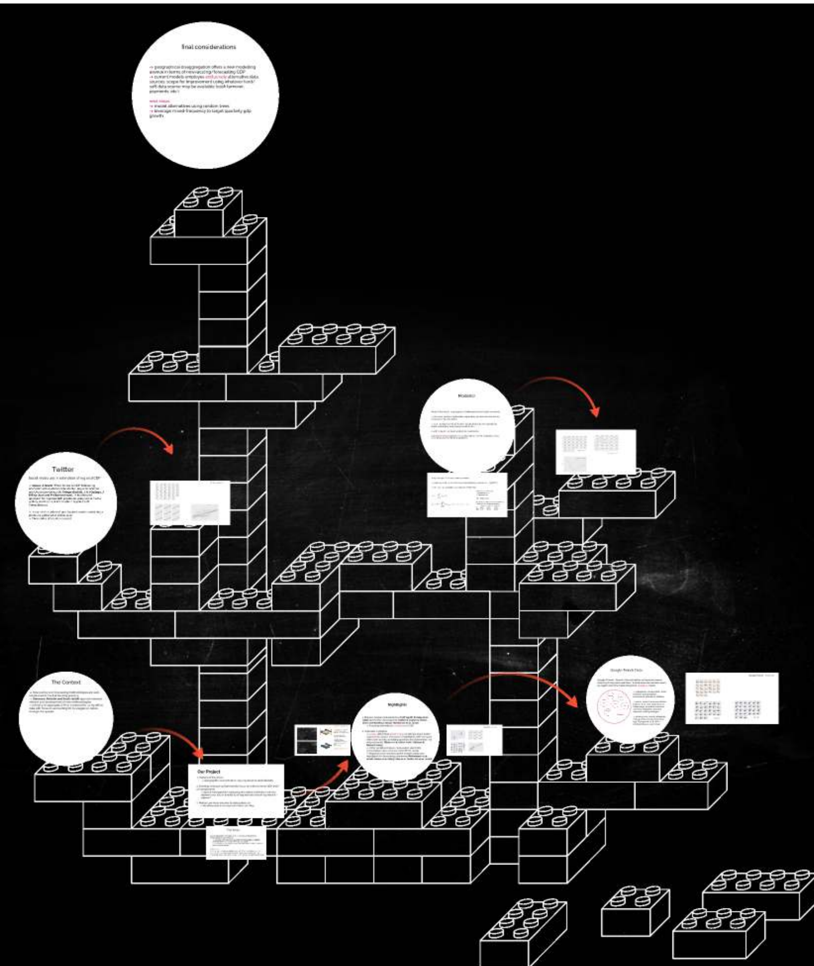
Warcasting-Nowcasting GDP without economic data

Constantinescu, Kappner, Szumilo



Mihnea Constantinescu
National Bank of Ukraine and
Kyiv School of Economics

BCC Conference
September 22-23, 2022

The Context

>> Nowcasting and forecasting methodologies are well-established in Central Banking practice
-> **Giannone, Reichlin and Small (2008)** spurred renewed interest and development of new methodologies
-> primarily of aggregate GDP or components, using official data with focus on accounting for its staggered nature through the quarter

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Covid19

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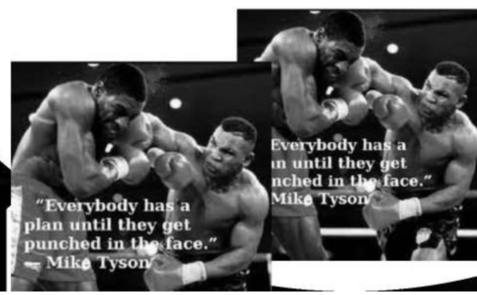

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Our Project

1. Nature of the shock
   -> Geographic concentration, varying duration and intensity

2. Existing nowcasting frameworks focus on national level GDP and/or components
   -> Spatial heterogeneity: replicating the national estimation exercise depends crucially on availability of regional data (assuming national = regional)

3. Martial Law froze any and all data collection
   -> No official stats or surveys from March until May

First Steps

Rely on alternative indicators and build bayesian hierarchical models of key macro variables

-> using payments data as in **Galbraith and Tkacz (2018)**, **Chapman and Desai (2021)** : unavailable timespan and depth

-> using electricity and google/apple mobility data: no longer available due to security reasons;

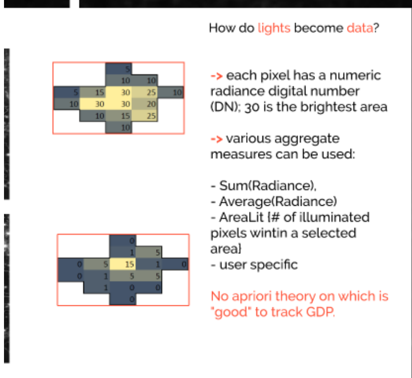
Bottom-line:

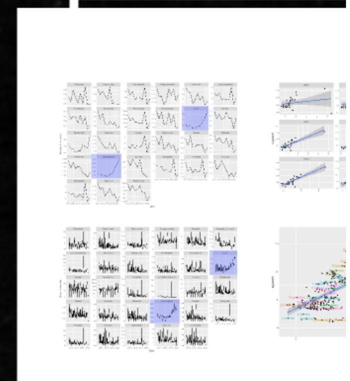
1. Some regional data available (yearly GDP at oblast level) but no regional variables as needed in established nowcasting exercise
2. Available data: nightlights, social media activity, Google Search Data

Nightlights

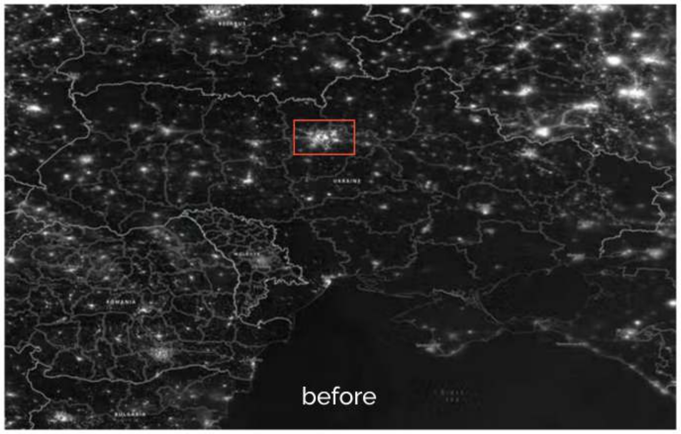
1. Mature literature kickstarted by **Croft (1978), Elvidge et al. (1997)** and further developed by **Sutton & Costanza (2002), Chen and Nordhaus (2011), Henderson et al. (2012)**
   -> Focusing primarily on country level GDP

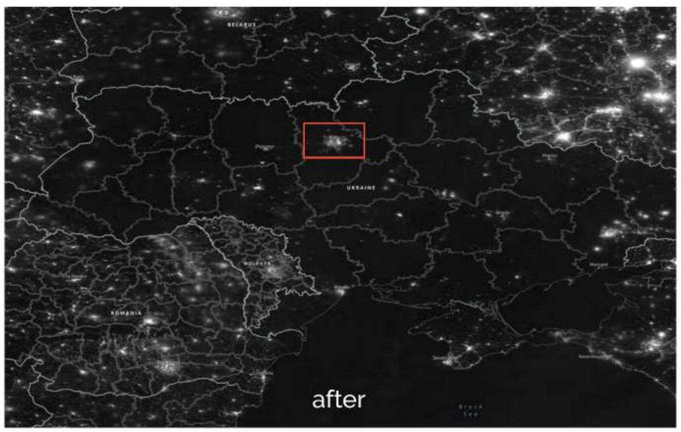
2. Important highlights
   -> Levels rather than growth rates of GDP are much better captured by various measures of nightlights (GDP can grow with urban activity spreading upwards and downwards, not only outwards); **Gibson et al. (2020, 2021), Addison & Stewart (2015)**
   -> Other variables in levels (population, electricity consumption) also correlate well with NL levels
   -> Regional cross-sectional panel models using only nightlights for developing economies **Bickenback et al. (2016), Keola et al. (2015), Xiao et al. (2021), Lin et al. (2022)**





How do lights become data?





-> each pixel has a numeric radiance digital number (DN); 30 is the brightest area

-> various aggregate measures can be used:

- Sum(Radiance),
- Average(Radiance)
- AreaLit {# of illuminated pixels wintin a selected area}
- user specific

No apriori theory on which is "good" to track GDP.

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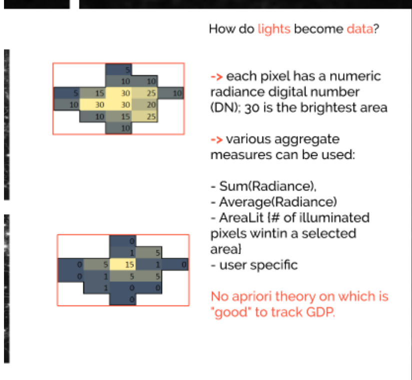
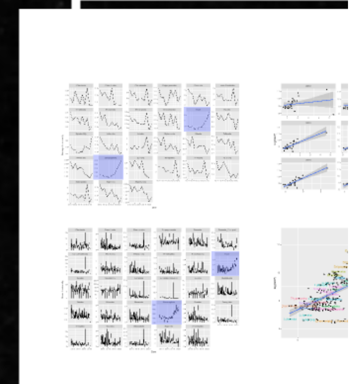
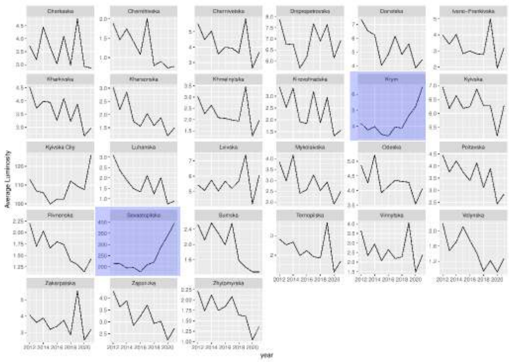
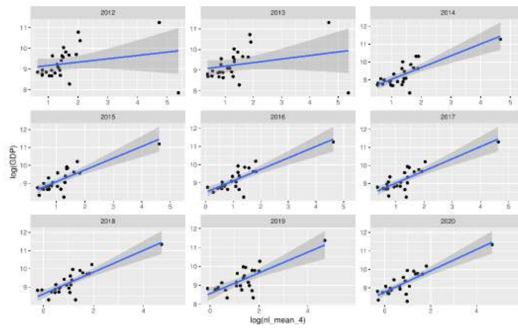
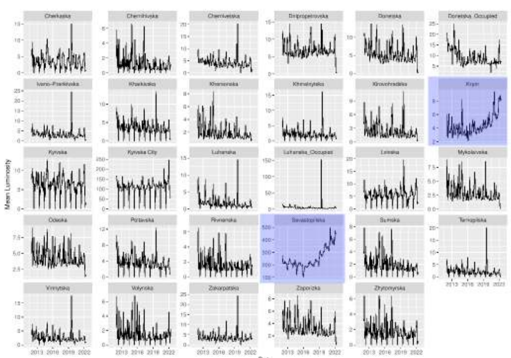


