National Bank of Ukraine

Tracking the War in Real Time

preliminary

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- Participants of the NBU internal research seminar for their comments and suggestions
- Everyone who supports Ukraine!

It is the 13th month of a 9-year war

- 2014: russia annexed Crimea and occupied Donetsk and Lugansk regions
  - Macroeconomic imbalances
  - Inflation peaks at 60%, recession, currency and bank crises

- 2022: full-scale russia's aggression
  - 15 mln Ukrainians left the country (half of them are now back), internal migration
  - Destroyed capital and infrastructure, no investments
  - Inflation about 30%, currency depreciation, fiscal and external deficits
  - Economic activity declined by about 30% in 2022 according to preliminary estimates of the State Statistic Service of Ukraine

- Unprecedented effects on local, regional, and global environment
  - Destruction of supply chains, energy price shock, migration

Motivation

- Prudent policies require a thorough understanding of the past, present, and future
- Nowcasting – assessing the current economic stance – important for policymaking as official data comes with considerable lag and at low frequency for some important variables (e.g., GDP, unemployment)
- Rich literature on nowcasting
  - Data handling, estimation frameworks, model selection, forecast performance
  - See, for example Bańbura, Giannone, Modugno, Reichlin (2013) for a comprehensive overview
- Challenges to existing approaches for Ukraine during the war
  - Data limitation – most of the official data is unavailable and existing models do not perform
  - Structural breaks and inversion of historical correlations – no experience in historical data and no ability to assess the forecast performance
  - Regional heterogeneity – crucial for areas with active military actions

What we do

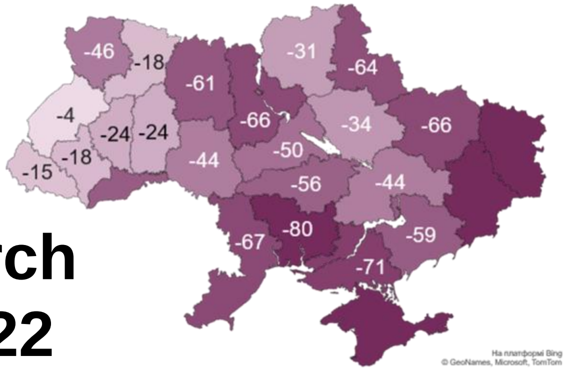
Develop a nowcasting model to asses the current economic stance in Ukraine after a full-scale russia's aggression

- Data:
  - Google trends
  - Night light intensity (satellite images)
  - Online vacancies and wages
  - Commercial banks' cash and non-cash transactions
- Higher-frequency regional perspective
  - Index of Key Sectors Output at monthly frequency and regional level to approximate economic activity
- Framework
  - Panel principal components for each data source
  - A battery of randomly specified models, controlling for inversion of historical correlations, forecast averaging

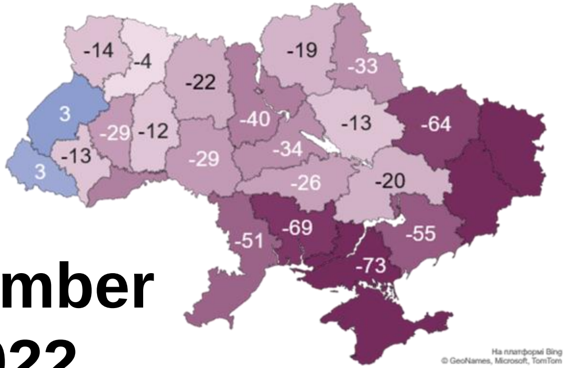
Summary results

Economic activity in Ukraine dropped by half in March 2022 (y-o-y) and by third in 2022 (annually)

- In line with official preliminary GDP estimates
- The effect of full-scale aggression is highly heterogeneous across regions



March 2022



November 2022

Brief literature overview

Nowcasting – prediction of the present:

- See Bańbura et al. (2013) for a comprehensive review of existing frameworks
- Empirical models based on historical relationships
- A key principle in nowcasting is to use all the available information.

Major topics and challaneges for nowcasting:

- Mixed frequency, missing data, ragged edges, dimensionality
  - Dynamic Factor Models (DFMs) in a state-space representation (Giannone, Reichlin, and Small, 2008 and Evans, 2005), MIDAS and «bridge models» (Clements and Galvão, 2009, 2008)
- Model selection and forecast performance
  - Statistical criteria to select proper models (see, Boivin and Ng, 2006) and forecast avereging to control for model sensitivity
  - Machine learning techniches to train and validate the model (e.g., LASSO, elastic net, see Zou and Hastie, 2005) through out-of-sample real-life forecast performance (RMSE, MAE, etc.)

