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. However, assessing the scale of this collapse is proving difficult as official data is scarce. To complement qualitative measures obtained through rapid surveys of the population, we employ monthly nightlights data as a proxy measure for changes in economic activity. By combining a synthetic control approach with nightlights data from neighboring countries, our analysis reveals a significant shift in Afghanistan's economic trajectory: from positive growth to a deep recession, even considering the impact of the Covid pandemic. Our estimations suggest that Afghanistan's GDP has declined by approximately 15% from 2020 to 2022, notably less than the World Bank's current survey-based measure of a 28% decline in 2021 alone. In contrast to other available estimates, our reporting includes confidence intervals to convey the uncertainties surrounding these point estimates. This study showcases the potential applicability of our methodology and the use of appropriately processed monthly nightlights data in scenarios where administrative data is limited or unreliable.

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 2022*a*), a number revised downward more recently to approximately 28% (World Bank 2023). For 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). 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 7% 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. For example, the World Bank's Afghanistan Private Sector Rapid Survey was administered to 100 formal businesses over the phone and online between October 15 and November 15, 2021 (World Bank 2022*b*). 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*c*, 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, and to advance the utilization of the monthly cloud-free DNB composite VIIRS nightlights data set in the study of regional economic activities, particularly in settings where administrative reporting is scarce or non-existent. Nightlights have been widely used as proxy measures of economic activity since the innovative 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). Further, nightlights are utilized in other data scarce settings such as the study of the spatial distribution of economic activity in North Korea following trade sanctions (Lee 2018). We note, however, that the vast majority of existing studies compare annual nightlights measurements with GDP data and are able to make use of official statistics for bench-marking purposes, which is not possible for Afghanistan after 2020.

The novelty of our study is to use monthly NTL as the basis for a nowcast of the current Afghan GDP and to combine this with a relatively new synthetic control methodology for constructing counterfactual estimates. As part of this, we introduce a workflow to prepare and process the monthly cloud-free DNB composite VIIRS nightlights data set for using it as a proxy indicator for economic activity. 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 the change from 2020 to 2022 is a 15% decline, which is notably less than the World Bank's current estimate of a 28% decrease in 2021 alone. Unlike the World Bank and other international organizations, we further report confidence intervals around our economic measurements, highlighting the uncertainty surrounding these reported point estimates. On the importance of reporting confidence intervals, see Romer (2020). Overall, we believe our methodology has broad implications for researchers studying economies where data are sparse, unavailable, or unreliable. In particular, our approach expands on previous works combining nightlights and synthetic controls Pfeifer et al. (2018) and permits researchers to obtain faster, and potentially more accurate, economic assessments than surveys, providing yet another, complimentary method for economic analysis.

This paper proceeds in five 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 income increased by 75% 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. 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 (**?**). 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 that are captured in a 3000 km swath 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 ($\mathrm{nW} \cdot \mathrm{sr}^{-1} \cdot \mathrm{cm}^{-2}$).

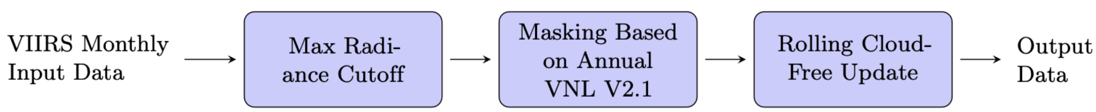
While there are many GeoTiff data sets available, we utilize monthly stray-light corrected cloud-free composites from January 2015 to December 2022. Additionally, we use annual VIIRS nightlights (VNL) 2.1 average-masked data from 2014 to 2021 which employ an adaptive, multi-year data range threshold to remove extraneous features such as biomass burning, auroras, and background noise (Elvidge et al. 2021). The remaining lights captured in these composites are primarily associated with urban economic activity (Gibson et al. 2020). 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. Afghanistan imports approximately 80% of its electricity. Despite ongoing payment difficulties, the country's key suppliers, Uzbekistan and Tajikistan, did not halt their exports and only briefly reduced them during the time under consideration (Putz 2022, Lillis 2022). Given this relatively stable supply of electricity, we expect nightlights to provide an insightful proxy to economic activity in Afghanistan during this tumultuous time period, even with reports of occasional power outages and cuts.

Beyond nightlights data, we also use the available annual GDP data from 2015 to 2022 for Afghanistan, as well as Armenia, Azerbaijan, Bangladesh, Bhutan, Georgia, India, Iran, Iraq, Jordan, Kazakhstan, Kyrgyzstan, Lebanon, Sri Lanka, Nepal, Pakistan, Syria, Tajikistan, Turkmenistan, Turkey, and Uzbekistan, which we retrieved from the World Bank online database. At the time of writing, annual GDP data is not available for Bhutan and Lebanon in 2022 and for Syria and Turkmenistan in both 2021 and 2022. We also exclude the World Bank's preliminary, survey-based estimate for Afghanistan's GDP in 2021. Lastly, note that there was an outage of the VIIRS sensors collecting the data for the monthly DNB composite data in August 2022 and the available composite measurement for that month was generated based on alternative data sources. This appears to coincide with slight drop in brightness throughout the region under consideration, but since it only affects a single month, we assume the impact of this on our findings is negligible.

Data Processing and Extraction

Overall, we process the monthly Monthly Cloud-free DNB Composite VIIRS nightlights data in a three step process to prepare it for our analysis as shown in Fig 1. First, 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 most likely not associated with economic activity including ephemeral sources of light such as aurora and fires as well as (non-light) background noise (Gibson et al. 2021). The radiance for raster fields associated with such ephemeral light or non-light background noise is then set 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. This means if the radiance of a raster field in the annual average-masked observation for 2020 is zero, we set the radiance of this field to zero in the monthly observations from January to December 2021. We use preceding annual observations rather than concurrent annual observations to enable the processing of monthly data for 2022 for which no VNL 2.1 annual observation 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.