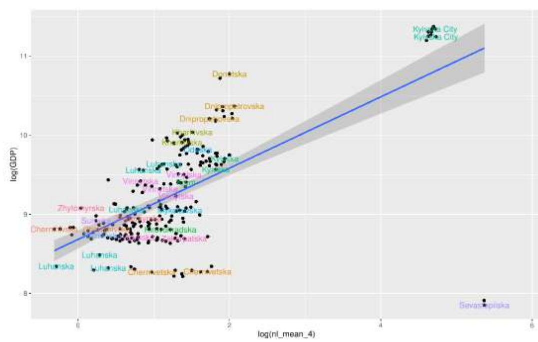


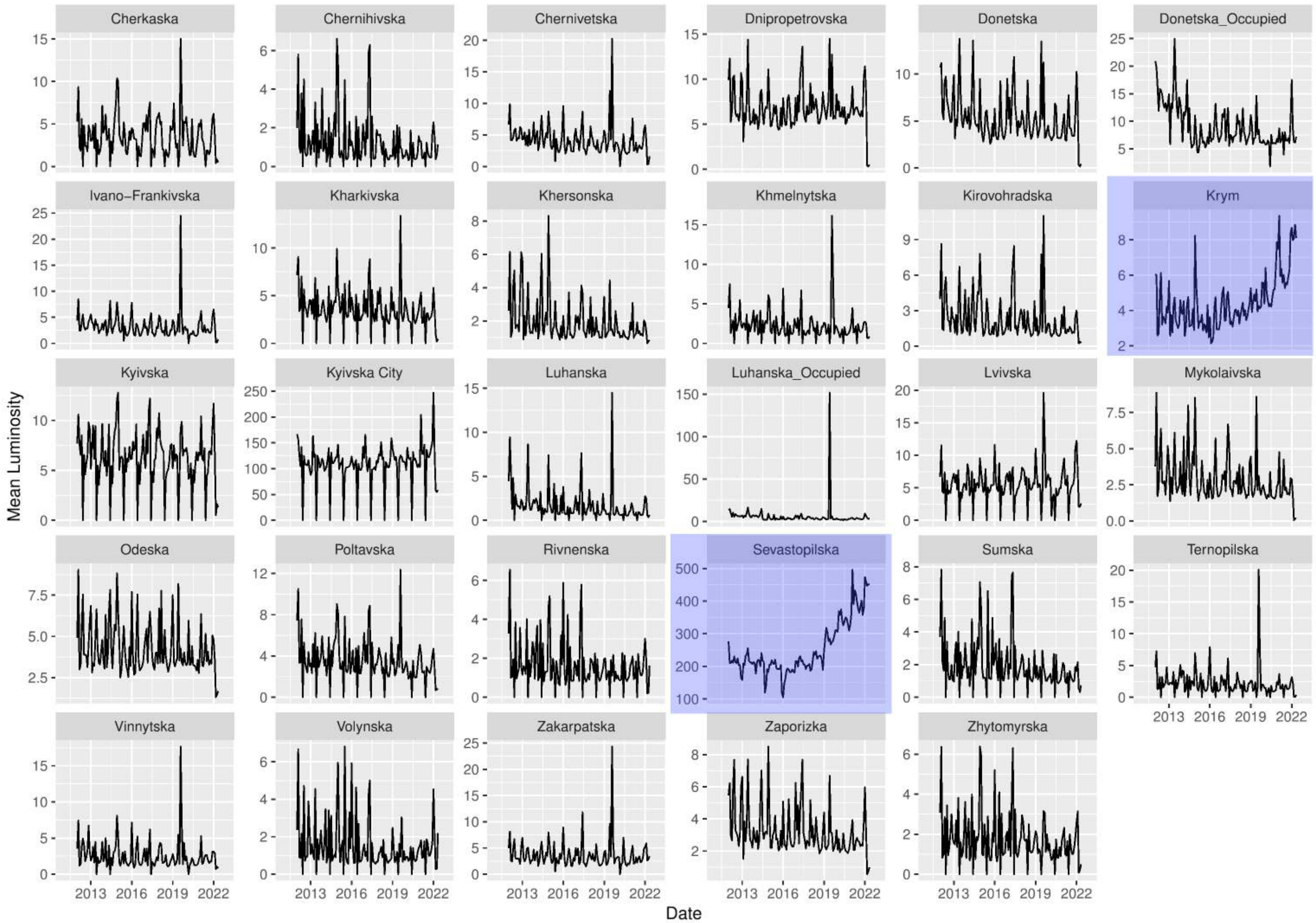
Nighlights - empirics











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Mean Luminosity
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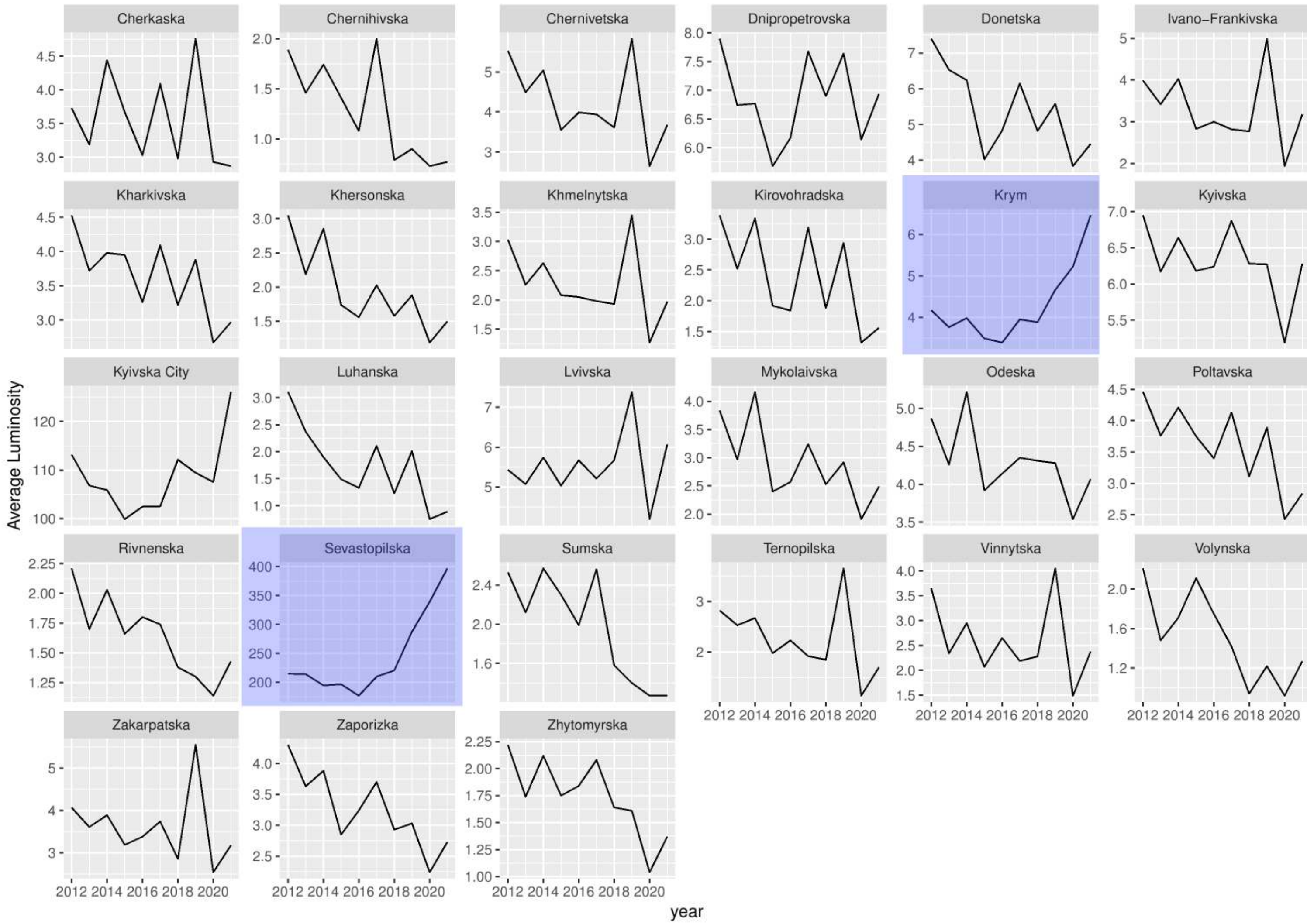
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Average Luminosity
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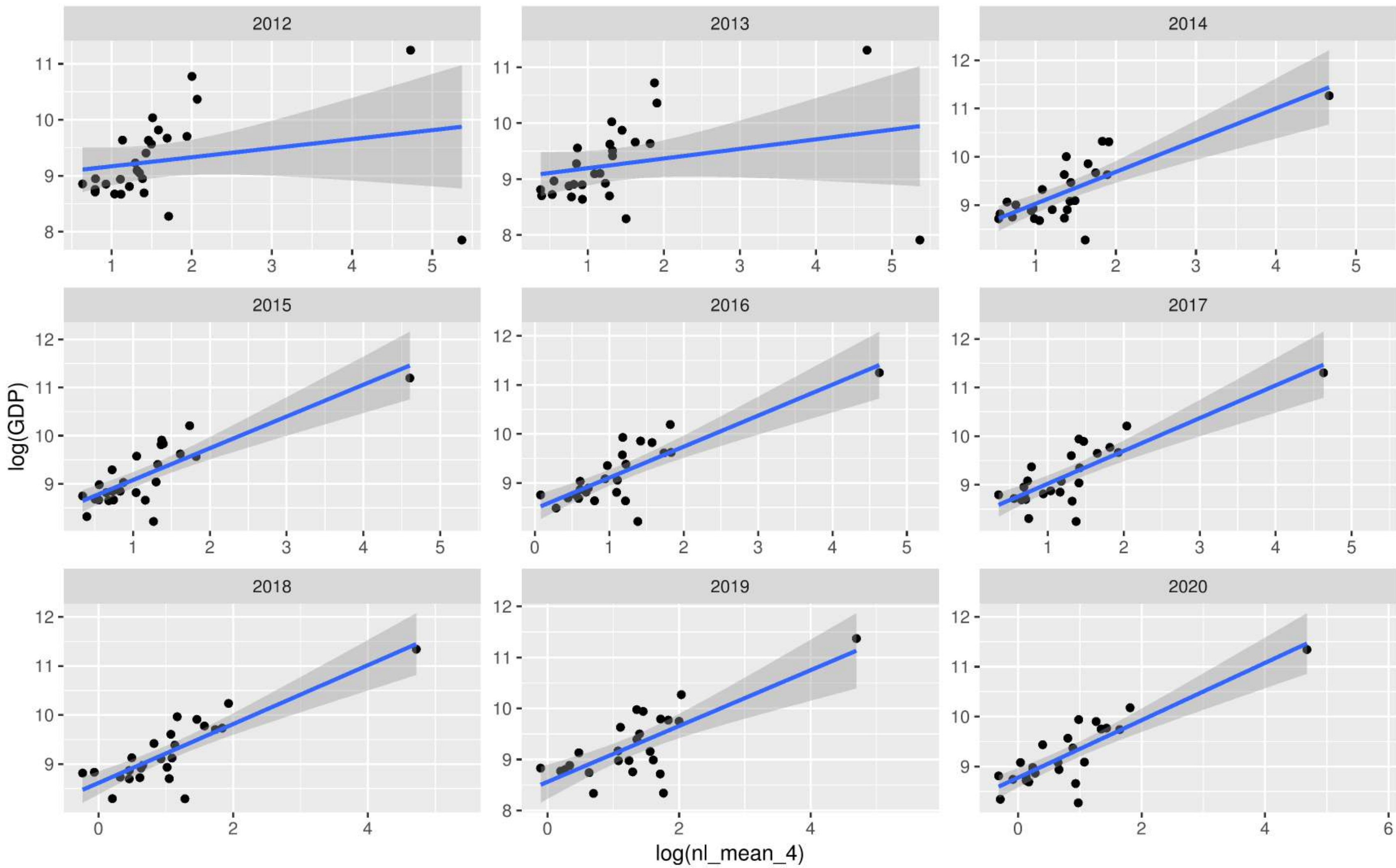
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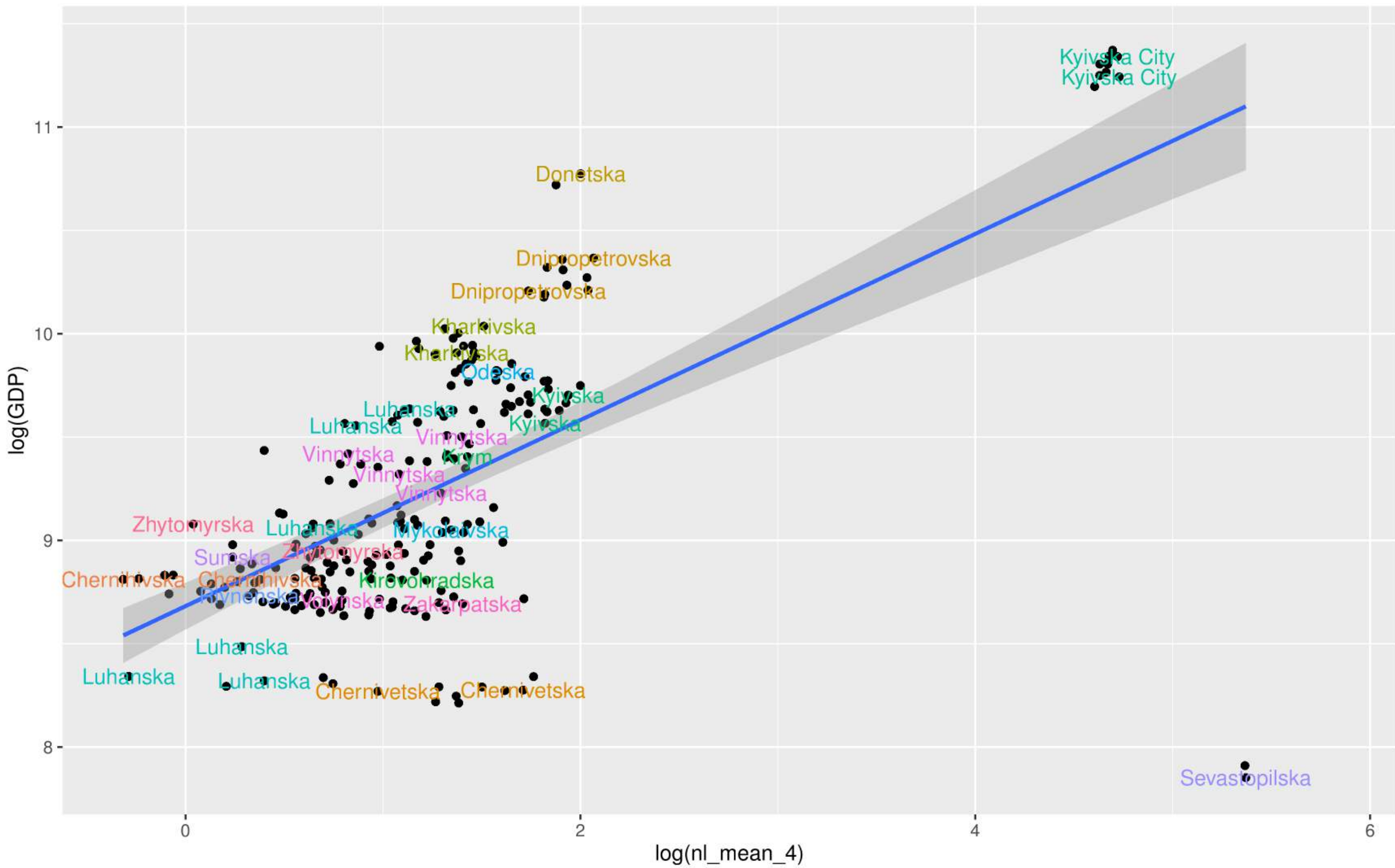
log(GDP)
log(nl_mean_4)


