The Economic Impact of Covid-19 and Associated Lockdown Measures in China

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Abstract

This paper assesses at the local level the economic impact of Covid-19 and associated lockdown measures in China using high frequency nighttime lights data. Building a model of monthly light intensity, lights dropped by a factor ranging between 13 and 18 percent in early 2020. This corresponds to a decline in economic activity of between 9 and 12 percent and a decline in employment of between 2.6 and 3.6 percent. At the local level, the majority of administrative entities followed a v-shaped recovery, while a smaller number followed a u-shaped recovery or a double dip. At province level, light intensity is explained by the number of cases and a lockdown measure. In particular, the increase in stringency index from 0 in December 2019 to 78 in April 2002 explains a decline in lights by 7.4 percent.

Keywords: Covid-19, lockdown, China, nighttime lights, big data

JEL classifications: 011, 018, R11, R12

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1 Introduction

This paper assess the local impact of the Covid-19 pandemic and the associated lockdown measures in China using high frequency nighttime lights data. The Covid-19 pandemic was first identified in Wuhan in China at the end of January 2020. The identification of the virus in different provinces of China as well as in other countries led to extensive local lockdown measures in the absence of medical treatments. One important feature of the crisis was the local specificities of the pandemic and the fast evolution of the number of cases and the related decisions by local authorities.

In order to capture the local and time dimensions of the Covid-19 crisis, we need a geographically disaggregated and high-frequency measure of economic activity. To this end, we use nighttime lights satellite images on a monthly frequency and at a disaggregated level first and second level administrative entities in China. National account statistics available on a monthly basis and at the subnational level are only partial and are produced with a time lag. Conversely, nighttime lights satellite images are available on a near real time frequency for most areas of the world and at a resolution of 500m2[1] (Henderson et al., 2012). In addition, we combine nighttime lights data with a database capturing the number of cases, number of deaths and lockdown measures on daily basis at province level produced by Petherick et al. (2021).

This paper makes a twofold contribution. First, this paper contributes to the literature measuring the impact of Covid-19 and related policies on economic activity. Beyer et al. (2021) rely on daily electricity consumption data at the state level and monthly nighttime lights data at the district level in India finding a L-shape impact of the crisis. Roberts (2021) relies on regional nighttime lights data in Morocco and shows the persistence of the shock as well as the heterogeneity of the impact at the regional level. This paper is the first to apply this approach to China. It also goes a step beyond existing works by mobilizing subnational pandemic data and subnational lockdown data. A related paper is Furceri et al. (2021), which used daily measures of nitrogen dioxide and carbon monoxide at country level to measure the impact of Covid-19 vaccines on economic activities. Second, this paper contributes to the literature on nighttime lights that uses light intensity to track economic activity at the local level and at high frequency. This paper looks at the newest generation of satellites (viirs) while the existing literature has focused primarily on the 1992-2013 DMSP satellites. Another contribution is to estimate a lights/employment elasticity to measure the impact on the labour market as well. Oliu-Barton et al. (2022) measures the impact of Covid certificates on vaccine uptake and the economy in France, Germany and Italy. They rely on the OECD weekly tracker of economic activity to build a proxy of economic activity.

The impact of lockdown measures on light intensity is estimated trhough a model that takes into account the trend in lights over time as well as monthly seasonality in the data. The model runs for the period 1993M1 to 2020M12 at the country level as well as in a panel specification across 31

[1] Near the equator.

provinces and 344 prefectures. The deviation from trend triggered by the lockdown at the end of January 2020 ranged between 13 and 18 percent depending on the specifications. This result is robust to different measures of lights and different specifications including controlling for the effect of the Chinese New Year. This magnitude is similar to that found in India and Morocco (Beyer et al., 2021; Roberts, 2021).

We estimate the lights to GDP elasticity and the lights to employment elasticity to translate variations in lights into meaningful economic magnitudes. We find a light/GDP elasticity of 0.674 at province level and a light to employment elasticity of 0.12, which is consistent with an Okun's coefficient of one third.

Looking at the shape of the economic trajectory in the aftermath of the first infection, light intensity followed a W-shape dynamic at country level. The drop in economic activity was followed by a short lived rebound in April 2020 as light intensity declined again in May/June and in September/October 2020. In addition, we can identify different patterns at province and prefecture levels: a v-shaped recovery in one third of the provinces, a u-shaped trajectory in 7 out of 31 provinces and a double dip in 6 provinces.

We then make use of the Oxford Covid-19 Government Response Tracking database to discuss the impact of infections and the related lockdown measures on light intensity at the subnational level (Hale et al., 2021; Petherick et al., 2021). We look at three variables: number of cases, number of deaths and stringency index at province level. The coefficients associated with these three variables are negative and of similar magnitudes. However, the strongest effect is associated with the stringency index. The stringency index is built from news information while the number of cases has the potential to be underestimated due to the difficulty of tracking infections.

The correlation between the number of Covid-19 cases as well as the stringency index is negative and significant. We find that nighttime lights drop by 4.6 percentage points with every new 100 reported infections. The small number of reported cases can explain this large effect. In addition, the increase in the stringency index from 0 in December 2019 to 78 in April 2020 led to a decline in light by 7.4 percentage points. In return, for every 100 new cases of Covid-19, the stringency index increases by 2.8.

The rest of the paper is organized as follow. Section 2 presents the data. Section 3 presents the lights model and estimates the deviation from trend associated with Covid-19. Section 4 discusses the lights to GDP/employment elasticities. Section 5 discusses heterogeneity at province level. Section 6 explores the causes behind the drop in lights. Section 7 concludes.

