Estimating the Collapse of Afghanistan’s Economy Using Nightlights Data

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Abstract

The Taliban’s takeover of Afghanistan in August 2021 is associated with a rapid collapse of the Afghan economy. In lieu of official data, attempts to measure the scale of the collapse have relied on rapid surveys of the population. We validate these qualitative measures by using nightlights as a proxy measure for changes in GDP. Utilizing a synthetic control and nightlights data of neighboring countries, we find that Afghanistan’s regime change was associated with a shift from a positive growth trajectory towards a deep recession, even after taking the Covid pandemic into account. We estimate that Afghanistan’s GDP has fallen on the order of 28% since mid-2021, consistent with the World Bank’s survey measures. However, unlike the World Bank, we report confidence intervals conveying the uncertainties surrounding these point estimates. This study demonstrates the potential applicability of our methodology in settings of scarce or unreliable administrative data.

Keywords: Nighttime Lights, Synthetic Control, Afghanistan, Gross Domestic Product, Data Scarcity

JEL Codes: C82, O1, O4, P4, R1

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1 Introduction and Motivation

The fall of the Government of the Islamic Republic of Afghanistan (GIROA) in August 2021 and the subsequent takeover by the Taliban has been associated with a rapid deterioration in the country’s economic conditions. Foreign journalists based in the nation’s capital Kabul reported on an economy on the verge of "collapse" in the days and weeks following the regime change (Trofimov 2022). The World Bank initially estimated that Afghanistan’s GDP had fallen by about one-third between 2020 and the end of 2021 (World Bank 2022a), a number revised downward more recently to approximately 26% (World Bank 2023).¹ This far exceeds preliminary estimates of the economic contraction associated with the Covid epidemic in Afghanistan, which was projected at the time to be on the order of 5 to 6% of GDP (World Bank 2020).

Measurements of the current size of the Afghan economy are based largely on "rapid" surveys with a relatively small number of respondents. It is unclear to what extent such estimates are reliable or representative in the current political and social environment. According to the World Bank, "official GDP statistics are not being produced" by the Taliban government, further complicating the task of economic analysis under conditions of data scarcity (World Bank 2022b, p. 186).

The purpose of this paper is to complement existing measurements of the Afghan economy by using changes in nighttime lights (NTL, or nightlights) to estimate the decline in GDP. Nightlights have been widely used as proxy measures of economic activity since the pioneering work of Henderson et al. (2011) and the related discussion by Chen & Nordhaus (2011). Recent publications have made use of nightlights to study not only advanced economies like China (Liu et al. 2021, Zhou et al. 2022) and the United States (Gibson & Boe-Gibson 2021), but also the effects of conflict in countries such as Yemen (Jiang et al. 2017) and the reliability of GDP estimates published by dictatorships (Martinez 2022). We note, however, that the vast majority of existing studies that compare nightlights measurements with GDP data are able to make use of official statistics for bench-marking purposes, which is not possible for Afghanistan after 2020.

¹For its part, the United Nations Development Program (UNDP) estimated that the GDP decline was around 20% within a year of the Taliban takeover in August 2021 (UNDP 2022) and that it may reach 30% in the coming years (UNDP 2021).
The novelty of our study is to use NTL as the basis for a nowcast of the current Afghan GDP and to combine this with a synthetic control methodology for constructing counterfactual estimates. Specifically, we use a weighted average of the nightlight radiance in provinces of neighboring countries such as Pakistan and Iran as the control. It is this gap between the current reality on the ground as reflected in the NTL data and the counterfactual of "what might have been" that captures the entirety of the macroeconomic change since August 2021. Our point estimate of this change is 28%, which is in-line with the World Bank’s current estimate. Unlike the World Bank and other international organizations, however, we report confidence intervals around our economic measurements, highlighting the uncertainty surrounding these reported point estimates.\(^2\)

This article’s novel contribution to research in economic development is its combination of monthly nightlights data with a newly devised approach to synthetic control predictions (Cattaneo et al. 2021).\(^3\) We believe this methodology has broad implications for researchers studying economies where data are sparse, non-existent or unreliable. Our approach permits researchers to obtain more rapid, and potentially more accurate, economic assessments than surveys. Especially in settings where accurate and representative information is difficult to gather from firms, households, and the government, this approach could be used to complement and validate existing techniques using independent data.

This paper proceeds in four sections. Following this introduction, Section 2 provides some more context and describes our data while Section 3 introduces our methodology. The results of this estimation are discussed in Section 4. We conclude and discuss future research in Section 5.

