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Working Paper

On the use of satellite-based vehicle flows data to assess local economic activity: The case of Philippine cities

ADB Economics Working Paper Series, No. 652

Provided in Cooperation with:

Asian Development Bank (ADB), Manila

Suggested Citation: Go, Eugenia; Nakajima, Kentaro; Sawada, Yasuyuki; Taniguchi, Kiyoshi (2022) : On the use of satellite-based vehicle flows data to assess local economic activity: The case of Philippine cities, ADB Economics Working Paper Series, No. 652, Asian Development Bank (ADB), Manila,
<https://doi.org/10.22617/WPS220079-2>

This Version is available at:

<https://hdl.handle.net/10419/259490>

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ON THE USE OF SATELLITE-BASED VEHICLE FLOWS DATA TO ASSESS LOCAL ECONOMIC ACTIVITY

THE CASE OF PHILIPPINE CITIES

Eugenia Go, Kentaro Nakajima, Yasuyuki Sawada, and Kiyoshi Taniguchi

NO. 652

March 2022

ADB ECONOMICS
WORKING PAPER SERIES

ADB Economics Working Paper Series

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Eugenia Go, Kentaro Nakajima, Yasuyuki Sawada, and Kiyoshi Taniguchi

No. 652 | March 2022

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We gratefully acknowledge financial support from the Asian Development Bank and the Japan Society for the Promotion of Science (Grant No. 20K20753). The paper benefited from comments from participants at the ADB Economic Research and Regional Cooperation Department seminar. We are also grateful to Jiang Yi for sharing his insights on the use of mobile phone data for estimating mobility patterns. We are grateful to Manfred Kiefer and Christian Lapie Abeleda from ADB's Private Sector Operations Department for sharing vital information about Cebu's airport renewal project. Orbital Insights shared their satellite-derived data for this study. We thank Albert Park, John Gibson, Elaine Tan, Daniel Boller, Arturo Martinez Jr. as well as participants at the 2022 Economists' Forum of the Asian Development Bank for constructive comments and Shungo Nishikawa, Shinpei Noguchi and Marco Zaplan for their superb research assistance.



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ISSN 2313-6537 (print), 2313-6545 (electronic)
Publication Stock No. WPS220079-2
DOI: <http://dx.doi.org/10.22617/WPS220079-2>

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ABSTRACT

The lack of suitable data is a key challenge in ex-post policy evaluations. This paper proposes a novel data to measure local economic activities using vehicle counts in each 500 meter (m) x 500 m tile. The metric is derived from high resolution satellite images using a machine learning algorithm. Using the opening of the new international airport terminal in Cebu, Philippines, as a quasi-experiment, we estimate the impact of the new infrastructure on the local economy of Metro Cebu. Results of the difference-in-differences analysis show that the new terminal significantly increased vehicle traffic in urban Cebu. The effect decays with distance from the airport, is stronger in areas where hotels are located, and is most pronounced in the peak months for international tourists. These findings imply that the opening of the new international terminal has enhanced Cebu's local economy through international tourism.

Keywords: transportation infrastructure, satellite imagery data

JEL codes: R11

I. INTRODUCTION

A key challenge in ex-post policy evaluation is to obtain suitable data in the ideal time frame and spatial granularity for the analyses. Most ex-post policy evaluations rely on official government statistics, which have several limitations, as highlighted in the context of the coronavirus disease (COVID-19) pandemic (Chetty et al. 2020). First, the lack of timeliness in compiling data from surveys to analysis and publication. Difference-in-differences (DID) analyses, a workhorse methodology for ex-post policy evaluations, necessitate multiple periods of observations before and after the policy change being evaluated for both its treatment and control groups. Second, official government statistics typically lack the frequency ideal for an evaluation analysis. For example, the effects of the development of transportation infrastructure often have large seasonal variations between peak and off-peak seasons. Finally, traditional data sources usually lack spatial granularity even as policies, especially large-scale interventions such as physical infrastructure programs, often have heterogeneous effects across regions. For example, in the case of the development of railroads, the impact in commercial areas around the station may be pronounced, but the impact on areas farther from the station may be relatively small, which may increase the disparity within the city. It is difficult to obtain enough data from government statistics to analyze such heterogeneity in effect at each area in a city.

Against this backdrop, this paper proposes using vehicle traffic volume data obtained from a machine learning algorithm applied to daytime satellite images as a novel, granular, and high-frequency measure of local economic activities for policy evaluation. The technology used in this paper allows us to count the number of vehicles at the level of 500 m x 500 m tiles, captured by multiple satellite images throughout the year. These provide an opportunity to capture the spatial and seasonal heterogeneity of the impacts of a policy. We use the opening of the new international terminal at the Mactan-Cebu International Airport (MCIA) in the Philippines as a quasi-experiment to estimate the impact of the new terminal on Cebu's local economy. The method is suitable for application in the urban areas of Cebu, where rail transport systems are lacking, and therefore vehicle transport tends to accompany economic activities of commuting, logistics, business communication, shopping, and others. This is especially true in areas where public transportation is scarce.

First, we conduct validation exercises of our new data by comparing with data from the census and nightlight luminosity data. The latter is widely used as a measure of local economic activities (Gibson et al. 2021, Donaldson and Storeygard 2016). Our analyses indicate that vehicle traffic data is significantly correlated with census data such as population, households, and establishments. We also find a strong correlation between luminosity data and vehicle traffic. However, nightlight luminosity data do not perfectly predict the vehicle traffic data and the prediction error is positively correlated with the presence of the commercial and tourism sectors. This suggests that the nightlight luminosity data is insufficient to capture economic activities in areas with large commercial and tourism sectors. In such cases, vehicle traffic volume can more appropriately capture economic activities.

Next, using our new data, we estimate the impact of the new terminal to Cebu's local economy. Specifically, we use DID, assigning areas surrounding the MCIA as a treatment group and areas surrounding two other major regional airports as control groups, i.e., Davao International Airport in Davao City, the largest city in the Philippines in terms of land area, and the third most populous city

in the Philippines after Quezon City and Manila, and Clark International Airport located 80 kilometers northwest of Manila.

The DID results are summarized as follows. First, the opening of the new terminal significantly increased the volume of vehicular traffic in Metro Cebu. While this effect is greatest in the vicinity of the MCIAT and attenuates with distance, the effect is greater in the areas where hotels are located than those without hotels. Second, the effect of the new terminal coincides with the peak months of international passengers. The magnitude of the effect is positively correlated with hotel cluster locations during the peak months of international travel. These results show that the opening of the new international terminal has an overall positive impact on Cebu's local economy through the increased number of international visitors staying in the city.

We believe that this paper contributes to the literature that measures economic outcomes using satellite imagery data. There have been extensive studies in this field that use nightlight luminosity data to approximate economic activities (e.g., Henderson, Storeygard, and Weil 2012; Donaldson and Storeygard 2016; Gibson et al. 2021). However, such studies have their limitations: For example, the Visible Infrared Imaging Radiometer Suite (VIIRS) data, which is currently recommended for less aggregated data (e.g., Gibson et al. 2021), is nighttime luminosity data captured at 1:30 a.m., and the source of light is essentially urban streetlights. While streetlights reflect urban economic activities in general, the impact on the tourism sector, which is a critical element of transport infrastructure studied in this paper, may not be sufficiently captured. For example, the effectiveness of nightlight luminosity data in capturing seasonal changes of economic activities is limited by nature because street light coverage and intensity do not change a lot over a short period of time. Moreover, resort hotels and beach establishments like the ones Cebu is famous for tend to be in the suburbs and do not necessarily favor the glitter of lights. For these reasons, our proposed vehicle count data, which to our knowledge, is used for the first time in economic research, can complement analyses using nightlight data.

This paper contributes to the emerging literature on the impact evaluation of transportation infrastructure (e.g., Asher and Novosad 2020; Raitzer, Blöndal, and Sibal 2019; Redding and Rossi-Hansberg 2017; Redding and Turner 2017; Donaldson 2015). While most studies on transportation infrastructure focus on impacts to commuting, business trips, or aggregated economic activities, this paper focuses on the impact on the tourism sector, which remains insufficiently investigated in the literature, albeit the sector's economic importance (Faber and Gaubert 2019).

