Estimating the Collapse of Afghanistan's Economy Using Nightlights Data

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Abstract

The Taliban's takeover of Afghanistan in August 2021 led to the withdrawal of much of the West's massive financial support to that country. The consequences are widespread for the government and its people, and news reports suggest that the economy is in "collapse." In this article, we go beyond qualitative and survey-based measures of the Afghan economy by using nightlights as a proxy measure for changes in GDP. Utilizing a synthetic control based on provinces of other countries in the region, we find that the Taliban takeover caused a shift from a positive growth trajectory towards a deep recession. Specifically, we estimate that Afghanistan's GDP has likely fallen by about 15 percent since mid-2021, a shock comparable to the annual economic downturn of the United States during the peak of the Great Depression.

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1 Introduction and Motivation

The collapse of the Government of the Islamic Republic of Afghanistan (GIROA) in August 2021 and the subsequent takeover by the Taliban led to a rapid deterioration in the country's economic conditions. Foreign assistance and Western military spending – which provided 45 percent of GDP and 75 percent of the government budget – was largely withdrawn. Overall, the World Bank estimates that Afghanistan's GDP has fallen by more than one-third (World Bank 2022*a*). For its part, the United Nations Development Program (UNDP) estimated that the GDP decline was around 20 percent within a year of the Taliban takeover in August 2021 (UNDP 2022) and that it may reach 30 percent in coming years (UNDP 2021).

These estimates by international organizations 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 2022*b*, p. 186).

The purpose of this paper is to improve upon existing measures by using changes in nighttime lights (NTL, or nightlights) to estimate the collapse of Afghanistan's economy, in particular, the fall in its 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 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 describe our data and its processing in Section 2.

To compute the full impact of the Taliban takeover, however, one has to take into account not solely the scale of the economic collapse, as international organizations have attempted, but also the counterfactual of what the country's economic trajectory might have been had the previous regime remained in power with Western support. It is this gap between the current reality on the ground and the counterfactual that captures the entirety of the Taliban's macroeconomic impact since August 2021. This is the essence of a "synthetic control" methodology, a technique for constructing counterfactual estimates.

In this analysis, we use a weighted average of the nightlight radiance in provinces of neighboring countries such as Pakistan and Iran as the control. Details of our construction of the synthetic control are provided in Section 3. By charting the changes in Afghan nightlights vs. those of its neighbors, we are able to isolate the effects of the Taliban takeover on the country's nightlight radiance; we then use the change in nightlights to estimate the magnitude of the associated shock to GDP. This article combines monthly nightlights with a newly devised approach to synthetic control predictions (Cattaneo et al. 2021) to study a macroeconomic shock.[1]

The results of this estimation are discussed in Section 4. We conclude and discuss future research in Section 5, emphasizing that our work showcases the potential of combining new, passive data sources with the synthetic control methodology to complement traditional approaches to economic analysis, particularly in cases of data scarcity. Our method permits researchers to obtain more rapid (and potentially more accurate) economic assessments than surveys conducted in settings where accurate and representative information is difficult to gather from firms, households, and the government, and thus could be used to compliment existing techniques.

2 Context and data

Prior to August 2021, Afghanistan depended heavily upon foreign aid and military spending to fuel its economy. Due to these inflows, the country's GDP "grew by more than seven percent per year on average over 2001-2020, with GDP increasing by 180 percent between 2001 and 2020. Real per capita income increased by 75 percent between 2002 and 2018" (World Bank 2022*a*, p. 1). Foreign assistance provided direct budget support to the Government, enabling the provision of services such as health care and education, while military spending boosted consumption and reduced poverty, especially where military activity was most intense (Floreani et al. 2016).

With the Taliban takeover, the Afghan economy faced multiple shocks, including the loss of external support, the loss of access to Central Bank foreign currency holdings due to West-

[1] For an earlier effort that combines nightlights and synthetic controls, see Pfeifer et al. (2018).

ern sanctions, the flight of human capital, and a likely reduction in domestic private sector investment due to pervasive uncertainty about the nation's future. Calculating the scale of these shocks is challenging, however, in the absence of reliable data.

To overcome this 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[2]. 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). 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 ($nW \cdot sr^{-1} \cdot cm^{-2}$).