## 2 Context and data

Prior to August 2021, Afghanistan depended heavily upon foreign aid and military spending to fuel its economy. Largely due to these inflows, which provided 45% of GDP and 75% of the government budget, the country "grew by more than 7% per year on average over 2001-2020, with GDP increasing by 180% between 2001 and 2020 [while] real per capita in-

\(^2\)On the importance of reporting confidence intervals, see Romer (2020).
\(^3\)An earlier work combining nightlights and synthetic controls is Pfeifer et al. (2018).
come increased by 75% between 2002 and 2018” (World Bank 2022a, p. 1). Foreign assistance provided direct budget support to the government, enabling the provision of services such as health care and education. Military spending boosted consumption and reduced poverty, especially where military activity was most intense (Floreani et al. 2016).

Even before the Taliban takeover, the Afghan economy went into lockdown during the Covid epidemic in 2020. Yet owing to the rural character of the Afghan economy, the effects were perhaps less acute than those felt in more industrialized societies. As previously noted, the World Bank at the time projected a fall in GDP of somewhere between 5 and 7% (World Bank 2020). This decline is not reflected in the currently available GDP data for 2020 (World Bank 2023). Following the takeover, however, the Afghan economy faced multiple shocks, including the loss of external support, the loss of access to Central Bank foreign currency holdings due to Western sanctions, the flight of human capital, and a likely reduction in domestic private sector investment due to pervasive uncertainty about the nation’s future. Absent reliable data, measuring the scale of these shocks poses a challenge to analysts.

To overcome this data paucity, we utilize nightlights in the form of satellite-derived radiance to estimate economic output. Specifically, we use Visible Infrared Imaging Radiometer Suite Day-Night Band (VIIRS DNB) data\(^4\). This generation of nightlight sensors was originally launched in 2011 and presents a substantial improvement in measurement accuracy, range, and spatial resolution over the earlier Defense Meteorological Satellite Program (DMSP) (Gibson et al. 2020, 2021). The measurements are available as GeoTiff (geo-referenced Tiff) files based on images of the earth’s surface at a resolution of 500 meters at nadir. The surface of the earth is effectively divided into a grid and the observed radiance of these grid fields are reported as matrices of raster data in nanowatts per steradian per square centimeter (nW · sr\(^{-1}\) · cm\(^{-2}\)).

While there are many GeoTiff data sets available, we utilize monthly stray-light corrected cloud-free composites from January 2015 to June 2022. Additionally, we use annual VIIRS nightlights (VNL) 2.1 average-masked data from 2014 to 2021 which employ an adaptive, multi-year data range threshold to remove extraneous features such as biomass burning, auroras, and background noise (Elvidge et al. 2021). The remaining lights that are captured in these composites are primarily associated with urban economic activity (Gibson et al.\(^4\)).

\(^4\)Data available under https://eogdata.mines.edu/products/vnl/.
We have not found any evidence of Taliban-imposed curfews or restrictions on economic activity that might disproportionately affect the nightlights thus measured post Taliban takeover. Beyond nightlights data, we also use the available annual GDP data from 2015 to 2021 for Afghanistan as well as Armenia, Azerbaijan, Georgia, Kyrgyzstan, Iran, Iraq, Pakistan, Turkmenistan, Tajikistan, and Uzbekistan, which we retrieve from the World Bank online database.\(^5\)

### 2.1 Data Processing and Extraction

We utilize the annual VNL 2.1 data to reduce the noise of the monthly cloud-free composites as follows. The annual data has been pre-processed to identify and filter out nightlights that are not associated with economic activity by setting the radiance for such raster fields to zero. Hence, we extract the fields of zero radiance for a given annual observation and then set the radiance of these fields to zero for all monthly observations of the following year.\(^6\)

Following Jiang et al. (2017), we also introduce an upper bound for the brightness of each raster field at 300 nW \cdot sr\(^{-1}\) \cdot cm\(^{-2}\). This threshold reduces outliers associated with disproportionately bright processes, primarily gas flares observed at night. While enforcing this threshold has a negligible effect on the observations in Afghanistan, it is relevant for neighboring countries with larger oil and gas industries, such as Iran.

The monthly cloud-free DNB composite data also includes indicator data which states the number of unobstructed observations for each raster field in a given month. A low number of cloud-free observations is associated with a less reliable observation of the respective raster field for that month. Thus, we introduce a conditional rolling update. For our final processed composite, each raster field is updated with the next month’s radiance value only if the next month includes more than five unobstructed observations of the respective raster field. Otherwise, we keep the radiance value of the previous month.

