TGIF: A Quasi-Experimental Analysis of Pre-Weekend Productivity

Yonggeun Jung*

This paper investigates the pre-weekend decline in productivity by leveraging a unique quasi-experiment: the United Arab Emirates' (UAE) 2022 weekend shift from Friday-Saturday to Saturday-Sunday. Using a difference-in-differences (DiD) framework, we analyze high-frequency proxies for work-related attentiveness, including a novel Google Trends index and Dubai's financial market volume. We show that the engagement dip did not vanish but shifted from Thursday to Friday in line with the new weekend. This causal evidence demonstrates that the decline arises from the day's status as the pre-weekend. The findings, confirmed through robust placebo and bootstrap tests, suggest that the workweek's structure itself drives end-of-week behavior and offer implications for alternative work schedule policies.

JEL Classification: J22, D91, M54
Keywords: Quasi-Experiment, Difference-in-Differences, Google Trends, Productivity
DOI: 10.23299/bokeri.2025.31.3.002

* Ph.D. Student in Economics. Department of Economics, University of Florida, PO Box 117140, Gainesville, Florida, USA, 32611. (E-mail: yonggeun.jung@ufl.edu, Tel: +1-352-709-3510)

I sincerely thank the editor and the anonymous referees for their insightful comments and constructive suggestions. I am also grateful to Sooji Kim and Chenhui Lu for their valuable feedback and helpful suggestions. All remaining errors are my own. The replication package is available at https://www.dropbox.com/scl/fo/ea8n7u3i24sa83kaalype/AHQmSR6f-JGAKQlu82M7thc?rlkey=gvyofz4drk7x1ntwpwf5754eo&st=pou84ty7&dl=0.

Received: 7 July 2025, Received in revised form: 9 August 2025, Accepted: 30 September 2025.

I. Introduction

Are people truly productive on Friday afternoons, as the weekend approaches? While it is intuitively plausible that anticipation of the weekend dampens focus and efficiency, empirically verifying this effect has been challenging due to the lack of high-frequency measures of labor productivity. Yet as discussions around AI and the future of work —including the possibility of shorter workweeks—gain momentum, understanding the temporal patterns of human productivity has become increasingly important. A unique opportunity to investigate this question arose in the United Arab Emirates (UAE), which shifted its official weekend from Friday-Saturday to Saturday-Sunday in January 2022 (Omar and Cranny, 2021).[1] This policy change provides a quasi-experimental setting to test whether productivity on Fridays is systematically lower. Leveraging this natural experiment, we examine behavioral and market-level indicators using high-frequency, publicly available proxies—namely, daily Google search trends and financial market activity—to assess whether a measurable drop in productivity indeed occurs as the weekend approaches.

Prior research shows that worker performance can vary across the week. Elsheikh et al. (2010) document day-of-week and time-of-day fluctuations in screening accuracy among cytotechnologists, with performance often declining on Mondays, Fridays, and in the afternoon. Roh et al. (2023) use computer usage data from a Texas firm to show

1) In November 2021, the UAE government announced that effective January 1, 2022, the public sector weekend would shift from Friday-Saturday to Saturday-Sunday to align with international standards. Additionally, Friday working hours for the public sector were changed to mornings only. While the private sector was not obligated to follow suit, it was anticipated that many sectors would adopt the revised standards following the government's change. However, although the stock market's operating week shifted from Sunday-Thursday to Monday-Friday, its operating hours remained unchanged. Notably, Sharjah, one of the UAE's emirates, also announced the implementation of a 4-day workweek. The financial data used in this study is based on Dubai, while the Google Trends data covers the entire UAE. This will be discussed in further detail later in the main text.

that employees type fewer words and make more typos on Fridays. While these studies offer compelling evidence at the micro level, the underlying mechanisms for this "Weekend Eve Effect" are debated. One explanation is cumulative fatigue, where self-regulation is viewed as a limited resource that becomes depleted over the course of a workweek, reducing effort on the final day (Baumeister et al., 2018). An alternative, complementary view is temporal motivation theory, which posits that motivation is a function of the proximity of a reward; as the weekend approaches, its perceived value increases dramatically, diminishing the relative motivation to continue working (Steel and König, 2006). A third perspective points to organizational slack, suggesting that workplace norms and managerial leniency may informally permit reduced output as the week concludes (Dalton and Mesch, 1990). Our study's design, which observes whether the productivity dip shifts in alignment with a new weekend structure, is particularly well-suited to test theories anchored in temporal framing, such as temporal motivation.

This study connects these behavioral observations to core principles in economics. The observed pre-weekend decline in work-related attention is a real-world manifestation of temporal discounting and present bias—foundational concepts in behavioral economics where immediate rewards (leisure) are valued disproportionately more than delayed ones (work-related accomplishments). While often demonstrated in experimental settings, our research provides rare, national-scale causal evidence of these principles shaping economic behavior in response to an institutional shock. Furthermore, our findings contribute to labor economics. While prior economic research has established a link between longer working hours and declining marginal productivity (Hamermesh, 1996; Pencavel, 2015), our study shifts the focus to intra-week variations. We illustrate how the structure of the workweek, a critical non-pecuniary job characteristic, directly influences work effort on a daily basis. This has direct implications for policy discussions surrounding alternative work schedules, such as the four-day workweek, by showing that productivity dynamics are strongly anchored to the perceived end of the work cycle.

It is indeed difficult to obtain daily labor productivity data at the national level for most countries. In the case of the UAE, despite the availability of some economic indicators, access to high-frequency, high-quality national-level data remains limited, making it challenging to identify credible proxies.[2] Therefore, this study constructs plausible proxy measures by combining several data sources: (i) Google Trends,[3] from which we extract daily search activity for work- and leisure-related terms to construct a composite search index; and (ii) financial market activity in Dubai.

We conduct a difference-in-differences (DiD) analysis using one year of data before and after the UAE's weekend shift on January 1, 2022. This allows us to test whether productivity proxies systematically decline on days preceding the weekend, relative to other weekdays. Assuming parallel patterns across 2021 and 2022—we control for potential biases by including a range of fixed effects and control variables. Moreover, to assess the robustness of our findings, we implement placebo tests using symmetric windows in 2020-2021 and 2022-2023, as well as bootstrap procedures.

Our analysis reveals a statistically significant shift in pre-weekend behavior following the policy change. The composite Google Trends index, which measures the relative search volume of work-related terms versus leisure-related terms, shows a distinct drop on Fridays after the reform, a pattern previously observed on Thursdays. Similarly, the trading volume on the Dubai Financial Market (DFMGI) exhibits a corresponding decline on the new pre-weekend day. These results

2) While daily electricity usage, traffic, or port activity data could potentially serve as proxies, the author was unable to find publicly available sources for such datasets in the UAE.

3) Choi and Varian (2012) is a pioneering study demonstrating the use of Google Trends as a variable in empirical economic research. Subsequent studies have applied similar methods across a range of contexts. See Cebrián and Domenech (2023), Eichenauer et al. (2022), and Woloszko (2020).

are robust to the inclusion of various control variables, such as global financial indicators and local economic activity proxies, and are further validated by bootstrap procedures and placebo tests. This confirms that the observed weekend eve effect in attentiveness is not an artifact of our data but a behavioral pattern that realigned with the new workweek structure.

This paper contributes to the literature in several ways. First, it provides rare, national-scale empirical evidence for day-of-the-week variations in work-related attentiveness, a phenomenon often discussed but seldom quantified at a macro level. While national contexts differ, the findings can serve as an important reference point—and a potential starting point for new research—amid ongoing debates in Korea over reduced working hours and the adoption of a four-day workweek. Second, by leveraging a unique quasi-experimental setting, we offer a causal interpretation of the pre-weekend productivity dip, demonstrating how it is anchored to the structure of the workweek itself. Third, we demonstrate the utility of high-frequency, publicly available data—namely Google Trends and financial market activity—as credible proxies for tracking national-level economic and behavioral patterns, which is particularly valuable in contexts where official data is sparse. Finally, our findings inform the ongoing global discourse on alternative work schedules, such as the four-day workweek, by highlighting the powerful influence of temporal framing on worker behavior.

The remainder of this paper is organized as follows. Section 2 describes the data sources and preliminary analysis to understand data construction and characteristics. Section 3 provides institutional background and details the empirical methodology. Section 4 presents the main estimation results, along with a series of robustness checks, including bootstrap and placebo tests. Section 5 concludes with a discussion of its limitations and policy implications.