Figure 1: Processing flow of the Monthly Cloud-free DNB Composite VIIRS nightlights data.



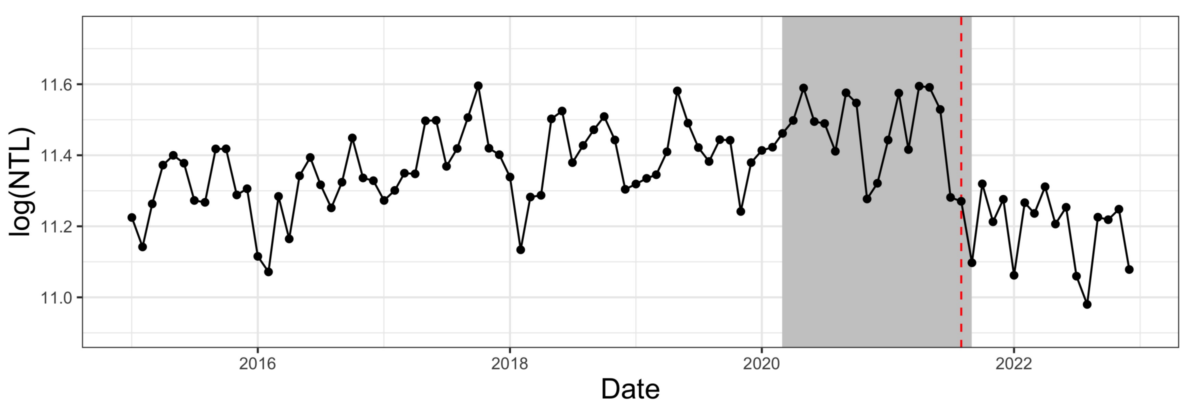
Following Jiang et al. (2017), we also introduce an upper bound for the brightness of each raster field at 300 $\text{nW} \cdot \text{sr}^{-1} \cdot \text{cm}^{-2}$. This threshold reduces outliers associated with disproportionately bright processes, primarily gas flares observed at night. While enforcing 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 Afghanistan, Armenia, Azerbaijan, Bangladesh, Bhutan, Georgia, India, Iran, Iraq, Jordan, Kazakhstan, Kyrgyzstan, Lebanon, Sri Lanka, Nepal, Pakistan, Syria, Tajikistan, Turkmenistan, Turkey, and Uzbekistan. These countries are chosen for their geographic and economic proximity and similarity. Overall, the region of study approximately consists of $5° - 55°$ N and $25° - 100°$ E. We consciously excluded some countries from our analysis that fall into this region, yet have very differently structured economies such as Saudi Arabia, Qatar, and the United Arabic Emirates.

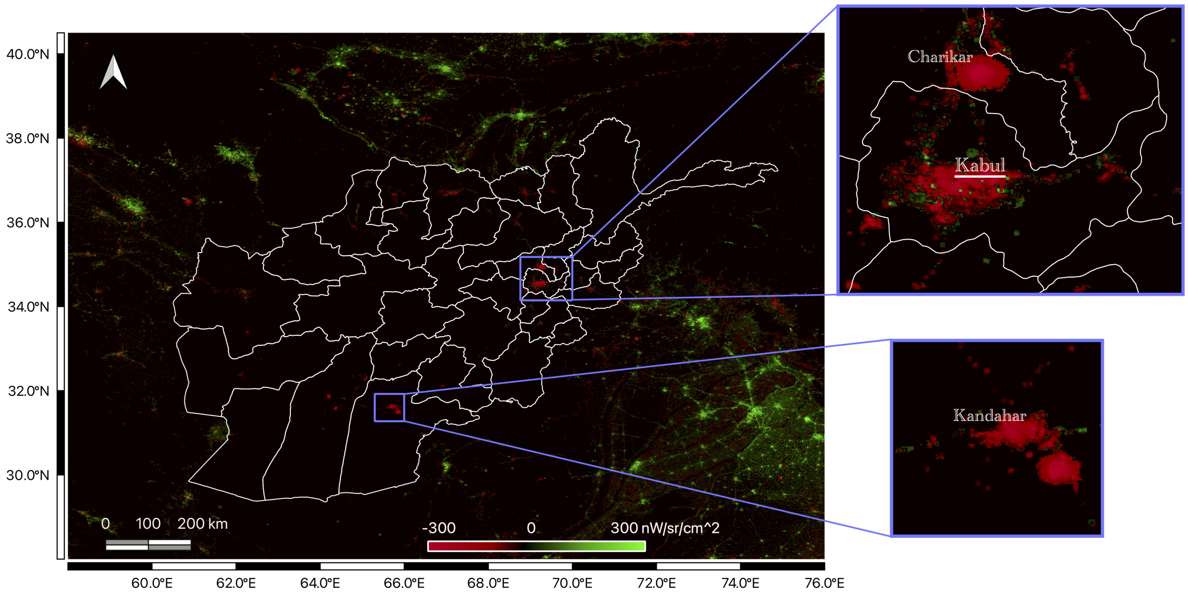
Fig 2 displays the aggregated, logged nightlight radiance for Afghanistan. The dashed vertical line highlights the sudden drop in radiance following the Taliban takeover beginning in mid-2021, which is the effect we seek to isolate. Fig 3 shows a map of the change in radiance for Afghanistan between 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 2: Aggregated extracted nightlight radiance (NTL) for Afghanistan



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

Figure 3: Mapping of the Change of Nightlight Radiance in Afghanistan



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.

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 given change in nightlights using a country fixed effects model.

Synthetic Control Methodology

We utilize the synthetic control methodology first introduced by Abadie & Gardeazabal (2003), and recently expanded by Cattaneo et al. (2021) 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. We utilize provinces instead of countries in this weighted average to achieve a more granular and more precise approximation of pre-takeover Afghanistan. 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*. Details on the derivations of the synthetic control prediction and the prediction intervals are included in the Appendix.

