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APPLYING VERY HIGH RESOLUTION SATELLITE IMAGERY IN NOWCASTING[1]

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Abstract This paper explores the application of very high-resolution (VHR) satellite imagery for economic nowcasting. VHR optical satellite imagery is globally available in near real-time, offering a valuable alternative data source for regions with limited conventional data, especially those affected by crises. By analyzing changes in vehicle numbers, my findings accurately reflect the shifts in Kyiv's economic activity immediately following the full-scale russian invasion. This observed change was primarily by population displacement.

JEL Codes C82, O11, E01

Keywords nowcasting GDP, alternative data, satellite imagery, very high resolution, wartime economics

1. INTRODUCTION

Russia's imperial ambitions in Ukraine have materialized into tangible actions, beginning with the annexation of Crimea, escalating into the war in the Donbas, and culminating in the full-scale invasion since February 2022. As a result, Ukraine faces an existential threat.[2] To maintain its functionality, the Ukrainian state is not only grappling with the loss of access to parts of its territory but also facing significant challenges in monitoring its economy (Constantinescu et al., 2024). A functioning economy, even with aid from international partners, forms the bedrock for all expenditures necessary for Ukraine's defense. Therefore, economic monitoring is crucial for preserving order and the state's monopoly on violence (Weber, 1922). When existing methods prove insufficient, new approaches are essential.

Constantinescu et al. (2024) addressed the challenge of economic monitoring by utilizing data from nightlights, social media and internet searches – the most useful data available at the time. However, war-related disruptions were not the sole complication for data collection. For instance, Twitter (now named X), one of their data sources, subsequently became unavailable for public use.

To expand upon their work, I leverage VHR optical satellite imagery combined with machine learning algorithms for vehicle detection. The counts of detected vehicles serve as a proxy for economic activity. This method introduces a novel approach to data collection for nowcasting, utilizing an alternative data source. To my knowledge, this specific method has not been previously employed. The increasing availability of optical satellite imagery, with the potential for multiple daily coverage of any global location, offers immense potential for deriving economic measures, and will undoubtedly play a growing role in future research.

While my specific approach is new, it connects with and builds upon established methods. The field of GDP nowcasting emerged to overcome the challenges of timely data collection for National Accounts. The fields aims to exploit correlates of economic activity that are available at shorter intervals, thereby providing more timely estimates of economic development (Giannone et al., 2008; Landefeld et al., 2008; Bok et al., 2018;

[1] The author thanks Professor Kalle Kappner and one anonymous referee for the academic supervision of this paper.
[2] https://understandingwar.org/ backgrounder/ukraine-conflict-updates

Proietti et al., 2021; Cimadomo et al., 2022). However, this often requires extensive datasets. Given that timely estimates are particularly crucial during crises, researchers have applied nowcasting in various crisis contexts, such as the Syrian civil war or the economic crisis following the COVID-19 pandemic (Chetty et al., 2023; Qadir et al., 2016; Constantinescu et al., 2024; Stokes and Román, 2022; Li and Li, 2014; Schippers and Botzen, 2023).

Commonly used correlates of economic activity include mobility and traffic data. Often derived from mobile phone data, other sources like toll stations or ship tracking can also be utilized (Askitas and Zimmermann, 2013; Pappalardo et al., 2016; Chetty et al., 2023; Węcel et al., 2024). Beyond nowcasting, the relationship between road, rail, and other means of mobility and economic activity has been investigated (Iacono and Levinson, 2016; Gaudry and Fridstrøm, 2023; Zheng and Kahn, 2013).

To address unreliable or unavailable data, researchers frequently turn to the intensity of nightlights. This data source is particularly useful in developing countries or undemocratic states with unreliable statistical services (Martínez, 2022; Nordhaus and Chen, 2015; Henderson et al., 2011; Michalopoulos and Papaioannou, 2014; Gibson et al. 2021).

By exploiting VHR optical satellite imagery, I have developed a novel method for measuring economic activity. This alternative data source has not yet been utilized in the field of nowcasting. The existing literature already describes the relationship between economic activity and vehicle counts. My results align with the findings of Constantinescu et al. (2024) for Kyiv, Ukraine. Specifically, I estimate that at the end of March 2022, economic activity in Kyiv was approximately 60% of its pre-invasion level. Following the russian retreat from the north of Kyiv, economic activity quickly recovered to pre-war levels. This suggests a faster and steeper recovery in Kyiv compared to the rest of the country, though reliable regional data for confirmation is lacking. Therefore, despite the limited amount of data, I argue that this demonstrates the fundamental suitability of the method. These findings are also robust against different scenarios concerning the elasticity of rising fuel prices.

However, despite the alignment of results with expectations, this method requires validation against reliable statistics. Therefore additional data from other regions with accurate measures of regional or local economic activity is needed. Moreover, the specific relationship of cars and trucks with economic activity should be further explored, as they likely represent different types of economic activities and reflect different sectors, potentially introducing bias when treated equally. The distinction between parked and moving cars did not significantly alter the results. While this distinction is not critical in the contexts of rapid population changes, it could significantly affect results in other scenarios, such as changes in economic activity due to COVID-19. The detailed relationship of vehicles counts as proxy for traffic (parts of which are economic in nature) and population remains unclear. This includes the measurement of both levels and growth rates. These relationships, similar to the ongoing debate in the nightlights literature, require further investigation, which is a promising area for future research.

The paper is organized as follows. Section 2 provides background on GDP nowcasting, the use of nightlights and mobility data as proxies for economic activity, and the effects of war-induced structural breaks in an economy. Section 3 describes the data sources used. Section 4 details the economic modelling, followed by the results in Section 5. Section 6 offers a discussion of the findings and methods, and Section 7 contains the conclusions of the paper.

2. BACKGROUND

2.1. Nowcasting GDP

Since the dawn of economic statistics, institutions and researchers consistently sought more timely and reliable data, especially during crises. While the focus a century ago was on the reliability and precision of statistics, the advent of national accounts shifted interest towards producing accurate estimates more quickly[3] (Landefeld et al., 2008). This shift led to the emergence of GDP nowcasting, a field dedicated to estimating current economic development in the shortest possible timeframe. It achieves this by utilizing correlates and alternative measures of economic activity (Giannone et al., 2008). These measures can encompass various data source, including government statistics, surveys, transport figures, consumer behavior data, and broadly, any information linked to economic activity (Bok et al., 2018; Proietti et al., 2021; Chetty et al., 2023; Beck et al., 2023).

[3] For an exemplary overview of delay times of revised statistics see Table B.1 of Proietti, Giovannelli, et al. (2021).

Methodologically, nowcasting employs predictive models such as field equations and dynamic factor models (Cascaldi-Garcia et al., 2023). Researchers also use Vector Autoregression (VAR) to handle the complexity and frequency of data (Cimadomo et al., 2022).

However, crises or wars often introduce breaks in data collection, necessitating different approaches (Constantinescu et al., 2024; Qadir et al., 2016). While modern technologies offer new opportunities, they also present unforeseen challenges. These can include the shutdown of data collection due to security concerns, personnel shortages, or the breakdown or sabotage of communication and electricity infrastructure. In such data-scarce situations, high-dimensional models are not feasible. Researchers must instead rely on available data to obtain the most accurate measures possible. Even in a low-dimensional setting, combining individual measures significantly benefits estimation accuracy (Armstrong, 2001; Bec and Mogliani, 2015).

2.2. Alternative Data

Nigntlights

Nightlight Intensity (NLI) or Nighttime Lights (NTL), is a widely used, open-access global estimate of economic activity. Two primary data sources for nightlights are available: the U.S. Air Force Defense Meteorological Satellite Program (DMSP) and NASA's Black Marble nighttime lights product suite, which utilizes the Visible Infrared Imaging Radiometer Suite (VIIRS) (Chen and Nordhaus, 2019; Román et al., 2018). While nightlights do not equally represent all sectors of GDP, economists commonly use them, especially in regions with insufficient traditional statistics (Martínez, 2022; Nordhaus and Chen, 2015; Henderson et al., 2011; Gibson et al., 2021; Michalopoulos and Papaioannou, 2014).