log(GDP)
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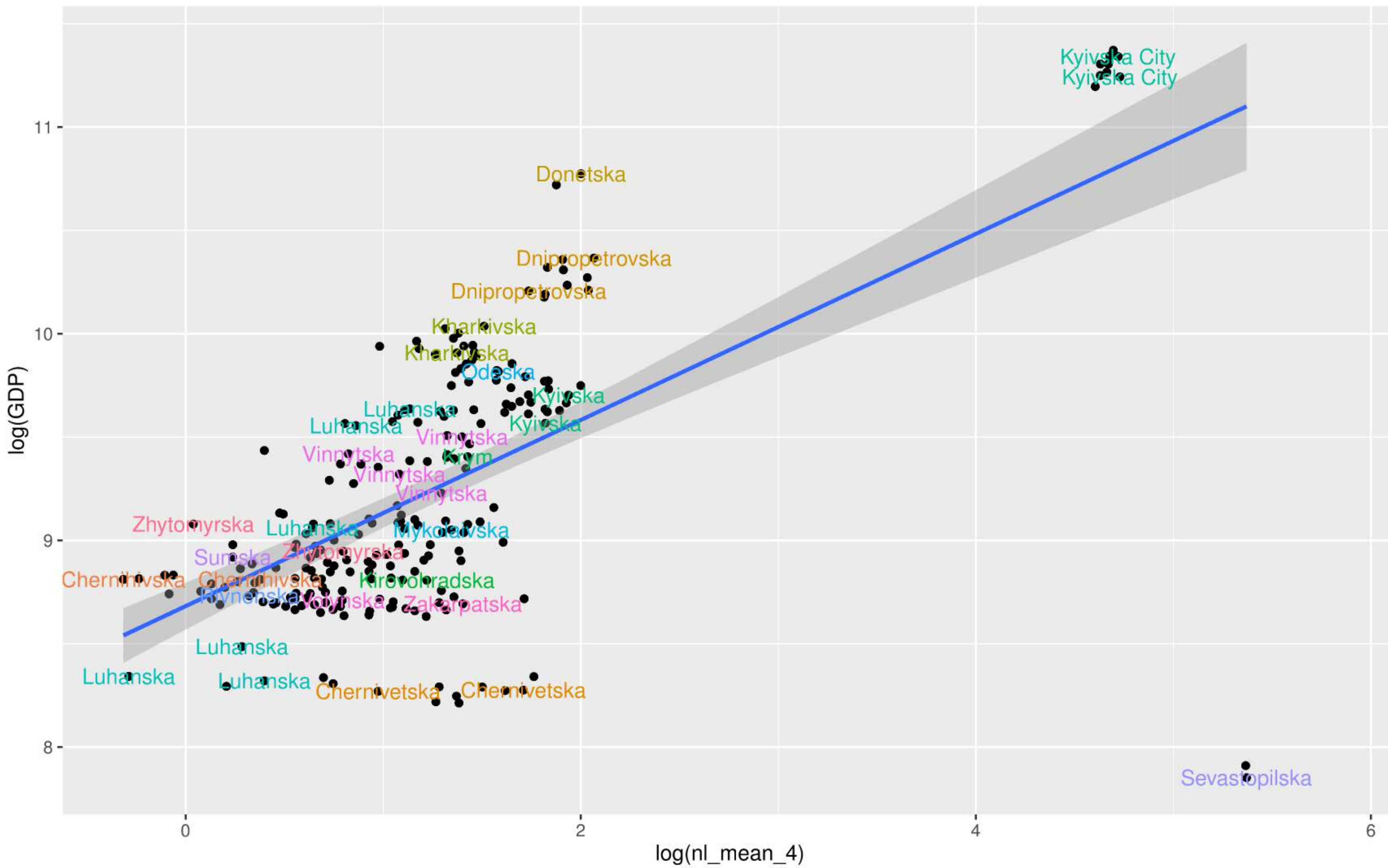

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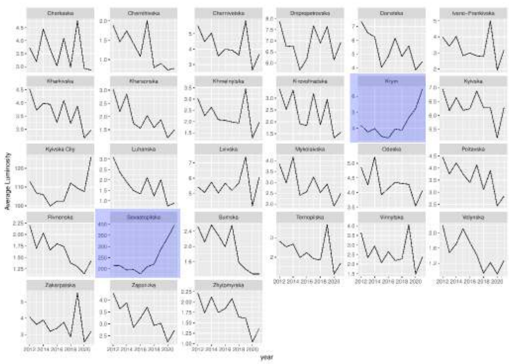
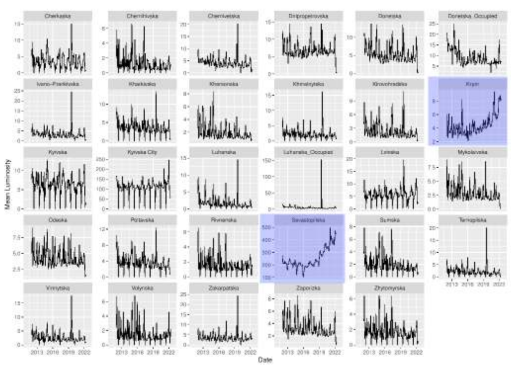
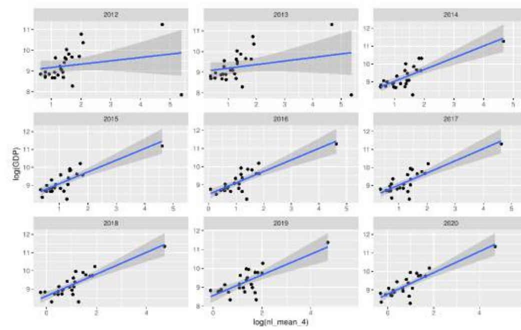
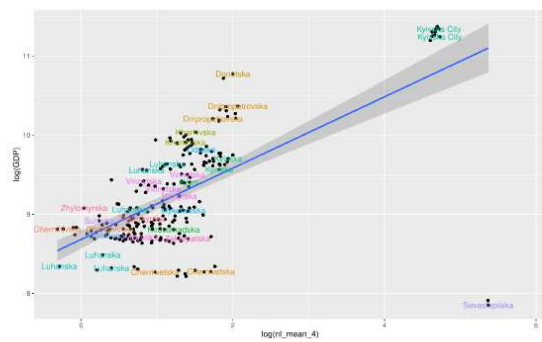
Nighlights - empirics









Key Takeaways

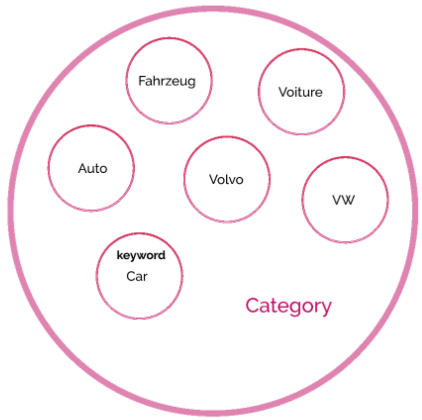
-> strong support for relationship in the cross-section in levels (log-log); stable over time

-> regions have different levels of nightlights

-> within region, no clear longitudinal relationship

Google Trends Data

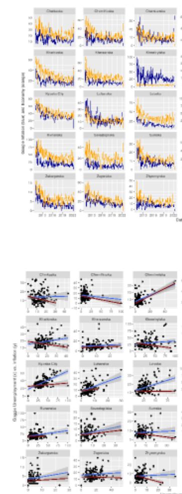
Google Trends = Search Volume indices of keyword search intensity (# keyword searches/ # total searches) broken down by region and time frame {Keyword, Category, Topic}



-> categories: consumption, labor markets, transportation, investment, education, inflation

-> some issues: these are relative indices (w.r.t. total searches); as total usage increases over time and new categories become relevant, ranking changes.

