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ROADS NOT TAKEN: A BRIEF ON CENTRAL BANK RESEARCH AND MANAGEMENT DURING AN INVASION

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Abstract

This study describes the various modeling options considered in extending the nowcasting and forecasting toolkit employed at the National Bank of Ukraine during the early stages of the 2022 russian invasion. It centers on a large palette of alternative data and modeling avenues, while also providing some general observations about the managerial and logistical challenges of continuing policy-relevant analytical work under conditions of exceptional stress. Unlike a traditional survey, this article provides an overview of numerous options considered potentially valuable in a war context but that have only partially been explored due to data limitations. The reasons for second or third best choices are described, as these may offer guidelines for similar contexts where looser data constraints may allow various alternatives to be estimated and tested. Some roads taken are also described.

1. INTRODUCTION

Roads not taken keep the minds of researchers in a perpetual state of wondering. The speculative "What if" at various bifurcations in choosing what to model and how to model it produces a seemingly endless menu of possible solutions. In this paper, I describe some of the considerations associated with developing various forecasting and nowcasting models for the Ukrainian economy in the months immediately following February 2022. The roads not taken may offer fruitful outcomes in other settings where the constellation of available data changes the functional constraints of nowcasting and forecasting economic activity.

Model choice cannot be divorced from the quality and fundamental characteristics of its input data. For most tasks in the modelling unit of a central bank, good quality, timely statistics are almost always available. Alternative, non-statistical data has been increasingly used in recent decades after proving their worth as complements to existing established variables (Bok et al., 2018; Groen and Kapetanios, 2016) – but many times only in tandem with existing statistical series. The need for alternative-data-only estimation was a rather rare occurrence before the COVID-19 epidemic. The full-scale invasion and imposition of Martial Law in Ukraine added new items to the list of constraints made apparent by the outbreak of the virus.

The nature of the shock, the distributional characteristics of the alternative data and a reliance on novel machine-learning techniques are the trinity of factors guiding current model development. One of the distinguishing aspects of the 2022 invasion is the *nature of the shock* inflicted on the Ukrainian economy. Although the statistical sample is of non-negligible size when considering russian invasions of its neighbors, the 24 February 2022 invasion stands out as a mix of military actions that were damaging both in the short and the medium term, both to capital and to labor, and both to tangible reality and projected paths shaping expectations. The damage to critical infrastructure and large industrial facilities resulted in an immediate loss of capital. The blockading of low-cost seaborne export routes further reduced the efficiency of remaining stock.

The bombing of social infrastructure (schools, hospitals, residential areas) pressured many households to seek refuge in safer areas in western oblasts, or abroad. The continued attacks on large urban areas have kept them away from their homes. The natural processes of integration of Ukrainians in their new places of residence are withdrawing substantial amounts of potential labor from the Ukrainian economy, profoundly influencing possible reconstruction options. The level of potential output will bear the scars of the invasion along its forecasted path for a long time to come.

The time evolution of the shock also poses its own distinct challenges. Whereas the first months of war were a textbook full-scale invasion, by the end of 2022 and the beginning of 2023 the conflict had transformed into a nuanced, geographically condensed variant more closely resembling the regional eastern and southern invasion of 2014. What initially presented itself as a shock of horrific magnitude eventually morphed into a series of less intense yet by no means less damaging shocks of varied types and spatial distribution.

The morphological characteristics drawing the profile of the shock – time, space, aggregation level – determine the models that are likely able to capture its effect. Most macro-econometric studies reviewed consider diverse shocks that resemble the invasion along one dimension quite closely, yet understandably hold the other two fixed. Some also adhere quite strictly to their JEL inheritance with little academic cross-over or mutation that would allow more flexibility in modeling and interpretation.

How should one analyze the impact of these shocks in an environment lacking updated statistics? This is the second distinguishing aspect of this undertaking: the ***temporary absence of any official statistical data updates*** beyond what was available publicly in January-February 2022. Martial law suspended all data gathering and dissemination by official bodies until roughly Q3 of 2022. Security concerns also led to access restrictions from large digital service providers (such as Google and Apple), mobile phone operators and electricity distributors – all of which were inputs in the pre-war mixed-frequency models. Promising data on payments and specialized web-searches from local actors were, unfortunately, also not available to the regulator in the immediate aftermath of the invasion.

Statistical data is gathered with a precise goal in mind. The purpose, scope, target population, and intended uses of the data guide all gathering and subsequent processing choices. Objectives need to be specific enough to determine relevant concepts, definitions, appropriate sources, geographical representation, and collection frequency. Although the explicit purpose of describing the characteristics and evolution of a selected economic process is clear, there are several design choices that rely on an implicit causal model. For example, income is surveyed to represent different household sizes, education levels and geographies. This is because urban and rural economic processes are sufficiently different to be analyzed with different causal lenses. Other characteristics exert their own influence on the evolution of the aggregate. Geography, for example, plays an important role in how income is generated and spent, and this is reflected in how statistics are collected and computed. In our case, geography will represent an important differentiation dimension, as the shock is also of varying intensity in space and time. Reliability and validity are key characteristics of statistical data, yet are not to be expected on many of the considered alternative sources.

