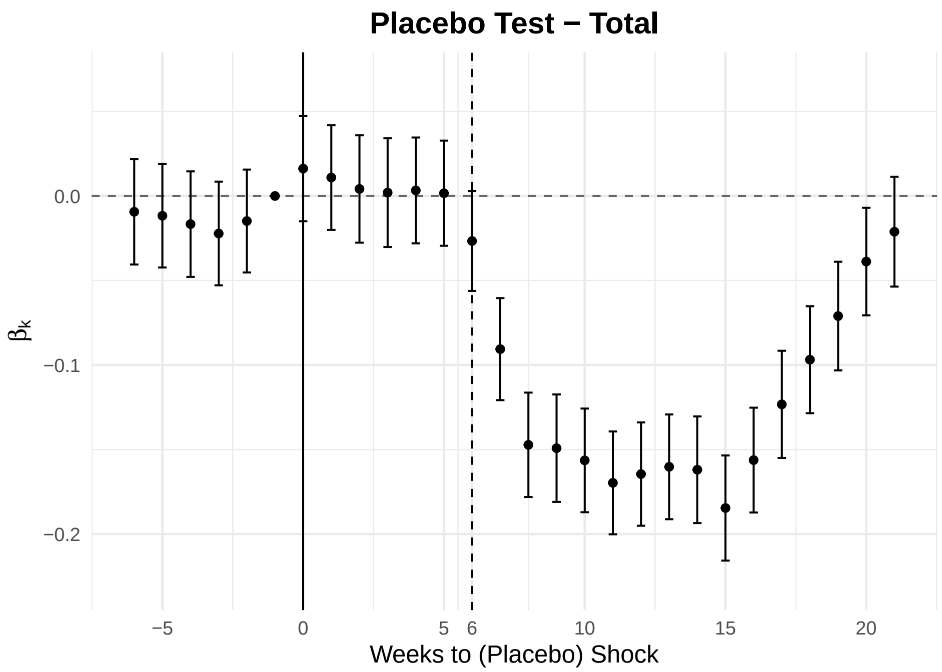

Figure 4: Placebo Event-Study estimates of total weekly electricity consumption in Tehran. The figure plots coefficients (β_k) from the Event-Study specification, where the treatment date is artificially shifted six weeks earlier than the actual onset of COVID-19. The coefficients fluctuate around zero before and after the placebo shock, with no systematic or significant deviations, reinforcing that the main results are not driven by spurious dynamics or arbitrary treatment timing.

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.

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 de-

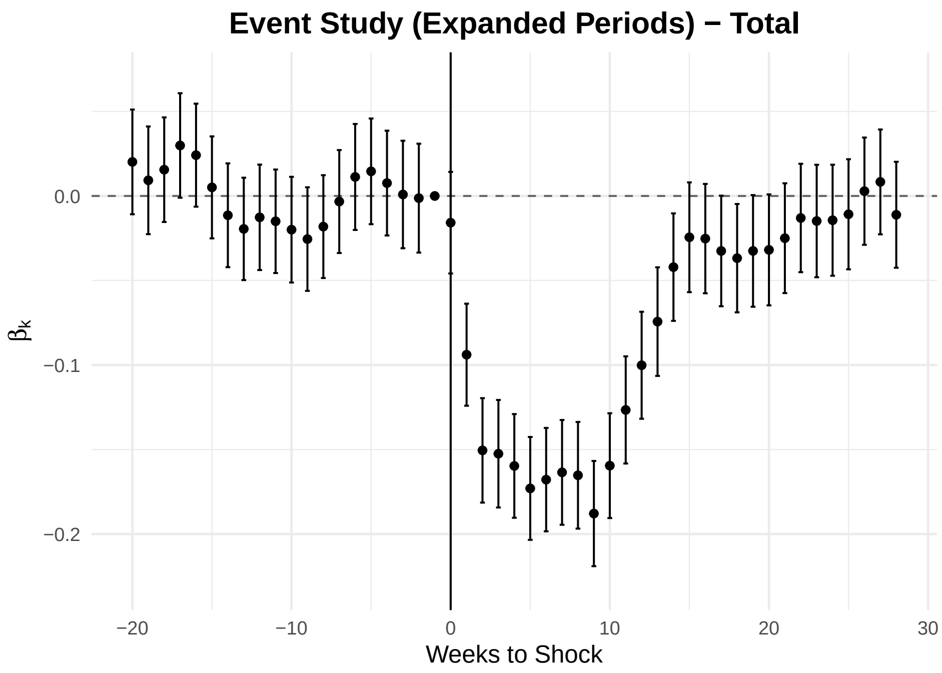

Figure 5: Event-Study estimates of total weekly electricity consumption in Tehran with an expanded time window. The figure plots coefficients (β_k) from the Event-Study specification using a horizon of $[-20, 28]$ weeks around the onset of COVID-19 (week 0). The extended pre-treatment period shows coefficients statistically indistinguishable from zero, reinforcing the parallel trends assumption, while post-treatment periods exhibit a sharp and persistent decline followed by gradual recovery.

mand 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 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.

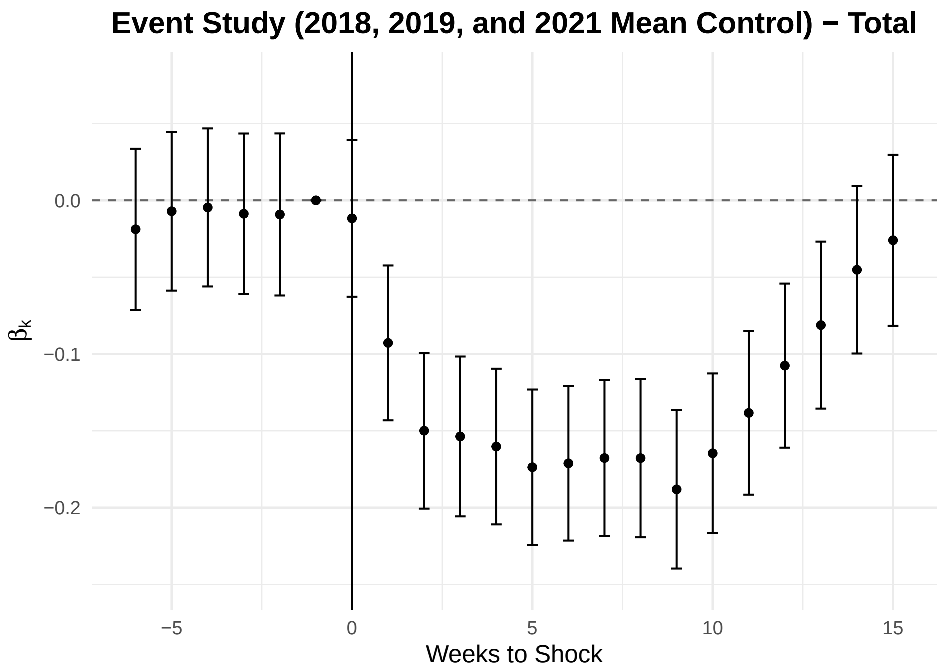

Figure 6: Event-Study estimates of total weekly electricity consumption in Tehran using an alternative counterfactual. The control group is constructed as the mean of 2018, 2019, and 2021 consumption, excluding 2020. Results confirm the robustness of the baseline specification: pre-treatment coefficients are centered around zero, while post-treatment periods exhibit a sharp decline and gradual recovery that closely match the main results.

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.