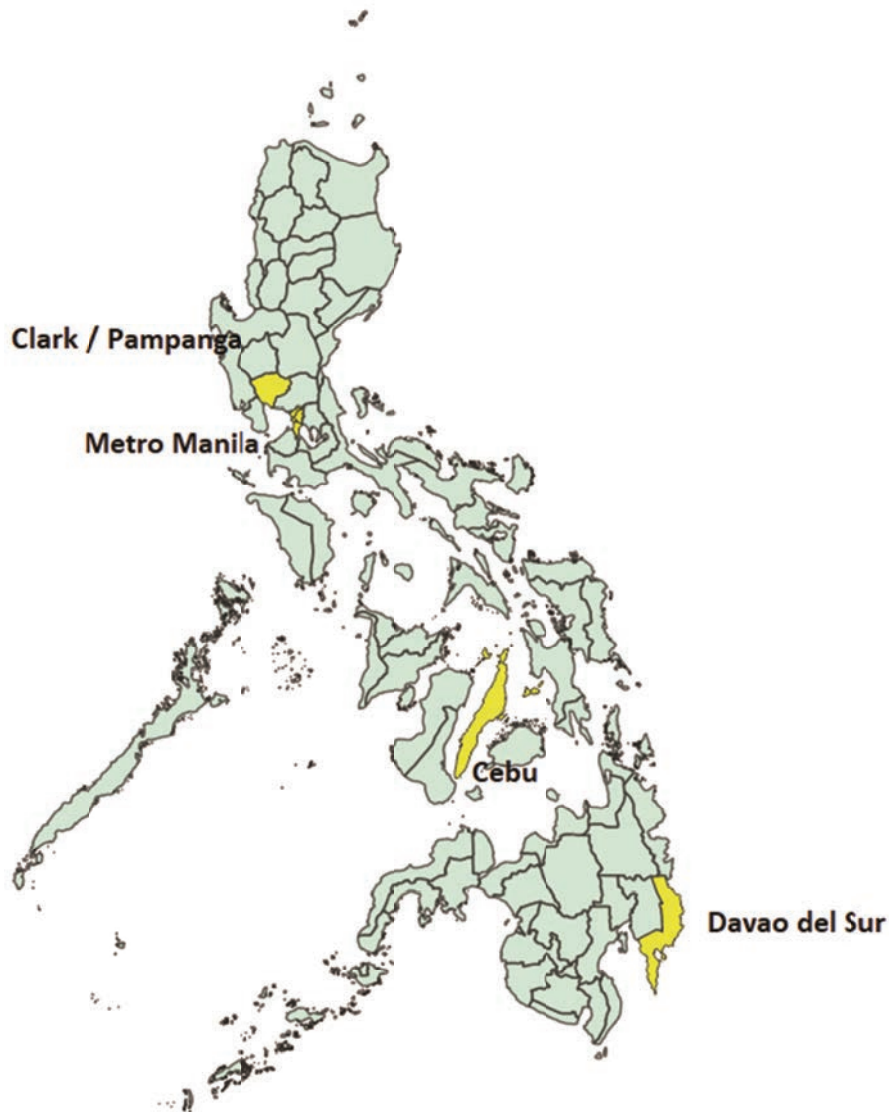
II. INSTITUTIONAL BACKGROUND

The Philippines is an archipelago of over 7,000 islands, and connectivity is a major challenge. Luzon in the north is the country's center of economic gravity, with Metro Manila and the surrounding regions of Central and Southern Luzon accounting for almost half of national output in 2019, while having 30% of the country's population (PSA 2020 and 2017). Even though Central Visayas, where Cebu is located, accounts for merely 5% of national gross domestic product (GDP) and 6% of the country's population, the province of Cebu, geographically situated in the center of the country as shown in Figure 1, serves as an important regional hub for the provinces in the central and southern part of the country. Thirty percent of the volume and value of domestic maritime trade pass through the province

(PSA 2016a). Air traffic statistics in 2015 also show Cebu as a tourism hub, accounting for 17% of domestic and international tourism throughput. This places MCI A only second to the Manila airport, which has over 50% of domestic and 70% of international tourism arrivals (DOT 2016). Indeed, the tourism sector has become one of the leading sectors in the development of economies around the world, including the Philippines (ADB 2021, Faber and Gaubert 2019), and is playing a critical role in recovery from the COVID-19 pandemic.

Investing in transport infrastructure in Cebu, especially those that support intermodal connectivity, is therefore perceived as a cornerstone to the economic foundations of areas in the central and southern provinces, but also to the overall economic integration of the country.

Figure 1: Map of the Philippines

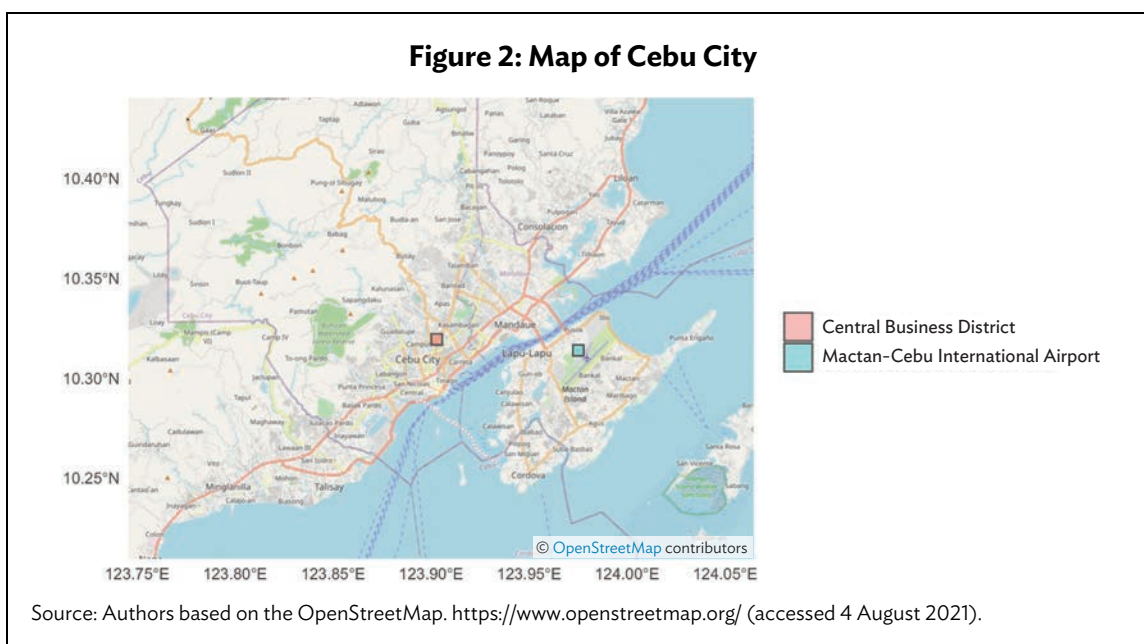


Note: Key regions and provinces relevant to the analysis are highlighted.
Source: Authors.

A. Cebu City

Figure 2 displays the map of the Cebu built-up area. Metro Cebu is the second-largest metropolis in the Philippines, comprising seven cities and six municipalities with a total population of 3.2 million (PSA 2017). The central business district (CBD) located in Cebu City is indicated by the red tile in Figure 2. Metro Cebu has some of the densest cities outside of mainland Luzon, with over 14,400 persons per square kilometer (km) in Mandaue City and 7,000 persons per square km in Lapu-Lapu City (PSA 2017). In comparison, the national average is only 337 persons per square km, whereas the figure is around 21,000 in Metro Manila.

The MCIA is located on Mactan Island, southeast of Cebu City, shown by the green tile. Mactan Island is a world-renowned resort area and is a key attraction to international tourists.



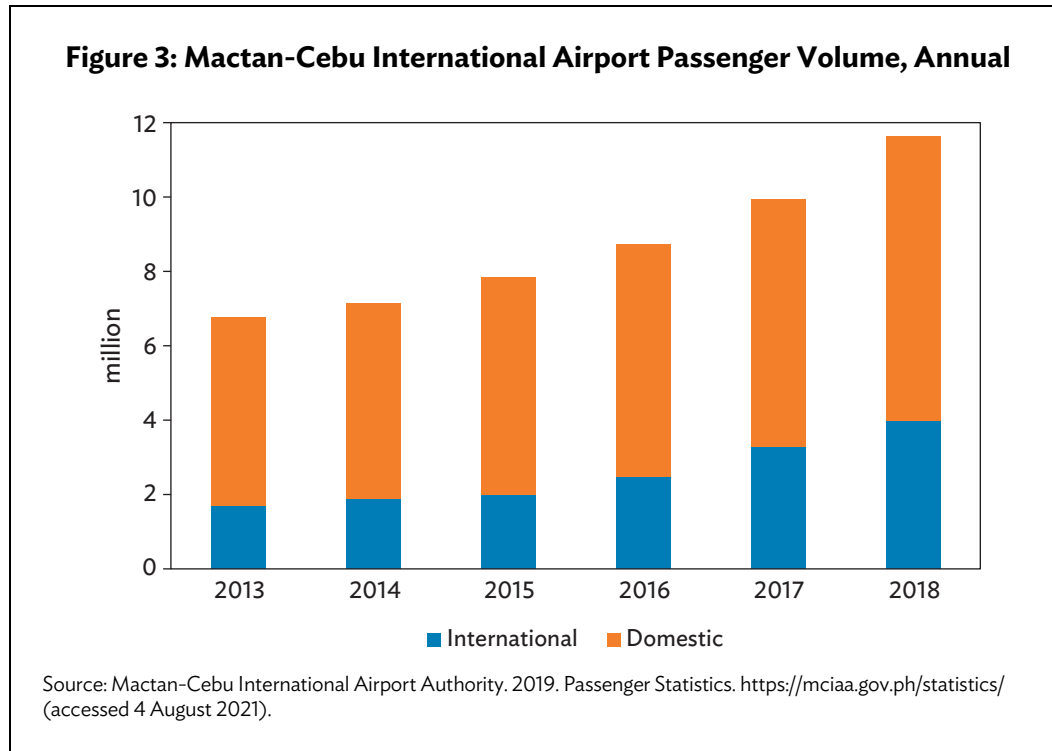
B. The Mactan-Cebu International Airport and Terminal Renewal

The MCIA is the international gateway to Central Visayas. There are no other airports in the region designed to handle a high volume of international traffic. Opened for commercial operations in the 1960s, MCIA was originally designed to serve 4.5 million passengers per annum (MPPA). Yet the airport was catering to more than 6.7 MPPA in 2012. This has strained airport infrastructure, resulting in congestion and delays, especially during peak periods (ADB 2014).