3.1 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. Given the limited data in the intersection of available VIIRS data and GDP data for the countries under consideration, we fit a parsimonious linear relationship between log GDP and log NTL, similar to existing nightlights literature (Henderson et al. 2011, Gibson et al. 2020). Specifically, we utilize a country fixed effect model of the form

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

where N is the number of countries under consideration, $1, \ldots, S$ are the years in the range from 2015 to 2022, $\bar{Y}_{is}$ 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 2022 according to $\log(\widehat{GDP}_{is}) = \widehat{\alpha}_i + \bar{Y}_{is}\widehat{\beta}$. In the results section, we also discuss alternative model specifications including annual fixed effects, time trends and country specific time trends.

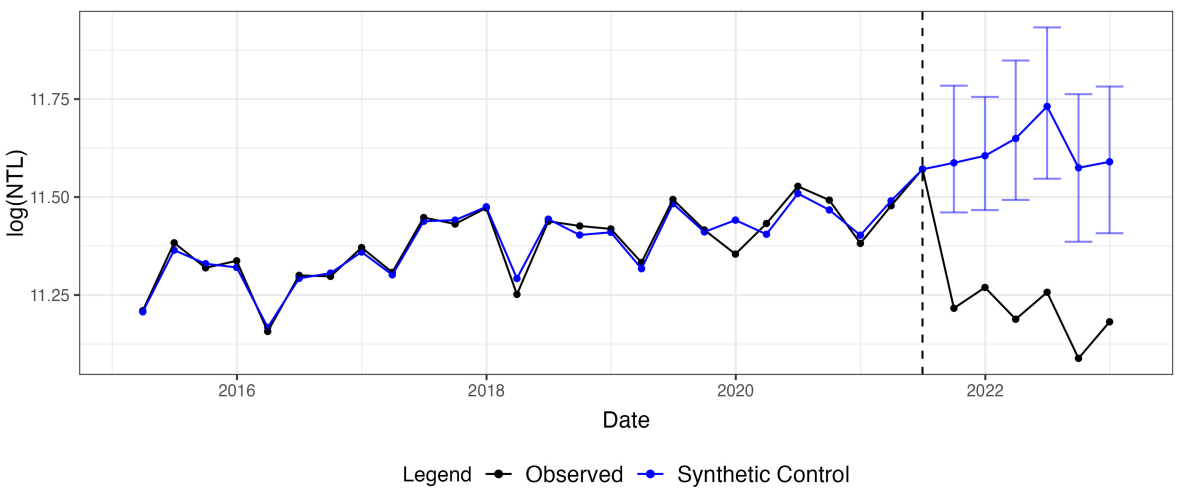
4 Results

4.1 Synthetic Control Results

Fig 4 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 11.2. Thus the average prediction for the treatment effect is approximately 0.4 in terms of log NTL. The Supporting Information section includes corresponding results based on monthly and bi-annual data in Fig 6 and an overview of the non-zero elements of the chosen weights $\hat{\mathbf{w}}$ for each model in Table 3.

Figure 4: Synthetic control results



Synthetic control (blue) for Afghanistan's nightlights based on quarterly data (black) from January 2015 to December 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 seven 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, country-specific time trends, and annual fixed effects as collected in Table 1 and 2. Table 4 and 5 in the Supporting Information section provide an overview of the regression results for the different model specifications. We used 10-fold cross-validation on the entire dataset and leave-one-out cross-validation, focusing on predicting Afghanistan's GDP for 2015 to 2020, to assess the out-of-sample prediction accuracy of the different model specifications, as shown in Table 1 and 2.

While the model specifications (4), (5), (6), and (7) all achieve a high in-sample adjusted R^2 and good cross-validation performance across all countries that we analyzed, models (4) and (5) perform the best when focusing on predicting Afghanistan's GDP.

We also ran likelihood ratio tests to assess the goodness of fit of our different model specifications, which are summarized in Table 6 in the Supporting Information section. Specifically, we fail to reject the null hypothesis that model (4) describes the true underlying data-generating process as well as model (5) does, with a p-value of 0.076. Hence, we utilize model (4), the country fixed-effect model, for the out-of-sample nowcasting of Afghanistan's GDP in 2021 and 2022.

Table 1: Overview of 10-fold cross-validation performance of the different model specifications

Model specification	R^2	RMSE	MAE	R^2 SD	RMSE SD	MAE SD
(1) NTL	0.74	0.86	0.69	0.11	0.11	0.08
(2) NTL and time-trend	0.76	0.87	0.69	0.09	0.12	0.09
(3) NTL and annual fixed effect	0.72	0.90	0.72	0.12	0.12	0.10
(4) NTL and country fixed effect	0.99	0.16	0.12	0.00	0.03	0.02
(5) NTL, country fixed effect, and time trend	0.99	0.16	0.12	0.01	0.04	0.03
(6) NTL, annual and country fixed effect	0.99	0.15	0.11	0.01	0.04	0.03
(7) NTL, country specific time trend and fixed effect	0.99	0.14	0.10	0.00	0.04	0.02

All of the reported statistics are the mean values over 10 folds of cross-validation while SD indicates their standard deviation across those folds.

Table 2: Overview of leave one out cross-validation performance, focused on Afghanistan

Model specification	R^2	RMSE	MAE	R^2 SD	RMSE SD	MAE SD
(1) NTL	-	0.06	0.06	-	0.02	0.02
(2) NTL and time-trend	-	0.06	0.06	-	0.03	0.03
(3) NTL and annual fixed effect	-	0.07	0.07	-	0.04	0.04
(4) NTL and country fixed effect	-	0.04	0.04	-	0.03	0.03
(5) NTL, country fixed effect, and time trend	-	0.04	0.04	-	0.02	0.02
(6) NTL, annual and country fixed effect	-	0.07	0.07	-	0.05	0.05
(7) NTL, country specific time trend and fixed effect	-	0.05	0.05	-	0.04	0.04

All of the reported statistics are the mean values over the 5 cross-validations while SD indicates their standard deviation across those folds. Note that the prediction R^2 is not reported as leave one out cross-validation only produces a singular prediction.