Given the final, reduced-noise monthly composites, we aggregate radiation by summing over all raster fields in a province. Thus, we construct a time series panel of monthly ra-

\(^5\)At the time of writing, annual GDP data is not available for Turkmenistan 2020-2021. We also exclude the World Bank’s preliminary, survey-based estimate for Afghanistan’s GDP in 2021.

\(^6\)We use preceding annual observations rather than concurrent annual observations to enable the processing of monthly data for 2022 for which no complete NTL data set is available at the time of writing. The change to using concurrent annual observations has little impact on the resulting extracted data for 2015-2021.
dance for the provinces of Afghanistan, Armenia, Azerbaijan, Georgia, Kyrgyzstan, Iran, Iraq, Pakistan, Turkmenistan, Tajikistan, and Uzbekistan. Figure 1 displays the aggregated, logged nightlight radiance for Afghanistan. The dashed vertical line highlights the sudden drop in radiance following the Taliban takeover beginning in mid-2021, which is the effect we seek to isolate. Figure 2 shows a map of the change in radiance for Afghanistan between the 6-month average before and after the Taliban takeover. This highlights the decline in radiance in Afghanistan in contrast to neighboring regions. The most populous cities, Kabul and Kandahar, appear to be particularly affected. Note that for different aspects of our empirical analysis, we aggregate Afghanistan’s provincial data at the national level through summation and take non-overlapping averages over quarterly, bi-annual, and annual time frames.

Figure 1: Aggregated extracted nightlight radiance (NTL) for Afghanistan

Aggregated nightlight radiance for Afghanistan based on monthly, reduced-noised observations. The grey period indicates the ongoing American withdrawal from March 2019 to late August 2021 while the red line indicates the Taliban takeover in August 2021.

3 Methodology

To evaluate the impact of the Taliban takeover in August 2021 on Afghanistan’s economy, we proceed in two steps. First, we construct a counterfactual post-treatment nightlights time series to predict the causal impact of the takeover on Afghanistan’s nightlights using the synthetic control approach. Second, we estimate the economic downturn associated with the
Mapping of the difference between the 6-month average radiance from February 2021 to July 2021 and the 6-month average from August 2021 to January 2022. Green and red indicate an increase and decrease in brightness respectively. Inset maps highlight the two most populous regions of Afghanistan: Kabul and Kandahar.

given change in nightlights using a country fixed effects model. 7

3.1 Synthetic Control Methodology

We utilize the synthetic control methodology first introduced by Abadie & Gardeazabal (2003) and Abadie et al. (2010) to construct the counterfactual nightlights (NTL) data for Afghanistan. This counterfactual quantifies how Afghanistan’s nightlights might have developed in the absence of the Taliban takeover. Specifically, the synthetic control is a weighted average of provinces of Afghanistan’s neighbors excluding China, chosen to reproduce characteristics of Afghanistan before the takeover. Using the terminology of the synthetic control literature, the Taliban takeover is the treatment, while untreated provinces of Iran, Pakistan, Tajikistan, Turkmenistan, and Uzbekistan constitute the donor pool.

Following the common notation and the setup in Cattaneo et al. (2021), let \( i \in \{1, \ldots, J + 1\} \).
be the regions whose aggregated log NTL, denoted $Y_{it}$, we observed. Here, $i = 1$ denotes Afghanistan, and thus $i \in \{2, \ldots, J + 1\}$ corresponds to the $J$ untreated regions. Denote the time periods for which we observed $Y_{it}$ by $t \in \{1, \ldots, T\}$ and let $t = T_0$ be the time period of Taliban takeover. For each region $i$ and time period $t$, let $Y_{it}(0)$ and $Y_{it}(1)$ denote the outcome in the absence of treatment and under treatment respectively. Thus, the observed outcomes are given by

$$
Y_{it} = \begin{cases} 
Y_{it}(0), & \text{if } i \in \{2, \ldots, J + 1\} \text{ and } t \in \{1, \ldots, T\} \\
Y_{it}(0), & \text{if } i = 1 \text{ and } t \in \{1, \ldots, T_0\} \\
Y_{it}(1), & \text{if } i = 1 \text{ and } t \in \{T_0 + 1, \ldots, T\}.
\end{cases}
$$

This allows us to express the treatment effect of the Taliban takeover on Afghanistan’s NTL as follows:

$$
\tau_t := Y_{1t}(1) - Y_{1t}(0), \quad t > T_0. \tag{1}
$$

**Step 1 - Prediction:**

To extract $\tau_t$ from the expression above, it is imperative to construct a good prediction of the counterfactual $Y_{1t}(0)$ for $t \in \{T_0 + 1, \ldots, T\}$ which corresponds to NTL in Afghanistan if the takeover had not taken place.