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. 2020). Beyond nightlights data, we also use the available annual GDP data from 2015 to 2021 for Afghanistan as well as Iran, Iraq, Lebanon, Pakistan, Syria, Turkmenistan, Tajikistan, and Uzbekistan, which we retrieve from the World Bank online database.[3]

2.1 Data Processing and Extraction

We first utilize the annual VNL 2.1 data to reduce the noise of the monthly cloud-free composites. As 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, we extract the fields of zero radiance for a given annual observation and then set the

[2]Data available under https://eogdata.mines.edu/products/vnl/

[3]At the time of writing, annual GDP data is not available for Syria in 2019-2021, for Turkmenistan 2020-2021, and for Afghanistan and Iran in 2021.

radiance of these fields to zero for all monthly observations of the following year [4].

Following Jiang et al. (2017), we also introduce an upper bound for the brightness of each raster field at 300 $\mathrm{nW} \cdot \mathrm{sr}^{-1} \cdot \mathrm{cm}^{-2}$. 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.

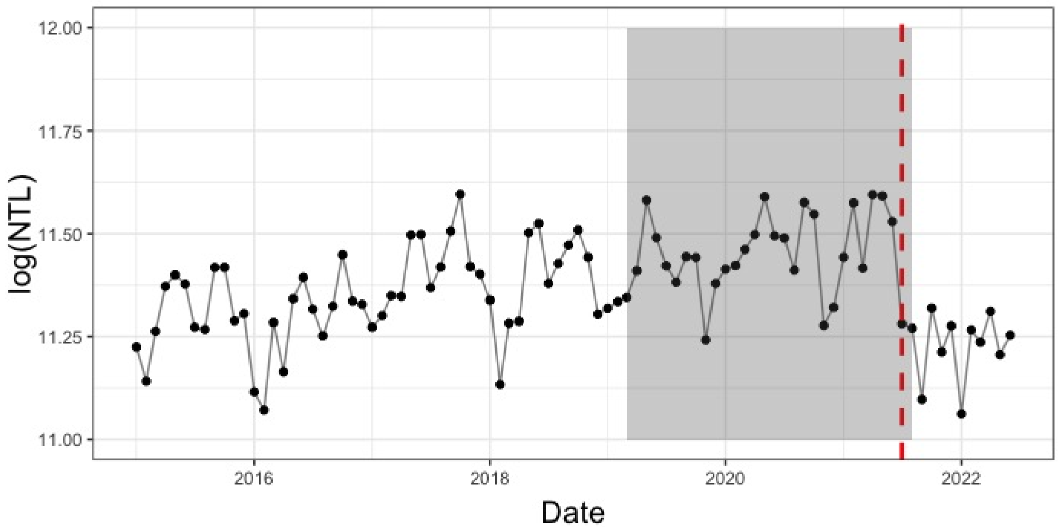
Given the final, reduced-noise monthly composites, we aggregate radiation by summing over all raster fields in a province. Thus, we construct a time series panel of monthly radiance for the provinces of Afghanistan, Iran, Iraq, Lebanon, Pakistan, Syria, Turkmenistan, Tajikistan, and Uzbekistan. Figure 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. 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.

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 nightlight time series to predict the causal impact of the withdrawal on Afghanistan's nightlights using the synthetic control approach. Second, we estimate the economic downturn associated with the

[4] Preceding annual observations are used rather than concurrent annual observations to enable the processing of monthly data for the ongoing year of 2022. The change to using concurrent annual observations has little impact on the resulting extracted data for 2015-2021.

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.

given change in nightlights using a country fixed effects model. [5]

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 neighboring countries, 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 neighboring countries constitute the *donor pool*.

Following the common notation and the setup of 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 $i \in \{2, ..., J+1\}$ 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

[5]As a technical aside, note that we "predict" the results of our synthetic control model because we assume the treatment to be a random variable whereas we "estimate" the relationship between NTL and GDP as we assume it to be non-random, following the literature (Henderson et al. 2011).

