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Abstract

This study quantifies the economic impacts of SARS on the four affected Asian economies and the two most affected Chinese regions using synthetic control methods with macroeconomic and remote-sensing nightlight data. For the four affected economies (China, Hong Kong, Taiwan, and Singapore), we find only very short-term identifiable adverse impact on per capita GDP. These economies grew at a very fast pace in the post-SARS period, showing a strong V-shaped recovery. We detect a persistent decrease of 2-4 percent in the affected Chinese regions, Guangdong and Beijing; and this identifiable downturn appears to be robust to placebo analysis with standard synthetic control methods, but not when using the Augmented Synthetic Control method (ASCM). The ASCM analysis suggests that even the decline in the most heavily affected Chinese regions was fairly short lived. Overall, these finding suggests that the benign picture that emerges from the analysis of national-level data might be somewhat misleading; but that SARS did not eventually lead to statistically observable declines in economic activity, given its relatively limited spread to other countries, and the affected countries ability to stop its spread within very quickly. Obviously, by now it is clear that the picture emerging for COVID-19 is very different.

JEL-Codes: I150, I180, O110.

Keywords: disease, epidemic, pandemic, SARs, COVID-19, economic impact.

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1. Introduction

The current COVID-19 pandemic has already had a catastrophic economic impact across the world, but in spite of a rapidly growing literature, the likely overall impacts of this pandemic are still largely unknown (*e.g.*, Altig et al., 2020; Baker et al., 2020; Hailu, 2020). Therefore, it may be instructive to revisit the economic impacts of previous disease outbreaks. Such information may also have significant policy implications because a government's decisions over timing and extent of reopening depend critically on the likely future path of the epidemic-economic curve. Indeed, several existing studies have looked at the economic impacts of previous epidemics. For example: HIV/AIDS (Barnett et al., 2000), avian influenza H5N1 (Bloom et al., 2005; Tamura and Sawada, 2009), the H3N2 influenza pandemic of 1968 (Ta et al., 2020), and Dengue (Castañeda-Orjuela et al., 2012).

More recent research, motivated by the COVID-19 crisis, suggests that the adverse economic impacts of pandemics may persist for a long period of time (Jordà et al., 2020). Other recent studies have examined the evidence about the economic impact of the 1918-1919 pandemic flu, and the 2014 Ebola epidemic in West Africa, to better understand the potential economic impacts of COVID-19 (*e.g.*, Barro et al., 2020; Geloso and Bologna Pavlik, 2020; Noy et al., 2020; and Oldstone and Rose Oldstone, 2017).

The SARS epidemic in 2003 is an interesting case, given the similarities between the two coronaviruses themselves, and the ways in which the affect economies reacted. Some previous studies have already analyzed the impacts of SARS on the affected Asian economies. For instance, in a widely cited paper, Lee and McKibbin (2004) estimate that SARS had caused 2.63, 1.05, 0.49, 0.47 percentage point decline in annual GDP for the most heavily affected countries of Hong Kong, China, Taiwan, and Singapore, respectively. Based on a computable general equilibrium model for Asia-Pacific, they examined the direct and indirect economic impacts of SARS rather than focusing only on the affected industries such as healthcare, tourism or retail service sector as previous studies have done (*e.g.,* Chou et al., 2003; or Siu and Wong, 2004). Here, we examine post-pandemic data, rather than rely on semi-real-time structural modelling as is done by Lee and McKibben (2004).

We believe our study makes an important contributions by introducing two novelties in re-examining the economic impacts of SARS: *First*, we apply new methodologies - Synthetic Control Method (SCM; Abadie et al., 2010) and the Augmented Synthetic Control Method (ASCM; Ben-Michael et al., 2020). These allow us to rigorously estimate the counterfactual growth trajectory without the epidemic. *Second*, we employ both conventional and new data sets, *i.e.*, macroeconomic data and nightlight data from satellites, data which were not available in the immediate aftermath of the epidemic when most previous research was done. More specifically, we examine the impacts of SARS on the affected Asian economies - China, Hong Kong, Singapore, and Taiwan. In China, however, we also examine the impacts of SARS more locally, focusing particularly on Beijing and Guangdong, since these were the provincial-level divisions that were affected the most.[1]

We find primarily negative effects of the SARS epidemic on economic growth. However, we find that such effects were very short-lived for the four Asian economies; the adverse economic impacts of SARS lasted only during the immediate post-epidemic quarter. Yet, we also find that more localized impacts persisted somewhat longer: When we apply the synthetic control method (SCM) to the nightlight data from Beijing and Guangdong, the adverse effect at the local level appears to be longer lasting (though these findings are not statistically robust when using the ASCM).

The findings are not entirely consistent with the widely held optimistic view of a V-shaped recovery after the SARS pandemic. It seems that national economies have indeed bounced back quickly, but more local economies have taken longer to recover.

This paper is organized as follows. The next section provides a review of the literature, while the methodology is presented in Section 3. The results are discussed in Section 4. Robustness checks are in Section 5 and the last section concludes with some directions for future research.

[1] Strictly speaking, Guangdong is a province and Beijing is a municipality. But both are one administrative step below the central government (a province-level administrative division). To simiplify, we call both 'provinces.'

2. Literature review

2.1 The economic impacts of past epidemics[2]

The economic impacts of disease outbreaks have been getting sporadic interest from economists for many years, though most past research efforts have been directed at understanding the economic impact of non-infectious (or non-epidemic) diseases, and health more broadly, (Baldwin & Weisbrod, 1974; Weisbrod Burton et al., 1974; Gillies et al., 1996). The one epidemic that has received more research attention is HIV/AIDS, especially within the context of African development, but also in high-prevalence countries or regions elsewhere. Dixon et al. (2002), for example, found that the spread of AIDS led to reductions of labor supply, productivity, exports and overall economic development in Africa in the 1990s. More recently, Kabajulizi and Ncube (2017) evaluate the transition of the management of AIDS into a chronic condition requiring investment in continuing treatment, and investigate the impact of these fiscal costs on Uganda's economic development.

Besides research on the economics of HIV/AIDs, and besides of course the many new contributions on COVID-19, the literature on epidemics is quite limited. Several papers, starting from Almond (2006), have investigated the long-term impact of exposure to an epidemic on in-utero human development by focusing specifically on the 1918–19 influenza pandemic (see also Brown and Thomas, 2018; and Beach et al., 2018). Karlsson et al. (2014) focus on Sweden's experience with the 1918–19 influenza to describe in more detail the impact of the pandemic on poverty and other macroeconomic outcomes, while Noy et al. (2020) do the same for Japan's experience with the 1918–19 event (for a review of the myriad literatures that have looked at non-economic impacts of the same pandemic, see Beach et al., 2020).

Others have attempted to estimate the economic impact of epidemics by looking at a panel of country-level macroeconomic data together with a historical record of past epidemics. For example, Jordà et al. (2020) use the rates of return on assets with data going back to the 14th century to study medium and long run impacts of pandemics. They find

[2] While the literature on the economic impacts of COVID-19 has been extensive already, we do not survey this literature here. For a literature review, see Brodeur et al., (2020).

that the macroeconomic after-effects of pandemics can persist for decades. Barro et al. (2020) use cross-country comparisons in the aftermath of the 1918–19 influenza to identify declines in GDP and consumption of 6 and 8 percent, respectively.

2.2 The economic impact of SARS

The most significant presence of SARS was registered in four Asian economies: China, Hong Kong, Singapore, and Taiwan. Accordingly, the number of international visitors fell precipitously in these economies. Brahmbhatt & Dutta (2008) estimated that the GDP loss amounted to US$ 13 billion. By all descriptive accounts, these losses did not affect any of these national economies for more than a couple of quarters and even the most heavily affected countries were already growing rapidly by Q3 2003. The observed affects were distributed unequally across sectors; disproportionately affecting tourism, leisure, and transport, especially airlines.

In Hong Kong, international visitor arrivals dropped by 65% on the previous year's figure during April 2003 (APEC, 2004). Airlines, and specifically the city's carrier - Cathay Pacific - cancelled over 45% of their scheduled flights during the epidemic's peak, and their monthly passenger rate fell by 80% (Noy and Shields, 2019). Notably, cross-border trade, and especially the Hong Kong-China movement of goods, continued without significant disruption. Even the stock market reaction was comparatively mild, with the Hong Kong Seng Index dropping by 1.78% between March 12th and April 30th.

The main channel of impact during the SARS epidemic was the behavioral change of millions of individuals (Noy and Shields, 2019). Indeed, public opinion surveys at the height of the epidemic reveal that 23% of respondents in Hong Kong, for example, thought that they were either very or somewhat likely to become infected with SARS, which was dramatically incommensurate with the eventual infection rate of only 0.0026% (Leung et al., 2004). Similar exaggerated perceptions were recorded in Taiwan where 74% of survey respondents rated the likelihood of death following SARS contraction as 4 or 5 on a 5 point scale (Liu et al., 2005). Disproportionate risk assessments were even found in places hardly affected by the epidemic, such as the U.S. where 16% of survey respondents felt that they or their family were 'somewhat' or 'very likely' to get infected with SARS in the next 12 months (Brahmbhatt & Dutta, 2008).