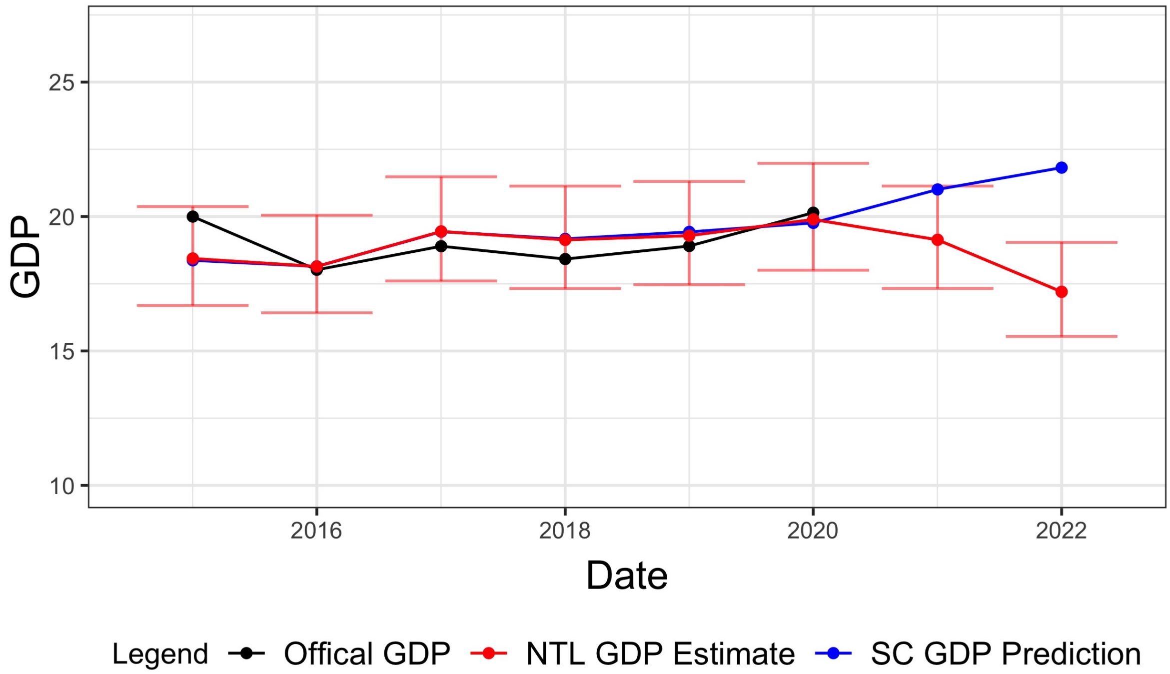
Fig 5 shows the estimated GDP for Afghanistan based on model (4) at 19.13 billion USD in 2021 and 17.20 billion USD in 2022. This corresponds to a fall of 15% of GDP over the 2 years since the last official GDP publication in 2020. However, we also report 90 % confidence intervals associated with our point estimates. Given the issues of data scarcity and quality, large confidence intervals are to be expected and indeed this is what we find. Further, the different model specifications lead the notably differing point estimates and confidence intervals as shown in the overview Figure 7 in Supporting Information section. With this model specification, we are arriving at a relatively conservative estimate of the decline. 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.

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 stresses the importance of evaluating the impact of the Taliban takeover relative to the counterfactual growth in the absence of the takeover, not the measured economic level immediately before the takeover.

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 15%. This is a notably lower estimate than currently available survey-based measurements. Further, we also present confidence intervals and alternative model specifications that suggest caution in interpreting point estimates derived from this setting. Still, even with these uncertainties, there is little doubt that Afghanistan has suffered a major economic shock following the Tal-

Figure 5: GDP-nowcasting with country fixed effects and country-specific time 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.

iban 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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References

Abadie, A. & Gardeazabal, J. (2003), 'The economic costs of conflict: A case study of the Basque Country', *American Economic Review* **93**(1), 113–132.

Blumenstock, J. E., Ghani, T., Herskowitz, S. R., Kapstein, E., Scherer, T. & Toomet, O. (2018), 'Insecurity and industrial organization: Evidence from Afghanistan', *World Bank Policy Research Working Paper* (8301).

Cattaneo, M. D., Feng, Y., Palomba, F. & Titiunik, R. (2022*a*), '`scpi`: Uncertainty quantification for synthetic control estimators', *arXiv preprint arXiv:2202.05984* .

Cattaneo, M. D., Feng, Y. & Titiunik, R. (2021), 'Prediction intervals for synthetic control methods', *Journal of the American Statistical Association* **116**(536), 1865–1880.

Cattaneo, M., Feng, Y., Palomba, F. & Titiunik, R. (2022*b*), *`scpi`: Prediction Intervals for Synthetic Control Methods with Multiple Treated Units and Staggered Adoption*. R package version 2.0.0.
URL: *https://CRAN.R-project.org/package=scpi*

Chen, X. & Nordhaus, W. D. (2011), 'Using luminosity data as a proxy for economic statistics', *Proceedings of the National Academy of Sciences* **108**(21), 8589–8594.

Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F.-C. & Taneja, J. (2021), 'Annual time series of global VIIRS nighttime lights derived from monthly averages: 2012 to 2019', *Remote Sensing* **13**(5), 922.

Floreani, V., López-Acevedo, G. & Rama, M. (2016), 'Conflict and poverty in Afghanistan's transition', *World Bank Policy Research Working Paper* (7864).