6 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

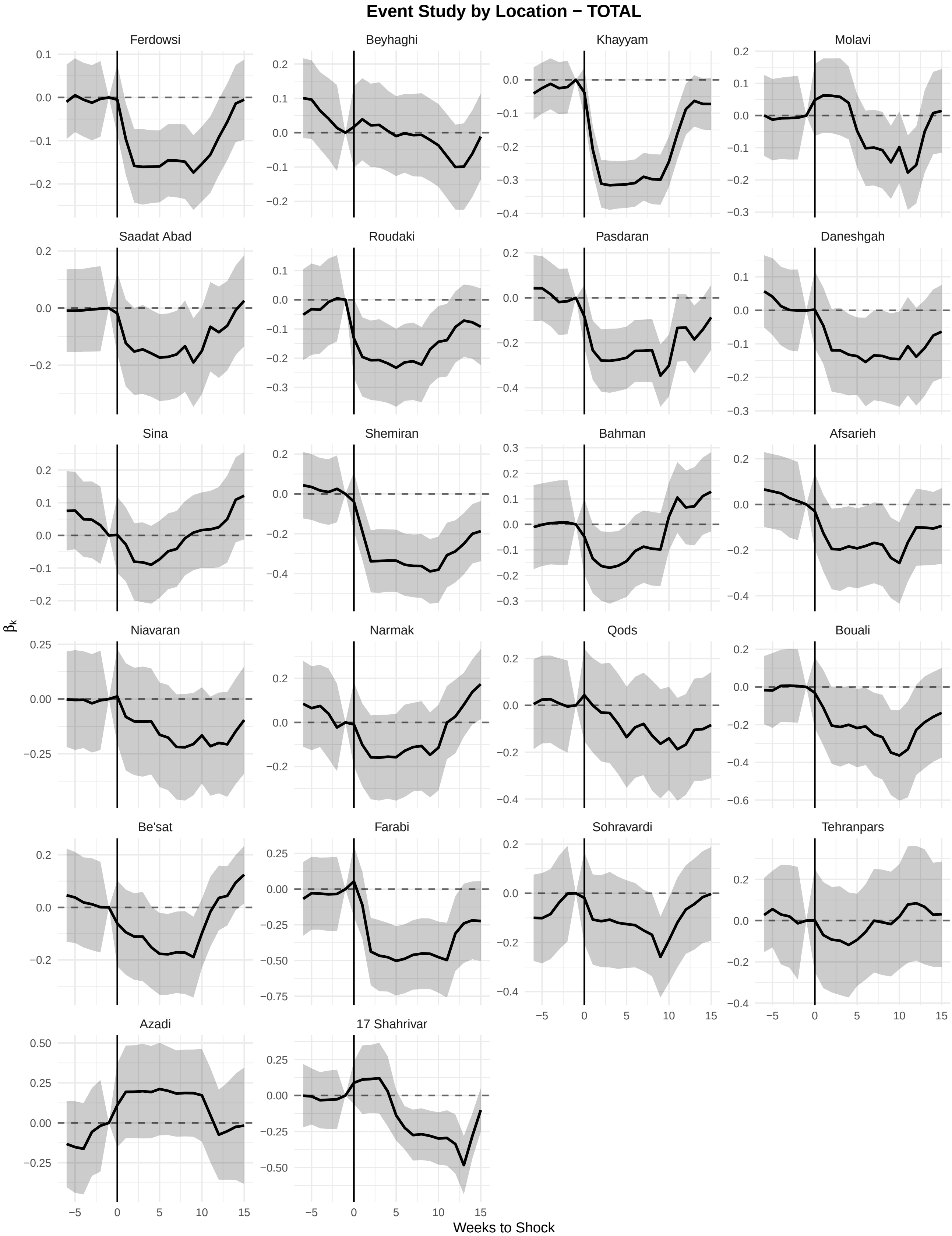

Figure 7: Event-Study for Total Consumption by Location

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 et al. (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.

7 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.

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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.

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)

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

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

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.

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)

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

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

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.

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)

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

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

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.

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)

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

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

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.

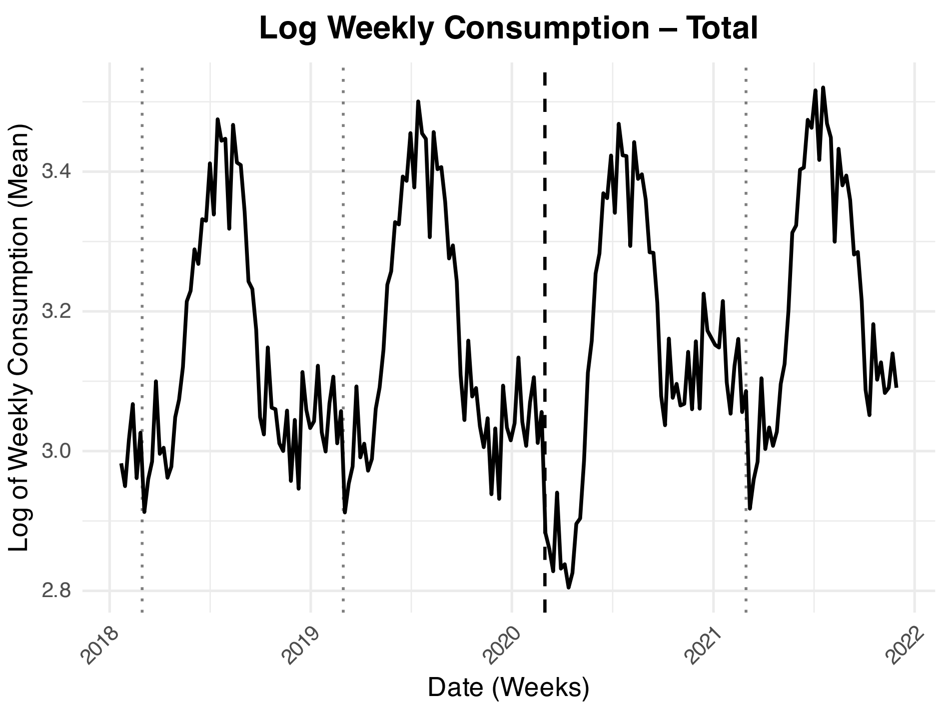

Figure B.1: Weekly total commercial electricity consumption in Tehran, 2018–2021. Seasonal peaks in summer and troughs in winter are evident, with a sharp break in 2020 coinciding with the COVID-19 outbreak.

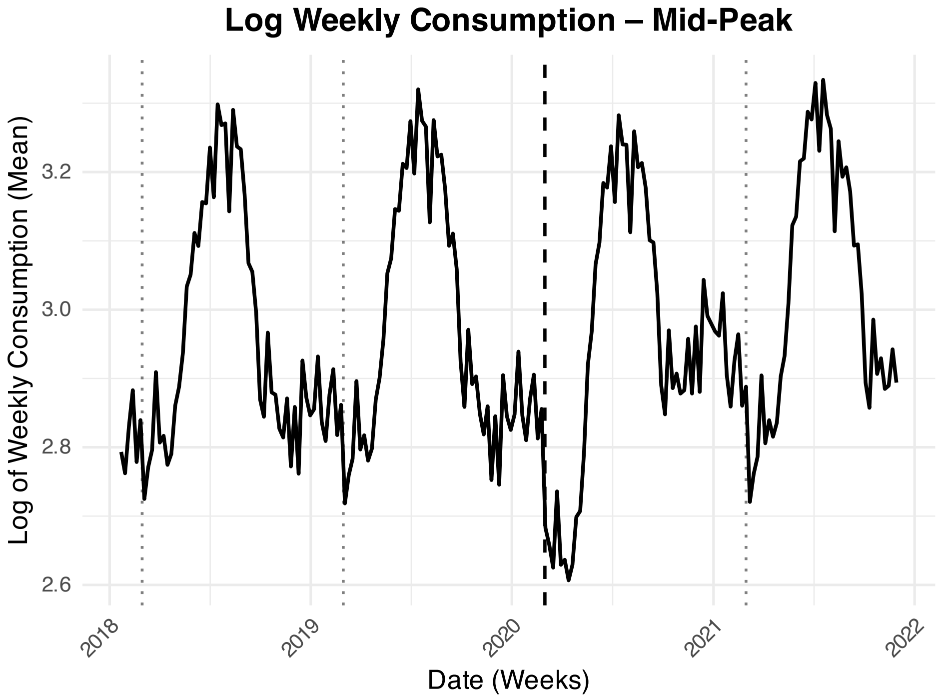

Figure B.2: Weekly mid-peak commercial electricity consumption in Tehran, 2018–2021. Mid-day and early-evening demand shows the steepest contraction in 2020 relative to seasonal norms.