To construct this prediction, let $y \in \mathbb{R}^{T_0}$ denote the pre-treatment NTL observations of Afghanistan and let $X \in \mathbb{R}^{T_0 \times J}$ denote the pre-treatment NTL observations of the donor pool with $X_t$ denoting its $t$-th row. This allows us to fit

$$
\begin{pmatrix} \hat{\mathbf{w}} \\ \hat{r} \end{pmatrix} \in \arg \min_{\mathbf{w} \in \mathcal{W}, r \in \mathbb{R}} ||y - X \mathbf{w} - r||^2_2, \tag{2}
$$

where $\mathcal{W} := \{\mathbf{w} \in \mathbb{R}_+^J : \|\mathbf{w}\|_1 = 1\}$. Thus $\hat{\mathbf{w}}$ are the weights used to construct the weighted average and $\hat{r}$ is an intercept parameter essentially corresponding to a fixed effect for Afghanistan. The weights vector $\hat{\mathbf{w}}$ is constrained to be within $\mathcal{W}$ to achieve sparsity, as well as to prevent overfitting and implausible relationships such as $w_i < 0$. Following the average-weighted model (2), the out-of-sample predictions for the counterfactual are given by

$$
\tilde{Y}_{1t}(0) = \hat{r} + \sum_{i=2}^{J+1} \hat{w}_i Y_{it}(0) = \hat{r} + X_t \cdot \hat{\mathbf{w}} \quad \text{for } t \in \{T_0 + 1, \ldots, T\}.
$$
Step 2 - Prediction Intervals:

To validate empirically that the predicted treatment effect $\hat{\tau}_t$ based on (1) is statistically signif-
ificant, we adopt the recently proposed methodology of Cattaneo et al. (2022a) and software of
Cattaneo et al. (2022b) to construct prediction intervals. We begin by denoting the error term of the out-of-sample prediction by

$$e_t := Y_{1t}(0) - \hat{Y}_{1t}(0) = Y_{1t}(0) - \hat{\tau} - X_t \cdot \hat{\mathbf{w}}$$

for $t \in \{T_0 + 1, \ldots, T\}$.

Further, if $\hat{\mathbf{w}}$ and $\hat{\tau}$ are concentrating around $w_0 \in \mathcal{W}$ and $r_0 \in \mathbb{R}$ respectively, we can express
the total uncertainty regarding the prediction of the treatment effect in two parts:

$$\hat{\tau}_t - \tau_t = Y_{1t}(1) - \hat{Y}_{1t}(0) = e_t - ((\hat{\tau} - r_0) + X_t \cdot (\hat{\mathbf{w}} - \mathbf{w}_0))$$

for $t \in \{T_0 + 1, \ldots, T\}$.

The first part is the out-of-sample error $e_t$ related to potential misspecification along with any
additional noise occurring during the post-treatment periods $t > T_0$. For our implementation,
we assumed a low probability for large out-of-sample prediction errors, and thus assumed $e_t$
to be sub-Gaussian.

The second part captures the in-sample uncertainty $((\hat{\tau} - r_0) + X_t \cdot (\hat{\mathbf{w}} - \mathbf{w}_0))$ stemming
from the construction of $\hat{\mathbf{w}}$ and $\hat{\tau}$ in (2) based on pre-treatment data which is carried over into
the prediction $Y_{1t}(0)$ for $t > T_0$. This uncertainty is quantified by estimating the covariance
matrix of the in-sample residuals

$$e_t := Y_{1t}(0) - \hat{Y}_{1t}(0) = Y_{1t}(0) - \hat{\tau} - X_t \cdot \hat{\mathbf{w}}$$

for $t \in \{1, \ldots, T_0\}$, re-sampling this error term 500 times, and estimating quantiles for the associated difference
between $\hat{\mathbf{w}}$, $\hat{\tau}$ and $\mathbf{w}_0$, $r_0$. Estimating these two sources of uncertainty separately and comb-
ing them using the union bound allows for the construction of the prediction interval for
$\tau_t$.