Ⅱ. Data

1. Data Description

This section describes the construction of our main variables and controls. Table 2 reports the summary statistics for all variables except for dummy variables used in the analysis. All data are collected for the period from January 1, 2020 to December 31, 2023. For our main DiD analysis, we focus on the years 2021-2022, which span the weekend reform, while the 2020-2021 and 2022-2023 periods are used for placebo tests to assess the robustness of the results. Observations corresponding to weekends and public holidays are excluded. Additional details on the data are also provided in the Appendix A.

Google Trends. We randomly select 20 work-related and 20 leisure-related keywords, as shown in Table 1,[4] and retrieve their daily search volumes in the UAE from Google Trends.[5] Google Trends provides relative search volumes for up to five keywords per query over a selected time window, normalizing each request so that the most frequently searched term within that request is scaled to 100. When the selected period exceeds six months, Google Trends returns weekly—rather than daily—data. Since our analysis requires daily resolution, we divide the 40 keywords into sets of four and collect data in consecutive six-month intervals from January 2020 to December 2023.

A key technical challenge is that normalization is performed separately for each request, making values from different requests not

4) To minimize arbitrary interpretation, all keywords were assigned equal weights when aggregated. However, since Google provides data for only up to five keywords per request and reports search volumes relative to the most popular term within that set, the reported values for a given keyword may vary slightly depending on the set in which it appears. We therefore group keywords in sets of four—two work-related and two leisure-related—and made all codes and procedures publicly available in the replication package.

5) See https://trends.google.com/trends/.

〈Table 1〉 Keywords Used for Google Trends Extraction

Work-related				Leisure-related			
1	Meeting	11	PowerPoint	1	Brunch	11	Movie
2	Exchange rate	12	Research	2	Gym	12	Hotel
3	Email	13	Outlook	3	Weekend	13	Cinema
4	Industry	14	Function	4	Beach	14	Vacation
5	Report	15	Microsoft	5	Holiday	15	Music
6	Teams	16	Finance	6	Park	16	Mall
7	Presentation	17	Data	7	Party	17	Game
8	Zoom	18	Project	8	Travel	18	Restaurant
9	Excel	19	Pivot	9	Concert	19	Sport
10	Analysis	20	Template	10	Flight	20	Shopping

Note: Daily Google searches in the UAE, January 2020–December 2023 (including the placebo test period). Work- and leisure-related keywords were randomly selected by the authors, and equal weights were assigned to all keywords to minimize arbitrary interpretation.

directly comparable. To address this, we use the weekly series (available when querying a period longer than six months) as a common reference scale. For each keyword and month, we compute the ratio of its weekly average to its daily average, and multiply the daily values by this ratio to align them to the common scale. We then construct the daily index by summing the rescaled work-related terms and subtracting the rescaled leisure-related terms, yielding a consistent daily measure across the entire sample period.

Specifically, we build the daily Google Trends index for the UAE in four steps:

(i) **Keyword set**: Use the 20 work-related and 20 leisure-related terms in Table 1, and retrieve daily country-level search interest for January 2020-December 2023. Google Trends normalizes each request to a 0-100 scale relative to the most popular term in that request.

(ii) **Retrieval strategy**: Because Google Trends returns weekly data for windows longer than six months and normalizes within each request, we pull data in six-month windows and in batches of four keywords per request to retain daily frequency and control normalization.6)

(iii) **Stitching (scaling across requests)**:7) We align segments using overlapping weekly series as a benchmark. Let $D_{k,m}$ denote the daily search volume for keyword k in month m, with monthly average:

$$\overline{D_{k,m}} = \frac{1}{|T_m|} \sum_{t \in T_m} D_{k,t}, \tag{1}$$

where T_m is the set of days in month m.

Let $W_{k,m}$ denote the weekly search volume, with monthly average:

$$\overline{W_{k,m}} = \frac{1}{|W_m|} \sum_{w \in W_m} W_{k,w}, \tag{2}$$

where W_m is the set of weeks overlapping month m. The scale factor is:

$$S_{k,m} = \frac{\overline{W_{k,m}}}{\overline{D_{k,m}}}, \tag{3}$$

and each daily observation is rescaled as:

$$V_{k,t} = S_{k,m} \cdot D_{k,t}, \quad t \in T_{m}. \tag{4}$$

(iv) **Composite index**: For each day t,

$$GoogleTrends_t = \sum_{\mathrm{k} \in \mathcal{W}} \mathrm{V}_{\mathrm{k,t}} - \sum_{\mathrm{k} \in \mathcal{L}} \mathrm{V}_{\mathrm{k,t}}, \tag{5}$$

where $\mathcal{W}$ and $\mathcal{L}$ are the sets of work- and leisure-related terms, respectively.

This index, by construction, reflects the relative emphasis on work versus leisure,8) and thus serves as a proxy for workers' daily interest in work or level of attentiveness.9)

---

6) The Python script to retrieve the Google Trends data is available at https://www.dropbox.com/scl/fo/ea8n7u3i24sa83kaalype/AHQmSR6f-JGAKQlu82M7thc?rlkey=gvyofz4drk7x1ntwpwf5754eo&st=pou84ty7&dl=0.

7) This process is replicated in the file 'Google_trends_generating_index.xlsx' included in the replication package. Interested readers may refer to the file for details on the function structure and implementation.

8) Analyses based on indices composed solely of work-related or leisure-related keywords are presented in Appendix B.

9) Further details on API-based data collection are provided in Appendix A.

Dubai Financial Market. A key advantage of financial market data is its daily availability. We use the trading volume of the Dubai Financial Market General Index (DFMGI) as one of our proxies. While prices and trading volume are generally correlated, prices tend to be more sensitive to various external shocks. In contrast, trading volume may better capture patterns related to workers' attentiveness or engagement during working hours. While trading volume has the advantage of reflecting market participants' attentiveness and activity, the decline in volume on specific days such as Fridays may also stem from financial motives —for instance, risk-averse investors' preference to close positions before the weekend—rather than from reduced productivity alone (Kiymaz and Berument, 2003). Therefore, caution is warranted when interpreting trading volume as a proxy, and it should be regarded as a complementary indicator.[10)]

Control Variables. To address potential concerns about the parallel trends assumption, we include control variables such as the S&P 500 index, Crude Oil West Texas Intermediate (WTI) prices, and nighttime lights (NTL). Alfreedi (2019), Alotaibi and Mishra (2015), and Hammoudeh et al. (2009) show that the US stock market has spillover effects on Middle Eastern markets, including the UAE. Moreover, oil plays a critical role in the UAE economy.[11)] Recent studies also recognize NTL as a valid proxy for economic activity in emerging markets (K. Chen et al., 2025; X. Chen and Nordhaus, 2011; Donaldson and Storeygard, 2016; Elvidge et al., 1997; Jung, 2025; Pinkovskiy and Sala-i-Martin, 2016). Accordingly, we use NTL as a control variable in our

10) However, our DiD design in Section 3 does not rely on the absolute level of trading volume. Rather, it exploits the shift in its end-of-week pattern. By examining whether the decline in trading volume moves from Thursday to Friday in line with the weekend change, we can isolate the behavioral component tied to the workweek's structure. In this sense, trading volume remains a valid proxy for shifts in collective market engagement, even if its absolute level may be driven by financial motives.

11) Given the one-day time lag between the US and UAE markets, we use lagged values of the S&P 500 and Crude Oil WTI.

regressions. In addition, we control for other confounding factors such as pre-holiday effects, Ramadan,[12] week-of-year, month, and year fixed effects.

Except for the Google Trends index, which contains negative values, all variables are log-transformed. Additional details on data collection and preprocessing are provided in Appendix A.[13]

〈Table 2〉 Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Time Window For Main Regression: 2021-2022					
Google Trends	480	-205.348	81.936	-450.730	95.524
DFMGI (log)	480	4.780	0.597	3.315	7.039
Crude Oil (log)	480	4.394	0.202	3.924	4.808
S&P 500 (log)	480	8.337	0.073	8.182	8.476
NTL (log)	480	13.443	0.807	3.543	14.078
Time Window For Placebo Test1: 2020-2021					
Google Trends	480	-154.661	120.803	-490.302	207.863
DFMGI (log)	480	5.040	0.663	3.298	7.039
Crude Oil (log)	480	3.972	0.327	2.948	4.414
S&P 500 (log)	480	8.212	0.169	7.713	8.475
NTL (log)	480	13.381	0.639	7.992	13.935
Time Window For Placebo Test2: 2022-2023					
Google Trends	481	-226.491	76.243	-481.936	-29.727
DFMGI (log)	481	4.847	0.523	3.446	6.900
Crude Oil (log)	481	4.482	0.124	4.281	4.808
S&P 500 (log)	481	8.338	0.067	8.182	8.476
NTL (log)	481	13.405	0.948	3.543	14.078

Notes: DFMGI denotes the Dubai Financial Market General Index's trading volume. NTL stands for Nighttime Light intensity. Google Trends is the difference between work-related and leisure-related search volume indices. All logs are natural logs.