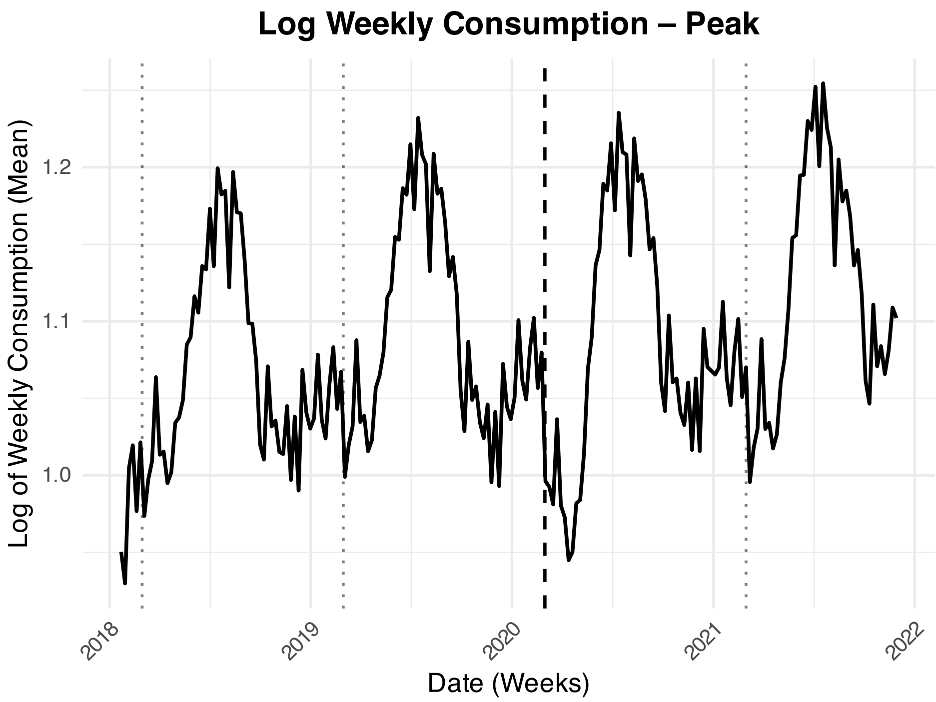

Figure B.3: Weekly peak-hour commercial electricity consumption in Tehran, 2018–2021. Demand falls visibly in 2020, though less sharply than in mid-peak hours.

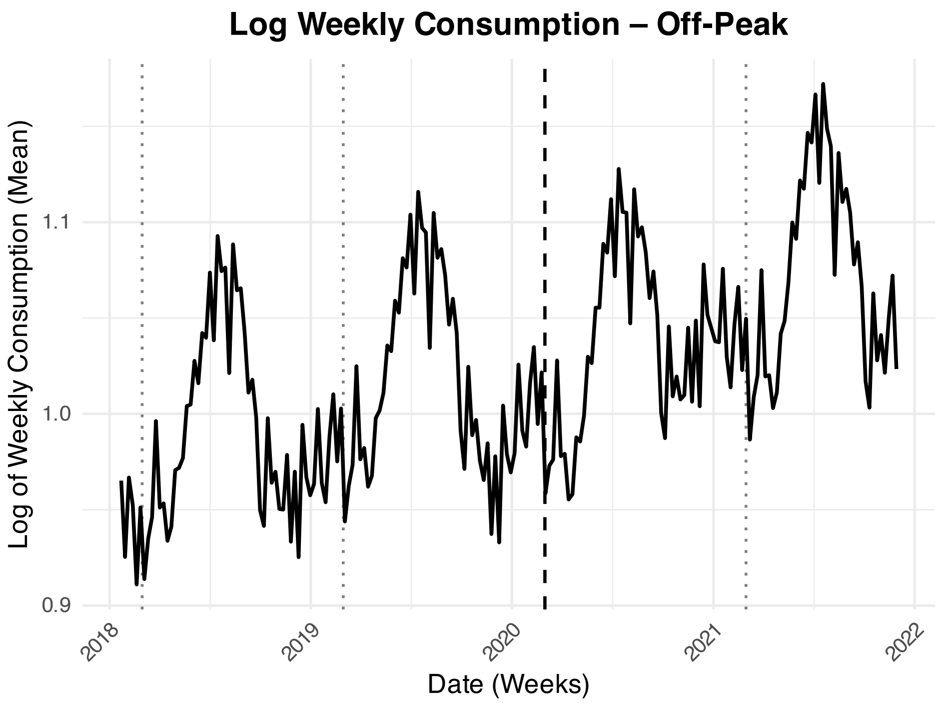

Figure B.4: Weekly off-peak commercial electricity consumption in Tehran, 2018–2021. Night-time demand is relatively stable, with only a modest downturn during the early months of 2020.

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-

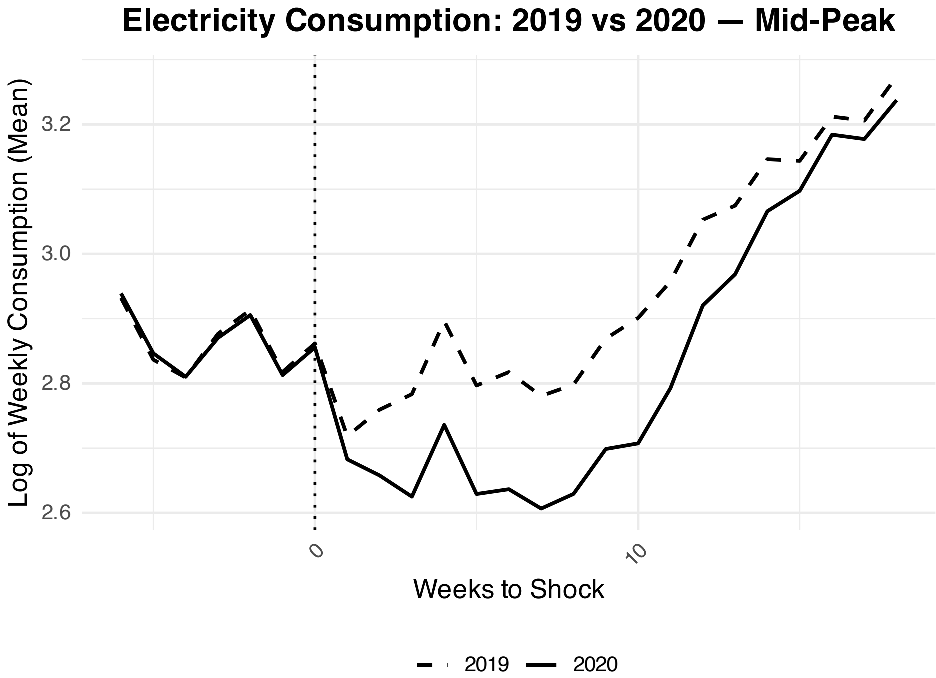

Figure B.5: Weekly mid-peak electricity consumption in 2019 and 2020. Pre-shock paths overlap closely, after which 2020 consumption drops sharply, indicating strong COVID-related contraction during business hours.

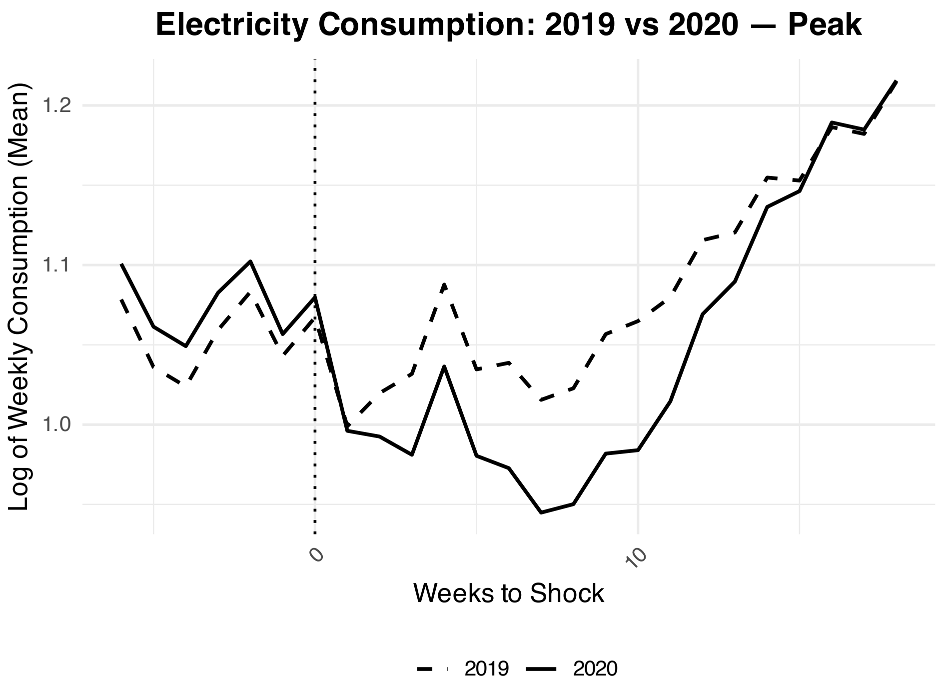

Figure B.6: Weekly peak electricity consumption in 2019 and 2020. Trends are parallel before the shock, validating the identification design. Peak demand contracts in 2020, though less than mid-peak demand.

