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Abstract

Spatially and seasonally granular measures of local economic activities are increasingly required in a variety of economic analyses. We propose using novel vehicle density data obtained from daytime satellite images to quantify the local economic activity involving human and goods traffic flows. Validation exercises show that vehicle density is a good proxy for local economic levels. We then apply our data to evaluate the impact of a new international airport terminal opening in the Philippines on local economies. The results show that the opening of the new terminal has spatially and seasonally heterogeneous impacts that conventional data cannot capture.

Keywords: Satellite imagery data; Measure local economic activities; Transportation infrastructure; Impact evaluation; Tourism
JEL Codes: R11, O18, R40

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1 Introduction

A key challenge in ex-post policy evaluation is obtaining relevant data over the ideal time frame and spatial granularity for analyses. Most ex-post policy evaluations rely on official government statistics, which have several limitations, as highlighted during the new coronavirus (COVID-19) pandemic (Lazer et al., 2009, 2020; Chetty et al., 2022).[1] First, there is a lack of timeliness in compiling data from surveys for analyses and publication. Difference-in-differences (DID) analyses, a workhorse methodology for ex-post policy evaluations, necessitate multiple periods of observation before and after the policy change for both the treatment and control groups. Second, official government statistics typically lack an ideal frequency for evaluation analysis. For example, the effects of transportation infrastructure development often exhibit significant seasonal variations between peak and off-peak seasons. However, capturing seasonal heterogeneity requires higher-frequency data than the more typically available annual data. Finally, traditional data sources usually lack spatial granularity, even when policies, especially large-scale interventions such as physical infrastructure programs, often have heterogeneous effects across areas within an administrative district. For example, the impact of railroad development depends on the existing distribution of economic activities along its access points and the natures of these activities, which greatly influences the intensity or dissipation of spatial clustering. However, it is difficult to obtain sufficiently granular data from government statistics to analyze such policy effects. Furthermore, few government statistics are available, especially in developing countries.

Against this backdrop, this study proposes the use of vehicle traffic volume data from daytime high-resolution satellite images by machine learning as a novel, granular, and high-frequency measure of local economic activities for policy evaluation. The vehicles observed at a given location represent human traffic in the area and can appropriately proxy local economic activity involving human flows. Satellite images have global coverage and are obtained multiple times throughout a year globally, thus providing an opportunity to capture the spatial and seasonal heterogeneity of the impacts of a policy, even in data-scarce developing countries.

We detect vehicles on the road and build vehicle density data at the 500 m $\times$ 500 m tile-level as a measure of local economic activity. To demonstrate the value-added of our new data, we employ it to evaluate the impacts of building a new international airport terminal at the Mactan–Cebu International Airport (MCIA) in the Philippines. Cebu is the second largest metropolitan area in the Philippines in terms of population and has a large tourism industry, especially represented by resorts. As is typical in large cities in developing countries, rail public mass transit system remains undeveloped and road vehicles are the dominant mode of transportation in Cebu. Therefore, the number of vehicles is expected to accurately represent the human as well as goods flows in the city.

First, we conduct validation exercises of the vehicle density data by comparing them with nightlight luminosity data, which are widely used to measure local economic activity (e.g., Henderson et al., 2012; Chen and Nordhaus, 2011). We also use cellphone-based human flow data, which are currently being used in the literature to capture human mobility, to validate that our data proxies human flows well (e.g.,

[1] Chetty et al. (2022) publish the real time data collected from private companies as the Opportunity Insights Economic Tracker. https://opportunityinsights.org/tracker-resources/

Athey et al., 2021; Couture et al., 2022; Gupta et al., 2022; Kreindler and Miyauchi, 2021; Atkin et al., 2022; Büchel et al., 2020; Miyauchi et al., 2021). We find that the vehicle density data significantly correlates with nightlight luminosity and cellphone-based human inflow data. We also find a significant correlation between vehicle density data and census data, such as the number of populations and establishments in industry sectors. Notably, the correlation between vehicle density and the number of establishments in the accommodation sector is particularly strong. This suggests that vehicle density appropriately captures economic activity, especially in the tourism sector.

Second, using the new dataset, we evaluate the impact of the opening of the new terminal on Cebu's local economy. Specifically, we use the difference-in-differences (DID) method, assigning areas surrounding the MCIA to the treatment group and areas surrounding the Davao International Airport in Davao City, the third most populous city in the Philippines, to the control group. The results can be summarized as follows. First, the new terminal opening significantly increased vehicle density in Metro Cebu. Second, this impact has large spatial heterogeneity. The impact is greatest in the vicinity of the MCIA and attenuates with the distance from the airport. The impact is greater in areas where hotels are clustered compared to hotel-sparse areas. Third, the impact has large seasonal heterogeneity. This impact coincides with the peak months for international passengers. The magnitude of the effect is positively correlated with hotel cluster locations during the peak months of international travel in Cebu. These results show that the opening of the new international terminal positively affects Cebu's local economy by increasing the number of international visitors staying in the city.

The spatial heterogeneity within small geographic areas and seasonal heterogeneity at the monthly level in the policy impact observed in this study are crucial policy issues. However, these are difficult to capture using traditional data sources. The vehicle density data we propose have the advantage of enabling timely policy evaluation that can capture the spatial and seasonal heterogeneity of policy impacts.

This study thus contributes to the literature by measuring economic outcomes using nontraditional data sources. Extensive studies in this field have used nightlight luminosity data to approximate economic activities (e.g., Henderson et al., 2012; Chen and Nordhaus, 2011; Bleakley and Lin, 2012; Michalopoulos and Papaioannou, 2013, 2014; Hodler and Raschky, 2014; Storeygard, 2016; Pinkovskiy and Sala-i-Martin, 2016; Lee, 2018; Harari, 2020). However, nightlight luminosity data also have limitations. For example, 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., the source of light being essentially urban streetlights. While streetlights reflect urban economic activities in general, the impact on the tourism sector, which is a critical element of the transport infrastructure studied in this paper, may not be sufficiently captured. For instance, the effectiveness of nightlight luminosity data in capturing the seasonal changes in economic activities is limited by nature because streetlight coverage and intensity do not change significantly over a short period. Moreover, resort hotels and beach establishments like the ones in Cebu are famous for being in the suburbs and do not necessarily favor the glitter of lights. However, road vehicle density, which captures economic activities that involve human flows, is expected to react quickly to changes in the economic environment. Therefore, vehicle density data have the advantage to capture economic activities that involve human flows and their changes both in the short and long run. We believe that our proposed vehicle density data can complement nightlight luminosity data as a measure of local economic activity.

An increasing number of studies have measured local mobility and economic activity using cellphone GPS and call detail records (CDRs) (e.g., Athey et al., 2021; Couture et al., 2022; Gupta et al., 2022; Kreindler and Miyauchi, 2021; Atkin et al., 2022; Büchel et al., 2020; Miyauchi et al., 2021). Although cellphone-based data have been demonstrated to be good measures of human flows, these data are typically difficult to obtain due to privacy protection reasons. In contrast to cellphone-based data, vehicle density data are based on a vehicle's shape from satellite images and privacy-related information such as license plates cannot be obtained. Furthermore, satellite images are readily available globally, making them useful for policy evaluation, especially in developing countries with scarce data resources.

Recently, several studies have exploited various types of information from daytime satellite images using machine learning. For example, to measure household wealth, Marx et al. (2019) detected the material of a dwelling's roof, while Huang et al. (2021) used a machine learning technique to identify the footprint of the dwelling as well, as the roof material from satellite images. Closely related to our study, Katona et al. (2018) and Gerken and Painter (2022) used the number of vehicles detected in satellite images. They showed that the number of vehicles parked in a parking lot can predict a company's performance. In contrast to these studies, we propose a new application of vehicle density from a satellite image to measure the level of a local economy.

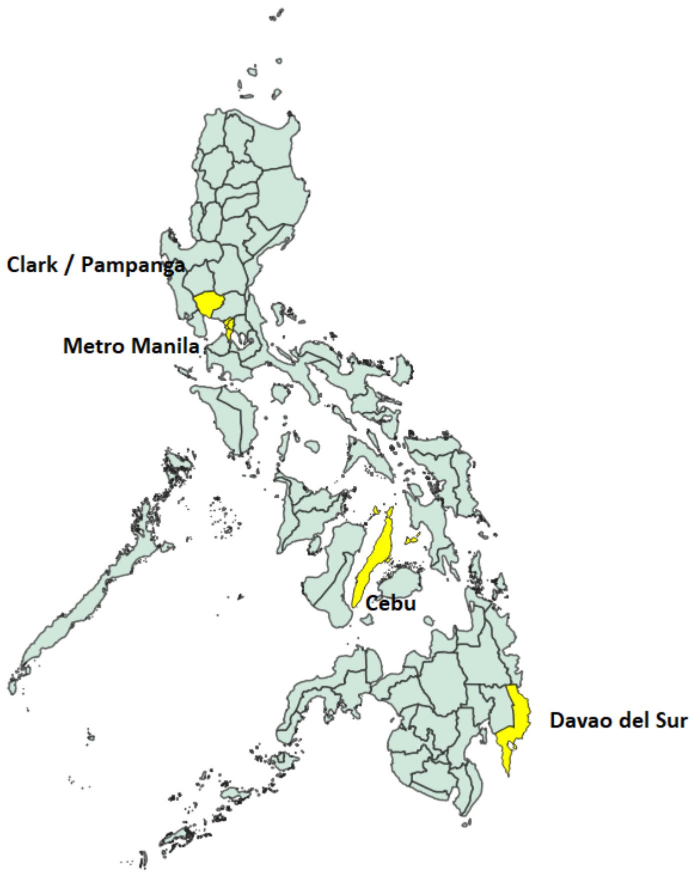
This study also contributes to the emerging literature on the impact evaluation of transportation infrastructure (e.g., Asher and Novosad, 2020; Raitzer et al., 2019; Redding and Rossi-Hansberg, 2017; Redding and Turner, 2017; Donaldson, 2015; Brooks and Donovan, 2020). While most studies on transportation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

2 Institutional Background

The Philippines is an archipelago of over 7,000 islands, meaning connectivity is a major challenge. Luzon in the north is the country's center of economic activities, with Metro Manila and the surrounding regions of Central and Southern Luzon accounting for almost half of the national output in 2019 and being home to 30% of the country's population (Philippine Statistics Authority, 2020, 2017). As in many developing countries, tourism is an important source of economic activity in the Philippines, accounting for over 12% of the gross value-added before the COVID-19 pandemic (Asian Development Bank, 2021; Faber and Gaubert, 2019; Philippine Statistics Authority, 2020).