Nowcasting Ukrainian output during the war

See NBU's Inflation Report (July, 2022, Box 3) for an overview of the features and methods of GDP nowcasting during the war by the National Bank of Ukraine

- **Expert assessments of changes in economic activity at sectoral and regional level** (based on the sectoral and regional structure of GDP and a number of high-frequency indicators: biweekly flash surveys of enterprises' operations conducted by the NBU from March to May; the number and turnover of cafés and restaurants at work; data from some of the largest retail chains; the number of new buildings put up for sale; electricity generation and consumption figures, etc.)
- **Business Expectations Index (BEI) to forecast GDP using ARDL and VAR models**. BEI is an aggregated index of NBU's quarterly business outlook surveys.
- **Approximation of economic activity using alternative data sources**
  - This project
  - Related project by Nikodem Szumilo (UCL), Kalle Kappner (Humboldt University), and Mihnea Constantinescu (NBU) (VOX column)

Target variable: Index of Key Sectors Output (IKSO)

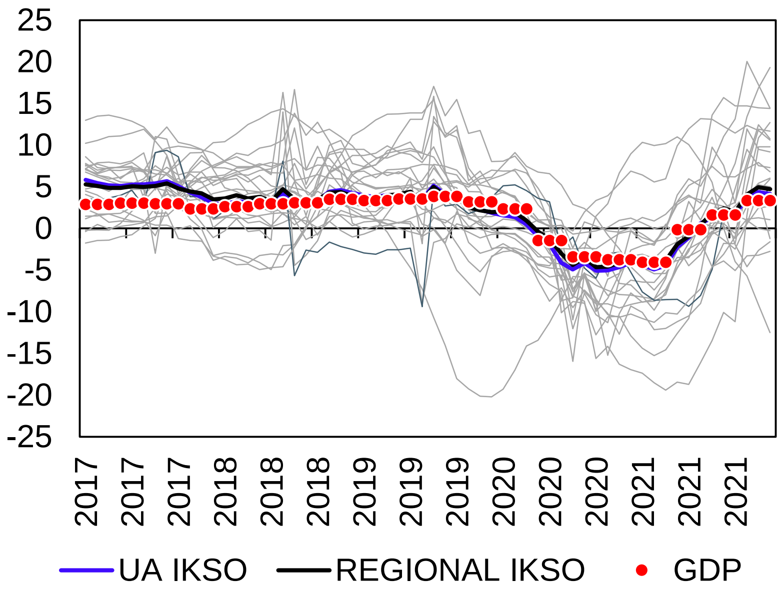
Index constructed by the National Bank of Ukraine to assess economic activity at monthly frequency

- Covers about 50% of total GDP
- 9 Sectoral Indexes weighted using GDP value added
  - Agricultural, Mining, Manufacturing, Electricity, Construction, Retail & Wholesale Trade, Freight & Passenger Transportation
- Solid performance for GDP nowcasting (especially during crises)

We extend the construction of the index to cover regional perspective

- 23 regions (excluding Crimea, Sevastopol, Lugansk and Donetsk)
- Some indexes are easily available, some are collected manually, some are approximated
- Aggregated using GDP value added weights

IKSO* and GDP, annual change, %



** Constructed as rolling 12-month average of y-o-y changes for comparison purposes with GDP*
Note: gray curves represent IKSO for specific regions

Input data

- Google trends
  - Source: Google
  - Principal components across 25 categories at regional level
  - Useful for nowcasting: Choi and Varian (2009), Choi and Varian (2012), Woloszko (2020)
- Night light intensity
  - Source: NASA satellite images
  - Standard deviation of pixel intensity within a region (better captures changes in economic activity as compared to average pixel intensity within region)
  - Useful for nowcasitng: Henderson, J. V., Storeygard, A., Weil, D. N. (2012)
- Online vacancies and wages
  - Source: Work.ua (online job offering platform)
  - Principal components across 28 job categories at regional level
  - Wages are deflated by regional CPI series
  - Useful for nowcasitng: Štefánik, Lyócsa, and Bilka (2022)
- Commercial banks' cash and non-cash transactions
  - Source: NBU (limited access)
  - Principal components for 29 types of operations at regional level
  - Deflated by regional CPI
  - Useful for nowcasitng: Aprigliano, V., Ardizzi, G., Monteforte, L. (2019)