The economic consequences of a disaster can usually be delineated into direct and indirect impacts. Direct impacts include lost income and output due to death and symptomatic illness as well as increased healthcare costs, whereas indirect costs arise, specifically in this case, from aggregate behavioral changes driven by the public's perception of the epidemic outbreak or by government directives.[3] Because there was relatively limited mortality and morbidity associated with SARS, its economic analysis differs from some other notable epidemics. Typically, economic losses in such epidemics as HIV/AIDs in the 1980s-1990s, or the Pandemic Influenza of 1918–19 were first, and maybe foremost, measured via the cost of illness and death and the loss of income associated with that mortality and morbidity. This cannot be the basis for an evaluation of the economic impacts of SARS as such an approach will severely under-estimate the cost of that pandemic.

3. Data and research design

3.1 Data

We constructed quarterly GDP per capita data using quarterly GDP series (in 2010 USD) taken from the Global Economic Monitor (GEM) of the World Bank. Data on imports and exports are extracted from the International Financial Statistics (IFS) of the International Monetary Fund (IMF) and the Organization of Economic Cooperation and Development (OECD) Statistics. Unemployment rate data are from the International Labour Organization (ILO).[4] Our data covers the period from the first quarter of 1999 to the fourth quarter 4 of 2006.

We also use two alternative data sources for China's provincial GDP growth. The first source is the official statistics, provided by National Bureau of Statistics of China. The second one is constructed from nightlight remote sensing data by aggregating data from the Defense Meteorological Program Operational Line-Scan System (DMSP-OLS) of US National Oceanic and Atmospheric Administration (NOAA).[5] The satellite nightlight data is

[3] Yet, the difference between the two is often very hard to disentangle (Katafuchi et al., 2020)).
[4] Unemployment rate for Indonesia, Brazil, India, and Vietnam are only available annually.
[5] We use Version 4 DMSP-OLS Night-time Lights Time Series.

available in annual frequency from 1992 to 2013.[6] The sensor in the DMSP-OLS data is not sensitive enough for bright light, so in densely populated urban areas it always registers the highest reading possible throughout the city. Hence, the data can only be used aggregated to the provincial level. Night-time light data has been considered as a useful proxy for regional economic activity (Chen and Nordhaus, 2011; Henderson et al., 2012) and have been specifically preferred in the Chinese context, in Clark et al. (2017). We find that the correlation between night-time lights and GDP for Chinese provinces in our study period is positive and statistically significant (Table A4 and Figure A1).

Quarterly GDP data from GEM are available for 94 countries. We exclude 31 countries in which quarterly GDP is missing for any time in the period (Q1, 1999 to Q4, 2006). Also, we drop nine countries as data of all other predictors are not available in the pre-intervention period (Q1, 1999 to Q4, 2002). We assume that the treated group includes countries with more than 100 cases of SARS. As we aim to examine the economic impacts of SARS in East and Southeast Asia, we drop Canada from the treatment group although it was hit by SARS as well. After all this, our sample includes 4 treated countries (China, Hong Kong, Singapore, and Taiwan) and 49 control countries (see Appendix *Table A1*).

3.2 Methodology

We employ the synthetic control methodology, originally developed in Abadie and Gardeazabal (2003), to identify the impact of SARS. The SCM has previously been used in estimating the impact of extreme sudden-onset shocks in many settings (e.g., Cavallo et al., 2013). The approach involves the calculation of a synthetic counterfactual, i.e., observation of the SARS-affected region without the epidemic, by weighting the average off all countries in the donor pool that have not been directly or were marginally affected by the 'treatment' of the SARS 2002-2003 epidemic.

Following Abadie et al. (2010), let Y_{it} be the GDP per capita for country i at time t (quarterly). We set $i = I$ for the treated country, where $i \in \{1, \dots, I, \dots N\}$. Then Y_{It} is the outcome for provinces/countries exposed to the epidemic at time t and Y_{it} is the outcome for areas not exposed to the epidemic, where $i \neq I$. As the SARS epidemic ended in Q1,

[6] Visible Infrared Imaging Radiometer Suite (VIIRS), a newer nightlight data is available at higher resolution and frequency, and can be fruitfully used for city-level analysis. Yet, the data is only available after 2012.

2003, we set $T_0 = \text{Q4}, 2002$, where $t \in \{1, \dots, T_0, \dots T\}$. Our sample includes 32 time periods, in which there are 16 pre-intervention periods and 16 post- periods. The economic impact of SARS would be observed by the GDP per capita for country i at time t, where $t \geq T_0 + 1$. The assumption is that the epidemic had no effect on the outcome before the event, *i.e.*, $Y_{It} = Y_{it}$, where $i \in \{1 \dots N\}$ and $t \leq T_0$.[7]

For traditional SCM, the critical assumption is that the synthetic algorithm is able to replicate the trajectories of the treated units in the pre-intervention period. There is a growing literature that develops methods to improve the ability or accuracy of the SCM algorithm to replicate accurately pre-intervention given the multiple possibilities for how to do so (e.g., Robbins et al., 2017; Abadie and L'Hour, 2020), or alternatively relax the assumptions required for the original SCM (e.g. Powell, 2018; Doudchenko and Imbens, 2017). We use the Augmented Synthetic Control Method developed by Ben-Michael et al., (2020); it is a derivative of SCM, which seeks to improve the pre-intervention fit of the counterfactual to the factual time series of the treated units.

Ben-Michael et al. (2020) use a model-based augmentation to estimate the bias due to infeasible pre-intervention fit and then implement a bias correction. As discussed in Ben-Michael et al. (2020), the augmented estimator is a weighting estimator to adjust the SCM weights and then de-bias the original SCM estimate. The bias in the pre-intervention outcomes between the treated units and the synthetic estimated by an outcome model, m, is $\widehat{bias_m}$. ASCM adds a bias term to the original SCM estimator: ${Y_{it}}^{\widehat{ASCM}} = {Y_{it}}^{\widehat{SCM}} + \widehat{bias_m}$.[8] Using a ridge-regularized linear regression as the outcome model, ASCM replicates the pre-intervention trajectory more closely. In this framework, the treated units may be outside the convex hull of control units. Thus, the Ridge ASCM allows non-negative weights to improve the SCM pre-intervention fit, but penalizing extrapolation from the convex hull.[9]

[7] See further details in Abadie et al. (2010).
[8] See specification details in Ben-Michael et al. (2020).
[9] When the original SCM satisfies the pre-intervention fit, Ridge ASCM and original SCM approach the same weights.

4. Results and discussion

4.1 The economic impacts of SARS: evidence from Asian countries

Figure 1 presents the actual evolution of GDP per capita in the four affected countries, compared against the synthetic counterfactual (what that evolution would have been had the 2002–2003 event not occurred. It shows a short-term V-shaped decrease of GDP per capita in the outbreak period of SARS in Hong Kong, Singapore, and Taiwan. The V-shaped short-term decline is less apparent in China, where only a few provinces were affected by the virus (not unlike what happened in 2020 with COVID-19). With the synthetic algorithm, we are not able to provide an ideal counterfactual (synthetic) for the post 2003 period, the economies of the affected countries grew unusually rapidly in this period when compared to other (control) countries. The reasons for that have nothing to do, most likely, with the SARS event itself.

In *Figure 2*, we present the placebo results. The findings for China fail to pass the placebo test, as the gap line (the gap between the actual and the counterfactual) is clearly indistinguishable from the placebo gaps. The placebos for many control units also show a dip, indicating the violation of stable unit treatment value assumption (SUTVA) possibly due to spillover effects of the pandemic.[10] For Hong Kong, Singapore, and Taiwan, we only find a short-time negative effect in the SARS outbreak (Q2, 2003). The results indicate that indeed these economies bounced-back quickly after the epidemic.

[10] The assumption requires the observed outcome of one particular unit to be independent from other units.

