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PREFACE BY THE EDITOR-IN-CHIEF

Dear readers,

The current issue of the Visnyk of the National Bank of Ukraine encompasses investigations that are valuable for macroprudential policy, propose novel data-driven solutions to enhance central banks' research and forecasting capacity, reveal how weather conditions affect economic activity, and examine the impact of foreign aid on consumption inequality. The insights from these studies can be employed to support policy and investment decisions, to improve the quality of models in use, and/or to consider additional factors affecting economic performance in the short run.

The first article of the issue, *Consumer Lending in Ukraine: Estimation of the Equilibrium Level*, by Atilla Csajbok, Pervin Dadashova, Pavlo Shykin, and Balazs Vonnak, proposes an analytical framework for the timely detection of risks caused by the rapid growth of consumer lending. The findings suggest that the level of consumer lending in Ukraine is below its equilibrium level, despite the double-digit growth in recent years.

In the second article, *Data Science Opportunities at Central Banks: Overview*, Dmytro Krukovets thoroughly examines various data-science techniques employed by central banks, and shows their pros and cons. The author reviews recent developments in Machine Learning algorithms such as Naïve Bayes, various types of Neural Networks, Support Vector Machine, Random Forest and others, which mostly outperform standard econometric models in forecasting macroeconomic variables (inflation, GDP, unemployment). In addition, the author emphasizes the growing importance of text analysis, which allows central banks to accurately measure economic agents' expectations as well as the public's reaction to the policy conducted.

In the third article, *The Impact of Weather Conditions on Economic Activity in Ukraine*, Hanna Yatsenko sheds light on how temperature and precipitation affect economic activity in the key sectors of Ukraine's economy. The study highlights heterogenous responses between sectors, with substantial impact on agriculture, construction, manufacturing, and the energy sector. The author also suggests venues for prospective research.

The fourth article, *Foreign Assistance and Consumption Inequality: Does the Structure of Aid Matter?*, by Nestor Cheryba, estimates the influence of aid (decomposed into grants and loans) on inequality in 75 countries. The overall effect appears to be positive, with the net reduction in inequality being reached through a proper combination of grants and loans.

The Editorial Board of the Visnyk of the National Bank of Ukraine invites research contributors to explore the most challenging research questions in economics and finance and submit their research for publication in our journal.

Best regards,
Dmytro Sologub

CONSUMER LENDING IN UKRAINE: ESTIMATION OF THE EQUILIBRIUM LEVEL

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Abstract In line with Kiss et. al (2006), we have constructed an analytical framework for the timely detection of risks connected with the rapid growth of consumer lending, based on an econometric model for the equilibrium level of household and consumer loans. Results from an estimation on a panel of countries were extrapolated to the Ukrainian banking sector. The model suggests that after two waves of strong deleveraging starting in 2009 and in 2014, the consumer credit stock in 2019 is still well below its equilibrium level in Ukraine, despite the recent strong nominal dynamics.

JEL Codes C54, E47, G21, G38

Keywords consumer lending, equilibrium model, error-correction model, mean group estimator.

1. INTRODUCTION

After a period of strong deleveraging, caused by military aggression and economic crises, the volume of consumer lending has been rapidly swelling in Ukraine. Figure 1.a demonstrates the magnitude of Ukrainian household deleveraging in comparison with other countries. For the last two years, its year-on-year growth has not been lower than 30%. The continued high pace of growth was sustained by a loosening of banks' lending conditions and by a rapid increase in household income. The combination of these factors promotes the realization of previously postponed demand of households and stimulates their appetite for credit.

The main driver of credit growth is small-size unsecured loans, while secured long-term mortgages form only 2% of the amount of newly issued loans. In a regional comparison, the dominance of retail loans characterizes the Ukrainian household loan portfolio (see figure 1.b). While the credit-to-GDP ratio remains comparatively low, the fast accumulation of unsecured debt with a high interest rate burden puts additional risks on households, making them vulnerable to external shocks.

As the demand for credit increases, the competition between banks for new borrowers, which typically have low income in Ukraine, is very tough The necessity to maintain a strong pace of lending provokes banks to ease the underwriting criteria, which causes deterioration of the risk profile of the average borrower. As banks aspire to compensate for the arising risks by setting higher interest rates, excessive lending may lead to an increase in the debt burden for low-income households.[2]

These stylized facts suggest that continuing rapid growth of consumer lending in Ukraine generates a variety of potential risks that have to be managed to avoid challenges to financial stability in the medium and long run. Therefore, there is a growing need for the regulator to develop an analytical framework to analyze and detect risks related to the rapid growth of consumer lending. The primary interest is in estimating benchmarks for "normal" growth rates and levels for household indebtedness based on sound empirical foundations. Such a framework is useful not only to define the equilibrium level, but also to analyze the speed of convergence to it. This may help policymakers to manage the possible overheating of this segment by applying, in a timely manner, effective macroprudential instruments to restrict consumer lending growth.

In this paper, we derive equilibrium levels of household and consumer credit for Ukraine. For this purpose, we use a two-step approach. First, we estimate the relationship between equilibrium credit-to-GDP and the fundamentals

[1] At the time of the work underlying this paper, Mr. Csajbok was with the World Bank Financial Sector Advisory Center (FinSAC). FinSAC financed the technical assistance project behind this paper.
[2] For more details please see Box 3. "Results of a Survey of Consumer Lending by Banks: Borrowers with Low Income Are Mostly Indebted" in the Financial Stability Report of the NBU (June 2019)

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with the Common Correlated Effect Estimator from the dataset obtained from the European Credit Research Institute (ECRI). This dataset includes data for EU-member states and non-EU advanced and emerging countries. The second step is to estimate the same relationship for Ukraine, which is done by treating the panel estimation results as prior information, and combining it with Ukrainian data using Bayes` rule.

With the estimated equilibrium credit stock for Ukraine, we also estimate short-term dynamics around the equilibrium with an error correction specification. Even if the short-term dynamics have no fundamental interpretation, they offer a useful benchmark to assess whether the actual credit growth observed in the data can be regarded as a normal convergence to the trend.

2. LITERATURE REVIEW

Empirical studies usually focus on the identification of excessive credit growth for particular economies. Some authors consider expansion with a growth rate higher than a particular "speed limit" as an indicator of a credit boom. For example, Duenwald et al. (2005) investigated credit booms in three countries (Romania, Bulgaria, and Ukraine) in 2000-2004. Comparing three credit boom scenarios, the authors found that the economic and institutional circumstances of each country imply different "natural" levels of such ratios and, as a result, varying paces of adjustment to them. As a result, it becomes challenging to distinguish between excessive credit growth and equilibrium movements of credit. For example, in 2001-2004, the Bulgarian credit-to-GDP ratio rose on average by 7 p.p. per year (from 14.5% in 2001 to 35.4% in 2004). The estimates of Cotarelli et al. (2005) show that such rapid growth can be identified as excessive. Before the crisis in Mexico (1994), Korea (1997), and Indonesia (1997), their credit-to-GDP growth rate was 3-5 p.p. per year. Nevertheless, banks in Bulgaria remained well-capitalized and liquid, with healthy profitability and low level of non-performing loans in spite of ongoing credit acceleration.

Another approach is to identify the trend in credit dynamics based on univariate time-series analysis, typically smoothing with the Hodrick-Prescott filter. For example, Gourinchas et al. (2001) used the credit-to-GDP ratio, smoothened by the HP-filter, as the long-term trend. They define boom periods when credit-to-GDP is higher than the trend value plus a threshold. Such a threshold can be defined in absolute or relative terms. This approach can be applied to emerging economies with sufficiently long time series. Nakornthab et al. (2003) pointed to the necessity of long period data availability in their investigation of the credit boom in Thailand. They estimated the trend component of credit-to-GDP for the 50-year horizon (1951-2002). However, in transition economies with a comparatively short period and possible structural breaks, such as the Ukrainian one, univariate filtering may yield misleading results.

Another widely used approach is to model the relationship between the equilibrium credit-to-GDP path and its determinants. Calza et al. (2001 and 2003), used an error correction model (ECM). As explanatory variables, they choose GDP and interest rates (both short- and long-term). Boissay et al. (2005) estimated the vector error correction model (VECM) for 11 CEE countries individually. Brzoza-Brzezina (2005) used ECM with the amount of loans to the private sector and the GDP deflator as fundamental variables to estimate long-time relationships for three CEE countries independently. The pool of countries and variables chosen in the papers mentioned above was constrained by data availability and the length of the time series. To cope with this problem, Cotarelli et al. (2005), Backe et al. (2006) and Kiss et al. (2006) used panel data of various groups of countries for estimating the long-run relationship and then impose obtained estimates on CEE countries out of sample. This is the approach adopted in our estimation, too.

To exploit the information content of panel data, one has to impose cross-country restrictions on some parameters of the model. While Boissay at al. (2005) assumed common short-run dynamics, but a different long-run relationship, Kiss et al. (2006) proceeded the other way around. Following Pesaran and Smith (1995), they estimated a model with the same relationship between the credit-to-GDP ratio and economic fundamentals for all countries, and country specific short-term dynamics, with the pooled mean group estimator.

The applicability of out-of-sample estimation depends on the homogeneity between samples. Maeso-Fernandez, F., C. Osbat and Schnatz (2004) admitted that different levels of institutional and economic development between countries used for estimation and countries of interest may cause bias when extrapolating. To eliminate the problem of possible heterogeneity, the authors proposed using the mean-group estimator, which implies country-by-country estimation of the coefficients of the long-run relationship and averaging them across countries. They argue that this approach can provide consistent estimates even in the case of heterogeneity. The similar method to cope with the problem of extrapolation was used in various papers: Baltagi and Moscone (2010), Bond et al. (2010), Fleisher et al. (2010), Holly et al. (2010) and Serlenga and Shin (2007) among others.

3. METHODOLOGY

Our aim is to estimate the long-run relationship between certain credit aggregates and the fundamental variables explaining the permanent shifts in credit. Since most of these variables are non-stationary, the task is to find the cointegrating relationship. We label the implied credit stock as equilibrium, because the fundamental variables are related to the sustainable level of indebtedness of the private sector. As a next step, we also give an estimate of the short-run dynamics that can be used for assessing whether observed credit growth is consistent with a typical convergence to the equilibrium level.

As the Ukrainian time series on bank credit and fundamental variables are not sufficiently long enough to estimate an equilibrium relationship, we use panel estimation techniques. Our preferred estimator of the cointegrating relationship is the already mentioned CCE, which is built on the mean group estimator (Pesaran and Smith, 1995). The mean group estimator has good properties when there is heterogeneity in the slope coefficients, including the constant term, and neither the cross-section nor the time dimension of the panel is too small.[3] The model can be written as

$$y_{it} = \beta_i x_{it} + u_{it}, \tag{1}$$

[3] The possible heterogeneity in the slope coefficients would make a conventional fixed effect model misspecified and would lead to inconsistent estimates. For details, see Pesaran and Smith (1995).

where y is the dependent variable (in our case the credit-to-GDP ratio), x is the vector of explanatory variables (in our case the "fundamental" variables), β_i is the parameter vector of interest for country i, and u is the stationary dynamics around the equilibrium. The cointegrating relationship is estimated for all individuals separately by OLS, and then the coefficient estimates are averaged to get the mean group estimator:

$$\hat{\beta}^{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i, \tag{2}$$

It is important to note that although the model does not restrict the long-run relationship to be homogenous across countries, the mean group estimator is used for out-of-sample predictions because it might be more appropriate than any of the individual country estimates.

If there is a latent common factor influencing both the explanatory variables (x_{it}) and the dependent variable via u_{it}, the estimator will be inconsistent due to endogeneity. Our problem is very likely to be affected by such type of endogeneity bias, as credit cycles (left-hand side) and business cycles (appearing on the right-hand side in several variables) have been synchronized to some extent within and across the countries we are going to use for the estimation. Since these common cycles do not purely reflect the causal effect of GDP on lending, but also the simultaneous effect of unobserved variables (confidence, expectations etc.) on GDP and lending, one has to control for that in order to get a consistent estimate of the long-run relationship.

This is why we used the CCE estimator of Pesaran (2006). The CCE augments the regressors used in the mean group estimation with cross-sectional averages of the dependent variable and the individual-specific regressors, and Pesaran (2006) shows that it is a consistent estimator of the slope coefficients even in the presence of common latent factors.

Having (consistent) estimates of the long-run coefficients, one can impose the same relationship for Ukraine and calculate the equilibrium level of credit by taking the appropriate linear combination of the Ukrainian fundamental variables. However, this fully out-of-sample approach may result in equilibrium estimates implausibly far from actual data.[4] The main reason for this is that usually there remains lots of unexplained time-invariant heterogeneity that is captured by the country-specific constant terms.

In order to balance the huge information content of a large panel with the specific information embedded in the short Ukrainian time series, we adopted a Bayesian approach. We took the result from the panel estimation as prior information and combined it with the Ukrainian observations according to Bayes' rule to get the posterior distribution of the parameters of interest. More specifically, we use normal-inverse-gamma conjugate prior where the conditional distribution of the coefficients is multivariate normal with the mean being equal to the panel estimates of the coefficients ($\hat{\beta}^{MG}$) and the covariance matrix being equal to the panel estimate of the coefficients' covariance matrix ($\hat{\Sigma}^{MG}$), that is:

$$\beta|\sigma^2 \sim \mathcal{N}\left(\hat{\beta}^{MG}, \hat{\Sigma}^{MG}\right), \tag{3}$$

where

$$\sigma^2(X'X)^{-1} = \hat{\Sigma}^{MG}, \tag{4}$$

and σ^2 has an inverse gamma distribution (X is the stacked matrix of the panel explanatory variables). Then, the posterior distribution of the coefficient vector is from the Student's t distribution family with analytically computable moments.[5]

Finally, when we derive the equilibrium path of the credit stock, we use the Hodrick-Prescott trend of fundamental variables, because they may contain short-term fluctuations that do not reflect changes in "sustainable" or "equilibrium" level of credit. The final estimate of the equilibrium is given by

$$l_t^{eq} = \sum_k \beta_k^{post}\tilde{x}_t^k, \tag{5}$$

where l_t^{eq} is the equilibrium level of the logarithm of the credit-to-GDP ratio at period t, β_k^{post}-s are the Bayesian mean coefficient estimates, and $\tilde{x}^k$-s are the smoothened fundamental variables, including the constant.

In the next stage, we used the panel data set again to estimate a typical speed of convergence to the equilibrium level. First, we calculated the (Bayesian) equilibrium levels for each country in the panel, as explained above.[6] Then we estimated a standard error correction model (ECM) of the following form:

$$\Delta l_t = -\varphi\left(l_{t-1} - l_{t-1}^{eq}\right) + \alpha_l \Delta l_{t-1} + \sum_k \alpha_k \Delta x_{t-1}^k + c\,, \tag{6}$$

The change in the credit stock is partly determined by how far it is from the equilibrium level, represented by the first term on the right-hand side. The so-called "speed of adjustment" coefficient (φ) is normally positive, implying that if the credit-to-GDP ratio is lower than the equilibrium level, lending typically catches up and the gap will be closed. We estimated the parameters by OLS from the pooled sample.

4. VARIABLES AND DATA

We are primarily interested in the equilibrium level of consumer credit. However, there is some degree of substitutability between consumer and housing loans, and the share of consumer and housing loans within total household debts can be influenced by several unobservable factors. Thus, the equilibrium level of total household debt and the distance of the actual level from it can be sometimes as informative as the consumer credit gap itself, even if one tries to assess the sustainability of the dynamics of the latter. For this reason, we estimate our models to both credit categories (total household loans and consumer loans only).

[4] First, we experimented with this approach, but the implied equilibrium credit path was significantly lower in each period than the actual data for Ukraine.
[5] For further details see the third chapter of Walter and Augustin (2009).
[6] In this way, we took individual country data twice into account, because they are all included in the panel estimation as well. However, that would not result in much difference from re-estimating the panel model by dropping each country one-by-one because of their large number.