Data collection should be standardized to minimize errors and biases. Using consistent instrumentation, trained personnel, detailed protocols, and pilot studies improves reliability. Validation checks ensure the data truly reflect the real-world phenomena of interest. Few of these features are present in the alternative data considered. Social media usage, and more broadly internet usage, is dependent on the existence of IT infrastructure. This is unequally distributed across space, with notable differences between urban and rural areas. Access to this infrastructure requires an income level which often implies some degree of sampling bias. Beyond these background factors, each source of online data source reflects different parts of the link between economic activity and internet or platform usage. Whereas Google Trends and keyword searches may reflect different interests in the underlying population – thus having applicability in disentangling links to investment consumption and trade – social media usage will reflect primarily income and wealth levels in a particular geography. Recent advances in image segmentation and text analysis may nevertheless extract additional relevant signals for forecasting a wider range of economic and financial variables.

The heterogeneous regional intensity of military action was the main condition leading to a sub-national analysis resolution. In an ideal case, assuming sufficient regional and urban economic data were available, one may consider a model that builds bottom-up, considering various levels of geographical detail (large MSAs, regions or large administrative units). In the case of Ukraine, gross regional product is gathered and published only on a yearly basis for oblasts (which are the primary sub-national administrative unit). If spatial and temporal resolutions match, variables tracking industrial production, employment, company births and deaths may also become valuable estimation features.

2. MODELLING IN A DATA-RICH BUT STATISTICS-POOR ENVIRONMENT

Many policy decisions require timely updates of the state of the economy. Well-developed machinery, created and thoroughly tested, can provide backcasts, nowcasts, and near-term forecasts of aggregated national statistics. Comparatively less attention is paid to modelling regional dynamics – a quick review of the Working Paper series of major central banks shows an overwhelming majority of studies use national level data. Given the nature of the invasion shock, tracking regions is of utmost importance to be able to build a credible, policy-useful narrative of the observed national fluctuations. In peacetime, more attention to sub-national evolutions may also prove useful by further clarifying possible sources and channels of persistent household and firm inequality. It may also better depict the institutional-economic scaffolding supporting successful innovation and entrepreneurship, something that is lost somewhat in the averaging of national statistics.

Furthermore, aggregate models work well provided they are well fed with timely, signal-rich statistical time series. Older and newer literature in development economics provided many useful hints for estimating economic activity when no official statistics are present. Data that was easily available included rather noisy satellite luminosity and signal-poor internet-based activity and performance. Methods had to be developed to account for the presence of many spurious and irrelevant variables – something that rarely has to be done in an environment with many high-quality data sources. This data noise was a notable obstacle in picking an off-the-shelf model for estimating key macro variables. Another limitation was the focus on designing variable-specific estimation methodologies, which is also a natural evolution given the distributional characteristics of key macro variables. A more flexible modeling philosophy may prove a good replacement for well-designed but highly variable-specific models, when quick work by one generalist researcher needs to replace a thorough analysis performed by many specialized analysts, who may be unavailable.

Traditionally, regional GDP estimation relies on information from governmental sources, such as tax records, employment statistics, and industry outputs. This data is reliable but often delayed and at a low frequency, limiting its usefulness for real-time analysis. The advent of big data has profoundly improved regional GDP estimation. Sources like social media activity, satellite imagery, and mobile phone usage provide a more detailed and timelier picture of economic activity. These data types, however, may suffer from issues of representativeness, as hinted above. These are most of the time tackled via targeted surveys of both households and firms.

2.1. Regional Models

Regional GDP estimates offer more granular insight into economic performance than national aggregates. These models uncover important subnational disparities in growth and activity levels by incorporating data on local production, incomes, employment and other economic and financial indicators. Gross regional product derived from output measures or gross value added through the expenditure approach provide richer detail on the source, propagation and impact of shocks beyond their place of emergence. Assumptions required about commuter flows and industry input-output, price deflators and informal sectors can nevertheless introduce distortions that are hard to quantify in the absence of disaggregated data.

Computable general equilibrium (CGE) is the modeling workhorse often used to evaluate the impact of economic shocks and policies of subnational regions (Partridge and Rickman, 1998; McGregor et al., 2010; Ghaith et al., 2021). This is performed employing regional industrial structures, trade linkages and specific production factors. By quantifying inter-regional spillovers and non-linear impacts, these enhance and extend a purely national analysis. CGE models require extensive regional data and rely on non-trivial assumptions about consumer and company rationality, utility and profit functional forms, market clearance (for both products and factors of production) and price adjusting mechanisms. Their micro-level complexity, while making them more realistic, also create challenges in terms of the calibration/estimation of key structural parameters and optimal aggregation to match observed higher-level dynamics.

Augmented Solow equations for regional growth decompose national determinants like savings, population growth, technology progress and human capital into localized variants to describe heterogeneous development trajectories. Subnational tailoring strengthens explanatory power over simpler cross-country versions. Operationalizing empirical proxies for some variables such as regional productivity, however, comes with its own set of challenges: data availability and quality unfortunately lag substantially in Ukraine as compared to its counterparts in the EU.[1]

Wartime conditions cause rapid and unpredictable economic shifts, making it hard for CGE models, which are typically based on equilibrium assumptions, to adapt quickly. In a situation in which reliable data are scarce, updating parameters becomes almost an impossible mission. The standard assumptions of CGE models, all drawing on market equilibrium and stable consumer behavior, will most likely not hold during wartime. This discrepancy will cause inaccuracies in the model's predictions or impulse response functions. Wars disproportionately positively affect certain sectors (such as defense) while making others shrink or disappear completely (such as tourism). CGE models need to be recalibrated to account for these sector-specific impacts, which is often challenging due to the lack of data. In conjunction with these structural changes, policy and institution simultaneously suffer profound changes.