Gibson, J. & Boe-Gibson, G. (2021), 'Nighttime lights and county-level economic activity in the United States: 2001 to 2019', *Remote Sensing* **13**(14), 2741.

Gibson, J., Olivia, S. & Boe-Gibson, G. (2020), 'Night lights in economics: Sources and uses 1', *Journal of Economic Surveys* **34**(5), 955–980.

Gibson, J., Olivia, S., Boe-Gibson, G. & Li, C. (2021), 'Which night lights data should we use in economics, and where?', *Journal of Development Economics* **149**, 102602.

Henderson, V., Storeygard, A. & Weil, D. N. (2011), 'A bright idea for measuring economic growth', *American Economic Review* **101**(3), 194–99.

Indaco, A. (2020), 'From twitter to GDP: Estimating economic activity from social media', *Regional Science and Urban Economics* **85**, 103591.

Jiang, W., He, G., Long, T. & Liu, H. (2017), 'Ongoing conflict makes Yemen dark: From the perspective of nighttime light', *Remote Sensing* **9**(8), 798.

Lee, Y. S. (2018), 'International isolation and regional inequality: Evidence from sanctions on north korea', *Journal of Urban Economics* **103**, 34–51.

Lillis, J. (2022), 'Afghanistan pays electricity debts to Uzbekistan but still owes Tajikistan', *Eurasianet* . Last visited 2023-07-20.
URL: *https://eurasianet.org/afghanistan-pays-electricity-debts-to-uzbekistan-but-still-owes-tajikistan*

Liu, H., He, X., Bai, Y., Liu, X., Wu, Y., Zhao, Y. & Yang, H. (2021), 'Nightlight as a proxy of economic indicators: Fine-grained GDP inference around chinese mainland via attention-augmented CNN from daytime satellite imagery', *Remote Sensing* **13**(11).

Martinez, L. R. (2022), 'How much should we trust the dictator's GDP growth estimates?', *Journal of Political Economy* **130**(10), 2731–2769.

Pfeifer, G., Wahl, F. & Marczak, M. (2018), 'Illuminating the World Cup effect: Night lights evidence from South Africa', *Journal of Regional Science* **58**(5), 887–920.

Putz, C. (2022), 'Central Asia Continues to Supply Electricity to Afghanistan', *The Diplomat* . Last visited 2023-07-20.
URL: *https://thediplomat.com/2022/01/central-asia-continues-to-supply-electricity-to-afghanistan/*

Romer, D. (2020), In praise of confidence intervals, Working Paper 26672, National Bureau of Economic Research.
URL: *http://www.nber.org/papers/w26672*

Trofimov, Y. (2022), 'Afghanistan's Disintegrating Economy Puts Pressure on the Taliban to Negotiate', *The Wall Street Journal* . Last visited 2022-10-31.

URL: *https://www.wsj.com/articles/afghanistans-collapsing-economy-puts-pressure-on-the-taliban-to-negotiate-11629746738*

UNDP (2021), Afghanistan Development Update, Technical report, The United Nation Development Programme, New York City. Last visited 2022-10-31.

URL: *https://www.undp.org/afghanistan/publications/afghanistan-socio-economic-outlook-2021-2022*

UNDP (2022), One Year in Review-Afghanistan since August 2021, Technical report, The United Nation Development Programme, New York City. Last visited 2022-10-31.

URL: *https://www.undp.org/afghanistan/publications/one-year-review-afghanistan-august-2021*

World Bank (2020), Afghanistan Development Update, Technical report, The World Bank, Washington, DC. Last visited 2022-10-31.

URL: *https://openknowledge.worldbank.org/bitstream/handle/10986/34092/Afghanistan-Development-Update-Surviving-the-Storm.pdf?sequence=4isAllowed=y*

World Bank (2022*a*), Afghanistan Development Update, Technical report, The World Bank, Washington, DC. Last visited 2022-10-31.

URL: *https://thedocs.worldbank.org/en/doc/5f01165822f3639224e0d483ba1861fc-0310062022/original /ADU-2022-FINAL-CLEARED.pdf*

World Bank (2022*b*), Afghanistan's Private Sector Rapid Suvery, Technical report, The World Bank, Washington, DC. Last visited 2023-07-20.

URL: *https://thedocs.worldbank.org/en/doc/ced9ff1a094dd92886271f532f3c9754-0310062022/original/AFG-Private-Sector-Rapid-Survey-Report-Apr-2022-Final.pdf*

World Bank (2022*c*), Macro Poverty Outlook, Technical report, The World Bank, Washington, DC. Last visited 2022-10-31.

URL: *https://thedocs.worldbank.org/en/doc/77351105a334213c64122e44c2efe523-0500072021/related/mpo-sm22.pdf*

World Bank (2023), 'GDP - Afghanistan'. Data retrieved from World Bank Open Data. Last visited 2023-02-11.

URL: *https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=AF*

Zhou, Y., Xue, L., Shi, Z., Wu, L. & Fan, J. (2022), 'Measuring housing vitality from multi-source big data and machine learning', *Journal of the American Statistical Association* **117**(539), 1045–1059.