We worked with a panel of yearly data of 30 countries spanning from 1995 to 2007. The dependent variable in both cases is the corresponding credit stock divided by nominal GDP. The explanatory or "fundamental" variables were chosen based on some theoretical considerations, as well as the existing empirical literature (e.g. Cottarelli et al, 2005; Égert et al, 2006; Kiss et al, 2006).

One of the most important and usually statistically significant explanatory variables is the country's development, as measured by per capita GDP. The idea is that when an economy is more developed, the role of financial intermediation is more important, resulting in a larger outstanding stock of loans.

The interest rate is another standard explanatory variable in the literature. Without borrowing constraints, it is the real interest rate that matters first of all. In reality, banks are unwilling to lend to the extent that would increase the probability of default too much. This risk is usually contained by limiting the payment-to-income ratio, which depends on the nominal interest rate. Therefore, we decomposed the nominal interest rate into real interest rate and consumer price inflation and used both variables in the regression. We used long-term interest rates because they reflect lending rates in the real economy more accurately than short-term rates, e.g. overnight interbank rates.

The share of consumption in total GDP may depend on time preferences or other structural factors (like demographic features) that can affect the equilibrium credit stock. This is particularly relevant when one investigates consumer lending, and therefore we include it, as in Gersl and Seidler (2011).

We also experimented with other candidates to explain the long-term credit stock that are justified either theoretically or empirically. These candidates included the share of young cohorts in the population, the disposable income-to-GDP ratio, both appearing in Lang and Welz (2018). These variables proved to be insignificant. We could not use measures of income inequality, another potential candidate variable, because the available time series were too short to fit our panel data set.

Sectoral credit data is taken from the commercially available dataset compiled by the ECRI. The household credit is divided into three categories there: housing loans, consumer credit and other loans. The distinction between housing and consumer loans is based on the purpose of the loan. Housing and consumer loans are thus defined as the amount of loans at the end of the year granted by the resident MFI sector to resident households and to non-profit institutions serving households (NPISHs) for housing and consumption purposes, respectively. Other loans are those other than for consumer credit and for home-buying extended to households and NPISHs for special purposes such as business needs, the procurement of office equipment, debt consolidation, education, the purchase of securities, etc. All the credit data show the stock at the end of the year and is divided by the nominal GDP in the same year.

The ECRI dataset spans the time period from 1995 to 2017 and covers all the EU member states, plus a number of non-EU advanced and emerging countries. In our sample, we included all the EU member states plus Norway, Iceland, Switzerland, the U.S., Canada, Japan, Australia, Mexico and India. Altogether 30 countries and more than 500 observations were included in the sample. The choice of countries was based on the availability of long-enough time series.

Per capita GDP, the consumption-to-GDP ratio and consumer price inflation data were taken from the ECRI database, too. The source of the long-term interest rate is the OECD database, which contains time series of government bond yields of 10-year maturity.

5. RESULTS AND DISCUSSION

The first step is the estimation of the long-run relationship between the credit stock and the explanatory variables from the panel data using the cross-correlated effect estimator. We experimented with total household loans, the narrow definition of consumer credit, and the broad definition that is the sum of the latter and other loans. With the broad definition, we obtained more significant estimates at the first stage than with the narrow one. Therefore in what follows, we will present results for total household credit and the sum of consumer credit and other loans (which we label simply as "consumer credit"). Table 1 shows the results of the two loan categories.

The development of the economy is positively related to the depth of financial intermediation, as expected. A one percent increase in the per capita GDP is typically accompanied by almost two percent more household credit-to-GDP. This relationship is highly significant. According to the second column, the same relationship with consumer credit is much weaker and not significant. This may be a reflection of the stylized fact that in more developed countries, the share of housing loans is higher. Another factor to mention is that consumer credit data presumably contain more noise.

The consumption-to-GDP ratio is highly significant in both regressions. Its impact seems to be larger on total household credit than on consumer loans. The interpretation is the following: in countries and time periods with one percentage point higher than the consumption-to-GDP ratio, the equilibrium household (consumer) credit-to-GDP ratio is 4.5 (3.6) percent higher.

Neither the real interest rate, nor the inflation is significant in either regression. Still, we kept them in the model as they are standard explanatory variables in similar empirical studies and their sign and magnitude is plausible in each specification. The similar coefficient estimates suggest that it is their sum, the nominal interest rate that really matters in equilibrium.[7] According to the coefficient estimates, it can be said that a one percentage point permanent increase in the long-term nominal interest rate reduces the household (consumer) credit-to-GDP ratio by one (one and a half) percent.

The huge standard error of the estimated constant indicates extreme uncertainty in the level of equilibrium credit. For example, the 2.6 in the case of the consumer loans means that the upper bound of the two standard error

[7] This is indeed reflected in the results of an alternative (restricted) specification where we used the nominal interest rate instead of the real interest rate and inflation, and the estimated parameter turned out to be significant

wide confidence band is more than 13 times larger than the point estimate and more than 180 times larger than the lower bound if we look at only the error of the estimated constant.[8] This is a possible consequence of the fact that there may be many country-specific factors that we could not control for in our regression. This problem is raised explicitly in Kiss et al (2006) and justifies using a Bayesian update of the panel mean group estimates at a later stage.

The chi-square statistics measure the joint significance of the estimated coefficients and thus can be interpreted as the relevance of our models. The joint significance is high in both cases, especially in the model for total household credit. This fact, and the multicollinearity of the explanatory variables, reflected in large standard errors and low individual statistical significance, motivated us to keep seemingly insignificant variables, like real interest rate, inflation, and in the case of consumer loans, per capita GDP.

As a next step, we derived the country specific Bayesian posterior estimates treating the panel regression result as a prior. Using the posterior mean coefficient estimates and the Hodrick-Prescott trend of the fundamental variables, we calculated the evolution of the credit gap (percentage distance from the equilibrium) for each country.

The dynamics of the credit gaps can be statistically modelled by an error correction specification. It relates the change in the credit-to-GDP ratio to the credit gap and the lagged changes in the dependent and explanatory variables. Table 2 lists the most important statistics of the pooled OLS estimation.

The explanatory power of the regressions is reasonably high, the estimated coefficients are jointly significant at all conventional levels.[9]

The estimated speed of adjustment to equilibrium, which is the coefficient of the error correction term, is similar for both credit categories. Its value is roughly 0.12, meaning that the driving force towards the equilibrium per se can reduce the credit gap by 12 percent in one year. However, the total speed of adjustment is affected by the lagged dynamics of all variables. Based on the estimated coefficients and their significance, the most important lagged determinant is the change of the credit-to-GDP ratio in the previous year. The value above 0.5 indicates substantial inertia. The persistence in trend has implications for the adjustment dynamics too. If, for instance, the credit stock is above the equilibrium level and is growing at a high pace, the trend inertia may completely offset the attraction of the equilibrium quantified by the “speed of adjustment” coefficient of the error correction term. In contrast, when the gap is closing, the total speed of adjustment can be faster than one implied by the value of 0.12, because the trend of the previous period adds to the normal error correction mechanism.

Having obtained all the panel estimates of short- and long-term credit dynamics, we can calculate the equilibrium level of credit in Ukraine, as well as the expected adjustment dynamics. We obtained the long-term coefficients by combining the pooled mean group estimates with the Ukrainian data using Bayes’ rule. Then we derived the equilibrium credit stock using these coefficients and the Hodrick-Prescott smoothened time series of the Ukrainian fundamental variables. We also used their forecasted values. The forecast was based on the inflation report of the NBU (January 2019).[10]

Figure 2 depicts the evolution of Ukrainian (a) household and (b) consumer credit-to-GDP ratio, which consists of the estimated equilibrium paths with confidence bands based on two standard errors in each direction. Values denoted by a solid bright-green line are forecast based on the error correction estimates.

Our equilibrium models are written in terms of credit-to-GDP ratios. However, the focus of policymakers is often on growth rates of credit rather than on credit-to-GDP. The original concerns in Ukraine were about the close to 30 percent nominal growth rate of the net (of provisions) consumer credit. In order to put these growth figures in the context of our equilibrium model, we applied an official NBU projection of a roughly 30 percent nominal growth rate of net consumer loans. The projections are shown in Figure 2, together with a 95 percent confidence interval constructed around the estimated adjustment path.[11] As can be seen, a continued 30 percent nominal growth of consumer loans in the next two years would represent a somewhat faster increase than what is implied by the estimated adjustment path. However, even with this high nominal growth rate, consumer credit-to-GDP would remain within the 95 percent confidence interval of the estimated adjustment path.

Although theoretically the estimated adjustment path and the confidence interval around it do not say much about equilibrium dynamics (rather they represent the average speed of adjustment in the panel sample), they may provide a useful benchmark to assess credit dynamics before credit reaches and possibly goes above the estimated equilibrium level.

6. CONCLUSION

The main story is independent of whether we look at the consumer loans or the total household loans, only the magnitudes are different. There was rapid credit growth between 2006 and 2009 (at the beginning of our Ukrainian sample), with the stock being roughly twice as much as the estimated equilibrium. The boom stopped abruptly, and household indebtedness dropped dramatically, reaching the estimated equilibrium by 2012-2013. Starting from 2014, there was a second wave of contraction in lending, and the credit stock fell well below the equilibrium. By 2017, the credit gap reached minus 60-70 percent.

[8] Of course, the total error of our regression can be much smaller, because the error of the constant can be correlated with those of other coefficients estimates in a way that they offset each other to some extent.

[9] In an alternative specification, we also estimated the short-term dynamics using the short-term interest rate (instead of the long one). These results are very close to those of the original specification, namely, it is only the distance from the equilibrium (ECM term) and the lagged first difference of the credit stock that matters. All the other coefficients were negligible, insignificant. The value of the first two coefficients changed only slightly.

[10] When forecasting the GDP, we used the NBU’s forecast of potential GDP instead of the headline. We assumed that the population and the consumption share will not change in the next three years. We also took the NBU’s inflation forecast as given.

[11] The confidence interval around the adjustment path cannot be derived analytically. We constructed it by doing simulations, taking 10,000 draws from the joint distribution of the estimated parameters (assumed to be normally distributed) combined with draws from the distribution of the residuals (also assumed to be normal) for each forecasting horizon. The 2.5 and 97.5 percentiles of the resulting forecast distributions gave us the lower and upper bounds of the 95 percent confidence interval.

According to our forecast, the turnaround is expected to take place slowly. The reason is the above-mentioned inertia in the trend, which implies that even if the gap is negative, the decreasing trend of the previous years may partly or fully offset the mean-reverting forces. Therefore, our estimates predict a slight increase in credit-to-GDP for the following couple of years.

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APPENDIX A. TABLES

Table 1. Estimated Relationship between Equilibrium Credit Stock and its Fundamentals

	Dependent variable	
	Δlog(Household credit to GDP)	Δlog(Consumer credit to GDP)
log(Per capita GDP)	1.848**	0.237
	(0.346)	(0.448)
C/Y	4.520***	3.601**
	(1.033)	(1.452)
Real interest rate	-0.010	-0.017
	(0.015)	(0.002)
Inflation	-0.011	-0.014
	(0.014)	(0.022)
Constant	-3.911	2.382
	(2.160)	(2.600)
N	571	484
Number of groups	30	26
Wald chi-square (4)	32.870***	10.750***
Wald p-value	0.000	0.030

Table 2. Panel Estimates of Short-Term Dynamics Around the Equilibrium

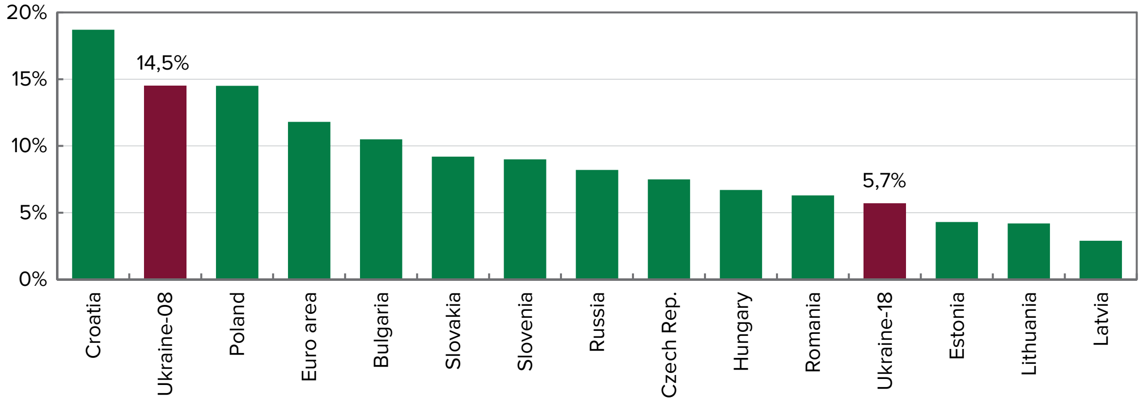
		Dependent variable	
		Δlog (Household credit to GDP)	Δlog (Consumer credit to GDP)
	Error correction term	0.117***	0.120***
		(0.012)	(0.015)
	Lagged dependent	0.579***	0.556***
		(0.028)	(0.035)
First difference of lagged explanatory variables	log(Per capita GDP)	0.010	0.220
		(0.094)	(0.133)
	C/Y	-0.234	-0.098
		(0.308)	(0.468)
	Real interest rate	0.000	0.004
		(0.002)	(0.003)
	Inflation	0.003	0.009***
		(0.002)	(0.003)
	Constant	0.012***	0.000
		(0.003)	(0.004)
	N	511	432
	R-squared	0.609	0.490
	Wald F(6, # obs-7)	130.780***	68.130***
	Wald p-value	0.000	0.000

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Standard errors are in parentheses.

APPENDIX B. FIGURES

(a) Consumer Loans** to GDP Ratio



(b) Fraction of Consumer Loans** in Total Portfolio

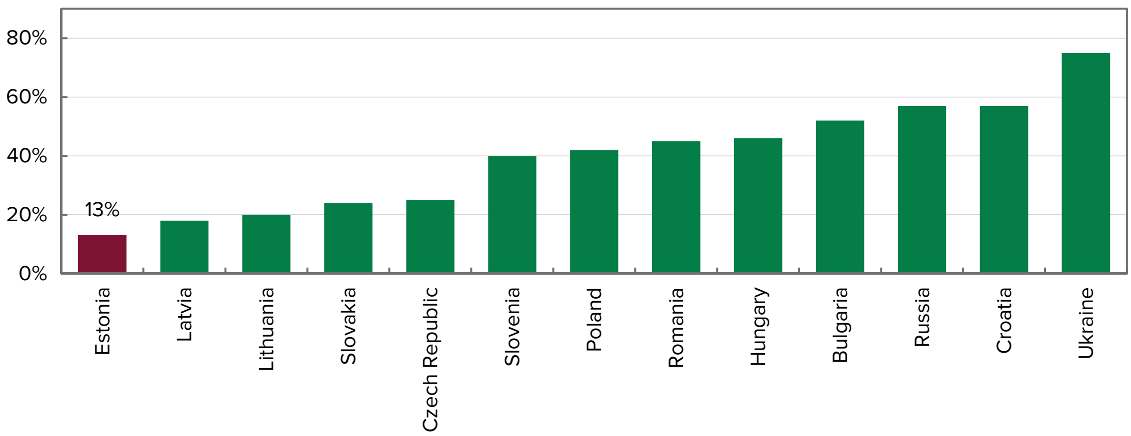


Figure 1. Characteristics of Consumer Loans by Region
*as of 1 October 2018
**For Ukraine – gross consumer and other loans (except for loans for buying and reconstructing property)