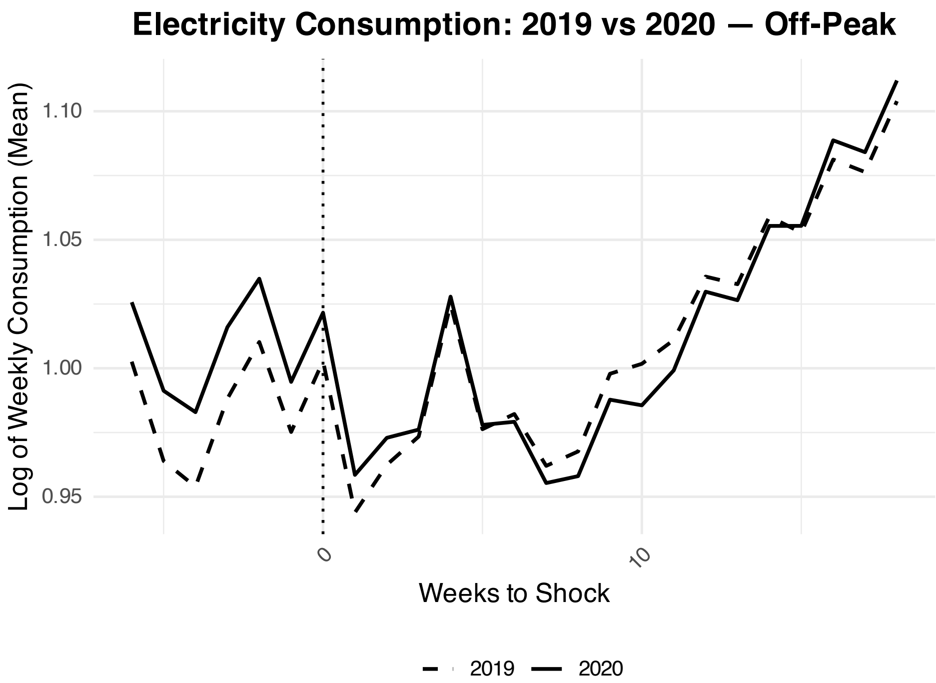

Figure B.7: Weekly off-peak electricity consumption in 2019 and 2020. Differences are modest, reflecting the stability of baseline nighttime usage such as refrigeration and security systems.

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 consumption falls moderately, and off-peak demand is largely unaffected. This robustness check

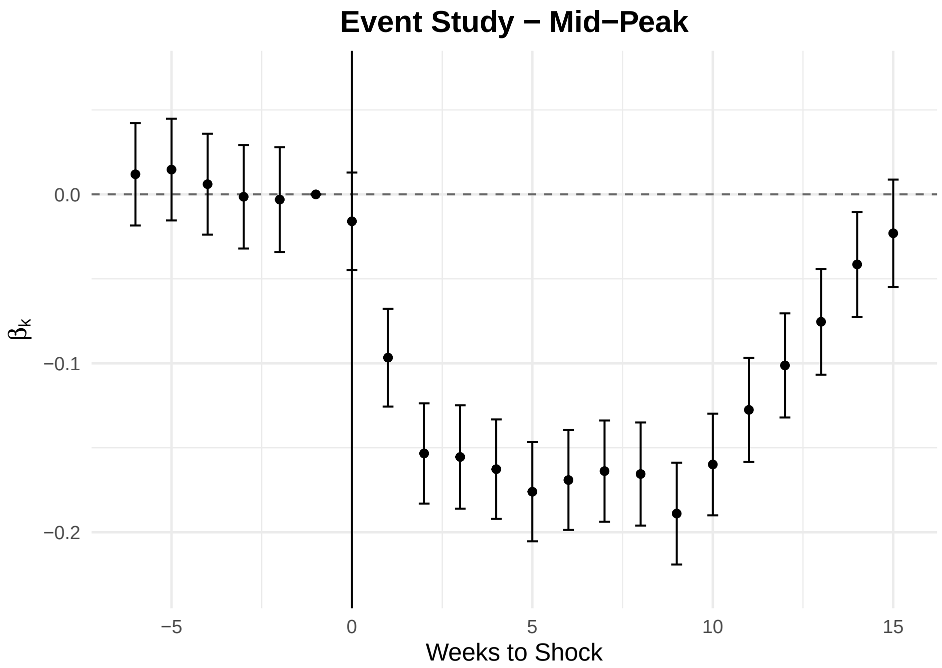

Figure B.8: Event-study estimates of mid-peak electricity consumption. A sharp contraction is observed after week 0, with losses approaching 20% at the trough.

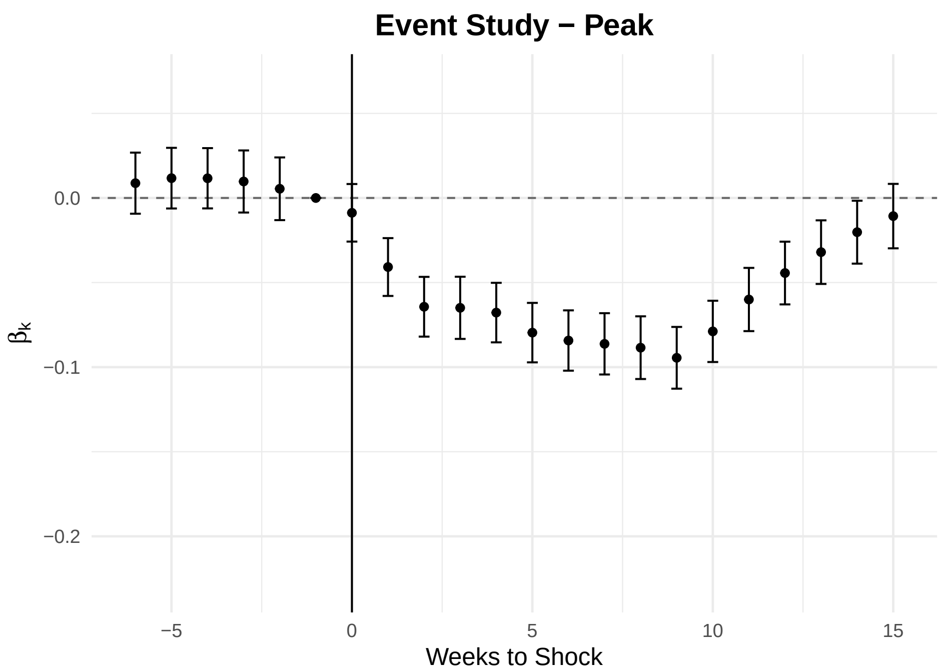

Figure B.9: Event-study estimates of peak electricity consumption. Declines are more moderate than mid-peak, indicating partial resilience in essential evening activities.