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

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

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

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

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

$$\widehat{Y}_{1t}(0) = \widehat{r} + \sum_{i=2}^{J+1} \widehat{\mathrm{w}}_i Y_{it}(0) = \widehat{r} + \mathbf{X}_t \cdot \widehat{\mathbf{w}} \quad \text{for} \quad t \in \{T_0+1,\ldots,T\}.$$

Step 2 - Prediction Intervals:

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

$$e_t := Y_{1t}(0) - \widehat{Y}_{1t}(0) = Y_{1t}(0) - \widehat{r} - \mathbf{X}_t \cdot \widehat{\mathbf{w}} \quad \text{for} \quad t \in \{T_0 + 1, \ldots, T\}.$$

Further, if $\widehat{\mathbf{w}}$ and $\widehat{r}$ are concentrating around $\mathbf{w}_0 \in \mathcal{W}$ and $r_0 \in \mathbb{R}$ respectively, we can express the total uncertainty regarding the prediction of the treatment effect in two parts:

$$\widehat{\tau}_t - \tau_t = Y_{1t}(1) - \widehat{Y}_{1t}(0) = e_t - (\mathbf{X}_t \cdot (\widehat{\mathbf{w}} - \mathbf{w}_0) + (\widehat{r} - r_0)) \quad \text{for} \quad t \in \{T_0 + 1, \ldots, T\}.$$

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 $(\mathbf{X}_t \cdot (\widehat{\mathbf{w}} - \mathbf{w}_0) + (\widehat{r} - r_0))$ stemming from the construction of $\widehat{\mathbf{w}}$ and $\widehat{r}$ 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

$$\epsilon_t := Y_{1t}(0) - \widehat{Y}_{1t}(0) = Y_{1t}(0) - \widehat{r} - \mathbf{X}_t \cdot \widehat{\mathbf{w}} \quad \text{for} \quad t \in \{1, \ldots, T_0\},$$

re-sampling this error term 500 times, and estimating quantiles for the associated difference between $\widehat{\mathbf{w}}$, $\widehat{r}$ and $\mathbf{w}_0$, r_0. Estimating these two sources of uncertainty separately and combining them using the union bound allows for the construction of the prediction interval for τ_t.[6]

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

[6]We refer to Cattaneo et al. (2021) for a detailed derivation of the the prediction intervals.

existing nightlight 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

$$\log(GDP_{is}) = \alpha_i + \bar{Y}_{is}\beta + u_{is} \quad \text{for} \quad s = 1, \ldots, S \text{ and } i = 1, \ldots, N \tag{3}$$

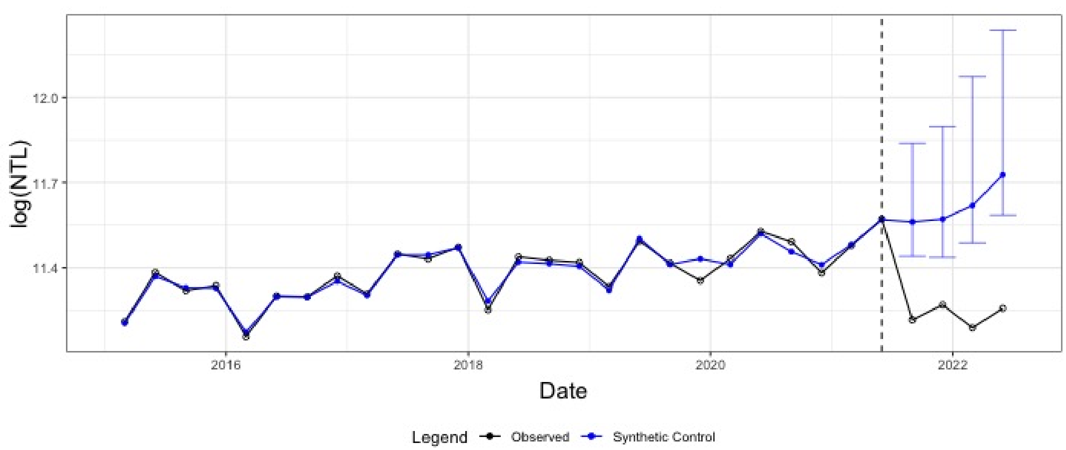
where N is the number of countries under consideration and $1, \ldots, S$ are the years in the range from 2015 to 2021. $\bar{Y}_{is}$ denotes the annual average of aggregated log NTL data for country i in year s, while α_i denotes the respective country fixed effect and u_{is} denotes the error term. Using this model, we nowcast the log GDP of Afghanistan for 2021 and for the current average of 2022 according to $\log(\widehat{GDP}_{it}) = \widehat{\alpha}_i + \bar{Y}_{it}\widehat{\beta}$.

4 Results

4.1 Synthetic Control Results

Figure 2 shows the synthetic control based on quarterly averages of nightlight data to further reduce noise and potential seasonality of the monthly observations. [7]

Figure 2: Synthetic control results



Synthetic control (blue) for Afghanistan's nightlight 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.