The islands in the central part of the Philippines are famous destinations for both local and international tourists. Although Central Visayas, where Cebu is located, accounts for only 5% of the national gross domestic product (GDP) and 6% of the country's population, the province of Cebu, being 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 parts of the country. Thirty percent of the volume and value of domestic maritime trade passes through the province (Philippine Statistics Authority, 2016a). Air traffic statistics for 2015 also show Cebu is a tourism hub, accounting for 17% of the domestic and international tourism throughput. This places MCIA second only to Manila airport, which has over 50% of the domestic and 70% of international tourism arrivals (Department of Tourism, 2016).

Figure 1: Map of the Philippines



Note: The key regions and provinces relevant to the analysis are highlighted.

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

2.1 Cebu City

Figure 2 shows a map of the Cebu metro area. Metro Cebu is the second most populous metropolis in the Philippines, comprising seven cities and six municipalities, with a total population of 3.2 million (Philippine Statistics Authority, 2017). The central business district (CBD) located in Cebu City is indicated by the red tile in Figure 2. Metro Cebu is one of the densest populated cities outside mainland Luzon, with over

14,400 persons per square kilometer (km^2) in Mandaue City and 7,000 persons per km^2 in Lapu-Lapu City (Philippine Statistics Authority, 2017). By comparison, the national average is only 337 persons per km^2, whereas the figure is approximately 21,000 in Metro Manila.

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

Figure 2: Map of Cebu City

Note: The figure is based on OpenStreetMap. https://www.openstreetmap.org/ (accessed 4 August 2021).

2.2 The Mactan-Cebu International Airport and Terminal Renewal

The MCIA is an international gateway to Central Visayas. No other airports in the region are designed to handle high volumes of international traffic. Opened for commercial operations in the 1960s, MCIA was originally designed to serve 4.5 million passengers per annum (MPPA). However, the airport catered to more than 6.7 MPPA in 2012. This has strained airport infrastructure, resulting in congestion and delays, particularly during peak periods (Asian Development Bank, 2014).

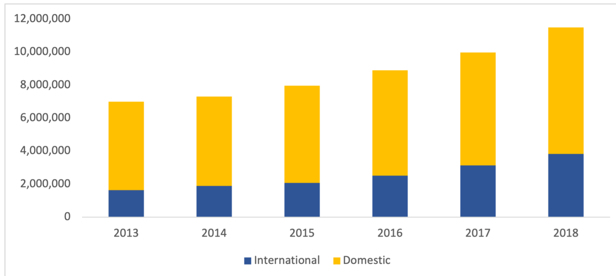
Accordingly, the Department of Transportation and MCIA Authority planned a new airport terminal to cater to international passengers as a response and in anticipation of the increased passenger traffic. The consortium of GMR Infrastructure Ltd. and Megawide Construction Corporation was formally awarded the construction bid on April 22, 2014 and the new passenger terminal of MCIA was inaugurated in July 2018.[2]

The opening of the new international airport greatly increased the airport's capacity by almost three times, from 4.5 to 12.5 MPPA before the opening of the terminal. Figure 3 shows the number of domestic and international passengers in the MCIA. The number of passengers has been increasing even before the opening of the new terminal. Nonetheless, the increase was more pronounced after the terminal opening. Passenger growth rates from 2015 to 2017 were 8% per year, whereas the growth rate from 2017 to 2018

[2]The project cost ₱33 billion ($747 million) and is one of the few government projects financed through a public-private partnership. (https://blogs.adb.org/blog/cebu-airport-expansion-clears-path-future-large-scale-ppps-philippines)

increased to over 12%. The increase in the number of international passengers is the main contributor to growth.

Figure 3: Mactan-Cebu International Airport passenger volume, annual

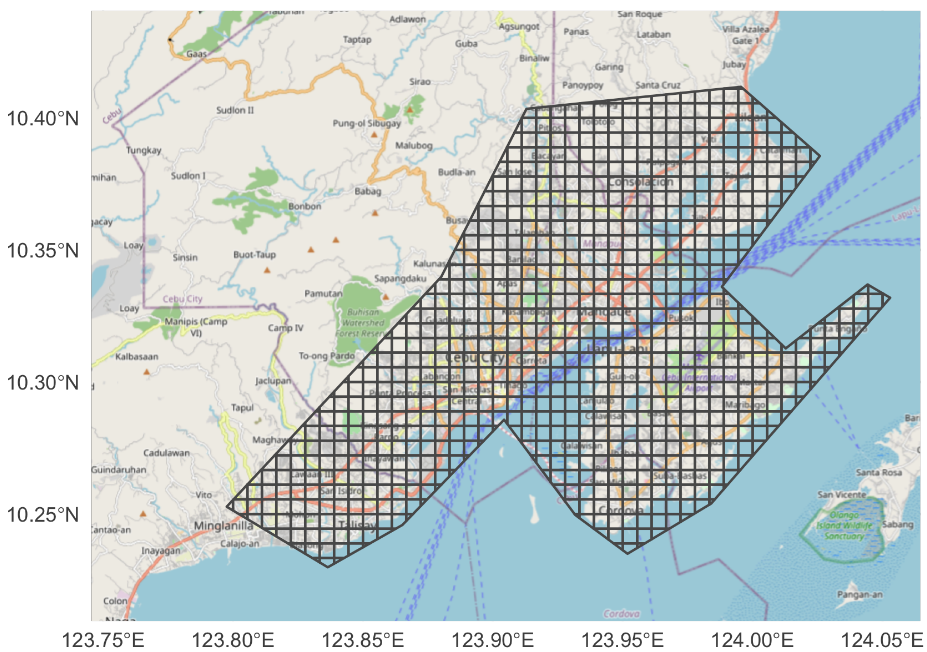


Note: The data are provided by the Mactan-Cebu International Airport Authority. 2019. Passenger Statistics. https://mciaa.gov.ph/statistics/ (accessed 4 August 2021).

3 Data

The unit of observation is the 500 m × 500 m tile in Cebu Metro area. Figure 4 shows the research area and the observation units. The research area covers the built-up areas in Cebu City and Mactan Island, where many accommodations and related service sectors are located.

Figure 4: Unit of observation and satellite data coverage in urban Cebu



Note: The map is based on OpenStreetMap. Tile information is provided by Orbital Insight.

3.1 Vehicle Traffic Volume Data

3.1.1 Data Collection and Processing

We built the vehicle density data at the 500 m $\times$ 500 m tile level from daytime satellite images. The recent development of convolutional neural network (CNN) technology has made it possible to identify vehicles using high-resolution satellite images. We obtained data from Orbital Insight, a leading company that produces vehicle count data from satellite images by exploiting machine learning algorithms.

The primary data used in this study are high-resolution daytime satellite images. We used satellite images from Maxar and Airbus Defense and Space and the second largest catalogs of historical satellite imagery for our study area. We use satellite imagery with a 0.5 m ground sample distance (GSD),[3] which is the highest resolution available for commercial application. Because only a small number of satellites can produce images at this resolution, on average, approximately 14.7 images per year per city were included in the analysis.

We limited our study coverage to vehicles on roads, which are more appropriate representations of human flows as a proxy for economic activity than the cars parked in parking lots. Satellites follow sun-synchronous orbits, implying that images are captured between 10:00 am and 2:00 pm. As such, although peak road and airport rush hour traffic may not be represented, the data still reasonably captured regular business or leisure activities.

From the satellite images, we built the vehicle density data at the 500 m $\times$ 500 m tile level. The first step in detecting vehicles on roads was to download the polygon information of roads from OpenStreetMap and identify the roads in the satellite image by layering the polygon with the satellite image. The road type information in OpenStreetMap allowed us to divide roads into the following four categories: primary, secondary, tertiary, and residential. Next, vehicles on the road were detected and counted by road type for each 500 m $\times$ 500 m tile using an algorithm developed and fine-tuned by Orbital Insight based on the CNN. Finally, the density of the vehicles on the road was derived by dividing the number of vehicles by road area in a tile. The exercise yielded a dataset for each tile with multiple periods from January 1, 2014, to August 30, 2019.

Table 1 shows the summary statistics of the vehicle density in Cebu by year. The numbers of observations in 2014 and 2016 were relatively small owing to the lack of available satellite images. Figure 5 shows a map of the average vehicle density for each tile in 2017. The vehicle density is high around the CBD, whereas Mactan Island has a relatively low density. Nonetheless, the density of cars around airports tends to be high for Mactan Island.

Metro Cebu has no rail service and, therefore, public road transport mostly comprises buses, jeepneys (minibus), and taxis. We acknowledge that motorcycles and motorcycle taxis are increasingly featured as a means of road transport and are not captured in our data. Nonetheless, most international tourists use taxis and share-riding services and our data capture these well.

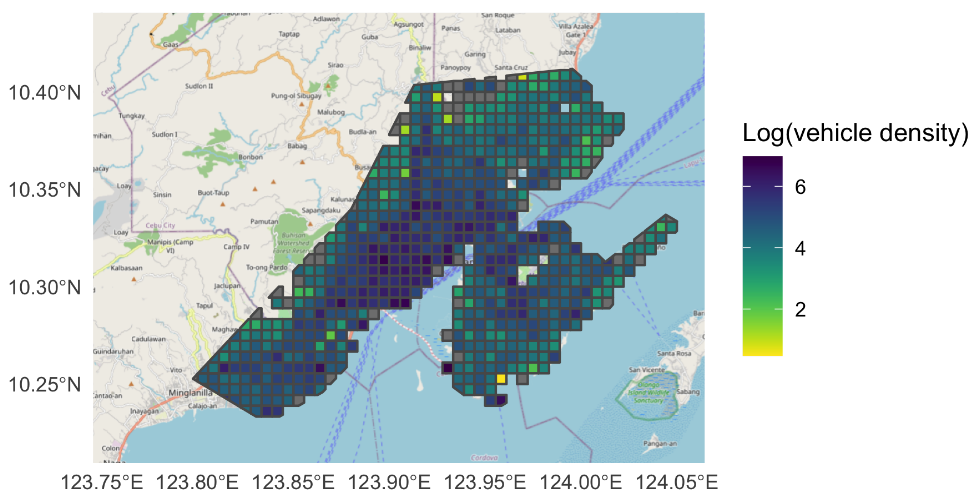
[3] GSD is the average distance between the centers of two adjacent pixels on a satellite image.

Table 1: Summary statistics of vehicle density

Year	Mean	SD	Min	Median	Max	No. obs
2014	183.74	357.35	0.00	65.38	5021.05	5,810
2015	313.88	572.92	0.00	105.05	8600.90	10,024
2016	273.64	593.38	0.00	85.98	19168.52	5,854
2017	204.40	420.77	0.00	74.03	8600.90	20,817
2018	321.46	624.04	0.00	100.37	9676.01	26,953
2019	303.89	565.30	0.00	118.58	11816.93	33,920

Note: Vehicle density is the number of vehicles divided by the area (unit: km^2) of road provided by Orbital Insights. The vehicle density data are available at each road type level and we pool all types of roads data to obtain summary statistics at the tile level.