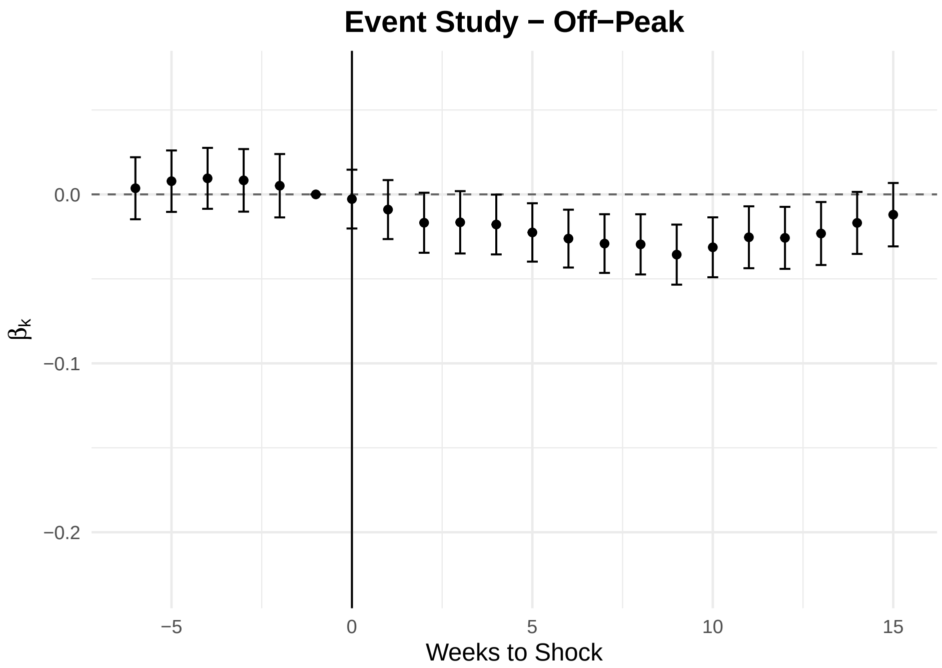

Figure B.10: Event-study estimates of off-peak electricity consumption. Coefficients remain close to zero, reflecting stable baseline nighttime usage.

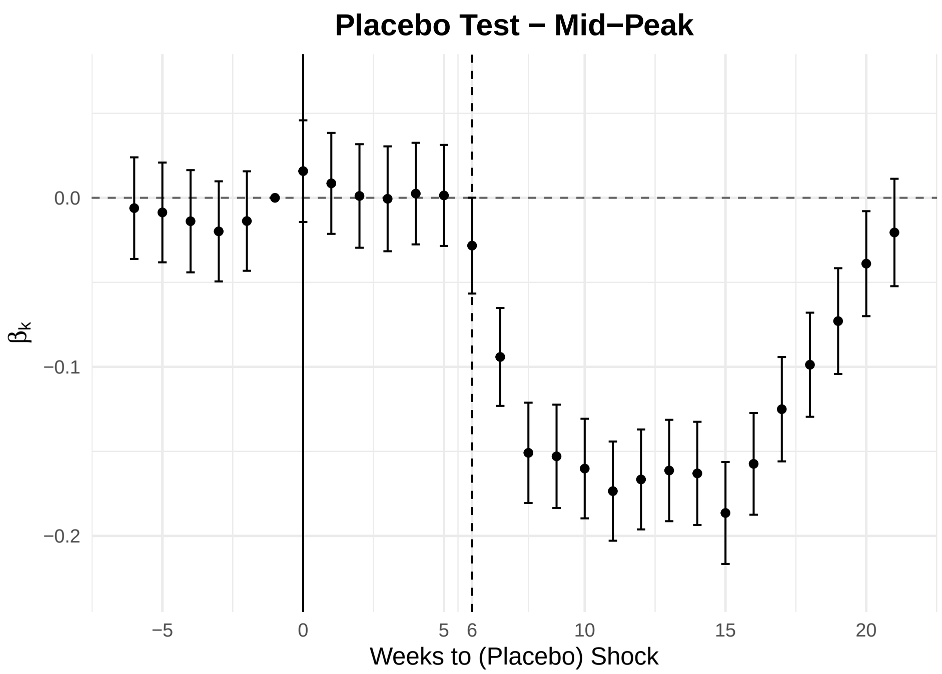

Figure B.11: Placebo test for mid-peak electricity consumption. No systematic post-placebo effect is visible.

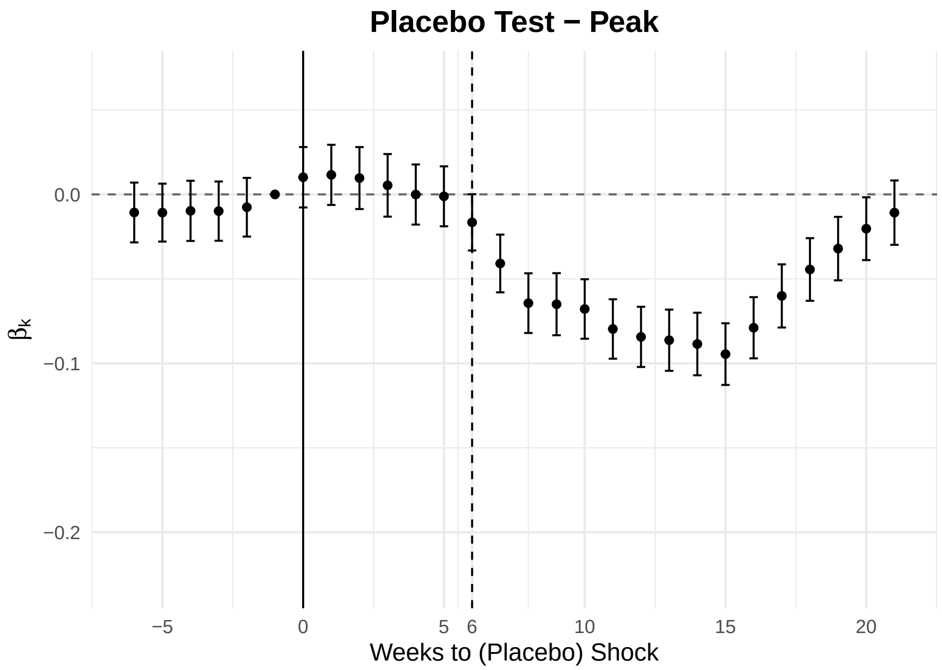

Figure B.12: Placebo test for peak electricity consumption. Estimated coefficients remain close to zero.

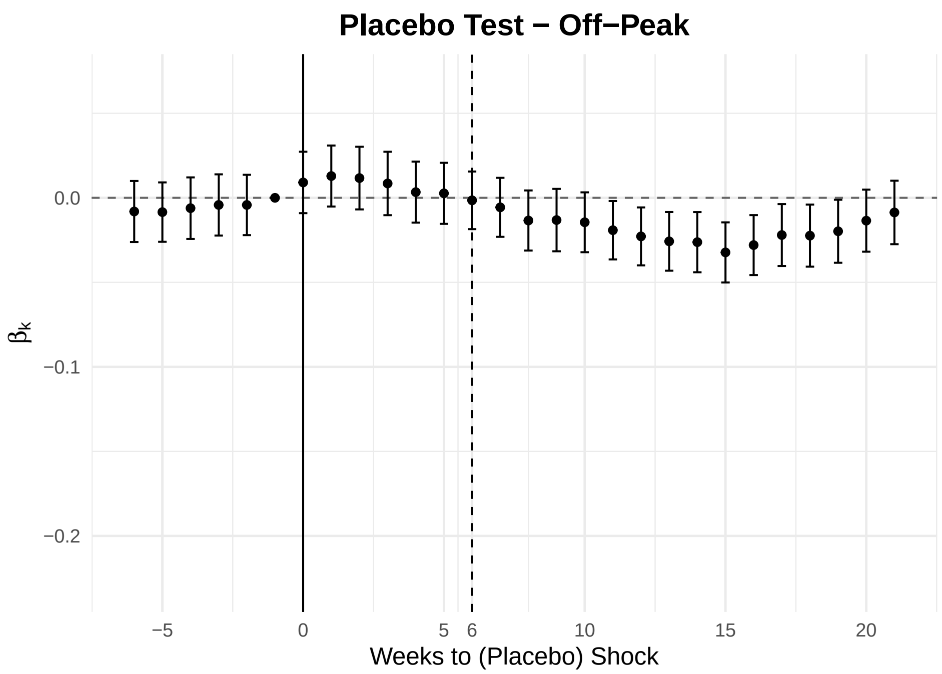

Figure B.13: Placebo test for off-peak electricity consumption. Results are null, consistent with the validity of the identification strategy.

shows that the baseline results are not an artifact of the narrower window choice.