We refer to Cattaneo et al. (2021) for a detailed derivation of the prediction intervals.
3.2 Nowcasting economic output

Next, we introduce the model for estimating the economic downturn associated with the observed reduction of nightlights in Afghanistan. Here, we switch to annual data as for the countries under consideration, GDP is only available on an annual basis. Building on the existing nightlights literature, we assume a linear relationship between log GDP and log NTL (Henderson et al. 2011, Gibson et al. 2020). Specifically, we utilize a country fixed effect model of the form

$$
\log(GDP_{is}) = \alpha_i + \beta \bar{Y}_{is} + \gamma_i s + u_{is} \quad \text{for} \quad s = 1, \ldots, S \text{ and } i = 1, \ldots, N
$$

(3)

where $N$ is the number of countries under consideration and $1, \ldots, S$ are the years in the range from 2015 to 2021. $\bar{Y}_{is}$ denotes the annual average of aggregated log NTL data for country $i$ in year $s$, while $\alpha_i$ denotes the respective country fixed effect, $\gamma_i$ denotes the country-specific time trend, and $u_{is}$ denotes the error term. Using this model, we nowcast the log GDP of Afghanistan for 2021 and based on the average of currently available data for 2022 according to

$$
\log(GDP_{is}) = \tilde{\alpha}_i + \tilde{\bar{Y}}_{is} \tilde{\beta} + \tilde{\gamma}_i s.
$$

4 Results

4.1 Synthetic Control Results

Figure 3 shows the synthetic control based on quarterly averages of nightlights data to further reduce noise and potential seasonality of the monthly observations. The treatment period is set to be Q2 of 2021, as conservatively defining the treatment period earlier than August 2021 allows for a better fit to the pre-treatment period in the presence of anticipatory effects. The included post-treatment prediction intervals for the counterfactual have at least 90% coverage probability, and the observed drop in Afghanistan’s nightlights consistently lies outside the intervals. We see point estimates of the counterfactual around 11.6 for the log of Afghanistan’s aggregate nightlight radiance, while the observed post-treatment values average approximately 11.25. Thus the average prediction for the treatment effect is approxi-

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9 The Appendix includes corresponding results based on monthly and bi-annual data in Figure 5 and an overview of the non-zero elements of the chosen weights $\tilde{w}$ for each model in Table 1.
Synthetic control (blue) for Afghanistan’s nightlights based on quarterly data (black) from January 2015 to June 2022 including post-treatment prediction intervals for the counterfactual with at least 90% coverage probability.

4.2 Nowcasting results

Next, we estimate the decline in GDP associated with the reduced nightlights in Afghanistan based on past correlations between GDP and nightlights in the region. We explored different specifications of linear models ranging from the simple linear model relating log NTL to log GDP to models including country fixed effects, a time trend, and country fixed effects with country-specific time trends. For the out-of-sample nowcasting of Afghanistan’s GDP, we utilize a country fixed effect model with country-specific time trends.\textsuperscript{10} We used likelihood-ratio tests to assess the goodness of fit of our different model specifications and found that the country fixed effect model with country-specific time trends is significantly more likely to describe the true data generating process than the alternatives. For example, the associated Chi-squared value when testing the country fixed effects model with a time trend against the country fixed effect model with country-specific time trends is 38.71 with 11 degrees of freedom, indicating that we can reject the hypothesis that the first model describes the data as well as the second with a p-value well below 0.1%.\textsuperscript{11} Further, the chosen model specifi-

\textsuperscript{10}Table 2 in the Appendix provides an overview of the different model specifications and their respective regression results.

\textsuperscript{11}Table 3 in the Appendix provides an overview of likelihood-ratio test results for different model specifications.
cation fits the in-sample observations of Afghanistan’s GDP best among the models under consideration\textsuperscript{12} and achieves a high in-sample adjusted $R^2$.

Figure 4 shows the estimated GDP for Afghanistan at 17.51 billion USD in 2021 and 14.45 billion USD in 2022. This corresponds to a fall of 28\% of GDP over the 1.5 years since the last official GDP publication in 2020. However, we also report 90 \% confidence intervals associated with our point estimates. Given the issues of data scarcity and quality, large confidence intervals are to be expected and indeed this is what we find. Still, the confidence intervals decisively enter negative territory for GDP changes relative to the baseline of 2020. Further, we included the GDP level associated with the annual averages of the point estimates for the synthetic control based on quarterly data. While the exact value of these should be interpreted cautiously due to the accumulated model uncertainty, they serve to highlight the change in the trajectory of Afghanistan’s GDP development. Instead of continuing on the upwards trend associated with our counterfactual prediction, this evidence indicates that the economy of Afghanistan has fallen into a deep recession.