Hybrid approaches combining multiple data sources may balance the costs and benefits of traditional regional surveys and alternative non-survey techniques. For example, blending high-frequency phone data or satellite imagery showing broad activity changes with periodic traditional surveys and administrative records may compensate for lagged reporting. During a conflict, when surveys are often suspended, these alternative indicators enable some degree of monitoring amid acute data deficits. However, most proxies have not been tested extensively or paired directly during wartime. Interpretability also suffers without appropriate benchmarking. The lack of a properly tested peacetime CGE model for Ukraine led to the abandonment of this avenue. Nevertheless, the availability of regional GDP kept open the possibility of a regional empirical model. This has been one of the avenues well explored in Constantinescu et al. (2022) and Faryna and Tsapin (2024).

2.2. Mobile Phone Metadata

The increased digitalization of our lives, augmented by the wider availability of high-performance mobile devices, opened an era of big data usage for tracking and estimating economic activity in near real-time. One source of data that has shown promise is mobile metadata – this represents information about mobile phone usage, such as call detail records, mobility traces, mobile money transactions and topological features of the network of phone calls. This data has been used to conduct large scale social and demographic analyses at the individual level, as in Eagle and Pentland (2006), Eagle et al. (2009), Blumnestock and Eagle (2010), with poverty levels being estimated by Blumenstock et al. (2015) and economic activity across different geographical hierarchical levels being tracked in Dong et al. (2017).

This field primarily revolves around analyzing call records (length, frequency) and mobile phone usage (number of towers accessed) to estimate socioeconomic status, mobility patters and wealth distribution, offering a real-time and high-resolution alternative to traditional surveys. These methods may be of great value in developing economies that lack a mature data gathering and processing infrastructure, as long as access to the mobile phone network is not restricted to high-income households.

During stable periods, mobile metadata provides valuable fine-grained insights into the movement of people and economic transactions, allowing for higher frequency tracking of indicators tied to regional GDP growth, as highlighted in Arhipova et al. (2020) for Latvia or Dong et al. (2017) for China. For example, mobility traces have been used to estimate commuting patterns and proxying labor market participation. Mobile money transaction data offers enhanced visibility into consumption expenditures. Leveraging these streams as inputs in machine learning methods, these data may enable day-to-day and week-to-week prediction of GDP and its components.

Various challenges remain when employing mobile big data for economic nowcasting. Biases can emerge in mobile metadata, especially in developing countries with lower mobile penetration rates. Linking specific mobile signals to real economic activity requires careful econometric modeling with location-specific training data – skills that may not be immediately available in a typical central bank research unit. Privacy also remains a concern with more granular user data.

During periods of conflict, both the benefits and challenges of mobile data for economic analysis are

[1] See https://www.comp-net.org/ for a harmonized database of European companies' financial and productivity variables.

amplified. Traditional statistics may be less reliable or completely unavailable in a war setting, leaving little room but to use non-traditional data sources. The very nature of the shock leads to structural shifts in economic activity and human mobility requiring specialized techniques that account for such shifts, or a sufficiently rich data sample that allows the easy updating of parameters (assuming there are no long-term anchors).

Military conflict introduces additional biases, volatility, and structural changes into the use of mobile phones that may potentially reduce the accuracy of models trained on peacetime data. In the case of Ukraine, the bombing of electricity production and distribution infrastructure led to the loss of mobile connectivity, at times for days, in areas that were hard to reach for technicians. Conflict also disrupts mobile networks and alters user behaviors in ways that may substantially diminish the value of mobile metadata.[2] For instance, phone usage can shift more towards disaster communication needs rather than economic transactions. A positive loading estimated using peacetime data, where more phone usage positively correlates to economic activity, would erroneously indicate more growth in higher conflict intensity areas instead of signaling more infrastructure destruction or the need to evacuate. Refugee migration also drastically alters mobility patterns.

Synthetic control approaches that blend mobile data with other available data sources can also help overcome data gaps during disruption to services. These may be daytime satellite images, where image segmentation can help assess car traffic. Subject to data availability, passenger traffic by train or gasoline sales may also be of help. Secure edge computing on metadata could provide economic insights even with brief network disruptions. But inherent uncertainties will remain high during extraordinary social disruptions or military conflict.

Several research avenues present themselves for these data types. They range from establishing the usefulness of this data across different demographic groups, to estimating the uneven impact of digitalization across various social milieus. Inequality in digital literacy may pose non-trivial challenges in the interpretation of parameters. Privacy issues in using phone metadata loom large in normal times, and during an invasion these issues become even more of a challenge due to security threats.

As this research field evolves, the previous brief methodological excursion highlights the balance that must be struck between innovative data use and ethical considerations. For security reasons[34], phone metadata was not available for economic modelling during the 2022 invasion.

2.3. Nighttime Radiance

An extensive literature has demonstrated the value of satellite nighttime images in tracking economic activity across and within countries during normal peacetime conditions. Pioneered by seminal studies like Henderson et al. (2012) and Nordhaus and Chen (2015), nightlights provide a consistent data source to estimate GDP where official statistics may be lacking. How does nighttime luminosity become useful data? In Figure 1, a stylized example is considered for the actual readings of the city of Kyiv before and after the invasion.

A geographical boundary is defined, in our toy-example above, this is the simplified orange box. The area of measurement is typically an administratively or statistically defined region like a city or a province, but the definition of area may itself be subject to additional testing, as for example cities tend to grow over time both in cyclical and non-cyclical aspects. In actual applications, Geographic Information System (GIS) software is used to create precise polygons delineating spatial boundaries, rather than the box used above. In the current setting, nighttime radiance data from NASA's VIIRS[5] on the Suomi NPP satellite is used.