In crisis regions, nightlights are not only used to directly infer economic activity but also to assess changes in population or land use resulting from conflict (Eun and Skakun, 2022; Li and Li, 2014; Jiang et al., 2017; Wang and Li, 2024). A notable advantage of nightlights is their ability to capture a broad range of economic activity, making them a useful proxy for overall economic development (Phan, 2023). However, the stability of the relationship between nightlights and GDP varies with spatial resolution and whether one is measuring GDP growth rates or levels. In smaller geographic entities, the relationship between growth rates and nightlights weakens compared to cross-sections of countries, whereas the relationship between GDP levels and nightlights strengthens (Constantinescu et al., 2024, Schippers and Botzen, 2023). Generally, this relationship is more robust in urban areas with a higher density of economic activity than in rural areas (Bickenbach et al., 2016). Additionally the specific economic sectors present in the area of interest influence accuracy (Phan, 2023). The primary source of error stems from the unequal distribution of light emission across different economic sectors. During wartime, additional uncertainties arise from factors such as fires, power outages, curfews and deliberate light shutdown (Constantinescu et al., 2024).

Given that nightlights are a well-established proxy for economic activity in data-scarce regions, I will use them extensively when discussing my results.

Mobility

Beyond nightlights, mobility data is widely used as predictor of economic activity (Qadir et al., 2016; Pappalardo et al., 2016; Li et al., 2020; Stokes and Román, 2022). Mobility can be measured in various forms, including motorway traffic flows, mobile phone data, and toll data (Askitas and Zimmermann, 2013; Proietti et al., 2021). The relationship between economic activity and traffic depends on GDP levels and urban density and evolves over time (Li et al., 2020; Matsumura et al., 2024; Gaudry and Fridstrøm, 2023). In addition to road traffic, maritime traffic is also used to measure variations in economic activity (Węcel et al., 2024).

It is essential to distinguish between two types of mobility. First, the mobility of individuals, often measured with mobile phone data, reflects personal activities related to consumption and labor supply. Second, measuring means of transportation, such as trucks or maritime traffic, correlates more closely with industrial production, for example.

During crises, the focus of measurement can shift from estimating precise economic activity to simply tracking general activity or estimating population changes in a given area. We saw this as seen during the COVID-19 pandemic and the Syrian civil war (Stokes and Román, 2022; Li and Li, 2014). This shift occurs due to structural breaks in the economy and altered individual behaviors during crises. This topic will be discussed further in the next chapter.

Satellite Imagery in Economics

While the use of satellite imagery in economics is not new, it remains less commonly applied beyond nightlights (Donaldson and Storeygard, 2016). Notably, though not previously mentioned in this paper, the Pléiades 1A and 1B satellites, with their 50cm resolution, were laun ched as early as 2012. Until now, the application of satellite imagery (excluding nightlights) has primarily focused on estimating land cover changes, mapping poverty, and assessing agricultural output (Lehnert et al., 2023; Sarmadi et al., 2024; Burke et al., 2021; Wüpper et al., 2024). However, nascent research is beginning to explore the use of satellite imagery to estimate broader economic activity (Engstrom et al., 2022; Goldblatt et al., 2020), and technical descriptions highlight potential challenges when using this data source in economic contexts (Jain, 2020). To my knowledge, satellite imagery beyond nightlights has not yet been employed for nowcasting purposes.

With an increasing volume of very high-resolution imagery becoming available, coupled with their worldwide coverage and near real-time availability, these images offer significant potential for expanded use in the field.

2.3. Economy during Wartime – How does War Affect the Economy?

Structural Breaks

To comprehend the shifts in Ukraine's economic output and the limitations of the measurements used, we must first understand the fundamental changes within an economy during wartime. While the term "war economics" is used across several fields of study within economics, it is most commonly associated with game-theoretic models of conflict (Kimbrough et al., 2020; Brauer, 2017). Furthermore, the long-term impacts of wars and destruction have been studied (Schumann, 2014; Singhal, 2019; Brakman et al., 2004).

From a macroeconomic perspective, war can be interpreted as a shock or multi-shock, as it disrupts various aspects of economic activity, including labor demand and supply, economic geography, and the prices of raw materials and goods (Nordhaus, 2002; Gorodnichenko et al., 2024; Liadze et al., 2023; Borko et al., 2022; Bachmann et al., 2022). This paper adopts a more short-run perspective on these impacts, highlighting key changes that must be considered to validate the measurements employed.

Generally, supply-side restrictions lead to inflationary pressure, a phenomenon recognized as far back as the First World War and the Second World War (Pethick-Lawrence, 1915; Pigou, 1940). The same holds true for Ukraine, where the State Statistic Service of Ukraine (SSSU) reported an inflation rate of 26.6% for 2022 and 5.1% for 2023.[4] Additionally, the destruction of physical capital, particularly energy infrastructure, forcibly alters the economy's productivity potential (KSE, 2024).

Human resources constitute another crucial part of the economy. Structural breaks caused by people fleeing an area can significantly disturb and shape economic development (Schumann, 2014; Testa, 2021). Ukraine has experienced internal displacement not only since the full-scale invasion but also starting from 2014 (Mykhnenko et al., 2022). The World Bank estimates that following the full-scale invasion, the Ukrainian population shrank from roughly 44 million people to 38 million people in 2023.[5] I lack more specific regional and monthly data, and the estimation itself does not clarify which territories are considered. This is relevant given that large parts of Ukraine are currently occupied by russian forces. Furthermore, this broad estimation misses more short-lived and regional population changes such as those observed during the Battle of Kyiv. Therefore, although the countrywide change after one year is drastic, it conceals important regional and temporal fluctuations, which I will critically discuss.

Beyond displaced people, human resources are also affected by large-scale conscription and call-ups from reserves, which prevent individuals from not pursuing their normal economic activity.

Implications for Measurements

War profoundly disrupts many activities and our statistical measurements of them. It can shift the geographic location of economic activity itself and the recorded statistical location due to people working remotely or being called up from reserves. This also affects light emissions and their geographic distribution. Additionally, people react to changed incentives and objectives. For instance, on the russian side, competitive wages were used to primarily recruit poorer individuals from rural areas into the army. This disparity

[4] SSSU. Consumer Price Indices 1992–2023 (to December of previous year). Last accessed: 2024-09-05. URL: https://www.ukrstat.gov.ua/operativ/operativ2020/ct/isc_rik/isc1992-2020gr_pr.xls
[5] https://data.worldbank.org/indicator/SP.POP.TOTL?locations=UA

between civilian and military wages can be leveraged to estimate regional mobilization differences within russia (Solanko, 2024).

Compounding these issues is the matter of foreign military and financial aid. From January 2022 to June 2024, the Ukraine Support Tracker by ifw Kiel recorded U.S. $218.5 billion in foreign financial and military aid to Ukraine (Trebesch et al., 2024). This amount in nearly equivalent to Ukraine's GDP during that period. This influx further alters objectives and incentives; for example, military equipment requires logistical support, and monetary aid enables the state to finance additional spending.

3. DATA

3.1. Satellite Imagery

My analysis utilizes optical remote sensing imagery captured over a specific area of Kyiv.[6] Specifically, I used data from the Pléiades Neo, Pléiades 1A and Pléiades 1B satellites, operated by Airbus Space and Defence. The imagery was delivered as pan sharpened color images with four bands: the first three representing visible spectrum colors red, green and blue (RGB), and the fourth serving as an alpha or near-infrared (NIR) band. In this context, the fourth band indicates image transparency, reporting distortions such as cloud cover. All images selected for this study had zero cloud coverage or other distortions in the fourth channel, allowing us to disregard this factor, which would otherwise reduce image usability.

Pléiades Neo has a resolution of 30 cm per pixel, while the 1A and 1B satellites offer 50 cm resolution.[7] Consequently, a car, depending on its size, appears as approximately 10 to 20 pixels in length and 4 to 7 pixels in width in the Pléiades Neo data, and between 6 to 12 pixels in length and 3 to 4 pixels in the Pléiades 1A and 1B data.[8] These resolutions are generally lower than those of standard datasets used for car detection such as COWC, DLR-MVDA, KIT AIS, and half of the VEDAI dataset (Mundhenk et al. 2016; Liu and Mattyus, 2015; Schmidt, 2012; Razakarivony and Jurie, 2016). While the DOTA1 dataset employs multiple scales (Xia et al., 2018), even the best resolution available for this paper could not match that of some commonly used training datasets, e.g. by Stuparu et al. (2020).