A Appendix

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 $i \in \{2, ..., J+1\}$ 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

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

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

$$\tau_t := Y_{1t}(1) - Y_{1t}(0), \quad t > T_0. \tag{2}$$

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

$$\begin{pmatrix} \widehat{\mathbf{w}} \\ \widehat{r} \end{pmatrix} \in \underset{\mathbf{w} \in \mathcal{W}, \mathbf{r} \in \mathbb{R}}{\arg\min} ||\mathbf{y} - \mathbf{X}\mathbf{w} - r||_2^2, \tag{3}$$

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 (3), the out-of-sample predictions for the counterfactual are given by

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

Step 2 - Prediction Intervals:

To validate empirically that the predicted treatment effect $\widehat{\tau}_t$ based on (2) 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. 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:

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

where $e_t := Y_{1t}(0) - r_0 - \mathbf{X}_t \cdot \mathbf{w}_0$. 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 $((\widehat{r} - r_0) + \mathbf{X}_t \cdot (\widehat{\mathbf{w}} - \mathbf{w}_0))$ stemming from the construction of $\widehat{\mathbf{w}}$ and $\widehat{r}$ in (3) 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

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

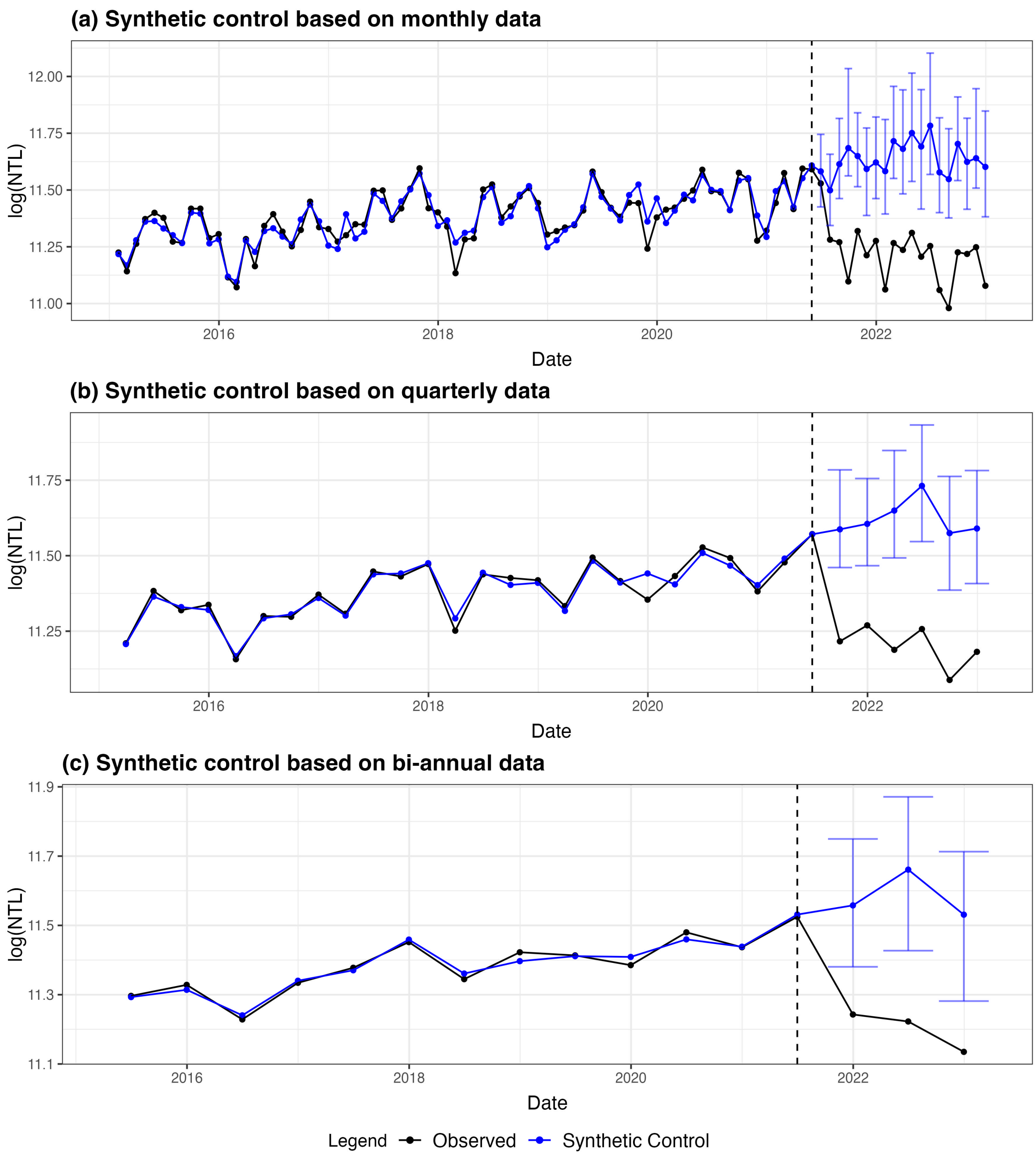
re-sampling this error term 500 times, and estimating quantiles for the associated difference between $\widehat{\mathbf{w}}$, $\widehat{r}$ and $\mathbf{w}_0$, r_0. Estimating these two sources of uncertainty separately and combining them using the union bound allows for the construction of the prediction interval for τ_t.[1]