\textsuperscript{12}Figure 6 in the Appendix shows the fitted values for Afghanistan’s GDP based on different model specifications.
Annual GDP data for Afghanistan as well as estimates based on annual averages of observed NTL radiance including 90% confidence intervals and point estimates based on synthetic control NTL predictions.

5 Conclusion

This paper highlights the promise of using monthly nightlights data in estimating regional economic shocks and trends when facing data scarcity or a complete lack of traditional economic indicators. We provide a novel estimate of the economic shock that Afghanistan has suffered by combining nightlights data with the use of the synthetic control methodology. Our methodology provides a reminder that this shock is not solely what happened relative to Afghanistan’s GDP before the Taliban takeover, but relative to the alternative path that the economy might have taken had the status quo been preserved.

In this application, we identified a significant fall in the nightlights of Afghanistan and derived an associated point estimate of the downturn in GDP of approximately 28%. Unlike the previously available survey-based measurements, however, we also present confidence intervals that suggest caution in interpreting point estimates derived from this setting. Still, even with these wide confidence intervals, there is little doubt that Afghanistan has suffered a
major economic shock following the Taliban takeover, likely due to reductions in international aid and Western military spending (Floreani et al. 2016). More specifically, our work serves to isolate the economic shock associated with the Taliban takeover, shifting the country from a positive growth trend to a deep recession.

For many countries beyond Afghanistan, traditional economic data remains unavailable or unreliable, creating a need for innovative approaches to data gathering and analysis. Indeed, with a growing number of countries turning away from democracy, the number of cases of such data-scarce regions may grow (Martinez 2022). In these settings, the use of relatively high-frequency data such as nightlights enables researchers to get closer to real-time analysis. Even at the present time, researchers could potentially use this methodology to explore such questions as the effects of Western sanctions on the Russian or Iranian economies.

When confronted with data scarcity or unreliability, future research might also explore and incorporate additional sources of economic information including call data records of mobile phones (Blumenstock et al. 2018), social media posts (Indaco 2020), and combinations of such data (Zhou et al. 2022). These new data sources, alongside the synthetic control methodology, promise more accurate and faster evaluations of regional shocks, providing researchers and policy-makers with a powerful tool in support of economic analysis and potential interventions.

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URL: [http://www.nber.org/papers/w26672](http://www.nber.org/papers/w26672)


A Appendix: Figures

Figure 5: Overview of synthetic control results

(a) Synthetic control using monthly data

(b) Synthetic control using quarterly data

(c) Synthetic control using bi-annual data

Synthetic control NTL for Afghanistan including post-treatment prediction interval for the counterfactual with at least 90% coverage probability. The treatment period is set to be May 2021 for the model based on monthly data and June of 2021 for the models based on quarterly and bi-annual data.
Figure 6: Overview of GDP-nowcasting models

(a) NTL based model

(b) NTL based model including country fixed effects

(c) NTL based model including country fixed effects and a time trend

(d) NTL based model including country fixed effects and country-specific tie trends

Annual GDP data for Afghanistan as well as estimates based on annual averages of observed NTL radiance including 90% confidence intervals and point estimates based on synthetic control NTL predictions. Figures correspond to different model specifications.
## B Appendix: Tables

Table 1: Estimates of $\hat{r}$ and nonzero elements of $\hat{w}$

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<td>Uzbekistan</td>
<td>Namangan</td>
<td>0.08</td>
<td>0.18</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Intercepts $\hat{r}$ and weighted average vectors $\hat{w}$ for synthetic controls based on monthly, quarterly, and bi-annual pre-treatment observations (January 2015 to May 2021 / Q1 2015 to Q2 2021) based on model (2).
Table 2: Overview of different models