2 Data

Nighttime lights are taken from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) produced by the Earth Observations Group (EOG) from the Colorado School of Mines.[2] We download monthly VIIRS images over the period 2013m1-2021m6 covering the tiles 75N060E. The image resolution is 15 arc second around 500m at the equator. The radiance is measure in $nW/cm2/sr$. The images are already filtered for lightning, lunar illumination and cloud-cover. Cloud-cover is identified by a viirs cloud mask product (VCM). Available for download is an additional stray-light correction (VCMSL), but the lower quality of the data leads us to work with the VCM data. Monthly data are the product of an averaging of daily data. At the monthly frequency, it is likely that some area have no cloud free observations.

The monthly data are not corrected for background noise such as aurora, fires, boats and other temporal lights. In order to filter background noise, we rely on the available filtered annual VIIRS images that include such a correction.[3] The VNL V2 annual composites are an averaging of monthly averages and include filters for biomass burning, aurora and background noise. Background noise includes outlier removal to identify high and low radiance pixel. Further noise filtering is performed using a data range threshold. The idea behind the data range is to compare the radiance of each grid cell with the maximum minus minimum of the radiance of neighbouring cells. This data range threshold is weighted by the number of cloud free observations. The VNL V2 annual composites also include a cloud mask product (Elvidge et al., 2021). We identify cells with a positive radiance from the VNL V2 annual composite and apply this mask to the monthly data.

The size of the area considered implies a distortion between the actual size of the grid cells and the 2 dimensional projection of the grid cell. While the grid cells are rectangular at the equator, the grid cells are a triangle at the north and south pole. We therefore apply a latitude adjustment to the radiance of the grid cells. The centroid of each grid cell is identified as well as its latitude. The following transformation is then applied $cos(rad * a)$.[4]

The sum of lights for a given administrative entity is measured by summing the lights within an administrative area. Regarding China, three administrative entity levels are considered, country, 31 provinces and 344 prefectures. The shapefile of the administrative entities are taken from GADM.[5]

In section 3, we discuss the nighttime lights GDP elasticity. For this section, we build a panel of annual nighttime lights using the VNL V2 annual composite. The elasticity is estimated with a panel of 31 provinces and the regional domestic product data are in current 100M Yuan from the National Bureau of Statistics of China.

[2] https://payneinstitute.mines.edu/eog/nighttime-lights/
[3] https://eogdata.mines.edu/nighttime_light/annual/v20/
[4] a is a constant equal to 0.017453292.
[5] https://gadm.org/

3 Impact of lockdown on nighttime lights

To measure the impact of lockdown and COVID-19 on light intensity, it is necessary to control for factors affecting light emissions such as the growth of lights overtime as well as seasonality in the data. The monthly sum of lights for China over the period 1993-2020 is estimated with a regression that specify a time trend $Trend_t$, dummies for every month $Month_t$ and an additional set of dummies corresponding to every month comprised in the Covid-19 period $Covid_t$. The time trend gives an indication of the growth trend in light over time, while the month dummies capture monthly seasonality in lights. The impact of the Covid-19 can be estimated as deviation from the trend via the coefficients associated with the month dummies and Covid-19 interaction α_c. A similar approach is followed by Roberts (2021); Beyer et al. (2021). The lockdown in China started in Wuhan in late January 2020. January is identified as the first month of the lockdown period. The outbreak of Covid-19 took place in late January 2020 but this also corresponds to the Chinese New Year celebration (see our discussion below).

$$log(lights_t) = \alpha_c + \alpha_t Trend_t + \alpha_m Month_t + \alpha_c Covid_t + \epsilon_{i,t} \quad (1)$$

The regression is estimated for three levels of administrative entities, country, 31 provinces and 344 prefectures. The regression includes months fixed effects and administrative entity fixed effects in the panel configuration. The result of estimating eq 1 is displayed in Table 1. The time trend appears with a coefficient significant and ranging from 0.007 to 0.008 across the three specifications. The coefficients associated with the lock-down are significant and ranges between -14% and -18% for the first month. The coefficient increases with the geographic disaggregation of administrative entities for January 2020. However, geographic disaggregation does not seem to have an impact on the estimated coefficient beyond the first month. There is however a difference in terms of confidence interval as the lockdown dummies turns significant when disaggregation increases. The recession is short leaved in China as the deviation from trend is negative for the first three months only (January to March). A negative deviation from trend is also present for the months September to December corresponding to the second wave of Covid-19 in Europe and the United States.

At the monthly frequency, viirs images may not have a quality sufficient to observe lights either due to stray lights or an insufficient number of cloud free days. In China, in particular the month of June is associated with a lack of quality for a significant number of prefectures and provinces. In Column 4 to 6, we run the regression dropping the month of June. There is little impact on the coefficients. In particular, the magnitude of the effects associated with the lockdown dummies is similar. The regression explains well the fluctuations in lights especially at country level (80%) and prefecture level (75%). At province level, the $R2$ is slightly lower between 50 and 60% depending on the specification.