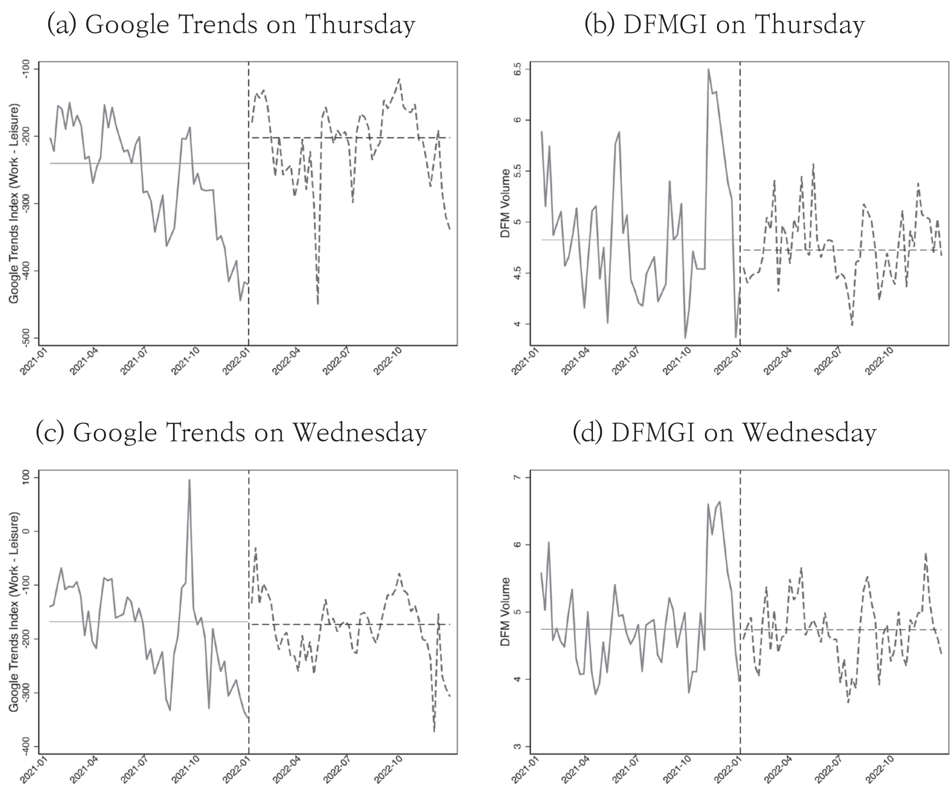
12) Ramadan is a month-long religious observance in Islam that typically affects working hours and business activity in Muslim-majority countries such as the UAE.

13) All data are publicly available. The replication package provides preprocessing code, and includes API-based data collection scripts for sources that support API access.

2. Preliminary Analysis

Daily Patterns. Figure 1 illustrates the patterns of Wednesday and Thursday for both the Google Trends index and DFMGI trading volume from 2021 to 2022. The horizontal lines represent the median values for each respective year. For Wednesday, the medians are highly similar across 2021 and 2022, supporting the parallel-trends assumption: as a weekday unaffected by the weekend reform, Wednesday shows no noticeable shift in behavior. In contrast, Thursday displays a more intriguing pattern. The Google Trends index rises substantially in 2022, when Thursday became a regular weekday rather than the last working

〈Figure 1〉 Daily Patterns in Google Trends Index and DFMGI Volume



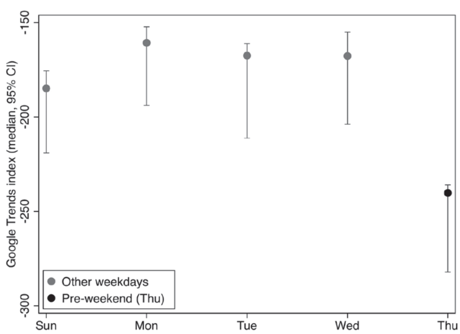
Note: DFMGI refers to the Dubai Financial Market General Index (trading volume, log-transformed), while Google Trends index is shown in its original scale (not log-transformed). The sample period is 2021-2022.

day of the week. This aligns with our hypothesis that pre-weekend days are associated with lower productivity or work-related engagement. The DFMGI volume, on the other hand, shows a slight decline in the 2022 median compared to 2021. It is unclear whether this reflects a shift in weekday productivity or is driven by high volatility in 2021.

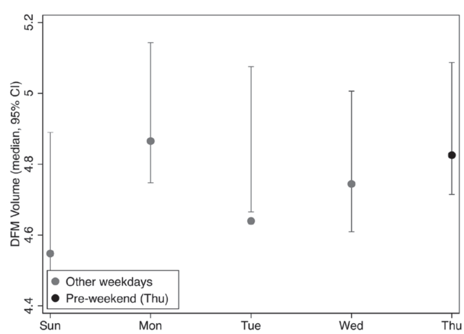
Figure 2 extends this view by showing the medians for all weekdays. While qualitatively similar to Figure 1, this static snapshot reveals that, for Google Trends, the pre-weekend day consistently registers lower index values than other weekdays in both the pre- and post-reform periods. This provides suggestive evidence that people are less focused

〈Figure 2〉 Pre- and Post- Medians of Google Trends and DFMGI

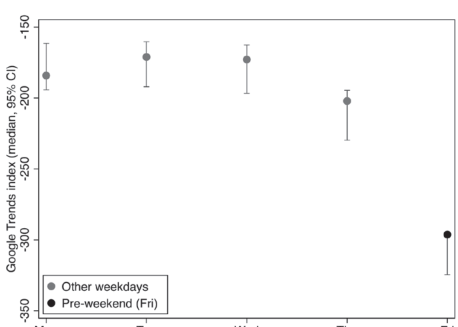
(a) Google Trends in 2021 (Pre-Change)



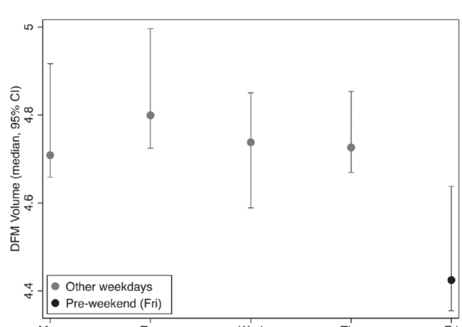
(b) DFMGI in 2021 (Pre-Change)



(c) Google Trends in 2022 (Post-Change)



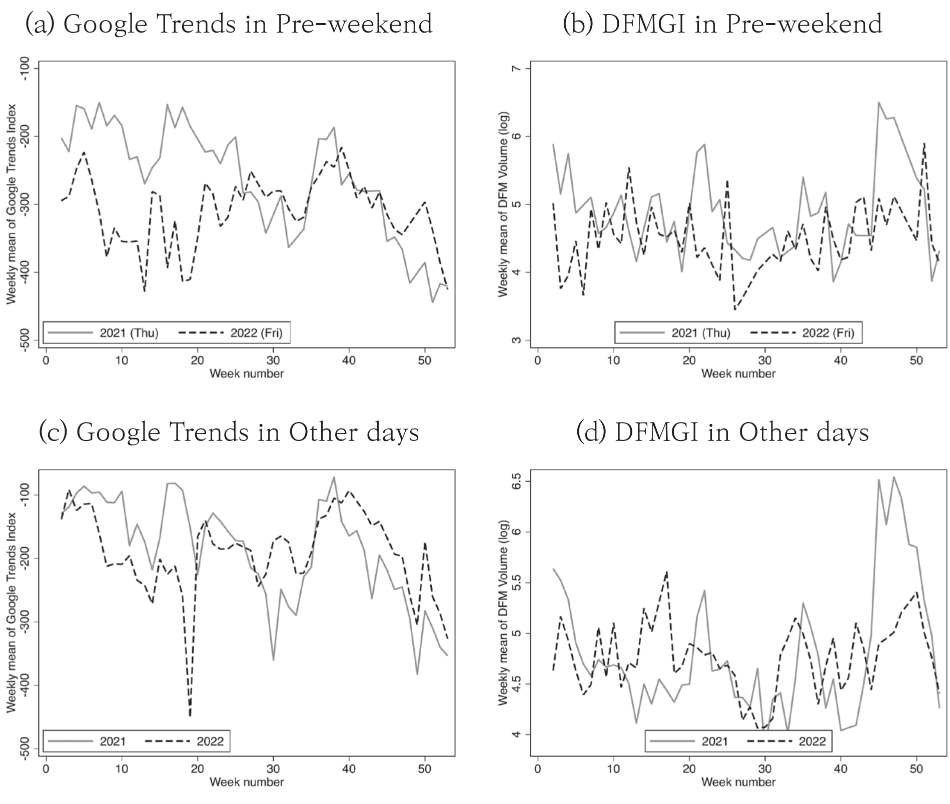
(d) DFMGI in 2022 (Post-Change)