Figure 5: Vehicle density in 2017



Note: The map is based on OpenStreetMap. Vehicle density data are the average density of each tile in 2017.

3.1.2 Comparison with Other Data on Economic Activities

As a validation exercise, we compare the characteristics of the vehicle density data with other data, such as nightlight luminosity and cellphone-based human flows, which are widely used to measure local economic activity. Additionally, we conduct comparisons using official data from the Philippine Census. For vehicle density data, we use the average for each period in 2017.

First, we compare the data with nightlight luminosity, which is widely used in the literature to indicate local economic activity. The nightlight luminosity data are obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) in 2017, which is recommended for the analysis of disaggregated spatial units (Gibson et al., 2021). We find that vehicle density and nightlight luminosity data are positively correlated. Nightlight luminosity data can explain 46% of the variation in the vehicle density data, as indicated by the R-squared values. The details of these validation exercises are presented in Appendix A.1.

Second, we compare vehicle density data with aggregated CDR data from one of the largest cellphone service providers in the Philippines. CDR data have been used in several studies to track human movement among locations (e.g., Kreindler and Miyauchi, 2021). CDR data allows us to retrieve a matrix of origin and destination flows between *barangay* (village) pairs. We use flows from 10 a.m. on January 15, 2020 (Wednesday) in Metro Cebu.[4] From these data, we calculate the number of human inflows in a *barangay* and estimated the correlation between vehicle density and the number of human inflows. The results show that vehicle density is positively correlated with the number of human inflows, as shown in Appendix A.2

Finally, we conduct validation exercises using demographic and economic data from the Census of Population and Housing (Philippine Statistics Authority, 2010, 2017). The census provides information on the population in 2015 and the number of establishments by economic sector in 2010 at the *barangay* level. We aggregated the 500 m $\times$ 500 m tile vehicle density data to the *barangay* level using shape files from the Philippine Statistics Authority (Philippine Statistics Authority, 2016b).

The results show that vehicle density is positively correlated with population, number of establishments in the commercial sector, and number of establishments in the accommodation sector. We also check the correlation patterns of the census data with nightlight luminosity and cellphone-based human inflows. In most cases, vehicle density data predict well local economic activities measured by census data and nightlight luminosity data. In particular, the vehicle density data strongly correlate with the number of establishments in the accommodation sector. This suggests that vehicle traffic volume appropriately captures economic activity, especially in the tourism sector. Details of the validation exercises are provided in Appendix A.3.

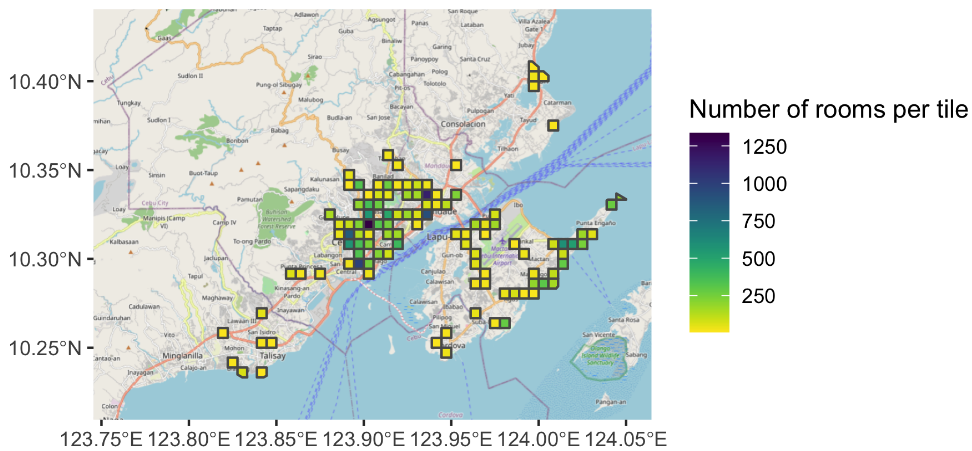
3.2 Hotel Location and Air Passenger Data

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 on each hotel's location and number of rooms. We aggregated the information to a 500 m $\times$ 500 m tile level to match the vehicle count data. Figure 6 displays the density of hotel rooms in each tile, showing that hotel room

[4] The data we use are a subset of the CDR data used by Jiang et al. (2022). The authors demonstrate CDR data are an appropriate proxy for human flow data, exhibiting a highly positive correlation with commuting time and census-based commuting flow data.

availability exhibits clusters on Mactan Island and the areas surrounding the CBD. The eastern shore of Mactan Island hosts large resort hotels that cater to international tourists.

Figure 6: Map of the number of hotel rooms



Note: The number of hotel rooms is obtained from the directory of accredited establishments provided by the Department of Tourism.

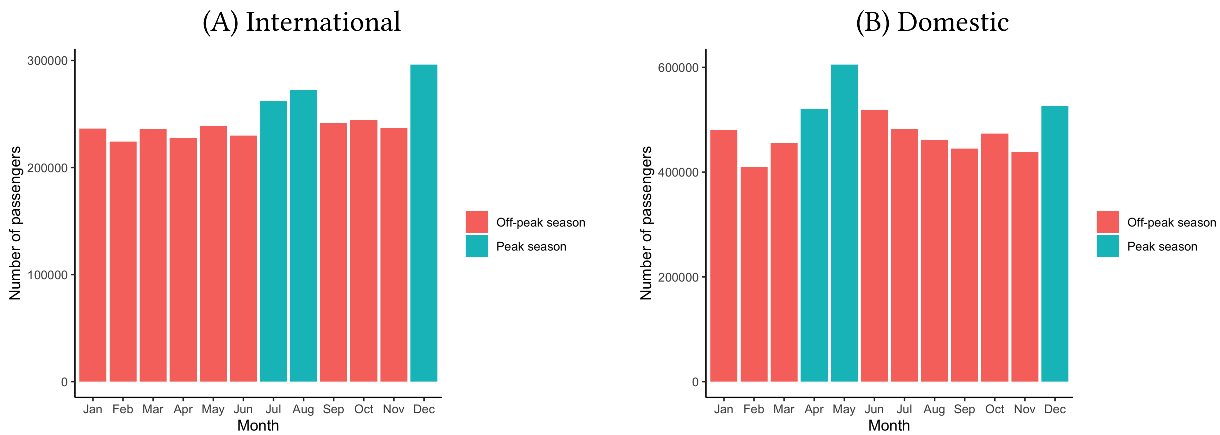
International and domestic monthly passenger data from the MCIA Authority are used to distinguish peak seasons in the MCIA. Figure 7 shows the number of airport users per month. Panel (A) depicts the international passenger and Panel (B) the domestic passenger movements. The blue bars indicate the three months with the largest arrivals for each passenger group. The peak months for international passengers were July, August, and December, whereas the peak months for domestic passengers were April, May, and December.

4 Empirical Strategy

We estimate the impact of opening a new international terminal in MCIA using DID. The treatment group pertains to tiles within the Cebu conurbation, whereas the control groups are tiles in Davao metropolitan area. Davao City is geographically situated at the southern end of the country, as shown in Figure 1 and is the most populous city in Mindanao. Similar to Cebu, Davao City hosts a key regional airport.[5] Similar to Cebu Metro, public transportation in Davao mainly comprises buses and taxis, with no rail service.

[5]In the appendix, we also show results based on a sample that includes data from surrounding areas of Clark International Airport located northwest of Manila as shown in Figure 1 as an additional control group. It has a capacity of four million passengers per year during the study period, which is approximately the same as MCIA prior to the terminal expansion. Clark's capacity has increased to 12 million after an expansion project was completed in 2020.

Figure 7: Mactan-Cebu International Airport passenger volume, seasonal



Note: Number of passengers on MCIA is provided by the MCIA Authority. The blue bars indicate that these are the peak months (i.e., top three months in terms of the number of airport passengers).

Table 2 shows the basic statistics for Cebu and Davao in 2015. There are no significant differences in basic economic indicators, such as population size, regional GDP, GDP per capita, and poverty rate. Davao, an important food processing hub, has a relatively higher share of output accruing to the agriculture sector. Meanwhile, Cebu has a relatively higher share of services in the GDP. The latter potentially reflects the greater role of tourism services in Cebu, accounting for approximately 4% of the regional GDP in Central Visayas, compared to approximately 2% in the Davao region Philippine Statistics Authority (2017).

Table 2: Summary official statistics (Cebu vs. Davao)

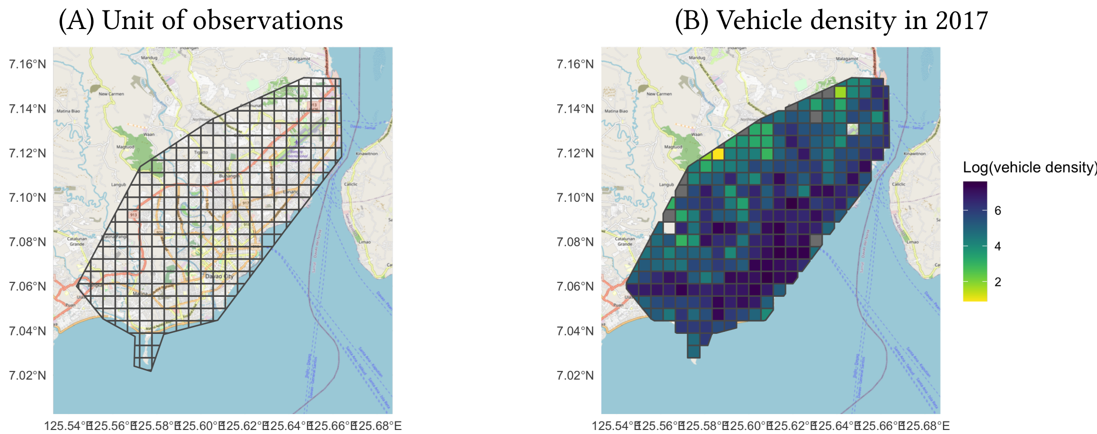
	Cebu	Davao
Population (million)	3.20	2.70
Regional GDP (million PhP)	1032.60	728.80
Regional GDP per capita (1000 PhP)	134.30	141.40
Poverty rate (%)	20.00	14.80
Share of Agriculture (%)	6.50	16.50
Share of Industry (%)	34.70	34.30
Share of Services (%)	58.80	49.10

Note: Population data are for the Metro Cebu and Metro Davao from Philippine Statistics Authority (2017). Poverty rate data are at the Cebu and Davao province level and from Philippine Statistics Authority (2019). All other data are at the regional level, with Cebu for the Central Visayas Region and Davao for the Davao Region from Philippine Statistics Authority (2020).

Panel A of Figure 8 shows the area of Metro Davao included in the study. The coverage of Metro Davao is geographically smaller than that of Metro Cebu, and the number of observations is also smaller. Panel (B) presents the vehicle density in Metro Davao in 2017, which shows that the stretch of areas surrounding Davao International Airport in the northeast to the CBD in the middle of the coastal area has high vehicle densities.