-> during a war, some categories may give the wrong impression (eg. Transportation & GDP in normal times vs. war times)



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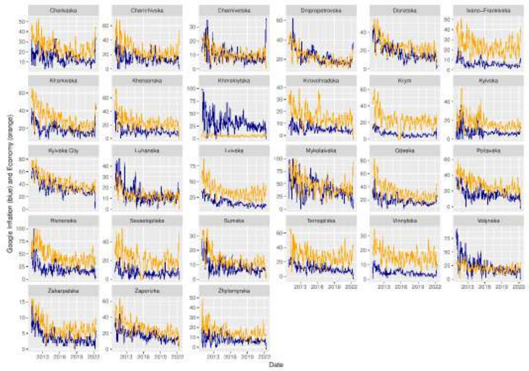
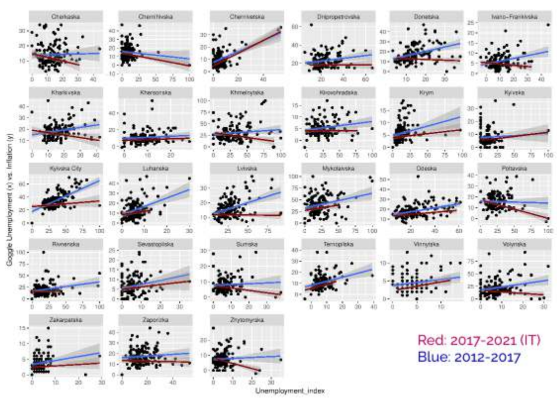
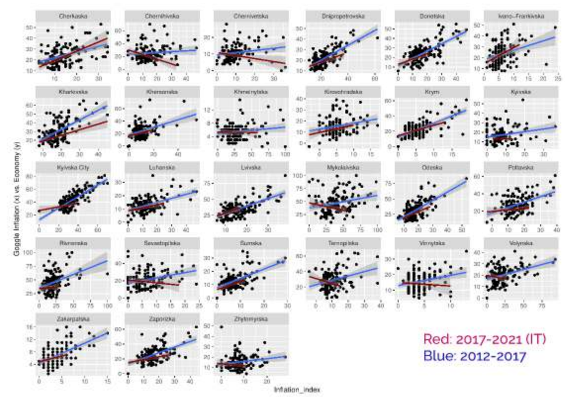




Red: 2017-2021 (IT)
Blue: 2012-2017



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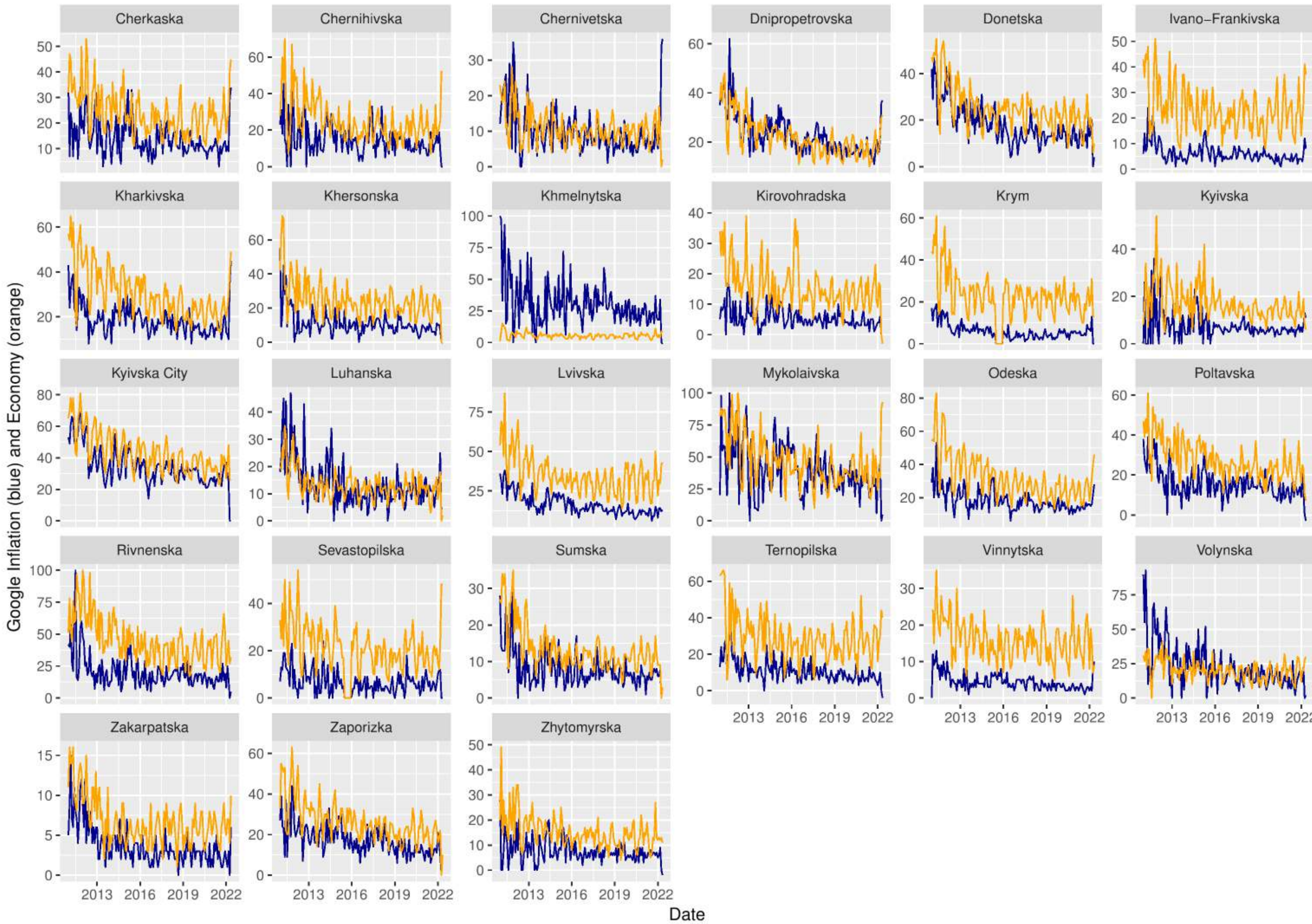
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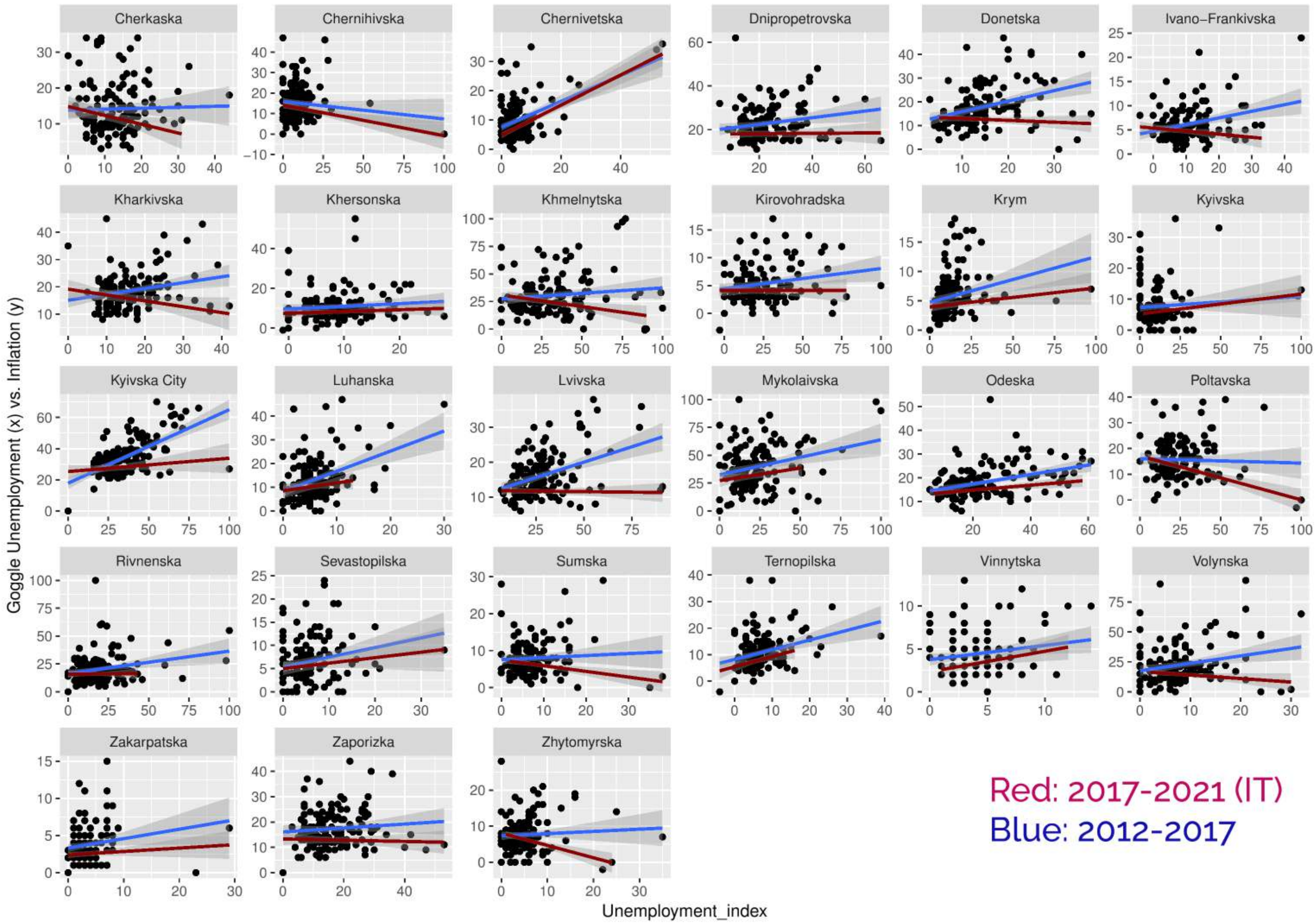
Google Inflation (blue) and Economy (orange)
Date
2013 2016 2019 2022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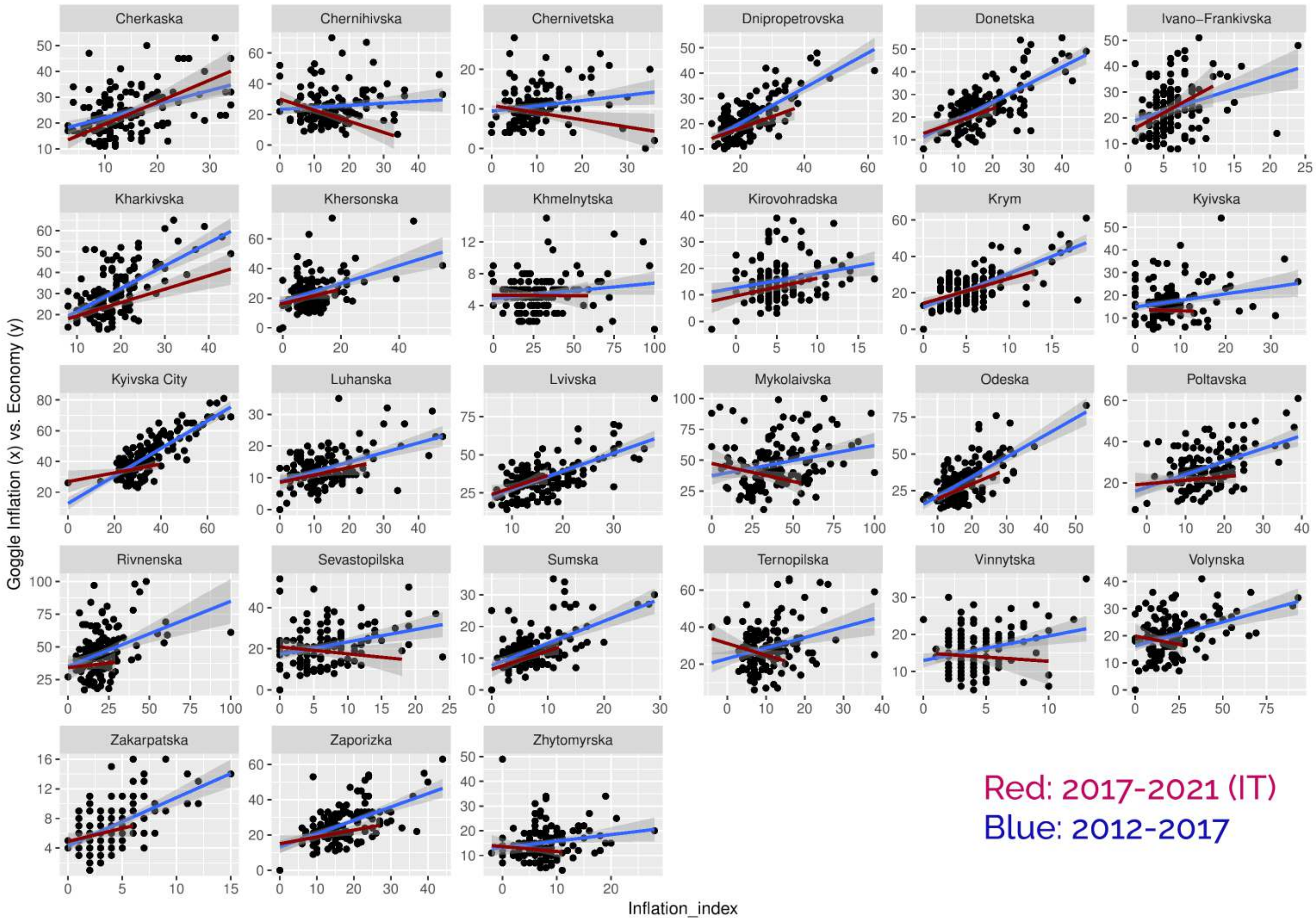
Goggle Unemployment (x) vs. Inflation (y)
Unemployment_index
Red: 2017-2021 (IT)
Blue: 2012-2017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Goggle Inflation (x) vs. Economy (y)
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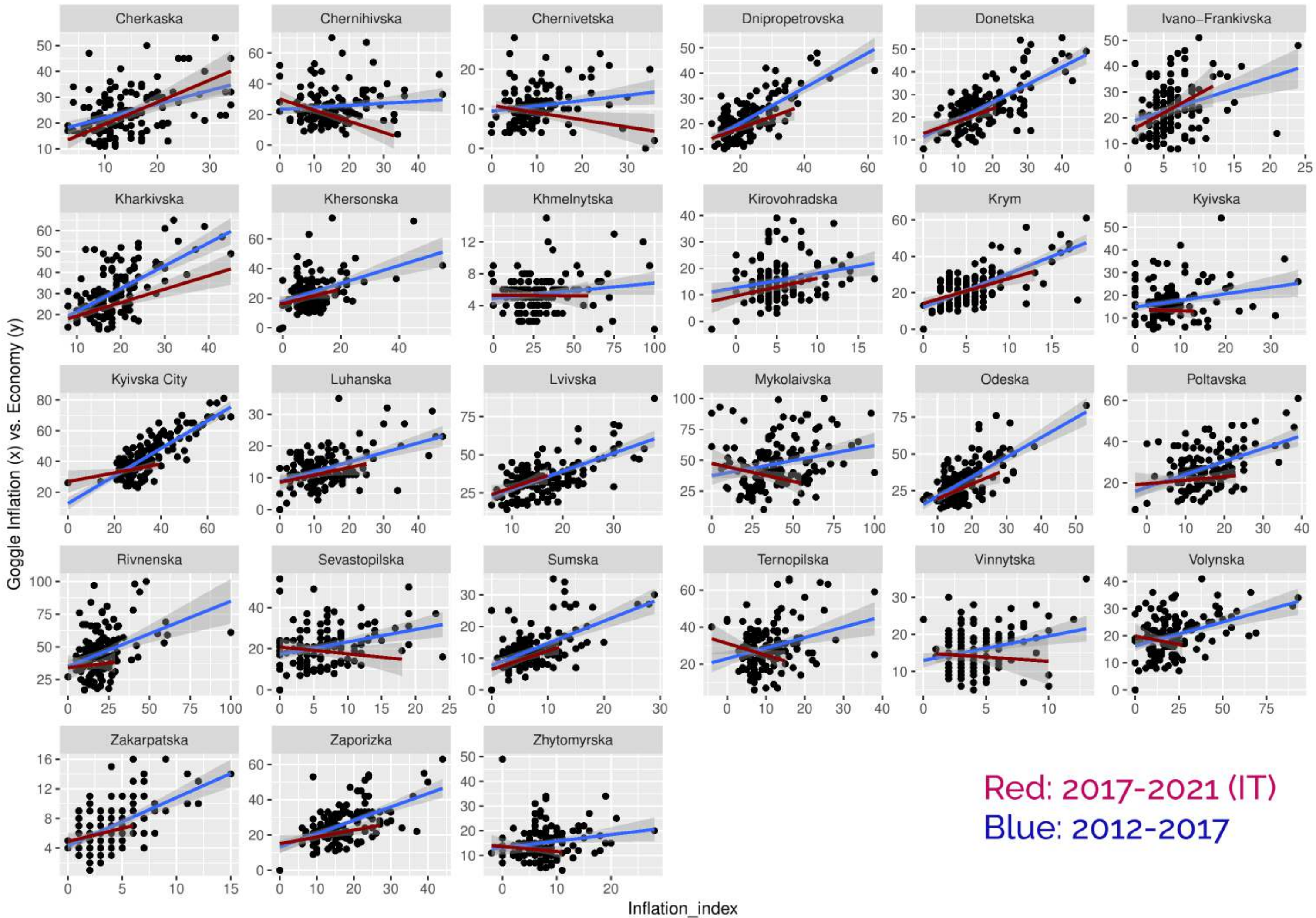
Blue: 2012-2017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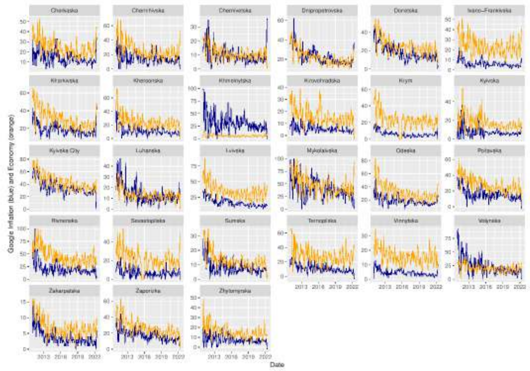
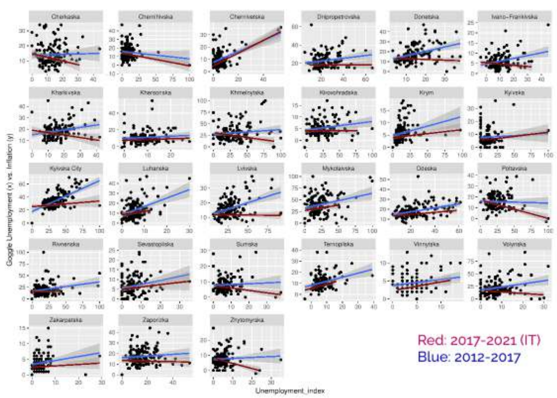
Google Trends - empirics