For object detection, I selected the one-shot, real-time classifier YOLOv11.[9] This algorithm demonstrates strong performance on the DOTA1 dataset in its publicly available standard version. Due to the differences in resolution across satellites, I created an annotated dataset sample and trained a separate algorithm for each satellite. This resulted in three distinct models used for vehicle detection. The standard classification initially included “small” and “large” vehicles, which prevented distinguishing between trucks and public transport (buses and trams). To address this, I created new classes for cars and trucks, along with other vehicles types not used in this study but necessary for accurate distinction.

Another challenge compared to the aforementioned datasets is the Off-Nadir angle, which is the angle between the orthogonal line from the satellite to Earth and the direct line from the satellite to the image area (Manakos, 2003). This angle causes vehicles to appear with slightly altered shapes and contours, potentially reducing algorithm accuracy. Furthermore, in cities with multi-storage buildings, a considerable portion of parking lots and streets can be obscured by these structures, leading to undetected vehicles. Following from the formula:

$$Hidden\ length = \frac{Building\ height}{tan(90 - Off{-}Nadir)}, \quad (1)$$

one can see that a 20 m high point hides approximately 8.06m of ground at the highest Off-Nadir value of 21.94°, compared to only 1.75 m at the lowest value of 5.01°.[10] The Off-Nadir angle also contributes to measurement error in nightlights, as light emissions shine more indirectly into the sensing satellite (Abrahams et al., 2018).

The elevation of the sun, determined by the time of day and year when an image is acquired, also cannot be neglected. While shadows cast by multi-story buildings at low sun elevations do not inherently hide objects, they significantly reduce the accuracy of detection algorithms, a commonly discussed problem in computer vision (Liu et al., 2021). Using standard pre-trained

[6] I have to thank Kongsberg Satellite Services (KSAT) and especially Charlotte Bishop and Hennes Henniger for providing me the imagery and enabling me to choose this topic.

[7] https://earth.esa.int/eogateway/catalog/pleiades-neo-full-archive-and-tasking

[8] This based on the range of size from Redaktions Netzwerk Deutschland. Datenanalyse: Autos werden nicht erst seit dem SUV-Boom größer. Last accessed: 202407-12. https://www.rnd.de/wirtschaft/datenanalyse-autoswerdennichterstseitdemsuvboomgrosser-6GTM66RRNJEC7EYHR3FQS7Y24Y.html

[9] Ultralytics YOLO11 https://github.com/ultralytics/ultralytics

[10] The exact hidden area depends on the direction of the Off-Nadir as well as the direction and height of the buildings.

models would introduce due to a lower probability of detecting objects within shadowed areas. However, by training my models on a dataset with a mix of shadowed and non-shadowed cars, I achieved similar accuracy values across the images from the different satellites. In a previous version, using a pre-trained version of a YOLO v8 OBB model, I observed differences of up to 20 percentage points primarily due to varying shadow casting.

Table 1 presents the available imagery information. The data arrived as TIFF files with four layers. In addition to the RGB (red, green, blue) layers, the alpha channel was reported but consisted only of zeros and was thus not considered further. The original 12-bit integer values were then scaled to 8-bit integers, reducing the range from 4,095 to 255. Conversion was necessary due to technical limitations and was performed manually using code by first applying a square root transformation and then rescaling contrast were raised, which improved the utility of the results.

Further refinement of this processing remains an area for future research. After processing, the images were split into batches of 640x640 pixels, as this is recommended and is the default value for the used algorithm.[11] Attempts to use 800x800 pixels batches resulted in lower accuracy. Finally, each detected object was categorized based on whether it was located within the intersection area of all images or not. This intersection area is shown in Figure 1, while the full spatial extent of all images is presented in Figure 6 in the Appendix. For the subsequent analysis, only observations within the intersection area were considered, as no further information on population or activity density, usage type, etc., was available to ensure the compatibility of observations outside this common region.

The specific algorithm used is YOLOv11n from Ultralytics. The YOLO (You Only Look Once) algorithm is a single-stage object detector based on deep learning methods (Diwan et al., 2023). It is provided as a pre-trained model in various versions, with the n-version being the smallest and fastest model, and x the largest and slowest. Both performed similarly in tests on my data, so I chose the n-version due to its significantly quicker inference time and reduced computational resource requirements.[12] The model is pre-trained on COCO, a widely used training dataset for object detection, segmentation and captioning. For aerial images, the Oriented Bounding Box or OBB variant of the model could also be used, as I explored in a previous version.[13] This variant is trained on the DOTA1 dataset, designed for aerial imagery.

However, implementing this would have entailed considerable extra effort with the annotated dataset and is therefore beyond the scope of this paper. For each trained model, I used the confidence level corresponding to the highest F1 value score observed during dataset validation and applied it during the detection process. The recall and precision values are also derived from this confidence level, representing the observed values from the annotated data.

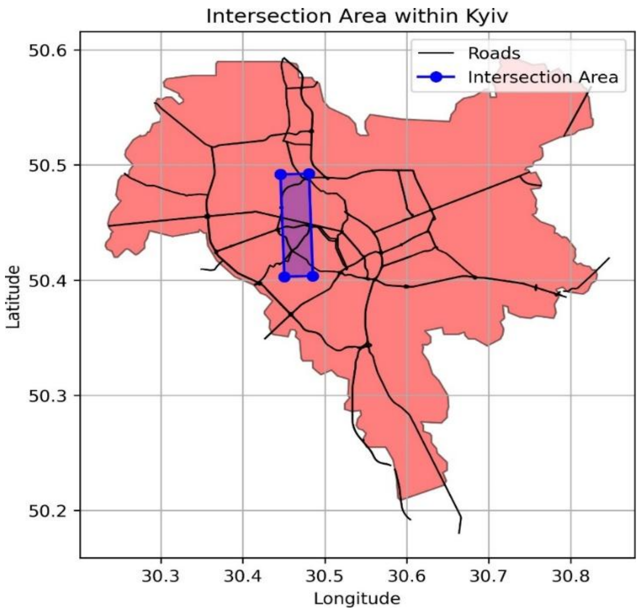

Figure 1. Intersection Area

From the corner coordinates of each detected object (provided as positions within the array) I translated their positions in the 640x640 pixel batches to the position in the full image. Next, I used the metadata provided with the satellite imagery to translate their corresponding position in the image to geographical coordinates. The Pléiades Neo satellites have a location accuracy of 3.5m CE90, while the Pléiades 1A and Pléiades 1B have an accuracy of 3 m CE90. CE90 (circular error at the 90th percentile) indicates that at least 90 percent of the measured points have a combined error in latitude and longitude less than the stated CE90 value (Digital Globe, 2016). This method allowed for precise and accurate detection of vehicles

[11] See for example the documentation for the YOLO algorithm.
[12] See the documentation of YOLO v11: https://docs.ultralytics.com/de/models/yolo11/.
[13] This means that instead of providing square boxes, this model returns boxes that match the shape of the object. See the description of Oriented Bounding Boxes: https://docs.ultralytics.com/datasets/obb/.

and their positions. Table 2 presents the number of counted vehicles. Figure 2 shows an exemplary image of Sevastopolska Square with detected cars and trucks.

Following vehicle detection, I calculated the shortest distance from each detected vehicle to the nearest road, using the Open Street Map dataset of Ukraine for road coordinates. As a single road lane is represented by a line without any width, I considered any vehicle within a 5-meter range as "moving" and beyond this range as "parked." While this is an imperfect measure, as it cannot definitively distinguish between cars parked at the roadside from moving cars, it provides an approximation that should reflect changes in traffic flow over time. I assume that the ratio of cars parked on the roadside and moving cars remains stable. The Figures 5a – 5f (Appendix A) show each detected vehicle plotted as a red dot onto a Kyiv roadmap.