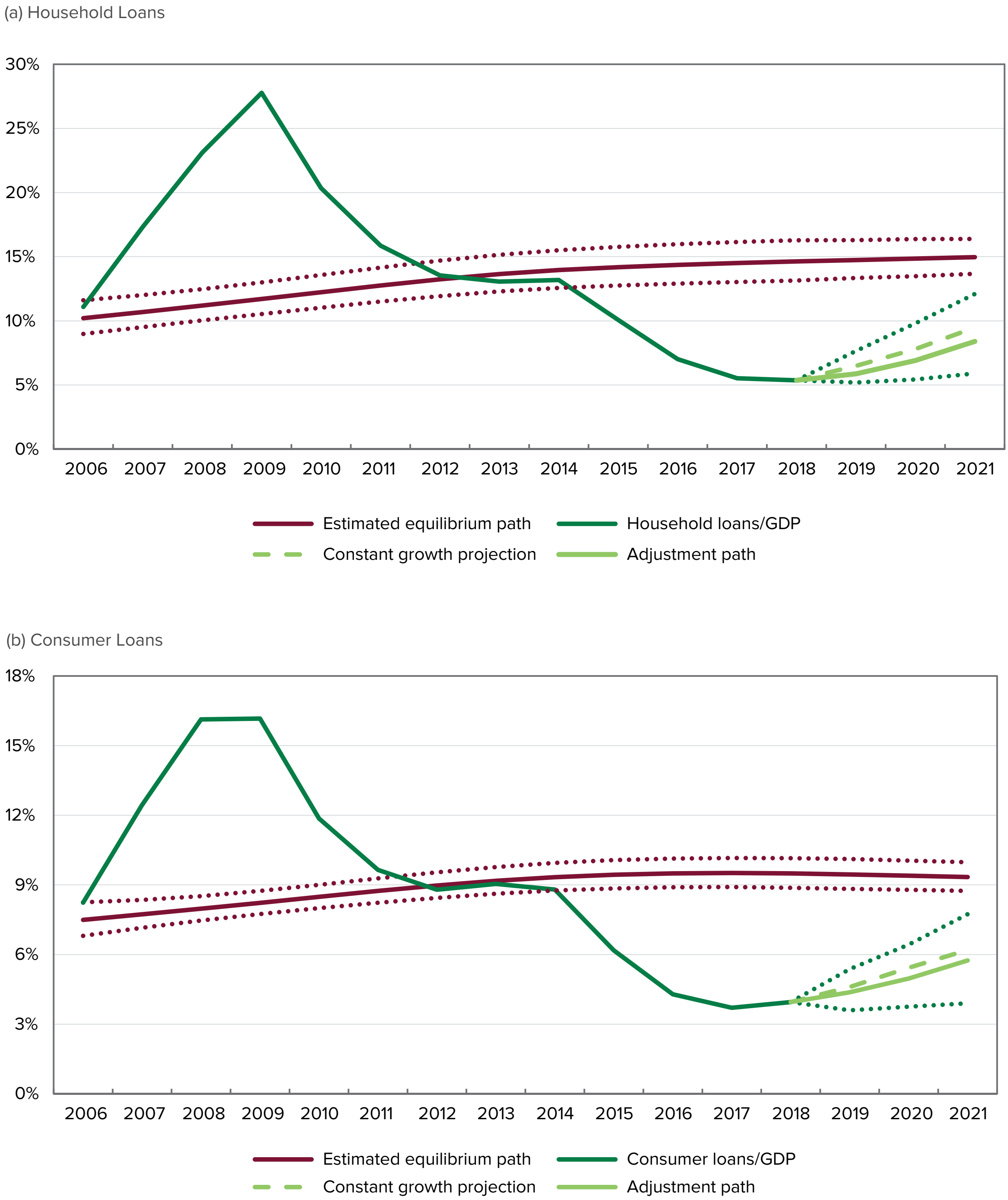


Figure 2. Projections of Household Loan Dynamics Assuming the Recent High Nominal Growth Rate vs. the Estimated Adjustment Path
*dotted lines represent 95% of confidence bands

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DATA SCIENCE OPPORTUNITIES AT CENTRAL BANKS: OVERVIEW

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Abstract This paper reviews the main streams of Data Science algorithm usage at central banks and shows their rising popularity over time. It contains an overview of use cases for macroeconomic and financial forecasting, text analysis (newspapers, social networks, and various types of reports), and other techniques based on or connected to large amounts of data. The author also pays attention to the recent achievements of the National Bank of Ukraine in this area. This study contributes to the building of the vector for research the role of Data Science for central banking.

JEL Codes C45, C53, C82, E27, E37

Keywords Data Science, Machine Learning, Natural-Language Processing, macroeconomics, forecasting

1. INTRODUCTION

Data Science techniques are an innovative way to solve traditional central bank problems. It is a broad term that unites Machine Learning and Data Processing. The first one is a collection of tools that learn with the given data, and understand patterns and interactions between series and values. They can observe relations when people are unable to do so (because of a large amount of data, and connections complexity). The second expresses the possible set of actions with the data itself: collection, manipulation, preparation, and visualization. Data Science brings more ability to work with a non-linear relationship in the system, contrary to econometrics that concentrates on solving non-linearity bias problems in the linear form. Another difference is that econometrics concentrate on method robustness, while Machine Learning algorithms become popularized with their outstanding performance.[1] Among major drawback of advanced Data Science techniques is a lack of interpretability. Thus, it is not always possible to use these techniques because central bankers are often required to explain the results, being specialists in other fields (Kuhn and Johnson, 2013).

The new rise of Data Science started at the beginning of 2010 when high-quality models for image recognition were created, computational power grew enough, and people in many areas realized the full potential of such an approach. Thus, the paper will pay special attention to instruments that were rarely used in economics and the financial sector before.

New features and tools start infiltrating into research activity and routine processes at central banks. Advanced predictive models, based on high-frequency data, improve the forecasting performance of the current toolbox and could be a decent compliment or even a substitute for existing models. Forecasting is not the only possible application field for Data Science algorithms. Natural Language Processing (NLP) techniques are a part of Data Science for text analysis. They can support analysis of the text (news, social networks) to evaluate public reaction to central bank policy and actions, or in their explanatory research work.

The paper aims to elaborate on the use of Data Science techniques in central banks and to show possible use cases. The focus will be on the techniques that are used in research activity, modelling, and forecasting. This paper will not dig deeply into popular Big Data technologies: web scraping, as well as Supervisory and Regulatory Technologies (SupTech and RegTech). The reason is that they focus on technical implementation and computer science, rather than statistics (econometrics) and mathematics.

The article is structured as follows. First, we'll go through the motivation for Data Science tools and algorithm usage at central banks. Then it will be an overview of forecasting models and approaches within the Data Science framework, which is continued by papers about text analysis and a wide range of use cases for this technology by central banks. We need an overview of other supplementary techniques to complete the picture. Finally, there will be a list of achievements by NBU researchers in the area and a short

[1] "A very revealing example is the XGBoost algorithm, which owes its success to its domination over several Machine Learning competitions rather than its mathematical demonstration". Citation from the article, which is available here: https://towardsdatascience.com/from-econometrics-to-machine-learning-ee182f3a45d7

Available at https://doi.org/10.26531/vnbu2020.249.02

summary of the abovementioned findings. All Data Science techniques, which are used in the referred papers, have a short description in Appendix A.

2. OVERVIEW OF DATA SCIENCE IN CENTRAL BANKS

Central banks are interested in Data Science for several reasons. The first argument is its novelty and potential to give more precise results. Second, such models are good for micro-level, rich, and granular data. Moreover, Data Science gives a breath to innovative sources of information that have not been used much (such as texts) for a better approximation of people sentiments and their expectations from the economy, central bank actions, and related matters. Finally, more data contains not any less information; the question is how to squeeze it out.

There are already a few pioneers of Machine Learning implementation in central banking, which have given a nice start for researchers in the area. For example, the central banks of England, Canada, Poland, and Indonesia. However, an overwhelming number of banks exhibit no signs of using these techniques, which supports the claim that Data Science in central banking is in the embryo stage.

The majority of materials about Data Science in central banking are in an overview format. A solid example is the presentation of a Bank of England representative, Paul Robinson, in 2018. It is a discussion about policymaking issues such as bad measurements, too complex models and the imperfect theories behind them, and internal frictions. Broadly speaking, Big Data approaches and corresponding methods could assist in solving all these problems.

The presentation shows the possibilities that Machine Learning could provide as a complement to traditional models. As an example, the labour market was approximated and nowcasted with job ads and job search density data that was loaded via web-scraping tools. Despite these solid results, the statistics take into account only those users who are Google consumers, rather than those of Bing, Yahoo, or those who do not use the Internet at all. But even with this issue, this sub-sample offered adequate representation and could be adjusted using the basic aggregated statistics of Google users.

Unfortunately, with new approaches come new risks. First, abundant data does not necessarily mean lots of fresh information. Some events, such as extremely high inflation, liquidity traps, financial instability, and bank failures, are quite rare. Part of the reason is that central banks act in a manner to avoid them. No wonder information about these events is scarce, no matter how much data there is.

Second, Data Science models are mostly "black boxes" without much interior interpretability, which could be unacceptable for central banks, contrary to IT companies, the regular beneficiaries of such techniques. Finally, the more granular dataset increases the probability of confidential information popping-up, which imposes additional requirements at the security level.

A working paper from the Bank of England by Chakraborty and Joseph (2017) offers technical details and real use cases. The 90-page text provides an overview, in simple words and formulas, of data transformation, evaluation tools, and modern Machine Learning techniques: Naive Bayes, k-Nearest-Neighbours (k-NN), Neural Network, Support Vector Machine (SVM), K-means and others. The paper also discusses policy implementation and use cases.

The first example is a prediction of banking supervision results, a classical anomaly detection exercise. In this exercise, the model is trained to detect abnormal behaviour and capture outliers (anomalies). To build a robust model, the authors removed part of the data, which was used to create a target variable. Under these conditions, Random Forest turns out to be the best model after all evaluations (accuracy, precision, recall, F1-score).

The second case is a UK CPI forecasting, one of the most classical exercises for the majority of central banks. Data Science algorithms mostly outperform traditional econometric models and the best one is the combination of NN and SVM. However, the authors emphasize that these models are computationally expensive and require tons of data, which is not common enough in macroeconomics.

The last case in the article is about “unicorns” in financial technology. It tells a story about the top technology-driven firms that changed the rules for the whole sector. Examples are Uber (taxi driving), AirBnB (hotel industry), and Glovo (delivery business). Their activity changed the sector and the whole economy to some extent. Authors built a clustering model based on the CrunchBase[2] database and obtained a cluster, which consists mostly of "unicorns". However, even in this particular cluster, there are a lot of non-unicorns. Thus, the model is positive in understanding the necessary conditions for a firm to be successful, but not sufficient.

According to Per Nymand-Andersen (2017), European Central Bank (ECB) advisor, the "data service evolution" provides a great new field of possibilities. Central bankers should not miss it. Nowadays, the data stream could give almost a real-time snapshot of the economy, which might be used to develop short-run strategies, and adjust them for the long run. Financial institutions are practically forced to use more micro-level data to be competitive. The financial regulator might use this data as well to better understand the behaviour of financial agents and effectively perform supervisory tasks.

To summarize, Data Science is a viable complement to existing techniques. It gives new opportunities in forecasting, analysis, and processing of data. In the next chapters, we will dive into details about these algorithms and broaden our pool of use cases.

3. MACROECONOMIC FORECASTING AND MODELLING

Macroeconomic researchers have built many various econometric models throughout the decades. Models have grown into more sophisticated ones, able to deal with different biases. However, recent Machine Learning algorithms have become involved and taken the place of promising additions or alternatives. These new algorithms are more demanding in terms of data, but they have become less problematic in the current trends of world progress.

[2] Platforms with information about business and private companies collected a large and comprehensive dataset. https://data.crunchbase.com/docs/getting-started

We will start with inflation-forecasting, one of the most popular forecasting exercises in central banking, especially in these days of inflation-targeting as one of the main functions of the monetary policy regime.[3] Nakamura (2005) wrote the oldest paper in this review. In those times, neural networks were not a popular instrument, thus the number of papers was scarce. The author uses quarterly data from 1960 to 2003. His neural network is simple, with only two pairs of univariate equations, connected one-by-one. The method to find the best coefficients is significantly different from a modern one, taking a hundred random initial values and choosing between them, instead of a backpropagation optimization solution. Even with such a primitive approach, the neural network showed a better performance than the AutoRegressive (AR) benchmark on the forecasting horizon of one to four quarters ahead. This comes from the ability of neural networks to capture nonlinearity. The main conclusion is that neural networks might be a solid addition to the pool of forecasting models already in use.

The complexity of networks and methods builds up with the popularity of the field. Choudhary and Haider (2012) shows neural network performance in different countries' datasets and compares it to the AR(1). This paper has more sophisticated architectures than the previous one: two networks are called hybrid-network and dynamic-network (the latter is closer to the Recurrent Neural Network (RNN), but simpler), followed by two of their combinations. As a result, using the database with monthly inflation from 07.1991 to 06.2008 for 28 OECD countries, the neural network mostly outperforms the AR(1) model in short-term forecasting. The author claims that the continuous comparison of econometric and other models is a preferable strategy because of the results' instability. Thus, the building of a toolbox with a wide range of instruments fits the strategy well.

Nevertheless, model complexity is not the only difference. The world is on its way to the "Big Data Land", where the quality and amount of data increased. It influences the forecasting process and predictive models. Medeiros et al. (2018) used a very rich monthly-based dataset called FRED-MD, which contains hundreds of features to forecast U.S. inflation. The paper goes through some models, from benchmarks and traditional econometric to Data Science models. First, algorithms are barely able to capture non-linearities that ML models can, for example, the relationship between inflation and employment. Thus, Random Forest has worked best on most of the horizons, while Ridge/Lasso regressions have performed decently too. Most models produced a sub-product: a list of features that were selected as the most important for variance explanation for each horizon. The results among the models were quite different. Lasso regression produced output and prices as significant variables for inflation explanation. In its turn, Random Forest and Ridge regression have employment, prices, and interest rate. There is a lot of space for analysis and comparison of different model results. That is why it is always beneficial to widen the range of models in use, even when they employ the same variable set, in order to investigate the matter from different perspectives.

Jung et al. (2018) offers a comprehensive example of using a few Machine Learning techniques – namely Elastic Net, Super Learner and RNN – to forecast GDP growth in several representative countries. The main interest is to compare these models' performance with official WEO predictions that are based on more traditional models. Elastic Net and Super Learner have rapidly better accuracy rates (35 to 80 percent higher than the benchmark) for one quarter ahead. But on an annual basis, there was much less certainty (RNN was better for the U.S., U.K., and Germany, while WEO for Spain, Mexico, and Vietnam). These algorithms work well for short-run forecasting and might be useful in long-run cases.

Nowcasting is a technique to forecast the value of variables "in a moment", if they are published with a large time gap, such as GDP. This exercise is widely described in the literature, for example by Richardson et al. in 2019 (based on their paper in 2018, but more advanced and with more data used). The available toolkit is quite rich: Ridge/Lasso regression, Bayesian VAR, neural network, boosting algorithms, SVM, and k-NN. The dataset is rich too: domestic and international statistics, surveys, and financial data. Data frequency varies from daily to quarterly. This paper represents how much work can be done in the area of nowcasting of GDP. The methodology can be translated to other macroeconomic variables too.

One more example of GDP nowcasting is given by Bolhuis and Rayner, 2020. The dataset consists of hundreds of variables about the Turkish economy, some of which are represented several times with different transformations. There are classic unemployment or current account variables that are paired with different confidence indexes and survey-based variables. The method is a combination of several standard Machine Learning techniques: SVM, GBM, and RF. Authors claim that these models complement each other and a combination of their nowcasts leads to reduced error. There were different types of combinations: with equal weights and based on the relative RMSE of the single models. The result is the complete outperformance of ensembles to single methods and to the benchmark (traditional for the exercise of GDP nowcasting – dynamic factor model).

A few steps aside from such a classical application as inflation or macroeconomic forecasting leads to the various ways of Machine Learning usage. Gogas et al. (2014) explain the output and inflationary gap via different yield curves. The SVM model forecasts future deviations, which allows swift and appropriate policy responses. In the same spirit, research by Gogas et al. (2019) estimates an SVM model using a monthly dataset based on the Eurocoin Index and money aggregates (M1, M2, M3). It is made by Gogas et al. (2019). The authors show that money supply data can forecast euro-area economic activity. It means a significant dependency between economic activity and money supply. The hypothesis that monetary policy is effective cannot be rejected for the euro-area.