Accordingly, the Department of Transportation and MCIA Authority conceived of plans to construct a new airport terminal to cater to international passengers in response and anticipation to increased passenger traffic. The consortium of GMR Infrastructure Ltd. and Megawide Construction Corporation was formally awarded the construction bid on 22 April 2014. The new passenger terminal of MCIA was inaugurated in July 2018.¹

¹ The project costs ₱34.4 billion (\$766 million) and is one of the few government projects financed through public-private partnership. A total of about ₱11.4 billion (\$254 million) in equity was raised for the project, while about ₱23.0 billion (\$512 million) in debt was raised on a project finance basis.

Figure 3 shows the number of domestic and international passengers in the MCI. Passengers have been increasing even before the opening of the new terminal. Nonetheless, the increase is more pronounced after the terminal opening. Passenger growth rates from 2015 to 2017 were at 8% per year, while the growth rate from 2017 to 2018 jumped to over 12%. The increase in international passengers is shown to be the main contributor to the growth.



III. DATA

In our empirical analyses, the unit of observation is 500 m x 500 m tile. Figure 4 shows the tiles in the Cebu built-up area.

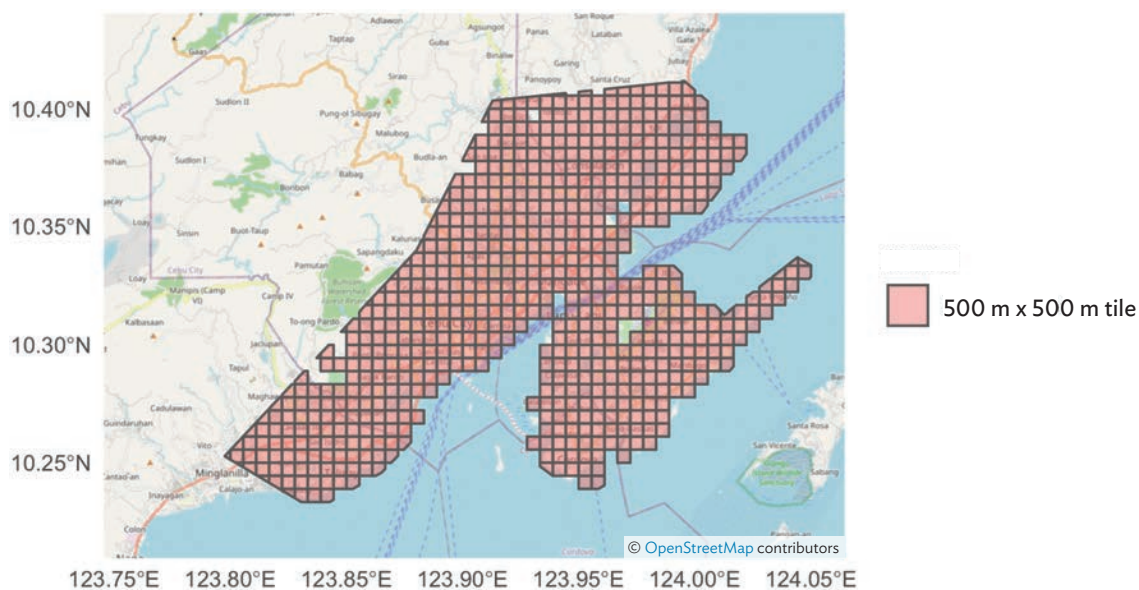
A. Vehicle Traffic Volume Data

1. Data Collection and Processing

The primary data for this paper is the vehicle traffic volume derived from a machine learning algorithm applied to satellite images. The recent development of Convolutional Neural Network (CNN) technology makes it possible to identify vehicles from high resolution satellite images. The technology of identifying vehicle from satellite image is developed by a private company Orbital Insights, which we use in the paper.

One important limitation is the number of observations. Satellite images for the analysis come from Maxar and Airbus Defense and Space with 0.5 m ground sample distance (GSD),² which is the highest resolution available for commercial use. There are only a small number of satellites capable of imaging the earth at a sub-meter resolution necessary for vehicle detection. Maxar has the world's largest catalog of historical imagery for the region involving our study area, and we use every available cloud-free image to capture the richest possible historical information. We also use images from Airbus Defense and Space to leverage the world's second-largest commercially available high resolution catalog. As a result, on average, around 14.7 images per year per city were included in the analysis. Satellites follow sun-synchronous orbits, implying images are captured between 10:00 am and 2:00 pm local time. As such, while peak road and airport rush hour traffic may not be represented, we believe that the data captures regular business activities reasonably.

Figure 4: Unit of Observation and Satellite Data Coverage in Urban Cebu



Source: OpenStreetMap. <https://www.openstreetmap.org/> (accessed 4 August 2021).

The number of vehicles is detected and counted from satellite imagery, including vehicles on the road while excluding the stationary vehicles in outdoor parking areas. The first step is to download the polygon information of the road from the OpenStreetMap and identify the road in the satellite image by layering the polygon with the satellite image. The road type information in OpenStreetMap allow us to distinguish roads into the following three categories: primary, secondary, and residential roads. Vehicles on the roads were detected and counted by road type for each 500 m x 500 m tile using an algorithm developed and further fine-tuned by Orbital Insight based on the CNN. The exercise yielded a dataset for each tile with multiple time periods from 1 January 2014 to 30 August 2019.

² GSD is the average distance between the centers of two adjacent pixels of a satellite image.

2. Comparison with Nightlight Luminosity Data

We compare the characteristics of the traffic volume data obtained from satellite imagery data with the nightlight luminosity data widely used in the literature as an indication of economic activity. The nightlight luminosity data used is from the VIIRS in 2017, which is recommended for the analysis of less aggregated spatial units (Gibson et al. 2021).

The following findings were obtained. First, the traffic volume data and nightlight luminosity data are positively but imperfectly correlated—according to the R-squared, nightlight luminosity data can explain 46% of the variation in traffic volume data. Second, activities in the tourism sector are not fully captured by nightlight luminosity data. We predict traffic volume by nightlight luminosity data by linear regression. The positive value of the residual means that vehicle densities are larger than the values predicted by nightlight luminosity. This implies additional economic activities that cannot be captured by the luminosity data in the area. The correlation between the residual and the number of hotels in the area is very strong, suggesting that luminosity data is not enough to capture the economic activity of high tourism areas. Details of these validation exercises are shown in Appendix A.

3. Comparison with Economic Data by Census

We also conduct validation exercises using demographic and economic data from the Census of Population and Housing (PSA 2010). The census provides information on populations and the number of establishments by economic sectors at the *barangay* (village) level. We aggregate the 500 m x 500 m tile traffic volume data to *barangay*-level using shape files from the Philippine Statistics Authority (PSA 2016b).