3.2. GDP

As previously mentioned, the SSSU has published GDP values for both 2022 and 2023.[14] There reported values cover periods during which statistical collection was temporarily halted (Constantinescu et al., 2024), and are presented on a quarterly basis. However, regional values were not provided. The SSSU offered the following explanation in a footnote: "Information in full volume is to be released after the end of the period for the submission of statistical and financial reporting established by Ukraine's law on protection of interests of entities that submit reporting and other documents during the period of martial law or state of war".[15]

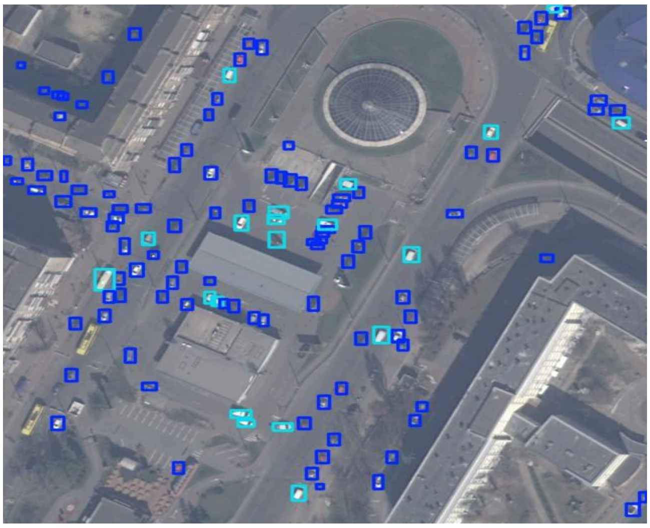

Figure 2. Example Image with Detected Vehicles

Notes: Example image with detected vehicles from Sevastopolska Square from 2022-04-15. Cars are in indicated in dark blue. Trucks (including Vans) are in light blue.

Table 1. Descriptives

Satellite	Resolution	Timestamp	Off-Nadir	Covered Area	Sun Elevation	Snow
PHR1B	50 cm/px	2019-12-06 09:00	15.39°	52.78 km^2	16.39°	-
PHR1A	50 cm/px	2022-02-04 09:16	10.29°	46.18 km^2	22.36°	✓
PNEO4	30 cm/px	2022-03-25 08:53	21.94°	31.81 km^2	38.57°	-
PNEO4	30 cm/px	2022-04-15 08:57	13.97°	26.02 km^2	46.95°	-
PHR1A	50 cm/px	2023-02-10 09:11	19.70°	52.78 km^2	23.89°	✓
PNEO4	30 cm/px	2023-09-28 09:08	5.01°	37.91 km^2	37.42°	-

Table 2. Recall, Precision and Counted Vehicles

Satellite	Timestamp	Annotated Data	Recall	Precision	Cars	Trucks	% Moving
PHR1B	2019-12-06 09:00, Friday	32/564	0.55/0.40	0.35/0.67	23,478/46,124	734/2,057	21.3/24.5
PHR1A	2022-02-04 09:16, Friday	48/462	0.50/0.61	0.51/0.60	17,549/31,931	603/1,246	20.3/21.9
PNEO4	2022-03-25 08:53, Friday	43/938	0.81/0.85	0.80/0.89	11,106/14,072	1,395/2,248	20.1/17.6
PNEO4	2022-04-15 08:57, Friday	35/642	0.87/0.78	0.82/0.85	19,175/19,569	2,200/2,290	19.9/15.7
PHR1A	2023-02-10 09:11, Friday	26/564	0.48/0.54	0.59/0.78	9,597/19,268	347/769	22.6/20.2
PNEO4	2023-09-28 09:08, Thursday	56/1,095	0.81/0.80	0.78/0.86	23,444/33,610	2,300/4,063	21.6/17.7

Notes: Annotated data is reported like annotated images / full dataset. Recall, Precision and % Moving are reported Cars / Trucks while Cars and Trucks columns are reported intersection area count / full image count.

[14] SSSU. Gross Domestic Product. Last accessed: 2024-09-05. https://www.ukrstat.gov.ua/operativ/operativ2022/vvp/vvp_kv/vvpf_23_ue.xls
[15] Found for example under the information available from this statistic for GDP in 2021: https://www.ukrstat.gov.ua/imf/arhiv/nr/nr_post_e.htm.

Consequently, unlike Constantinescu et al. (2024) in their Warcast Index, I do not have access to specific GDP data for Kyiv, nor is this data expected to become available in the foreseeable future.

4. MODEL

Given the limited number of data points, a regression or model framework such as that used by Constantinescu et al. (2024), is not feasible. As data is available for only one municipality, fixed effects models are not applicable. Furthermore, the limited data precludes a robust validations against official statistics. Therefore I apply corrections only to the observed raw vehicles using the procedure described below.

First, as can be seen in Table 2, the images exhibit significant variations in precision and recall both across different images and between car and truck detections within the same image. Consequently, the raw number of counted vehicles within the intersection area is corrected using their observed precision and recall values. Second, as previously discussed, vehicle usage is subject to elasticity of demand with respect to changing prices. Therefore corrections based on reported elasticity ranges will be applied, and these results will be presented in the robustness checks subsection in the discussion. This results in the following formula for the corrected number of vehicles:

$$C = \frac{\hat{C} * Prec}{Rec} (* \epsilon_d), \tag{2}$$

where $\hat{C}$ represents the raw number of counted vehicles in the inter-section area, $\boldsymbol{Prec}$ the respective precision, $\boldsymbol{Rec}$ the respective recall and ϵ_d the demand elasticity with regard to prices.

5. RESULTS

This chapter presents the study's results. As shown in Figure 3, all values are normalized to 2021. It is immediately apparent that the relative in car numbers in Kyiv following the full-scale russian invasion is more pronounced than the countrywide GDP contraction. Following the russian retreat from the area, car numbers suggest that Kyiv experienced a rapid recovery in economic activity, contrasting with the slower countrywide GDP recovery. This appears to corroborate the results of Constantinescu et al. (2024). The sharper decline in Kyiv could align with the established relationship between proximity to fighting and lower economic activity. Interestingly, by the end of 2023, the number of cars increased to levels much higher than those observed before the full-scale invasion.

Assuming a linear proportional relationship between GDP and vehicle counts, this trend could stem from several factors: First, the economic situation in Kyiv might have been more severely impacted than the rest of country. Second, the quarterly reported GDP numbers may conceal significant shorter-term variations that are captured by the satellite imagery. Another factor relates to the differing natures of what each metric captures: If people left Kyiv with their car but continued to work remotely, their economic output (added value) would still be attributed to Kyiv in GDP

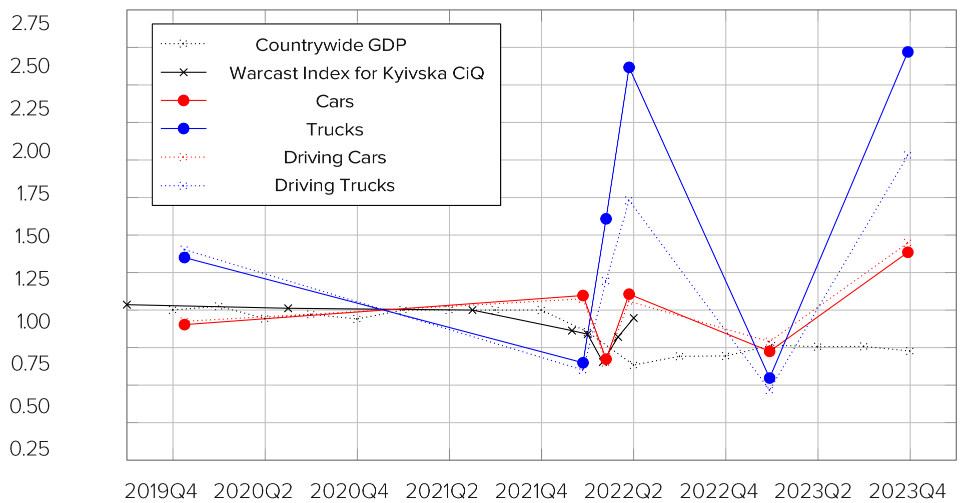

Figure 3. GDP, Detected Vehicles and Nightlights Values from Q4 2021 to Q4 2023
Notes: Vehicle data at the timepoints as described in Table 2. Values are normalized to 1 for 2021. For vehicle data, the average of the first two available values (December 2019 and February 2022) was normalized to 1.

statistics, whereas vehicle detection would not register their presence. While this distinction is less critical for countrywide GDP, it must be considered when future regional data becomes available.