There is not only macroeconomics but also the financial side of central bank activity. Petropoulos et al. (2018) discussed tougher supervisory actions by regulators. There is a classical trade-off between less restrictive rules and financial safety. Thus, algorithms for analysis and prevention for different kinds of risk are in high demand at the moment. The authors produced a rich, combined semi-annual dataset with loan data from over 10 years and 354 time series of financial ratios and macroeconomic variables. A ratio between the number of features and observations leads to the "curse of dimensionality", so as to the poor

[3] According to the IMF Annual Report on Exchange Arrangements and Exchange Restrictions, 2018.

generalization. The solution is to reduce the number of features with the Boruta algorithm, which is based on the Random Forest, to extract the most important 65 variables. Then the authors used eXtreme Gradient Boosting (XGBoost) and Deep Neural Network (DNN), and compared them with Latent Dirichlet Analysis (LDA) and logit models. XGBoost showed the best performance (measured with AUROC) and gave a variable importance table. The most important were returns on equity, availability of working capital, and interest expense coverage. These results might be used in both risk-scoring and further analysis of the area.

Scoring in the financial sector is one of the most promising vectors for Data Science usage. There are several reasons for that, among them are a lot of high-frequency data, a complex structure of the data, alternative sources and types of data that might not be easily met in classical econometric models. Bazarbash (2019) presented a deep discussion about the pros and cons of ML algorithms in credit scoring, especially for emerging economies with weak financial institutions, that was accompanied by a general methodology overview. Authors highlighted several strengths of Data Science in credit scoring: small costs to analyze a small borrower with decent accuracy when it's unprofitable to hire a financial analyst; the ability to harden soft information, making it more quantitative; and capturing non-linearities and reducing the sharpness of information asymmetry.[4] Among the weaknesses, there are privacy and ethical issues, and classical data-driven models issues such as bad responses for structural breaks.

Debatable papers, to be useful, should be reinforced with some technical ones that produce a measurable result. Munkhdalai et al. (2019) have tested a set of Data Science models to build a credit-scoring system and compare it with judgmental credit scoring (FICO). In the process of system building, authors used an automated grid search to find hyper-parameters for DS models (brute force over several options for all algorithms), and distinct feature engineering algorithms (to reduce their amount and to avoid overfitting problems). The result of the system is, expectedly, better than for benchmarks.

Another approach to perform Data Science in the financial market is to support decision-making in the credit market. Arora et al. (2019) write about horizontal or vertical slicing during portfolio building. These strategies support correct liquidity management, which is important because it holds the risks of large redemptions that can destabilize the financial sector. One of the tools is the ability to quantify the impact of sales on the market state. The Random Forest method works well for this purpose, predicting the response relatively better than the more mainstream model.

The last paper for this chapter is a quite unusual forecasting exercise that was studied by Hatko in 2017. The paper deals with nonresponses in a survey for business firms. Such observations are usually ignored or accounted for with a dummy. Another approach is a prediction for the variable of interest that is based on all responses from other companies with similar characteristics and responses for other questions by this firm. The author divided the global problems into a few sub-exercises: unit non-response (when there is no response at all) and item non-response (when there are some unanswered questions). The first one was solved by generating a response probability with a combination of logistic regression and k-means clustering. The second part was about using GBM and XGBoost on the datasets with missed data and its imputation. The quality was evaluated using several mean-based methods (cross-entropy) and out-of-sample forecasting exercises.

Special attention is required by fully developed packages that use several tools described above. They have a simple user interface and give comprehensive solutions to particular problems that a central bank faces. The Mindbridge.ai project has an award as the best Machine Learning solution at the annual Central Banking FinTech RegTech Global Awards.[5] Their product analyzes information about agents and builds their risk score, which is a proxy for the probability of a particular one to be fraudulent. Moreover, they have developed a search engine that allows the regulator to find and compare with the rest of the industry, and to visualize different features of an economic agent. Hereinafter, they have become a part of the Bank of England Fintech Accelerator project and won a Central Banking Award in 2018 as the best innovation, which emphasizes once again the openness of the Bank of England to new technologies such as Machine Learning algorithms. This project supports the further digitalization of supervising processes to increase the quality and speed of the audit by pairing human and AI performance.

A majority of use cases might be done using traditional econometric models. However, Data Science approaches can provide additional accuracy. Most papers claim that new models are solid complements to the current toolbox. The full potential of Data Science will be revealed in the next chapter, in a field where there are no decent alternatives.

To finish this chapter, it's worth reviewing the discussed use cases of Data Science algorithms once more: 1) forecasting of important macroeconomic variables such as inflation, GDP, unemployment and others, possibly using additional datasets; 2) analyzing whether some variables could be predicted with another, meaning the influence of the second variable on the first one; 3) building different indices for decision-making; 4) finding alternatives to expert judgement in areas where classical econometrics models seem to be unable to capture and use all the information provided; and 5) filling in gaps and unobservables in the data.

4. TEXT ANALYSIS

With the rise of Data Science, central banks have become able to use alternative sources of information. As an example, the Monetary Policy Authority of Singapore screens the news to detect events that require further attention (alerts). David R. Hardoon describes this issue in his presentation at IFC 2018. Analysts can do the job of looking through loads of text and discarding irrelevant news. However, it is a rather routine job. Alternatively, machine algorithms can take over, do this exercise faster, and save analysts time.

Unpredictable human sentiments are one of the biggest sources of error in current macroeconomic models. A general way to address this issue is to use aggregated data and make the assumption that, on average, agents act

[4] More about hard and soft information in finances might be found in the paper by Liberti and Petersen, 2019.
[5] Generally described in the article on a Medium: https://medium.com/reciprocal-ventures/mindbridge-analytics-why-we-invested-9cdb2099ba

rationally and behavioural effects can be neglected. These effects might be also approximated with the data from news, social networks and other text-based sources. Such techniques that help to solve the problem will be the main focus of this chapter.

A field of Data Science called Natural Language Processing (NLP) studies algorithms that can "understand" the text instead of simply collecting statistics about it. It is a broad field with several stages and tools for data preparation and processing, which differ upon the issue that this model should solve. Bholat et al. (2015) overview fundamental techniques in this area, as well as the comprehensive motivation for their usage and why are they underestimated. In most of the papers that are presented in this chapter, the used techniques are the same as described in this article: dictionary building, LDA and other.

Text mining is not a new area of study, but previous attempts by central banks to automate working with a text have been not particularly successful. In the IFC 2018 presentation by Hansen, a history of these attempts is shown. In 2007-2011, tools were mostly about finding some particular words or combination of words to determine the emotional exteriors of articles. The critique of such an approach is as follows: an article with the phrase "Central bank has a poor performance," and another one with the phrase, "Many articles say that central bank has a poor performance, but, in fact, it's the opposite," have contrary meanings, but might be judged as similar. Modern literature offers better methodology due to the better computational efficiency and higher interest: it starts from advanced dictionary methods that use psychological insights and goes to the LDA and RNN techniques that can capture the context throughout the text. Real use cases include the impact of a BoE Inflation Report release text on bond prices and the relationship between Fed statements and Romer and Romer shocks.[6] There are decent results (76% accuracy), which allow for applying the model to get complementary information about the economy and its dynamics.

The news is a solid proxy of social reaction. Thus, some methods are called to construct time-series indicators that help explain important macroeconomic variables. In the paper by Nicholas Apergis and Ioannis Pragidis, 2019, the authors built an index based on news sentiments and used it for prediction of stock returns over a database with articles and word-based statistics. The classical for financial purposes EGARCH-X model shows increased performance with news-based indices.

Another case described the model that explains bond spreads with these news indices (on a local and global level) via panel data. It is written by Fulop and Kocsis in 2018. The main output is a model with news that shows a huge increase in the R-squared, compared to a simple macro-based model. It is one of the best examples when NLP techniques and news data give the main contribution, rather than being a simple compliment for an additional few percentage points of explained variance.

Indices for models are not the only purpose of news mining. Rybinski (2019) showed a model that analyzes 20 years of articles about the Narodowy Bank Polski in Rzeczpospolita, the main newspaper in Poland. Text mining helps estimate the link between hot topics in the economy (proxied by news scores) and the Monetary Policy Committee (called RPP in Polish) talks score. NBP is a key decision-maker in several areas (e.g. inflation or interest rates). But in other areas, it is not (e.g. public finance, fiscal sector). The model suggests that the former topics are highlighted by media strongly in the periods of MPC activity, while the latter are not.

"Words are the new numbers: A newsy coincident index of the business cycle" is the speaks-for-itself name for a paper written by Thorsrud in 2016. The core idea is an approximation for the U.S. business cycle using the LDA model. The author investigated business newspaper topics, their dynamics (a measure of the topic heat in the particular day), and quarterly GDP growth in the time-varying dynamic factor model.

On many occasions, central banks need to estimate agents' expectations about the economy to build a strategy. The usual way is based on surveys. However, they are quite expensive, especially when high quality is needed (robustness to many factors, size, and homogeneity of the sample, etc). The ability to estimate expectations via news is a good addition to the central bank toolbox. Zulen and Wibisono (2018) implement such a model, which predicts society expectations about policy rate changes based on the news (four categories: no information, no change, no hike or no cut), and compared the results with the Bloomberg Survey Index. The results were quite satisfactory (up to 84% accuracy for XGBoost in this classification exercise), which is great for such small costs and an advantage in speed. The benefits are crucial for nowcasting and a better understanding of the current economic state.

Monitoring news helps predict shocks, such as armed conflicts. Originally, despite the impressive predicting power of modern forecasting tools, there is a room for shocks that could not be detected earlier as long as they might have had an unusual or rare nature, no seasonal pattern, etc. Mueller and Rauh (2017) wrote a paper about the prediction of political violence, such as armed conflicts or civil wars. The authors took some country news, extracted topics and evaluated whether there would be a conflict inside the country via dynamics exploration, different Bayesian techniques, the Gibbs sampler, and many other tools. The results were remarkable: a model can predict with 70% probability – and only 20% false positives – that there is an armed conflict coming. These kinds of models might strongly improve the quality of structural economic model output and might be used for better scenario design.

Social network data is powerful, but a strongly underused source of the real-time micro-level information that central banks can use. Thus, it is an innovative field of study that might give even better results than news-based models. Currently, there are some unfinished projects in the field, for example, Angelico et al. (2018) criticized surveys for being available on a monthly or lower frequency level, which does not allow analyzing an immediate response for particular events. Thus, they propose to use filtered and prepared data from Twitter to build inflation expectations. The result is highly correlated with survey-based and market-based indexes, however, with real-time feature and low costs. It might complement traditional methods for beliefs estimation.

[6] Romer and Romer shocks (RR shocks) described in the corresponding paper in 2004.

Corea (2016) describes another use case for Twitter data to approximate investor sentiments on the stock market. For example, as of 2016, there were 88,000 tweets about Apple stocks. Their analysis might approximate public expectations, thus forecast behaviour. Unfortunately, the results were are quite mixed, which speaks to the necessity to use complex models and devote more attention to data preparation.

Social-network data is continuous. This feature offers the ability to capture sentiments that are not obtained with surveys regularly. Thus, it might be used not only for forecasting but for research too. Stiefel and Vives (2019) found a significant relationship between the index of intervention by ECB perception to bond spreads. Such data allow for working with sentiment dynamics and with rumours, which is nearly impossible with other instruments. To conclude, using social network data might be used both as a support for forecasting models and as an independent technique for distinct research.

At the end of the section, there are few papers about communication between different agents in the economy. There are government authorities, people who are living in the country and other institutions (international). The first paper, written by Fayad et al., (2020), gives a small insight into the analysis of communication between government authorities and the IMF during Article IV Consultations.[7] About 2,600 staff reports construct the dataset from 2000 to 2018, which allow for analyzing the dynamics too. In the beginning, several "relevant" paragraphs were extracted from each report and topics were assigned to them using a "dictionary method", which offers 89% accuracy (compared to the smaller train set, made by hands). Then, the state-of-the-art NLP solution BERT is applied to extract the sentiments from these paragraphs with an 81% accuracy and did relatively well when authorities agreed or disagreed with IMF advisers, though failing in the case when the answer was mixed. These IMF advisers might find these results helpful in order to improve their program and find the most efficient vectors to work with.

The analysis of internal communications (e.g. MPC discussions) at a central bank could contribute to many areas, including improvements in transparency, which is one of the features that central banks care a lot about. Recently, studies about the transparency effect were limited by using periodical dummies. Nowadays, it is possible to track the effect directly through the topic dynamics in corresponding periods (before, during, and after changes to the more transparent behaviour). A paper about this issue, written by Hansen et al. (2018), shows the proof of hypotheses about the positive discipline effect and negative conformity effect due to the transparency increase, parallel to the hypothesis about its structural changes. Based on the transcripts from the FOMC, the authors found that communication between members increased significantly (discussion of the same topics), as long as there was discipline (preparation before meetings, which increases informativeness) and conformity (avoiding the expression of the true views, which decrease informativeness). The main conclusion, despite the necessity of transparency, is that NLP techniques open a window for research in areas that had been mostly unavailable.

The last paper for the chapter is made by Cedervall and Jansson in 2018. It is strongly connected to the previous paper and serves as an example of topic dynamics analysis. The authors paid special attention to the "business value" of this exercise, such as creating a quick overview of the report via machine techniques. For businesses in the world of available data, those who win understand the data and sign first, rather than obtain completed reports with a delay. Thus, they will be happy to have this raw and pressed information. The conclusion is as follows: transparency depends not only on the quality of one communication stream but also on the diversity of these streams, while some might perceive the information in one or another way better. This instrument helps to build diversity with relatively low costs.

To conclude the chapter, text mining is a broad field of study, even when we are talking about news analysis, but not only about that. For the moment, central banks haven't taken advantage of much of the analysis of social networks to predict behaviour, making it a good area to pioneer research. Many use cases were described throughout the chapter: 1) digging for news to build an index that helps to predict different macroeconomic and financial series, such as bond spreads and stock returns; 2) designing an index of credibility, transparency and other social interactions, based on the news; 3) predicting the probability of shocks, that couldn't be predicted, but could be guessed by experts previously; 4) examining proxy survey results about expectations for different series, for example, inflation expectations; 5) researching about different effects built on communication; 6) easing the routine job process in some cases; and 7) exploring one of the best places to understand individual behaviour and moods – social networks.

5. OTHER ALGORITHMS

Data Science is not bounded by the above-mentioned algorithms. There are a lot of techniques at the junction with data analysis, statistics, and IT. Among the most widely used techniques for researchers is web-scraping. The tool takes real-time data directly from the websites. The well-known macroeconomic project that uses web-scraping is called "Billion Prices Projects", which scrapes prices from retail websites and uses this data instead (or as a complement to) the official price level data. There were many papers about this project, among them by Cavallo (2013). He used the project-produced data to challenge the credibility of the official inflation in Argentina. He aggregated series into components, similar to the official basket to represent some part of the goods basket inflation. The results between the scrapped and official prices might be different in this case due to the inconsistencies in methodology and other issues. But in this paper's case, the scraped inflation was twice as high, which is taken as evidence of manipulations with official data.

Google Trends is another web-based technique, which is close to web-scraping but uses the search data produced by users. It was launched in 2006, but the number of papers in the classical economics environment about its usage started to grow 5-10 years later. Per Nymand-Andersen in IFC 2018 showed a model for predicting car registration data, which comes with a lag in the official stream, with the data from Google Trends (or several searches related to the car buying). The hypothesis was proven that if people start to search for opportunities of buying a car, then many of them will do it soon.

[7] This is a series of consultations with an individual country representative, according to the Article IV in the IMF Article of Agreement. A short description might be found here: https://www.imf.org/external/about/econsurv.htm

Other techniques that are rather about "Big Data" are actively discussed by the central banking community. Building and maintaining a database is a crucial part of the implementation of Data Science algorithms, which corresponds to the Erwin Rijanto key opening speech at the IFC 2018 conference. Renaud Lacroix further discusses this question in his presentation about the project to build a multidisciplinary granular data platform, which took place at the same conference. Soramaki (2018) gives a good example of a widely popular Regtech and Suptech solution. He described the FNA Ltd. product for analyzing, monitoring, and visualizing transactions between companies and institutions, their interaction in financial terms. Several graphical approaches and statistics support the understanding of the network (financial system). A few use cases were about prices for housing right before, during, and after the Global Financial Crisis, fraud detection in money transfers and others. However, it is less about research, thus out of the paper's scope.