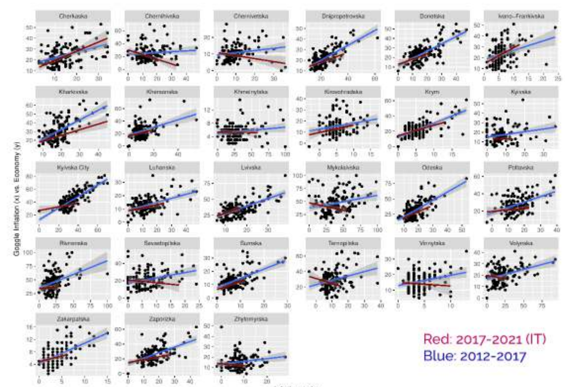


-> About 30 categories are used

-> Monthly time series contain plenty of variation (too much?)

-> Cross-index correlations appear reasonable at first sight but large number implies some shrinkage/ dimensionality reduction is needed





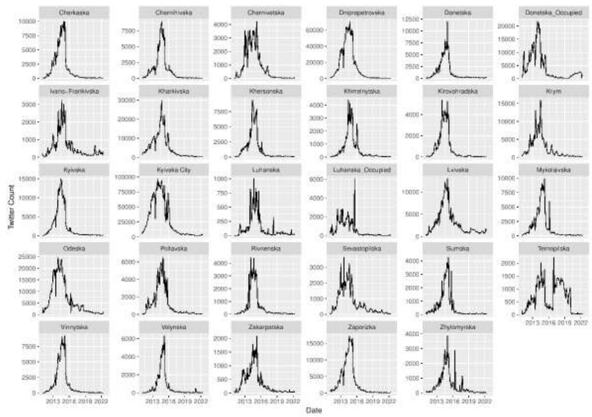
Twitter

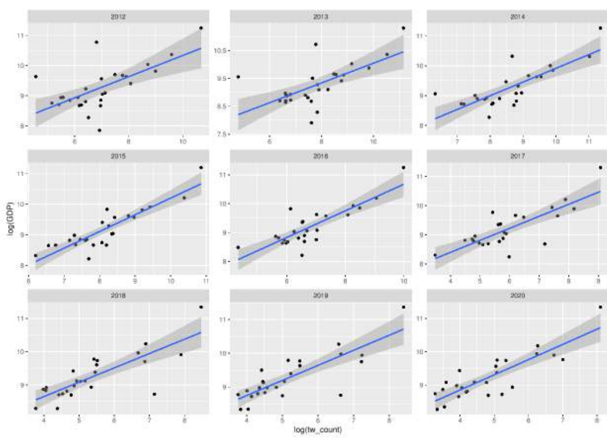
Social media use in estimation of regional GDP