Table 1: Covid-19 and light intensity - Country, provinces and prefectures

	(1)	(2)	(3)	(4)	(5)	(6)
			log lights			
time trend	0.007***	0.008***	0.008***	0.008***	0.008***	0.009***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
lockdown months=1	-0.140*	-0.153***	-0.181***	-0.136*	-0.153***	-0.177***
	(0.071)	(0.048)	(0.018)	(0.071)	(0.046)	(0.018)
lockdown months=2	-0.047	-0.043	-0.031***	-0.043	-0.043	-0.027**
	(0.067)	(0.032)	(0.012)	(0.067)	(0.032)	(0.012)
lockdown months=3	-0.032	-0.029	-0.021***	-0.028	-0.029	-0.017**
	(0.073)	(0.028)	(0.008)	(0.073)	(0.026)	(0.008)
lockdown months=4	0.117	0.118***	0.103***	0.120	0.118***	0.107***
	(0.090)	(0.028)	(0.022)	(0.090)	(0.028)	(0.022)
lockdown months=5	-0.059	-0.439*	0.014	-0.056	-0.439*	0.018
	(0.064)	(0.222)	(0.039)	(0.064)	(0.222)	(0.039)
lockdown months=6	-0.044	0.327	-0.059			
	(0.070)	(0.222)	(0.041)			
lockdown months=7	0.125*	0.177*	0.115***	0.128*	0.177*	0.119***
	(0.069)	(0.098)	(0.031)	(0.069)	(0.097)	(0.031)
lockdown months=8	0.055	0.041	0.052***	0.058	0.041	0.056***
	(0.088)	(0.025)	(0.020)	(0.088)	(0.025)	(0.020)
lockdown months=9	-0.037	-0.095**	-0.100***	-0.033	-0.095**	-0.096***
	(0.065)	(0.036)	(0.018)	(0.065)	(0.036)	(0.018)
lockdown months=10	-0.033	-0.083*	-0.058***	-0.029	-0.083*	-0.054***
	(0.076)	(0.042)	(0.012)	(0.076)	(0.041)	(0.012)
lockdown months=11	0.082	0.087***	0.094***	0.086	0.087***	0.098***
	(0.090)	(0.024)	(0.011)	(0.089)	(0.023)	(0.011)
lockdown months=12		-0.044	-0.036***		-0.045	-0.032**
		(0.033)	(0.012)		(0.032)	(0.012)
R^2	0.80	0.49	0.75	0.73	0.59	0.76
N	95	2838	30780	87	2669	29116
Province FE	No	Yes	No	No	Yes	No
Prefecture FE	No	No	Yes	No	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

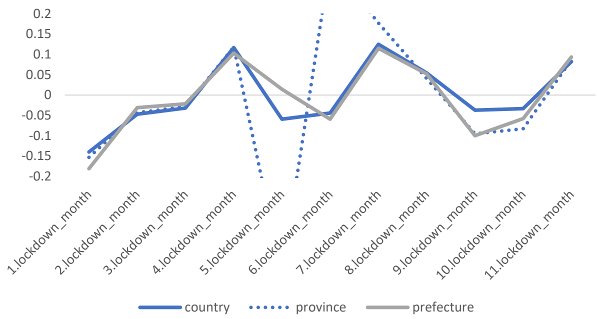
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the baseline specification using three level of administrative entities, country (1), 31 provinces (2) and 344 prefectures (3) as well as including or excluding the month of June.

This drop in light intensity with respect to the trend is smaller than the drop in electricity consumption measured in India from daily electricity consumption (-20% to -30% from trend through the month of April 2020, Beyer et al. (2021)). The magnitude is more in line with the measured reduction in light intensity in India comprised between 10 to 15%. The magnitude is also slightly larger than the drop in lights for Morocco at the trough (-11% deviation from trend in April 2020 and July 2020). In terms of shapes, the daily electricity consumption drops and recovers but stay below the trend in India. In Morocco, the shape follows a W, a recovery followed by a double dip. Similarly in China, a W-shaped recovery takes place. After a rebound in April, light intensity declines again in May/June and again in September and October. The last two months corresponds to the second wave in Europe.

Figure 1: Shape of drop and recovery at country level



(a) W-shaped

This figure presents the deviation from trend at country, province and prefecture level.

In general, throughout the year 2020, light intensity is characterised by sharp fluctuations above and below the trend (see Figure1). The fluctuations are very similar for the three level of administrative entity, which confirms the good performance of the monthly lights model presented in 1. One exception is the point estimated for June and July at province level, which display excessive amplitude (see our discussion of the two provinces that seem to explain this variation below).

We now look whether the results are sensitive to different specifications. A first modification of the baseline regression is to include a dummy variable for the Chinese New Year. The Chinese New Year is a bank holyday and is similar to a seasonal pick. Importantly, the Chinese New Year and the start of the pandemic both took place in January 2020. As the Chinese New Year takes place either in January or February we match the dummy with the corresponding month every year of the sample.

The Chinese New Year is associated with a positive and significant impact on light intensity. In addition, the dummy associated with January 2020 is now associated with a larger and more negative impact whether estimated at country level -20%, at province level -22% or at prefecture level -25% (see appendix columns 1 to 3 of Table 6).

A second robustness check is that we exclude the two provinces Liaoning and Nei Mongol for which there are less cloud free days observations. Excluding these two provinces that displayed large drops in light in May 2020 tends to reduce the coefficient associated with this month from -0.439 to -0.151 at province level while the impact is small at prefecture level (see appendix columns 4 and 5 of Table 6).

A third robustness check is to exclude the pixel with less than two cloud free days in a given month in order to correct for drop in light associated with cloud cover. The drop in lights associated with the month of January is now slightly smaller from -0.14 to -0.13 at country level, from -0.153 to -0.118 at province level and from -0.181 to -0.171 at prefecture level. In addition, the large fluctuation associated with the month of May at province level are smoothed out (see appendix columns 1 and 6 of Table 7).