<table>
<thead>
<tr>
<th>Model</th>
<th>$\log(GDP_{is}) = \alpha + \beta \bar{Y}_{is}$</th>
<th>$\log(GDP_{is}) = \alpha + \beta \bar{Y}<em>{is} + \gamma s + u</em>{is}$</th>
<th>$\log(GDP_{is}) = \alpha + \beta \bar{Y}<em>{is} + u</em>{is}$</th>
<th>$\log(GDP_{is}) = \alpha + \beta \bar{Y}<em>{is} + \gamma s + u</em>{is}$</th>
<th>$\log(GDP_{is}) = \alpha + \beta \bar{Y}<em>{is} + \gamma s + u</em>{is}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>14.10 (0.56)***</td>
<td>14.19 (0.56)***</td>
<td>19.06 (1.28)***</td>
<td>13.70 (1.64)***</td>
<td>12.25 (2.17)***</td>
</tr>
<tr>
<td>NTL</td>
<td>0.81 (0.04)***</td>
<td>0.81 (0.04)***</td>
<td>0.41 (0.11)***</td>
<td>0.89 (0.15)***</td>
<td>1.01 (0.19)***</td>
</tr>
<tr>
<td>year</td>
<td>-0.04 (0.03)</td>
<td>-0.04 (0.03)</td>
<td>-0.05 (0.01)***</td>
<td>-0.05 (0.01)***</td>
<td>-0.03 (0.03)</td>
</tr>
<tr>
<td>factor(country)Armenia</td>
<td>-0.14 (0.12)</td>
<td>0.26 (0.14)</td>
<td>0.48 (0.26)</td>
<td>0.48 (0.26)</td>
<td>0.48 (0.26)</td>
</tr>
<tr>
<td>factor(country)Azerbaijan</td>
<td>0.44 (0.15)**</td>
<td>-0.07 (0.18)</td>
<td>-0.34 (0.27)</td>
<td>-0.34 (0.27)</td>
<td>-0.34 (0.27)</td>
</tr>
<tr>
<td>factor(country)Georgia</td>
<td>-0.36 (0.11)**</td>
<td>-0.60 (0.11)***</td>
<td>-0.67 (0.17)***</td>
<td>-0.67 (0.17)***</td>
<td>-0.67 (0.17)***</td>
</tr>
<tr>
<td>factor(country)Iran, Islamic Rep.</td>
<td>1.22 (0.48)*</td>
<td>-0.80 (0.62)</td>
<td>-0.98 (0.82)</td>
<td>-0.98 (0.82)</td>
<td>-0.98 (0.82)</td>
</tr>
<tr>
<td>factor(country)Iraq</td>
<td>0.81 (0.43)</td>
<td>-0.98 (0.55)</td>
<td>-1.38 (0.70)</td>
<td>-1.38 (0.70)</td>
<td>-1.38 (0.70)</td>
</tr>
<tr>
<td>factor(country)Kyrgyz Rep.</td>
<td>-1.11 (0.11)***</td>
<td>-1.34 (0.11)***</td>
<td>-1.26 (0.16)***</td>
<td>-1.26 (0.16)***</td>
<td>-1.26 (0.16)***</td>
</tr>
<tr>
<td>factor(country)Lebanon</td>
<td>0.44 (0.14)**</td>
<td>0.01 (0.15)</td>
<td>0.18 (0.26)</td>
<td>0.18 (0.26)</td>
<td>0.18 (0.26)</td>
</tr>
<tr>
<td>factor(country)Pakistan</td>
<td>1.78 (0.30)***</td>
<td>0.56 (0.38)</td>
<td>0.31 (0.49)</td>
<td>0.31 (0.49)</td>
<td>0.31 (0.49)</td>
</tr>
<tr>
<td>factor(country)Syrian Arab Rep.</td>
<td>-0.54 (0.14)***</td>
<td>-1.00 (0.16)***</td>
<td>-0.77 (0.20)***</td>
<td>-0.77 (0.20)***</td>
<td>-0.77 (0.20)***</td>
</tr>
<tr>
<td>factor(country)Tajikistan</td>
<td>-0.88 (0.09)***</td>
<td>-0.87 (0.08)***</td>
<td>-0.71 (0.16)***</td>
<td>-0.71 (0.16)***</td>
<td>-0.71 (0.16)***</td>
</tr>
<tr>
<td>factor(country)Turkmenistan</td>
<td>-0.08 (0.24)</td>
<td>-1.07 (0.31)***</td>
<td>-1.54 (0.43)***</td>
<td>-1.54 (0.43)***</td>
<td>-1.54 (0.43)***</td>
</tr>
<tr>
<td>factor(country)Uzbekistan</td>
<td>0.51 (0.23)*</td>
<td>-0.37 (0.28)</td>
<td>-0.28 (0.37)</td>
<td>-0.28 (0.37)</td>
<td>-0.28 (0.37)</td>
</tr>
<tr>
<td>year:factor(country)Armenia</td>
<td>-0.04 (0.04)</td>
<td>0.03 (0.04)</td>
<td>-0.00 (0.04)</td>
<td>-0.00 (0.04)</td>
<td>-0.00 (0.04)</td>
</tr>
<tr>
<td>year:factor(country)Azerbaijan</td>
<td>0.03 (0.04)</td>
<td>0.00 (0.04)</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
</tr>
<tr>
<td>year:factor(country)Georgia</td>
<td>0.03 (0.04)</td>
<td>0.00 (0.04)</td>
<td>-0.01 (0.04)</td>
<td>-0.01 (0.04)</td>
<td>-0.01 (0.04)</td>
</tr>
<tr>
<td>year:factor(country)Iran, Islamic Rep.</td>
<td>-0.04 (0.04)</td>
<td>-0.07 (0.04)</td>
<td>-0.02 (0.04)</td>
<td>-0.02 (0.04)</td>
<td>-0.02 (0.04)</td>
</tr>
<tr>
<td>year:factor(country)Iraq</td>
<td>-0.04 (0.04)</td>
<td>-0.07 (0.04)</td>
<td>-0.02 (0.04)</td>
<td>-0.02 (0.04)</td>
<td>-0.02 (0.04)</td>
</tr>
<tr>
<td>year:factor(country)Kyrgyz Rep.</td>
<td>-0.01 (0.04)</td>
<td>-0.04 (0.04)</td>
<td>-0.07 (0.04)</td>
<td>-0.07 (0.04)</td>
<td>-0.07 (0.04)</td>
</tr>
<tr>
<td>year:factor(country)Lebanon</td>
<td>-0.01 (0.04)</td>
<td>-0.04 (0.04)</td>
<td>-0.07 (0.04)</td>
<td>-0.07 (0.04)</td>
<td>-0.07 (0.04)</td>
</tr>
<tr>
<td>year:factor(country)Pakistan</td>
<td>-0.10 (0.05)*</td>
<td>0.08 (0.05)</td>
<td>0.08 (0.05)</td>
<td>0.08 (0.05)</td>
<td>0.08 (0.05)</td>
</tr>
<tr>
<td>year:factor(country)Syrian Arab Rep.</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
</tr>
<tr>
<td>year:factor(country)Tajikistan</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
</tr>
<tr>
<td>year:factor(country)Turkmenistan</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
</tr>
<tr>
<td>year:factor(country)Uzbekistan</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
<td>-0.08 (0.04)*</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.80</td>
<td>0.81</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.80</td>
<td>0.80</td>
<td>0.98</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>87</td>
<td>87</td>
<td>87</td>
<td>87</td>
<td>87</td>
</tr>
</tbody>
</table>