General data issues

- Regional and sectoral volatility
  - Higher level of disaggregation results in higher volatility
  - Decision: remove region-specific means and divide by region-specific standard deviation
- Changes in historical correlations
  - While some input series historically had negative correlation with IKSO, after a full-scale war most series dropped considerably
  - Example of inverse correlation: during the COVID-19 crises people spent more time online and google searches in “games” category increased. However, during the war, the searches dropped considerably and, hence, the model would predict the increase in GDP instead of expected decline.
  - Decision: a battery of randomly specified models – exclude specifications if inversed correlation detected
- Multicollinearity
  - Not a big issue in “peaceful” times, but aggravates forecast sensitivity if shocks are large
  - Decision: Principal Components for selected groups, controlling for inverse correlations
- Lugansk and Donetsk regions, Crimea
  - Volatile (patterns different to UA-wide)
  - Poorly represented in work.ua, google trends datasets
  - Decision: exclude regions

Estimation and model selection

- Panel data estimation (fixed effects). Sample: 2017m1 – 2021m12, 23 regions

$$IKSO_{i,t} = a_1 Google_{i,t} + a_2 Light_{i,t} + a_3 Vacancy_{i,t} + a_4 Wage_{i,t} + a_5 Cash_{i,t} + \epsilon_i + \varepsilon_{i,t}$$

  - where $Google, Vacancy, Wage,$ and $Cash$ state for up to 3 first principal components
  - Squared values of regressors are also included to control for potential nonlinearity
  - For estimation: 12-month rolling average y-o-y changes (to imitate annual GDP)
  - For nowcast: y-o-y changes

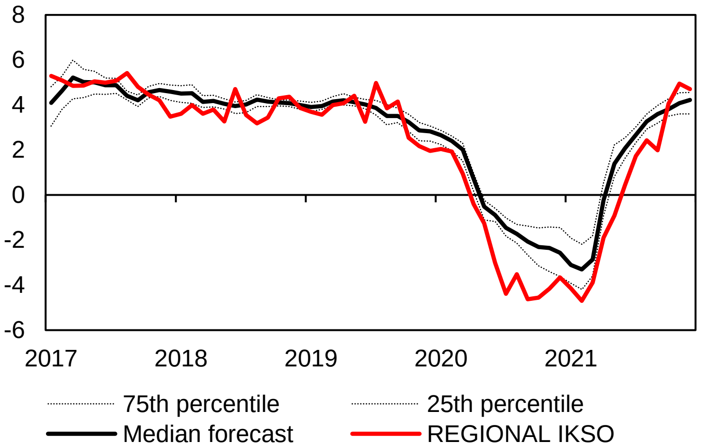
- A battery of randomly specified modes, controlling for inverted correlations, and forecast averaging
  - Estimation of 1 mln models randomly including and excluding regressors
  - Selection of models with no inversion of historical correlations after the full-scale aggression
    - Assuming that economic activity in regions with active military actions is expected to terminate
  - Selection of 10% of best models (based on in-sample model fit)
  - Forecast averaging for selected models (mean, 25th and 75th percentiles for tolerance band)
  - Weighted forecast averaging (based on out-of-sample model fit)

Results

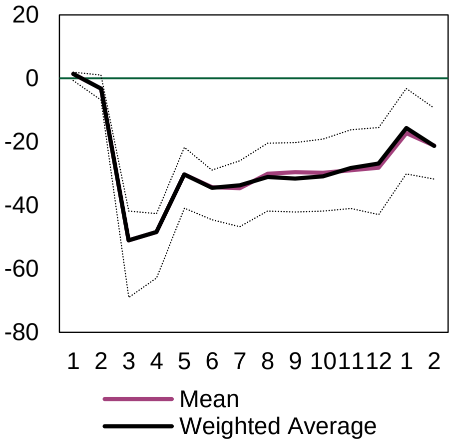
About 2700 selected models with max R2 of 41%

- Google trends series (principal components) in 42% of selected models
- Night lights – 60%
- Online vacancies – 97%
- Online wages – 18%
- Cash operations – 93%