4 Nighttime lights GDP/Employment elasticities in China

In this section, we discuss the translation of variation in light intensity into meaningful economic magnitudes. We discuss three ways to translate light intensity into income or employment variations: light/GDP elasticities, Okun's law and light/employment elasticities.

Regarding light/GDP elasticities, most of the papers looking at this elasticity have relied on the DMSP satellite covering the period 1992-2013. Little work is available on the VIIRS satellite for the more recent period 2013-current. Henderson et al. (2012) estimate a panel 1992-2008 between DMSP data and GDP at country level $z_j = \hat{\psi} x_j + e_j$, with x_j log of lights and z_j log of income including country and time fixed effects. GDP is measured in log real term, constant LCU. Lights are measured in log lights per area. The baseline regression produces a ψ of 0.277.

Similar results are found by World-Bank (2017) for South Asia (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka). The regression estimated is: $log(GDP_{i,t}) = a + \delta log(lights_{i,t}) + b_t + c_i + \epsilon_{i,t}$ with GDP: gross domestic product measured in constant local currency, lights: sum of lights over the surface in km2, b_t and c_i fixed effects. The coefficients are 0.267 for the world, 0.266 for the World excluding South Asia and 0.248 for South Asia. World-Bank (2017) also estimates a growth relationship: $\Delta log(GDP_{i,t}) = a + \delta \Delta log(lights_{i,t}) + b_t + c_i + \epsilon_{i,t}$. The coefficient is 0.0547 for the World, 0.0557 for the World excluding South Asia and 0.0741 for South Asia.

Elliott et al. (2015) estimates light GDP elasticity in China in a study that looks at the impact of typhoon on economic activities for 340 Chinese cities with a proximity to the coast. The period coverage is 2013-2012 and the satellite generation is DMSP rather than VIIRS. They esti-

Table 2: GDP / lights elasticity - province level China

			Panel A		
	(1)	(2)	(3)	(4)	(5)
	log GRP current 100M Yuan				
log lights	1.086***	1.093***	1.093***	0.674***	0.033
	(0.032)	(0.032)	(0.032)	(0.060)	(0.049)
time trend			-0.019		
			(0.020)		
R^2	0.80	0.81	0.81	0.62	0.80
N	186	186	186	186	186
Province FE	No	No	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes
Trend	No	No	Yes	No	No
			Panel B		
	(1)	(2)	(3)	(4)	(5)
	log GRP current 100M Yuan per pixel				
log lights per pixel	1.100***	1.102***	1.102***	0.674***	0.033
	(0.013)	(0.014)	(0.014)	(0.042)	(0.066)
time trend			-0.020		
			(0.019)		
R^2	0.95	0.95	0.95	0.62	0.80
N	186	186	186	186	186
Province FE	No	No	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes
Trend	No	No	Yes	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the baseline regression between nighttime lights and GDP in current 100M Yuan at province level in China Panel A. Both variables are scaled down by number of pixel in Panel B.

mates an equation in which GDP in dollar is measured per area and is also deflated with 2013 prices: $\left(\frac{GDP}{AREA}\right)_{i,t} = \alpha + \beta_{NL} NTLs_{i,t} + \pi_t + \sigma_i + \epsilon_{i,t}$, with GDP: county gross domestic product in USD deflated with 2013 prices, AREA: area in square kilometers, NTLs: nighttime lights per square kilometers, π_t: time fixed effects, σ_i: county fixed effects. Each unit of nightlights per square kilometer translate into 0.036 income per square kilometer. The elasticity found appears very small compared to existing studies.

For China, the GDP/nighttime lights elasticity is estimated based on a panel of 31 provinces. The gross regional product is expressed in 100M Yuan at current price. At province level, the GDP data are only available at annual frequency. The elasticity is slightly above unity in the absence of province fixed effects $\beta = 1.1$ including when a time trend is specified (Table 2 Panel A). Adding province fixed effect reduces the elasticity to 0.674, which turns ultimately nonsignificant with both province and time fixed effects. The R2 is high at around 0.8. In the literature the light GDP elasticity is sometimes estimated scaled down by a measure of surface in km2 or in number of pixel. The regression using variable scaled down by the number of pixel is presented in Table 2 Panel B. The results are similar and the R2 is higher at 0.95.

Table 3: Okun's law - province level China

	(1)	(2)
	D.log_et_prov	*D.log_et2_prov*
D.log_grp	0.33^{*}	0.22^{**}
	(0.17)	(0.11)
_cons	0.06^{*}	0.07^{***}
	(0.03)	(0.02)
id FE	yes	yes
time FE	yes	yes
N	248	248
R^2	0.043	0.141

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Given the short time dimension of the VIIRS satellite (2013-2019), the inclusion of time fixed effects has a strong impact on the coefficient estimated due to Hurwitz bias. The coefficient drops to 0.033. The coefficient is closer to the coefficient estimated by Elliott et al. (2015). However, it is not significant. Given the risk of Hurwitz bias, we choose to exclude time fixed effects. Note that as well that if the relationship is estimated in the difference of the log, the elasticity is 0.07 and significant very much in line with the elasticity estimated for South Asia 0.074.