The satellite provides daily global scans from 1:30AM to 10:15PM local time, and is sensitive to low-light visible and infrared imagery at a 750m spatial resolution. This defines the size of the pixels depicted above. NASA's Black Marble[6] application processes the VIIRS data by filtering out fires, clouds, moon and water reflections, as

[2] Pearson, J., Marrow, A. (2023). Hackers linked to Russian spy agency claim cyberattack on Ukrainian cell network. Reuters, December 13. Retrieved from https://www.reuters.com/technology/cybersecurity/ukraine-says-russian-intelligence-linked-hackers-claim-cyberattack-mobile-2023-12-13/
[3] CBS News (2023). Unauthorized use of cellphones by Russian soldiers led to Ukrainian strike that killed 89 troops, military says (January 4). Retrieved from https://www.cbsnews.com/news/ukraine-news-russia-military-blames-cell-phones-strike-soldier-deaths/
[4] Vlamis, K. (2022). Ukrainian forces used Russian soldiers' 'panicked' cell phone calls to pinpoint their locations and pick them off, report says. Business Insider, December 23. Retrieved from https://www.businessinsider.com/ukraine-used-russian-soldiers-panicked-cell-phone-calls-locate-them-2022-12
[5] https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/viirs/
[6] https://blackmarble.gsfc.nasa.gov/

well as other background noise. Stable emission pixel values from VIIRS imagery are then aggregated to get total light estimates over time for the chosen geographical regions defined previously. In our simplified example, nighttime radiance for Kyiv would be computed as the sum of the radiance values of the pixels inside the orange box.

One major benefit of this data type stems from the relative objectivity of space-based imagery. As Sutton et al. (2007) discuss, geospatial analysis of luminosity enables fine-grained spatial monitoring that is highly correlated with several economic processes (employment, GDP), as well as gross electricity usage. Consistency over time in user behavior may help uncover important trends in economic fluctuations in each area. New technologies improving energy-efficiency affect values and behaviors.

It's not all benefits though. Various measurement issues pose challenges when employing nightlights, especially at local scales. Bickenbach et al. (2016) note relationships between luminosity and income growth generally lose robustness at regional versus country levels for India and Brazil. Overglow can cross-contaminate measures for adjacent areas, an issue recognized and tackled to a good degree by the VIIRS data. And critically, nighttime brightness captures mainly formal sector activity, missing informal elements comprising close to one half of the output of developing economies. It is therefore important to complement any analysis with other indicators which correlate with GDP.

Wartime conditions further strain assumptions underpinning observed luminosity patterns. Conflict onset dramatically alters socio-economic behaviors and institutions in ways that undermine the standard assumptions supporting the nightlight-income relationship observed during peacetime. Curfews, blackouts for military concealment, evacuations and forced displacements, infrastructure targeting – wartime dynamics such as these directly impact the measured luminosity. Links to actual economic production are far less stable compared to peacetime. The flight of refugees from an area translates into decreases in nightlights. Rebuilding infrastructure initially shows luminosity recovery amidst persistent output losses after bombardments. Conflict inevitably shifts nightlight-income elasticities in ways satellite imagery alone cannot untangle. Combining their use with on-the-ground damage assessments can potentially approximate economic activity when wars degrade the information value of nightlights.

Figure 2 (Appendix A) shows the rather stable time relation between yearly mean luminosity and output, both in logs, for Ukrainian oblasts. Each dot represents a tuple (Gross Regional Product – Luminosity) where luminosity is the sum of all pixels related to the oblast.

Kyiv city holds the crown in terms of economic importance. Its average yearly luminosity is several times larger than that of most other oblasts. It is worth noting that luminosity tracked the effects of the first stage of the invasion in 2014-2015 quite well. Figure 3 (Appendix A) disaggregates luminosity at the regional level. Both Luhansk and Donetsk show a substantial contraction in 2014 followed by some recovery in the following years. Starting from 2018, radiance increases sharply in Sevastopol and Crimea – both areas with critical military infrastructure.

Doll et al. (2006) use night-time light remote sensing data to show its strong positive correlations with Gross Regional Product (GRP) across a range of spatial scales. This correlation was observed in 11 European Union countries and the United States, validating the use of night-time light data as a proxy for economic activity at various sub-national levels. The strength of this relationship nevertheless varies from country to country. In countries like the Netherlands, the relationships between night-time light data and economic indicators at different NUTS levels were very similar, indicating a robustness in the correlation between night-time light data and economic activity across various spatial scales.

Most promising research avenues for using nightlights are centered around uncovering potential drivers both for causal analysis and variable selection in forecasting models at finer spatial scales. This is made possible by the recent improvement in Very High Resolution (VHR) imagery and the concurrent accelerated digitalization of many economic activities. The decreasing cost of commercial satellite imagery, particularly Synthetic Aperture Radar, offers additional opportunities.

To better understand the relationship between nightlight intensity and economic activity, a closer examination of micro- and meso-foundations would be beneficial. As Bickenbach et al. (2016) for India and Brazil and Bundervoet et al. (2015) note for Kenya and Rwanda, the strength of the sub-national relationship between nightlights and economic activity depends on the industrial structure of the observed region. Areas with higher shares of agriculture have weaker correlations between luminosity and GDP – an expected outcome given that most agricultural activities take place during the day. This also indicates the need to leverage both day and nighttime satellite imagery.