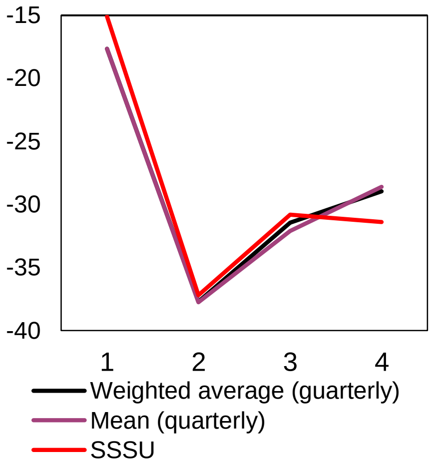
Historical performance*



Monthly nowcast 2022**



Quarterly nowcast***

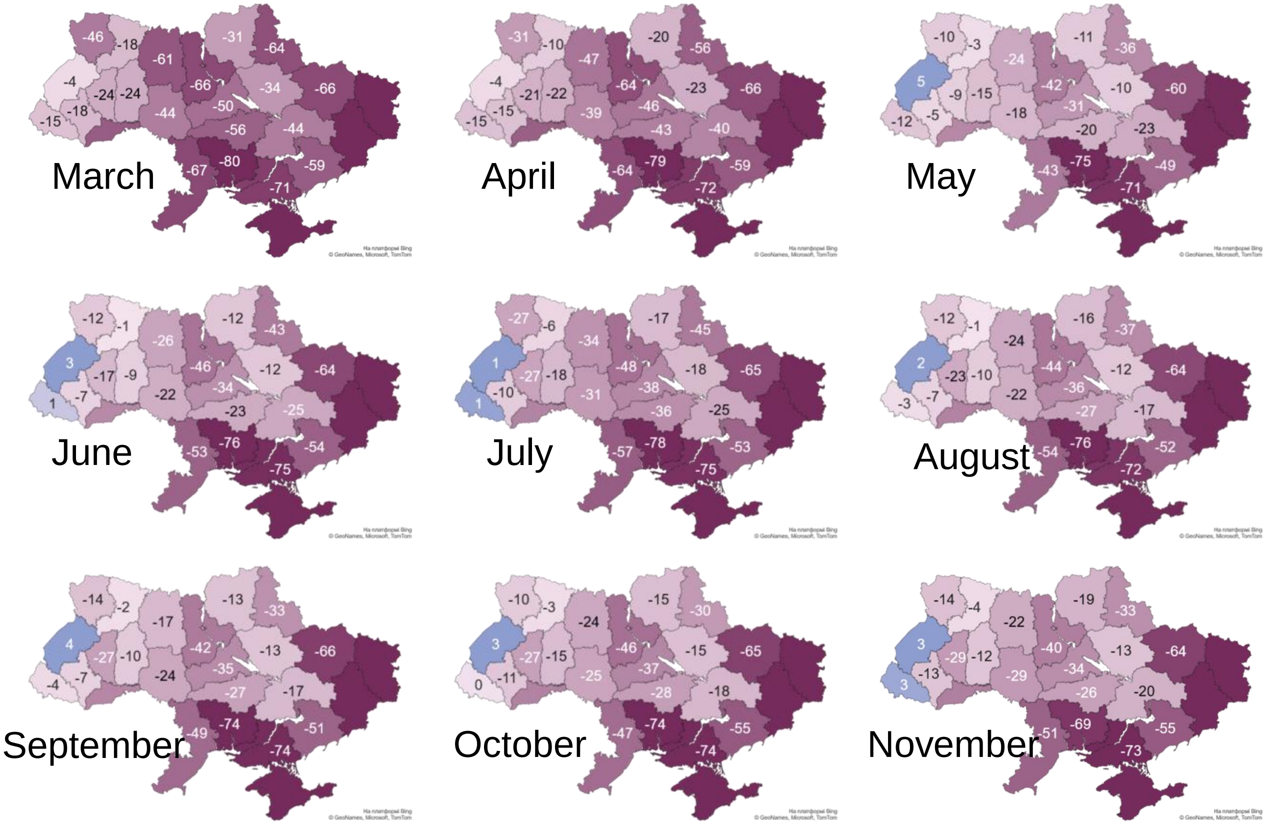


*Rolling 12-month average of y-o-y changes (comparable to annual GDP)

** Changes to corresponding month of previous year

*** Changes to corresponding quarter of previous year

Nowcast by region



Conclusions and further work

- We develop a nowcasing tool to track economic activity in Ukraine after the full-scale russian aggression under conditions of limited data, unprecedented structural break, and regional heterogeneity
- We show that
  - Alternative data sources (google trends, night lights, online vacancies, banks’ cash and non-cash transactions) are useful for nowcasting even under extreme conditions and capable of reflecting unprecedented size of the shock which has never been experienced in the past
  - Random model specification, controlling for inversion of historical correlations, forecast averaging can be useful to deal with forecast uncertainty and sensitivity
- Further work is needed to improve
  - Estimation techniques to deal with inverted historical correlations
  - Estimation at sectoral level (poor results so far)