In order to convert income magnitudes into employment magnitudes, we can rely on an Okun's law. The Okun's law looks at the relationship between changes in income and changes in unemployment rate. In countries lacking unemployment insurances, a preferred estimation is between changes in

Table 4: Employment / lights elasticity - province level China

	(1)	(2)	(3)	(4)	(5)	(6)
		log et			log et2	
log lights	0.450***	0.120***	0.048***	0.420***	0.071***	0.032***
	(0.116)	(0.032)	(0.011)	(0.119)	(0.019)	(0.007)
R^2	0.13	0.08	0.69	0.12	0.07	0.61
N	186	186	186	186	186	186
Province FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	No	Yes	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the regression between nighttime lights and Employment at province level in China.

income and changes in the employment rate. In China, employment data are available at province level. However, there is a discrepancy between aggregate employment statistics and provincial employment statistics. At province level, employment is given for two categories: "number of employed persons in urban units" and "number of engaged persons in private enterprises and self-employed individuals". One important category is missing at province level: "farmers, employed persons in rural unit". With this limitation in mind, we present the Okun's estimation for et: "number of engaged persons in private enterprises and self-employed individuals" (10 000 persons) as well as for $et2$: "et + "number of employed persons in urban units" (10 000 persons). Gross regional product is in 100M Yuan. The regressions are estimated using the difference of the log. Regression (1) and (2) are Okun estimates with intuitive coefficients Table 3. The coefficient is 0.33 and 0.22 very much in line with existing results.

In order to go beyond income measures, one may want to look at the link between lights and employment. An indirect way is to estimate a lights/GDP elasticity and to combine this elasticity with the coefficient from the Okun's law as shown in the previous two tables. A more direct way it to estimate directly an lights/employment elasticity. Table 4 presents these elasticities for both measure of employment and for different set of fixed effects. The elasticity is stable across the two definitions. It is however changing depending on the set of fixed effects. The province fixed effects produces a coefficient comprised between 0.7 and 0.12, which seems reasonable given the light GDP/elasticity and the Okun's elasticity. The GDP/light elasticity is 0.6 and the Okun's coefficient is 0.33, which produces a coefficient of 0.18. Note that there are measurement issue related to employment at province level that could explain the difference.

5 Heterogeneity at province level and prefecture level - monthly frequency

The spread of the pandemic and the associated response of the authorities has a strong local dimension. This section explores heterogeneity at province level and prefecture level. Eq 1 is estimated for each province and for each prefecture, i.e. the time trend the monthly seasonality and the Covid-19 dummies have coefficients that are area specific. As an illustration, Figure 2a displays the heterogeneity over time and at province level. We see that provinces are affected differently on impact and over time as provinces are distributed above and below zero. In January 2020, 19 out of 31 provinces experienced a negative impact. The three largest drops are found in Western provinces: Gansu, Qinghai and Xizang. The province of Hubei where the virus started experienced a 17 percent decline in lights. Despite the intense lockdown measures implemented in Wuhan, this region did not displayed the largest drop in light as underlined as well in other studies (Elvidge et al., 2020). Two provinces experienced significant increase in lights intensity in January 2020 are Heilongjiang, Jilin. In addition, some provinces are displaying strongly negative impact on month 3 and month 4. On month 3, the province of Beijing shows a large decline in lights. On month 4, it is the two provinces of the North, Inner Mongolia and Liaoning that display large drops in lights. A similar pattern emerges when looking at the prefecture level in Figure 2b with heterogeneity increasing over time.

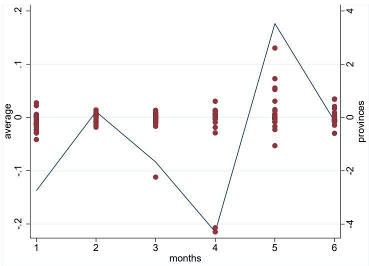
To go in more details, Figures 2d and 2d look at he shape of the recovery across provinces by plotting the estimated coefficient for the month of December followed by the coefficient for the dummy variable corresponding to the lockdown going from January 2020 to April 2020. The 33 provinces are classified into four groups: "v-shaped", "u-shaped", "double dip", "heterogenous" (not showed here). The first category gathers 12 out of 31 provinces. Most of the provinces have recovered to or above pre-lockdown trend in April 2020. In some other provinces, the shock is rather persistent. The u-shaped group is composed of 7 provinces and the recovery is slower than the v-shaped group. Lastly, we put together 6 provinces which are characterized by a double dip.

6 Factors explaining the drop in light intensity

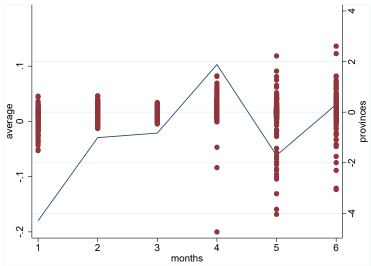
In this section we look at the factors impacting nighttime lights intensity. In particular, we are interested in measuring the impact of the Covid-19 pandemic and the associated lockdown down measures on light intensity. We rely on the policy response database at province level put together by the Oxford Covid-19 Government Response Tracking (OxCGRT) (Petherick et al., 2021). In particular, we are interested with the number of Covid-19 cases and the number of death as variables measuring the intensity of the pandemic. These variables are daily measures and cumulative over time. We take the number of cases and number of deaths in the last day of each month.