Davao International Airport (DIA), located in Davao Metro at the eastern end of the map, is less than half the size of MCIA, with 3,903,687 annual passengers as of 2017. DIA has not undergone any major infrastructure investment during the period analyzed in this study and the number of its users has remained

Figure 8: Map of Metro Davao area coverage

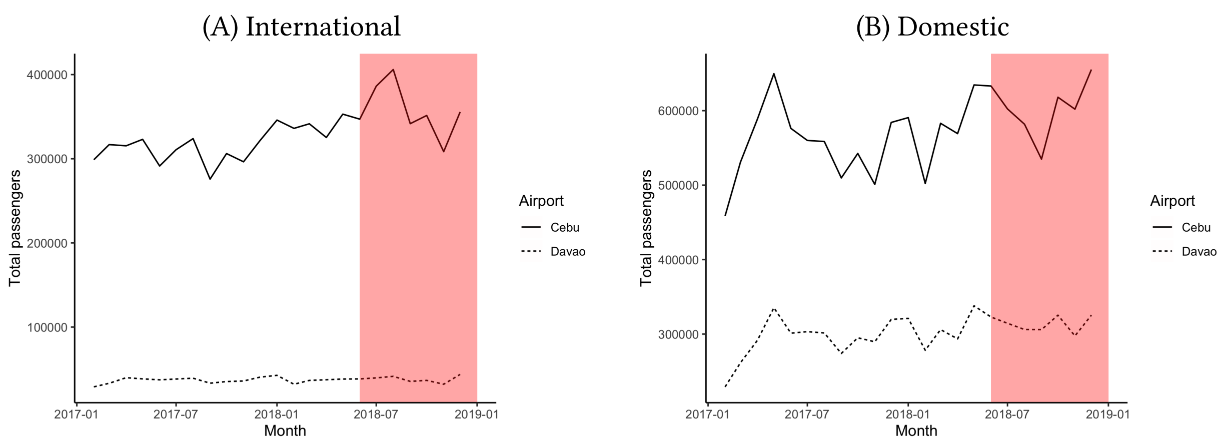


Note: The map is based on OpenStreetMap. Tile information is provided by Orbital Insight.

relatively stable.

Figure 9 plots the number of monthly passengers of MCIA and DIA and shows that the traffic of both international and domestic passengers in DIA does not change with the MCIA new terminal. To some extent, this precludes substitution effects between the airports, such as DIA users moving to MCIA with the opening of a new international terminal. In fact, because Davao, unlike Cebu, does not have a large tourism industry, the substitution of international tourists from Davao to Cebu is unlikely.

Figure 9: Number of passengers for MCIA and Davao International Airport



Note: The number of passengers is from OAG Aviation Worldwide limited.

Table 3 shows the average vehicle density in the Cebu and Davao Metro areas in 2017. Metro Davao has a smaller area and denser vehicle traffic, on average, than Cebu. The lower vehicle density in Cebu may be because the research coverage area in Cebu includes Mactan Island, which has more resort areas and a relatively high percentage of undeveloped land. We discuss this further in Appendix C.

Using Davao Metro as the control group, the estimation equation is as follows:

Table 3: Summary statistics of vehicle density in 2017 (Cebu vs. Davao)

Year	Mean	SD	Min	Median	Max	No. obs
Cebu Metro	137.62	144.55	0.00	92.54	1068.06	666
Davao Metro	450.58	457.42	0.00	273.14	2008.93	271

Note: Vehicle density is the number of vehicles divided by the area (unit: km^2) of road which provided by Orbital Insights. The vehicle density data are available at each road type level and we pool all types of road data obtain summary statistics at the tile level.

$$\log(\text{Density of vehicles}_{irt}) = \beta(\text{Cebu}_i \times I[\text{July 2018} \leq t]) + \eta_i + \xi_r + \zeta_t + \varepsilon_{irt}, \tag{1}$$

where Density of vehicles$_{irt}$ denotes the density of vehicle counts for road type r in tile i in period t; Cebu$_i$ is a dummy variable that 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 are tile fixed effects; ξ_r are road type fixed effects; and ζ_t are year and month fixed effects. The estimated coefficient, β, shows the impact of MCIA on economic activities. It is estimated using ordinary least squares (OLS), which excludes tile observations with zero vehicles. Then, as a robustness check, we estimate the equation using Poisson pseudo maximum likelihood (PPML) to allow for the inclusion of a substantial share of observations with zero vehicle observations. We use the Conley spatial HAC standard error, allowing correlations within 2 km to account for potential spatial correlation of the error term.

5 Results

The baseline estimation results are summarized in Table 4, where column 1 shows the OLS results. We can observe the statistically significant positive effects of the treatment. Vehicle density increases by 10.4% after opening the new terminal. Column 2 shows the PPML results for zero observations and the treatment effects become larger. The opening of the new terminal increases vehicle density by 17.5%.[6] The inclusion of month fixed effects in columns 3 and 4 to address monthly heterogeneity results in a treatment effect. The coefficients become slightly smaller than the results, excluding month fixed effects. The larger estimated treatment effects in the zero-inflated sample in PPML also indicated that the extensive margin is a potentially larger source of economic gains than the intensive margin. In summary, the opening of the new terminal can be associated with a positive impact ranging from 8.7% to 17.5% on urban Cebu's local economy.

5.1 Spatially Heterogeneous Treatment Effects

To determine, at least partly, the underlying mechanisms behind the observed positive impact of MCIA, we identify individual treatment effects to examine the spatial heterogeneity of the new terminal by estimating

[6] $\exp(0.162) - 1 = 0.175$.

Table 4: Baseline results

Dependent Variable:	Vehicle density			
Model:	(1)	(2)	(3)	(4)
	OLS	Poisson	OLS	Poisson
Variables				
Cebu × After Opening New Terminal	0.104***	0.162***	0.087**	0.127***
	(0.040)	(0.029)	(0.042)	(0.036)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes
Month			Yes	Yes
Fit statistics				
Adjusted R^2	0.58869		0.59641	
Pseudo R^2	0.27395	0.56107	0.27976	0.56939
Observations	73,410	86,872	73,410	86,872

Notes: This table shows the OLS (columns 1 and 3) and PPML (columns 2 and 4) estimates of the DID analysis. Each observation is at the road-tile-time level. The dependent variable is vehicle density. The regressor is the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy. Year, tile, and road fixed effects are included in columns 1 and 2 and year, tile, road, and month fixed effects are included in columns 3 and 4. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * p<0.10, ** p<0.05, *** p<0.01.

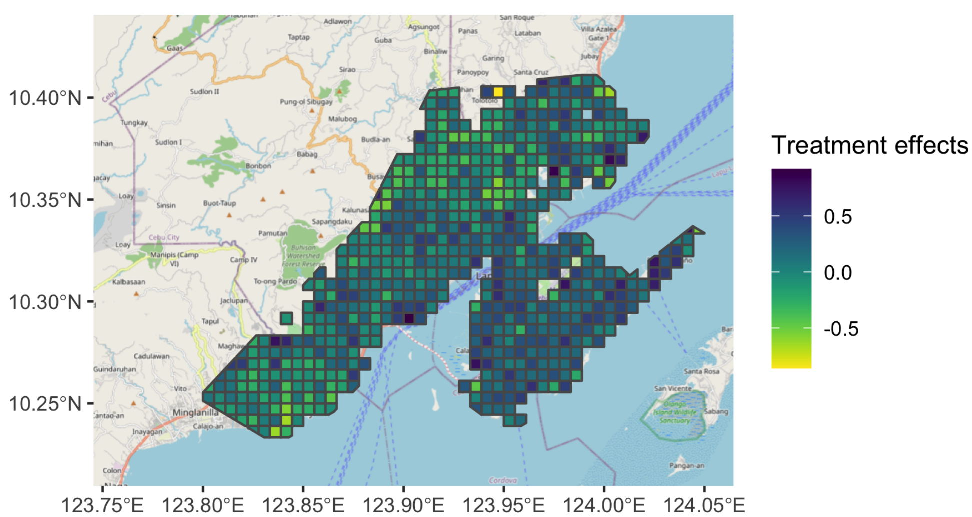
the following equation:

$$\log(\text{Vehicle density}_{irt}) = \sum \beta_i(\eta_i \times I[\text{July 2018} \leq t]) + \eta_i + \xi_r + \zeta_t + \varepsilon_{irt}$$

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

Figure 10 shows the geographic distribution of the estimated individual treatment effects. Darker colors imply greater treatment effects. The treatment effect is stronger on 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 with foreign tourists, shows stronger treatment effects, consistent with the tourism-facilitating effect of the new terminal.

Figure 10: Map of individual treatment effects



Notes: The map shows the estimated individual treatment effects of the impact of new terminal opening at MCIA at the tile level. Darker color shows stronger treatment effects. The map is based on OpenStreetMap.

In addition, we employ a triple-difference (DDD) analysis to formally test whether the estimated treatment effect is attributable to the opening of the new international terminal. In this setup, we measure the travel time of each tile from the airport[7] and estimate the interaction effect between this and the treatment variable, allowing the treatment effect to be a linear function of distance.

The results are presented in Table 5. In both OLS (column 1) and PPML (column 2), the coefficient on the interaction variable, Cebu $\times$ After Opening New Terminal, is positively significant, whereas the coefficients on the triple-difference terms are negative and significant. This suggests that the treatment

[7]We use the Open Source Routing Machine (OSRM) to calculate travel times (http://project-osrm.org). This service provides road travel times between arbitrary points by using road information from OpenStreetMap. The travel time from the airport to each tile is defined as the travel time by car from the representative point coordinates of the airport terminal to the central point coordinates of each tile.

effect is stronger for tiles closer to airports. Since the resort hotel cluster is also located on Mactan Island and is close to the airport, these results are consistent with the assumption that the opening of the new international terminal induces more tourism activities.