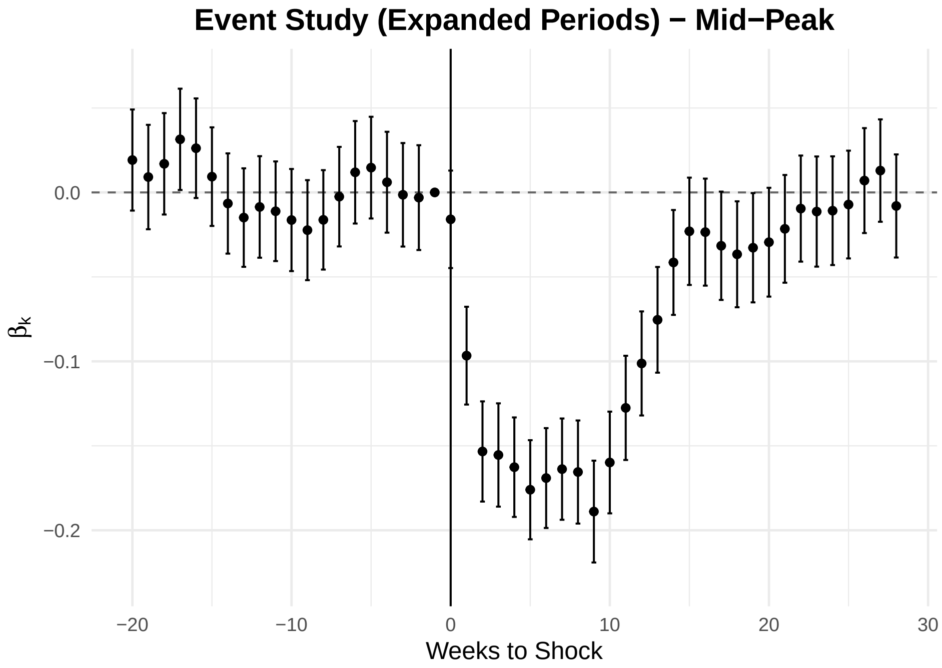

Figure B.14: Event-study estimates for mid-peak consumption using an extended estimation window. Results are consistent with the main specification.

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 consumption drops sharply in the weeks immediately following the COVID-19 shock, with recovery

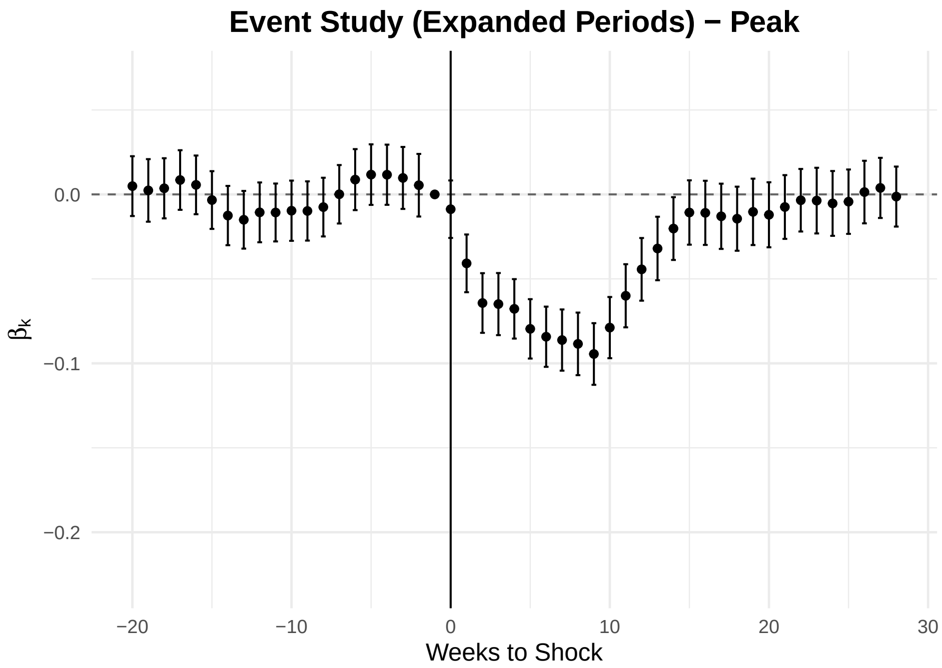

Figure B.15: Event-study estimates for peak consumption using an extended window. Declines are moderate and robust across specifications.

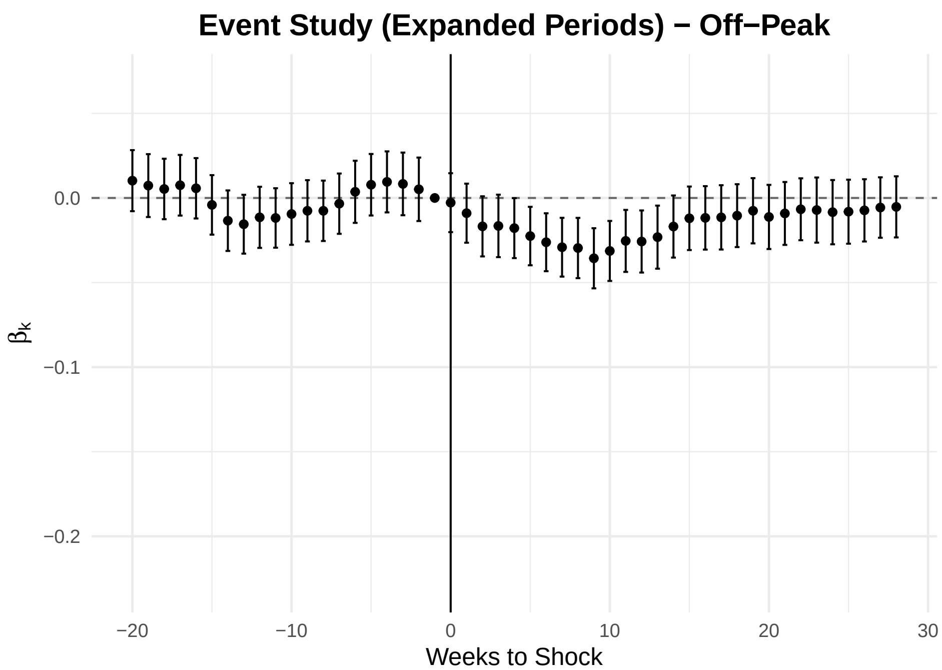

Figure B.16: Event-study estimates for off-peak consumption using an extended window. Demand remains stable.

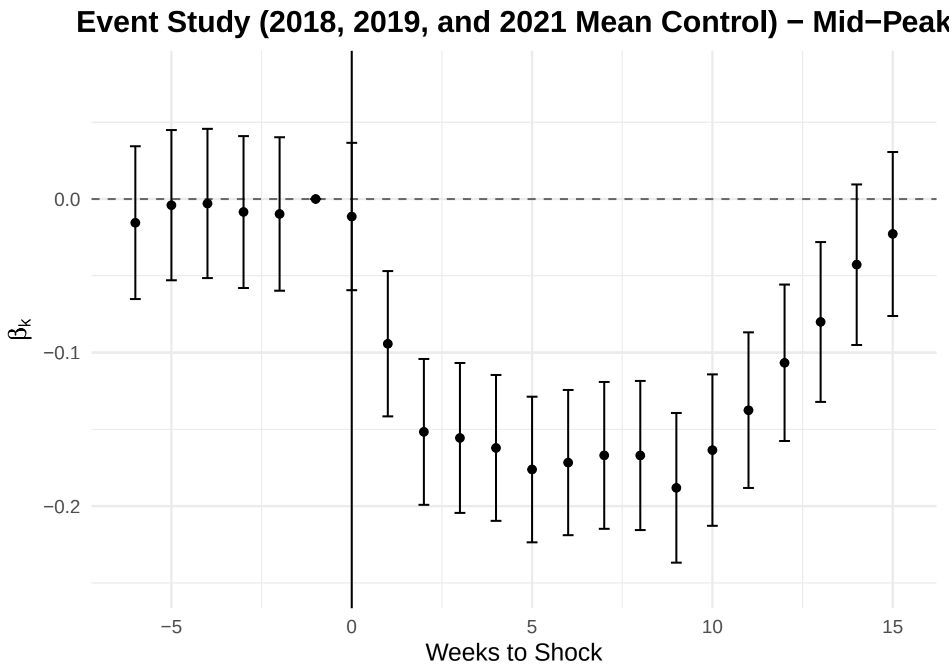

Figure B.17: Event-study for mid-peak consumption using an alternative counterfactual (mean of 2018, 2019, and 2021). Results closely track the baseline estimates.