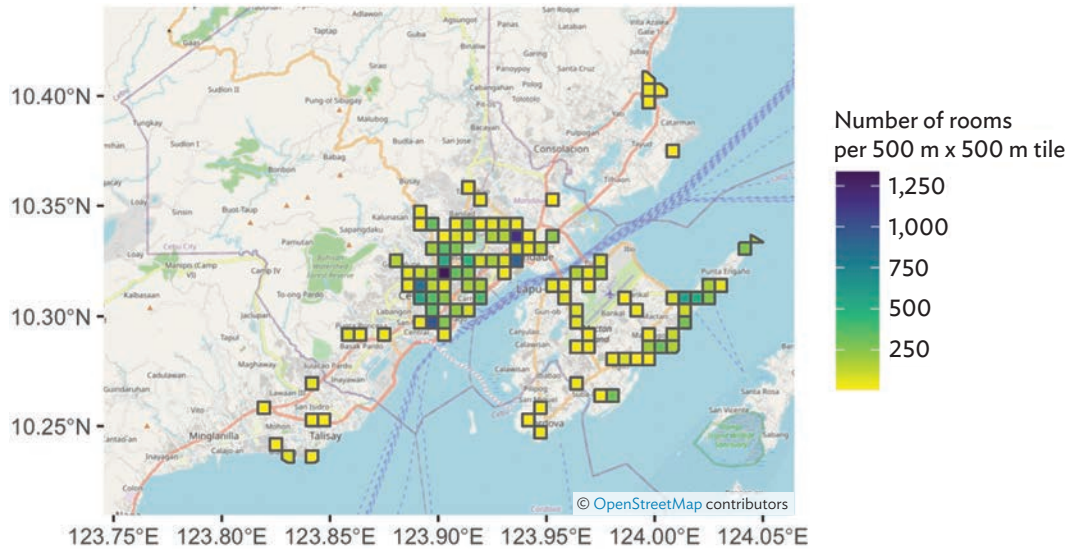
The results show that traffic volume is positively correlated with the population, the number of establishments in the commercial sector, and the number of establishments in the accommodation sector. Similarly, nightlight luminosity is positively correlated with these variables. On the other hand, the prediction error of traffic volume by nightlight luminosity data as estimated in the previous section is not correlated with population but is positively correlated with the number of establishments in the commercial sector and the number of establishments in the accommodation sector. These results suggest that nightlight luminosity may not be able to adequately capture the economic activities of these sectors.

The validation exercises confirm traffic volume data as reflective of changes in local economic activities, especially in capturing activities in tourism and commercial sectors. The details of those validation exercises are shown in Appendix A.

B. Other Data

We use the Department of Tourism's directory of accredited establishments as of March 2021 to distinguish the impact of the new terminal on the tourism sector. The database provides information of each hotel location and their number of rooms. We aggregate the information to 500 m x 500 m tile level to match the vehicle count data. Figure 5 displays the density of hotel rooms in each tile, showing that hotel room availability exhibits clusters in Mactan Island and areas surrounding the CBD. The eastern shore of Mactan Island hosts large resort hotels catering to international tourists.

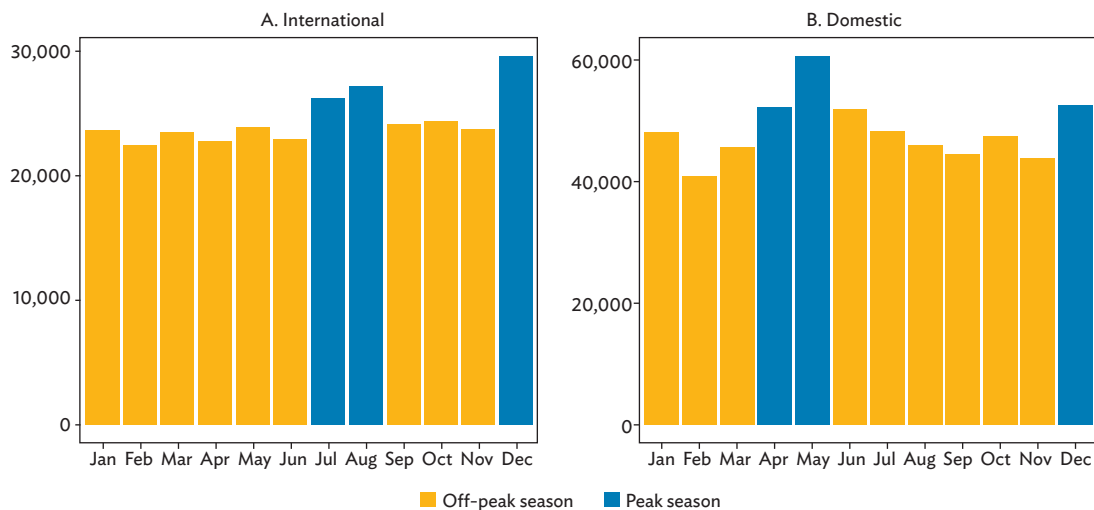
Figure 5: Map of Number of Hotel Rooms



Source: Department of Tourism. 2021. Directory of accredited establishments; OpenStreetMap. <https://www.openstreetmap.org/> (accessed 4 August 2021).

International and domestic monthly passenger data from the MCI Authority are used to distinguish the peak seasons in MCI. Figure 6 shows the number of airport users by month. Panel A shows international passengers, and Panel B shows domestic passenger movements. The blue bars indicate the three highest months for each passenger group. The peak months for international passengers were recorded in July, August, and December, while the peak months for domestic passengers were recorded in April, May, and December.

Figure 6: Mactan-Cebu International Airport Passenger Volume, Seasonal



Source: Mactan-Cebu International Airport Authority. 2019. Passenger Statistics. <https://mciiaa.gov.ph/statistics/> (accessed 4 August 2021).

IV. EMPIRICAL STRATEGY

We estimate the impact of the opening of the new international terminal in MCIA using DID. The treatment group pertains to tiles within the Cebu conurbation, while the control groups are tiles in Davao metropolitan areas and areas surrounding Clark International Airport located 80 kilometers from Metro Manila. Davao City is the most populous city in Mindanao and likewise hosts a key regional airport. The Clark International Airport is about the size of MCIA.³ In this sense, those tiles can be considered as counterfactual for tiles in Cebu. The estimation equation is as follows:

$$\text{Log}(\text{Number of vehicles}_{it}) = \beta \times \text{Cebu}_i \times I[\text{July 2018} \leq t] + \eta_i + \zeta_t + \varepsilon_{it} \quad (1)$$

where $\text{Number of vehicles}_{it}$ denotes vehicle counts in tile i in period t . Cebu_i is a dummy variable which takes the value of one if tile i is in Metro Cebu, $I[\text{July 2018} \leq t]$ is the post treatment dummy which is equal to one if t is after the opening of the new terminal (July 2018), η_i is tile fixed effects, and ζ_t is year and month fixed effects. The estimated coefficient, β , shows the impact of the MCIA on economic activities. This is estimated using ordinary least squares (OLS), which excludes observations with zero number of vehicles. Then as robustness check, we estimate the equation by Poisson Pseudo Maximum Likelihood (PPML) to allow for the substantial share of observations with zero vehicle observation.

V. RESULTS

The baseline estimation results are summarized in Table 1 where column 1 shows the OLS results. We observe statistically significant positive treatment effects. Vehicle density increased by 2.6% after the opening of the new terminal. Column 2 shows the PPML results to address zero observations, and the treatment effects become larger. The opening of the new terminal increases vehicle density by 10%. The inclusion of month-fixed effects in columns 3 and 4 to address monthly heterogeneity results in a treatment effect that is positive but not significant in the column 3 OLS results, while the results from the PPML in column 4 remain significant, albeit with a smaller coefficient. These suggest that seasonality is an important factor in local economic activities. The stronger results in the zero-inflated sample in PPML also indicate that the extensive margin is potentially a larger source of economic gains than the intensive margin. In summary, the opening of the new terminal is associated with a positive impact on urban Cebu's local economy.

³ Clark International Airport has a capacity of 4 million passengers per year during the study period, which then increased to 12 million after the terminal expansion in 2020.

Table 1: Baseline Results

Dependent Variable:	Vehicle Density			
	(1)	(2)	(3)	(4)
Model:	OLS	PPML	OLS	PPML
Cebu × After Opening New Terminal	0.026*	0.103***	0.009	0.067***
	(0.014)	(0.018)	(0.015)	(0.019)
<i>Fixed-effects</i>				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes
Month			Yes	Yes
Pseudo R ²	0.271	0.572	0.275	0.577
Log-likelihood	-121,696	-20,587,409	-120,971	-20,329,920
Observations	101,628	126,798	101,628	126,798

Note: Standard errors are clustered at the tile level. * = $p < .10$, *** = $p < .01$.

Source: Authors' calculations.

A. Heterogeneity in Treatment Effects by Area

We estimate the individual treatment effects to examine the spatial heterogeneity of the new terminal by estimating the following equation,

$$\text{Log}(\text{Number of vehicles}_{it}) = \sum_{i=1} \beta_i \times \eta_i \times I[\text{July 2018} \leq t] + \eta_i + \zeta_t + \varepsilon_{it} \quad (2)$$

where the β_i captures the treatment effect of new terminal opening on tile i .

Figure 7 displays the geographic distribution of estimated individual treatment effects. Darker colors imply larger treatment effects. The treatment effect is stronger in Mactan Island, where the MCIA is located. Furthermore, the coastline of the northern peninsula of Mactan Island, one of the largest clusters of resort hotels popular to foreign tourists, has stronger treatment effects. The result implies that the opening of the new terminal induces international tourists.

In addition, we employ a triple-difference (DDD) analysis to formally test that the estimated treatment effect is attributable to the new international terminal opening. In this setup, we measure the distance of each tile from the airport and estimate the interaction effect between this and the treatment variable, allowing the treatment effect to be a linear function of the distance.