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

Supporting Information

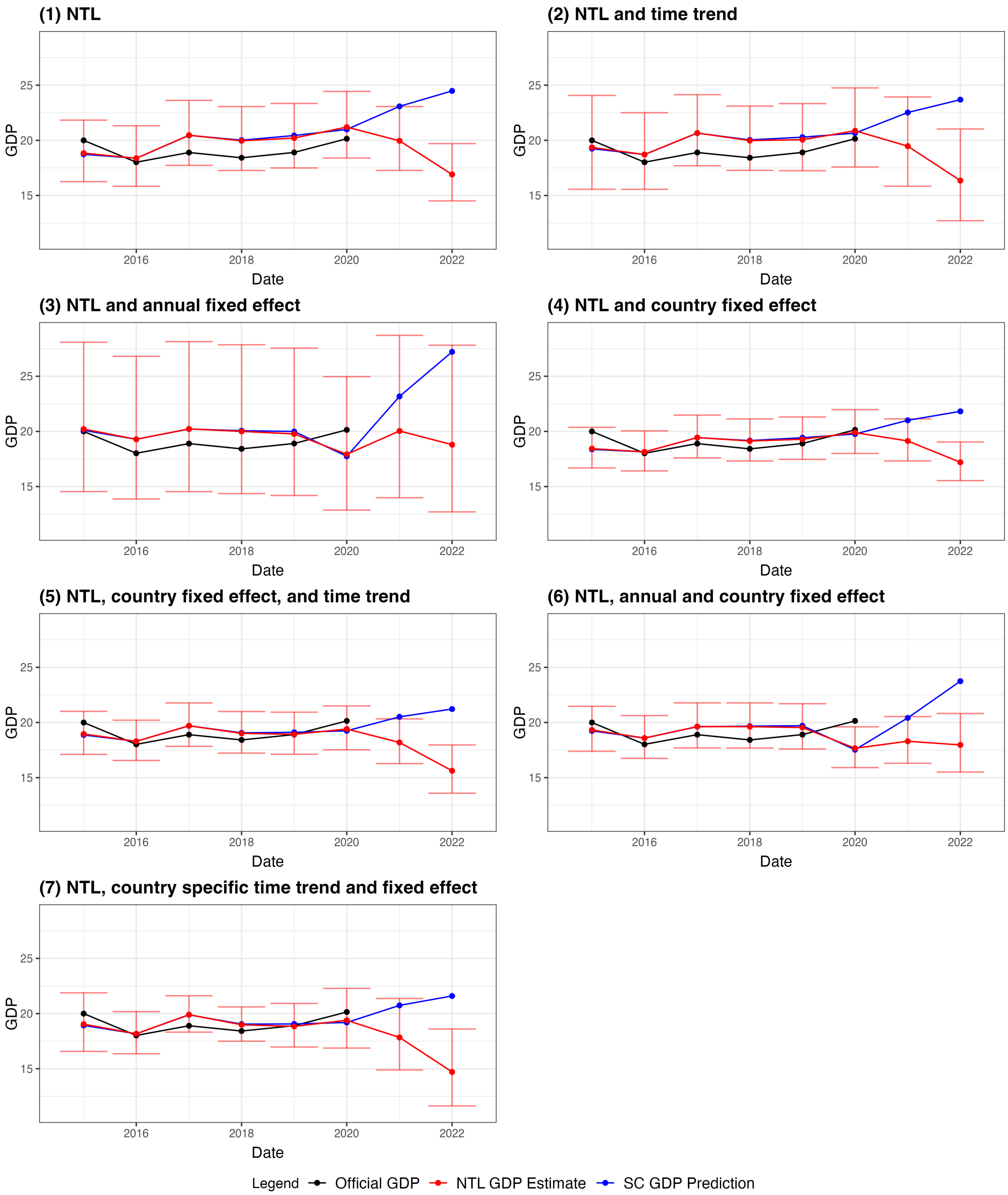
Additional Figures

Figure 6: Overview of synthetic control results



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 7: Overview of GDP-nowcasting models



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.

Additional Tables

[H]

Table 3: Estimates of $\widehat{r}$ and nonzero elements of $\widehat{\mathbf{w}}$

Country	Province	Monthly data	Quarterly data	Bi-annual data
Intercept	-	1.29	1.50	0.96
Iran	Hormozgan	0.06	0.00	0.00
Iran	Tehran	0.02	0.00	0.00
Iran	West Azarbaijan	0.00	0.00	0.11
Iran	Bushehr	0.03	0.01	0.00
Iran	Zanjan	0.00	0.02	0.00
Pakistan	F.A.T.A.	0.17	0.20	0.19
Pakistan	Northern Areas	0.09	0.08	0.01
Tajikistan	Dushanbe	0.25	0.22	0.05
Tajikistan	Khatlon	0.01	0.00	0.04
Tajikistan	Tadzhikistan Territories	0.00	0.01	0.00
Turkmenistan	Ashgabat	0.09	0.18	0.17
Turkmenistan	Chardzhou	0.05	0.00	0.00
Turkmenistan	Mary	0.04	0.00	0.00
Uzbekistan	Andijon	0.05	0.02	0.11
Uzbekistan	Sirdaryo	0.00	0.00	0.01
Uzbekistan	Tashkent City	0.00	0.00	0.12
Uzbekistan	Bukhoro	0.05	0.00	0.00
Uzbekistan	Kashkadarya	0.00	0.07	0.11
Uzbekistan	Namangan	0.08	0.18	0.09

Intercepts $\widehat{r}$ and weighted average vectors $\widehat{\mathbf{w}}$ 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 Eq (3).

Table 4: GDP nowcasting regression results (1/2)

	Model (1)	Model (2)	Model (3)	Model (4)
(Intercept)	14.51 (0.49)***	31.91 (62.44)	14.58 (0.53)***	17.76 (0.74)***
NTL	0.81 (0.04)***	0.81 (0.04)***	0.81 (0.04)***	0.52 (0.07)***
year		−0.01 (0.03)		
factor(year)2016			−0.02 (0.27)	
factor(year)2017			−0.08 (0.27)	
factor(year)2018			−0.07 (0.27)	
factor(year)2019			−0.09 (0.27)	
factor(year)2020			−0.24 (0.27)	
factor(year)2021			−0.07 (0.28)	
factor(year)2022			0.04 (0.29)	
factor(country)ARM				−0.03 (0.09)
factor(country)AZE				0.37 (0.11)***
factor(country)BGD				2.30 (0.10)***
factor(country)BTN				−0.85 (0.18)***
factor(country)GEO				−0.40 (0.09)***
factor(country)IND				2.43 (0.33)***
factor(country)IRN				0.74 (0.29)*
factor(country)IRQ				0.40 (0.26)
factor(country)JOR				−0.07 (0.14)
factor(country)KAZ				0.79 (0.20)***
factor(country)KGZ				−1.16 (0.09)***
factor(country)LBN				0.33 (0.10)**
factor(country)LKA				1.54 (0.08)***
factor(country)NPL				0.81 (0.09)***
factor(country)PAK				1.50 (0.19)***
factor(country)SYR				−0.65 (0.10)***
factor(country)TJK				−0.87 (0.08)***
factor(country)TKM				−0.29 (0.15)
factor(country)TUR				1.63 (0.28)***
factor(country)UZB				0.30 (0.15)*
R^2	0.74	0.74	0.74	0.99
Adj. R^2	0.74	0.74	0.73	0.99
Num. obs.	160	160	160	160

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

This overview of the seven GDP nowcasting models under consideration is based on annual data GDP and annualized nightlights data from 2015 to 2022. The overview continues with models (5), (6) and (7) on the next page, in Table 5.