In terms of policy variables, the OxCGRT build an index to measure the stringency of containment and closure policies that summarizes school closing, workplace closing, cancelation of public events,

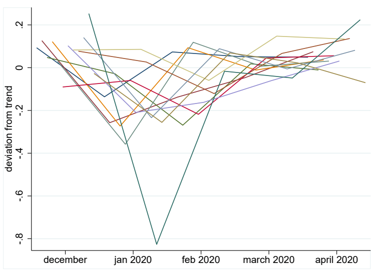
Figure 2: Heterogeneity at province and prefecture level



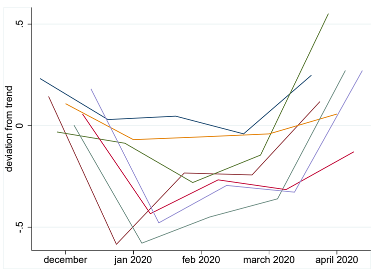
(a) Provinces - average



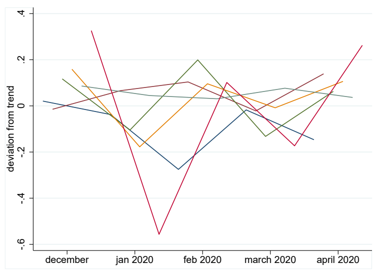
(b) Prefectures - average



(c) V-shaped - selection



(d) U-shaped - selection



(e) Double dip - selection

Figures (a) and (b) display the drop in lights for each province and prefecture January to June 2020. Figure (c) illustrates provinces with a v-shaped recovery, (d) u-shaped recovery and (e) double dip.

restrictions on gathering, public transport limitation, stay at home requirement, internal movement restrictions, international travel restrictions. The OxCGRT also provides an index to measure the economic policy response to alleviate the effect of lockdown measures on the economy such as income support, debt relief for households or fiscal measures. The OxCGRT also proposes an index to measure health system response to Covid-19, which includes information campaign, testing, contact tracing, emergency investment in health system, investment in vaccine, facial covering, vaccination policy and protection of elderly people. Lastly, a global measure of policy response based on these different indexes is also available (Hale et al., 2021). As a start, we will focus on the stringency index.

We start with the variables measuring the severity of the pandemic and the lock-down effect. We estimate a panel regression with the difference of the log in nighttime intensity as the dependent variables. The difference of the log is taken from one month to the other. Since the variables "number of cases", "number of deaths" and "stringency index" aim at capturing the same effect (the severity of the pandemic), we integrate these variable one at a time. For each variable, we present 5 specifications. A simple regression in column 1. We then add a lagged dependent variable to estimate a dynamic panel. The equation is augmented with a time trend in column 3. In column 4, we compare the coefficient when the variable controlling the severity of the pandemic is lagged one period. Lastly, as robustness check, the year-on-year difference of the log is also considered as a depend variable. The time coverage spans from January 2013 to June 2021 (see Table 5).

Table 5: Pandemic response and light intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
		D.lights log			yearly diff log lights			D.lights log		yearly diff log lights		D.lights log			yearly diff log lights
Nber of cases log	-0.010**	-0.009**	-0.012**		-0.013***										
	(0.004)	(0.004)	(0.005)		(0.003)										
L.Nber of cases log				-0.010*											
				(0.006)											
Nber of deaths log						-0.019	-0.016	-0.015		-0.026**					
						(0.014)	(0.013)	(0.013)		(0.011)					
L.Nber of deaths log									-0.018						
									(0.015)						
Stringency index log											-0.017**	-0.015**	-0.020**		-0.026***
											(0.006)	(0.006)	(0.008)		(0.006)
L.Stringency index log														-0.018**	
														(0.008)	
L.diff log lights				-0.263***					-0.263***					-0.263***	
				(0.064)					(0.064)					(0.064)	
L.yearly diff log lights					0.188***					0.189***					0.188***
					(0.054)					(0.054)					(0.054)
time trend			0.000	0.000	0.003***			-0.000	-0.000	0.002***			0.000	0.000	0.003***
			(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.001)
R^2	0.01	0.61	0.61	0.61	0.16	0.00	0.58	0.58	0.57	0.07	0.00	0.60	0.60	0.60	0.17
N	2903	2791	2791	2791	2523	2903	2791	2791	2791	2523	2903	2791	2791	2791	2523
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the correlation between the change in log intensity and variables measuring the pandemic intensity and the lockdown measures.

We include province fixed effects. The pandemic variables show no variation over time before the Covid-19 period and including a month dummy would only capture the policy change. We therefore do not include month fixed effects in the regression. The errors are clustered at the level of provinces. Since the number of cases, deaths and the stringency index are reported as 0 before January 2020, we apply the following transformation to these variables: $log(1 + x)$.

A first result is that the effect is negative and significant for two of the three variables while one variable is non-significant ("number of deaths"). The effects are also similar in magnitude ranging from -0.01 to -0.02. There is also a ranking between the three variables that may reflect the difficulty to measure some of these variables. The number of cases and the number of deaths display the smallest effects, or no effects compared to the stringency index. There are challenges to measure accurately the first two variables. In addition, these variables are constructed from official statistics. However, the third variable is an index build from public news at province level. It follows that the third measure might give a more realistic view of the impact of the lockdown on light intensity.

In terms of specifications, the inclusion of a lagged dependent variable has little impact on the size of the coefficient. The inclusion of a time trend has a small positive effect. Taking a lag of the explanatory variable has a small positive effect on the estimated coefficient. Lastly, taking the annual difference of the log rather than the monthly difference of the log yields larger coefficient estimates.