The results are shown in Table 2. In both the OLS (column 1) and PPML (column 2), the coefficient for the interaction variable, *Cebu × After Opening New Terminal*, is positively significant, whereas the coefficients for the triple-difference terms are negative and precisely estimated. These suggest that the treatment effect is stronger in tiles closer to the airport. Since the resort hotel cluster is also located on Mactan Island and closer to the airport, these results are consistent with the story that the opening of the new international terminal induces a larger number of foreign tourists.

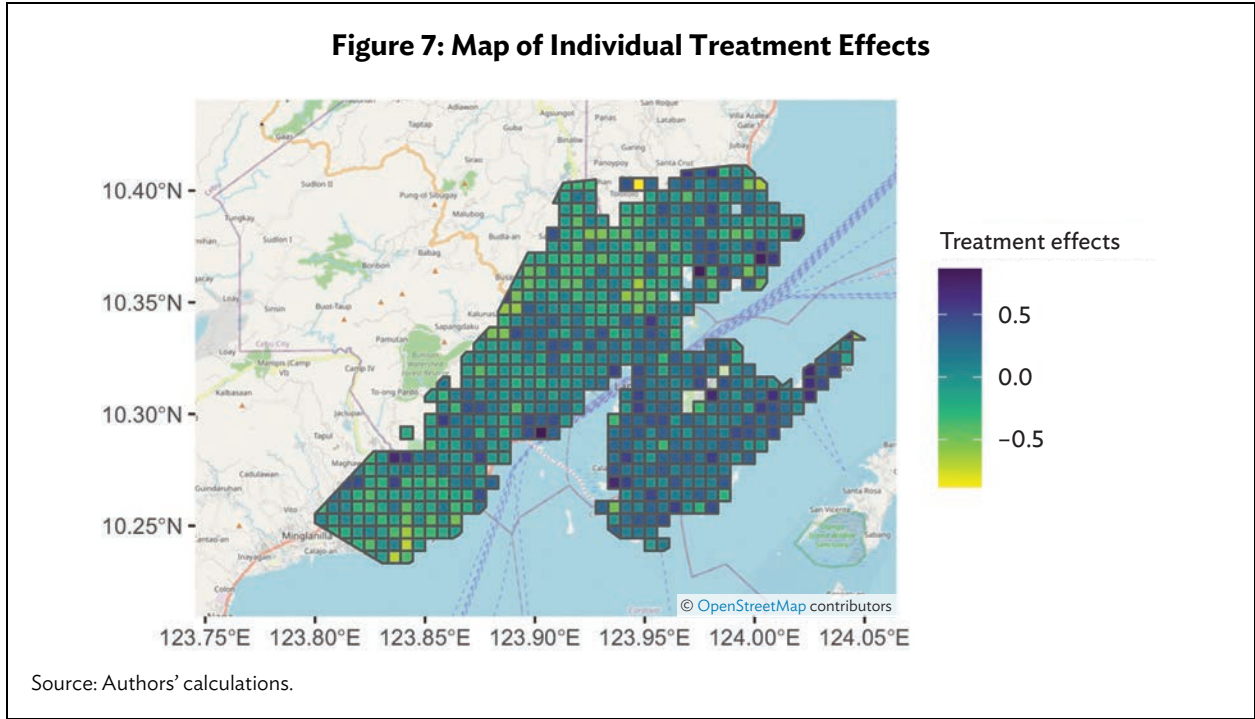


Table 2: Triple-Difference with Distance to Airport

Dependent Variable:	Vehicle Density					
	(1)	(2)	(3)	(4)	(5)	(6)
Model:	OLS	PPML	OLS	PPML	OLS	PPML
Cebu × After Opening New Terminal	1.45*** (0.212)	1.11*** (0.217)	-0.440*** (0.127)	-0.311*** (0.107)	1.02*** (0.251)	0.147*** (0.045)
Cebu × After Opening New Terminal × log(Distance from Airport)	-0.153*** (0.023)	-0.112*** (0.024)			-0.140*** (0.022)	-0.022*** (0.004)
Cebu × After Opening New Terminal × log(Distance from CBD)			0.050*** (0.014)	0.044*** (0.012)	0.034** (0.014)	0.007*** (0.002)
<i>Fixed-effects</i>						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R ²	0.275	0.577	0.275	0.577	0.275	0.043
Log-likelihood	-120,936	-20,323,221	-120,958	-20,325,647	-120,930	-187,347
Observations	101,628	126,798	101,628	126,798	101,628	101,628

CBD = central business district, OLS = ordinary least squares, PPML = Poisson pseudo maximum likelihood.

Note: Standard errors are clustered by tile level. ** = p < .05, *** = p < .01.

Source: Authors' calculations.

Another possible channel through which the new international terminal opening has a positive impact on Cebu's local economy is by increasing the number of business travelers and facilitating face-to-face contact and business relationships. To test this possibility, we calculate the distance from the central business district (CBD) in each tile and conduct a similar DDD analysis. In both OLS (column 3) and PPML (column 4), the coefficient for the interaction variable, *Cebu × After Opening New Terminal*, is negatively significant, whereas the triple-difference term coefficient interacted with the distance from CBD is positively significant. These suggest that the treatment effect is much weaker in the CBD area where traffic is heavy even without the new terminal. This may suggest that the effect is mainly from international tourists who visit resorts, and not so much for business purposes, so the effect from resorts around the airport away from the CBD is dominant. In columns 5 and 6, we include interaction terms both with distance from the airport and CBD. The results are qualitatively unchanged. The positive effects of the opening of the new international terminal are largest on Mactan Island and mainly mediated through the increase of foreign travelers who stay there.

We use the hotel location data to divide the sample into tiles with hotels and tiles without hotels, and conduct DID analysis for each subsample (Table 3). The subsample with hotels in columns 1 and 2 show positive treatment effects in both OLS and PPML. On the other hand, the subsample of tiles without hotels in column 3 exhibits negative effects, which is significant in OLS but insignificant in the PPML. The presence of positive treatment effects is only observed in the subsample of tiles with hotels is a strong indication that the new international terminal opening contributed to Cebu's local economy through facilitating tourism.

Table 3: Treatment Effects on Hotel Area and Non-Hotel Area

Dependent Variable:	Vehicle Density			
	(1)	(2)	(3)	(4)
Model:	OLS	PPML	OLS	PPML
Sample	Hotel zone	Hotel zone	Non-hotel zone	Non-hotel zone
Cebu × After Opening New Terminal	0.140*** (0.030)	0.125*** (0.027)	-0.035** (0.016)	0.033 (0.026)
<i>Fixed-effects</i>				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Pseudo R ²	0.204	0.456	0.264	0.551
Log-likelihood	-33,589	-7,273,371	-87,112	-12,981,689
Observations	27,019	30,489	74,609	96,309

OLS = ordinary least squares, PPML = Poisson pseudo maximum likelihood.

Note: Standard errors are clustered by tile level. ** = $p < .05$, *** = $p < .01$.

Source: Authors' calculations.

B. Heterogeneity in Treatment Effects by Period

The effect of the new terminal on tourism is expected to vary according to seasons. We test this hypothesis by distinguishing peak periods for international and domestic passengers.

We conduct a DDD analysis, introducing the international peak dummy, which equals one if the month is July, August, and December, and the domestic peak dummy which equals one for April, May, and December (Figure 6). The results are shown in Table 4, where columns 1 and 2 show the results introducing the triple-difference term with the domestic peak dummy. In both OLS and PPML, the coefficients for triple-difference terms are negatively significant. The treatment effects are weaker and tend toward negative during domestic peak periods. On the other hand, the results for the international peak dummy, as shown in columns 3 and 4, show the coefficients for triple-difference terms are positively significant in both OLS and PPML. Columns 5 and 6 show the results that include both domestic and international peak effects. The results are similar to the results in columns 1 to 4, which strongly suggest that the positive impact of new international passenger terminal opening comes from the increase of international travelers. In contrast, the negative treatment effects during the domestic peak seasons might have captured overall lower-than-the usual level of economic activities during the domestic holidays. This finding has implications for the government’s regional strategy on tourism. Indeed, the National Tourism Development Plan reveals that domestic and international tourism activities could have qualitatively different effects on the local economy. On average, an international tourist spent \$107 per day, whereas a domestic tourist spent less than \$50 per day in 2015 (DOT 2016).