The last example of the Big Data usage is less about central bank activity, but it is a very good example of the complex structure in economics that might be explained or approximated with Data Science techniques. Fan Liang et al. in 2018 described a project of Chinese authorities for scoring the trustworthiness of Chinese citizens and organizations. The model includes numerous factors: what people buy in shops, where they spend their time, whether they paid their loans in time, who are their friends and many others. This data supports building a score, which represents the probability of a credit loan return. There is a system with rewards and punishment for those who have high and low social credit scores, respectively. It is possible to obtain a lot of data about a single person and its interconnections to build this score, which represents a behaviour in a particular situation. It is the ultimate technology that might be used by central banks to understand public attitudes and expectations with overwhelming accuracy. However, questions about costs and ethics arise. The conclusion from this paper and this product as follows: most things, including such unstable ones like personal behaviour, might be approximated and forecasted with great accuracy. Everything depends upon the data.

In conclusion, there are lots of methods and tools that are associated with this topic and should be mentioned, but do not directly represent the paper's objective.

6. NATIONAL BANK OF UKRAINE PROJECTS

Many DS-based projects are at different stages of completion at the National Bank of Ukraine. This section's purpose is to highlight them.

A project for official monthly disaggregated inflation data aims to find distances between series and cluster them into several groups. This will challenge the rationality of the current division of headline inflation into four main categories, reveal the series with the highest exchange rate pass-through, and investigate relative prices between tradable and non-tradable goods.

A few small supplementary models for inflation forecasting are also in use. They are based on the Random Forest and GBM approaches (XGBoost in particular), fitted to forecast core inflation components. Further research on forecasting capabilities is still under development.

The attention of the NBU as an oversight authority, concerned about financial stability, is geared towards risks in the credit sector. Researchers investigate them in different contexts of credit risk, ranging from individual agent data to the aggregated indexes over the whole set of clients in a particular bank. The logistic regression serves as a main documented benchmark. One of the reasons is an explanatory power of this approach when there is a need to prohibit credit issuance and offer the reasoning. As for supplementary tools, we can recall a paper by Pokidin, 2015, that investigates whether an SVM is superior to the main benchmark and a few other models in terms of company-level credit risk. The answer is "slightly". Another case is an XGBoost-based project for SME fraud detection.

A paper by Rashkovan and Pokidin in 2016 reviews banks clustering into a few types, according to their crediting business model. The authors investigate their density during the major changes in the banking sector during 2014-2016 and search to determine which of them were the riskiest. To do so, the authors used an algorithm from the expansions to Neural Networks. In the end, a risk indicator for the banking sector was constructed and it has been able to locate 92% of defaulted banks. Thus, it's an informative and useful product for regulatory authorities.

In the NBU, the question about estimating public sentiment is an open one. Despite numerous different surveys, there is a search for the more effective ways to approximate it from both the cost point of view and accuracy. So, a news analysis algorithm is on its way to completion. The project will consist of a model (and a few research papers based on it) to study the field of the media environment in Ukraine from different angles.

A web-scraping of prices for goods from online retail stores is a hot project with much research and models based on the data. One was already published in 2018 by Faryna, Talavera and Yukhymenko, where they built a model that aggregates these series into components of an inflation basket. This dataset covers 46% of the total official basket of goods determined by Ukrstat. The purpose of the paper was to investigate how well online prices correspond to official statistics and what are the drivers for inflation to be represented well by its scraped counterpart. This project is developed further to treat new problems such as series pairing, like in the Abe, Shinozaki, 2018 project. A similar technique is present in a few more projects about the labour market and densities inside it.

NBU researchers are doing well and are active in most important areas, with projects in different stages of completion. However, there is much more to be done.

7. CONCLUSION

The number of papers completed, even with consistent growth during recent years, leaves much to be desired. A quote from the review to one of the papers presented in the previous chapter is as follows: "The important point to note here being that the poverty of publications in this area is not because of some intrinsic limitations of ML's applicability to the domain, it's just that its early days". This phrase was written on January 11, 2018, and things have gotten better since those times. But there is still room for improvement.

As expected, the most effective and well-described Data Science models in central banking belong to the forecasting area. As long as the quality and diversity of the data grow, there is an opportunity to improve the predicting toolbox with models that connect different disaggregated series in a complex, “black box-like” manner. The best bet for modelling units is to invest time in this area.

On the other hand, text analysis finds its use too. It is a rather difficult task, especially in countries where English is not the main language. This comes from the necessity to have a robust vocabulary. For developed economies, this area is interesting because it is a new way to further improvement of existing economic understanding, which better accounts for people’s behaviour. Nevertheless, for emerging economies, the cost-to-benefit ratio is low and it might not be worth investing too much time here.

New sources of data (web-scraping, Google Trends) are viable and low-cost supplements to the existing toolbox, which might give more opportunities to use advanced Data Science techniques. A similar reason is related to improved communication with other central banks. Joint projects might improve data quality and diversity even further. Conditions for this are favourable, there are big conferences and frequent meet-ups in the area.

Hopefully, this paper will guide and encourage further research activity on the frontier between central banking and Data Science, offering a flavour of what are the most promising vectors.

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APPENDIX

Short description of Data Science tools that are used in the papers

Elastic Net – method of regression regularization. It adds into the original OLS minimization problem a product of lambda with coefficient beta and another lambda with beta squared. It helps to penalize too high values of beta because high beta increases loss function value according to the magnitude of lambda.

$$\underbrace{\hat{\beta} \equiv \underset{\beta}{argmin}(\|y - X\beta\|^2)}_{Original\ min.problem} \Rightarrow \underbrace{\hat{\beta} \equiv \underset{\beta}{argmin}(\|y - X\beta\|^2 + \lambda_1\|\beta\| + \lambda_2\|\beta\|^2)}_{Elastic\ Net\ min.problem}$$

Lasso regression – a particular case of the Elastic Net where $\lambda_1 = \lambda$, $\lambda_2 = 0$.

Ridge regression – a particular case of the Elastic Net where $\lambda_1 = 0$, $\lambda_2 = \lambda$.

Bagging – an ensemble technique that divides the total dataset on subsamples uniformly and trains models on each of the subsamples. Then the resulting coefficients should be combined by some kind of averaging (different for the particular method and task to which bagging is applied).

Decision Trees – an algorithm that builds a tree (graph), in which every node is a "question" to the observation features. Answers to these questions leads to the leaf, which represents some value or class.

Random Forest (RF) – a combination of Bagging and Decision Trees, where trees are building for different subsets of features and then combined together.

Gradient Boosting Method (GBM) – an ensemble algorithm, which claims that the aggregated result from a few weak learners might present a solid solution. It trains weak models and adds them to the strong combination iteratively. During each iteration, data is reweighted and gives more weight to those that are badly predicted.

EXtreme Gradient Boosting (XGBoost) – an open-source library for a gradient boosting framework. It has become very popular and has several advantages over other libraries (LightGBM, CatBoost). However, it also has some drawbacks, leaving open the discussion of which is library is better.

Super Learner – algorithm, based on stacking, the third main ensemble technique. It has two stages: train many weak learners (not necessarily homogeneous, i.e. could be different techniques); train a meta-learner that uses outputs from these models to make a real prediction.

Clustering – a set of tools for grouping objects by their similarity.

K-Means – one of the most popular clustering algorithms. It randomly puts k points as cluster centres, then iteratively move them to the centroid of it and the nearest point. This approach minimizes in-cluster variance.

Support Vector Machine (SVM) – a model for a hyperplane construction to separate observations into several groups. It maximizes the distance from a hyperplane to the nearest observations from both sides (set margins).

k-Nearest Neighbours (k-NN) – a classification model. It assigns a class to the new point, according to how many points of this class are in k nearest points overall.

Naïve Bayes – it is a Bayes Theorem, used for the data with an assumption whose features contribute to the probability independently (that is why it is called naive).

Dimensionality reduction – a set of tools to reduce the number of dimensions (feature) without much loss of information.

Neural Network (NN) – this algorithm is composed of a few parts. There are nodes, layers, connections and activation functions. Nodes consist of some values and they form ordered layers. All nodes in the first layer are connected to all nodes in the second, second to the third, etc. The first layer has input data and the last gives an output. A node value is equal to the weighted sum of values in all nodes from the previous layer (connected nodes), transformed with the activation function (which produces, traditionally, a value between 0 and 1, like in the logistics regression). The goal of the algorithm is to calibrate weights in a way to minimize deviations between fitted and real output.

Deep Neural Network (DNN) – it is a NN, but with a much higher number of layers. In some cases, it improves the precision significantly, but the approaches of how to work with an algorithm are slightly different too.

Recurrent Neural Network (RNN) – it is a NN, but some nodes can be recurrent. It means that it takes not only values from the previous layer but its own value too (which corresponds to the definition of recurrence).

Latent Dirichlet Allocation (LDA) – an algorithm, used mostly in NLP and topic modelling. It allocates a set of topics to a set of documents and a set of words to reduce the number of direct connections, according to the Dirichlet distribution.

Bidirectional Encoder Representation from Transformers (BERT) – a state-of-the-art technique for different NLP tasks (at the moment of publishing). It uses transformers that reads the entire sequence of words, embeds them into vectors, replaces some words with a “mask” token (to improve contextual learning) and gives them to the neural network.

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THE IMPACT OF WEATHER CONDITIONS ON ECONOMIC ACTIVITY IN UKRAINE

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Abstract This article explores the impact of weather conditions on core sectors of the Ukrainian economy and the composite index of economic activity in Ukraine. We build autoregressive distributed lag (ARDL) models using statistical data provided by the Central Geophysical Observatory named after Boris Sreznevsky (CGO) and the State Statistics Service of Ukraine for the period 2004-2019. The obtained outcomes show that fluctuations in the air temperature and precipitation are significant determinants of output in different sectors (specifically agriculture, construction, manufacturing, and energy). Therefore, the inclusion of weather conditions into models may potentially improve the modeling properties and forecasting of economic activity.

JEL Codes C51, E01, O44

Keywords weather conditions, autoregressive distributed lag

1. INTRODUCTION

Is there a connection between weather conditions and economic growth? According to Financial Times analyst Gavyn Davies, the slowdown in the Eurozone and the UK was due, among other things, to adverse weather conditions (Davies, 2018). Research by Bloomberg and Reuters also confirms that economic losses are partly caused by exceptional weather conditions (Sullivan and Doan, 2012; Barlyn, 2019). In addition, central banks also take weather factors into account when preparing monetary policy analysis materials. One example is the Inflation Report of the Bank of England (Bank of England, 2018).

Weather conditions are traditionally understood as a set of meteorological indicators (air temperature, precipitation, atmospheric pressure, relative humidity, solar radiation, wind speed and direction, etc.) and atmospheric phenomena that are observed at a certain point in time at a particular point in space. Weather conditions may influence economic activity through several channels (International Monetary Fund, 2017). First, weather conditions have a significant impact on the level of labor productivity, which in turn is reflected in changes in real GDP.[1] Second, weather factors (including air temperature, precipitation, and solar radiation) have a direct impact on the volume of agricultural production, especially crop farming (Acevedo et al., 2018).

Weather factors have a notable impact on the dynamics of individual macroeconomic indicators in developing countries (including Ukraine), as potentially weather-sensitive industries (e.g. agriculture) constitute the core sectors of these countries' economies. For example, an early start to the harvesting season in Ukraine in June 2019, thanks to accelerated spring vegetation amid favorable weather conditions, resulted in an increase in early crop yields (compared to the same period a year before) harvested by Ukrainian farmers. This had a positive impact on Ukraine's real GDP growth in Q2 2019 (to 4.7% yoy).

Other economic sectors besides agriculture are influenced by weather factors. In particular, the cold spring weather in Ukraine in March 2018 fueled growth in the energy sector (+24.2% yoy), while, for example, heavy snowfall in March 2013 paralyzed motorway, rail, and air transportation. This had a noticeable, albeit short-term, impact on the dynamics of passenger and freight transportation as well as volumes of retail trade.

Thus, given the sensitivity of the Ukrainian economy to changes in weather conditions, this article aims to provide a methodology to estimate the contribution of weather to output in the core economic sectors. This approach could lay the groundwork for improving the accuracy of forecasting the current value of IKSO, the composite index of economic activity, and hence the accuracy of nowcasting quarterly real GDP.[2]

This article is structured as follows: the second section provides a review of the literature on the subject matter; the

[1] Chen (2015) notes that labor productivity decreases with the rise of air temperatures above 30°C, while low air temperatures demonstrate no effect on labor productivity.
[2] Index of Key Sectors Output (IKSO) is a composite index of economic activity calculated by the NBU. It is a key indicator of real economic growth.

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third section describes the methodology and data used in the study; the fourth section presents the results of model calculations, namely quantitative evaluation of the impact of weather conditions on the monthly indices of certain economic activities in Ukraine; and the final section contains conclusions.

2. LITERATURE REVIEW

Economic literature use both linear and nonlinear models to study the influence of weather conditions on the dynamics of macroeconomic indicators (i.e. a country's GDP, employment, economic activity, etc.). Empirical studies apply a comprehensive multiple regression analysis, where changes in the air temperature and precipitation generally serve as independent variables.

To estimate the impact of long-term changes in weather conditions on GDP, researchers traditionally use a production function which also covers the so-called "loss" function".[3] The latter characterizes the impact of changes in the air temperature on the level of economic activity (Batten, 2018). The functional form of the loss function is such that in the absence of long-term changes in the average air temperature, GDP losses from the influence of weather factors equal to zero, while in response to rising air temperatures, GDP losses increase. To this end, the Weitzman (2009) study, for example, used the exponential "loss" function.

Dietz and Stern (2015) consider different ways of incorporating a factor that characterizes changes in weather conditions into the production function. The first way is to include this factor in the equation describing labor productivity.[4] The second way involves constructing an equation that characterizes the level of physical capital stocks in the economy[5]: that is, in each period of time, investment contributes to an increase in capital stocks, while a decrease in capital stocks depends on physical wear and weather changes.

Hissler (2010) found a statistically significant effect of weather factors (including changes in precipitation) on agricultural production in the African Sahel. The study demonstrated that agriculture in the countries analyzed remains sensitive to the variability of precipitation over time.

Bloesch and Gourio (2015) revealed a considerable, though short-term, impact of winter weather on economic activity in US economic sectors such as housing, construction, and retail, whereas for other industries this impact turned out to be insignificant.

Continuing the previous study, Gourio (2015) assessed the impact of weather conditions (air temperature and snowfall) on US GDP. The author's calculations showed a noticeable effect of weather conditions on the dynamics of indicators in monthly terms. However, the study noted that this effect was neutralized within two months, becoming imperceptible in quarterly data. François Gourio believes that retail and industry are the most sensitive sectors as far as weather changes are concerned.

Burke et al. (2015) and Acevedo et al. (2017) emphasize the existence of a statistically significant nonlinear relationship between air temperature and real GDP per capita. According to the Acevedo et al. (2017) study, rising air temperatures reduce economic activity in countries with relatively high average annual air temperatures; however, the effect is the opposite in countries with a cold climate.

The Dell et al. (2014) study also recognizes the inverse relationship between air temperature and per capita income. However, such relationship is true only for poor countries where agriculture serves as the main driving force.

Our article is most closely related to the study presented researchers of the Bank of England (Bank of England, 2018). The latter, in particular, assesses the impact of heavy snowfalls on the performance of the economy as a whole and its individual sectors (namely electricity, construction, retail, and services provision).

The authors of the Bank of England report came to the conclusion that weather conditions have a temporary effect on total product output. That is if a change in weather causes a shortfall in economic output in a certain quarter, we should expect to make up for lost opportunities in the next quarter and, as a result, the impact of weather conditions on semi-annual and annual indicators is smoothed and becomes insignificant. In contrast to the Bank of England study, we also analyze the impact of weather on the dynamics of selected individual economic sectors, albeit focusing on the average monthly air temperature and monthly rainfall.