Conversely, the number of trucks shows a strong increase after the full invasion. This is somewhat counterintuitive, as trucks are typically more directly linked to economic activity. This unexpected rise might reflect reports of a shift in oil logistics from pipelines and ports to road transport. Given that this represents a structural break in the relationship between truck activity and overall economic activity, it is unclear if this also reflects a general change in economic activity.

It is important to note the unusually low values for both cars and trucks on 02-10-2023. Since the ground was snow-covered, these low figures could reflect a bias from undetectable snow-covered vehicles. Simultaneously, they might also indicate a genuine downturn in economic activity. Compared to the values from 02-04-2022, when snow was also present, these figures appear anomalous.

6. DISCUSSION

6.1. Error Terms of Detected Vehicles and GDP

Error Terms of Detected Vehicles

The scarcity of available data is evident and limits the comprehensiveness of the results. Specifically, the data currently available do not sufficiently illuminate the effects of the structural breaks discussed in section 2.4 on wartime economic impacts. While the impact of structural breaks on nightlights is directly evident through curfews and energy infrastructure bombardments, the limited vehicle data only allows for speculative analysis regarding these effects.

The potential divergence in the spatial distribution between vehicle-related measurement points (gas stations, repair shops, and dealerships) and actual economic activity remains unaddressed. This is particularly relevant for Kyiv, which functions as a first-level administrative unit, with while its suburbs are counted in the surrounding Kyiv Region. While these suburbs are only a few kilometers from the image boundaries, as indicated by the red dotted line in Figure 1, the jurisdictional separation complicates direct comparisons. However, since only countrywide GDP data was available for this study, no economic activity was inadvertently excluded from the overall measurement due to municipal boundaries. For future research, however, these distinct jurisdictional boundaries remain an issue. The problem of insufficient government statistics for proxy validation was also highlighted by Nordhaus and Chen (2015), who noted a lack of robust validation for their nightlights measures in developing countries.

Furthermore, the suspected increase in remote work, particularly during the occupation period in Kyiv Region, could induce bias. In such scenarios, the activity measured by vehicles might be located differently from where the measured economic output and wages are statistically recorded.

Given that the level of vehicles per capita is related to the GDP per capita level (Li et al., 2020; Beyzatlar et al., 2014) it is plausible that this relationship in Kyiv differs significantly due to its distinct economic characteristics (Constantinescu et al., 2024). On one hand, a higher GDP level might suggest a greater share of vehicles per capita; on the other hand, the availability of public transport and the urban nature of the area of interest could offset this effect. Lacking statistics on regional car ownership levels, I can only speculate on this matter. Within the scope of this paper, the focus is solely on Kyiv. However, a richer dataset in future research could provide the opportunity to employ fixed effects models and cluster analysis. Critically, the validity of this method hinges on the assumption that, even amid profound economic disruption and a massive reduction in economic activity, the relationship between car ownership and the new economic levels would require time to adjust. Therefore, assuming a constant relationship in the short run appears reasonable and is vital for this method's validity. This also highlights the challenge of distinguishing between aggregated GDP and GDP per capita. Without proper statistics for this short time period, it is impossible to disentangle these two concepts; thus, economic output per capita must be assumed stable.

Extending the argument regarding the level of GDP and its relationship to car ownership, a similar dynamic might exist between individual income levels and the decision to flee the war. Indeed, the very option to flee by car could influence the decision to flee or stay. A survey of 1,003 Ukrainian adults provides initial evidence of the high socio-economic status refugees, with 60% reporting higher education compared to 29% in the overall Ukrainian workforce (Mykhailyshyna, 2023; Pulina et al., 2023).

For the relationship between vehicles and GDP, this suggests apotential risk that the average GDP represented by vehicle counts might decrease if high-income individuals disproportionately flee. This further compounds the changes resulting from the structural break after the full-scale invasion. In Kyiv, the situation is further complicated by its role as a destination for internally displaced persons (IDPs) fleeing from eastern and southern parts of Ukraine since 2014 (Mykhnenko et al., 2022; Hrabynskyi et al., 2022). Thus, in this context, the structural break stems not only from changes within the existing population but also from the influx of new IDPs. Closely related is the impact of martial law, which largely prohibits men between 18 and 60 from leaving the country. This introduces further disturbance, as the between economic objectives and available vehicles within households is disrupted on a mass scale. Additionally, gender differences in economic activity also influence this relationship.

Another structural break resulting from the war can arise from altered public transportation usage patterns or the different exposure of various public transport means to conflict and local availability. Since underground stations also served as shelters, individuals might have been inclined to switch to private cars. Moreover, metro stations are not uniformly distributed geographically, and some areas depend more heavily on trains, trams or buses. To my knowledge, data on the development and variation of public transportation volumes are unavailable, leaving this aspect largely unknown. Related to this are altered commuting times. Particularly after nightly air raid alerts, it is likely that people adjust their normal schedules due to sleep depravation. Commuting times could also have been affected by imposed curfews, influencing both sleeping schedules and work shifts in factories and offices. Investigation into these changes could involve crawling activity data to track their development (Parady et al., 2023). For this purpose, data from The Economist and Solstad (2023) could also serve as a useful proxy for fighting activities, specifically bombing campaigns and air raids. Data on air alerts and news mentions of explosions can also be obtained from specific online sources, as Air Alarms in UA[16], Ukrzen[17].

Economic activity fluctuates by season, day of the week, and hour of the day (Proietti and Pedregal, 2023). From the literature on high-frequency data, we know, for example, about electricity consumption patterns and their correlation with economic activity. (Do et al., 2016; Arshad and Beyer, 2023; Fezzi and Fanghella, 2021; Stundziene et al., 2023; Lehmann and Möhrle, 2024). A similar issue can be expected for vehicle data. As shown in Table 2, five of the six images were made on a Friday, and one on a Thursday. The available data is too scarce to draw definitive conclusions on biases introduced by this distribution, thus it remains an area for future research.

Error Terms of GDP

Beyond the error terms and structural breaks affecting vehicle and nightlights data, similar considerations apply to GDP measurement. Errors in GDP measurement, particularly those stemming from the informal economy, lead to biased estimates worldwide (Phan, 2023; Ghosh et al., 2010). Until recently, Ukraine was considered to have one of the highest rates of informal economic activity globally (Williams and Schneider, 2016; Ostapenko and Williams, 2016). Despite recent improvements, a considerable share of economic activity is presumably still informal (OECD, 2022; European Commission, 2023). Historically, wars and other crises have often spurred improvements in national statistical systems, serving as a means for the state to preserve its capacity to successfully maintain order (Weber, 1922). Kuznets's work on National Income provides a notable example (Kuznets, 1934). Indeed, the premise for this paper stems from the halt in existing official data collection by statistical offices until June/July 2022. While Constantinescu et al. (2024) combined alternative methods to circumvent this issue, this paper seeks to contribute by providing an additional approach. However, counter-intuitively, recent successes in combating the informal economy and improving or restoring statistical capacity may introduce a new challenge: they also represent a structural break in the measurement of the economic structure. Assuming overall economic activity remains stable, these improvements could lead to an overestimation of Ukraine's economic development, as more economic activity would now be captured in official statistics. Conversely, the chaos of the war might have increased the share of the informal

[16] https://air-alarms.in.ua/en
[17] https://alerts.in.ua/en

economy, making the overall effect on GDP measurement unclear.