Note: DFMGI refers to the Dubai Financial Market General Index (trading volume, log-transformed), while Google Trends index is shown in its original scale (not log-transformed). The sample period is 2021-2022.

on work on the day immediately preceding the weekend. However, this pattern alone cannot confirm that the difference is because the day is pre-weekend, as other unobserved factors may also play a role. For instance, recurring corporate meeting schedules or payroll processing days could systematically affect search activity or trading volume on specific weekdays, regardless of their proximity to the weekend. The UAE weekend reform creates a natural setting in which to causally identify such effects. For DFMGI volume, in contrast, the first trading day after the weekend appears to be relatively low, while the pre-weekend day does not consistently show a distinct dip.

〈Figure 3〉 Parallel Trends of Google Trends Index and DFMGI Volume



Note: DFMGI refers to the Dubai Financial Market General Index (trading volume, log-transformed), while Google Trends index is shown in its original scale (not log-transformed). The sample period is 2021-2022.

Parallel Assumption. A key identifying assumption in the DiD design is that the treatment and control groups would have parallel trends in the absence of the policy change. Figure 3 plots weekly means for the treatment group (Thursday or Friday) and for the control group (Sunday-Wednesday), separately for Google Trends and DFMGI, using data from both 2021 and 2022. The plot suggests that, prior to the reform, the trajectories for the two groups move in tandem, with no discernible divergence.

However, visual inspection alone does not guarantee parallel pre-trends between the treatment and control groups. To formally test the identifying assumption, we restrict the sample to the pre-policy year (2021) and estimate

$$\overline{Y_{g,w}} = \alpha_0+\alpha_1 Weeknum_w+\alpha_2 Treatment_g+\alpha_3(Weeknum_w\times Treatment_g)+\varepsilon_{g,w}, \quad (6)$$

where w indexes weeks, and g denotes the group (treatment or control). $Weeknum_w$ is the calendar week number, $Treatment_g$ is a dummy variable equal to 1 for the treatment group and 0 for the control group, and $\varepsilon_{g,w}$ is an error term. The dependent variable $\overline{Y_{g,w}}$ is the within-week mean:

$$\overline{Y_{g,w}}=\frac{1}{N_{g,w}}\sum_{t\in(g,w)} Y_{g,t}, \quad (7)$$

where $N_{g,w}$ is the number of days t in week w belonging to group g. For the treatment group (Thursday), $N_{g,w}$ = 1; for the control group (Sunday-Wednesday), $N_{g,w}$ = 4.[14)]

The interaction coefficient α_3 measures the difference in pre-policy slopes between the treatment and control groups. Under the parallel-trends assumption, these slopes should be identical, implying α_3 = 0. A statistically insignificant estimate of α_3 therefore supports the validity of the assumption. As reported in Table 3, the interaction term is small in magnitude and far from statistically significant for both Google Trends and DFMGI, providing evidence in favor of the parallel-trends assumption.

14) Because the control group consists of multiple weekdays, its value in our DiD setting in Section 3 is naturally interpreted as the average across those days.

〈Table 3〉 Pre-period (2021) Parallel Test

	Google Trends (Weekly Mean)	DFMGI (log) (Weekly Mean)
Weeknum	-3.646*** (0.470)	0.010 (0.007)
Treatment (Thu)	-60.786*** (16.340)	0.348 (0.242)
Weeknum×*Treatment*	-0.504 (0.657)	-0.009 (0.010)
Constant	-87.466*** (11.446)	-4.525*** (0.171)
Observations	99	99
R^2	0.614	0.036

Notes: Weekly means are computed separately for the pre-weekend day (Thursday) and non-target weekdays (Sunday-Wednesday) in 2021. Robust standard errors are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Ⅲ. Methodology

1. Institutional Background

On December 7, 2021, the UAE announced a shift to a Saturday-Sunday weekend for the federal government and public schools, with a 4.5-day workweek and a half day on Fridays, effective January 1, 2022. Private-sector firms were permitted to adjust internal regulations at the employer's discretion. In parallel, domestic stock exchanges moved their trading week from Sunday-Thursday to Monday-Friday in the first week of January 2022 without changing trading hours. Our Google Trends measures cover the whole UAE, while financial-market variables come from Dubai.[15)]

Because private adoption was not mandated, estimates should be interpreted as intent-to-treat at the economy-wide level: if some firms

15) See Baycar (2023) for a discussion of the political and symbolic dimensions of the reform.

continued a full five-day week, the estimated effect is attenuated toward zero rather than spurious. In addition, while the public sector adopted a 4.5-day schedule, private firms could maintain five full working days, and the exchanges changed only the trading weekdays. We therefore use the market-based proxy as a complementary outcome.

Two aspects are key for identification. First, the reform shifted the pre-weekend day from Thursday to Friday at a known date, with other weekdays unchanged. Second, because private-sector adoption was not mandated, our estimates are intent-to-treat: incomplete compliance attenuates the effect toward zero rather than creating spurious changes. In a Mercer poll of over 190 private-sector firms, only 23 percent reported plans to adopt a half-day Friday, with the majority maintaining a full five-day workweek while switching to Saturday-Sunday weekends (Khaleej Times, 2021). These features provide a clear source of quasi-experimental variation in the identity of the pre-weekend day, allowing us to compare otherwise similar weekdays before and after the reform.

2. DiD Regression

This section describes the DiD regression model used in the analysis. The DiD framework estimates the causal effect of a policy intervention by comparing the change in outcomes for a treatment group to the change for a control group, before and after the policy. The DiD framework is particularly well-suited for this analysis. The UAE's weekend reform provides a clear quasi-experimental setting with distinct treatment groups (the day that is pre-weekend) and control groups (other weekdays) before and after a specific policy change. This structure allows us to isolate the causal effect of the workweek's temporal framing on productivity proxies. By comparing the change in outcomes for the pre-weekend day to the change for other weekdays, the model effectively controls for unobserved time-varying factors that would affect all days of the week simultaneously, such as macroeconomic shocks or seasonal trends (Lee and Sawada, 2020). This approach is widely used in empirical research exploiting quasi-experimental settings (Acemoglu and Angrist, 2001; Angrist and Krueger, 1999; Card and Krueger, 1994; Meyer et al., 1995), as it allows for straightforward estimation with dummy variables and the inclusion of additional controls.

Regression Model. Our main regression takes the form:

$$Y_t = \beta_0 + \beta_1 Target_t + \beta_2 Post_t + \beta_3 (Target_t \times Post_t) + \gamma' X_t + \delta_t + e_t, \tag{8}$$

where t indexes calendar days. The dependent variable Y_t is either the Google Trends index or the log of DFMGI trading volume. $Target_t$ equals 1 if t is the pre-weekend day—Thursday before the reform or Friday after the reform—and 0 otherwise.[16] $Post_t$ equals 1 if t falls on or after January 1, 2022, and 0 otherwise. The interaction $(Target_t \times Post_t)$ is the DiD treatment indicator.

Interpretation of Coefficients. The coefficient β_3 is the parameter of interest. At first glance, the structure of Equation (2) might be misread as capturing no effect if the pre-weekend productivity dip simply shifted from one day to another without changing its magnitude. However, this is not the case. The estimator β_3 is identified by comparing the change within the treatment group (the pre-weekend day) to the change within the control group (other weekdays). Because the identity of the treatment day changes (from Thursday to Friday) while the control days remain comparable, β_3 will capture the differential shift even if the size of the dip remains constant. Formally, it is identified as:

$$\begin{aligned}\beta_3 = {} & \underbrace{\mathbb{E}\,[Y_t \mid Target_t = 1, Post_t = 1] - \mathbb{E}\,[Y_t \mid Target_t = 1, Post_t = 0]}_{\text{Change for pre-weekend day (treatment)}} \\ & - \underbrace{\mathbb{E}\,[Y_t \mid Target_t = 0, Post_t = 1] - \mathbb{E}\,[Y_t \mid Target_t = 0, Post_t = 0]}_{\text{Change for other weekdays (control)}}.\end{aligned} \tag{9}$$

16) That is, Sunday-Wednesday before the reform and Monday-Thursday after the reform.