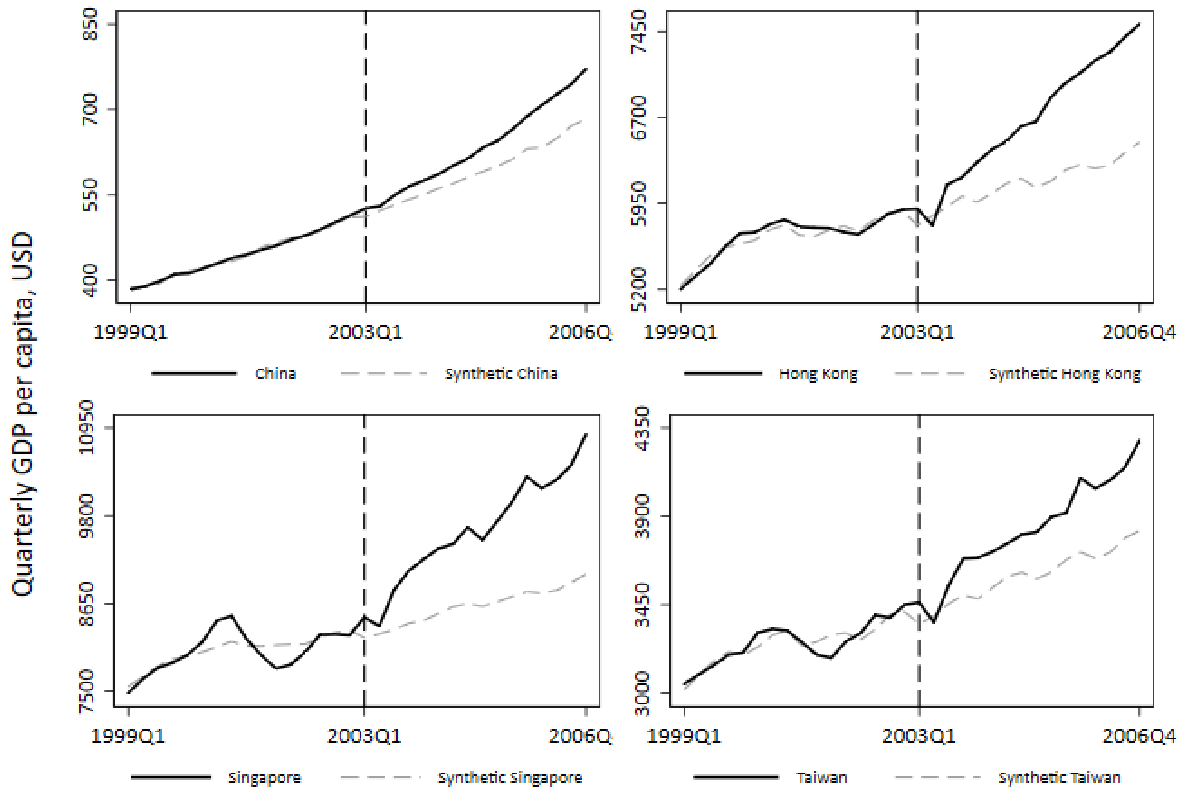

Figure 1. Synthetic analysis for GDP per capita: Asian countries
Notes: The dash line indicates the SARS outbreak. The graphs compare the quarter GDP per capita in treated country with the synthetic counterfactual (of the same country without SARS). The overall period includes 32 quarters. The pre-intervention period is Q1-1999 to Q4-2002, and post-intervention period is Q1-2003 to Q4-2006. We stop the post-intervention period in Q4-2006, as we aim to differentiate the effect of global financial crisis 2007-2008.

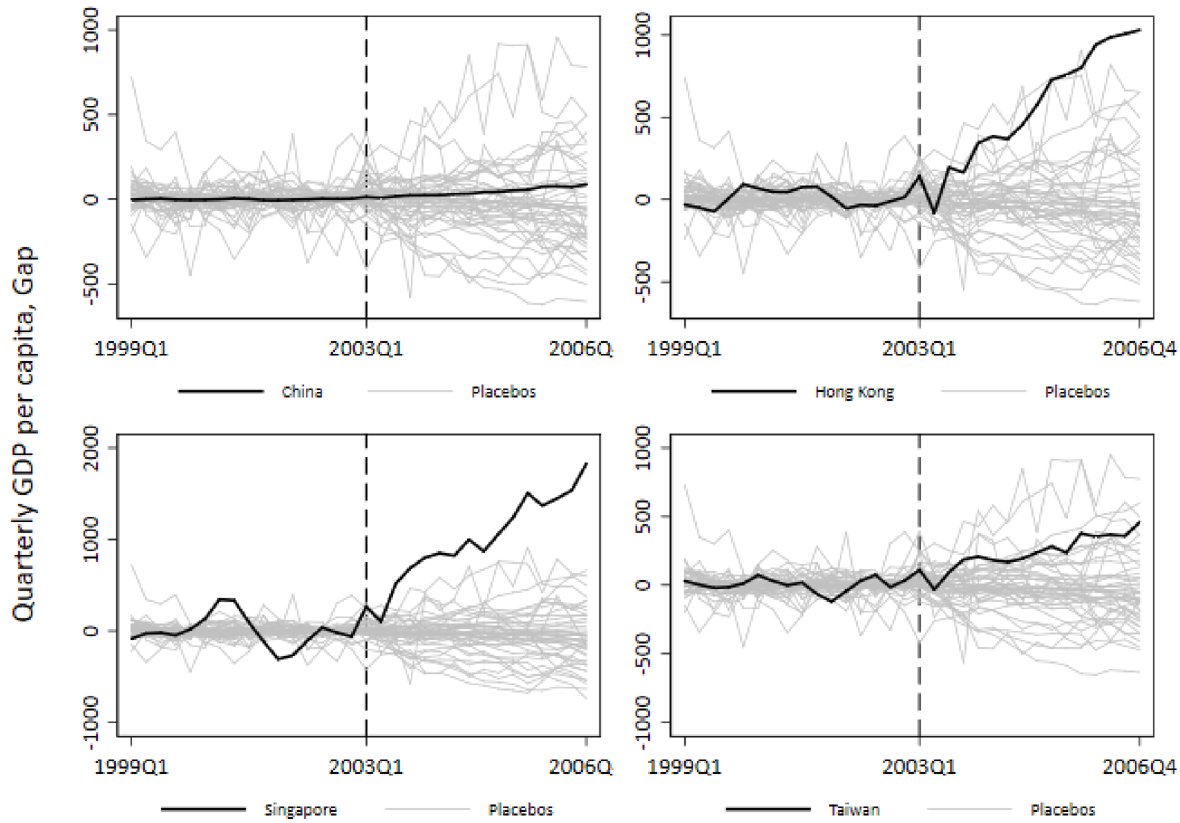

Figure 2. Placebo tests for GDP per capita: Asian countries
Notes: The graphs show the difference between quarterly GDP per capita of treated country and its synthetic counterfactual, the dark line. The grey lines are the difference of quarterly GDP per capita of each country in the donor pool and its counterfactual. The synthetic control of each country is a weighted average of all other countries excluding the treated country: China, Hong Kong, Singapore, Taiwan.

One explanation for the rapid take-off of the affected countries in the early 2000s, an explanation that has nothing to do with SARS, is the emergence of China as a dominant trading partner for these countries, after China had joined the World Trade Organization (WTO) in 2001. The other three economies were all heavily reliant on China's trade and were (and still are) to some extent entrepôt economies. In principle, what the synthetic algorithm captures is the impact of the 2002–2003 period. These simultaneous events pose a challenge to extract the pure economic impact of SARS.

4.2 The economic impacts of SARS: evidence from China provinces

An alternative strategy is to focus on heterogenous impact at lower administrative level by using disaggregated data from China. The SARS epidemic emerged in Guangdong in November 2002. Though the epidemic spread to 26 provinces, there were more than 2,500 and 1,500 cases reported in Beijing and Guangdong, respectively; this is significantly more than all the other provinces combined.

In using the synthetic control method, we set Beijing and Guangdong as the treated provinces whereas the control group includes 28 province-level administrative divisions.[11] Quarterly GDP of China's provinces are not available for long enough to run the synthetic control algorithm. Hence, we use annual GDP series from the National Bureau of Statistics of China. Covariates includes investment in fixed assets and household spending. We obtain data from 1993, the first year in which data is available, to 2013. As before, the pre-intervention period is before the year of 2003 ($T_0 = 2002$).

For the synthetic control analysis for GDP per capita in Beijing and Guangdong, the predictors include the lag (-1) of GDP per capita, household spending, and investment per capita. The goodness of fit over the pre-intervention period and the balance for all predictors indicate a plausible pool of control units. However, for Beijing, even for the pre-intervention period the synthetic is not able to replicate the trend of treated units. The placebo tests in *Figure 3* indicate there is little evidence that annual per capita income in Beijing and Guangdong was affected by the epidemic.

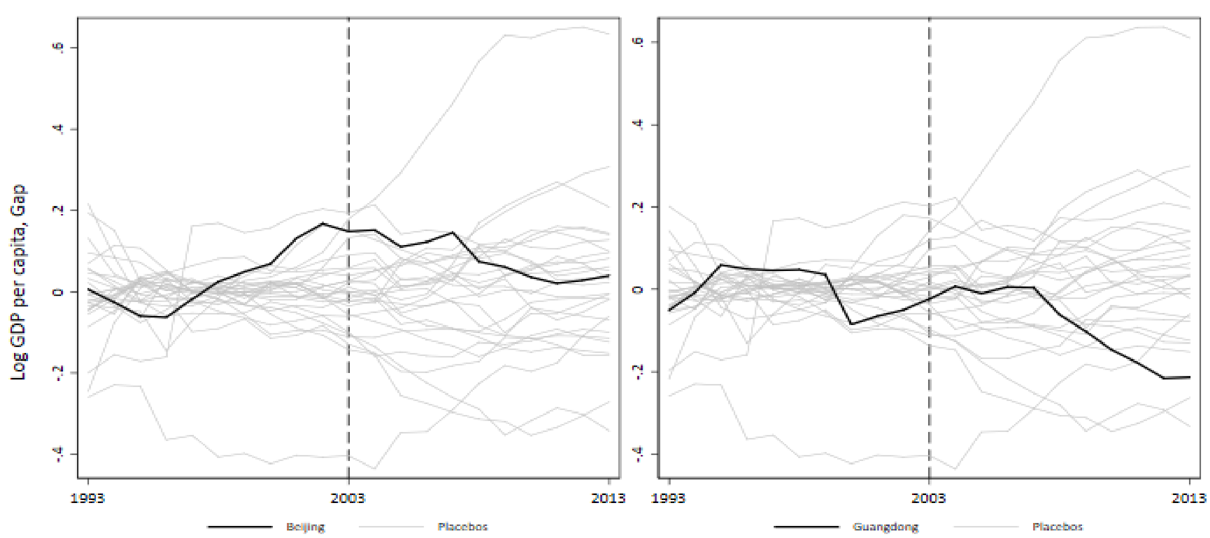

Figure 3. Placebo tests for GDP per capita: Beijing and Guangdong

[11] We drop Chongqing due to missing data.