At the regional level, additional factors like agglomeration economies, industry mix, and spillovers likely mediate the relationship between nightlights and GDP. Microeconometric analysis accounting for company entry/exit and investment responses would also be informative – nightlights may act differently on the intensive as compared to the extensive margin in employment and capital adjustment. The industry mix and clustering effects of companies are major determinants of growth that are not directly measurable through nightlights. Structural VAR analysis accounting for intersectoral input-output linkages will quantify indirect effects missing from nightlights.

Chen and Nordhaus (2011) show correlations between luminosities and GDP using cross-country data. But how does the relationship change for regions within less developed economies as infrastructure and institutions evolve? Subnational analyses by Asher et al. (2021) provide valuable insights from India. Their work confirms the usefulness of nightlights in estimating local economic activity, highlighting that elasticities depend substantially on the aggregation level of the data and on whether they are estimated in a cross-section or in a time-series setting. As regions develop, macroeconomic structural change occurs, shifting activity across broad sectors, which may alter nightlight-GDP elasticities at different stages of transformation.

2.4. Payments Data

Payments data, such as credit and debit card transactions, online payments, and cash withdrawals and deposits, have emerged as a valuable data source for estimating economic activity at the regional level (Galbraith and Tkacz, 2015; Aprigliano et al., 2019). There is increasing evidence in the regional economics and information systems literature that granular payments data can allow for timely and accurate measurement of regional output (Chapman and Desai, 2022; Rooj and Sengupta, 2021). One of the primary benefits of using electronic or cash payments data is that it allows for near real-time nowcasting of various economic and financial variables. This contrasts with survey-based approaches of standard statistical series, which can have publication lags of months or quarters.

Payments data provides greater specificity of the sectors and industries that are thriving or contracting. These insights become even sharper if geographical identifiers of payer and payee are available within a regional economy. Understanding nuanced sectoral impacts of shocks allows for better-targeted response policies. Blending multiple data signals like payments, employment, mobility and news trends, where available, produce more accurate predictive models compared to any single data stream (Chapman and Desai, 2022). This diversity allows for a holistic view of the economic landscape, encompassing consumer behavior, company activity, and associated economic activities.

Of course, not all transactions are cashless – in-person cash payments account for a large fraction of total payments in many developing economies. This can lead to biased estimates if only electronic payments data are considered. A large fraction of economic activity conducted informally, with transactions settled mainly with cash, further inflate this bias.

There are also important considerations regarding the inclinations of different demographic groups in using electronic payments. Younger, more affluent and digitally savvy consumers may conduct more cashless purchases. There can also be greater adoption of cashless payments in urban areas with an extended POS infrastructure. Methodologies must ensure there is a representative sample using geo-spatial mapping and possible survey data correction, something not always possible without running into substantial privacy concerns. Cash transactions data end up being less detailed in terms of the parties involved, the object of the transaction or location of counterparties. This will inevitably dilute the benefits of the electronic payments data described above.

Prior to the outbreak of a military conflict, anticipation of military activity can substantially impact household and business transaction behavior. As geopolitical uncertainty rises, there is often a spike in spending as consumers and companies stockpile necessities and key inputs in anticipation of supply chain disruption or access constraints. This can generate short-term distortions in payments data.

The still-fresh memories of the 2014-2015 Ukrainian banking collapse and substantial depreciation triggered large cash withdrawals and above-average currency conversion in the months preceding the 2022 invasion. Even absent this history, a surge in currency withdrawals is to be expected as individuals shift to cash holdings given perceptions of increased risks to digital payment infrastructure or risks of power outages.

As military operations commence, commercial and productive activities are severely restricted due to safety concerns, with transaction volumes shrinking in relation to this. Businesses witness sharp revenue reductions amid lowered production capacity, halts in trade, and decreasing consumer demand. The rebound in activity in mid 2022 was directly conditioned by the easing of the active phase of confrontation.

There is heavier reliance upon exchange in the shadows, most likely settled via cash. The result is an underrepresentation of true economic hardship amidst physical danger within observed payments data. While electronic payments data remains informative on pre-war economic trends, it markedly declines in accuracy as an indicator of real economic welfare conditions after warfare begins and the above behavioral changes take hold.

For Ukraine, the payments landscape is marked by low digital literacy and (compared to EU peers) low electronic payments penetration beyond major urban areas. Cash, both hryvnias and USD or EUR, remains an important means of transactions.

Oblast level cash turnover aggregates were available at monthly frequency and have been used in various nowcasting and forecasting exercises. Unfortunately, many useful features of the underlying transactions are missing in the oblast-level aggregate cash data. The network of transactions, the industries of the counterparties, to list only a few missing data dimensions, are not available for reasons of privacy. Granular electronic payments were unfortunately not available. Nevertheless, the preference for cash already present in the pre-war period provides good signal/noise input into several ML models.

Oblast-level nowcasting models are estimated using cash turnover series via partial least squares – a supervised machine-learning algorithm. Both the speed and depth of the contraction and subsequent rebound reflect the intensity of military conflict (Constantinescu, 2024). Simple aggregation, using GDP weights, tracks official statistical releases of national-level GDP.

3. MANAGING WAR-TIME RESEARCH AND ANALYSIS

While far from being a recipe on ensuring continuity of the analytical work in a central bank in wartime conditions, this section contains several important observations. War-related risks and their realizations also have similar characteristics to natural calamities – if the risk profile is similar, the managerial challenges may be quite similar.

The first stages of conflict, depending on the level of preparedness of the institution, may render several team members unavailable to perform their regular tasks. Communication will be impaired, IT infrastructure may be physically damaged, under cyber-attack, or be unreachable due to the presence of enemy forces. To prevent a complete breakdown of analytical work, the preparatory questions to consider are: “Who knows how to run a certain model/perform a needed analysis?” and “Are data and model files available?”