Conceptually, this compares the change in the pre-weekend day from Thursday (pre-reform) to Friday (post-reform) against the corresponding change for other weekdays:

$$(Friday_{post} - Other\ weekdays_{post}) - (Thursday_{pre} - Other\ weekdays_{pre}). \quad (10)$$

Before the reform, Thursdays showed a systematic dip in work-related activity relative to other weekdays (see Section 2). After the reform, this dip shifted to Fridays. If the weekend reform is the primary driver of this shift, the treatment group (new pre-weekend day) should exhibit a larger decline than the control group (other weekdays), implying $\beta_3<0$ in Equation (3). It is important to clarify that β_3 does not capture whether the size of the pre-weekend dip changes over time, but rather whether the change in the pre-weekend day's outcome differs from the change for other weekdays. Even if the magnitude of the dip remains the same and merely shifts from Thursday to Friday, β_3 will be nonzero: the treatment group (Thursday pre-reform, Friday post-reform) experiences a larger decline than the control group, implying $\beta_3<0$. Formally:

$$\begin{aligned} &\mathbb{E}\,[Y_t \mid Target_t=1,\ Post_t=1] - \mathbb{E}\,[Y_t \mid Target_t=1,\ Post_t=0] \\ &< \mathbb{E}\,[Y_t \mid Target_t=0,\ Post_t=1] - \mathbb{E}\,[Y_t \mid Target_t=0,\ Post_t=0], \end{aligned} \quad (11)$$

which yields a negative β_3. A negative estimate therefore reflects a shift of the pre-weekend productivity dip from Thursday to Friday. Given the partial adoption described in Section 3.1, the estimates should be interpreted as intent-to-treat effects, with any noncompliance attenuating the magnitude β_3.

The vector X_t includes pre-holiday and Ramadan dummies, as well as the log values of crude oil prices, the S&P 500 index, and nighttime lights (NTL). δ_t denotes time fixed effects, and e_t is the idiosyncratic error term. For leisure-related dependent variables, the sign interpretation of β_3 is reversed: a negative coefficient indicates a decline in leisure activity on the new pre-weekend day.

Sample Periods and Placebo Designs. Our main specification uses daily data from January 1, 2021 to December 31, 2022, with January 1, 2022 marking the start of the post-treatment period. This two-year window provides one year of pre-treatment and one year of post-treatment observations, excluding weekends and public holidays. To validate identification, we conduct placebo regressions over two alternative periods: 2020-2021 and 2022-2023. In each placebo window, Placebo_t is defined as if a reform occurred on January 1 of the second year, even though no actual weekend change took place. In such periods, the pre-weekend day remains the same, so we expect no systematic difference between treatment and control groups; hence, β_3 should be statistically indistinguishable from zero.

Ⅳ. Estimation Results

Table 4 presents the main DiD estimation results. As shown, the coefficient on $(Target_t \times Post_t)$ remains negative and statistically significant across all specifications, regardless of the choice of dependent variable or the inclusion of economic control variables. Recall that the interaction term compares the relative difference between the pre-weekend day and other weekdays, before and after the policy change. The estimates indicate that the typical dip in productivity or attentiveness on the last working day of the week persisted following the weekend reform, but shifted from Thursday to Friday in line with the new calendar structure.

〈Table 4〉 Main Regression Results (2021–2022)

	Google Trends		DFMGI (log)	
	(1)	(2)	(3)	(4)
Target	-81.349*** (4.824)	-82.611*** (4.599)	0.083 (0.065)	0.086 (0.065)
Post	-1.871 (10.731)	63.384*** (20.822)	-0.055 (0.093)	-0.579** (0.263)
Target × *Post*	-49.535*** (6.716)	-46.086*** (6.345)	-0.325*** (0.097)	-0.340*** (0.096)
Ramadan	5.755 (62.846)	17.366 (51.141)	0.020 (0.236)	0.033 (0.150)
Pre-holiday	-6.827 (26.888)	0.713 (16.166)	-0.654** (0.298)	-0.644** (0.294)
Crude Oil (log)		-218.477*** (58.605)		1.512** (0.642)
S&P 500 (log)		-161.888** (74.028)		-0.685 (0.741)
NTL (log)		-4.429 (3.546)		0.035 (0.031)
Constant	-135.803*** (6.745)	2155.113*** (477.625)	5.145*** (0.060)	4.390 (5.139)
Week FE	√	√	√	√
Month FE	√	√	√	√
Year FE	√	√	√	√
Observations	480	480	480	480
Adjusted R^2	0.670	0.790	0.428	0.456

Notes: Google Trends is the difference between work-related and leisure-related search volume indices. DFMGI denotes trading volume of the Dubai Financial Market General Index. *Target* is a dummy variable equal to 1 if the day of the week is Thursday (before January 1, 2022) or Friday (on or after January 1, 2022), and 0 otherwise. *Post* is a dummy variable equal to 1 if the date t is on or after January 1, 2022, and 0 otherwise. The coefficient of ($Target_t \times Post_t$) captures the differential change in the outcome variable on the pre-weekend day (Thursday pre vs. Friday post) relative to the change on other weekdays, after the policy implementation. NTL stands for Nighttime Light intensity. Robust standard errors clustered at the week number level are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Since the dependent variables are measured in abstract index units, we refrain from interpreting the magnitude of the coefficients. Nevertheless, the consistent direction and significance of the estimates across proxies suggest a robust behavioral pattern.

These results highlight the persistence of reduced attentiveness at the end of the workweek, even under institutional change. Rather than eliminating the dip, the reform appears to have merely shifted its timing, suggesting that workers' effort levels are anchored to the perceived end of the work cycle. This pattern points to a form of behavioral or temporal anchoring, whereby workers adjust their engagement based on calendar-based expectations. The fact that this adjustment follows the new workweek structure underscores the influence of temporal framing in shaping economic behavior.

While these results do not yet address the broader welfare or productivity implications of the reform, they establish a clear behavioral response that motivates further investigation. To assess the robustness of our findings, the next sections implement a bootstrap procedure to quantify the uncertainty around our estimates, and a placebo test using alternative policy dates to verify that the observed effects are not driven by chance or time-specific shocks.

The next step is to examine the robustness of these findings through additional checks, ensuring that the observed patterns are not driven by chance or model-specific assumptions. To assess the statistical significance of our estimates and ensure their robustness, we implement a non-parametric bootstrap procedure.[17]

This method involves creating 500 new samples by resampling observations with replacement from the original dataset (N=480) and re-

17) The non-parametric bootstrap is a simulation-based method for estimating the properties of an estimator by resampling from the original data. The core principle, often called the "bootstrap principle," is to treat the sample's empirical distribution as an approximation of the true, unknown data-generating process. By repeatedly drawing samples from our own data, we can simulate the process of drawing multiple samples from the true population, thereby estimating the sampling distribution of our coefficient (Hansen, 2022).

estimating the model for each sample. The results, presented in Table 5, show the mean coefficient estimates and standard errors (the standard deviation of the coefficient estimates) from these 500 replications.[18)]

Because the results are averaged across randomly drawn samples, the coefficient estimates differ slightly from those in Table 4, which are based on a single estimation of the original sample. This is an expected outcome of the bootstrap methodology.

The primary inference in this paper relies on the cluster-robust standard errors presented in Table 4, with the bootstrap analysis serving as a supplementary check. While alternatives like the wild cluster bootstrap are often useful when the number of clusters is limited, this method was not feasible for our model. The analysis period covers two years (2021-2022), resulting in 104 unique weeks (clusters). However, our inclusion of week-of-year fixed effects alongside week-level clustering led to perfect collinearity in some bootstrap samples, preventing model estimation. Therefore, we present the standard bootstrap results without clustering.[19)] As shown in Table 5, the statistical significance of our key interaction term, ($Target_t \times Post_t$), remains robust, reinforcing our main findings.

To ensure that the main results identified around the weekend policy reform are not driven by chance, we conduct a placebo analysis. In parallel with our main specification—which compares the year before and after the policy change (centered on January 1, 2022)—we consider two alternative time windows: 2020-2021 and 2022-2023. In the earlier window, all Thursdays are assigned as $Target_t$ = 1, while in the latter, all

18) The collection of all 500 coefficient estimates $\{\hat{\theta}_b^* : b = 1,\ldots,500\}$ forms an estimated sampling distribution for our estimator $\hat{\theta}$. This distribution provides richer information than a single standard error, as it captures the estimator's variance, skewness, and other properties. The standard error is simply the standard deviation of this estimated distribution.