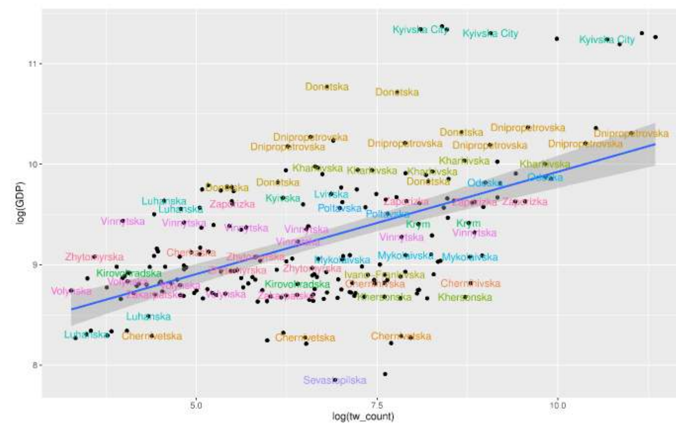
-> **Indaco, A (2020)**, "From twitter to GDP: Estimating economic activity from social media", Regional Science and Urban Economics 85; **Ortega-Bastida, J, A J Gallego, J R Rico-Juan and P Albarran (2021)**, "A Multimodal approach for regional GDP prediction using social media activity and historical information", Applied Soft Computing 111

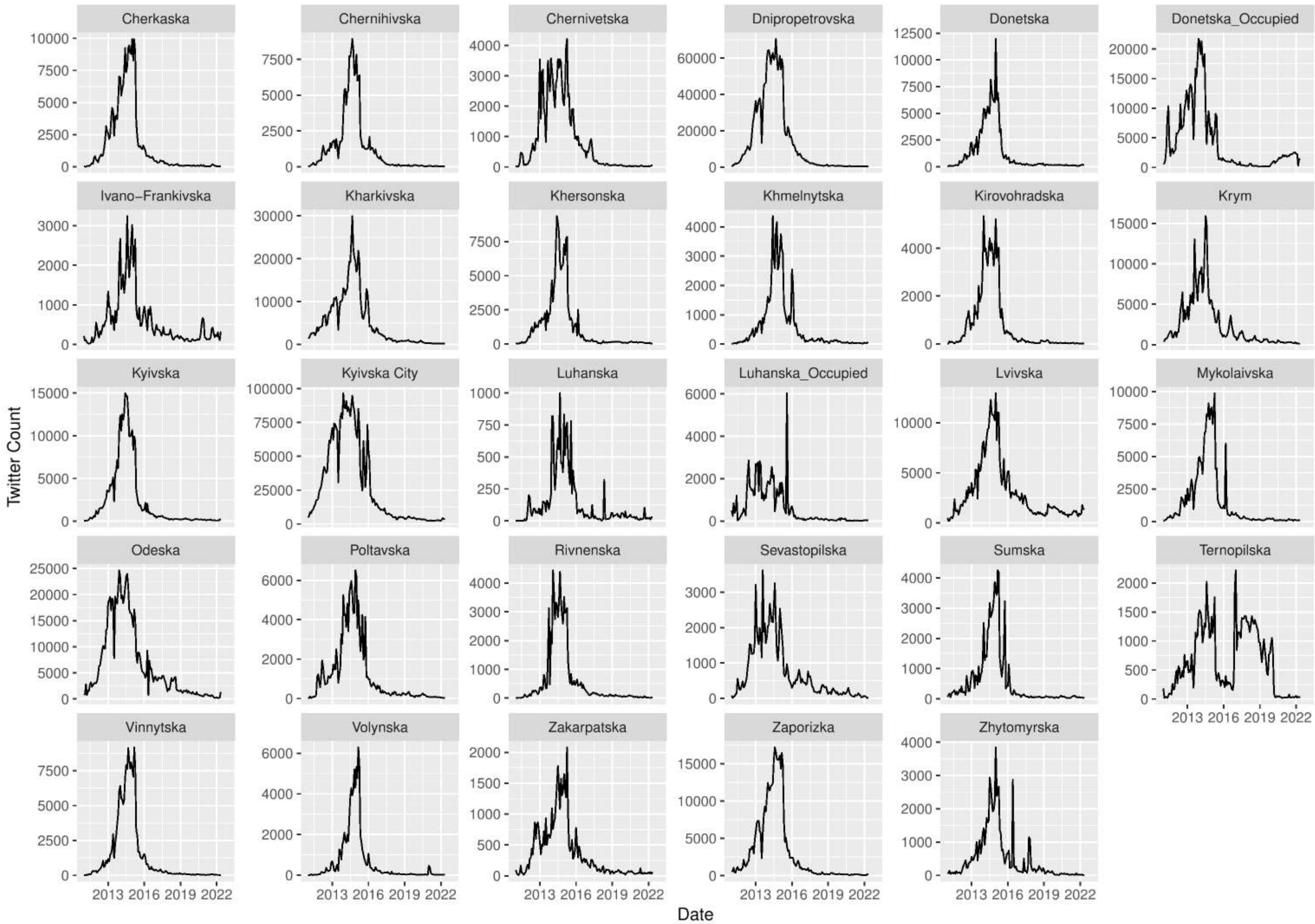
-> In our case, number of geo-located tweets containing a photo are gathered at oblast level
-> Time series of counts are used

Twitter - empirics





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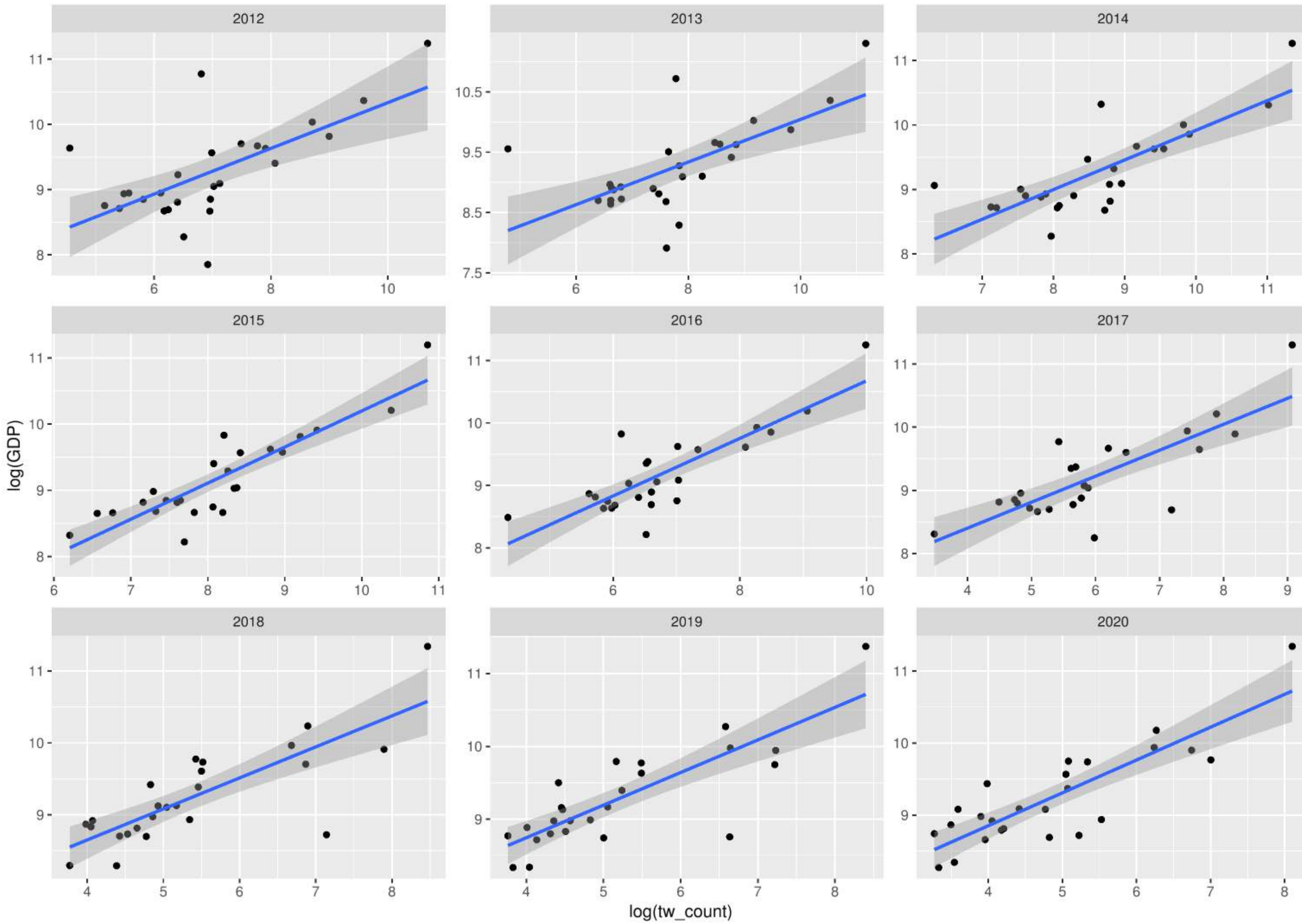
Twitter Count
Date
2013 2016 2019 2022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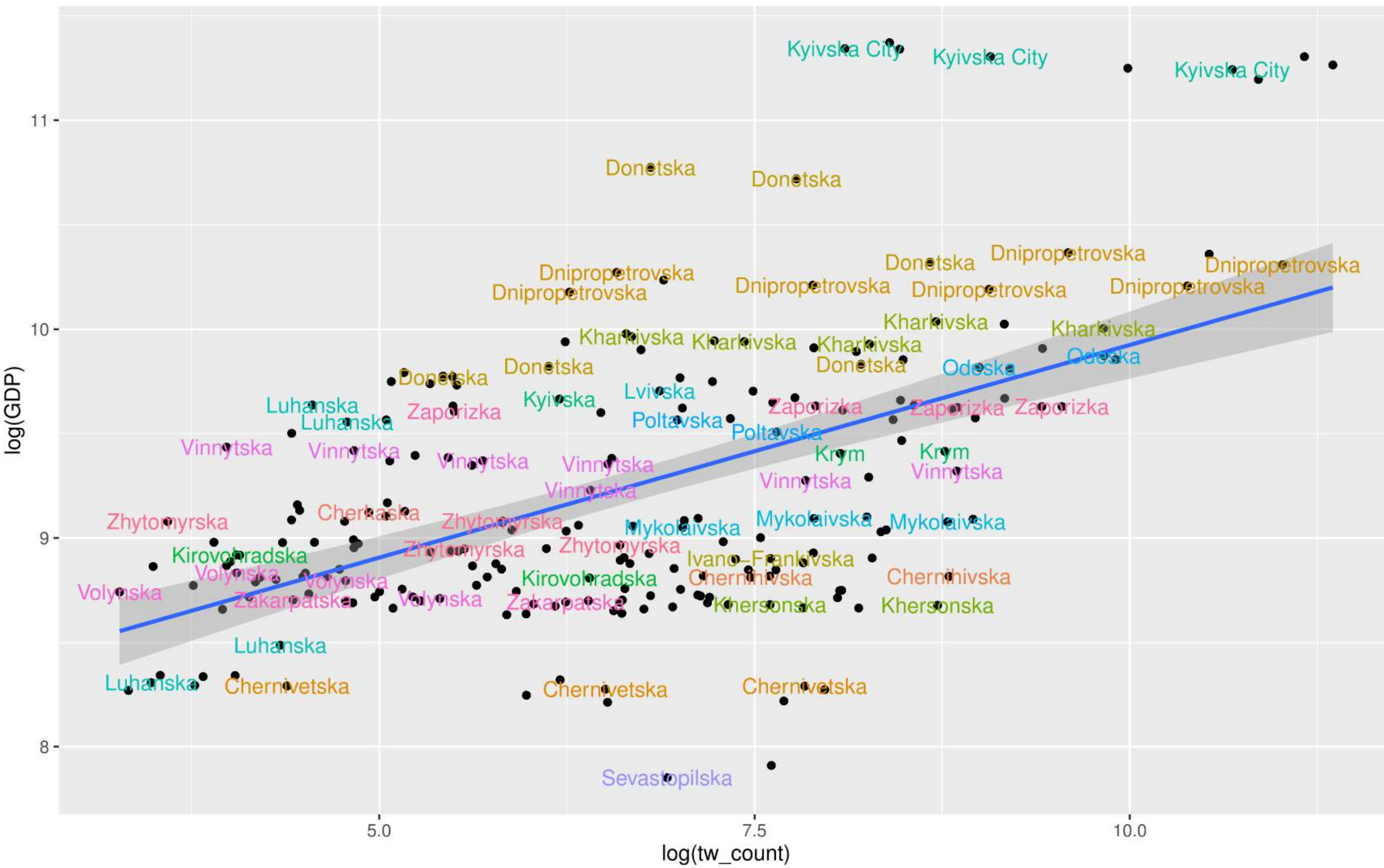
log(GDP)
log(tw_count)