Another concern regarding the reliability of GDP statistics pertains to the relationship between observed activity and officially measured economic activity, particularly in the light of the foreign aid flowing into the country. The magnitude of this aid was previously discussed in Section 2.4. For instance, donated weapon systems would be associated with the wages of the soldiers using them in GDP statistics, but not with the inherent value of the weapons themselves. Thus, the relationship between observed activity (e.g., within the logistical chain) and measured economic activity in GDP terms is likely to diverge from that in the private sector. This, too, constitutes a structural break, the impact of which remains speculative at this juncture.

Summarizing the discussion of error terms: The structural breaks resulting from the full-scale invasion affected all measures used in various, currently unknown, ways. For improved estimation results when combining correlates, it is preferable for the error terms to be uncorrelated. Thus far, error terms have been discussed in relation to curfews, commuting behavior and changes in public transportation, fires and power outages, geographic entities underlying public statistics, economic inequality, the informal equality, foreign aid, and overall GDP levels.

Correlation of Error Terms

While curfews are presumed to primarily affect nightlights negatively, their impact on vehicle activity, given that that satellite images are only taken in daylight, should be limited to possibly disturbed commuting schedules, probably in a positive direction (e.g., people rushing home before curfew). As these effects are presumably either uncorrelated or slightly negative correlated, combining these two methods should improve the estimation power with respect to curfew-related biases.

Changing patterns in commuting behavior and public transportation, when caused by curfews, typically occur outside the VIIRS satellite's measurement window. For changes unrelated to curfews, these patterns also do not affect nightlight measurements due to the differing times of data acquisition. Therefore, in this regard, the error terms are also uncorrelated, with vehicle data potentially being affected in an unknown direction and nightlights remaining unaffected.

Considering the effect of fires, bombings and power outages on nightlight measurement, as discussed previously, nightlights are likely heavily negatively disturbed by power outages and positively by fires. Without further data, the overall unknown direction of the combined effect remains unknown. The only certainty in this regard is that the error term increases, likely substantially. Specifically, fires misleadingly suggest economic activity in nightlights imagery, despite being purely destructive. Power outages, however, have an unknown impact on the relationship between economic activity and nightlights; it is unknown whether economic activity declines proportionally with electricity consumption (which would leave nightlight-economic activity relationship undisturbed) or disproportionately (which would lead to measurement errors in potentially both directions).

To infer the effect of fire, bombings and power outages on the relationship between economic activity and counted vehicles, one must examine bombing targets more closely. If infrastructure, such as roads or gas supply lines, is affected, vehicle usage will likely be negatively impacted. Reports of a shift to truck transport for gas supply, possibly causing the increasing observed truck numbers, could be a direct response to the bombardment of the energy infrastructure. The opposite effect could occur if power outages affect electrified public transportation, compelling people to switch to private cars. However, this is quite specific, and as it does not affect the core of the vehicle measurement itself, the associated error term is likely smaller compared to, for instance, nightlights.

The error term stemming from geographic entities is also likely uncorrelated. As discussed previously, vehicles often change locations from the place their economic activity is measured, and the people they transport also conduct their economic activity within a radius of locations. In contrast, nightlights, especially during curfews, capture stationary illumination. Here, the measurement error term is likely less problematic that the error term in GDP measurement, particularly when, for example, the average GDP per capita of Kyiv Region is applied to suburbs directly adjacent to the city of Kyiv, which likely exhibit higher economic activity than the parts of the region located near Chornobyl or the belarusian border.

Furthermore, regarding the informal economy, the error term is most likely attributed to the GDP measurement rather than the two proxies. One might argue that vehicles as more a granular measure, could capture informal economic activity better than nightlights, which rely on larger light emitters, but this remains speculative. Therefore, no definite conclusion can be made about the correlation of these specific error terms.

The effect of economic inequality on the error term of vehicles is more tangible than for nightlights. While the relationship between economic inequality and light emission in the context of population displacement is not well understood, the correlation between car ownership and increasing socio-economic status is well-established. Therefore, unfortunately, a conclusion about the correlation of these two error terms (for vehicles and nightlights related to inequality) is not possible.

The possible bias for vehicles due to foreign aid, as discussed above, is unlikely to affect nightlight measurement. Therefore, from this perspective, the error terms are uncorrelated, and an estimation using vehicles would likely be improved by combining it with nightlights.

Both measures have their own unique relationships with economic activity and reflect distinct facets of it, rendering them subject to changes in the composition of economic activity. Due to the limited scope of this work, I do not observe a systematic change in their relationship with overall GDP levels, which is more relevant over longer time periods. However, the structural break caused by the war could have led to composition changes in GDP, but the connection to individual economic sectors, their development over time, and change due to the full-scale invasion remain subjects for future research. Although there is anecdotal evidence of altered consumer behavior in car purchases and also policy changes in taxation and tariffs regarding cars, I was unable to obtain sufficient data to incorporate these developments into this work or to estimate their impact on the error term.[18]

Summarizing, as both measures clearly have error terms when measuring GDP, their differing natures suggest that these terms are not correlated to a large extent. This makes them useful to combine as a means to obtain a more precise estimate of economic activity. As discussed above, there are specific aspects to this, and for most aspects there is no obvious systemic correlation. However, despite this promising outlook, due to limited data availability, this remains an argumentative assertion without empirical evidence, left for future research.

Robustness Checks

The efficacy of counting vehicles as a proxy for economic activity hinges on a functional car market and consistent fuel availability; otherwise, the connection to economic activity is disturbed. Vehicle counts are also subject to demand responses to changes in fuel prices. Despite anecdotal evidence of even an improvement in car sales, fuel prices require a closer examination. To address this, I incorporated A-92 petrol prices reported by Minfin. While I specifically used A-92 petrol prices, other types of petrol showed similar price developments.[19] Alternatively, the monthly consumer price index category “Fuels and Lubricants” from the SSSU could have been used, but this also includes irrelevant subcategories and offers less temporal precision.[20] The price development is illustrated in Figure 7 in the appendix.

As can be seen, prices rose in June and July 2022 but remained fairly stable during the primary period of interest in 2022, increasing only in 2023. In terms of logistics, supply chains for fuel quickly adapted to truck transport after the full-scale invasion (Altman, 2023). The increase in fuel prices was partially mitigated by the decrease of the Value Added Tax (VAT) and the cancellation of the excise tax in late March 2022. Nonetheless, even without a sudden jump in consumer prices immediately after the invasion, assuming fully functional markets would overlook the supply shortages Ukraine faced. The long waiting lines at gas stations could further distort

[18] See for example these articles of an Ukrainian website with no government affiliation: https://visitukraine.today/blog/266/taxes-on-car-imports-have-been-abolished-in-ukraine, https://visitukraine.today/blog/2817/why-do-ukrainians-buy-more-expensive-cars-during-the-war#do-ukrainians-buy-fewer-cars-during-the-war, https://visitukraine.today/de/blog/4388/military-tax-on-cars-how-much-will-cars-rise-in-price-in-ukraine#car-price-rise-in-ukraine-due-to-military-duQ-details.

[19] https://index.minfin.com. ua/markets/fuel/

[20] SSSU. Consumer Price Indices for Goods and Services. Last accessed: 2024-12-13. https://www.ukrstat.gov.ua/operativ/operativ2023/ct/is_c/isc2023m_ue.xls

the number of observed vehicles. However, despite these imperfections, I aim to present scenarios demonstrating how the results might be influenced by price change given assumptions, serving as a starting point for critical discussion.

While the reported prices from Figure 7 in the appendix are not specific to Kyiv, I have no indication that petrol availability significantly differed from other major cities in the country.

As discussed in Section 4, I incorporated the elasticity of demand for fuel price changes into the formula. The results presented in Figure 4 are calculated with an estimated lower bound elasticity of -0.05 (Hössinger et al., 2017). I contend that this represents a realistic scenario, supported by the aforementioned literature and anecdotal evidence of a higher preference for cars and a sense of urgency during the period of interest. However, the literature also presents an elasticity of -0.15 as short-run upper bound scenario.

With these assumptions, the results are not significantly altered by fuel price elasticity. However, the elasticity in an urgent, crisis scenario has not, to my knowledge, been a subject of study. Furthermore, the long queues at gas stations could bias the results, as cars were on the streets for longer than usual. The results must therefore be interpreted with caution and serve only as a starting point for further discussion.