Tackling the first question indicates the benefits of having overlapping skills and abilities within the research unit or department. Naturally this “backup circuit” may be cost ineffective during peacetime, but optimal skills matching may improve team robustness in normal conditions as well. A suitably prepared team would need to insure, perhaps via semiannual workshops, that several members do indeed share common knowledge of the intricacies of a particular model, from estimation/calibration, all the way to interpretation of results and their model-dependent limitations.

In the expectation of official data being limited or absent, an alternative data sub-team should be assembled. Accessing and leveraging novel data sources, such as nighttime light, Google Trends or phone meta-data, necessitates specialized competences and workflows. The following few paragraphs set out a possible end-to-end process for assembling a capable team, acquiring satellite, social media and phone meta data, developing appropriate machine-learning algorithms, and ultimately operationalizing analytical insights by deploying predictive models.

To access, pre-process and derive value from satellite data via dedicated models, an ideal team should include data engineers to construct data pipelines and cloud infrastructure, data scientists to develop and test statistical and machine-learning models, geospatial analysts to preprocess satellite raster data, and domain experts in remote sensing and socioeconomics to compare the costs and benefits of various analytical directions. Depending on the scope and complexity of the downstream analytical questions, several roles and responsibilities can be merged. For example, the ML researcher may combine sufficient domain knowledge in remote sensing or economic analysis with model development, so only one FTE is required. In the same way, the data engineers developing the data pipeline may be able to work with raster data and different projection systems. Night-time satellite data products that map night-time radiance levels are increasingly available via application programming interfaces (APIs) from NOAA and NASA in convenient analysis formats. The data engineer(s) will access the provider APIs to systematically download the time series imagery and either process it locally or via cloud-hosted applications.

In addition to the night-time light raster data processed via NOAA or NASA APIs, the data engineering pipeline should also include Google Trends time series for relevant search terms like "employment" or "housing" on a regional basis, or social media interaction data (such as data from Facebook or X). The Google Trends API provides search volume indices normalized to the highest query share. Data engineers may use this API to obtain high-frequency time series at the regional level, matching the same geographical detail as the night-time radiance. Although only available for a fee, user interaction on popular social platforms such as X may also be accessed via API services. Joining the distinct data streams will enable enriched socioeconomic modeling (Constantinescu et al., 2022).

Given the processed alternative data, data scientists can leverage available tools to develop machine-learning models for multivariate spatiotemporal data. Numerous supervised learning techniques should be validated in order to predict target variables at high geographical resolution. The more all of the above happens in the cloud, the more robust the entire workflow will be. Available cloud platforms and the associated services will be immune to local electricity disruption or damage to hosting infrastructure.

Researchers will benefit from experimenting with region-specific models tailored to a given geographic area. It may be related to an administrative unit (say NUTS2 areas) or various sub-national areas with tightly connected economic bases. This approach is more likely to reveal regional heterogeneities between the alternative predictors and core socioeconomic target variables. Geospatial analysts can help determine meaningful modeling regions across the broader study area that balance intra-region homogeneity and inter-region heterogeneity.

Once well-performing models have been cross validated, these can be deployed to generate real-time predictive insights, which can then be made available to stakeholders (other government branches) via hosted web visualization dashboards or dedicated databases.

4. CONCLUSIONS

This article surveys the multitude of modeling alternatives and the associated data sources used when estimating economic activity in Ukraine following the 2022 russian invasion. The shock's unique characteristics challenge traditional macroeconometric approaches, necessitating alternative data and methods. The invasion inflicted immediate capital losses while also damaging future growth prospects. It caused population displacement, withdrawing vast amounts of labor and altering reconstruction options. The shock's spatial and temporal non-uniformity requires a sub-national analysis lens. However, both national and regional GDP statistics were suspended under martial law.

Several data sources are considered. Mobile phone metadata was one of the first avenues considered, given its high granularity for real-time tracking. But wartime biases like infrastructure targeting, altered user behaviors, and refugee migration reduce its accuracy. Nightlights satellite data also correlates with output but suffers from shifted assumptions under conflict. Curfews, blackouts, and evacuations all directly impact measured luminosity. Payments data enables near real-time measurement of regional economies. But informal, cash-based transactions are not captured, transactions decline amid conflict, and stockpiling before fighting all distort a proper estimation of the correlation of payments and economic activity.

Alternative regional GDP estimation combines multiple data signals, balancing costs and benefits of traditional surveys and new data streams. But most proxies lack extensive testing during wartime. Uncertainty thus remains high amid extraordinary disruptions.

Managing research and analysis during active military conflict relies on overlapping skills as teams become unavailable, communication/infrastructure is damaged, and data gaps emerge. Cloud computing adds resilience if the cloud is remote from the front lines. Assembling a specialized alternative data sub-team to construct robust data pipelines, develop ML models on satellite or social media data, and generate actionable insights can also add benefits in peacetime.