3. DATA AND METHODOLOGY

Estimating the impact of weather conditions on economic activity involves determining a set of meteorological elements to be included in the study (Bloesch and Gourio, 2015). Data from the Central Geophysical Observatory named after Boris Sreznevsky (CGO) served as the source of information on weather conditions for this article.[6] The CGO stores monthly measurements of many weather factors in Kyiv (in particular air temperature and humidity, soil temperature, wind direction and speed, atmospheric pressure, precipitation, cloudiness, and snow cover). The average monthly air temperature and the average monthly precipitation were the only values taken into account.[7]

In our study, we use monthly data for core sector output indices (agriculture, industry, construction, trade, and transport) from the official website of the SSSU.[8] The quality of time series of meteorological indicators was checked as follows. We analyzed both the number of deviations of weather conditions from the respective levels in the year before and from normative values. The descriptive statistics for the main variables used in this study are shown in Table 1. Note that the absence of a unit root in the time series, as evidenced by the data in Table 2, confirmed the possibility of using existing time series to build autoregressive models.

[3] Y_t=$A_t\,D(\Delta T_t)F(K_t,L_t)$, where A_t – technological efficiency indicator, L_t – labor factor, K_t – capital factor, $D(\Delta T_t)$ – "loss" factor due to temperature changes.
[4] $A_{(t+1)}$=$(1\text{-}D_t^A)\,A_t$, where D_t^A characterizes the quantitative impact of weather conditions on production efficiency indicators (including labor productivity).
[5] $K_{(t+1)}$=$(1\text{-}D_t^K)(1\text{-}\delta)\,K_t+I_t$, where D_t^K characterizes the degree of the losses of companies' stocks as a result of weather factors, δ – depreciation rate, I_t – capital investment.
[6] CGO named after Boris Sreznevsky is the oldest organization among meteorological agencies in Ukraine which has been collecting and storing hydrometeorological observations since the middle of the XIX century.
[7] Calculated as the arithmetic mean of daily values.
[8] State Statistics Service of Ukraine. Retrieved from http://www.ukrstat.gov.ua

At the preliminary analysis stage, the relationship between variables that describe weather conditions and the dynamics of output in the core sectors of the Ukrainian economy was determined on the basis of matrices of correlation coefficients. Table 3 concludes that there is a moderate negative relation between output in the energy sector and the change in the average monthly air temperature in autumn and winter. Thus, energy production is sensitive to weather. Accordingly, warmer weather in the cold season has an inverse relationship with the performance of this industry. For other sectors of the economy, there is a weak correlation between changing weather conditions and their output dynamics. Therefore, the variables of weather conditions alone are not sufficient to explain the dynamics of the core sectors of the Ukrainian economy. For example, one study (Doronin, 2014) notes that the efficiency of a grain sector largely depends on the size of sown areas, the state of grain sales infrastructure, loan interest rates, budget support for the industry, etc. Another study (OECD, 2019) states that the efficiency of the energy sector in Ukraine is dependent on the negative impact of outdated technologies, strict regulation of the sector, improper management of public institutions, and declining demand. The NBU's information and analytical materials (National Bank of Ukraine, 2020) also stress the importance of the latter factor while analyzing the dynamics of energy sector output.

We consider several specifications to identify the statistical significance of the influence of weather conditions on the indicators of economic activity in the Ukrainian economy's core sectors. As dependent variables, we used monthly indices of output in the core economic sectors $y_j(t), j=\overline{1,9}$[9]:

Specification one. We used the autoregressive approach, i.e. the values of the dependent variables $y_j(t\text{-}s)(s=\overline{1,p})$ were used as lag explanatory variables, where "s" is the order of the autoregressive process. In its general form, the autoregression model $AR(p)$ can be expressed as follows:

$$y_j\,(t)=f(c,\, y_j(t\text{-}s),\, \varepsilon_j), \tag{1}$$

where: c – is constant; ε_j – is a random component.

Specification two. We built autoregressive distributed lag models with , i.e. the list of variables used in the first stage was supplemented by lags of independent variables $x(t\text{-}l)$, where l – is the length of the lag. Given below is the general form of the autoregressive distributed lag model $ARDL(l,p)$:

$$y_j(t)=f(c,y_j(t\text{-}s),\, x(t\text{-}l),\, \varepsilon_j) \tag{2}$$

And, finally, *specification three*. The list of variables used in the previous stage, was supplemented by determinants of weather conditions (namely changes in the average monthly air temperature ΔT and monthly precipitation ΔP[10]). The general form of the regression equation is written as follows:

$$y_j(t)=f(c,y_j\,(t\text{-}s),x(t\text{-}l),\Delta T_t,\Delta P_t,\, \varepsilon_j) \tag{3}$$

Table 4 presents the specifications of equations (1)-(3) for each core type of economic activity. The implementation was carried out in the Eviews 8.0 environment. The best specifications of regression equations were selected based on the results of verification: adequacy of regression equations, statistical significance of beta coefficients, absence of residual autocorrelation (verification was performed on the basis of autocorrelogram, partial autocorrelogram, and Ljung-Box Q-statistics). Also, when choosing the regression equation, the following factors were taken into account: the coefficient of determination and information criteria of Akaike and Schwarz. Conducting the augmented Dickey-Fuller test, we rejected the null hypothesis that the residuals have a unit root, while the bell-shaped histograms of the residual distribution, the statistical insignificance of Jarque-Bera statistics, and the location of the quantile residues near the 45-degree baseline confirmed their compliance with the normal distribution.

Further, we evaluate the contribution of weather conditions to the dynamics of particular industries on the basis of selected regression equations. For this purpose, we added together the products of the coefficients near variables ΔT_t, ΔP_t with the changes in weather conditions calculated on the basis of the CGO data (average monthly air temperature and monthly precipitation).

As the last step, the following equation was used to estimate the contribution of weather conditions to IKSO as the composite index of economic activity:

$$C_{IKSO_t}=\sum_{j=1}^{9} w_j\cdot v_{jt}, \tag{4}$$

where w_j – weight of the industry in the Index of Key Sectors Output (IKSO) in period t; v_{jt} – contribution of weather conditions to the dynamics of industry j $(j=\overline{1,9})$.

4. ESTIMATION RESULTS

The preliminary analysis shows that agriculture, construction, manufacturing, and energy are the most sensitive to weather conditions. Figure 1 demonstrates that these sectors account for a significant share of Ukrainian GDP (e.g. 25.6% of GDP or UAH 1,018.6 billion in 2019). While the manufacturing industry's share of GDP shrank (particularly due to the loss of production in the occupied territories) and construction's share remained insignificant during 2015-2019, agriculture's GDP share increased. The growing role of agriculture was supported, in particular, by continued state support for farmers and increasing grain and oilseed yields.

In this section, we estimate the contribution of weather conditions to output dynamics in Ukraine's core economic sectors. In particular, the results of the econometric analysis presented in Table 4 show that the last of our three specifications, one that contains changes in weather conditions, yields the results with the highest explanatory power. Therefore, it is justified to supplement the regression equation with the determinants of weather conditions in assessing Ukrainian economic sectors' production dynamics.

At the same time, the quantitative estimates (see Table 4) demonstrate statistically significant effects of the air temperature and precipitation, primarily on those sectors that involve work in the open air (including open construction sites) or in unheated premises (namely agriculture, construction, manufacturing industry, and energy).

[9] The study focused on the following core sectors: agriculture, manufacturing and mining industries, energy, construction, retail and wholesale trade, and freight and passenger transportation.
[10] The author tested two options, namely changes in weather conditions compared to: a) the same period a year earlier, b) the norm. According to the results presented in Table 4, statistical characteristics of the equations set up on the basis of deviations of weather conditions as compared with the previous year's level are better.

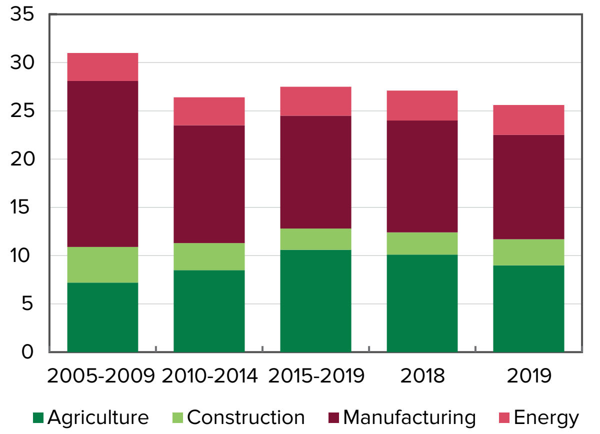

Figure 1. Core Economic Sectors' Share of GDP (in actual prices, % of total), on average for period
Note: In accordance with the SNA 2008 methodology. Starting from 2010, data exclude the temporarily occupied territory of Crimea, the city of Sevastopol, and part of the temporarily occupied territories of the Donetsk and Luhansk oblasts.
Sources: Author's calculations on the basis of SSSU data.

Given the significant role industry, agriculture, and construction play in the Ukrainian economy, we first interpret the estimation results of the impact of weather conditions for these particular sectors.

Agriculture

Weather conditions have a significant impact on agricultural production dynamics, primarily through their effect on crop farming (as measured by harvest volumes, harvest quality, and yields, among other things).[11] According to the model calculations presented in Table 4a, the absolute values of weather condition variables are marginal, but their impact is statistically significant at the 0.1 level of significance.

As shown in Table 4a, the influence of weather conditions on the growth and development of crops is multidirectional and, as noted in Yeremenko et al. (2018), depends on the phases of growth, the timing of seed formation and filling, etc. Specifically, crops require different amounts of heat and rainfall, depending on which stage they are at in their growth cycle. Higher air temperature in the fall compared to the previous year's level has been shown to have a significant positive impact on agricultural dynamics in Ukraine (through a positive effect on harvesting).[12] However, early-spring air temperature values that are lower than in the same period a year ago have a negative effect on wheat yields (including due to a phosphorus shortage in plants). More specifically, a 1°C decrease in the air temperature in March compared to the same month a year earlier cuts growth in the agricultural sector in June of the current year by an average 1.4 pp (all else held equal), according to my calculations presented in Table 4(A). At the same time, cool weather during the maize sowing period (late April through early May) limits the absorption of nutrients, slows the crop's development and reduces its yield, thus adversely affecting agricultural production dynamics in September-October (when maize is harvested).

As with temperatures, optimal precipitation levels depend on plant development phases. A rainless fall, for instance, is favorable for harvesting late grains but hinders the normal growth and development of winter crops, while scarce precipitation in winter adversely affects the volume and the quality of the future harvest. In particular, a 1 mm drop in precipitation in winter compared to a year earlier shaves 0.47 pp off growth in agriculture in the summer of the following year (all else held equal), according to my estimates.

Overall, these calculations show that the impact of weather conditions on agricultural sector dynamics is noticeable from June through November each year, while in other months of the year it is close to zero (see Figure 5). This is due to the fact that the domestic agricultural production index begins to trace crop farming dynamics in June, complementing livestock farming. Specifically, the positive contribution of weather conditions to agricultural production in June 2018 stemmed from an early start to the harvesting season, which was enabled by low rainfall and high air temperatures. In contrast, low night temperatures in November 2018, which had an adverse impact on the harvest volume of industrial crops and oilseeds, fueled a negative contribution of weather conditions to agricultural production dynamics (-2.1 pp, according to my calculations).

Taking into account the significant impact of weather conditions on agricultural sector performance, and assuming that this impact is primarily transmitted through the crop farming sector, we also tried to quantify the contribution of weather conditions to the production of major crops in Ukraine, specifically wheat and maize. These calculations are shown in Figures 2, 3. Weather conditions made a negative contribution to growth in the wheat harvest in 2019, according to our estimates.[13] Among other things, this was a consequence of insufficient precipitation in October and early November 2018. This led to unfavorable conditions for the initial growth and development of the future harvest of winter crops. However, early crop yields were positively affected by ample precipitation in April–May 2019, while mild weather in August had a positive impact on late crop yields (maize in particular). Meanwhile, the cool April weather and excessive rainfall in June-July this year were the unfavorable factors that depressed late crop yields. Overall, weather conditions made a negative contribution to growth in last year's corn harvest, according to my estimates (see Figure 3).[14]

Figures 2, 3 demonstrate clearly how weather conditions affect the dynamics of maize and wheat production in Ukraine. This result is in line with the calculations by other

[11] While crop farming accounts for 60%-70% of gross agricultural output, livestock farming represents only 30%–40%. This explains the definitive influence of crop farming indicators on the agricultural production index.
[12] A 1°C increase in the air temperature in the fall of the current year compared to the same period a year earlier accelerates growth in the agricultural sector by an average 1.75 pp (other things being equal) (see Table 4a).
[13] Weather's contribution to the increase in the wheat harvest was estimated using a regression equation. The following explanatory variables were used: deviations from the previous year's average rainfall in April–May and October–November (the variable was lagged one period), and an increase in sown areas under grains and legumes (excluding maize). Variation in the weather and sown area variables explained 66% of the variation in the dependent variable, the regression analysis showed. These explanatory variables had a statistically significant impact (Table 4(K)).
[14] To estimate the contribution of weather conditions to growth in the maize harvest, I ran a regression with the following independent variables: deviations of average monthly precipitation in June-July and average monthly air temperatures in April and August from the respective previous-year levels, and growth in the sown area under maize. Variation in the weather and sown area variables accounted for 72% of the variation in the dependent variable, the regression analysis showed (Table 4l).

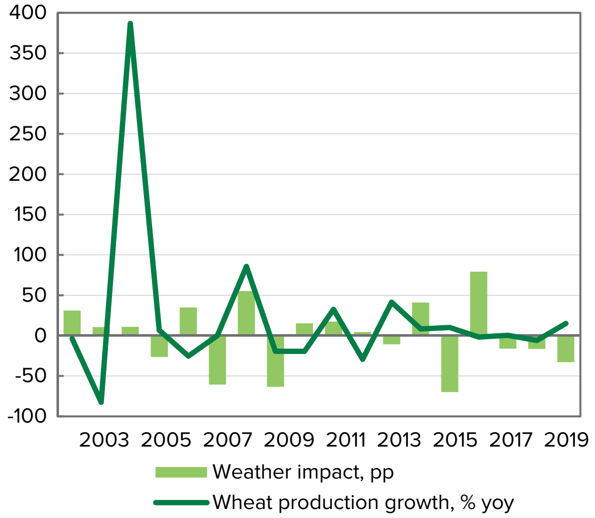

Figure 2. Weather Impact on Growth in Wheat Production, %
Sources: Author's calculations based on SSSU, NBU, and CGO data.

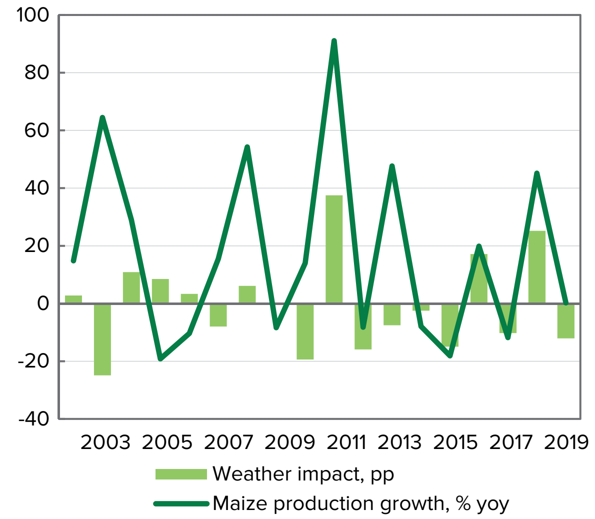

Figure 3. Weather Impact on Growth in Maize Production, %
Sources: Author's calculations based on SSSU, NBU, and CGO data.

authors, in particular Mendelsohn (2008), who writes that the crop farming sector is the main channel that transmits the impact of weather on economic activity in developing countries.