[7] The appendix includes corresponding results based on monthly and bi-annual data in Figure 4 and an overview of the non-zero elements of the chosen weights $\hat{\mathbf{w}}$ for each model in Table 1.

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 percent coverage probability, and the observed drop in Afghanistan's nightlight 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 approximately 0.35 in terms of log NTL.

4.2 Nowcasting results

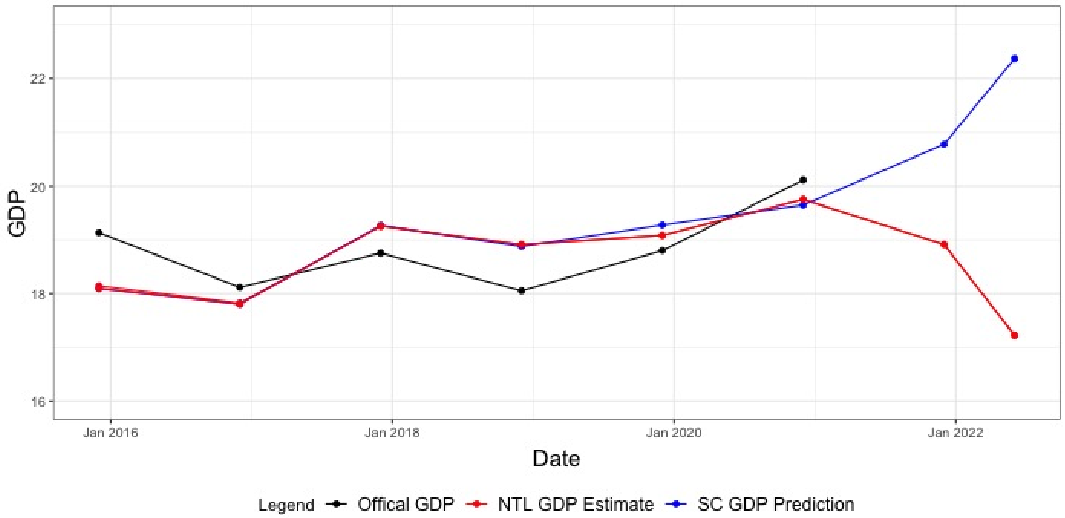
Next, we estimate the decline in GDP associated with the reduced nightlight for Afghanistan based on past correlations between GDP and nightlight in the region. Table 2 shows the estimates for different specifications of linear models for the relationship between annual log aggregated nightlight and log GDP for Afghanistan and the selection of neighboring countries. Table 2 includes model specifications ranging from the simple linear model relating log NTL to log GDP to models including country fixed effects, time trend, and two-way fixed effects.

For the out-of-sample nowcasting of Afghanistan's GDP, we utilize the country fixed effect model as it fits the observed data well and achieves a high in-sample adjusted R^2. Further, we chose not to include a time trend, as the models under consideration produce negative estimates for the time trend and we are cautious of linearly projecting this time trend in the future. Excluding this time trend will lead to a more conservative estimate of the reduction in Afghanistan's GDP. For similar reasons and to prevent overfitting to the limited number of observations, we did not choose the two-way fixed effects model specification which includes time-country level fixed effects. Again, this specification would have resulted in a larger estimate of the reduction in GDP.[8]

Figure 3 shows the estimated GDP for Afghanistan using the country fixed effect model. The estimated GDP of Afghanistan is 18.91 billion USD in 2021 and 17.22 billion USD in 2022. This corresponds to a fall of 14.4 percent of GDP over the 1.5 years since the last official GDP publication in 2020. Further, we included the GDP-level associated with the annual aver-

[8] Refer to Figure 5 for an overview of the nowcasting of Afghanistan's GDP using different model specifications.

Figure 3: GDP-nowcasting with country fixed effects



Annual GDP data for Afghanistan as well as estimates based on annual averages of observed NTL radiance and synthetic control NTL predictions.

ages 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 that the neighboring countries of Afghanistan, and hence the weighted-average counterfactual, are on, this evidence indicates that the economy of Afghanistan has fallen into a deep recession.