Table 5: Triple-difference with travel time to airport

Dependent Variable:	Vehicle density					
Model:	(1) OLS	(2) Poisson	(3) OLS	(4) Poisson	(5) OLS	(6) Poisson
Variables						
Cebu × After Opening New Terminal	0.544***	0.437***	-0.022	0.035	0.431**	0.063*
	(0.165)	(0.103)	(0.082)	(0.045)	(0.195)	(0.037)
Cebu × After Opening New Terminal × log(Travel time from Airport)	-0.171***	-0.119***			-0.168**	-0.026**
	(0.062)	(0.038)			(0.066)	(0.013)
Cebu × After Opening New Terminal × log(Travel time from CBD)			0.051	0.051***	0.050	0.011*
			(0.032)	(0.019)	(0.031)	(0.006)
Fixed-effects						
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
Fit statistics						
Adjusted R^2	0.59668		0.59692		0.59719	
Pseudo R^2	0.27990	0.56960	0.28025	0.57400	0.28038	0.04302
Observations	73,340	86,737	73,080	86,419	73,010	73,010

Notes: This table shows the OLS (columns 1, 3, and 5) and PPML (columns 2, 4, and 6) estimates of the triple difference analysis. Each observation is at the road-tile-time level. The dependent variable is vehicle density. The regressor is the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy, and the triple interaction with log of travel time from airport and log of travel time from CBD. Year, tile, road, and month fixed effects are included. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Another possible channel through which the opening of the new international terminal 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 travel time from the CBD to each tile and conduct a similar DDD analysis. In both OLS (column 3) and PPML (column 4), the coefficient on the interaction variable, Cebu × After Opening New Terminal, is negative, whereas the triple-difference term coefficient interacting with distance from the CBD is positively significant in PPML. This suggests that the treatment effect is weaker in the CBD area, where traffic is already heavy, even prior to the opening of the new terminal. This may suggest that the effect is mainly from international tourists who visit resorts and not so much due to business purposes, so the effect of resorts around the airport away from the CBD is dominant. However, the distances from the airport and CBD are correlated. Increasing the distance from the airport simultaneously decreases the distance from the CBD. To address this concern, in columns 5 and 6, we include interaction terms for travel time from both the airport and CBD. The triple-difference term coefficient interacting with the travel time from the airport is still negatively significant, but the triple-difference term coefficient interacting with the travel time from CBD becomes smaller and marginally significant. This suggests that the positive effects of the opening of the new international terminal are the largest on Mactan Island and are mainly mediated through the increase in foreign travelers who stay there.

We further analyze the channels of economic activity using hotel location data to divide the sample into tiles with hotels and tiles without hotels, and conduct a DID analysis for each subsample (Table 6). The subsample with hotels in columns 1 and 2 shows positive treatment effects for both OLS and PPML. However, the subsample of tiles without hotels in columns 3 and 4 shows smaller treatment effects, supporting the conjecture that tourism activities are the main channel through which the opening of the new international terminal contributed to Cebu's local economy.

Table 6: Treatment effects on hotel and non-hotel areas

Dependent Variable:	Vehicle density			
Sample	Hotel zone		Non hotel zone	
Model:	(1)	(2)	(3)	(4)
	OLS	Poisson	OLS	Poisson
Variables				
Cebu × After Opening New Terminal	0.221***	0.170***	0.033	0.095***
	(0.052)	(0.042)	(0.040)	(0.035)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Fit statistics				
Adjusted R^2	0.48435		0.56935	
Pseudo R^2	0.21456	0.45014	0.26965	0.54211
Observations	22,174	24,395	51,236	62,477

Notes: This table shows the OLS (columns 1 and 3) and PPML (columns 2 and 4) estimates of the DID analysis. Each observation is at the road-tile-time level. The sample is restricted to tiles having at least one hotel (columns 1 and 2) and those not having hotels (columns 3 and 4). The dependent variable is vehicle density. The regressor is the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy. Year, tile, road, and month fixed effects are included. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

5.2 Road Type Specific Heterogeneous Treatment Effects

OpenStreetMap allows the classification of road types. Accordingly, we calculate the density of vehicles by each type of road: primary, secondary, tertiary, and residential. We divide the sample by road type and conduct estimations by these types to account for the impact of heterogeneity among roads. Primary roads mainly serve as trunk roads, being mostly used for inter-city travel, and may not necessarily indicate the scale of economic activity at the tile level. Tertiary roads connect local establishments and other economic centers within a city, and the vehicles on these roads may be closely related to the local economic activity in a tile.[8]

Table 7 shows the results estimated using PPML. Columns 1, 2, and 3 show the results for vehicle density on primary, secondary, and tertiary roads as the outcome variables, respectively. The results show clear patterns of larger effects for more local road types. In other words, the effect is greater on roads with fewer vehicles for passing purposes. These results are consistent with the argument of intensified local economic activities after the opening of the new terminal. Column 4 shows the results using vehicle density on the residential road as the outcome variable, where the treatment effect is the smallest. Residential roads are primarily for traffic in residential areas, generally considered as areas with few service businesses, such as accommodations and restaurants. This result is consistent with the finding that the opening of the new terminal affected the Cebu economy through increased tourism.

Table 7: Treatment effects by road type

Dependent Variable:	Vehicle density			
Road type	Primary	Secondary	Tertiary	Residential
Model:	(1)	(2)	(3)	(4)
Variables				
Cebu × After Opening New Terminal	0.114***	0.165***	0.172***	0.070**
	(0.040)	(0.046)	(0.051)	(0.034)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Fit statistics				
Pseudo R^2	0.47814	0.52686	0.56396	0.63561
Observations	16,207	11,182	15,742	42,135

Notes: This table shows the PPML estimates of the DID analysis. Each observation is at the road-tile-time level. The sample is restricted to primary (column 1), secondary (column 2), tertiary (column 3) and residential (column 4) roads. The dependent variable is vehicle density. The regressor is the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy. Year, tile, and month fixed effects are included. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

5.3 Seasonally Heterogeneous Treatment Effects

The effect of the new terminal on tourism is expected to vary by season. We tested this hypothesis by distinguishing between the peak periods of international and domestic passengers.

We conduct a DDD analysis by 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 7). The results are shown in Table 8, where columns 1 and 2 show the results of introducing the triple-difference term with the domestic peak dummy. In both the OLS and PPML, the

[8] On the detailed definition of road type, see the website of OpenStreetMap. https://www.openstreetmap.org

coefficients on the triple-difference terms are negatively significant. The treatment effects are weaker and tend to become negative during domestic peak periods compared with other periods, including international peak periods. However, the results for the international peak dummy, as shown in columns 3 and 4, have triple-difference coefficients that are positive and significant for both OLS and PPML. Columns 5 and 6 show the results, including both the domestic and international peak effects. The results are similar to those in columns 1 to 4, but the negative effects for the domestic periods become smaller. This suggests that the positive impact of the opening of the new international passenger terminal comes from the increase in international travelers and the impacts during domestic peak periods are negligible. These results have implications for the government's regional tourism strategies. The National Tourism Development Plan revealed that domestic and international tourism activities have qualitatively different effects on the local economy. On average, a international tourist spent $107 per day, whereas a domestic tourist spent less than $50 per day in 2015 (Department of Tourism, 2016).Hence, it would be critical for the government to invest in tourism infrastructure including an airport to target international visitors.

Table 8: Treatment effects on peak and off-peak seasons for airport passengers

Dependent Variable:	Vehicle density					
Model:	(1) OLS	(2) Poisson	(3) OLS	(4) Poisson	(5) OLS	(6) Poisson
Variables						
Cebu × After Opening New Terminal	0.119***	0.147***	-0.004	0.026	0.023	0.037
	(0.043)	(0.040)	(0.051)	(0.045)	(0.050)	(0.048)
Cebu × After Opening New Terminal × Peak months of domestic passengers	-0.111***	-0.074**			-0.080***	-0.034
	(0.033)	(0.037)			(0.030)	(0.033)
Cebu × After Opening New Terminal × Peak months of international passengers			0.279***	0.298***	0.266***	0.292***
			(0.079)	(0.061)	(0.079)	(0.062)
Fixed-effects						
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
Fit statistics						
Adjusted R^2	0.59670		0.59778		0.59792	
Pseudo R^2	0.27999	0.56952	0.28080	0.57110	0.28091	0.57113
Observations	73,410	86,872	73,410	86,872	73,410	86,872

Notes: This table shows the OLS (columns 1, 3, and 5) and PPML (columns 2, 4, and 6) estimates of the triple difference analysis. Each observation is at the road-tile-time level. The dependent variable is vehicle density. The regressors are the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy, and the triple interaction with peak months for domestic passengers dummy and peak months for international passengers dummy. Year, tile, road, and month fixed effects are included. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

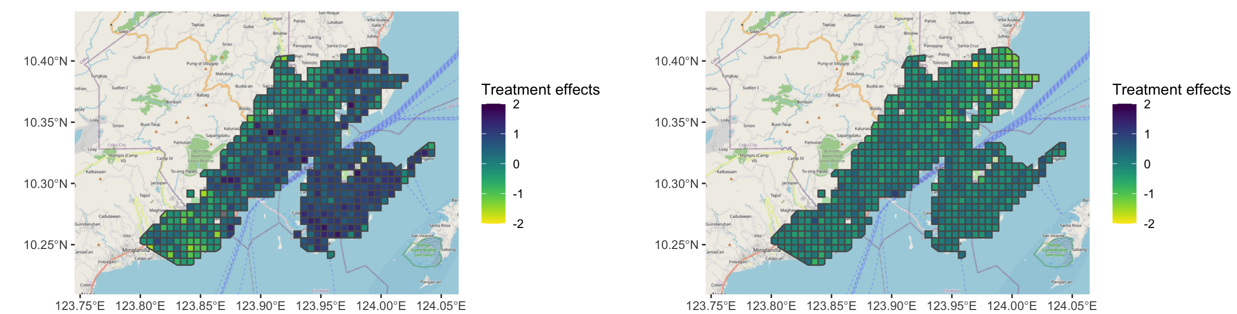
5.4 Spatially and Seasonally Heterogeneous Treatment Effects

Finally, we conduct an analysis to account for the heterogeneity of treatment effects in both the seasonal and spatial dimensions. We estimate the individual treatment effects for the peak and off-peak months for international passengers and investigate the characteristics of the differences between areas. The map of the estimated individual treatment effects by season is shown in Figure 11 using the same scale. Compared to off-peak months, peak months had larger treatment effects, on average. Furthermore, the spatial distribution of the treatment effect in the off-peak is relatively uniform, whereas that in the peak is more skewed, with stronger treatment effects concentrated on Mactan Island.

Figure 11: Individual treatment effects (peak vs. off-peak periods of international passengers)

(A) Peak

(B) Off-Peak



Notes: The map shows the estimated individual treatment effects of the impact of new terminal opening in MCIA at the tile level. Panel (A) restricts the sample to peak months for international passengers and Panel (B) to other months in estimating individual treatment effects. Darker color shows stronger treatment effects. The map is based on OpenStreetMap.

The correlation between estimated individual treatment effects and hotel density is shown in Table 9. Column 1 uses the number of hotel rooms as the right-hand variable and the estimated individual treatment effects in peak months as the left-hand side variable. The coefficient on 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. However, if we use the estimated treatment effects in the off-peak months, the coefficients on both 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 an increase in foreign tourists.

6 Robustness Checks

6.1 Traffic Restrictions due to Terminal Construction

The construction of new terminal began in 2015. During the construction period, vehicle density may have been directly affected by construction work, such as traffic restrictions and road closures. In addition, vehicle density may have increased independently from local economic activities, especially at the end of construction and during preparations for the terminal's opening.