The lack of clear results in *Figure 3* may be attributed to measurement errors in macroeconomic data. Indeed, Clark et al. (2017) questions the quality of China's official regional GDP statistics. Using the night-time lights to compute the optimal weights for a battery of economic activities, Clark et al. (2017) argue that China's actual GDP growth may be higher than in official reports. Given the absence of satisfactory macroeconomic data, we use the night-time light data as an alternative proxy for economic activity. We identify the economic impacts of SARS in Beijing and Guangdong, the two locations that were most heavily hit by the virus. The series has 30 provincial-level administrative regions, including Beijing and Guangdong as treated units and 28 control units.[12] The predictors include: the lag (-1) of outcome (nightlight), and the population density.

We run the synthetic control algorithm with the average per-province annual nightlight data to examine changes in nightlight around the SARS period in 2003. The results, in *Figure 4*, do suggest a noticeable decline in economic activity during the SARS period in the two affected areas that are associated with SARS. As described earlier, the actual provincial per capita GDP data, which might be perceived as less reliable, does not corroborate that. The night-time lights (NTL) per capita declines by around 2 percent and 4 percent in Beijing and Guangdong, respectively, against the counterfactual rapid growth that the synthetic model predicts.

[12] We also drop Chongqing as the population data, one of the predictors, is missing before 1997.

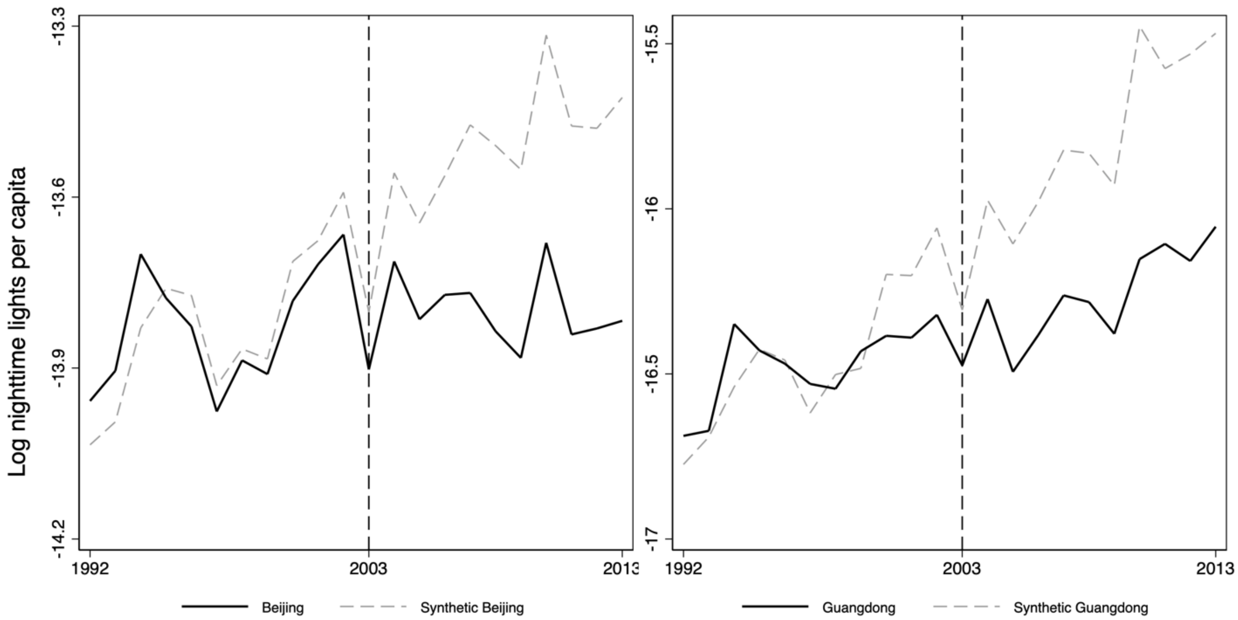

Figure 4. Synthetic analysis for nightlights per capita: Beijing and Guangdong

Figure 5 provides the placebo effects for all other provinces. The validity of our results will be in doubt should we find many placebo (SARS-unaffected) provinces with similarly negative effects. But the results in *Figure 5* seem to confirm our findings of a negative and significant impact of SARS on Guangdong and Beijing. We also ran the synthetic control algorithm for Shanxi and Hebei, two neighboring provinces that were also affected by the epidemic.[13] Shanxi and Hebei also show a drop in nightlights, though one that is significantly smaller.[14] This provides further support for our finding of a negative impact of the epidemic in heavily affected Chinese provinces.

[13] See Tables A2-A3.
[14] See Figures A3-A3.

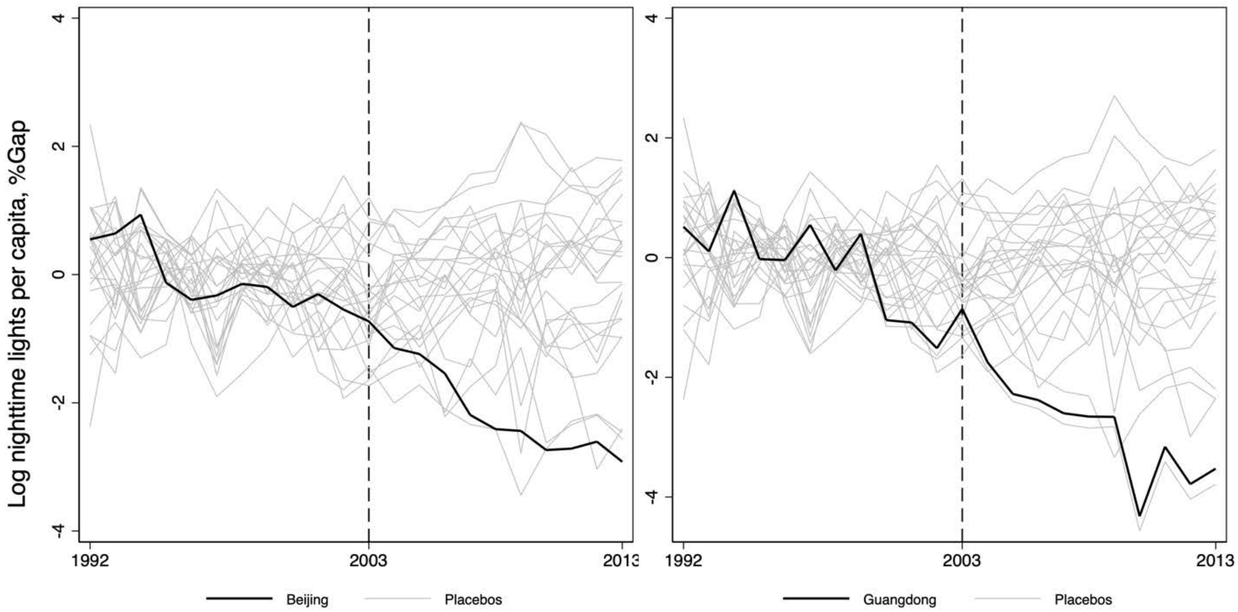

Figure 5. Placebo Tests of synthetic analysis for NTL per capita: Beijing and Guangdong

5. Robustness checks by Augmented Synthetic Control Method (ASCM)

Applying the ASCM analysis, as described above, we find a short-term drop in GDP per capita in Hong Kong, Singapore, and Taiwan (*Figure 6*). This result is similar to what we described above. Interestingly, China appear to experience a longer-term decrease of 3-5 percent in GDP per capita on average, followed by a recovery only after Q4 2005. However, these results are not statisitically significant.