Distinguishing Types of Economic Activity and Population

Nightlights have been widely used in research to correlate not only economic activity but also to estimate population (Li and Li, 2014; Schippers and Botzen, 2023; Sutton 2003). This is intuitive given the close and relatively stable short-term relationship between GDP and population. Similarly, since cars are closely linked to the individuals owning and driving them, using car counts as a proxy for population development, especially during immediate crises, seems promising. However, this fall soutside the scope and data availability of this paper and is therefore an area of future research.

Further refining our measurement could also involve investigating the differing relationships between cars and trucks and economic activity. As previously discussed, cars are more intuitively connected to labor supply and consumption, while trucks are more related to the production sector. This distinction could mean they respond differently in various economic crises, offering deeper insights into the economy's sectoral development. More granular tracking of different urban areas (commercial, residential or industrial) could also yield further insights, but this would require more detailed government statistics and satellite imagery. Thus, this presents another avenue for future research.

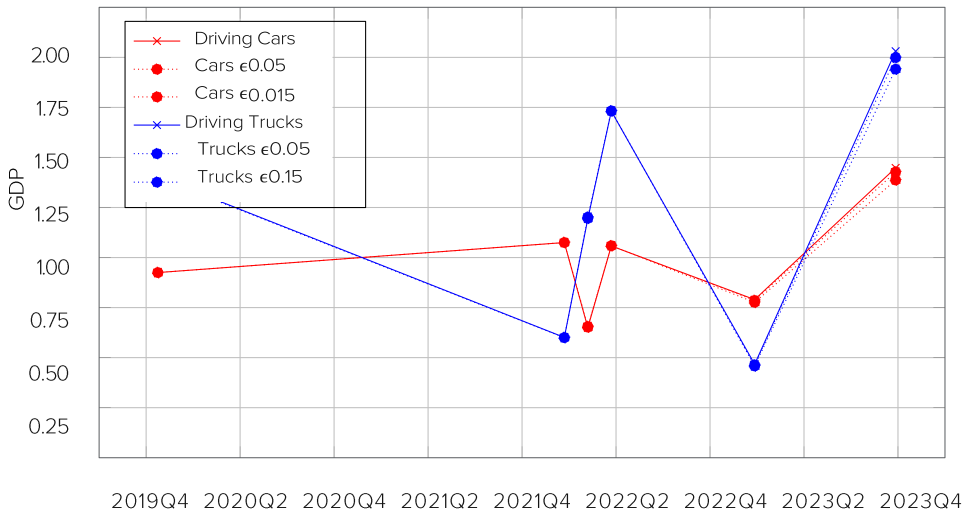

Figure 5. Detected Vehicles with Fuel Price Elasticity

Notes: Driving vehicle data at the timepoints described in Table 2. For vehicles, the average of the first two values was normalized to 1.

Technical Limitations

Beyond the economic aspects, the technical parts of this work also warrant critical discussion and possible improvements.

The precision and recall values, which fluctuate around 50% for 50 cm images and 80% for the 30 cm images, indicate room for improvement. This could be achieved by expanding the annotated dataset or combining multiple algorithms specifically trained for particular image characteristics, such as shadowed areas, snow, or non-road surfaces. On a positive note, despite varying sun angles and thus different proportions of shadowed areas, the 30 cm images showed no significant differences in related values. This contrasts with pre-trained algorithms, which were trained on the DOTA dataset without shadowed cars and subsequently performed poorly with shadows (Xia et al., 2018). Therefore, creating our annotated dataset and training algorithms resulted in much more robust estimations than using pre-trained algorithms. A very specific bias could arise in images with snow-covered surfaces. As shown in Table 2 and Figure 4, the February 2023 image, despite having worse precision and recall values, detected significantly fewer vehicles. This could be partly due to vehicles being covered in snow. Since these vehicles are not visible to the human eye if the snow is thick enough, the annotated data does not include them, and the algorithm's performance remains consistent with other images. This resulting bias could be addressed by incorporating weather data for snow coverage and deriving fixed effects for these days, which would be particularly beneficial in a larger dataset.

The annotated dataset also allowed us to deviate from the original algorithms classes and further distinguish large vehicles into public transport and trucks. As Figure 2 illustrates, yellow busses were not classified as trucks, thus not affecting the measurement. The bus depot is also not a source of bias, which it would otherwise be. While buses are part of public transportation, trucks are used for transporting goods. Considering the sectoral improvements discussed earlier, buses, like cars, are more representative of labor supply and consumption. This distinction allows for a more precise estimation of individual GDP sectors in future research.

However, a new bias could stem from the reclassification of vans from small vehicles to trucks. Since vans are mainly used for transporting smaller goods or tools, classifying them with trucks makes more sense from a sectoral point of view. However, as also seen in Figure 2, the algorithm has sometimes struggles with precise distinctions due to their only slightly larger size.

Occasionally, windows or old chimneys on rooftops are mistaken as cars. While this error was not observed with the pre-trained algorithms, and the recall and precision values still indicate overall precise classification, this remains an aspect that requires improvement through more training data and better algorithm training. The same applies to dark cars, which have a lower contrast against the generally dark ground surface.

One implicit assumption in this framework is that every car represents the same economic activity. This is challenged by the fact that some vehicles in the imagery are driving, while others are parked. While driving vehicles are actively engaged in at least one activity, which includes economic activity, there is no information available on how often parked vehicles are used. This weakens the connection to economic activity and increases the error term. Indeed, as discussed in Chapter 2.3, the fundamental idea of measuring mobility is to measure human activity. A parked car does not necessarily represent activity. In this framework, where people were fleeing the city, I would argue that it is a reasonable measure without distinguishing between them. However, in a different crisis scenario, like COVID-19, I suspect the relationship between counted vehicles in an entire city and economic activity would be weaker. That is why I distinguished cars by their proximity to the nearest roadway, and classified every car within a distance of five meters as "moving." With CE90 values of 3 – 3.5 m, the measures are reasonably precise. As Table 2 shows, the percentage of moving cars does not change much from image to image. While the informational value with the limited given data is low, in later scenarios with larger datasets, these fluctuations could offer further insights. Therefore, a more precise distinction of moving cars could be relevant, especially when combined with mobility data on commuting times. The car's angle towards the road could be exploited for this purpose.

Alternative Methods

Drawing inspiration from Cascaldi-Garcia et al., (2023) and Phan (2023) on Bayesian Inference for nowcasting GDP and utilizing nightlights, these methods could also be applied to estimating economic activity using detected vehicles. We could form initial assumptions about the expected amount of vehicles by considering factors like the distinction between parked and moving vehicles, the varying importance of cars and trucks, commuting times, the density and economic structure of an area, and the available road and public transportation infrastructure network in relation to the current GDP level. This could then be compared to the observed number of vehicles in different activity states to infer the development of economic activity in the area. While this approach extends well beyond the scope of this paper and the available data, it holds promise for more insights and reliable results.

As mentioned in the literature review, traffic and mobility data are often used to proxy specific economic sectors, depending on their type. This could also be done with the vehicle counts derived from our method. Although the available data is too limited, this could lead to more insightful results in the future. For example, considering the close relationship between trucks and industrial production or cars in shop parking lots and consumption could be particularly beneficial. The latter could also be combined with the aforementioned specific areas of interest, such as industrial zones or large shopping complexes.

Finally, a compelling avenue for future research would be to apply this method to areas beyond the current line of military control. By leveraging the relationship between (economic) activity and population, we could estimate development in regions where data collection is impossible and other proxies like nightlights, social media, or mobility data are either heavily biased or unavailable. Depending on the availability of satellite imagery and a deeper understanding of the stability of these relationships, this method could complement existing approaches for gaining insights into areas with missing or flawed data.

7. CONCLUSION

In this paper I utilized vehicle detection on satellite imagery to estimate the evolution of economic activity in Kyiv following russia’s full-scale invasion in 2022. This research aimed to complement the Warcast Index of Constantinescu et al., (2024), which estimated economic development for all of Ukraine. To gauge this development, I used aggregated car and truck counts as a proxy and compared them with available countrywide GDP data. My estimations suggest that Kyiv’s economic activity by the end of March 2022 was approximately 60% of its level pre-invasion level.