To address this concern, we first show an event study plot to understand the potential influence of timing on traffic flow and density. Figure 12 shows the event study plot for the corresponding half of each year. The period in the red-shaded area is after the second half of 2018, that is, after the terminal opening. The 95% confidence intervals for each coefficient straddle zero for most periods prior to the terminal

Table 9: Correlation between individual treatment effects and hotel density

Dependent Variable:	Treatment effects			
Season	Peak		Off-peak	
Model:	(1)	(2)	(3)	(4)
Variables				
Number of hotels	0.065**		0.010	
	(0.030)		(0.013)	
Number of hotel rooms		0.0005***		0.0001
		(0.0002)		(0.0001)
Fit statistics				
Adjusted R^2	0.01373	0.00930	-0.00051	0.00012
Observations	580	580	580	580

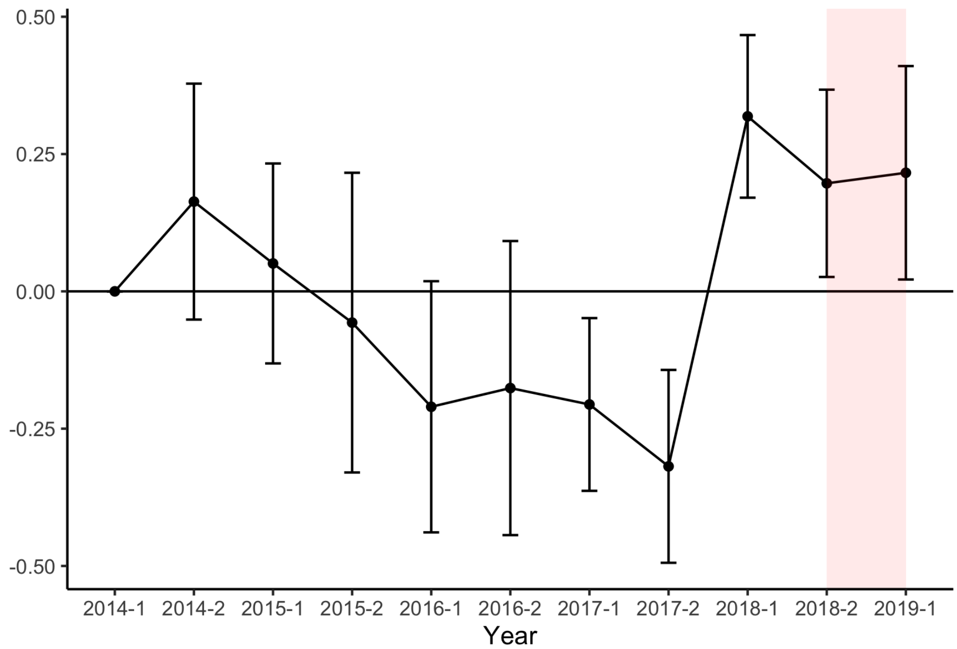
Notes: This table shows the OLS estimates of the relationship between estimated individual treatment effects and number of hotels and hotel rooms. Each observation is at the tile level. The dependent variables are estimated treatment effects in the peak months for international passengers in columns 1 and 2 and those in other months in columns 3 and 4. The regressors are the number of hotels and number of hotel rooms in the mesh. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

opening and indicate no statistically significant difference in vehicle density between the treatment and control groups prior to the terminal opening. However, the coefficients are negative from 2016 to 2017 and significant for the two periods when airport construction was close to completion. This result is consistent with the concern that traffic restrictions, especially around airports, reduced the density of vehicles in the vicinity as construction progressed. It also shows a positive and significant effect after the opening of the terminal. However, interestingly, the effect began in the first half of 2018, just before the terminal's opening, potentially owing to increased traffic flows from preparations for the opening of the new terminal.

We conduct an analysis in which the sample is divided by the road travel time from the airport to examine the possibility that the downward trend in vehicle density in Cebu from 2016 to 2017 is due to the traffic restrictions related to terminal construction. Specifically, we define the area within a 15-minute vehicle travel time from the airport as the airport proximity zone and constructed a similar event study plot with the sample in the airport proximity zone and the sample outside the zone, as shown in Figure 13. Panel (A) shows the results for areas close to the airport. In this area, near the airport, there is a significant drop in vehicle density from 2016 to 2017. However, Panel (B) shows the results for areas with more than 15 minutes of travel time from the airport and no drop in those periods. These results suggest that the temporary drop in vehicle density from 2016 to 2017 is likely due to traffic restrictions around the airport caused by construction work.

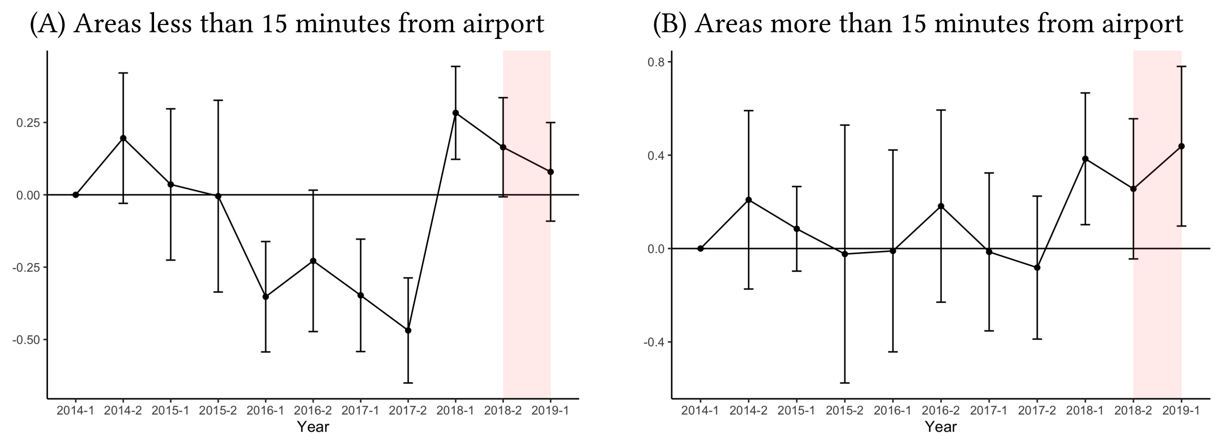
Table 10 shows the results of the baseline specification after restricting the sample to areas where travel time from the airport is more than 15 minutes. The effects of terminal expansion are robust to restricting the sample to areas where the effect of traffic restrictions during terminal construction on vehicle density reduction is expected to be small.

Figure 12: Event study plot



Notes: The figure presents the event study plot of the coefficients and confidence intervals of the PPML estimate of the estimation equation, $\log(\text{Vehicle density}_{rit}) = \sum_t \beta^t(\text{Cebu}_i \times \zeta_t) + \eta_i + \xi r + \zeta_t + \varepsilon_{irt}$. The time period is half year. Dots show the point estimates of β^t. Bars show that the 95% confidence interval based on the spatial HAC standard errors allowing 2-km correlations. We set the first half of 2014 as the baseline year. Red shaded area shows the treatment period (from the second half of 2018 to the first half of 2019).

Figure 13: Event study plot (close vs. far from airport)



Notes: The figure is the event study plot of the coefficients and confidence intervals of the PPML estimate of the estimation equation, $\log(\text{Vehicle density}_{rit}) = \sum_t \beta^t(\text{Cebu}_i \times \zeta_t) + \eta_i + \xi r + \zeta_t + \varepsilon_{irt}$. The time period is half year. Panel (A) restricts the sample to tiles less than 15 minutes from the airport and Panel (A) restricts it to tiles more than 15 minutes from the airport. Dots show the point estimates of β^t. Bars show that the 95% confidence interval based on the spatial HAC standard errors allowing 2-km correlations. We set the first half of 2014 as the baseline year. Red shaded area shows the treatment period (from the second half of 2018 to the first half of 2019).

Table 10: Results of baseline specification by areas more than 15 minutes from the airport

Dependent Variable:	Vehicle density			
Model:	(1) OLS	(2) Poisson	(3) OLS	(4) Poisson
Variables				
Cebu × After Opening New Terminal	0.124**	0.176***	0.169***	0.177***
	(0.059)	(0.032)	(0.042)	(0.028)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes
Month			Yes	Yes
Fit statistics				
Adjusted R^2	0.61742		0.62636	
Pseudo R^2	0.29301	0.59692	0.30021	0.60562
Observations	31,692	37,654	31,692	37,654

Notes: This table shows the OLS (columns 1 and 3) and PPML (columns 2 and 4) estimates of the DID analysis. Each observation is at the road-tile-time level. The sample is restricted to tiles more than 15 minutes from the airport. The dependent variable is vehicle density. The regressor is the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy. Year, tile, and road fixed effects are included in columns 1 and 2 and year, tile, road, and month fixed effects are included in columns 3 and 4. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

6.2 Alternative Control Group

We use areas in Metro Davao as the control group. There are a limited number of potential cities similar to Cebu City in terms of airport operations and economic profiles, which can be suitable as a control group. Nonetheless, the fact that only one city serves as a control group could be a potential concern. We add the area surrounding Clark International Airport (CIA) as another control group for a robustness check. CIA is the third busiest airport in the Philippines, after Manila and Mactan-Cebu in terms of the number of passengers. CIA is located northwest of Manila. The effect of opening a new terminal is robust to the inclusion of another control group with major airport operation. See Appendix D.1 for details.

The main outcome variable in this study is the density of vehicles on the road. This is reasonable when considering road capacity constraints. Nonetheless, we also use the number of vehicles rather than density as an indicator of economic activity and found that the results are robust to an alternative measure of vehicle counts. See Appendix D.2 for further details.

7 Comparing Costs and Benefits

The results indicate that the opening of the new terminal positively affected the Cebu economy through an increase in international passengers. Table 8 shows that the density of vehicles increased from 33.5% to 38.9%[9] during the peak month of international passengers after the opening of the new terminal. Using

[9] $\exp(0.023 + 0.266) - 1 = 0.335$ from OLS result shown in Column (5). $\exp(0.037 + 0.292) - 1$ from PPML result shown in Column (6).

these estimated impacts, the number of passengers per vehicle, and the amount of purchase per day by an international passenger, we can estimate the impact of the airport expansion on the Cebu economy.

The annual benefits of the opening new terminal at year t, B_t, can be calculated as follows:

$$B_t = E_t \times V_t \times P_t \times M_t \times T_t \times N_t,$$

where E is the estimated impact of the opening of the new terminal on vehicle density measured by a change rate; V is the baseline density, i.e., the average number of vehicle per tile on peak months of international passengers before opening of the new terminal in Cebu Metro; P is the number of passengers per vehicle; M is daily purchase per international passenger; T is the number of peak months (in days) of the international passengers; and N is the number of meshes in Cebu Metro. Here, we set the estimated impact, E, at 0.335; the average number of vehicles per mesh on peak months of international passengers before the opening of the international terminal, V, was 40.8; we set the number of passengers per vehicle, P, at 2, which can be taken as a lower-bound number; according to Department of Tourism (2016), the estimated daily expenditure per international passenger, M, would have been at \$107; and there are three main peak months of the international passengers, i.e., $T = 3$ months or 90 days. As a result, the annual economic impact of the terminal opening can be estimated to be \$176.6 million per year, indicating that it has a substantial effect on the Cebu economy.