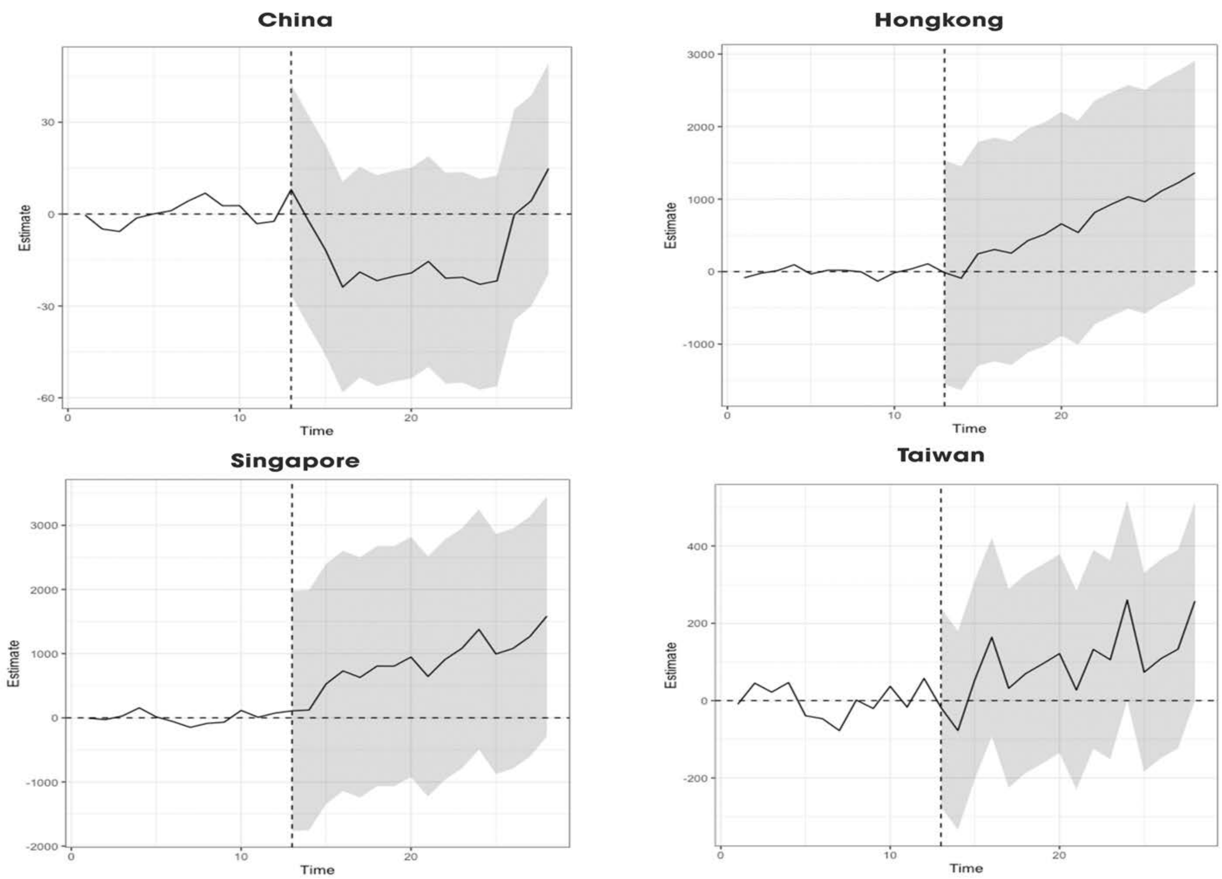

Figure 6. Difference in GDP per capita using ASCM: Beijing and Guangdong

In the China regional analysis, *Figure 7* shows that there is a decrease in per capita GDP in Beijing compared to the pretreatment averages. Again, confidence intervals are too wide to reject a null effect. For Guangdong, opposite to the hypothesis, the analysis by ASCM does not show an evidence about the effect of SARS 2003 on GDP per capita from 2003 to 2010.

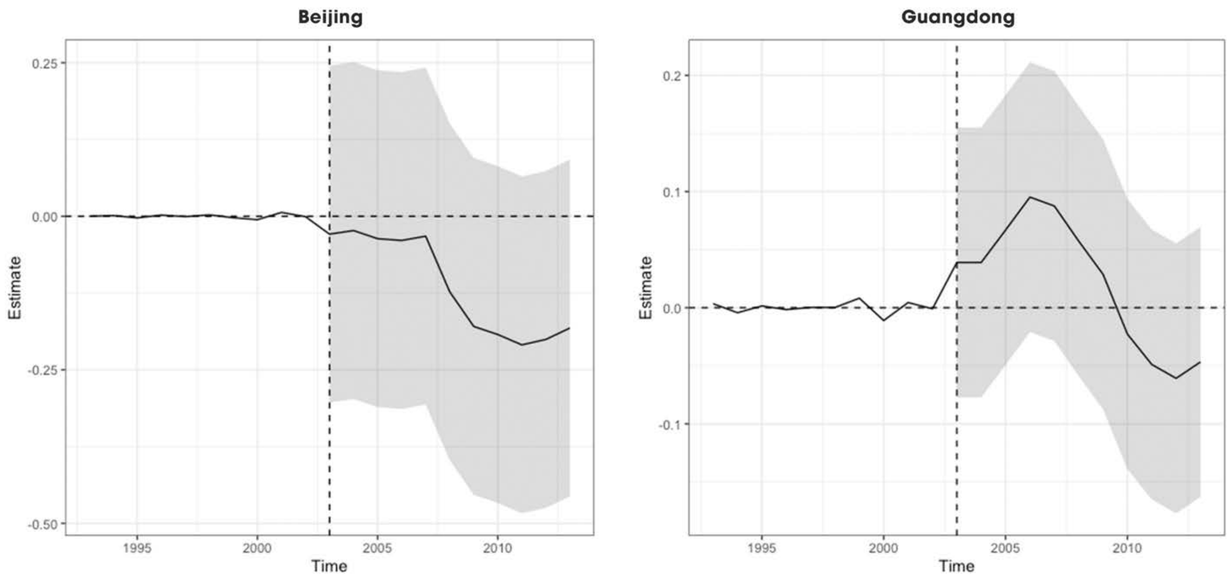

Figure 7. Difference in GDP per capita using ASCM: Beijing and Guangdong

There is a negative effect on NTL per capita, though the effect is still not statistically significant. In *Figure 8*, the synthetic (dashed line) closely replicate the mean trajectories in Beijing and Guangdong. In the post-intervention period, the observed NTL per capita for treated units (solid line) is constantly beneath the estimated synthetic (dashed). As consistent with previous results, on average, the post-treatment treated and synthetic units imply a reduction in logarithm of NTL per capita for Beijing and Guangdong of around 2 percent and 3 percent, respectively.

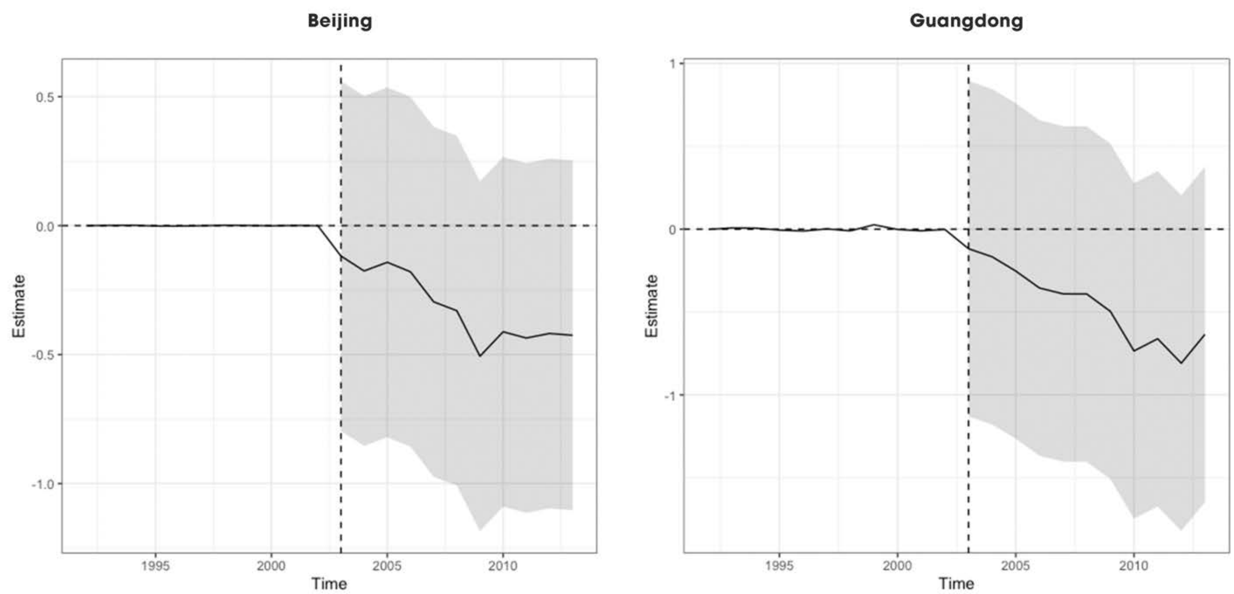

***Figure 8*. Difference in NTL per capita using ASCM: Beijing and Guangdong**

6. Conclusion

We quantify the effect of the SARS epidemic on the economic growth in Asian countries and Chinese provincial-level administrative regions. We measure economic growth with GDP and nighttime lights. We use the standard and an augmented synthetic control methods, to create a pre- and post-intervention comparisons between observed and counterfactual outcomes. We find a short-term negative effect of the epidemic on GDP per capita in Q2, 2003 in the heavily affected East Asian countries. Beyond that, in the aftermath of the epidemic's peak, we do not find any observable negative impact on economic activity at the national level. We conjecture that any plausible mild negative impact would have been masked by the economic boom that followed China becoming a full member of the WTO.