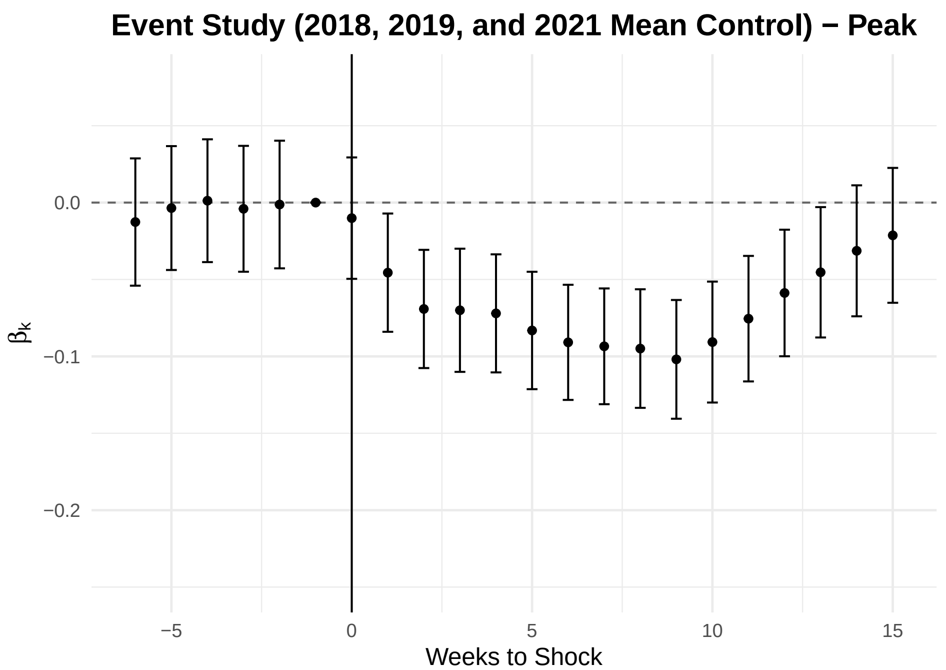

Figure B.18: Event-study for peak consumption with alternative counterfactual. Declines remain consistent in timing and magnitude.

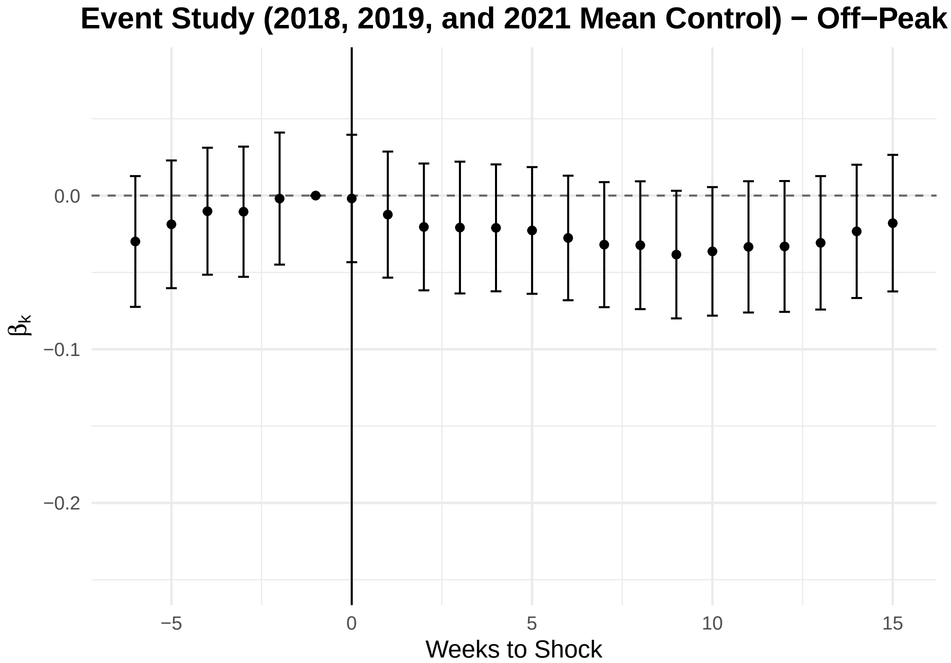

Figure B.19: Event-study for off-peak consumption with alternative counterfactual. No significant deviations are observed, confirming stability in baseline nighttime demand.

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.