How large is the annual economic impact of the terminal opening compared to the cost of construction? As mentioned in Section 2.2, the project cost was ₱33 billion (\$747 million). Assuming a discount rate of 15%, the benefits of opening the terminal would exceed the project cost in only six years. Thus, it can be seen that the opening of the new terminal in this study brought significant benefits to the Cebu City economy through the increase in international tourists.

8 Conclusions

This study proposes vehicle density data obtained from daytime satellite images as a new measure of local economic activities for policy evaluation. These data have the advantages of timeliness, frequency, and spatial granularity compared to traditional sources such as government-generated statistics. We show that vehicle density proxies for local economic activities well through a battery of validation exercises using administrative, nightlight luminosity, and cellphone-based human flow data. In particular, vehicle density represents economic activities in the tourism sector.

As an application of the data for policy evaluation, we use the case of opening a new international airport terminal in Cebu, the Philippines. The following results are obtained. First, the opening of the new terminal significantly increases vehicle density in the Cebu built-up area. This effect is greatest in the vicinity of the airport and attenuates with travel time from the airport. The treatment effects are larger in the tiles where hotels are located. Second, the effect of opening a new terminal is the largest during the peak months for international passengers at the MCIA. Indeed, there is a significant positive correlation between the treatment effect and spatial clustering of hotels during the peak months for international passengers. These results show that the opening of the new international terminal positively affects the economy of urban Cebu through increased traffic of international passengers staying within the area. According to our estimation results, the overall benefits reasonably exceed the initial construction costs within several years. These results also suggest that policy impacts have large spatial and seasonal heterogeneity. As such, our new data should be useful to capture the heterogeneity of the policy impact.

There is great demand for and advantages to using spatially and seasonally granular data to represent local economic activities. However, their availability is limited, particularly in developing countries. Hence, satellite images obtained multiple times throughout the year globally, even in developing countries, provide a means of meeting this demand gap. The data we propose augment the opportunity to undertake rigorous policy evaluations of large-scale infrastructure and other programs by providing a new measure of local economic activities, especially in developing countries.

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A Details on validation exercises of vehicle density data

We systematically compare and analyze vehicle density data with nightlight luminosity data, which are widely used as a proxy for economic activity and census data.

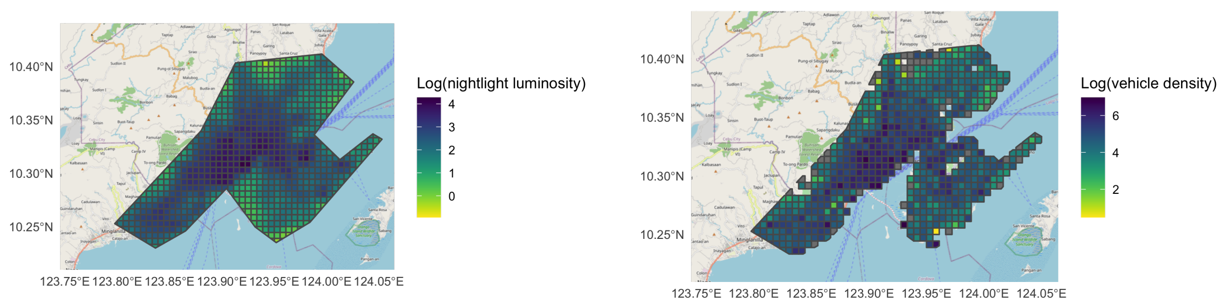
A.1 Comparison with nightlight luminosity

We use the VIIRS from the Earth Observation Group (EOG) website in 2017 for nightlight luminosity data, mapping them to match the 500 m $\times$ 500 m tiles of the vehicle count observation units.

In Figure A.1, panel A shows the map of nightlight luminosity intensity in 2017 and panel B the vehicle density for the same year. The intensity distributions in both datasets are highly correlated. In both figures, the areas surrounding CBD and the northwest of Mactan Island have higher luminosity and a greater density of vehicles.

Figure A.1: Nightlight luminosity vs. vehicle density

(A) Nightlight luminosity (B) Vehicle density



Note: The maps are based on OpenStreetMap.

Figure A.2 shows that the logs of the luminosity and vehicle density are positively correlated. The R-squared is 0.46.

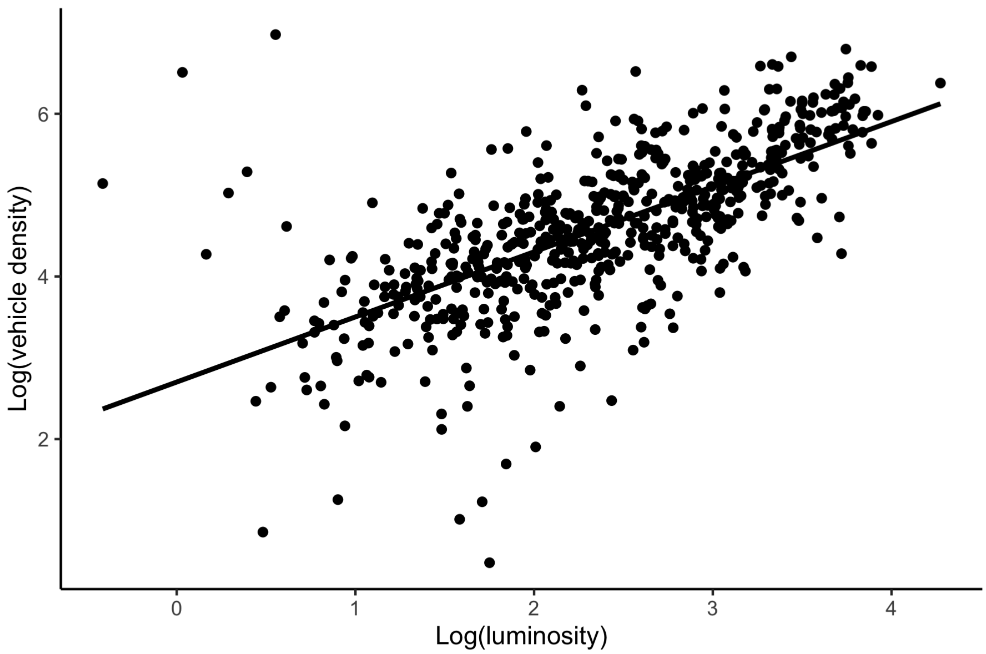
A.2 Comparison with cellphone-based human traffic data

We use aggregated CDR data from one of the largest phone service providers in the Philippines. The company processes the raw CDR data at the *barangay*-level origin and destination user flow data. We calculate the number of inflows of users from the origin and destination user-flow data in a *barangay* from 10 a.m. to the end of the day on January 15, 2020 (Wednesday) in Metro Cebu.

In Figure A.3, panel A shows cellphone-based human inflows and panel B vehicle density. The intensity distributions in both datasets were highly correlated. In both figures, the areas surrounding CBD and the center of Mactan Island have greater human inflows and vehicle density.

Figure A.4 shows that the log of cellphone-based human inflows and the vehicle density are positively correlated. The R-squared value is 0.36, which is smaller than that between nightlight luminosity and

Figure A.2: Correlation between luminosity and vehicle density

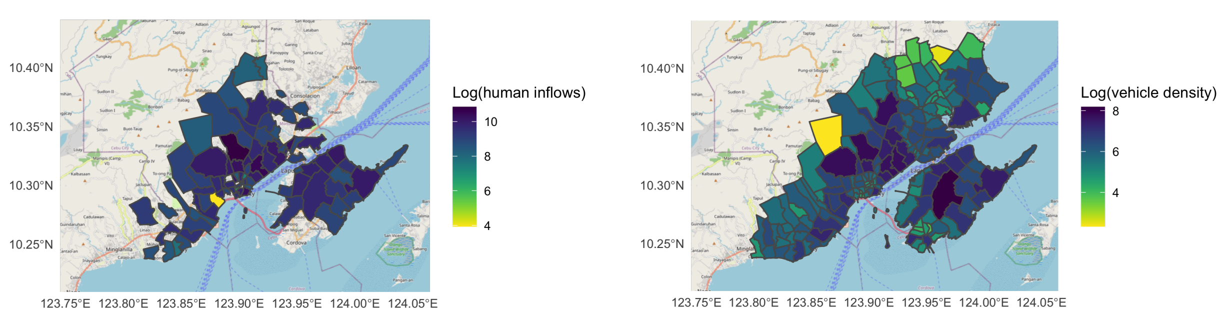


Notes: This figure shows the scatter plots of the log of vehicle density and log of nightlight luminosity in 2017. Each observation is at the tile level. The solid line shows the linear fitting curve.

Figure A.3: Cellphone-based human inflows vs. vehicle density

(A) Cellphone based human inflows

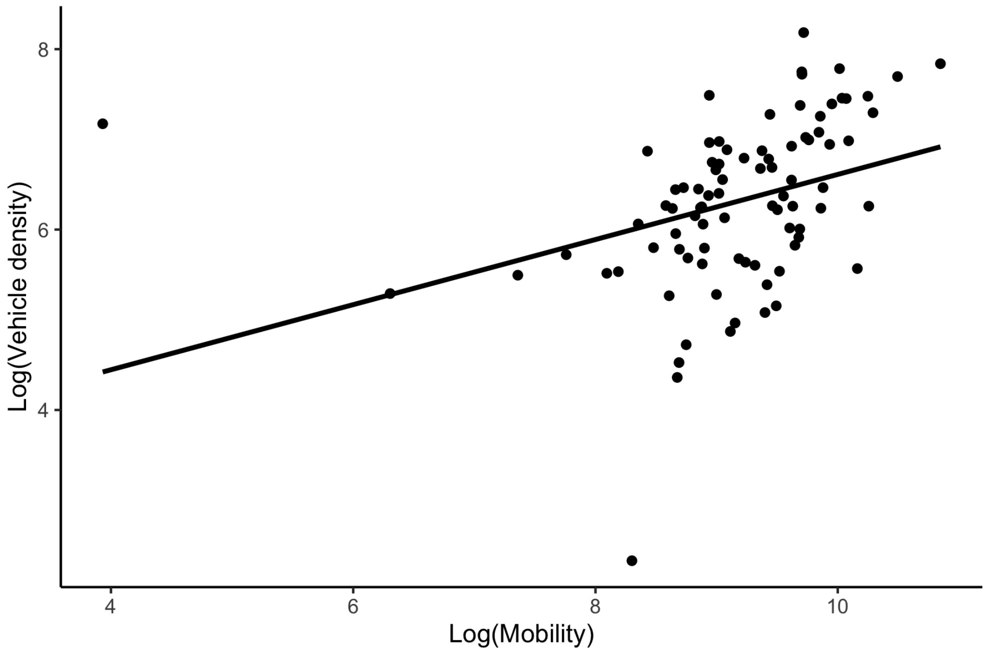
(B) Vehicle density



Note: The maps are based on OpenStreetMap. The observation unit is the barangay (village).

vehicle density because of the smaller number of observations and larger spatial aggregations.