5 Conclusion

This paper highlights the promise of using monthly nightlights data in estimating regional economic shocks or trends when facing data scarcity or a complete lack of traditional economic indicators. We provide an improved 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 estimate of the associated downturn in GDP of approximately 14.4 percent. This presents a conservative lower bound when compared to the survey-based estimates published by international institutions, and can be used to complement those efforts. Taken together, this body of work can provide a more accurate view of the country's economic situation and the impact of reduced international aid and military spending (Floreani et al. 2016). Specifically, our work serves to isolate the shift in trajectory associated with the Taliban takeover, from a positive growth trend to a deep recession.

For many countries beyond Afghanistan, traditional economic data remain unavailable or unreliable, creating a need for innovative approaches to data gathering and analysis. Particularly, the use of relatively high frequency data such as nightlights enables researchers to get closer to real-time analysis. Future research in settings of data scarcity might explore 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) to construct counterfactuals. Utilizing these new data sources, in combination with the synthetic control methodology, promises 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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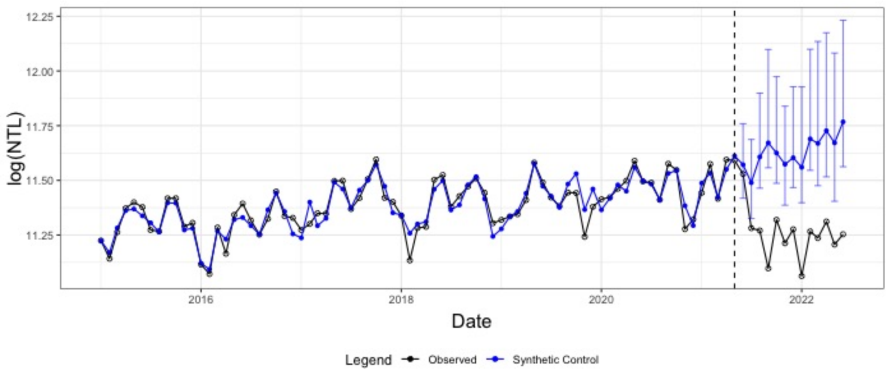
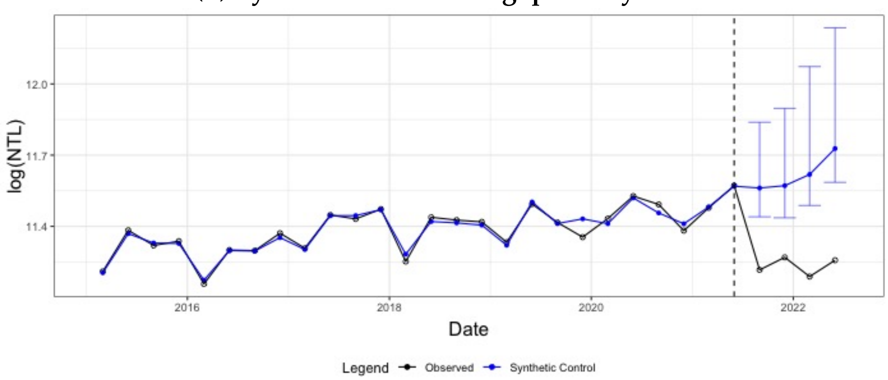
A Appendix: Figures

Figure 4: Overview of synthetic control results

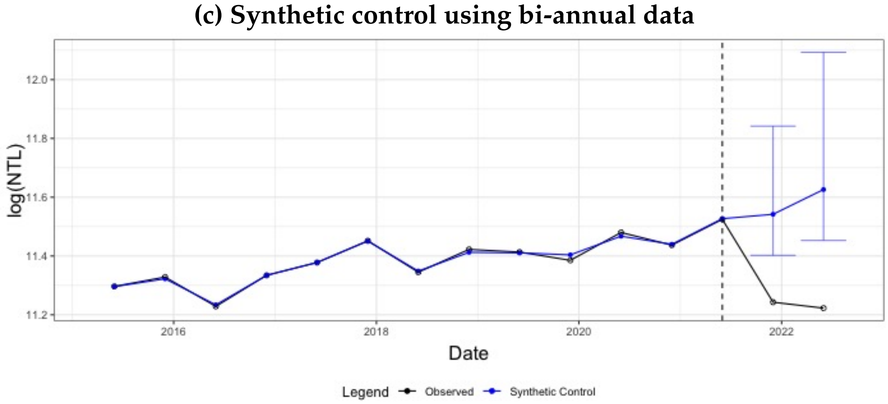
(a) Synthetic control using monthly data