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APPENDIX A. FIGURES

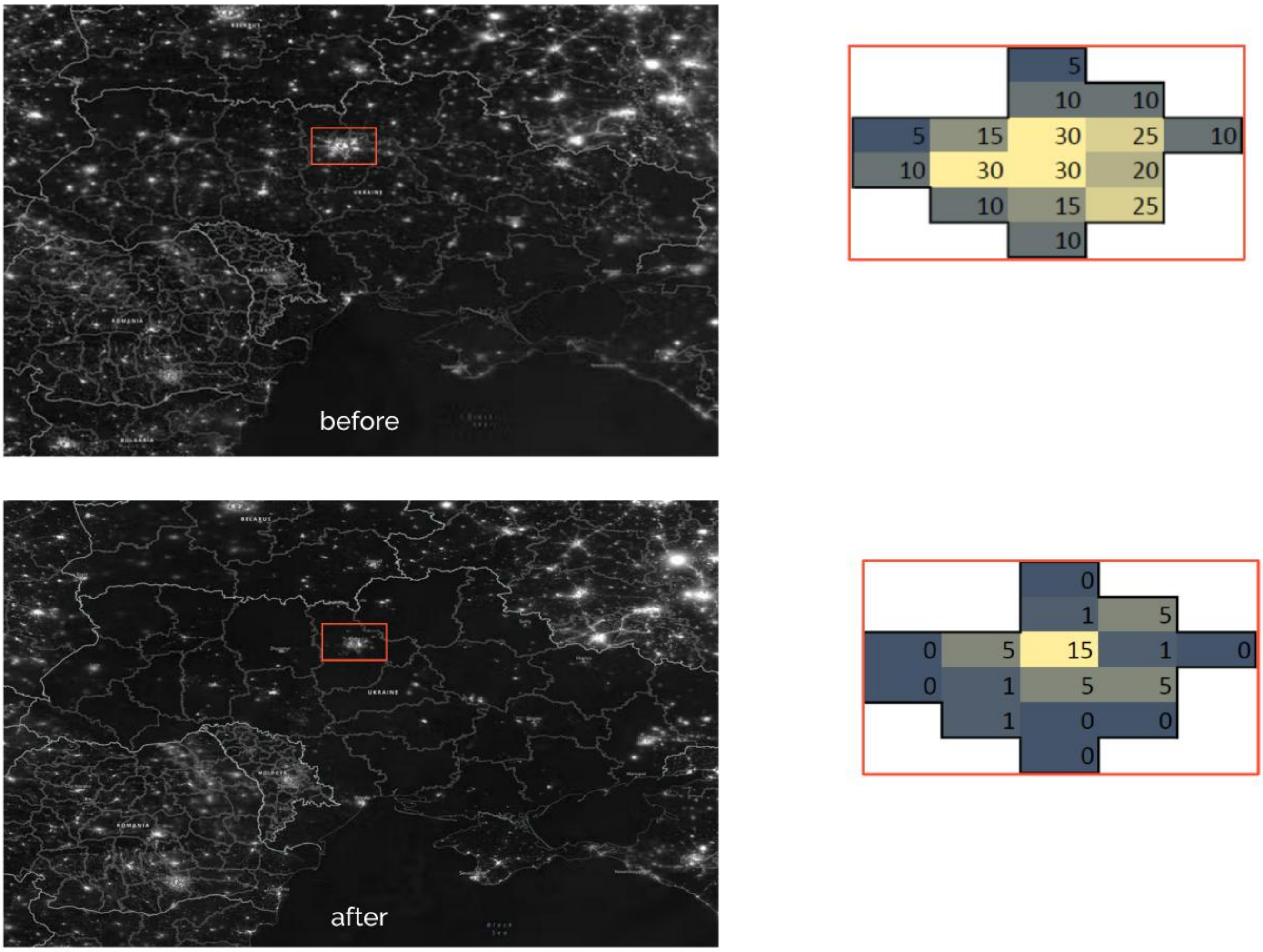

Figure 1. Maps of Ukraine in April 2021 (top left) and April 2022 (bottom left) from NASA Worldview Black Marble Nighttime at Sensor Radiance; Equivalent Representations of Pixel Luminosity for Selected Area