19) The standard errors reported in Table 5 are used to calculate p-values based on a normal approximation. An alternative, more direct approach is the bootstrap percentile interval, which constructs a 95% confidence interval using the 2.5th and 97.5th percentiles of the 500 bootstrap estimates. This method does not rely on the assumption of normality and directly uses the shape of the estimated sampling distribution.

〈Table 5〉 Bootstrap Regression Results (2021-2022)

	Google Trends		DFMGI (log)	
	(1)	(2)	(3)	(4)
Target	-79.450*** (5.305)	-81.722*** (5.049)	0.086* (0.071)	0.092* (0.071)
Post	-1.565 (11.203)	61.842*** (22.417)	-0.061 (0.105)	-0.622** (0.281)
Target × *Post*	-47.112*** (6.902)	-44.587*** (6.631)	-0.339*** (0.102)	-0.354*** (0.101)
Ramadan	6.223 (64.030)	18.775 (52.368)	0.031 (0.252)	0.038 (0.159)
Pre-holiday	-6.405 (28.014)	0.982 (17.220)	-0.623** (0.312)	-0.610** (0.309)
Crude Oil (log)		-212.984*** (59.818)		1.439** (0.658)
S&P 500 (log)		-157.005** (76.002)		-0.622 (0.761)
NTL (log)		-4.222 (3.645)		0.037 (0.032)
Constant	-132.234*** (7.003)	2112.341*** (489.223)	5.141*** (0.065)	4.281 (5.290)
Week FE	√	√	√	√
Month FE	√	√	√	√
Year FE	√	√	√	√
Observations	480	480	480	480
Adjusted R^2	0.661	0.775	0.412	0.442

Notes: Google Trends is the difference between work-related and leisure-related search volume indices. DFMGI denotes trading volume of the Dubai Financial Market General Index. *Target* is a dummy variable equal to 1 if the day of the week is Thursday (before January 1, 2022) or Friday (on or after January 1, 2022), and 0 otherwise. *Post* is a dummy variable equal to 1 if the date t is on or after January 1, 2022, and 0 otherwise. The coefficient of ($Target_t \times Post_t$) captures the differential change in the outcome variable on the pre-weekend day (Thursday pre vs. Friday post) relative to the change on other weekdays, after the policy implementation. NTL stands for Nighttime Light intensity. Results are based on 500 bootstrap replications. Reported coefficients are the means of the estimates from the 500 replications, and values in parentheses are the corresponding standard errors (standard deviations of the estimates). Bootstrap standard errors without clustering are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

〈Table 6〉 Placebo Test Results (2020–2021, 2022–2023)

	2020–2021		2022–2023	
	(1) GT	(2) DFMGI	(3) GT	(4) DFMGI
Target	-71.357*** (5.749)	0.042 (0.065)	-127.838*** (5.120)	-0.257*** (0.080)
Placebo	206.554*** (41.883)	0.756*** (0.267)	-38.490*** (11.160)	-0.156 (0.108)
Target × *Post*	-9.015 (8.012)	0.038 (0.087)	12.754* (7.006)	-0.001 (0.113)
Ramadan	39.270 (52.400)	-0.432** (0.200)	25.994* (13.770)	-0.162 (0.140)
Pre-holiday	-10.900 (35.280)	-0.589*** (0.190)	-58.335 (36.420)	-0.103 (0.112)
Crude Oil (log)	-203.414*** (60.380)	-0.039 (0.232)	-60.665 (80.550)	-2.294*** (0.782)
S&P 500 (log)	-672.534*** (142.731)	-4.076*** (1.221)	-225.851*** (60.002)	0.837 (0.955)
NTL (log)	-1.219 (3.908)	-0.021 (0.022)	0.444 (3.245)	0.063 (0.041)
Constant	-120.212*** (6.451)	5.210*** (0.072)	1980.123*** (478.223)	4.552 (4.421)
Week FE	√	√	√	√
Month FE	√	√	√	√
Year FE	√	√	√	√
Observations	480	480	481	481
Adjusted R^2	0.871	0.399	0.806	0.384

Notes: GT (Google Trends) is the difference between work-related and leisure-related search volume indices. DFMGI denotes trading volume of the Dubai Financial Market General Index. *Target* is a dummy variable equal to 1 if the day of the week is Thursday (before January 1, 2022) or Friday (on or after January 1, 2022), and 0 otherwise. *Placebo* mimic the structure of the policy dummy in periods where no policy change occurred. NTL stands for Nighttime Light intensity. Robust standard errors clustered at the week number level are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Fridays are treated as $Target_t = 1$. Instead of the original policy dummy $Post_t$, we introduce a placebo policy indicator, $Placebo_t$, which is coded as 0 in 2020 and 1 in 2021 (for the 2020-2021 window), and as 0 in 2022 and 1 in 2023 (for the 2022-2023 window). This variable is designed to mimic the timing structure of the true policy, but in periods where no reform actually occurred.

As shown in Table 6,[20] columns (1), (2), and (4) yield placebo interaction coefficients that are not only smaller in absolute magnitude but also statistically insignificant. Column (3), based on the 2022-2023 Google Trends data, shows a statistically significant positive coefficient at the 10% level. This suggests that the Google Trends index was, on average, higher on Fridays in 2023. However, rather than undermining our main findings, this anomaly is more plausibly attributed to idiosyncratic conditions in 2023 that fall outside the scope of our identification strategy.

V. Conclusion

This study leveraged the UAE's 2022 weekend transition from Friday-Saturday to Saturday-Sunday as a natural experiment to investigate pre-weekend productivity patterns. Using high-frequency data from Google Trends and the Dubai Financial Market as proxies for work-related attention and engagement, we employed a difference-in-differences framework to analyze behavioral changes before and after the reform.

Our findings consistently show that the dip in work-related activity and attentiveness, previously characteristic of Thursdays, shifted to

20) Unlike Tables 4 and 5, which report results with and without economic control variables, Table 6 presents only the specification with controls. This choice is due to space constraints, and the fact that the results with and without controls are similar in both magnitude and significance. Full placebo results without controls are available upon request or can be replicated using the replication package by uncommenting the relevant code sections.

Fridays following the implementation of the new workweek. The relative search interest for work-related topics declined on the new final workday, while leisure-related searches increased. This behavioral realignment, robust across multiple specifications and tests, suggests that workers' engagement levels are strongly anchored to the perceived end of the work cycle. The institutional change did not eliminate the end-of-week slump but merely displaced it, highlighting the persistence of temporal behavioral patterns.

These results carry important implications for policymakers and business leaders. While caution is needed when applying findings from the UAE directly to other nations with different economic and cultural structures, these results offer timely insights for countries like South Korea where discussions on a four-day workweek and reduced working hours are gaining momentum. Our analysis suggests that simply shortening the workweek may just shift the "Friday feeling" to Thursday, rather than eradicating the associated productivity decline. This implies that the expected efficiency gains from such policies could be partially muted if the pre-weekend dip in engagement persists. However, this does not necessarily mean a net reduction in output. Instead, it highlights an opportunity for strategic management. For example, firms could explore reallocating labor based on weekly rhythms or redesigning tasks on the final workday to prioritize creative or collaborative efforts. Introducing different incentive structures for pre-weekend days could also be a fruitful avenue for future research.

This study is not without limitations. First, the use of proxy variables, while innovative, is an indirect measure of productivity. Second, the findings are based on a policy change specific to the UAE, and therefore, direct application to other contexts like Western or Korean economies should be made with care. An additional limitation stems from the scarcity of high-frequency public data in the region, which constrained the number of daily control variables that could be included in our models. Future research could build on these findings by accessing more direct, micro-level data on worker output to see if these attentional shifts translate into concrete changes in performance.

Despite these limitations, this paper provides compelling evidence of a causally identified pre-weekend effect on a national scale. By demonstrating a robust method for tracking behavioral shifts with publicly available data, it opens new avenues for real-time economic analysis. Future studies could apply this framework to examine the long-term adaptation to the new workweek in the UAE or to analyze similar policy changes in other regions, further enriching our understanding of the relationship between time, work, and human behavior.

〈References〉

Acemoglu, D., and J. D. Angrist (2001), "Consequences of Employment Protection? The Case of the Americans with Disabilities Act," *Journal of Political Economy*, Vol. 109, No. 5, pp. 915-957.