Table 4: Treatment Effects on Peak and Off-Peak Season in Airport Passengers

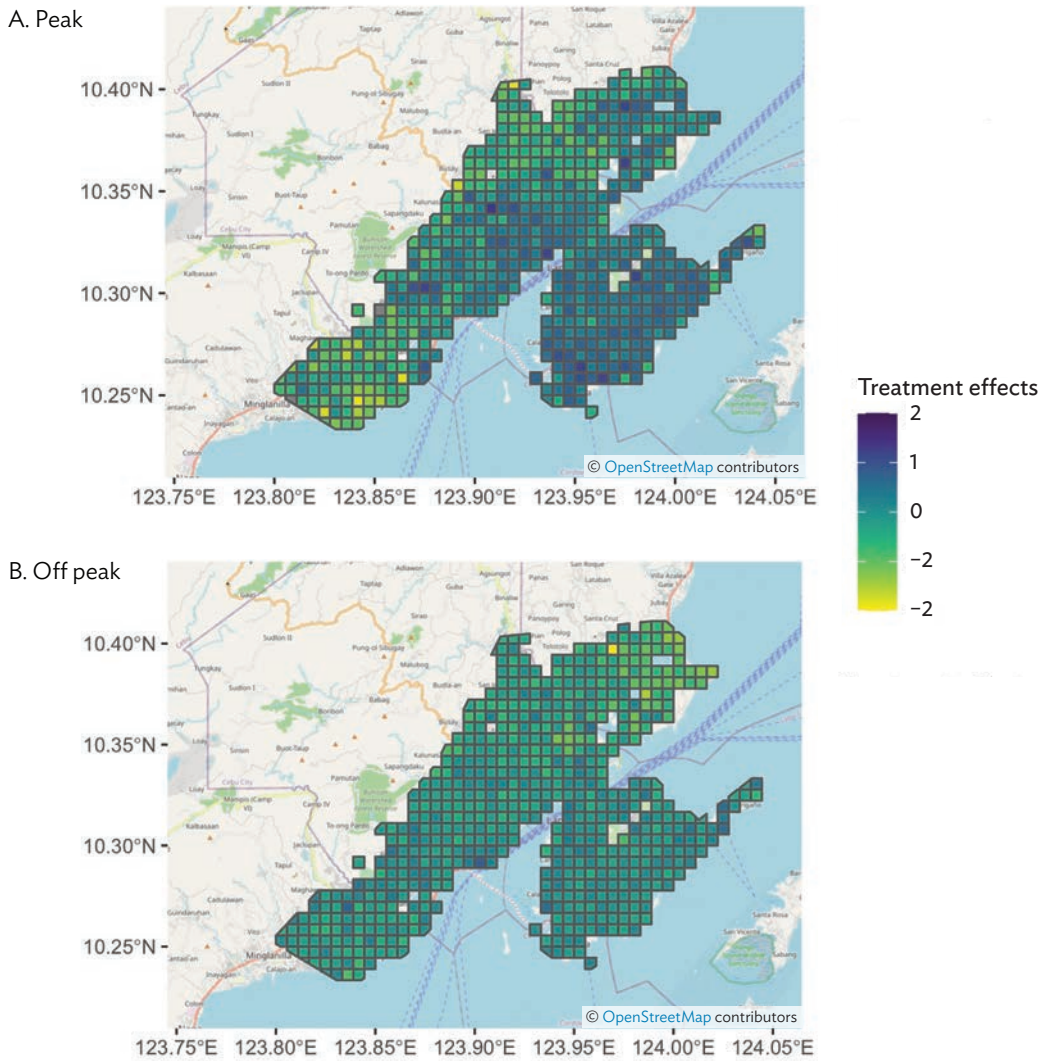
Dependent Variable:	Vehicle Density					
	(1)	(2)	(3)	(4)	(5)	(6)
Model:	OLS	PPML	OLS	PPML	OLS	PPML
<i>Variables</i>						
Cebu × After Opening New Terminal	0.057*** (0.015)	0.101*** (0.02)	-0.085*** (0.016)	-0.039* (0.021)	-0.041** (0.017)	-0.013 (0.022)
Cebu × After Opening New Terminal × Peak months of domestic passengers	-0.159*** (0.015)	-0.118*** (0.02)			-0.124*** (0.015)	-0.075*** (0.020)
Cebu × After Opening New Terminal × Peak months of international passengers			0.320*** (0.021)	0.337*** (0.022)	0.301*** (0.021)	0.326*** (0.023)
<i>Fixed effects</i>						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Pseudo R2	0.275	0.577	0.276	0.579	0.276	0.579
Log-likelihood	-120,911	-20,317,656	-120,790	-20,248,401	-120,754	-20,243,579
Observations	101,628	126,798	101,628	126,798	101,628	126,798

OLS = ordinary least squares, PPML = Poisson pseudo maximum likelihood.
 Note: Standard errors are clustered by tile level. * = p < .10, ** = p < .05, *** = p < .01.
 Source: Authors’ calculations.

C. Heterogeneity in Treatment Effects by Area and Period

Finally, we conduct an analysis to account for the heterogeneity of the treatment effects in both the temporal and spatial dimensions. We estimate the individual treatment effects for the peak and off-peak months of international passengers and investigate the characteristics of the differences between the areas. The map of estimated individual treatment effects is shown in Figure 8. The maps show the estimated individual treatment effects in the same color scale. Panel A shows the results in peak, and panel B shows those in off-peak. In comparison to off-peak, peak months have larger treatment effects on average. Furthermore, the spatial distribution of the treatment effect in off-peak is relatively uniform, while that in peak is more skewed, with stronger treatment effects concentrated in Mactan Island.

Figure 8: Individual Treatment Effects of International Passengers



Source: Authors' calculations.

The correlation between estimated individual treatment effects and hotel density is shown in Table 5. Column 1 uses the number of hotel rooms as the right-hand side variable and estimated individual treatment effects in peak months as the left-hand side variable. The coefficient for the number of rooms is positively significant. Similarly, using the number of hotel rooms as the right-hand side variable yields a significant and positive coefficient on the number of hotel rooms, as shown in column 2. On the other hand, if we use estimated treatment effects in the off-peak months, both coefficients for the number of hotels (as shown in column 3) and the number of hotel rooms (as shown in column 4) are not significant. The results strongly suggest that the positive treatment effects of the opening of the new international terminal are due to the increase of foreign tourists.

Table 5: Correlation between Individual Treatment Effects and Hotel Density

Dependent Variable:	Treatment Effects			
	(1)	(2)	(3)	(4)
Model:	Peak	Peak	Off-Peak	Off-Peak
Season	Peak	Peak	Off-Peak	Off-Peak
<i>Variables</i>				
Number of hotels	0.069*** (0.017)		0.009 (0.011)	
Number of hotel rooms		0.0006*** (0.000)		0.0001 (0.000)
<i>Fit statistics</i>				
Pseudo R ²	0.010	0.007	0.001	0.002
Log-likelihood	-521.09	-522.67	-202.68	-202.53
Observations	579	579	579	579

Note: Standard errors are clustered at the tile level. *** = $p < .01$.

Source: Authors' calculations.

VI. CONCLUSION

This paper estimates the impact of the new international terminal opening at MCIA on Cebu's local economy. The novelty of the paper rests on proposing a satellite image derived measure of vehicle traffic volume to capture economic activity at a granular level. The 500 m x 500 m vehicle traffic volume data was obtained by applying a machine learning algorithm from satellite imagery. This presents advantages of timeliness, frequency, and spatial granularity compared to traditional sources such as government-generated statistics.

We obtain the following results using DID analyses. First, the opening of the new terminal significantly increases the volume of vehicular traffic in the Cebu built-up area. This effect is greatest in the vicinity of the airport and attenuates with distance, and the treatment effects are larger in the tiles where hotels are located. Second, the effect of the opening of the new terminal is largest during the

peak months of international passengers at the MCI. In fact, there is a significant positive correlation between the treatment effect and the spatial clustering of hotels during the peak months of international passengers. These results show that the opening of the new international terminal has a positive impact on the economy of urban Cebu through the increased traffic of international passengers staying within the area.

Studies that employ satellite imagery data typically use nightlight luminosity to proxy for economic activities. However, this paper demonstrates that nightlight luminosity data may not be sufficient to capture the economic activities in the tourism industry. Nighttime lights may not capture the seasonal changes peculiar to the tourism industry, and activities in the tourism industry are not necessarily well-represented by nightlight luminosity. Alternatively, this paper shows that the number of vehicles captured by satellite imagery provides insights on economic activities of the tourism sector that cannot be fully captured by nightlight luminosity data. This paper opens possibilities of using satellite-derived vehicle data for other purposes, such as capturing economic activities in the agricultural sector, which has been difficult to represent using nightlight luminosity data. Future research is expected to develop this area.

APPENDIX

Validation Exercises Using Nightlight Luminosity Data

We systematically compare and analyze our vehicle count data with nightlight luminosity data, which is widely used to proxy for economic activity. We use the VIIRS from the Earth Observation Group (EOG) website in 2017 for nightlight luminosity data. This was aggregated into 500 m x 500 m tiles to match the units of observation for the vehicle count data in the study.

1. Correlation between Vehicle Density and Nightlight Luminosity

In Figure A1, panel A shows the map of luminosity in 2017, and panel B shows the number of vehicles for the same year. The intensity distributions in both datasets are well correlated. In both figures, areas surrounding CBD and the northwest of Mactan Island have higher luminosity and greater density of vehicles.