Table 5: GDP nowcasting regression results (2/2)

	Model (5)	Model (6)	Model (7)
(Intercept)	46.00 (17.12)**	16.79 (1.24)***	56.16 (56.35)
NTL	0.67 (0.11)***	0.61 (0.11)***	0.84 (0.14)***
year	−0.01 (0.01)		−0.02 (0.03)
factor(country)ARM	0.09 (0.12)	0.03 (0.11)	14.02 (71.41)
factor(country)AZE	0.22 (0.14)	0.27 (0.14)	−120.49 (66.60)
factor(country)BGD	2.16 (0.13)***	2.21 (0.13)***	−133.65 (67.71)
factor(country)BTN	−0.49 (0.28)	−0.63 (0.28)*	−96.19 (71.58)
factor(country)GEO	−0.47 (0.10)***	−0.45 (0.09)***	−37.78 (67.35)
factor(country)IND	1.72 (0.54)**	1.99 (0.53)***	−60.85 (67.00)
factor(country)IRN	0.12 (0.47)	0.36 (0.47)	107.77 (66.55)
factor(country)IRQ	−0.15 (0.42)	0.06 (0.41)	−16.53 (67.76)
factor(country)JOR	−0.31 (0.20)	−0.23 (0.20)	29.58 (67.74)
factor(country)KAZ	0.39 (0.31)	0.54 (0.31)	−48.19 (66.61)
factor(country)KGZ	−1.24 (0.10)***	−1.22 (0.10)***	−6.67 (68.76)
factor(country)LBN	0.20 (0.13)	0.26 (0.13)*	164.23 (72.68)*
factor(country)LKA	1.56 (0.08)***	1.54 (0.08)***	128.45 (68.19)
factor(country)NPL	0.91 (0.11)***	0.86 (0.10)***	67.08 (75.31)
factor(country)PAK	1.13 (0.29)***	1.26 (0.29)***	4.79 (67.10)
factor(country)SYR	−0.79 (0.13)***	−0.73 (0.13)***	157.60 (83.35)
factor(country)TJK	−0.86 (0.08)***	−0.87 (0.07)***	23.97 (68.43)
factor(country)TKM	−0.58 (0.24)*	−0.46 (0.23)*	−151.30 (79.57)
factor(country)TUR	1.04 (0.45)*	1.27 (0.45)**	98.85 (67.74)
factor(country)UZB	0.03 (0.22)	0.13 (0.21)	98.05 (67.13)
factor(year)2016		−0.02 (0.04)	
factor(year)2017		−0.05 (0.05)	
factor(year)2018		−0.03 (0.05)	
factor(year)2019		−0.04 (0.05)	
factor(year)2020		−0.18 (0.05)**	
factor(year)2021		−0.10 (0.06)	
factor(year)2022		0.01 (0.07)	
year:factor(country)ARM			−0.01 (0.04)
year:factor(country)AZE			0.06 (0.03)
year:factor(country)BGD			0.07 (0.03)*
year:factor(country)BTN			0.05 (0.04)
year:factor(country)GEO			0.02 (0.03)
year:factor(country)IND			0.03 (0.03)
year:factor(country)IRN			−0.05 (0.03)
year:factor(country)IRQ			0.01 (0.03)
year:factor(country)JOR			−0.01 (0.03)
year:factor(country)KAZ			0.02 (0.03)
year:factor(country)KGZ			0.00 (0.03)
year:factor(country)LBN			−0.08 (0.04)*
year:factor(country)LKA			−0.06 (0.03)
year:factor(country)NPL			−0.03 (0.04)
year:factor(country)PAK			−0.00 (0.03)
year:factor(country)SYR			−0.08 (0.04)
year:factor(country)TJK			−0.01 (0.03)
year:factor(country)TKM			0.07 (0.04)
year:factor(country)TUR			−0.05 (0.03)
year:factor(country)UZB			−0.05 (0.03)
R^2	0.99	0.99	1.00
Adj. R^2	0.99	0.99	1.00
Num. obs.	160	160	160

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

Table 6: Likelihood-Ratio test results

	Model (1) vs Model (2)	Model (2) vs Model (3)	Model (3) vs Model (4)
DF of H_0 model	3	4	10
DF of alternative model	4	10	23
Log-Likelihood of H_0 model	-203.06	-203.02	-202.43
Log-Likelihood of alternative model	-203.02	-202.43	91.57
Associated Chi-squared value	0.08	1.19	588
Associated p-value	0.779	0.977	2.2×10^{-16} ***

	Model (4) vs Model (5)	Model (5) vs Model (6)	Model (6) vs Model (7)
DF of H_0 model	23	24	30
DF of alternative model	24	30	44
Log-Likelihood of H_0 model	91.57	93.15	105.79
Log-Likelihood of alternative model	93.15	105.79	142.80
Associated Chi-squared value	3.15	25.28	74.02
Associated p-value	0.076	3.03×10^{-4} ***	3.58×10^{-10} ***

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

This table summarizes the results of some Likelihood-Ratio tests between the seven different model specifications for GDP nowcasting discussed in this paper.