Alfreedi, A. A. (2019), "Shocks and Volatility Spillover between Stock Markets of Developed Countries and GCC Stock Markets," *Journal of Taibah University for Science*, Vol. 13, No. 1, pp. 112-120.

Alotaibi, A. R., and A. V. Mishra (2015), "Global and Regional Volatility Spillovers to GCC Stock Markets," *Economic Modelling*, Vol. 45, pp. 38-49.

Angrist, J. D., and A. B. Krueger (1999), "Empirical Strategies in Labor Economics," *Handbook of Labor Economics*, Vol. 3, pp. 1277-1366, Elsevier.

Baumeister, R. F., E. Bratslavsky, M. Muraven, and D. M. Tice (2018), "Ego Depletion: Is the Active Self a Limited Resource?" *Self-Regulation and Self-Control*, pp. 16-44, Routledge.

Baycar, H. (2023), "The Politics of the Emirati Long Weekend: Between Modernity and Islam," *Politics*.

Card, D., and A. B. Krueger (1994), "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania," *American Economic Review*, Vol. 84, No. 4, pp. 772-793.

Cebrián, E., and J. Domenech (2023), "Is Google Trends a Quality Data Source?" *Applied Economics Letters*, Vol. 30, No. 6, pp. 811-815.

Chen, K., Q. Wang, J. Xu, and J. Yao (2025), "The International Spillover of Monetary Policy Shock: New Evidence from Nighttime Light," Working Paper.

Chen, X., and W. D. Nordhaus (2011), "Using Luminosity Data as a Proxy for Economic Statistics," *Proceedings of the National Academy of Sciences*, Vol. 108, No. 21, pp. 8589-8594.

Choi, H., and H. Varian (2012), "Predicting the Present with Google Trends," *Economic Record*, Vol. 88, pp. 2-9.

Dalton, D. R., and D. J. Mesch (1990), "The Impact of Flexible Scheduling on Employee Attendance and Turnover," *Administrative Science Quarterly*, pp. 370-387.

Donaldson, D., and A. Storeygard (2016), "The View from Above: Applications of Satellite Data in Economics," *Journal of Economic Perspectives*, Vol. 30, No. 4, pp. 171-198.

Eichenauer, V. Z., R. Indergand, I. Z. Martínez, and C. Sax (2022), "Obtaining Consistent Time Series from Google Trends," *Economic Inquiry*, Vol. 60, No. 2, pp. 694-705.

Elsheikh, T. M., J. L. Kirkpatrick, D. Fischer, K. D. Herbert, and A. A. Renshaw (2010), "Does the Time of Day or Weekday Affect Screening Accuracy? A Pilot Correlation Study with Cytotechnologist Workload and Abnormal Rate Detection Using the ThinPrep Imaging System," *Cancer Cytopathology*, Vol. 118, No. 1, pp. 41-46.

Elvidge, C. D., K. E. Baugh, E. A. Kihn, H. W. Kroehl, E. R. Davis, and C. W. Davis (1997), "Relation between Satellite Observed Visible-Near Infrared Emissions, Population, Economic Activity and Electric Power Consumption," *International Journal of Remote Sensing*, Vol. 18, No. 6, pp. 1373-1379.

Hamermesh, D. S. (1996), "Workdays, Workhours and Work Schedules: Evidence for the United States and Germany," *Upjohn Institute for Employment Research*.

Hammoudeh, S. M., Y. Yuan, and M. McAleer (2009), "Shock and Volatility Spillovers among Equity Sectors of the Gulf Arab Stock Markets," *Quarterly Review of Economics and Finance*, Vol. 49, No. 3, pp. 829-842.

Hansen, B. (2022), Econometrics, Princeton University Press.

Lee, M. J., and Sawada, Y. (2020), "Review on Difference in Differences," *Korean Economic Review*, 36(1), 135-173.

Jung, Y. (2025), "Machine Learning-Based Estimation of Monthly GDP," *arXiv preprint*, arXiv:2506.14078.

Khaleej Times (2021), "New UAE Weekend: Only 23% Private Sector Firms Will Adopt 4.5-Day Workweek," Khaleej Times, accessed August 9, 2025, based on

Mercer Middle East's New UAE Work Weekend Survey.

Kiymaz, H., and Berument, H. (2003), "The Day of the Week Effect on Stock Market Volatility and Volume: International Evidence," *Review of Financial Economics*, 12(4), 363-380.

Meyer, B. D., W. K. Viscusi, and D. L. Durbin (1995), "Workers' Compensation and Injury Duration: Evidence from a Natural Experiment," *American Economic Review*, Vol. 85, No. 3, pp. 322-340.

Omar, A. A., and M. Cranny (2021), "UAE Stock Markets to Shift to Monday-Friday Trading Week," Al Jazeera, accessed April 5, 2025, reporting attributed to Bloomberg within the article.

Pencavel, J. (2015), "The Productivity of Working Hours," *Economic Journal*, Vol. 125, No. 589, pp. 2052-2076.

Pinkovskiy, M., and X. Sala-i-Martin (2016), "Lights, Camera... Income! Illuminating the National Accounts-Household Surveys Debate," *Quarterly Journal of Economics*, Vol. 131, No. 2, pp. 579-631.

Roh, T., C. Esomonu, J. Hendricks, A. Aggarwal, N. T. Hasan, and M. Benden (2023), "Examining Workweek Variations in Computer Usage Patterns: An Application of Ergonomic Monitoring Software," *PLoS One*, Vol. 18, No. 7, e0287976.

Steel, P., and C. J. König (2006), "Integrating Theories of Motivation," *Academy of Management Review*, Vol. 31, No. 4, pp. 889-913.

Woloszko, N. (2020), "Tracking Activity in Real Time with Google Trends," OECD Economics Department Working Papers, No. 1634.

〈Appendices〉

A. Additional Data Description

Google Trends. Google Trends data can be retrieved either directly from the Google Trends website[21] or through an unofficial API.[22] [23] In this study, we use the API for convenience. The API automates the data extraction process from the website and does not compromise the reliability of the data itself. However, it may occasionally malfunction when Google updates the Trends platform, and excessive requests may lead to temporary rate-limiting or access blocks. In such cases, manual data collection via the website may be necessary.

The API allows users to specify the language for the query. Our main analysis uses English-language keywords. Although Arabic-language versions of the same keywords were also retrieved and are included in the replication package, they are not used in the main analysis. As of 2019, 87.9% of the UAE population were immigrants,[24] and Arabic search volumes are often reported as zero.

Financial Market. We use three financial time series: the DFM General Index (DFMGI), S&P 500, and Crude Oil WTI. Among them, DFMGI[25] and Crude Oil WTI[26] are obtained by downloading historical data directly from the website of investing.com. The S&P 500 data are retrieved using the Yahoo Finance API,[27] which does not require any separate registration. To account for the time zone difference between the US and the UAE, we use the one-day lagged values of the S&P 500 and Crude Oil WTI data. The relevant code for accessing and processing this data is included in the replication package.

21) https://trends.google.com/trends/.

22) https://github.com/GeneralMills/pytrends.

23) Replication package is available at https://www.dropbox.com/scl/fo/ea8n7u3i24sa83kaalype/AHQmSR6f-JGAKQlu82M7thc?rlkey=gvyofz4drk7x1ntwpwf5754eo&st=pou84ty7&dl=0.

24) See https://www.migrationpolicy.org/country-resource/united-arab-emirates.

25) https://www.investing.com/indices/dfmgi-historical-data.

26) https://www.investing.com/commodities/crude-oil-historical-data.

27) https://github.com/ranaroussi/yfinance.

Nighttime Light. While there are several sources of nighttime light data, we obtain the data from NASA via the Google Earth Engine API.[28) 29)]

We extract the country's land boundary using the FAO Global Administrative Unit Layers (GAUL), thereby excluding brightness over oceans. Then, for each day, we aggregate the brightness values of all pixels within the boundary. Since the dataset includes basic preprocessing procedures such as cloud masking, it can be used directly without major adjustments. However, due to weather-related factors and satellite limitations, a small fraction of days contain missing observations.[30)] To interpolate these missing values, we adopt a seasonal decomposition approach based on the following additive model:

$$\Phi_t = \tau_t + \sigma_t + \rho_t, \tag{12}$$

where Φ_t denotes the observed brightness value on day t, τ_t is the long-term trend component, σ_t captures weekly seasonal variation, and ρ_t is the residual component. Missing values in τ_t and ρ_t are linearly interpolated, and the time series is reconstructed as:

$$\hat{\Phi}_t = \hat{\tau}_t + \sigma_t + \hat{\rho}_t. \tag{13}$$

This method enables us to preserve both long-term dynamics and short-term periodicity in the brightness series. The corresponding Python code implementing this procedure is included in the replication package, and an indicator variable is also created to flag imputed dates, allowing users to account for these values in further analysis if necessary.