Figure A.4: Correlation between cellphone-based human inflows and vehicle density



Notes: This figure shows the scatter plots of the logs of vehicle density in 2017 and of cellphone based human inflows on January 15, 2020. Each observation is at the tile level. The solid line shows the linear fitting curve.

A.3 Correlation with Census data

We conduct validation exercises on our data by testing their correlation with government statistics. The Philippine Census of Population and Housing provides information on the population in 2015 and the number of establishments in the commercial and accommodation sectors in 2010. Unfortunately, the finest geographic scale of government statistics is the *barangay* level; therefore, we aggregate the tile-level information of vehicle density and nightlight luminosity data into *barangays*.

Table A.1 illustrates the correlation with population size. Column 1 shows the correlation with the log of nightlight luminosity, column 2 the correlation with the log of vehicle density, and column 3 the correlation with the log of human inflows. Nightlight luminosity and vehicle density data positively correlate with the population, implying that both measures predict the population level well. However, human inflows show a positive but not significant correlation. This suggests that vehicle density proxies the local population as well as nightlight luminosity.

In Table A.2, nightlight luminosity and vehicle density are positively correlated with the number of establishments in the commercial sector. The size of the coefficient and pseudo R^2 are similar for Columns (1) and (2). Vehicle density proxies local commercial economic activities and nightlight luminosity.

Similar to the results for the commercial sector, Table A.3 shows that nightlight luminosity and vehicle density data are positively correlated with the number of establishments. Human inflows are also positively

Table A.1: Correlation with census data (population)

Dependent Variable:	Population		
Model:	(1)	(2)	(3)
Variables			
Log(Vehicle density)	0.526***		
	(0.050)		
Log(Luminosity)		0.551***	
		(0.050)	
Log(Human inflow)			0.193
			(0.219)
Fit statistics			
Pseudo R^2	0.51440	0.57749	0.05318
Observations	164	164	87

Notes: This table shows the OLS estimates of the relationship between population density and local economic indicators. Each observation is at the barangay (village) level. The dependent variable is the population density. The regressors are the log of vehicle density, log of nightlight luminosity, and log of cellphone based human inflows. Heteroskedasticity-robust standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.2: Correlation with census data (commerce)

Dependent Variable:	Number of establishments (commerce)		
Model:	(1)	(2)	(3)
Variables			
Log(Vehicle density)	0.274***		
	(0.079)		
Log(Luminosity)		0.296***	
		(0.069)	
Log(Human inflow)			0.166
			(0.170)
Fit statistics			
Pseudo R^2	0.03925	0.05042	0.01032
Observations	164	164	87

Notes: This table shows the OLS estimates of the relationship between the number of establishments in the commerce sector and local economic indicators. Each observation is at the barangay (village) level. The dependent variable is the number of establishments in commerce sector. The regressors are the log of vehicle density, log of nightlight luminosity, and log of cellphone based human inflows. Heteroskedasticity-robust standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

correlated with the number of establishments in the accommodation sector. Pseudo R^2 is the highest in Column (1). Therefore, in the accommodation sector, vehicle density is the strongest predictor of local activity.

Table A.3: Correlation with census data (accommodations)

Dependent Variable:	Number of establishments (accommodations)		
Model:	(1)	(2)	(3)
Variables			
Log(Vehicle density)	0.803^{***}		
	(0.167)		
Log(Luminosity)		0.550^{***}	
		(0.182)	
Log(Human inflow)			0.951^{***}
			(0.176)
Fit statistics			
Pseudo R^2	0.18967	0.09800	0.15057
Observations	164	164	87

Notes: This table shows the OLS estimates of the relationship between the number of establishments in the accommodation sector and local economic indicators. Each observation is at the barangay (village) level. The dependent variable is the number of establishments in the accommodation sector. The regressors are the log of vehicle density, log of nightlight luminosity, and log of cellphone based human inflows. Heteroskedasticity-robust standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

B Impact evaluation exercise using luminosity data

B.1 Estimating the impact of the opening of the new terminal using nightlight luminosity data

It has been pointed out that nightlight luminosity data are less suitable for panel analysis in the short run (e.g., Gibson and Boe-Gibson, 2020; Chen and Nordhaus, 2019). To confirm this, we conduct DID analysis using nightlight luminosity data instead of vehicle density data. For this exercise, we collect annual VIIRS data in 2017 and 2019 and set 2019 as the post-treatment period. Similar to the main analysis, the tiles in Metro Cebu serve as the treatment group and those in Davao City serve as controls. The results are presented in Table B.1. Column (1) shows the baseline results for all samples. The estimated treatment effect is significantly negative. Consistent with the discussion in Gibson et al. (2021), the results suggest that nightlight luminosity data are not necessarily appropriate for comparing economic activities across periods.

C Land use patterns in Cebu and Davao Metro

On average, vehicle density is lower in urban Cebu as a treatment group than in Davao, which serves as a control. One possible reason is that the study coverage area for Cebu includes Mactan Island, which has large resort areas and a relatively high percentage of non-developed land. To analyze this difference in more detail, we investigate the land use pattern using the Normalized Difference Vegetation Index (NDVI)

Table B.1: Results of DID using luminosity data

Dependent Variable:	Log(Luminosity)		
Sample	ALL	Hotel zone	Non hotel zone
Model:	(1)	(2)	(3)
Variables			
Cebu × After Opening New Terminal	-0.289***	-0.338***	-0.281***
	(0.047)	(0.048)	(0.051)
Fixed-effects			
Tile	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Adjusted R^2	0.97092	0.96351	0.96630
Observations	2,310	324	1,986

Notes: This table shows the PPML estimates of the DID analysis using nightlight luminosity as the outcome variable. Each observation is at the tile-year level. The dependent variable is nightlight luminosity. The regressor is the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy. Year and tile fixed effects are included. Spatial HAC standard errors allowing 2-km correlations are in the parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table C.1: Land use in Cebu and Davao coverage areas

Area	Buildings		Forest		Grassland & Agricultural use		Roads	
	2014	2019	2014	2019	2014	2019	2014	2019
Cebu	13.0	14.7	49.7	51.5	26.8	22.6	10.6	11.3
Davao	18.6	20.0	50.5	47.8	16.3	15.3	14.6	17.0

Note: Land use data are provided by Orbital Insight. Data on Cebu are for 2015 due to data coverage limitations.

created from satellite images.

Table C.1 summarizes the land-use patterns of the research areas in Cebu and Davao in 2014 and 2019. Buildings and forests have roughly similar land use shares in the two areas, whereas roads have a higher share in Metro Davao. Meanwhile, Cebu has a larger share of grassland and agricultural areas. This suggests that, on average, Cebu had a smaller share of developed land in the research area.

D Robustness checks

D.1 Including additional control group

Here, we expand the control group to include the tiles surrounding Clark Airport.

Table D.1 presents the descriptive statistics. The areas surrounding Clark Airport have a denser vehicle density than Cebu Metro on average.

Table D.2 presents the DID results. The impact of opening the new terminal was smaller than that in the baseline results. However, the positive impact of the new terminal opening is robust to the expansion of the control group.

Table D.1: Summary statistics of vehicle density in 2017 (including areas surrounding Clark airport)

Year	Mean	SD	Min	Median	Max	No. obs
Cebu Metro	137.62	144.55	0.00	92.54	1068.06	666
Clark	178.38	233.08	0.00	93.16	1796.61	353
Davao Metro	450.58	457.42	0.00	273.14	2008.93	271

Note: Vehicle density is the number of vehicles divided by the area (unit: km^2) of road provided by Orbital Insights. The vehicle density data are available at each road type level and we pool all types of roads data to obtain summary statistics at the tile level.

Table D.2: Estimation results including the tiles surrounding Clark airport

Dependent Variable:	Car density			
Model:	(1)	(2)	(3)	(4)
	OLS	Poisson	OLS	Poisson
Variables				
Cebu × After Opening New Terminal	0.026	0.103***	0.009	0.067*
	(0.043)	(0.035)	(0.042)	(0.038)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes
Month			Yes	Yes
Fit statistics				
Adjusted R^2	0.58376		0.58962	
Pseudo R^2	0.27071	0.57159	0.27506	0.57695
Observations	101,628	126,798	101,628	126,798

Notes: This table shows the OLS (columns 1 and 3) and PPML (columns 2 and 4) estimates of the DID analysis including tiles surrounding Clark airport as an additional control group. Each observation is at the road-tile-time level. The dependent variable is vehicle density. The regressor is the interaction term between the Cebu dummy and after opening new terminal at MCIA dummy. Year, tile, and road fixed effects are included in columns 1 and 2 and year, tile, road, and month fixed effects are included in columns 3 and 4. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

D.2 Using the Number of Vehicles as the Outcome Variable

We conducte a DID analysis using the number of vehicles as the outcome variable instead of density. The results are listed in Table D.3 and are qualitatively similar and robust to when the number of vehicles is used instead of the density of vehicles.

Table D.3: Estimation results including the tiles surrounding Clark airport

Dependent Variable:	Number of Vehicles			
Model:	(1)	(2)	(3)	(4)
	OLS	Poisson	OLS	Poisson
Variables				
Cebu $\times$ After Opening New Terminal	0.095**	0.141***	0.080*	0.101**
	(0.039)	(0.035)	(0.042)	(0.040)
Fixed-effects				
Year	Yes	Yes	Yes	Yes
Tile	Yes	Yes	Yes	Yes
Road Type	Yes	Yes	Yes	Yes
Month			Yes	Yes
Fit statistics				
Adjusted R^2	0.52614		0.53310	
Pseudo R^2	0.22835	0.53657	0.23285	0.54549
Observations	73,410	86,872	73,410	86,872

Notes: This table shows the OLS (columns 1 and 3) and PPML (columns 2 and 4) estimates of the DID analysis. Each observation is at the road-tile-time level. The dependent variables are the number of vehicles. The regressor is the interaction term between the Cebu dummy and after opening the new terminal at MCIA dummy. Year, tile, and road fixed effects are included in columns 1 and 2 and year, tile, road, and month fixed effects are included in columns 3 and 4. Spatial HAC standard errors allowing 2-km correlations are between parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.