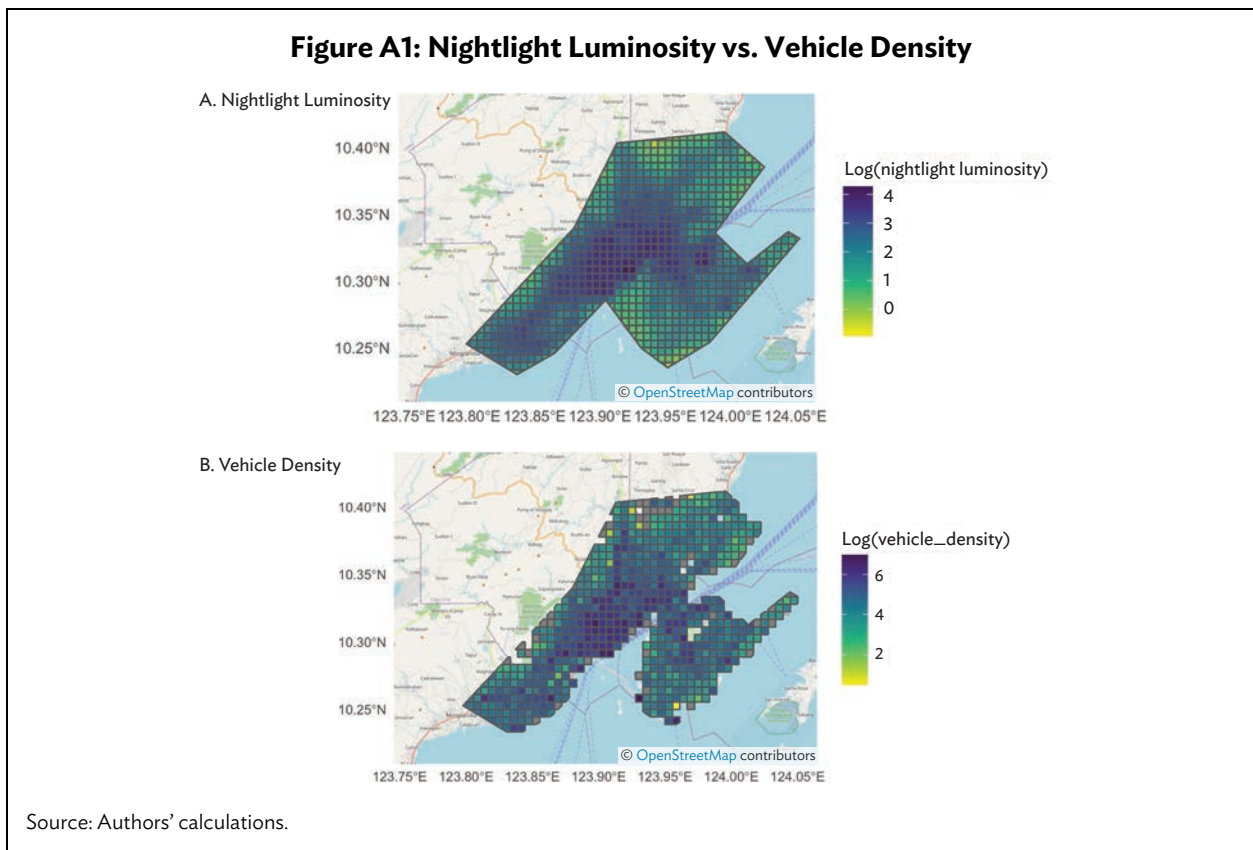


Figure A2 shows that the log of luminosity and vehicle density are positively correlated. However, the R-squared is 0.46, and there are large variations that are unaccounted for. The estimated residual from the regression of vehicle density on luminosity can be considered as the prediction error of the latter. The positive value of the residual implies that the vehicle density is larger than what luminosity predicts, which means that there are additional economic activities that cannot be captured by the luminosity data in the area.

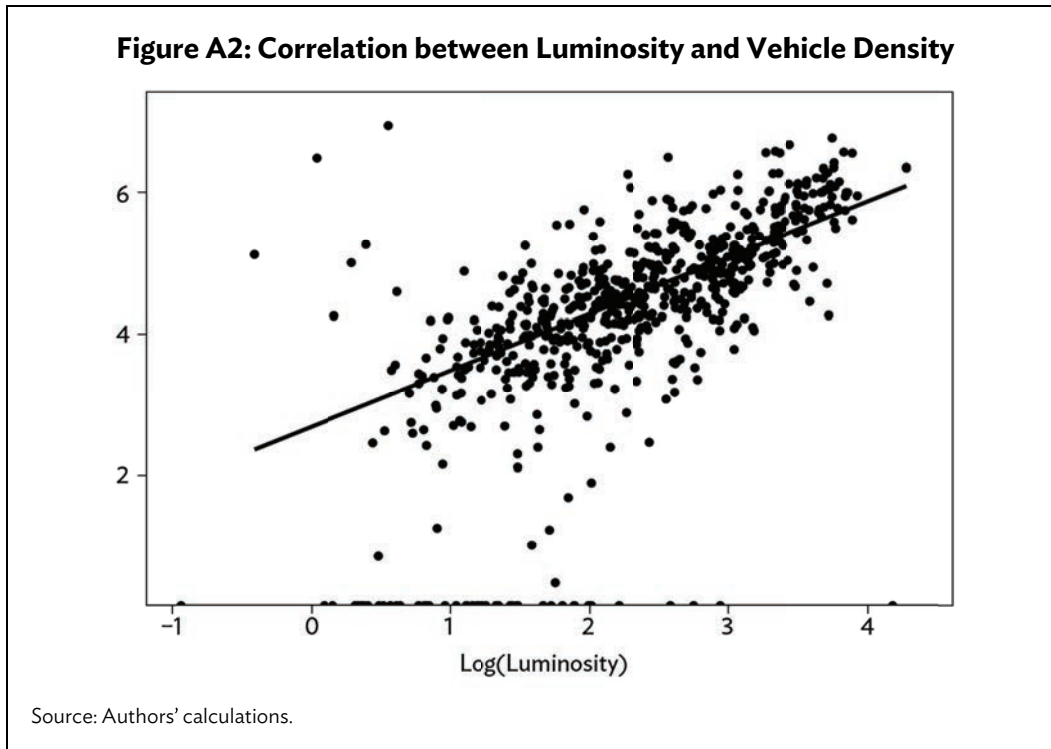
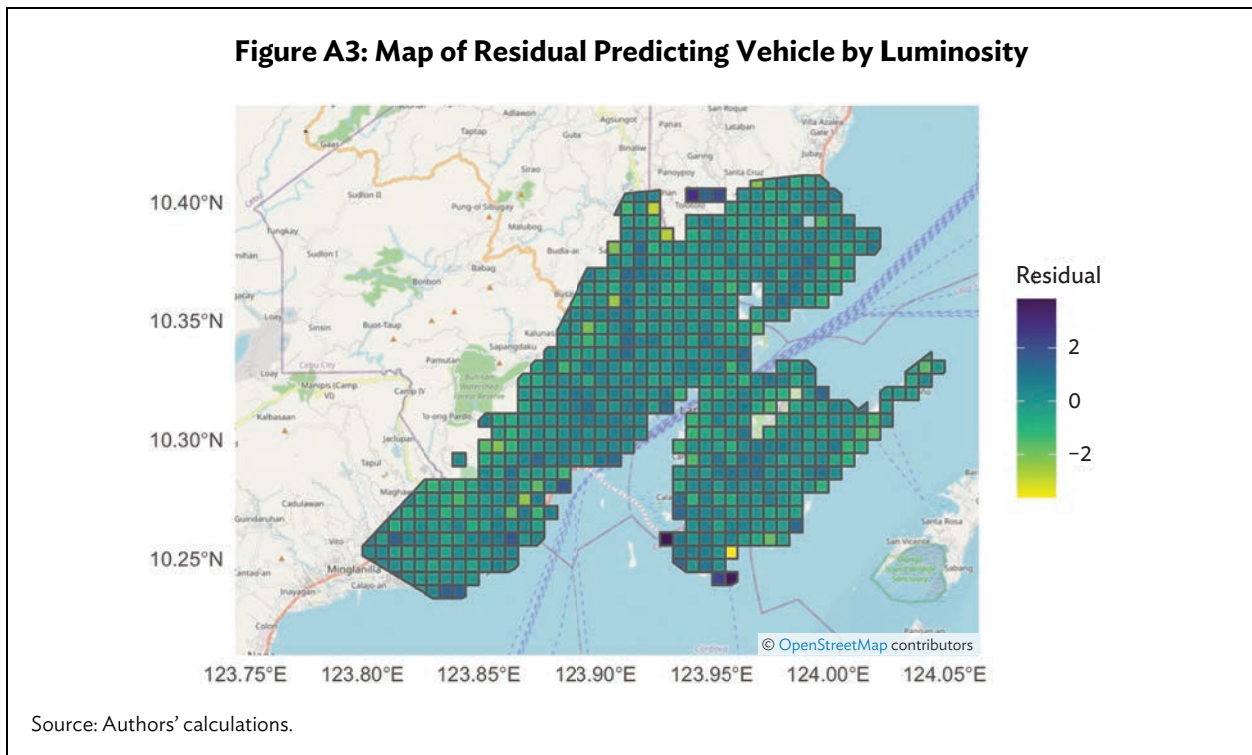


Figure A3 maps of the estimated residuals. The darker color shows the positive residual values. The areas surrounding CBD and southern areas of Mactan Island are relatively darker, coinciding with the location of resort hotel clusters.