The fact that weather effects and growth in the grain harvest (Figures 2 and 3) are not closely related confirms the view, expressed in Paltasingh and Goyari (2018), that crop yields are affected not only by weather but also by a number of other factors such as soil fertility, increases in sown areas under grains and legumes, use of selected varieties of grains, use of pesticides and fertilizers, etc.

Construction

Construction is the second most weather-sensitive sector. Strong wind, dense dust or fog, high or too low air temperatures, and excessive rainfall can cause serious injuries to workers and significantly damage rigging equipment and mounting devices. Lightning endangers the personnel who operate cranes and hoists. The occurrence of force majeure due to adverse weather conditions will in turn cause additional economic costs and delay the implementation of construction projects. In general, the dependence of construction dynamics on weather conditions is direct and most noticeable during cold seasons (December through March), according to my estimates. Specifically, at a significance level of 0.1, a 1°C increase (from a year earlier) in air temperatures in winter and early spring has the effect of accelerating the pace of construction work by about 1 pp, all else held equal (Table 4b). Model calculations show that favorable weather conditions in February-March 2020 (higher air temperatures and lower precipitation relative to the previous year) made a positive contribution to the change in construction output (Figure 5). This insight is in agreement with other studies, including Bloesch and Gourio F. (2015), who find that cold weather can cause delays in construction projects.

Energy

Weather conditions also affect industrial dynamics (including the energy sector) (Stulec et al., 2012). This impact is the most pronounced between October and March, the typical heating season in Ukraine when air temperatures significantly affect the volumes of natural gas and electricity consumption. In a given year, March temperatures that are colder yoy tend to accelerate growth in the energy sector by 0.6 pp with each 1°C drop in the air temperature (other things being equal), my estimates show. This effect is somewhat stronger in the winter months, with energy production rising by 0.7 pp as the air temperature falls by 1°C (Tables 4c, 4d). These calculations are reliable at a significance level of 0.1.

It can thus be inferred from these calculations that it was the relatively warm weather that led to a negative contribution of weather conditions to energy sector dynamics in the winter of 2019–2020 and March 2020 (Figure 5). I also attempted to estimate the impact on the energy sector of changes in the average monthly air temperature during the warm period of the year. However, as shown in Tables 4c, 4d, my assumption about the statistical significance of this effect was not confirmed. This result is in line with other studies. More specifically, Staffell and Pfenninger (2018), among others, indicate that electricity demand is seasonal, with a marked peak in winter and remaining virtually unchanged in summer.

Given that part of electricity is generated by hydroelectric power plants, production in the energy sector is probably also affected by the amount of precipitation. However, this effect is not statistically significant, as seen from my estimates presented in Table 4c.

It should also be emphasized that with the energy sector gradually transitioning towards clean and safe renewable sources, its performance in Ukraine has been increasingly affected by weather factors such as wind speed and solar radiation but these issues were not addressed in this paper and require further research.[15]

Manufacturing

Cold winter weather adversely affects the performance of manufacturing companies, particularly by reducing the

[15] Specifically, the solar power plants put into operation in the first nine months of 2019 had a total capacity of 2,033.2 MW (nearly six times the level of the same period a year before), while the capacity of newly launched wind power plants totaled 399 MW (up from 57.3 MW in the first nine months of 2018), according to data from the National Commission for State Regulation of Energy and Public Utilities.

productivity of employees working in unheated buildings (Table 4e). At the same time, colder temperatures during this period of the year also have a positive effect on, for example, the clothing and footwear industry by increasing demand for warm clothes. All else held equal, a 1°C decrease in the air temperature reduces the growth rate of manufacturing by 0.2 pp, according to my calculations. Thus, in contrast to the negative impact of warm weather in the winter of 2019-2020 on energy sector output, the estimated effect on the manufacturing sector was positive (Figures 5).

Precipitation also appears to be a factor affecting manufacturing dynamics. For instance, heavy snowfalls cause an increase in demand for snow blowers and motor vehicle parts and accessories. This, in turn, positively affects the engineering industry. However, within the entire manufacturing sector, this impact becomes insignificant.

Other Sectors

As shown by Locke P. et al. (2011), mining performance comes under the influence of precipitation in summer, as excessive rainfall can flood mines, reducing the production of iron ore, coal, and other minerals. According to my calculations, however, the impact of rainfall on the performance of the mining sector was negligible (with a 1 mm increase in precipitation slowing growth in production by 0.01 pp) and not statistically significant (Table 4f). On the other hand, low temperatures in winter complicate the conditions for open-pit mining, with a 1°C decrease in the air temperature knocking 0.5 pp off the production growth rate, according to my estimates, with all other things being equal. These calculations are reliable at a significance level of 0.01.

Retail trade figures are also affected by weather conditions, in particular through the clothing and footwear segment, as its growth may be held back by warm weather in the fall, among other things.[16] Weather conditions also affect the traffic of stores and other retail businesses.[17] Households may find themselves “cut off” from retail stores after a heavy snowfall, for instance. In addition, inclement weather affects deliveries to grocery stores, ultimately eroding their earnings. However, the impact of weather conditions on the performance of retail trade businesses is short-lived (lasts no more than several days), dies down with every month, and is therefore statistically insignificant (Table 4g).

Adverse weather conditions (significant precipitation, excessively low air temperatures, heavy fog) affect transport industry dynamics in the short run, in particular due to disruptions in public transit schedules and delays in passenger rail services (Leviäkangas et al., 2011). A 1°C decrease in the air temperature in the winter months from the same period a year before cuts an average 0.3 pp off economic growth in passenger turnover (all else held equal), according to my calculations. Heavy clouds, thunder, and lightning can cause large-scale flight delays. All of this affects the time spent waiting for transport and the time that passengers spend on the road, which in turn affects labor productivity elsewhere in the economy. Overall, however, the influence of weather conditions on the monthly dynamics of the transport industry (and on other industries through the productivity channel) is noticeable within a few hours (rarely, days), but weakens in the course of the next few months. This is confirmed by the conclusion about the unreliability of the regression equations constructed in this paper to assess the impact of weather conditions on the transport industry’s performance (Tables 5i, 5j).

Weather conditions also contribute to the dynamics of the services sector (e.g. through the impact on the activities of travel agencies, tour operators, and catering[18]), and through it affect GDP. However, as data on these particular activities are not publicly available, they (and estimation of associated weather impacts) were left outside the scope of this paper.

Therefore, the results of the calculations provided above confirmed our assumptions that the industries involving work in the open air or in unheated indoor facilities (agriculture, construction, manufacturing, energy) are more sensitive to changes in weather conditions. The impact of weather on other economic sectors is less pronounced. In general, the effect produced by the weather on the Index of Key Sectors Output (IKSO) is significant in selected months but not significant during most of the year (Figure 3). This is primarily due to the mixed effects of weather conditions on the dynamics of individual sectors (e.g. cold weather positively affects the performance of the energy sector but has a negative impact on construction and manufacturing).

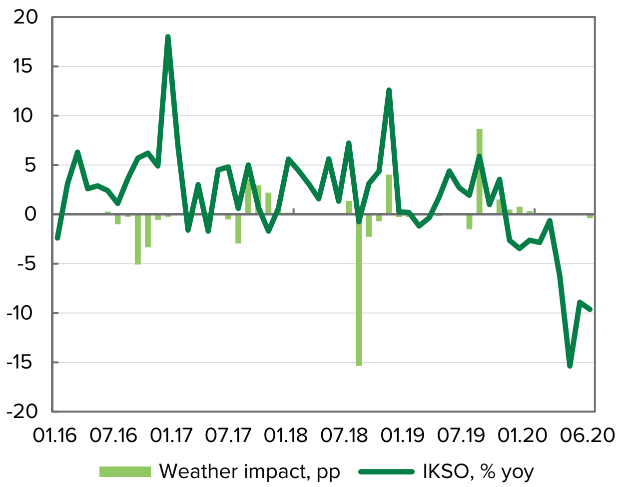

Figure 4. Ukraine’s Index of Key Sectors Output, % yoy
Source: Author’s calculations based on SSSU and CGO data.

5. CONCLUSIONS

This paper studies the influence of weather conditions on the core sectors of the Ukrainian economy. Overall, our findings support the view that weather has a noticeable but short-term impact on the dynamics of individual economic activities (including agriculture, construction, and industry). Weather’s contributions are the most pronounced in the energy sector (during the cold season) and the agricultural sector (during harvest time).

At the beginning of each year, the opposite effects of weather factors on production in different economic

[16] In 2019, this segment accounted for 4.5% of the goods trade turnover of retail businesses, according to SSSU data.
[17] NOAA Data Helps Retail and Manufacturing Business Minimize Impacts from Weather and Climate (2017). NOAA’s National Centers for Environmental Information. Retrieved from https://www.ncei.noaa.gov/news.
[18] These activities thus belong to the sections “Activities in the Field of Administrative and Support Services” and “Temporary Accommodation and Catering.”

sectors, by offsetting one another, mitigate the impact of weather conditions on IKSO dynamics. However, this impact becomes more noticeable starting in June, when the agricultural production index, in addition to reflecting livestock farming, begins to trace the dynamics of crop farming, the main channel transmitting the contribution of weather to domestic economic activity. As a result, while weather makes a negligible contribution to GDP dynamics in Q1-Q2, its GDP impact increases markedly in Q3-Q4 as the harvesting season progresses.

This study offers a methodological approach to estimating the contribution of weather conditions to the dynamics of Ukraine's core economic activities. This approach lays the groundwork for improving the accuracy of forecasting current IKSO values, and thus the accuracy of nowcasting quarterly real GDP. However, this study has certain limitations.

First, we only focus on the impact of a limited number of meteorological elements (including average monthly air temperature and precipitation) on core economic activities. For the time being, we omit weather factors such as wind direction and strength, humidity, and solar radiation from the scope of this paper. As a suggestion for further research, expanding the list of meteorological elements that factor into the estimation of weather's impact on economic activity could help quantify the contribution of renewable energy sources (wind and solar power) to growth in Ukraine's real GDP.

Second, available data provided by the Central Geophysical Observatory and used in this study were collected for the city of Kyiv only. It can be assumed that conducting similar research on a regional level may produce a potential measurement error due to regional heterogeneity. Therefore, another promising direction for future studies is to perform analyses based on regional data, making separate calculations for each of the Ukrainian regions and then aggregating them to arrive at a countrywide estimate, which would produce more robust estimates of weather impact on the dynamics of core economic activities.

And finally, testing hypotheses about the asymmetrical influence of weather conditions on regional economic activities is another research area worth attention.

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APPENDIX

Table 1. Descriptive Statistics

Variable	Mean	Median	Standard deviation	Min	Max
T	9.44	9.90	9.31	-10.00	24.60
ΔT^Y	0.15	-0.05	2.91	-8.10	9.60
ΔT^N	1.72	1.60	2.02	-5.80	7.70
P	51.38	42.00	35.68	2.00	210.80
ΔP^Y	-0.17	-0.50	49.44	-165.80	178.50
ΔP^N	-2.79	-9.85	34.91	-69.70	163.80
Δy_{agr}	4.24	1.77	17.36	-30.70	134.25
Δy_{constr}	0.68	4.85	21.67	-57.60	46.50
Δy_{energy}	-0.72	0.70	8.89	-25.94	22.80
Δy_{manuf}	0.10	1.27	12.23	-41.60	24.36
Δy_{mining}	-0.76	1.70	9.34	-31.65	22.90
Δy_{retail}	9.10	11.55	14.76	-29.00	38.10
$\Delta y_{wholesale}$	-1.13	0.15	13.34	-52.53	25.03
Δy_{pas}	1.06	1.46	9.46	-19.63	27.52
Δy_{cargo}	-1.77	0.57	11.54	-42.33	29.11

Note 1. Data cover the period from January 2004 through December 2019.
Note 2. T – actual average monthly air temperature data, °C; ΔT^Y – change in the average monthly air temperature compared to the same month of the previous year; ΔT^N – change in the average monthly air temperature compared to the norm; P – actual monthly precipitation data, mm; ΔP^Y – change in the monthly amount of precipitation compared to the same month of the previous year; ΔP^N – change in the monthly amount of precipitation compared to the norm; Δy_{agr} – change in the physical volume of agricultural production, % yoy; Δy_{constr} – change in production volume of construction products, % yoy; Δy_{energy} – change in industrial production of the energy sector, % yoy; Δy_{manuf} – change in production of industrial products in manufacturing, % yoy; Δy_{mining} – change in the volume of production of industrial products in mining,% yoy; Δy_{retail} – change in the physical volume of retail trade turnover, % yoy; $\Delta y_{wholesale}$ – change in the physical turnover of wholesale trade, % yoy; Δy_{pas} – change in passenger traffic, % yoy; Δy_{cargo} – change in the volume of freight traffic, % yoy.
Source: Author's calculations based on SSSU and CGO data.

Table 2. Results of the ADF Test to Analyze the Time Series of Meteorological Indicators (Average Monthly Air Temperature and Monthly Rainfall)

Variable	Value of τ-statistic in ADF test
T	-12.805^{***}
ΔT^Y	-7.242^{***}
ΔT^N	-12.231^{***}
P	-13.783^{***}
ΔP^Y	-14.377^{***}
ΔP^N	-14.682^{***}
Δy_{agr}	-11.451^{***}
Δy_{constr}	-2.380
Δy_{energy}	-2.959^{**}
Δy_{manuf}	-2.881^{**}
Δy_{mining}	-3.813^{***}
Δy_{retail}	-1.968
$\Delta y_{wholesale}$	-2.886^{**}
Δy_{pas}	-3.068^{**}
Δy_{cargo}	-3.704^{***}

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Data cover the period from January 2004 through December 2019.
Note 2. T – actual average monthly air temperature data, °C; ΔT^Y – change in the average monthly air temperature compared to the same month of the previous year; ΔT^N – change in the average monthly air temperature compared to the norm; P – actual monthly precipitation data, mm; ΔP^Y – change in the monthly amount of precipitation compared to the same month of the previous year; ΔP^N – change in the monthly amount of precipitation compared to the norm; Δy_{agr} – change in the physical volume of agricultural production, % yoy; Δy_{constr} – change in production volume of construction products, % yoy; Δy_{energy} – change in industrial production of the energy sector, % yoy; Δy_{manuf} – change in production of industrial products in manufacturing, % yoy; Δy_{mining} – change in the volume of production of industrial products in mining,% yoy; Δy_{retail} – change in the physical volume of retail trade turnover, % yoy; $\Delta y_{wholesale}$ – change in the physical turnover of wholesale trade, % yoy; Δy_{pas} – change in passenger traffic, % yoy; Δy_{cargo} – change in the volume of freight traffic, % yoy.
Source: Author's calculations in E-Views 8.0.

Table 3a. Correlation Matrix: Weather Deviations from the Previous Year's Levels and Production Dynamics in Selected Sectors of the Ukrainian Economy

	Agriculture	Construction	Energy sector	Mining	Manufacturing
	(1)	(2)	(3)	(4)	(5)
$\Delta T_{Dec,Jan,Feb}$	0.062	0.139	-0.281	0.080	0.083
$\Delta T_{Mar,Apr,May}$	0.014	0.113	-0.103	0.013	0.064
$\Delta T_{Jun,Jul,Aug}$	-0.064	-0.090	0.025	-0.079	-0.024
$\Delta T_{Sep,Oct,Nov}$	0.159	-0.075	-0.238	-0.034	-0.082
$\Delta P_{Dec,Jan,Feb}$	-0.113	-0.098	-0.127	-0.112	-0.017
$\Delta P_{Mar,Apr,May}$	0.009	-0.005	0.204	0.143	0.088
$\Delta P_{Jun,Jul,Aug}$	0.092	0.175	0.107	0.030	0.167
$\Delta P_{Sep,Oct,Nov}$	-0.208	0.051	0.121	0.147	0.081

Source: Author's calculations in E-Views 8.0.