Calendar. The calendar is available from General Blue website.[31)]

28) https://developers.google.com/earth-engine/datasets/catalog/NASA_VIIRS_002_VNP46A2

29) The code for downloading the data via the API is provided in the replication package Access to the Google Earth Engine API requires separate user registration, which is free for research purposes.

30) 57 out of 1,461 days between January 1, 2020, and December 31, 2023, accounting for 3.9% of the total.

31) https://www.generalblue.com/calendar/uae/.

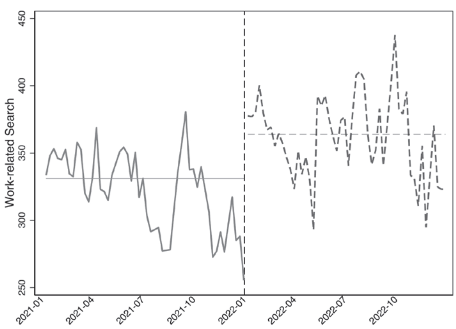
B. Disaggregated Analysis of the Google Trends Index

In the main analysis, we construct the Google Trends index by subtracting leisure-related search volume from work-related search volume.[32] In this section, we separately examine the work-related and leisure-related search volumes.

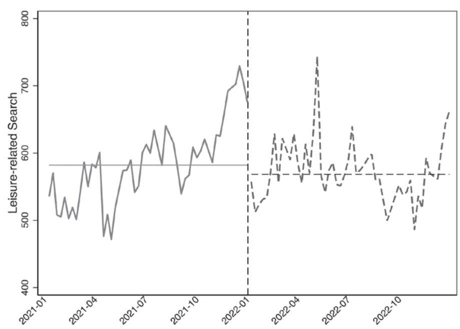
Figure B1 displays the patterns of each type of search volume on Wednesdays and Thursdays, comparing the year before and after the January 2022 weekend reform. As expected, work-related searches on

〈Figure B1〉 Google Search in Work- and Leisure-related Words

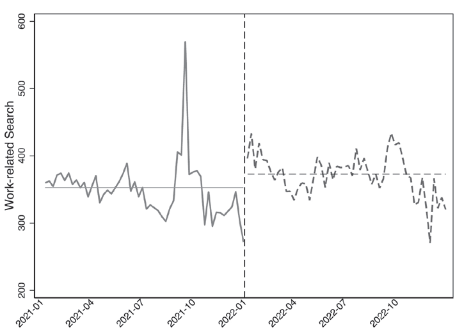
(a) Work-related Search on Thur.



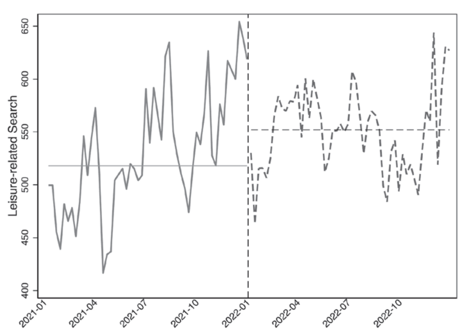
(b) Leisure-related Search on Thur.



(c) Work-related Search on Wed.



(d) Leisure-related Search on Wed.



Note: Work- and leisure-related keywords are reported in Table 1. The sample period is 2021-2022.

32) This structure captures both types of search behavior, with a higher index value indicating relatively greater engagement in work-related searches.

Thursdays increase in 2022 relative to 2021, suggesting that people conduct more work-related searches when Thursday is no longer the last working day of the week. For leisure-related searches, the opposite pattern emerges: Thursday searches are slightly higher in 2021 (when Thursday was the pre-weekend day) but decline in 2022 (when Thursday becomes a regular weekday), which aligns with our hypothesis. By contrast, Wednesday search volumes follow broadly similar patterns across the two years, although 2022 levels are somewhat higher. This underscores the importance of the regression analysis in Table B1, which helps to disentangle these dynamics more rigorously.

The DiD regression results are presented in Table B1. These results reinforce both the graphical evidence in Figure B1 and the main findings: the treatment effect is negative for work-related searches and positive for leisure-related searches. In other words, individuals in the UAE engage in fewer work-related searches and more leisure-related searches on pre-weekend days.

Importantly, the estimated coefficients on the interaction term ($Target_t \times Post_t$) in Table B1 confirm a significant shift in search behavior following the reform. Specifically, work-related search activity declines on the newly designated pre-weekend day (Friday), while leisure-related searches increase. Although the absolute magnitudes differ, the consistent change in opposite directions suggests a reallocation of online attention from work to leisure. This pattern supports the interpretation that individuals adjust their search behavior in response to the new timing of the weekend, rather than due to unrelated temporal shocks.

Finally, the inclusion of economic control variables in columns (2) and (4)—such as oil prices, the S&P500 index, and NTL—does little to alter the key coefficients of interest. This suggests that the results are not driven by broader macroeconomic fluctuations or seasonal patterns.

〈Table B1〉 Regressions by Work- and Leisure-related Google Trends

	Work-related		Leisure-related	
	(1)	(2)	(3)	(4)
Target	-21.396*** (2.471)	-21.967*** (2.443)	59.953*** (3.700)	60.644*** (3.535)
Post	25.289*** (4.046)	28.731*** (9.542)	27.161*** (8.447)	-34.653* (18.415)
Target × *Post*	-24.991*** (3.880)	-23.966*** (3.946)	24.545*** (5.826)	22.120*** (5.205)
Ramadan	-20.361 (20.572)	-17.316 (17.791)	-26.116 (44.571)	-34.682 (36.692)
Pre-holiday	-4.477 (5.998)	-1.490 (5.747)	2.351 (24.665)	-2.203 (14.638)
Crude Oil (log)		-18.593 (24.857)		199.884*** (51.549)
S&P 500 (log)		-59.086* (30.591)		102.802* (57.865)
NTL (log)		-3.118*** (1.055)		1.312 (3.085)
Constant	360.935*** (2.660)	972.631*** (190.292)	496.739*** (5.276)	-1182.482*** (377.722)
Week FE	√	√	√	√
Month FE	√	√	√	√
Year FE	√	√	√	√
Observations	480	480	480	480
Adjusted R^2	0.614	0.639	0.628	0.778

Notes: *Target* is a dummy variable equal to 1 if the day of the week is Thursday (before January 1, 2022) or Friday (on or after January 1, 2022), and 0 otherwise. *Post* is a dummy variable equal to 1 if the date t is on or after January 1, 2022, and 0 otherwise. The coefficient of ($Target_t \times Post_t$) captures the differential change in the outcome variable on the pre-weekend day (Thursday pre vs. Friday post) relative to the change on other weekdays, after the policy implementation. NTL stands for Nighttime Light intensity. Robust standard errors clustered at the week number level are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

금요일의 생산성 저하에 대한 준실험적 분석: 아랍에미리트(UAE) 사례를 중심으로

정용근*

본 논문은 2022년 아랍에미리트(UAE)의 주말 변경(금·토요일에서 토·일요일)이라는 준실험적 상황을 지렛대 삼아 주말 전일의 생산성 저하 현상을 분석한다. 이중차분(DiD) 모형을 바탕으로 구글 트렌드 검색지수와 두바이 금융시장의 거래량을 요일별 업무 집중도의 대리지표로서 활용하였다. 분석 결과, 주말 직전의 집중도 저하는 정책 변경 이후 목요일에서 금요일로 이동한 것으로 나타났다. 이는 집중도 저하가 주말 전날이라는 요일적 특성에 기인함을 인과적으로 보여준다. 이러한 결과는 위약(placebo) 검증과 부트스트랩 검정을 통해 강건하게 확인되었다. 본 연구는 주중 구조(workweek structure) 자체가 주말 전일의 생산성에 영향을 준다는 사실을 보여주며, 주 4일제 도입 등 근무제도 개편에 관한 정책적 시사점을 제공한다.

JEL classification: J22, D91, M54
핵심 주제어: 준실험, 이중차분법, 구글트렌드, 생산성
DOI: 10.23299/bokeri.2025.31.3.002

* 플로리다대학교 경제학 박사과정 (E-mail: yonggeun.jung@ufl.edu, Tel: +1-352-709-3510)

논문 투고일: 2025.7.7, 논문 수정일: 2025.8.9, 게재 확정일: 2025.9.30.