The correlation between the estimated residual and the number of hotels in the area is shown in Table A1. Column 1 shows the results using the number of hotels as the right-hand side variable. The coefficient for the number of hotels is positively significant. Column 2 shows the results using the number of hotel rooms as the right-hand side variable. The coefficient for the number of hotel rooms is also positively significant. These imply that in areas where there are many hotels, the luminosity data is not enough to capture the economic activity. The number of vehicles is a more fitting measure of economic activity in the tourism context.

Table A1: Correlation between Prediction Residual and Hotel Density

Dependent Variable:	Prediction Residual	
	(1)	(2)
<i>Model:</i>		
<i>Variables</i>		
Number of hotels	0.076*** (0.017)	
Number of hotel rooms		0.0003* (0.000)
<i>Fit statistics</i>		
Pseudo R ²	0.007	0.001
Log-likelihood	-653.73	-657.61
Observations	615	615

Note: Standard errors are clustered at the tile level. * = $p < 0.10$, *** = $p < .01$.

Source: Authors' calculations.

2. Correlation with the Economic Variables

We conduct validation exercises on our data by testing correlation with historical government statistics. The Philippine Census of Population and Housing has information on the population and the number of establishments in the commerce and accommodations sectors. Unfortunately, the finest geographic scale of the government statistics is *barangay*-level (village-level), so we aggregate the tile-level information of vehicle density and nightlight luminosity data into *barangays*.

Table A2 shows the correlation with population size. Column 1 shows the correlation with the log of nightlight luminosity, column 2 shows the correlation with the log of vehicle density, and column 3 shows the correlation with prediction error (residual from predicting vehicle density with nightlight luminosity in section A.1). Nightlight luminosity and vehicle density data are positively correlated with the population, which implies that both measures predict the population level well. Furthermore, the prediction error is not significantly correlated with the population level. This suggests that there is no significant difference in the pattern of correlation with a population size between the nightlight luminosity and vehicle density measures.

In Table A3, nightlight luminosity and vehicle density data are shown to be positively correlated with the number of establishments in the commercial sector. However, the prediction error is also positively correlated with the number of establishments. The positive correlation between the number of establishments in the commercial sector and unpredicted vehicle counts by the nightlight luminosity data suggest that the vehicle count data would be more appropriate for understanding economic activities in the commercial sector.

Table A2: Correlation with Census Data (Population)

Dependent Variable:	log(Population)		
Model:	(1)	(2)	(3)
<i>Variables</i>			
Log(Luminosity)	0.437*** (0.073)		
Log(Vehicle density)		0.523*** (0.051)	
Prediction error			0.006 (0.048)
<i>Fit statistics</i>			
Pseudo R ²	0.257	0.259	0.000
Log-likelihood	-145.67	-145.34	-196.15
Observations	164	164	164

Note: Standard errors are clustered at the tile level. *** = $p < .01$.

Source: Authors' calculations.

Table A3: Correlation with Census Data (Commerce)

Dependent Variable:	Number of Establishments (Commerce)		
Model:	(1)	(2)	(3)
<i>Variables</i>			
Log(Luminosity)	19.1*** (4.97)		
Log(Vehicle density)		21.6*** (6.22)	
Prediction error			7.87** (3.93)
<i>Fit statistics</i>			
Pseudo R ²	0.002	0.002	0.000
Log-likelihood	-1,056	-1,056	-1,057
Observations	164	164	164

Note: Standard errors are clustered at the tile level. ** = $p < .05$, *** = $p < .01$.

Source: Authors' calculations.

Similar to the results on the commercial sector, Table A4 shows that nightlight luminosity and vehicle density data are positively correlated with the number of establishments, and the prediction error is also positively correlated with the number of establishments in the accommodations sector. This suggests that the vehicle count data would be more appropriate for understanding economic activities in the accommodations sector.

In summary, nightlight luminosity predicts population size well but does not sufficiently capture the economic activities in the commercial and accommodation sectors. One possible reason for this is that nightlight luminosity data may correlate more strongly with nighttime population rather than daytime economic activity since the main source of nightlight luminosity is streetlights.

Table A4: Correlation with Census Data (Accommodations)

Dependent Variable:	Number of Establishments (Accommodations)		
	(1)	(2)	(3)
<i>Model:</i>			
<i>Variables</i>			
Log(Luminosity)	3.80*** (1.43)		
Log(Vehicle density)		6.86*** (2.01)	
Prediction error			3.80*** (1.47)
<i>Fit statistics</i>			
Pseudo R ²	0.004	0.010	0.007
Log-likelihood	-750.30	-745.94	-747.98
Observations	164	164	164

Note: Standard errors are clustered at the tile level. *** = $p < .01$.

Source: Authors' calculations.

3. Correlation with Mobility Flows

This section conducts a validation exercise using mobile phone records from Globe Telecoms, which allows us to retrieve a matrix of origin and destination flows between *barangay* pairs. We use the data from 10 a.m. on 15 January 2020 (Wednesday) in Metro Cebu to estimate the correlation between number of visitors with vehicle density, nightlight luminosity, and the prediction error of vehicle density from nightlight luminosity. The results are summarized in Table A5.

Both nightlight luminosity and vehicle density predict the number of visitors into a *barangay* well. There is no systematic bias of the prediction as shown in column 3. Furthermore, the coefficient provides the parameter to convert estimated treatment effects to visitor equivalents. The coefficient in column 2 suggests that a one percent increase in vehicle density implies a 0.3% increase in the number daily of visitors, taking 15 January 2020 as a representative work day. On average, there are 12,319 visitors per *barangay*. Thus, a one percent increase in vehicle density induces an average increment of 37 visitors to a *barangay*. Our estimates suggest that the opening of the new terminal increased vehicle density by 6.7%, translating to 252 more visitors in an average *barangay* in urban Cebu.

Table A5: Correlation with Mobility Data

Dependent Variable:	log(Number of visitors)		
	(1)	(2)	(3)
<i>Model:</i>			
<i>Variables</i>			
Log(Luminosity)	0.383*** (0.089)		
Log(Vehicle density)		0.333*** (0.095)	
Prediction error			0.044 (0.051)
<i>Fit statistics</i>			
Adjusted R ²	0.128	0.110	-0.006
Observations	87	87	87

Note: Standard errors are clustered at the tile level. *** = $p < .01$.

Source: Authors' calculations.

4. Estimating the Impact of the Opening of the New Terminal Using Nightlight Luminosity Data

Finally, we conduct a DID analysis using luminosity data in lieu of vehicle count data. For this exercise, we collect the annual-level VIIRS data in 2017 and 2019 and set 2019 as the post-treatment period. Like the main analysis, the tiles in urban Cebu are the treatment group, and tiles in Davao City and Clark areas serve as controls. The results are shown in Table A6. Column 1 shows the baseline result using all samples. The estimated treatment effect is negatively significant. Consistent with the discussion in Gibson et al. (2021), the results suggest that the nightlight luminosity data is not necessarily appropriate for comparing the economic activities across periods.

Table A6: Results of DID Using Luminosity Data

Dependent Variable:	Log(Luminosity)		
	(1)	(2)	(3)
<i>Model:</i>			
<i>Variables</i>			
Metro Cebu × After Opening New Terminal	-0.187*** (0.011)	-0.272*** (0.025)	-0.175*** (0.012)
Sample	All	Hotel zone	Non-hotel zone
<i>Fixed-effects</i>			
Tile	Yes	Yes	Yes
Year	Yes	Yes	Yes
<i>Fit statistics</i>			
Pseudo R ²	1.57	2.10	1.57
Log-likelihood	2,472	395	2,107
Observations	3,230	394	2,836

DID = difference-in-differences.

Standard errors are clustered at the tile level. *** = $p < .01$.

Source: Authors' calculations.

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On the Use of Satellite-Based Vehicle Flows Data to Assess Local Economic Activity

The Case of Philippine Cities

This paper demonstrates how satellite images can help overcome challenges in obtaining timely and spatially disaggregated data for impact evaluation. Satellite image-derived vehicle counts in 500x500-meter meshes were used to measure local economic activity following the opening of the new international terminal at the Mactan-Cebu International Airport in the Philippines. Results reveal that the terminal's opening has had positive impacts on Cebu's local economy. In this paper, a comparison of the vehicle count measure with luminosity-derived metrics suggests that the former is better at capturing seasonal and spatial variations in treatment effects, especially for beach tourism activities in Cebu.

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