log(GDP)
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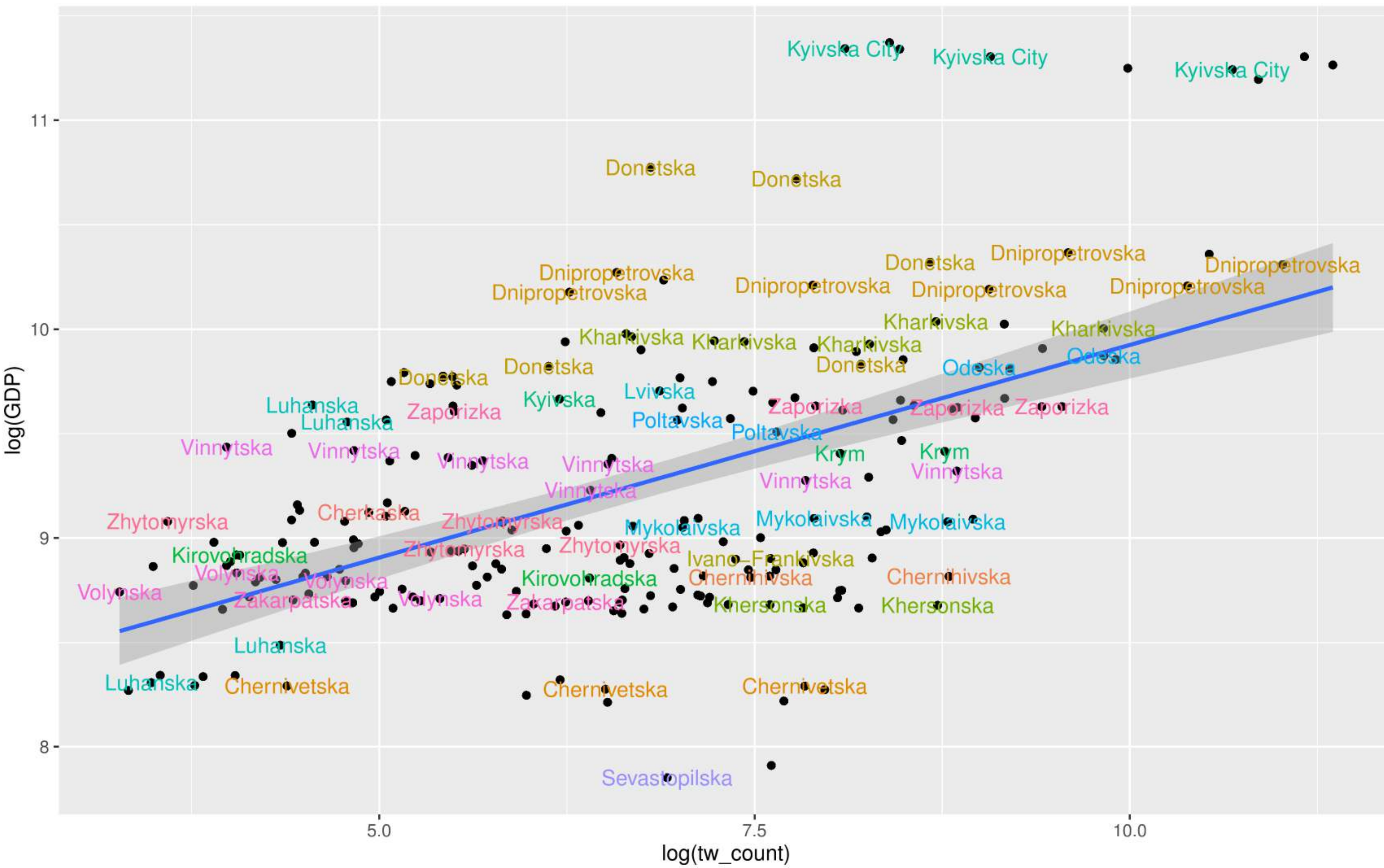
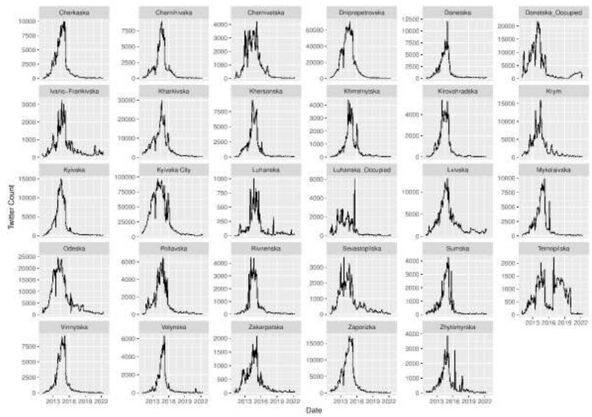
Kharkivska
Odeska
Lvivska
Kyivska
Luhanska
Zaporizka
Poltavska
Vinnytska
Krym
Zhytomyrska
Cherkaska
Mykolaivska
Kirovohradska
Volynska
Ivano-Frankivska
Chernihivska
Zakarpatska
Khersonska
Chernivetska
Sevastopilska



log(GDP)
11
10
9
8
5.0
7.5
10.0
log(tw_count)

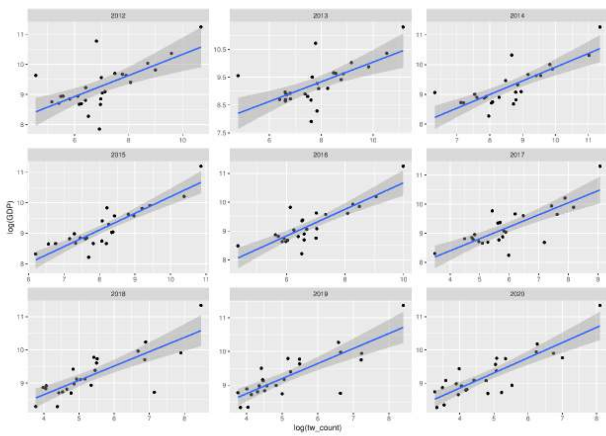
Twitter - empirics

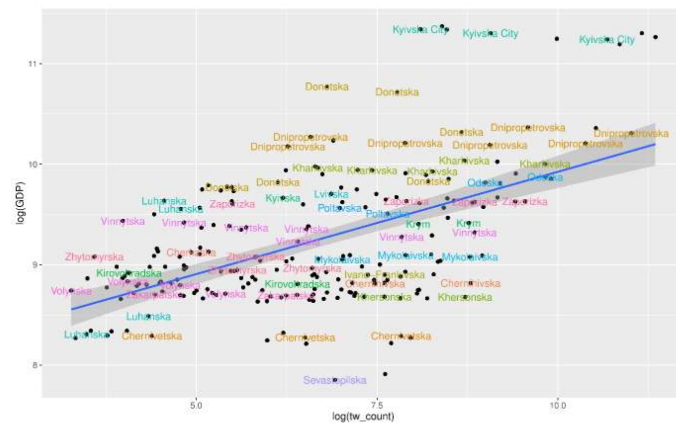


Key Takeaways
-> strong support for relationship in the cross-section in levels (log-log); failry stable over time

-> regions have markendly different levels of twitter activity

-> within region, no clear longitudinal relationship





Model(s)

Model is the result in equal parts of deliberate choice & data constraints

-> rich cross-section of potentially explanatory variables but too rich for a t=9 years, i=25 units panel

-> prior literature on (NL & Twitter) indicate levels are the variables to target; exploratory data analysis confirms this

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Considered shrinkage (added benefit is interpretability of the ML model) but unstable unless all Oblasts share the same parameters.

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A regional-specific factor model is estimated

-> each region has its own 3-factor model explaining observed y_i = log(GDP_i)

-> m = 3, p = 31 explanatory variables {GT, Twitter, NL}

$$Z_m = \sum_{j=1}^{p} \phi_{jm} X_j$$

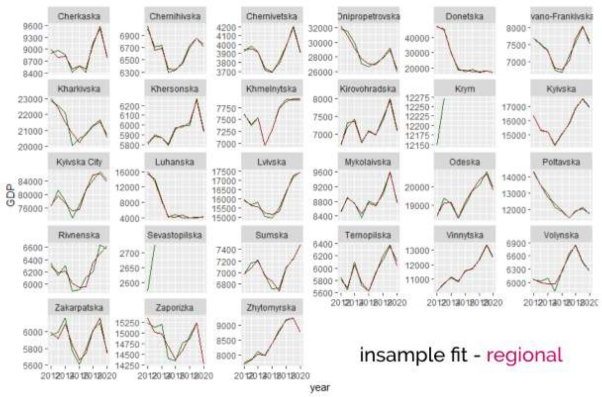
$$y_i = \theta_0 + \sum_{m=1}^{M} \theta_m z_{im} + \epsilon_i, \quad i = 1, \ldots, n,$$

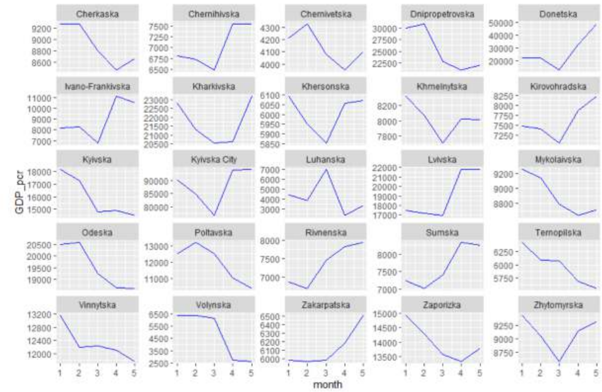
Data (Ivano-Frankivska):
X dimension: 9 31
Y dimension: 9 1

Fit method: svdpc

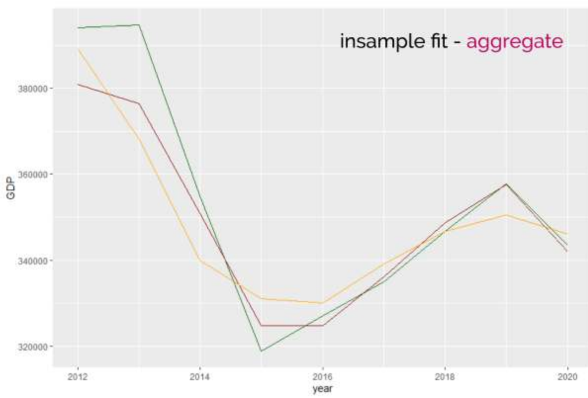
Number of components considered: 3
TRAINING: % variance explained