Using nightlight data, we find some evidence of a more persistent negative effect of SARS in Beijing and Guangdong, the two most heavily affected Chinese provinces. Even there, however, it is not possible to determine the duration or depth of this effect because the data series includes a time of dramatic change in the Chinese economy including the WTO accession in 2001 and the global financial crisis in 2008.

These estimations of the economic impacts of SARS epidemic indicate that, fortunately, the regional economies proved to be quite resilient to this temporary but large shock. This also suggests that, while country-level macroeconomic impact assessment will be useful for the central government to identify overall impacts, such macro-analysis may mask some local-level impacts. It is imperative to conduct disaggregated local/regional assessments of impacts of a pandemic in addition to any macroeconomic analysis. More detailed microeconomic data will shed more light on the possible mechanisms behind any observed decline as well as its duration. Such an analysis is part of our future research agenda.

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Appendix

Table A1. List of the treated unit and the synthetic unit

Treated group	Control group			
China	Argentina	Germany	Latvia	Romania
Hong Kong	Australia	Greece	Lithuania	Slovenia
Singapore	Austria	Hungary	Luxembourg	South Africa
Taiwan	Belgium	Iceland	Malaysia	Spain
	Brazil	India	Mexico	Sweden
	Bulgaria	Indonesia	Morocco	Switzerland
	Chile	Ireland	Netherlands	Thailand
	Cyprus	Israel	New Zealand	Turkey
	Denmark	Italy	Norway	United Kingdom
	Ecuador	Japan	Philippines	United States
	Estonia	Kazakhstan	Poland	Uruguay
	Finland	Korea	Portugal	Vietnam
	France			

Notes:
(i) We drop 31 countries with missing quarterly GDP: Albania, Algeria, Armenia, Bahrain, Belarus, Bosnia and Herzegovina, Colombia, Croatia, Georgia, Ghana, Guatemala, Honduras, Kenya, Kuwait, Malta, Mauritius, Moldova, Mongolia, Mozambique, Nicaragua, Nigeria, Oman, Panama, Peru, Qatar, Saudi Arabia, Sri Lanka, Tajikistan, Tunisia, Ukraine, Uzbekistan.
(ii) We exclude 9 countries with missing predictors data: Bolivia, Botswana, Czech Republic, Costa Rica, El Salvador, Jordan, Paraguay, Serbia, Slovakia.

Table A2. Predictors of synthetic analysis for GDP per capita: Asian countries

	China	Synthetic
Quarterly GDP per cap (-1)	426.821	427.825
Log GDP	13.237	11.641
Imports (% of GDP)	.102	.072
Exports (% of GDP)	.114	.074
Unemployment rate	3.825	4.368
	Hong Kong	Synthetic
Quarterly GDP per cap (-1)	5616.952	5598.179
Log GDP	10.541	10.8
Imports (% of GDP)	1.322	.441
Exports (% of GDP)	1.264	.509
Unemployment rate	5.879	4.549
	Singapore	Synthetic
Quarterly GDP per cap (-1)	7972.619	7969.203
Log GDP	10.395	11.22
Imports (% of GDP)	.913	.435
Exports (% of GDP)	.953	.485
Unemployment rate	3.925	6.077
	Taiwan	Synthetic
Quarterly GDP per cap (-1)	3211.453	3219.461
Log GDP	11.193	10.836
Imports (% of GDP)	.405	.396
Exports (% of GDP)	.449	.449
Unemployment rate	3.915	4.415

Table A3. Predictors of synthetic analysis for GDP per capita: Beijing and Guangdong

	Beijing	Synthetic
Household spending	823.232	814.648
Investment per capita	1008.266	1008.135
Log GDP per capita (-1)	7.583	7.571
	Guangdong	Synthetic
Household spending	553.627	533.942
Investment per capita	438.319	495.559
Log GDP per capita (-1)	7.117	7.114

Table A4: The association between NTL and GDP per capita

Dependent variable: log nighttime lights per capita	(1)	(2)
Pop density	-0.001***	-0.000***
	(0.000)	(0.000)
Log GDP per cap		0.552***
		(0.078)
Investment on fixed assets per cap		-0.000***
		(0.000)
Household spending		-0.000**
		(0.000)
Import per cap		-0.000***
		(0.000)
Export per cap		0.000
		(0.000)
_cons	-16.285***	-20.400***
	(0.031)	(0.568)
Obs.	677	647
R-squared	0.989	0.991

Notes: Data on import, export, investment on fixed assets, and household spending per province, from National Bureau of Statistics of China. We estimate the association between GDP per capita and night-time lights per capita by OLS. The estimation includes province fixed effects and year fixed effects. Robust standard errors are in parenthesis. **** p<0.01, ** p<0.05, * p<0.1*

Table A5: Predictors of synthetic analysis for NTL per capita: Beijing and Guangdong

	Beijing	Synthetic
pop density	762.46	763.411
log NTL per capita (-1)	-13.844	-13.918
	Guangdong	Synthetic
pop density	411.489	410.175
log NTL per capita (-1)	-16.489	-16.494

Table A6. Estimated average treatment effect on GDP per capita using ASCM: China

Quarter	Estimate	Lower Bound	Upper Bound	P-value
Q1 2003	8.023	-26.385	42.432	0.154
Q2 2003	-2.059	-36.468	32.349	0.846
Q3 2003	-11.672	-46.080	22.736	0.385
Q4 2003	-23.852	-58.260	10.556	0.308
Q1 2004	-18.938	-53.346	15.470	0.538
Q2 2004	-21.743	-56.152	12.665	0.308
Q3 2004	-20.305	-54.714	14.103	0.538
Q4 2004	-19.260	-53.668	15.148	0.769
Q1 2005	-15.476	-49.885	18.932	0.923
Q2 2005	-20.931	-55.340	13.477	1.000
Q3 2005	-20.662	-55.070	13.746	0.923
Q4 2005	-22.952	-57.361	11.456	0.923
Q1 2006	-21.808	-56.216	12.601	0.923
Q2 2006	-0.217	-34.625	34.191	0.538
Q3 2006	4.403	-30.005	38.811	0.462
Q4 2006	14.862	-19.546	49.271	0.462

Table A7. Estimated average treatment effect on GDP per capita using ASCM: Hong Kong

Quarter	Estimate	Lower Bound	Upper Bound	P-value
Q1 2003	-13.430	-1556.366	1529.506	0.923
Q2 2003	-91.167	-1634.104	1451.769	0.385
Q3 2003	245.198	-1297.739	1788.134	0.077
Q4 2003	304.681	-1238.256	1847.617	0.077
Q1 2004	254.477	-1288.459	1797.414	0.077
Q2 2004	428.790	-1114.147	1971.726	0.077
Q3 2004	514.906	-1028.030	2057.842	0.077
Q4 2004	659.001	-883.935	2201.937	0.077
Q1 2005	539.278	-1003.658	2082.215	0.077
Q2 2005	816.885	-726.051	2359.821	0.077
Q3 2005	929.374	-613.563	2472.310	0.077
Q4 2005	1032.106	-510.831	2575.042	0.077
Q1 2006	963.080	-579.857	2506.016	0.077
Q2 2006	1112.606	-430.330	2655.543	0.077
Q3 2006	1225.564	-317.373	2768.500	0.077
Q4 2006	1363.310	-179.626	2906.246	0.077

Table A8. Estimated average treatment effect on GDP per capita using ASCM: Singapore

Quarter	Estimate	Lower Bound	Upper Bound	P-value
Q1 2003	108.320	-1762.973	1979.614	0.615
Q2 2003	120.872	-1750.421	1992.166	0.615
Q3 2003	527.780	-1343.514	2399.073	0.231
Q4 2003	730.941	-1140.353	2602.234	0.077
Q1 2004	629.075	-1242.218	2500.369	0.231
Q2 2004	805.986	-1065.307	2677.280	0.154
Q3 2004	804.745	-1066.548	2676.039	0.154
Q4 2004	946.908	-924.386	2818.201	0.231
Q1 2005	644.640	-1226.654	2515.933	0.308
Q2 2005	907.421	-963.873	2778.714	0.308
Q3 2005	1082.662	-788.632	2953.955	0.308
Q4 2005	1377.766	-493.528	3249.059	0.385
Q1 2006	994.938	-876.356	2866.231	0.462
Q2 2006	1079.582	-791.712	2950.875	0.538
Q3 2006	1266.363	-604.930	3137.657	0.462
Q4 2006	1584.217	-287.076	3455.511	0.462

Table A9. Estimated average treatment effect on GDP per capita using ASCM: Taiwan

Quarter	Estimate	Lower Bound	Upper Bound	P-value
Q1 2003	-17.745	-274.736	239.246	0.923
Q2 2003	-77.473	-334.464	179.518	0.385
Q3 2003	54.181	-202.810	311.172	0.538
Q4 2003	163.873	-93.118	420.864	0.077
Q1 2004	31.731	-225.260	288.722	0.846
Q2 2004	69.802	-187.189	326.793	0.538
Q3 2004	94.986	-162.005	351.977	0.385
Q4 2004	121.570	-135.421	378.561	0.385
Q1 2005	27.240	-229.750	284.231	0.846
Q2 2005	132.528	-124.463	389.519	0.385
Q3 2005	105.741	-151.250	362.732	0.538
Q4 2005	260.168	0.000	517.159	0.308
Q1 2006	73.428	-183.562	330.419	0.846
Q2 2006	108.805	-148.186	365.796	0.615
Q3 2006	133.150	-123.841	390.141	0.615
Q4 2006	257.403	0.000	514.394	0.385