Given the rapid population shifts during this period the estimation of economic activity appears robust and yields results within the expected range. Due to data limitations, more extensive and precise verification was not feasible within the scope of this paper, and was left for future research. Furthermore, the relationship between vehicles counts as proxy for traffic and mobility, and its connection to the levels and growth of various measures of economic activity and population, warrants further clarification.

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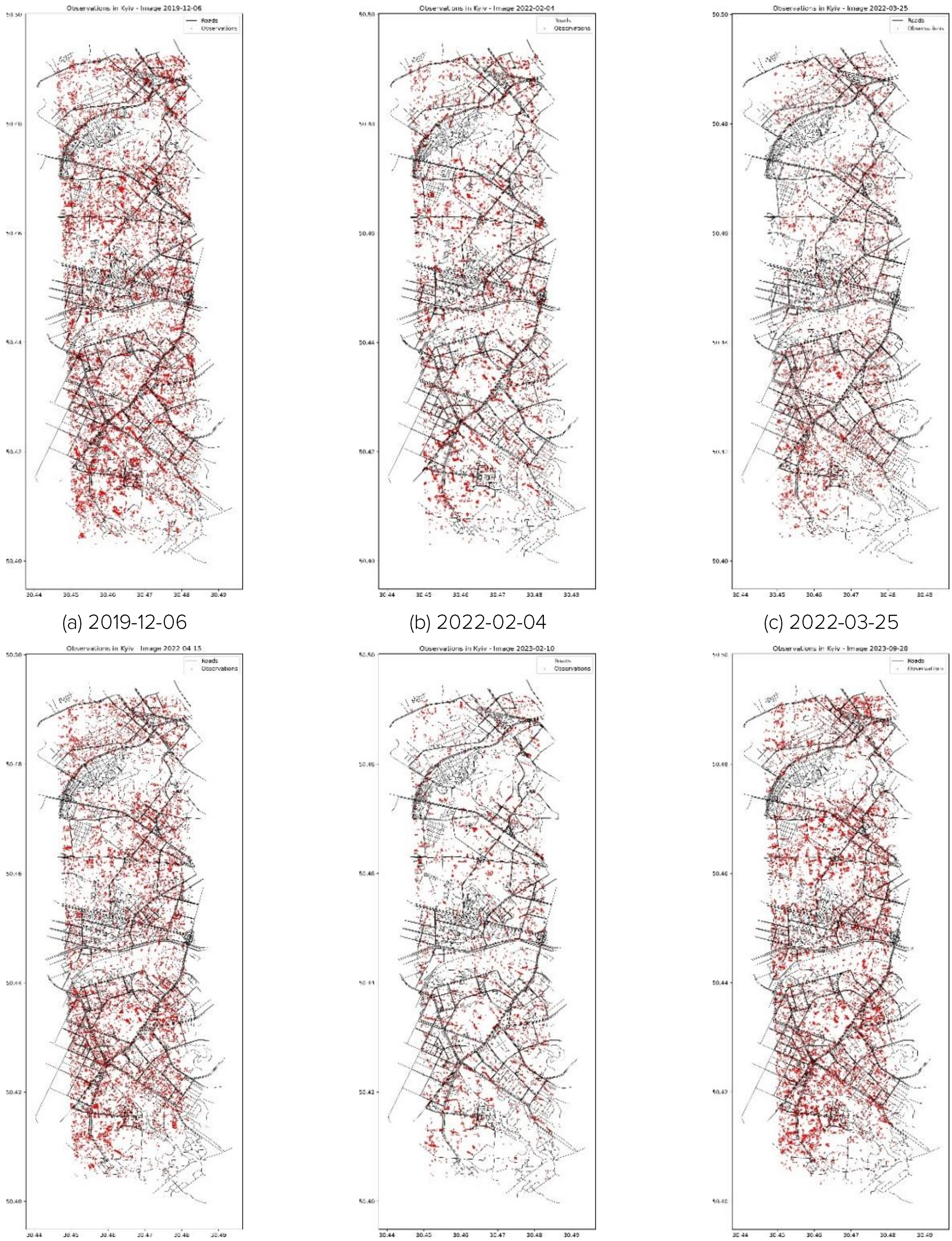
APPENDIX A. FIGURES



(a) 2019-12-06 (b) 2022-02-04 (c) 2022-03-25

(d) 2022-04-15 (e) 2023-02-10 (f) 2023-09-28

Figure 5. Intersection Area with Detected Vehicles for Each Image

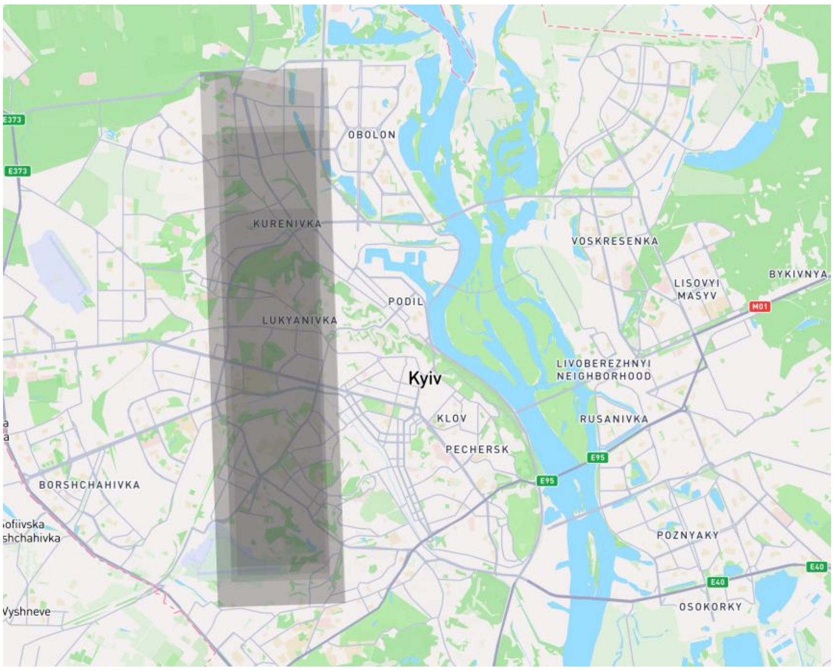


Figure 6. Covered Area of Satellite Imagery

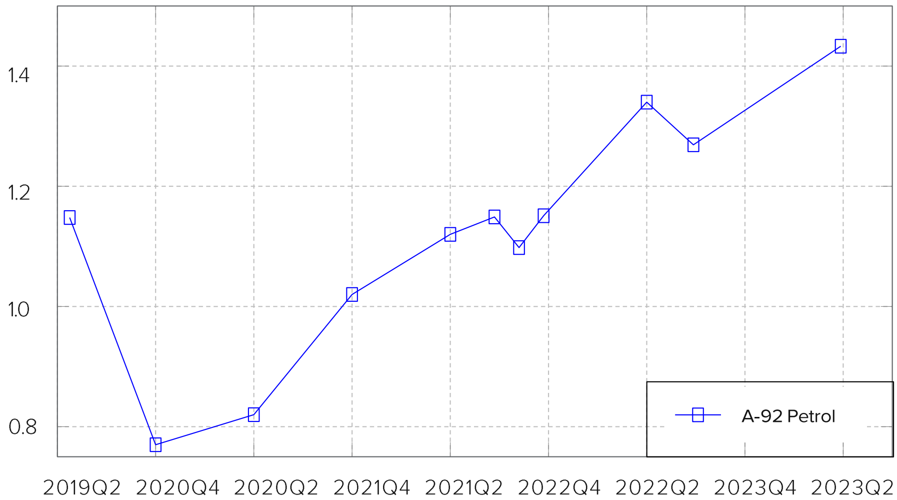


Figure 7. Fuel Prices from 2019Q4 to 2023Q4

Notes: Price in USD for A-92 petrol.

Source: Minfin, 2024.