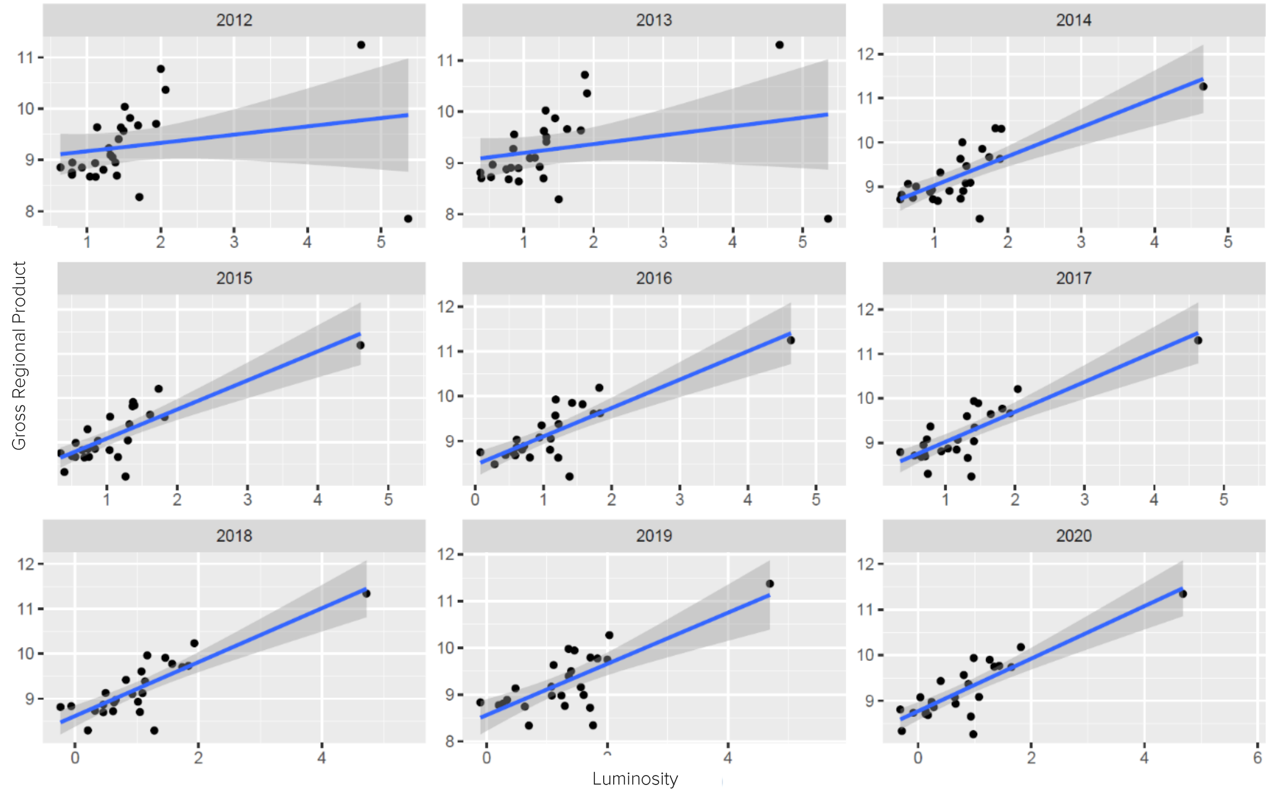

Figure 2. The Cross-Sectional Relationship over Time

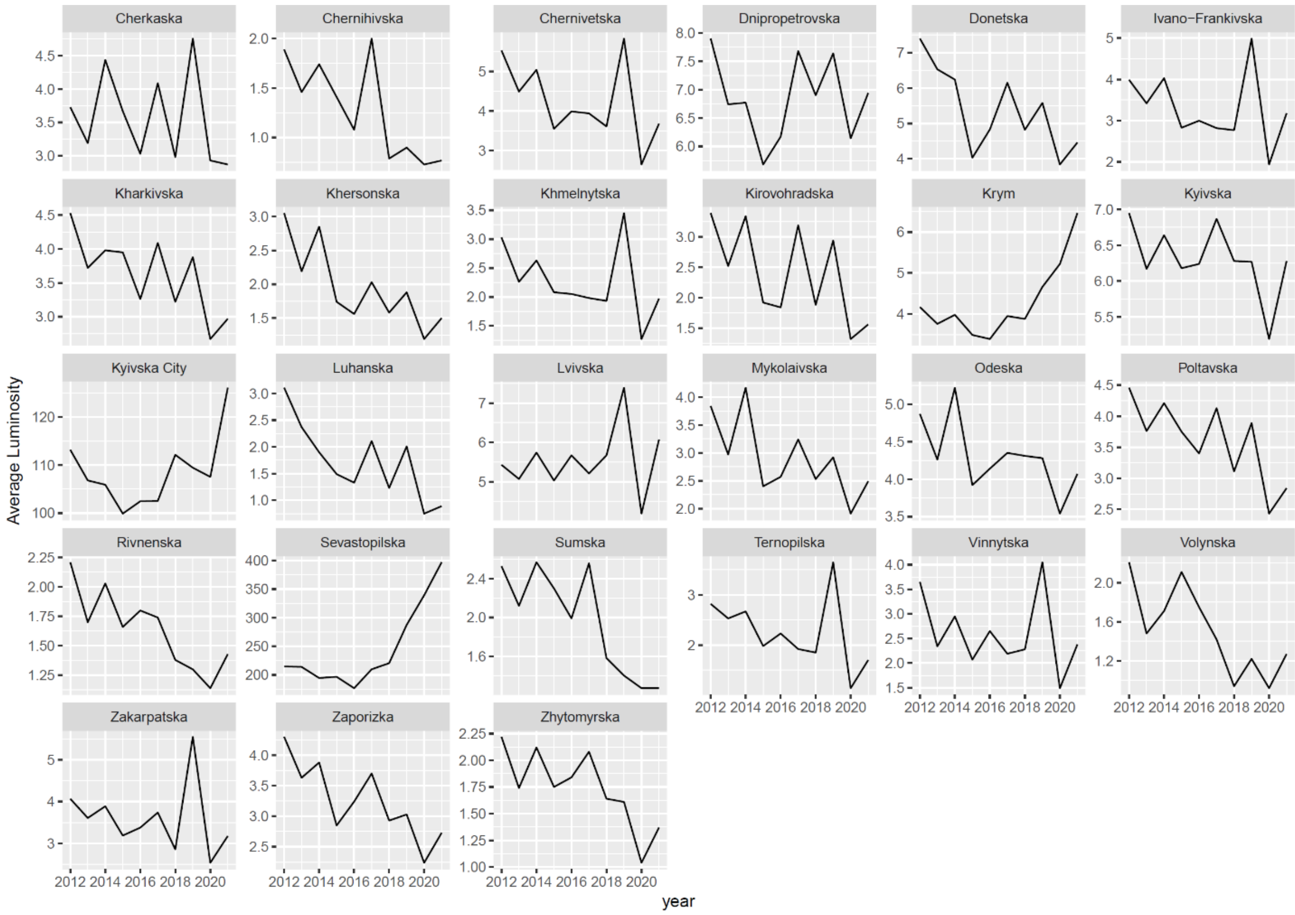

Figure 3. The Evolution over Time of Luminosity