(b) Synthetic control using quarterly data



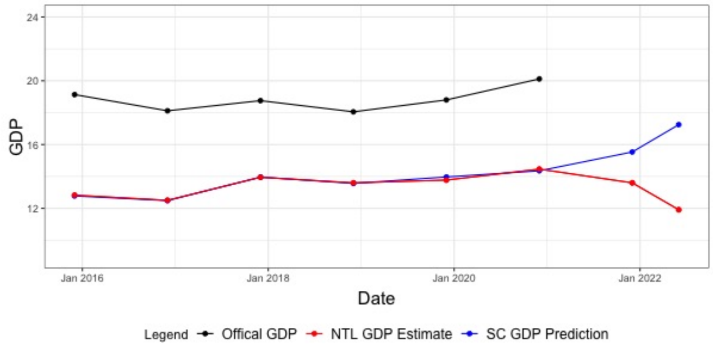
(c) Synthetic control using bi-annual data



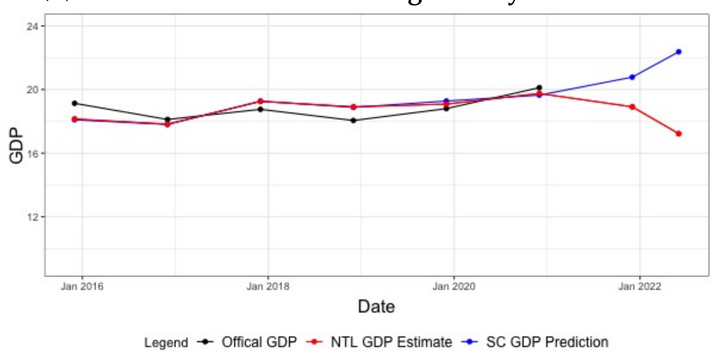
Synthetic control NTL for Afghanistan (January 2015 on-wards) including post-treatment prediction interval for the counterfactual with at least 90% coverage probability. The treatment period is set to be May 2021 for the model based on monthly data and June of 2021 for the models based on quarterly and bi-annual data.

Figure 5: Overview of GDP-nowcasting models

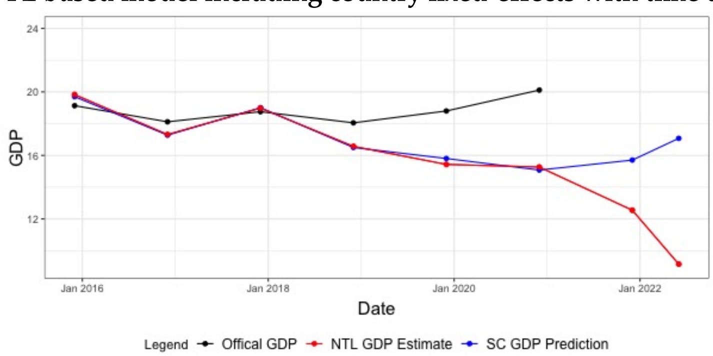
(a) NTL based model



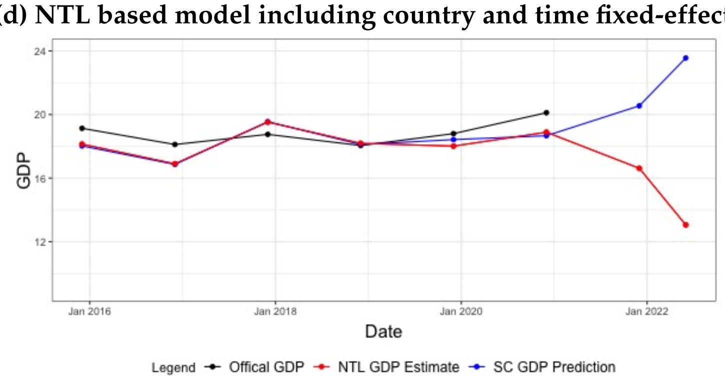
(b) NTL based model including country fixed-effects