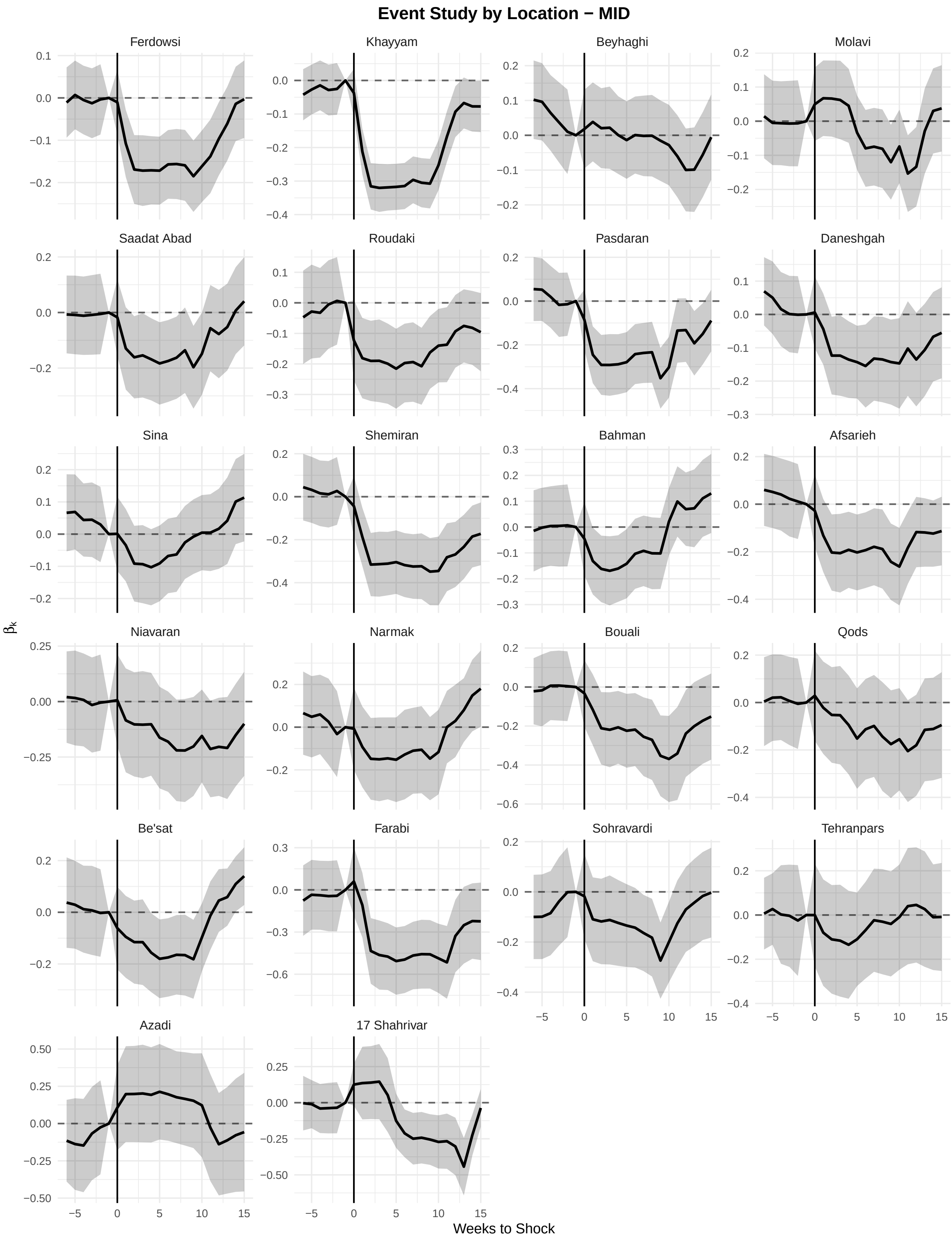

Figure B.20: Event-Study for mid-peak consumption by location

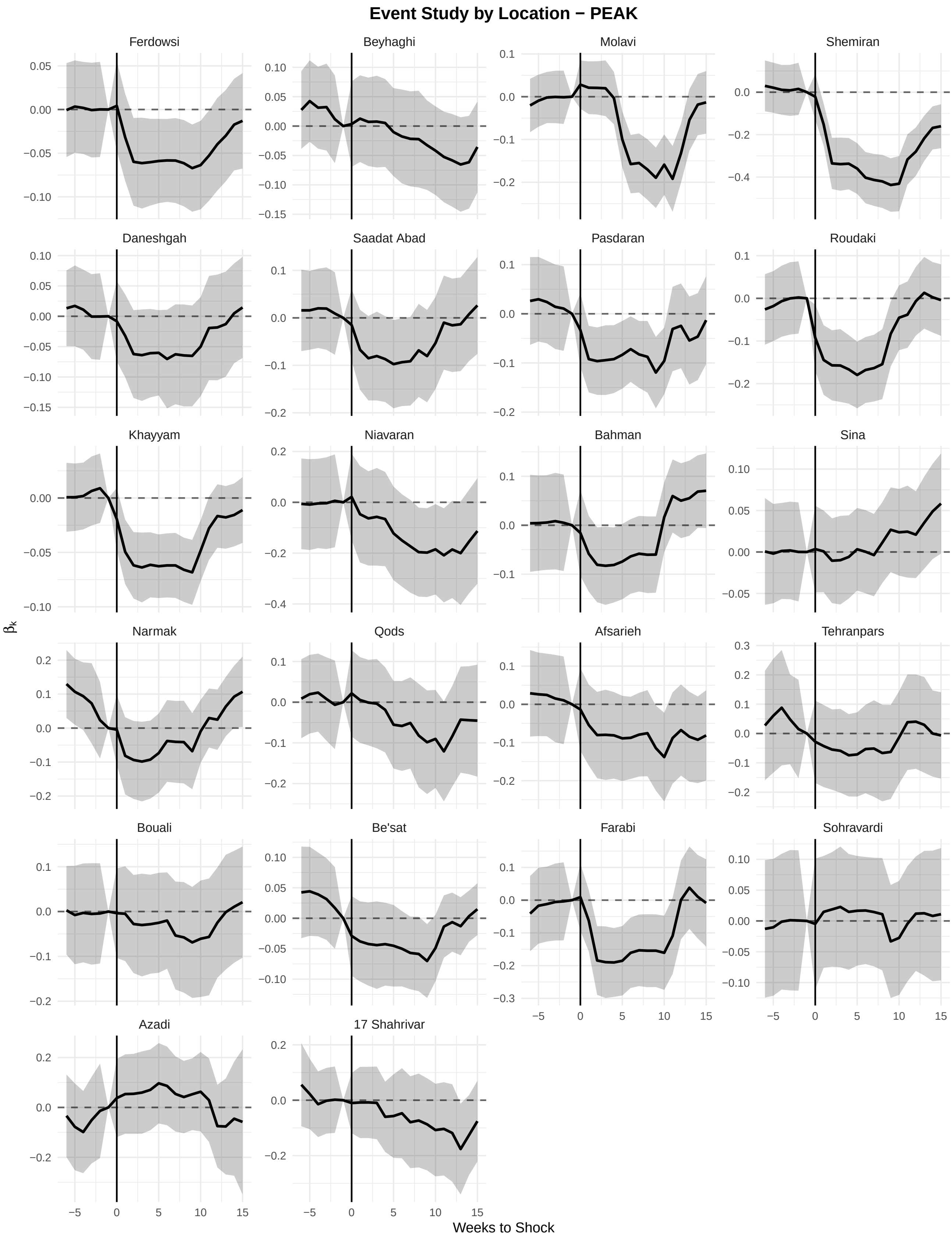

Figure B.21: Event-Study for peak consumption by location

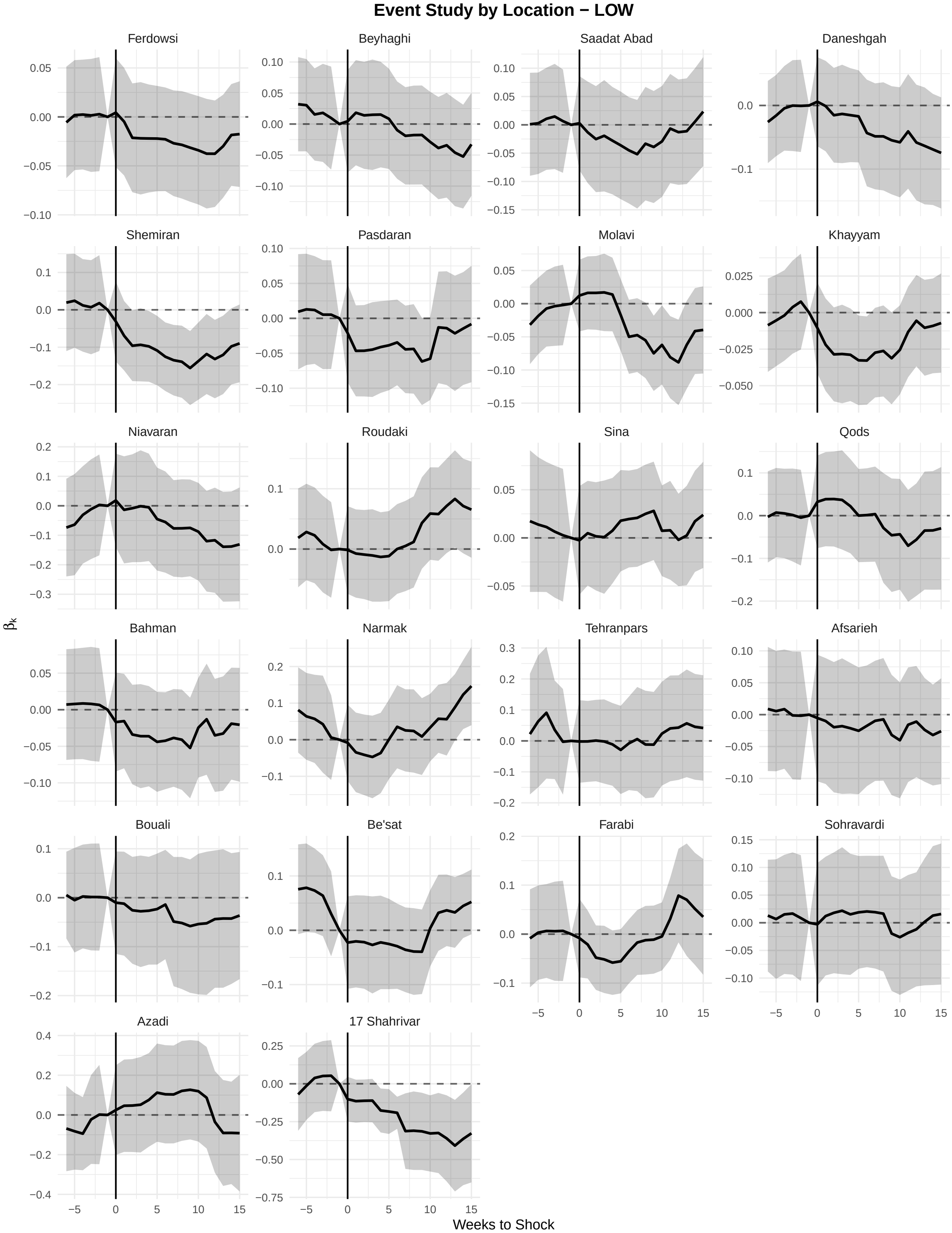

Figure B.22: Event-Study for off-peak consumption by location