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$
Table 3: Likelihood-Ratio test results for different model specifications

<table>
<thead>
<tr>
<th></th>
<th>Model 1 vs Model 2</th>
<th>Model 1 vs Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>DF of $H_0$ model</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>DF of alternative model</td>
<td>4</td>
<td>14</td>
</tr>
<tr>
<td>Log-Likelihood of $H_0$ model</td>
<td>-61.19</td>
<td>-61.19</td>
</tr>
<tr>
<td>Log-Likelihood of alternative model</td>
<td>-60.61</td>
<td>37.05</td>
</tr>
<tr>
<td>Associated Chi-squared value</td>
<td>1.15</td>
<td>196.47</td>
</tr>
<tr>
<td>Associated p-value</td>
<td>0.28</td>
<td>$2.2 \times 10^{-16}$ ***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Model 3 vs Model 4</th>
<th>Model 4 vs Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>DF of $H_0$ model</td>
<td>14</td>
<td>15</td>
</tr>
<tr>
<td>DF of alternative model</td>
<td>15</td>
<td>26</td>
</tr>
<tr>
<td>Log-Likelihood of $H_0$ model</td>
<td>37.05</td>
<td>47.22</td>
</tr>
<tr>
<td>Log-Likelihood of alternative model</td>
<td>47.22</td>
<td>66.57</td>
</tr>
<tr>
<td>Associated Chi-squared value</td>
<td>20.34</td>
<td>38.71</td>
</tr>
<tr>
<td>Associated p-value</td>
<td>$6.5 \times 10^{-6}$ ***</td>
<td>$5.9 \times 10^{-5}$ ***</td>
</tr>
</tbody>
</table>

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$