In terms of magnitude, the coefficient for the "number of cases" is -0.01. This coefficient implies that 100 covid-19 cases leads to the decline of light intensity by 4.6 percentage points ($-0.012 * log(1+100) = 0.055$). This number can be seen as large but the number of Covid-19 cases reported is small as well. China reports slightly more than 80000 cases during the first wave (82874 at the end of April 2020). In total, this would lead to a decline in light by -11.2% very much in line with the number discussed in the previous section. The coefficient associated with the number of deaths is not significant regardless the inclusion of a time trend. The number of deaths reported is small as well: a total of 4633 deaths at the end of the first wave for China as a whole.

The coefficient associated with the stringency index range from -0.017 and -0.02. The stringency index is comprised between 0 and 100. It goes from 21 at the end of January to reach 79 in December 2020. It then fluctuates between 50 and 70 until the end of the sample (June 2021). In June 2020, the stringency index reaches 78.46, which implies a decline in light intensity by 7.4 percentage points ($-0.019 * log(1 + 78.46) = 0.074$). This result confirms the strong impact of lockdown measures on light intensity. Since lockdown measures are taken in reaction to the number of infections, the two variables are strongly correlated. The coefficient associated with the log of the number of infections is 0.61 and is significant at 1% when the dependant variable is log of the stringency index. For every 100 new infection, the authorities take restriction measures that lead to an increase in the stringency index by 2.8 ($0.61 * log(1 + 100) = 2.81$).

7 Conclusion

The objective of this paper is to track the local impact of the Covid-19 pandemic on economic growth in China. In particular, this paper wants to estimate the short-term impact of the crisis on economic activity and the shape of the recovery at the local level. This paper is also interested in understanding the economic cost associated with the lockdown measures at the local level.

In order to do so, we rely on two innovative database that are available at a disaggregated geographical level and at high frequency. The proxy for economic growth is based on nighttime lights data that are available in real term and at a 500m2 resolution. We average this data at monthly frequency and for 31 provinces and/or 344 prefectures. The pandemic variables and the policy variables are taken from the Oxford Covid-19 Government Response Tracking database that provides daily measures of the number of cases, number of deaths and lockdown measures at province level in China.

We find a drop in lights ranging between 13 and 18 percent in early 2020. This corresponds to a decline in economic activity comprised between 9 and 12 percent and a decline in employment comprised between 2.6 and 3.6 percent. This result is in line with similar measures in India and Morocco. However, the shape of the recovery is a W when it is more of a L-shaped trajectory in many countries over the period 2020-2021. This underlines that despite the initial success of the zero Covid strategy, the Chinese economy continued to be impact by the pandemic through out 2020 and 2021.

We also find large heterogeneity at province and prefecture level. In addition to the provinces following a w-shape trajectory, a third of the province follows a v-shape recovery, and a significant number of provinces follows a u-shape recovery. This heterogeneity at province level is explained by the strength of the pandemic and the associated lockdown measures. The number of cases and the stringency index are highly correlated with the drop in lights and its recovery. An increase of the stringency index from 0 to 78 explains a drop in lights by 7.4 percent. We find in addition that the stringency index might be a better measure of the severity of the crisis than the number of cases in countries where tracking the number of cases is difficult.

References

Beyer, R. C., S. Franco-Bedoya, and V. Galdo (2021). Examining the economic impact of covid-19 in india through daily electricity consumption and nighttime light intensity. *World Development 140*, 105287.

Elliott, R. J., E. Strobl, and P. Sun (2015). The local impact of typhoons on economic activity in china: A view from outer space. *Journal of Urban Economics 88*, 50–66.

Elvidge, C. D., T. Ghosh, F.-C. Hsu, M. Zhizhin, and M. Bazilian (2020). The dimming of lights in china during the covid-19 pandemic. *Remote Sensing 12*(17).

Elvidge, C. D., M. Zhizhin, T. Ghosh, F.-C. Hsu, and J. Taneja (2021). Annual time series of global viirs nighttime lights derived from monthly averages: 2012 to 2019. *Remote Sensing 13*(5).

Furceri, D., M. P. Deb, S. Kothari, N. Tawk, D. Jimenez, and M. J. D. Ostry (2021, October). The Effects of COVID-19 Vaccines on Economic Activity. IMF Working Papers 2021/248, International Monetary Fund.

Hale, T., N. Angrist, R. Goldszmidt, B. Kira, A. Petherick, T. Phillips, S. Webster, E. Cameron-Blake, L. Hallas, S. Majumdar, and H. Tatlow (2021). A global panel database of pandemic policies (oxford covid-19 government response tracker. *Nature Human Behaviour 5*(4).

Henderson, J. V., A. Storeygard, and D. N. Weil (2012, April). Measuring economic growth from outer space. *American Economic Review 102*(2), 994–1028.

Oliu-Barton, M., B. Pradelski, N. Woloszko, L. Guetta-Jeanrenaud, P. Aghion, P. Artus, A. Fontanet, P. Martin, and G. Wolff (2022). The effect of covid certificates on vaccine uptake, health outcomes and the economy. *Bruegel Working Paper* (01).

Petherick, A., M. Di Folco, T. Hale, T. Phillips, Y. Zhang, T. Ge, K. Meng, and A. Wood (2021). Chinese provincial government responses to covid-19. *Blavatnik School Working Paper 041*(1).

Roberts, M. (2021, February). Tracking Economic Activity in Response to the COVID-19 Crisis Using Nighttime Lights : The Case of Morocco. Policy Research Working Paper Series 9538, The World Bank.