(c) NTL based model including country fixed-effects with time trend



(d) NTL based model including country and time fixed-effects



B Appendix: Tables

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

Country	Province	Monthly data	Quarterly data	Bi-annual data
Intercept	-	1.35	0.76	0.37
Iran	Hormozgan	0.01	0.00	0.00
Iran	Khuzestan	0.03	0.03	0.00
Iran	Kohgiluyeh and Buyer Ahmad	0.01	0.00	0.00
Iran	Markazi	0.00	0.02	0.00
Iran	Razavi Khorasan	0.01	0.00	0.00
Iran	Bushehr	0.03	0.05	0.00
Iraq	Wasit	0.00	0.00	0.18
Iraq	AlBasrah	0.00	0.11	0.15
Lebanon	Beirut	0.03	0.00	0.00
Pakistan	F.A.T.A.	0.18	0.22	0.09
Pakistan	Northern Areas	0.08	0.03	0.00
Pakistan	Sind	0.00	0.00	0.04
Syria	Idlib	0.00	0.00	0.06
Syria	Quneitra	0.00	0.01	0.05
Syria	Aleppo	0.00	0.02	0.00
Syria	Dayr Az Zawr	0.01	0.02	0.02
Syria	Hims	0.01	0.02	0.00
Tajikistan	Dushanbe	0.24	0.08	0.00
Tajikistan	Khatlon	0.01	0.00	0.00
Turkmenistan	Ashgabat	0.09	0.23	0.21
Turkmenistan	Chardzhou	0.07	0.00	0.00
Turkmenistan	Mary	0.05	0.00	0.00
Uzbekistan	Andijon	0.07	0.10	0.06
Uzbekistan	Bukhoro	0.01	0.00	0.00
Uzbekistan	Kashkadarya	0.00	0.06	0.14
Uzbekistan	Namangan	0.05	0.01	0.00

Intercepts $\widehat{r}$ and weighted average vectors $\widehat{\mathbf{w}}$ for synthetic controls based on monthly, pre-treatment observations (January 2015 to May 2021 / Q1 2015 to Q2 2021) based on model (2).

Table 2: Overview of GDP-nowcasting models

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	$13.98\ (0.54)^{***}$	$14.06\ (0.55)^{***}$	$17.05\ (2.98)^{***}$	$8.24\ (1.99)^{***}$	$8.87\ (2.32)^{***}$
NTL	$0.82\ (0.04)^{***}$	$0.83\ (0.04)^{***}$	$0.58\ (0.26)^{*}$	$1.38\ (0.18)^{***}$	$1.31\ (0.21)^{***}$
year		$-0.04\ (0.04)$		$-0.09\ (0.01)^{***}$	$-0.03\ (0.01)^{**}$
factor(country)Iran, Islamic Rep.			$0.50\ (1.11)$	$-2.88\ (0.77)^{***}$	$-2.06\ (0.89)^{*}$
factor(country)Iraq			$0.17\ (0.97)$	$-2.78\ (0.67)^{***}$	$-2.40\ (0.73)^{**}$
factor(country)Lebanon			$0.23\ (0.33)$	$-0.48\ (0.18)^{*}$	$-0.02\ (0.23)$
factor(country)Pakistan			$1.35\ (0.67)$	$-0.66\ (0.45)$	$-0.37\ (0.50)$
factor(country)Syrian Arab Republic			$-0.60\ (0.22)^{**}$	$-1.35\ (0.17)^{***}$	$-1.09\ (0.16)^{***}$
factor(country)Turkmenistan			$-0.42\ (0.52)$	$-2.05\ (0.40)^{***}$	$-2.12\ (0.42)^{***}$
factor(country)Tajikistan			$-0.87\ (0.05)^{***}$	$-0.84\ (0.07)^{***}$	$-0.61\ (0.16)^{***}$
factor(country)Uzbekistan			$0.19\ (0.50)$	$-1.25\ (0.34)^{***}$	$-0.77\ (0.36)^{*}$
year:factor(country)Iran, Islamic Rep.					$-0.14\ (0.03)^{***}$
year:factor(country)Iraq					$-0.03\ (0.02)$
year:factor(country)Lebanon					$-0.10\ (0.02)^{***}$
year:factor(country)Pakistan					$-0.03\ (0.02)$
year:factor(country)Syrian Arab Republic					$-0.05\ (0.04)$
year:factor(country)Turkmenistan					$0.08\ (0.03)^{**}$
year:factor(country)Tajikistan					$-0.07\ (0.04)$
year:factor(country)Uzbekistan					$-0.09\ (0.02)^{***}$

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Overview of models relating log(GDP) and log(NTL) based on available annual data from 2015 to 2021. HAC standard errors are computed using the "sandwich" R-package (Zeileis et al. 2020).