Table A10. Estimated average treatment effect on GDP per capita using ASCM: Beijing

Year	Estimate	Lower Bound	Upper Bound	P-value
2003	-0.029	-0.303	0.245	0.727
2004	-0.023	-0.298	0.251	0.909
2005	-0.036	-0.311	0.238	0.818
2006	-0.039	-0.314	0.235	0.818
2007	-0.032	-0.307	0.242	1.000
2008	-0.123	-0.397	0.151	0.909
2009	-0.179	-0.454	0.095	0.909
2010	-0.193	-0.467	0.082	0.818
2011	-0.209	-0.484	0.065	0.727
2012	-0.201	-0.475	0.074	0.818
2013	-0.182	-0.456	0.092	0.818

Table A11. Estimated average treatment effect on NTL per capita using ASCM: Beijing

Year	Estimate	Lower Bound	Upper Bound	P-value
2003	-0.118	-0.796	0.560	0.500
2004	-0.176	-0.854	0.502	0.333
2005	-0.142	-0.820	0.536	0.500
2006	-0.179	-0.857	0.499	0.417
2007	-0.295	-0.973	0.383	0.333
2008	-0.330	-1.008	0.348	0.167
2009	-0.506	-1.184	0.172	0.583
2010	-0.412	-1.090	0.266	0.417
2011	-0.436	-1.114	0.242	0.500
2012	-0.418	-1.096	0.260	0.500
2013	-0.425	-1.103	0.253	0.417

Table A12. Estimated average treatment effect on GDP per capita using ASCM: Guangdong

Year	Estimate	Lower Bound	Upper Bound	P-value
2003	0.039	-0.077	0.155	0.636
2004	0.039	-0.077	0.155	0.818
2005	0.067	-0.049	0.183	1.000
2006	0.095	-0.021	0.211	1.000
2007	0.088	-0.029	0.204	1.000
2008	0.057	-0.059	0.174	1.000
2009	0.029	-0.087	0.145	1.000
2010	-0.023	-0.139	0.093	1.000
2011	-0.049	-0.165	0.067	1.000
2012	-0.061	-0.177	0.055	1.000
2013	-0.047	-0.163	0.069	1.000

Table A13. Estimated average treatment effect on NTL per capita using ASCM: Guangdong

Year	Estimate	Lower Bound	Upper Bound	P-value
2003	-0.118	-1.130	0.894	0.667
2004	-0.167	-1.179	0.845	0.667
2005	-0.253	-1.265	0.759	0.667
2006	-0.355	-1.367	0.657	0.417
2007	-0.390	-1.402	0.622	0.417
2008	-0.391	-1.403	0.621	0.417
2009	-0.496	-1.508	0.516	0.667
2010	-0.735	-1.747	0.277	0.500
2011	-0.661	-1.673	0.351	0.500
2012	-0.809	-1.821	0.203	0.500
2013	-0.635	-1.647	0.377	0.583

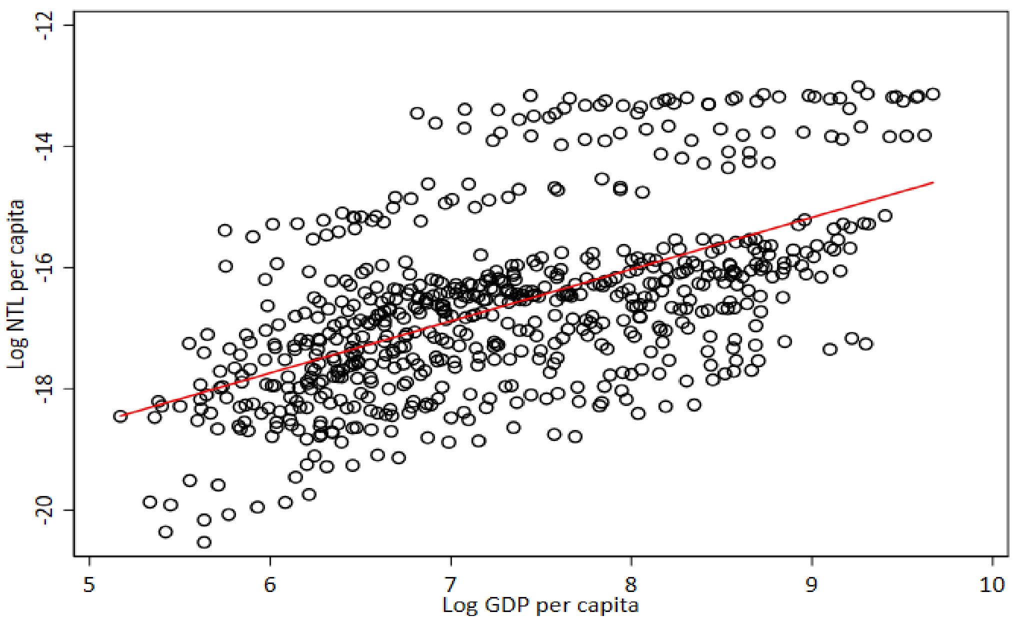

Figure A1: The association between NTL and GDP per capita

Note: This figure shows that correlation between average annual nightlights per province and provincial GDP per capita.

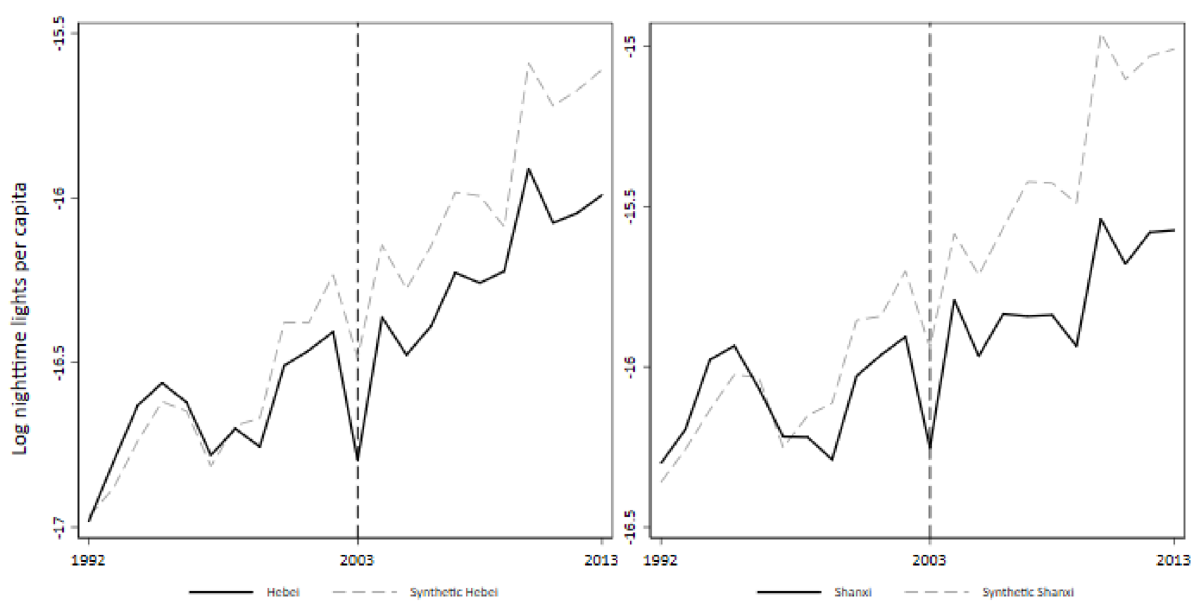

Figure A2. Synthetic analysis for NTL per capita: Hebei and Shanxi

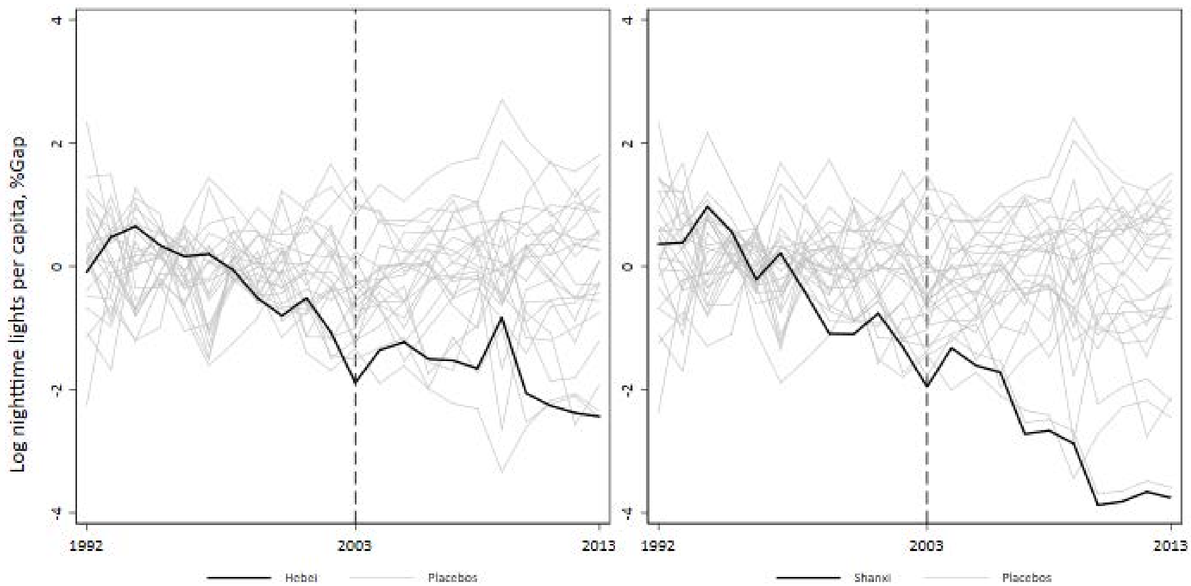

Figure A3. Placebo Tests of synthetic analysis for NTL per capita: Hebei and Shanxi
Notes: Hebei and Shanxi are neighbouring provinces of Beijing. The number of cases of SARS was highest in Beijing and Guangdong, followed by Shanxi and Hebei.