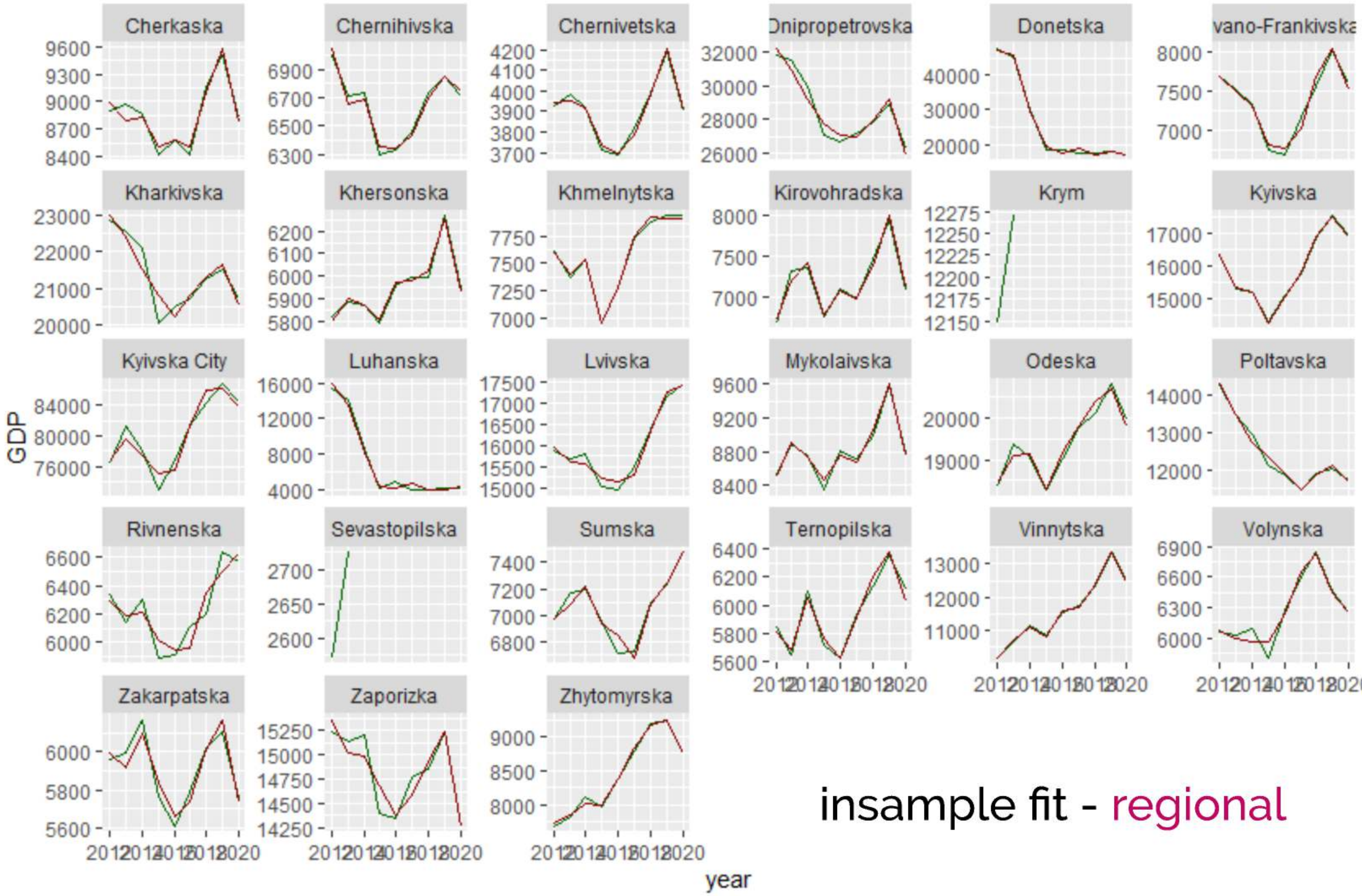
	1 comps	2 comps	3 comps
X	54.32	69.31	79.08
lng	15.17	68.76	81.61





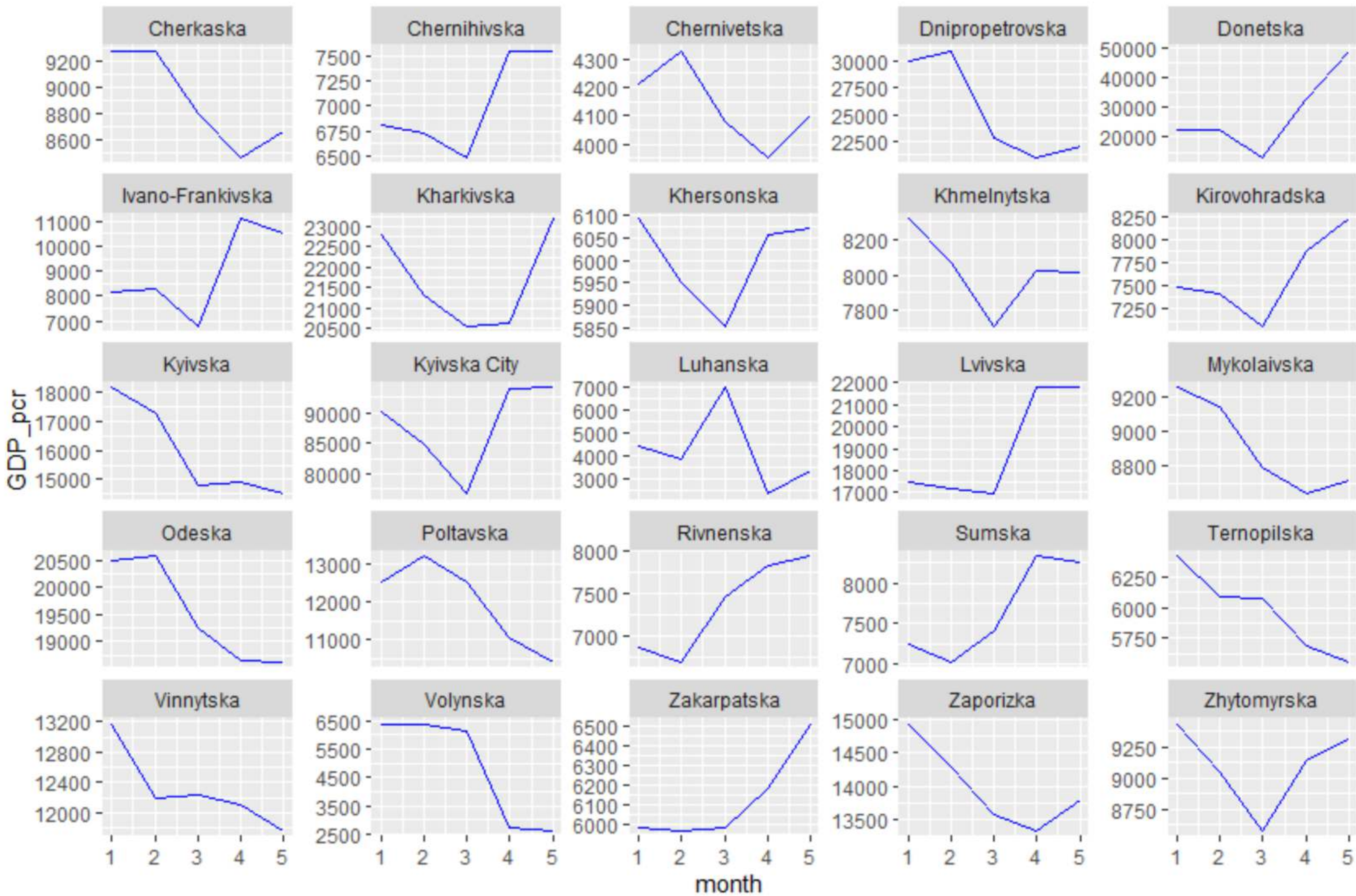
out-of-sample - regional





insample fit - regional


insample fit - aggregate
380000
360000
340000
320000
GDP
2012
2014
2016
2018
2020
year


GDP_pcr
month
Cherkaska
Chernihivska
Chernivetska
Dnipropetrovska
Donetska
Ivano-Frankivska
Kharkivska
Khersonska
Khmelnytska
Kirovohradska
Kyivska
Kyivska City
Luhanska
Lvivska
Mykolaivska
Odeska
Poltavska
Rivnenska
Sumska
Ternopilska
Vinnytska
Volynska
Zakarpatska
Zaporizka
Zhytomyrska

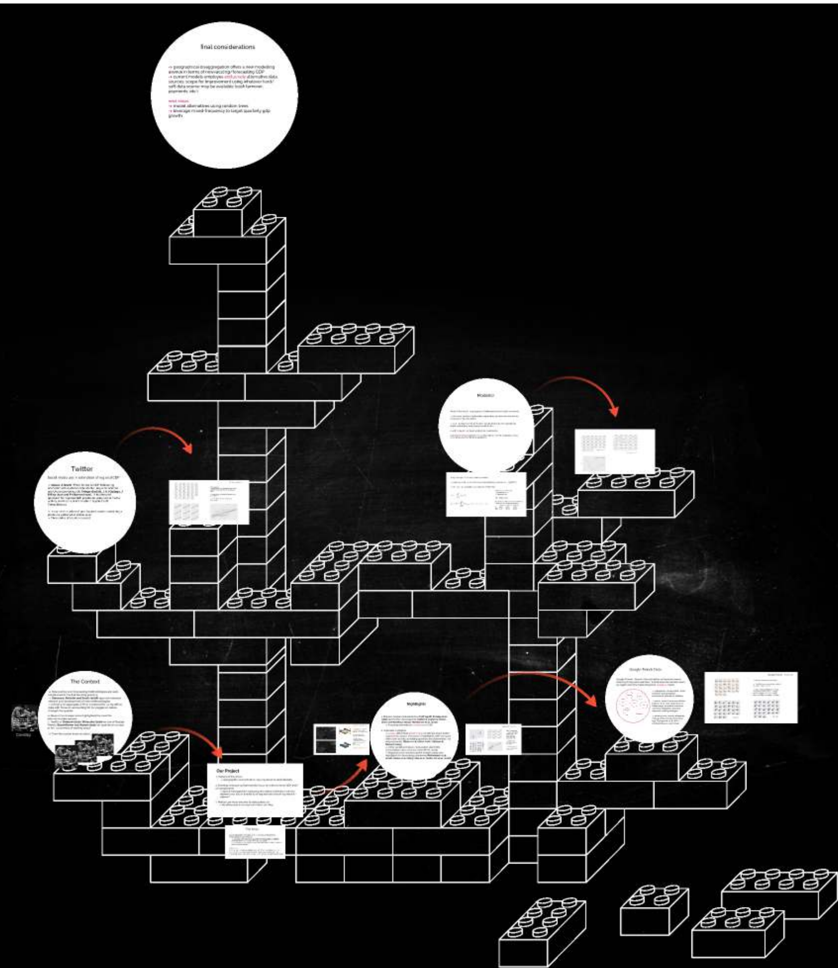
final considerations

-> geographical disaggregation offers a new modelling avenue in terms of nowvacsting/forecasting GDP
-> current models employes exclusively alternative data sources; scope for improvement using whatever hard/soft data source may be available (cash turnover, payments, etc.)

next steps:
-> model alternatives using random trees
-> leverage mixed-frequency to target quarterly gdp growth

Warcasting-Nowcasting GDP without economic data

Constantinescu, Kappner, Szumilo



Mihnea Constantinescu
National Bank of Ukraine and
Kyiv School of Economics

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