World-Bank (2017). South asia economic focus, fall 2017 : Growth out of the blue. Technical report, World Bank. https://openknowledge.worldbank.org/handle/10986/2839.

Table 6: Chinese new year dummy and Excluding two provinces (Liaoning, Nei Mongol)

	(1)	(2)	(3)	(4)	(5)
			log lights		
		Chinese new year		29 provinces	
time trend	0.007***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
chinese new year	0.089	0.090***	0.103***		
	(0.070)	(0.010)	(0.006)		
lockdown months=1	-0.203***	-0.218***	-0.255***	-0.144***	-0.179***
	(0.069)	(0.048)	(0.018)	(0.050)	(0.019)
lockdown months=2	0.016	0.021	0.043***	-0.026	-0.012
	(0.070)	(0.032)	(0.012)	(0.031)	(0.012)
lockdown months=3	-0.032	-0.029	-0.021***	-0.023	-0.019**
	(0.073)	(0.028)	(0.008)	(0.028)	(0.008)
lockdown months=4	0.117	0.118***	0.103***	0.113***	0.115***
	(0.090)	(0.028)	(0.022)	(0.029)	(0.017)
lockdown months=5	-0.059	-0.439*	0.014	-0.152	-0.011
	(0.065)	(0.222)	(0.039)	(0.105)	(0.032)
lockdown months=6	-0.044	0.327	-0.059	0.330	-0.062
	(0.071)	(0.222)	(0.041)	(0.222)	(0.041)
lockdown months=7	0.125*	0.177*	0.115***	0.234***	0.113***
	(0.070)	(0.098)	(0.031)	(0.068)	(0.031)
lockdown months=8	0.055	0.041	0.052***	0.049*	0.053***
	(0.089)	(0.025)	(0.020)	(0.026)	(0.019)
lockdown months=9	-0.037	-0.095**	-0.100***	-0.099**	-0.108***
	(0.065)	(0.036)	(0.018)	(0.038)	(0.019)
lockdown months=10	-0.033	-0.083*	-0.058***	-0.088*	-0.064***
	(0.077)	(0.042)	(0.012)	(0.045)	(0.012)
lockdown months=11	0.082	0.087***	0.094***	0.093***	0.096***
	(0.090)	(0.024)	(0.011)	(0.026)	(0.011)
lockdown months=12		-0.044	-0.036***	-0.034	-0.026**
		(0.033)	(0.012)	(0.034)	(0.013)
R^2	0.80	0.20	0.20	0.23	0.22
N	95	2838	30780	2671	28925
Province FE	No	Yes	No	Yes	No
Prefecture FE	No	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the baseline augmented with a dummy for Chinese new year columns 1 to 3 as well as excluding two provinces (columns 4 and 5).

Table 7: background noise + cloud free days >= 2

	(1)	(2)	(3)	(4)	(5)	(6)
	log lights	log lights	log lights	log lights	log lights	log lights
time trend	0.007***	0.007***	0.008***	0.008***	0.008***	0.009***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
lockdown months=1	-0.131*	-0.118**	-0.177***	-0.129*	-0.140***	-0.176***
	(0.077)	(0.049)	(0.020)	(0.077)	(0.047)	(0.020)
lockdown months=2	-0.024	0.011	0.022	-0.022	-0.011	0.023
	(0.067)	(0.041)	(0.016)	(0.067)	(0.041)	(0.016)
lockdown months=3	-0.024	0.001	0.003	-0.022	-0.021	0.004
	(0.077)	(0.030)	(0.013)	(0.077)	(0.028)	(0.014)
lockdown months=4	0.106	0.120***	0.087***	0.108	0.098***	0.088***
	(0.097)	(0.032)	(0.025)	(0.097)	(0.027)	(0.025)
lockdown months=5	-0.062	0.114	0.156***	-0.061	0.091	0.157***
	(0.065)	(0.146)	(0.047)	(0.064)	(0.152)	(0.048)
lockdown months=6	-0.081	0.175	-0.069			
	(0.075)	(0.155)	(0.055)			
lockdown months=7	0.095	0.124	0.085	0.097	0.102	0.086
	(0.074)	(0.185)	(0.054)	(0.074)	(0.178)	(0.053)
lockdown months=8	0.078	0.137*	0.057*	0.079	0.115	0.058*
	(0.088)	(0.070)	(0.034)	(0.088)	(0.068)	(0.033)
lockdown months=9	-0.089	-0.146**	-0.228***	-0.087	-0.168***	-0.227***
	(0.067)	(0.056)	(0.036)	(0.067)	(0.050)	(0.036)
lockdown months=10	-0.042	-0.128	-0.104***	-0.040	-0.150*	-0.103***
	(0.076)	(0.084)	(0.023)	(0.076)	(0.081)	(0.022)
lockdown months=11	0.106	0.143***	0.145***	0.108	0.121***	0.146***
	(0.092)	(0.032)	(0.017)	(0.091)	(0.029)	(0.017)
lockdown months=12		-0.024	-0.026*		-0.046	-0.026*
		(0.037)	(0.014)		(0.035)	(0.015)
R^2	0.81	0.17	0.14	0.74	0.19	0.15
N	95	2816	30604	87	2654	28970
Province FE	No	Yes	No	No	Yes	No
Prefecture FE	No	No	Yes	No	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results of the baseline specification using three level of administrative entities, country (1), 31 provinces (2) and 344 prefectures (3) as well as including or excluding the month of June. The data includes the exclusion of background noise as well as the exclusion of pixels with less than two days of cloud free days.