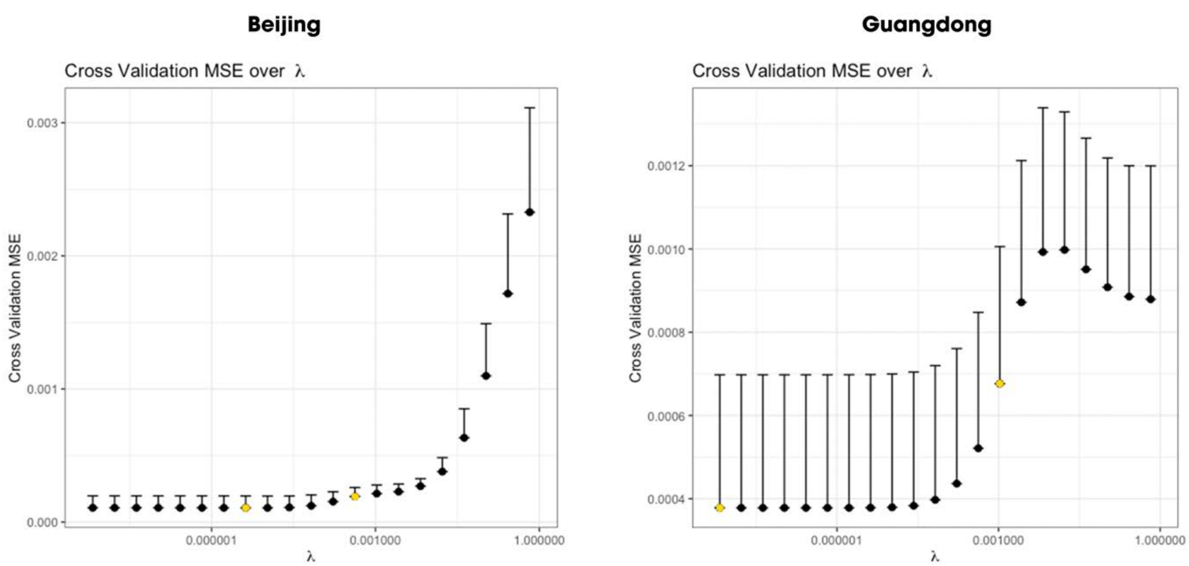

Figure A4. Cross validation MSE in NTL per capita analysis: Beijing and Guangdong

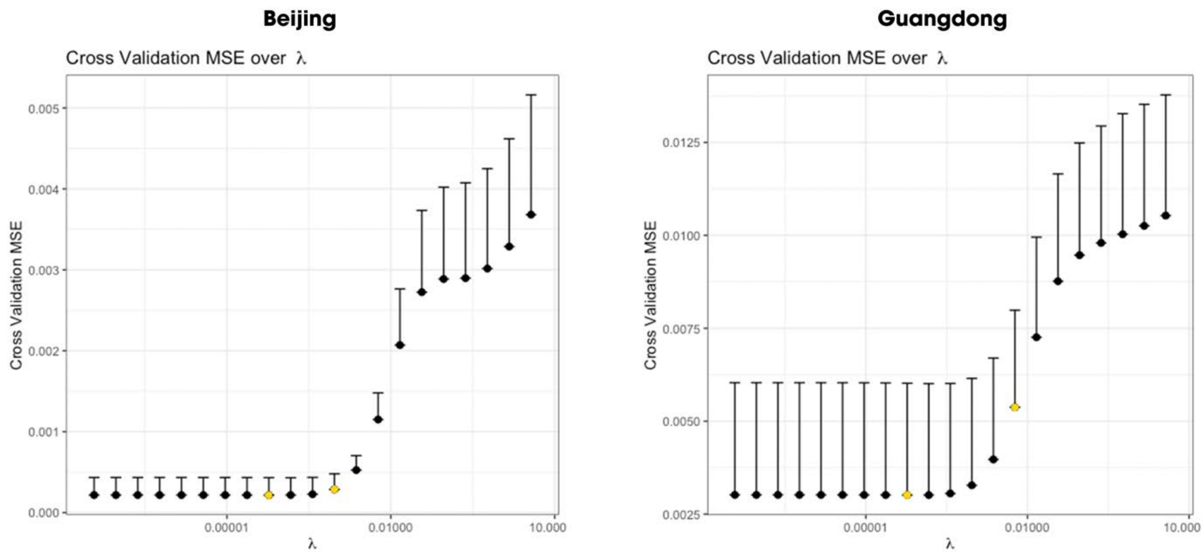

Figure A5. Cross validation MSE in NTL per capita analysis: Beijing and Guangdong

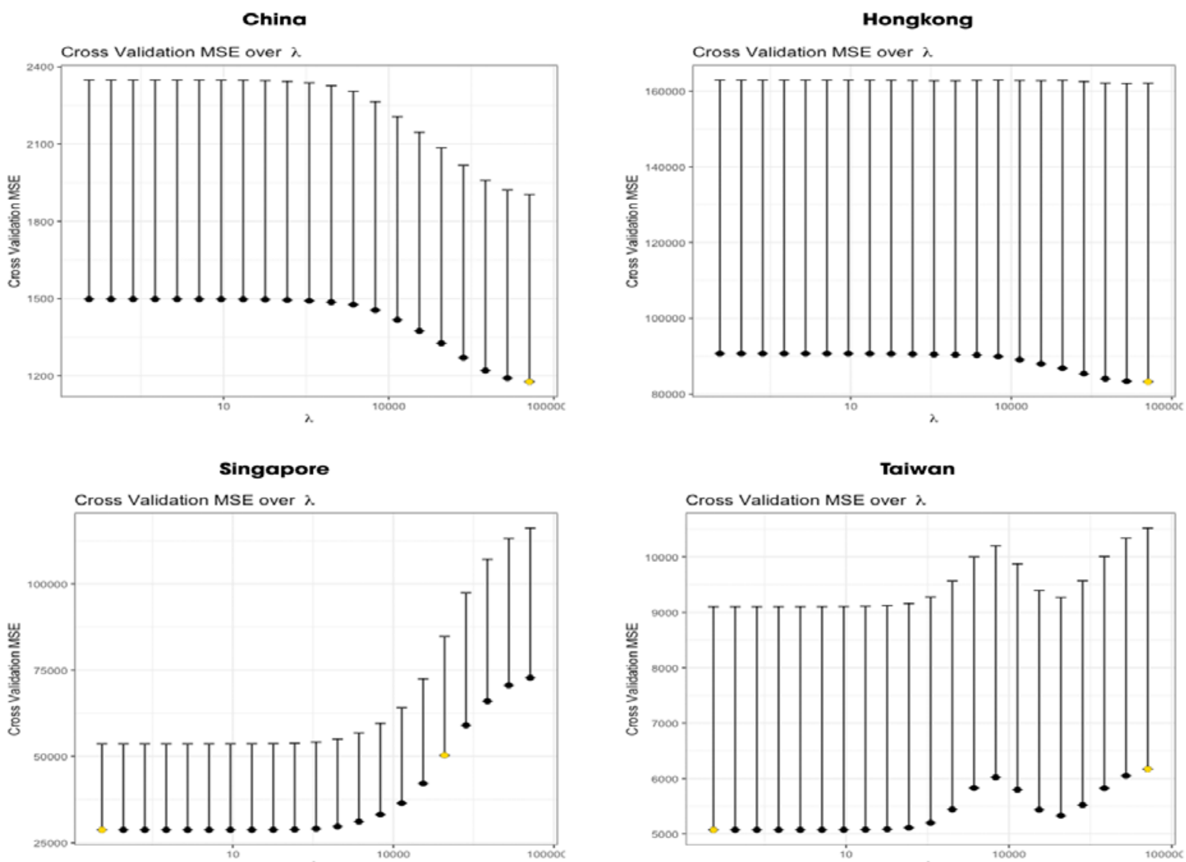

Figure A6. Cross validation MSE in GDP per capita analysis: Asian countries