Table 3a (continued). Correlation Matrix: Weather Deviations from the Previous Year's Levels and Production Dynamics in Selected Sectors of the Ukrainian Economy

	Retail trade	Wholesale trade	Passenger transport	Freight transport
	(6)	(7)	(8)	(9)
$\Delta T_{Dec,Jan,Feb}$	0.048	0.092	0.123	0.032
$\Delta T_{Mar,Apr,May}$	0.075	-0.031	0.101	-0.021
$\Delta T_{Jun,Jul,Aug}$	-0.026	-0.035	0.005	-0.062
$\Delta T_{Sep,Oct,Nov}$	-0.053	-0.118	-0.079	-0.062
$\Delta P_{Dec,Jan,Feb}$	-0.046	-0.042	-0.043	-0.148
$\Delta P_{Mar,Apr,May}$	0.051	0.060	-0.103	0.096
$\Delta P_{Jun,Jul,Aug}$	0.076	0.072	0.112	0.091
$\Delta P_{Sep,Oct,Nov}$	0.112	0.129	0.147	0.196

Source: Author's calculations in E-Views 8.0.

Table 3b. Correlation Matrix: Weather Deviations from the Norm and Production Dynamics in Selected Sectors of Ukrainian Economy

	Agriculture	Construction	Energy sector	Mining	Manufacturing
	(1)	(2)	(3)	(4)	(5)
$\Delta T_{Dec,Jan,Feb}$	0.046	0.058	-0.260	-0.036	-0.003
$\Delta T_{Mar,Apr,May}$	-0.056	0.057	-0.088	-0.046	0.011
$\Delta T_{Jun,Jul,Aug}$	0.048	-0.026	0.061	-0.018	-0.028
$\Delta T_{Sep,Oct,Nov}$	0.100	-0.066	-0.110	0.023	-0.074
$\Delta P_{Dec,Jan,Feb}$	-0.063	-0.073	-0.014	-0.027	0.001
$\Delta P_{Mar,Apr,May}$	0.005	-0.027	0.098	0.047	0.002
$\Delta P_{Jun,Jul,Aug}$	0.149	0.088	0.156	0.140	0.167
$\Delta P_{Sep,Oct,Nov}$	-0.098	-0.013	0.030	0.032	0.020

Source: Author’s calculations in E-Views 8.0.

Table 3b (continued). Correlation Matrix: Weather Deviations from the Norm and Production Dynamics in Selected Sectors of Ukrainian Economy

	Retail trade	Wholesale trade	Passenger transport	Freight transport
	(6)	(7)	(8)	(9)
$\Delta T_{Dec,Jan,Feb}$	-0.006	0.037	0.079	-0.039
$\Delta T_{Mar,Apr,May}$	0.004	-0.064	0.066	0.001
$\Delta T_{Jun,Jul,Aug}$	-0.038	0.002	-0.013	0.001
$\Delta T_{Sep,Oct,Nov}$	-0.045	-0.063	-0.041	-0.011
$\Delta P_{Dec,Jan,Feb}$	-0.035	-0.026	-0.107	-0.053
$\Delta P_{Mar,Apr,May}$	-0.011	0.028	-0.123	0.052
$\Delta P_{Jun,Jul,Aug}$	0.198	0.058	0.129	0.073
$\Delta P_{Sep,Oct,Nov}$	0.030	0.059	0.085	0.088

Source: Author’s calculations in E-Views 8.0.

Table 4a. Estimated Weather Impact on Output: Agriculture

	$\Delta y_{agr}(t)$			
	(1)	(2)	(3)	(4)
$\Delta_{y_1}(t\text{-}1)$	0.70***	0.99***	0.08	0.28
	(0.145)	(0.072)	(0.156)	(0.175)
$\Delta_{y_1}(t\text{-}5)$	0.02	-0.11	-0.47***	-0.26*
	(0.088)	(0.083)	(0.141)	(0.158)
$\Delta_{y_1}(t\text{-}10)$	-0.11*	-0.01	-0.36***	-0.34**
	(0.072)	(0.050)	(0.121)	(0.147)
$GRAIN(t)$		0.05*	0.11***	0.10***
		(0.035)	(0.025)	(0.037)
$POTATOES(t)$		0.28**	0.48***	0.38***
		(0.120)	(0.077)	(0.109)
$\Delta T^{Y}_{Mar,Apr,May}(t\text{-}3)$			-1.43**	
			(0.639)	
$\Delta T^{Y}_{Sep,Oct,Nov}(t)$			1.75*	
			(1.021)	
$\Delta P^{Y}_{Sep,Oct,Nov}(t)$			-0.11**	
			(0.052)	
$\Delta P^{Y}_{Dec,Jan,Feb}(t\text{-}7)$			-0.47***	
			(0.093)	
$\Delta T^{N}_{Mar,Apr,May}(t\text{-}3)$				-2.65***
				(0.750)
$\Delta T^{N}_{Sep,Oct,Nov}(t)$				0.99
				(0.960)
$\Delta P^{N}_{Sep,Oct,Nov}(t)$				0.22***
				(0.062)
$\Delta P^{N}_{Dec,Jan,Feb}(t\text{-}7)$				-0.39**
				(0.149)
C	2.13	2.41	-0.68	1.72
N	60	60	60	60
R^2(adjusted)	0.11	0.26	0.48	0.39
F	2.09	3.34	5.12	3.95
DW	1.93	1.99	1.83	1.93
AIC	8.04	7.89	7.60	7.74
SIC	8.32	8.23	8.08	8.23

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note 1. Standard errors are in parentheses.

Note 2. $\Delta y_{agr}(t)$ – change in the physical volume of agricultural production in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (3), and compared to the norm $\Delta T^{N}(t)$, column (4); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (3), and compared to the norm $\Delta P^{N}(t)$, column (4); $GRAIN(t)$ – growth rates of grain and legume production in month t, % yoy; $POTATOES(t)$ – growth rate of potato production in month t, % yoy.

Source: Author's calculations based on SSSU and CGO data.

Table 4b. Estimated Weather Impact on Output: Construction

	$\Delta y_{constr}(t)$		
	(1)	(2)	(3)
$\Delta y_{constr}(t\text{-}1)$	0.56***	0.59***	0.58***
	(0.067)	(0.069)	(0.069)
$\Delta y_{constr}(t\text{-}2)$	0.41***	0.38***	0.39***
	(0.068)	(0.070)	(0.070)
$\Delta y_{constr}(t\text{-}12)$	-0.13***	-0.12***	-0.12***
	(0.032)	(0.031)	(0.032)
$\Delta T^{Y}_{Dec,Jan,Feb}(t)$		0.83***	
		(0.260)	
$\Delta T^{Y}_{March}(t)$		0.78*	
		(0.415)	
$\Delta T^{N}_{Dec,Jan,Feb}(t)$			0.51
			(0.363)
$\Delta T^{N}_{March}(t)$			0.46
			(0.517)
C	0.55	0.46	0.24
N	180	180	180
R^2(adjusted)	0.84	0.85	0.84
F	308.40	199.90	185.95
DW	2.00	2.04	2.00
AIC	7.18	7.13	7.19
SIC	7.25	7.23	7.29

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{constr}(t)$ – change in the physical volume of production of construction products in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3).
Source: Author's calculations based on SSSU and CGO data.

Table 4c. Estimated Weather Impact on Output: Energy

	$\Delta y_{energy}\,(t)$			
	(1)	(2)	(3)	(4)
$\Delta y_{energy}(t\text{-}1)$	0.67***	0.83***	0.83***	0.83***
	(0.099)	(0.076)	(0.078)	(0.077)
$Electricity_{prod}(t)$		1.03***	0.81***	0.96***
		(0.104)	(0.127)	(0.113)
$\Delta T^{Y}_{Dec,Jan,Feb}(t)$			-0.73***	
			(0.194)	
$\Delta T^{Y}_{March}(t)$			-0.61*	
			(0.320)	
$\Delta P^{Y}_{Dec,Jan,Feb}(t)$			-0.03	
			(0.023)	
$\Delta T^{N}_{Dec,Jan,Feb}(t)$				-0.68**
				(0.293)
$\Delta T^{N}_{March}(t)$				-0.47
				(0.362)
$\Delta P^{N}_{Dec,Jan,Feb}(t)$				0.01
				(0.030)
C	-3.22	0.73	-0.18	1.02
N	59	59	59	59
R^2(adjusted)	0.43	0.78	0.83	0.79
F	45.40	104.18	56.22	44.91
DW	2.04	1.72	1.66	1.69
AIC	6.49	5.56	5.37	5.56
SIC	6.56	5.66	5.58	5.77

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{energy}(t)$ – з change in the physical volume of production of industrial products in the energy sector in month t, % yoy; $\Delta T(t)$– change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (3), and compared to the norm $\Delta T^{N}(t)$, column (4); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (3), and compared to the norm $\Delta P^{N}(t)$, column (4); $Electricity_{prod}(t)$ – electricity production (according to monthly data from Ukrenergo NPC), % yoy.
Source: Author's calculations based on SSSU and CGO data.

Table 4d. Estimated Weather Impact on Output: Energy (no variable $\Delta P_{Dec,Jan,Feb}$)

	$\Delta y_{energy}(t)$			
	(1)	(2)	(3)	(4)
$\Delta y_{energy}(t\text{-}1)$	0.67***	0.83***	0.82***	0.83***
	(0.099)	(0.076)	(0.079)	(0.076)
$Electricity_{prod}(t)$		1.03***	0.82***	0.97***
		(0.104)	(0.128)	(0.111)
$\Delta T^{Y}_{Dec,Jan,Feb}(t)$			-0.75***	
			(0.195)	
$\Delta T^{Y}_{March}(t)$			-0.63*	
			(0.328)	
$\Delta T^{N}_{Dec,Jan,Feb}(t)$				-0.68**
				(0.290)
$\Delta T^{N}_{March}(t)$				-0.46
				(0.358)
C	-3.22	0.73	-0.18	1.02
N	59	59	59	59
R^2(adjusted)	0.43	0.78	0.83	0.79
F	45.40	104.18		44.91
DW	2.04	1.72	1.66	1.69
AIC	6.49	5.56	5.37	5.56
SIC	6.56	5.66	5.58	5.77

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{energy}(t)$ – з change in the physical volume of production of industrial products in the energy sector in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (3), and compared to the norm $\Delta T^{N}(t)$, column (4); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (3), and compared to the norm $\Delta P^{N}(t)$, column (4); $Electricity_{prod}(t)$ – electricity production (according to monthly data from Ukrenergo NPC), % yoy.
Source: Author's calculations based on SSSU and CGO data.

Table 4e. Estimated Weather Impact on Output: Manufacturing

	$\Delta y_{manuf}(t)$			
	(1)	(2)	(3)	(4)
$\Delta y_{manuf}(t\text{-}1)$	0.65***	0.82***	0.85***	0.83***
	(0.099)	(0.099)	(0.099)	(0.020)
$\Delta y_{manuf}(t\text{-}2)$	0.09	-0.14	-0.17*	-0.15*
	(0.102)	(0.103)	(0.103)	(0.104)
$\Delta y_{manuf}(t\text{-}5)$	0.14**	0.15**	0.15**	0.15**
	(0.070)	(0.067)	(0.067)	(0.068)
$Food_{exp}(t)$		7.41***	7.09***	7.33***
		(1.654)	(1.626)	(1.643)
$Real_{wage}(t)$		0.36***	0.35***	0.36***
		(0.101)	(0.101)	(0.101)
$\Delta T^{Y}_{Dec,Jan,Feb}(t)$			0.22*	
			(0.125)	
$\Delta T^{N}_{Dec,Jan,Feb}(t)$				0.22
				(0.181)
C	-5.03	-14.50	-14.10	-14.60
N	103	103	103	103
R^2(adjusted)	0.73	0.79	0.80	0.80
F	91.01	79.01	67.69	66.43
DW	1.97	1.97	1.96	1.97
AIC	5.63	5.37	5.36	5.37
SIC	5.73	5.52	5.53	5.55

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note 1. Standard errors are in parentheses.

Note 2. $\Delta y_{manuf}(t)$ – change in the volume of industrial production in manufacturing in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (3), and compared to the norm $\Delta T^{N}(t)$, column (4); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (3), and compared to the norm $\Delta P^{N}(t)$, column (4); $Food_{exp}(t)$ – food exports, % yoy; $Real_{wage}(t)$ – real wage, % yoy.

Source: Author's calculations based on SSSU and CGO data.

Table 4f. Estimated Weather Impact on Output: Mining

	$\Delta y_{mining}(t)$		
	(1)	(2)	(3)
$\Delta y_{mining}(t\text{-}1)$	0.85***	0.87***	0.86***
	(0.038)	(0.037)	(0.038)
$\Delta y_{mining}(t\text{-}12)$	-0.09***	-0.08**	-0.08**
	(0.038)	(0.037)	(0.037)
$\Delta T^{Y}_{Dec,Jan,Feb}(t)$		0.48***	
		(0.134)	
$\Delta P^{Y}_{Jun,Jul,Aug}(t)$		-0.01	
		(0.011)	
$\Delta T^{N}_{Dec,Jan,Feb}(t)$			0.40**
			(0.193)
$\Delta P^{N}_{Jun,Jul,Aug}(t)$			-0.01
			(0.015)
C	-1.14	-1.21	-1.36
N	180	180	180
R^2(adjusted)	0.74	0.76	0.74
F	256.82	140.78	131.29
DW	2.01	1.94	1.98
AIC	6.00	5.94	6.00
SIC	6.05	6.03	6.09

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{mining}(t)$ – change in the volume of industrial production in mining in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3).
Source: Author's calculations based on SSSU and CGO data.

Table 4g. Estimated Weather Impact on Output: Retail Trade

	$\Delta y_{retail}(t)$		
	(1)	(2)	(3)
$\Delta y_{retail}(t\text{-}1)$	0.57***	0.56***	0.58***
	(0.100)	(0.099)	(0.020)
$\Delta y_{retail}(t\text{-}3)$	0.37***	0.38***	0.36***
	(0.101)	(0.020)	(0.101)
$\Delta T^{Y}(t)$		0.21	
		(0.206)	
$\Delta T^{N}(t)$			0.56**
			(0.301)
C	2.30	2.34	0.85
N	72	72	72
R^2(adjusted)	0.79	0.79	0.79
F	131.50	88.09	91.93
DW	2.07	1.99	2.03
AIC	6.39	6.40	6.37
SIC	6.49	6.53	6.50

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note 1. Standard errors are in parentheses.

Note 2. $\Delta y_{retail}(t)$ – change in the physical volume of retail trade turnover in month t, % 2; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3).

Source: Author's calculations based on SSSU and CGO data.

Table 4h. Estimated Weather Impact on Output: Wholesale Trade

	$\Delta y_{wholesale}(t)$		
	(1)	(2)	(3)
$\Delta y_{wholesale}(t\text{-}1)$	0.56***	0.58***	0.57***
	(0.064)	(0.064)	(0.064)
$\Delta T^{Y}_{Sep,Oct,Nov}(t)$		-1.21**	
		(0.614)	
$\Delta T^{Y}_{Mar,Apr,May}(t)$		-0.75	
		(0.471)	
$\Delta T^{N}_{Sep,Oct,Nov}(t)$			-0.96
			(0.714)
$\Delta T^{N}_{Mar,Apr,May}(t)$			-1.02
			(0.630)
C	-0.98	-0.91	-0.17
N	167	167	167
R^2(adjusted)	0.31	0.33	0.32
F	76.50	28.33	27.30
DW	2.44	2.46	2.45
AIC	7.66	7.65	7.66
SIC	7.70	7.72	7.73

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{wholesale}(t)$ – change in the physical volume of wholesale trade turnover in month t, % 2; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3).
Source: Author's calculations based on SSSU and CGO data.

Table 4i. Estimated Weather Impact on Output: Passenger Transportation

	$\Delta y_{pas}(t)$		
	(1)	(2)	(3)
$\Delta y_{pas}(t\text{-}1)$	0.84***	0.85***	0.84***
	(0.042)	(0.041)	(0.043)
$\Delta T^{Y}_{Dec,Jan,Feb}(t)$		0.32**	
		(0.146)	
$\Delta T^{N}_{Dec,Jan,Feb}(t)$			0.16
			(0.214)
C	0.57	0.60	0.52
N	155	155	155
R^2(adjusted)	0.73	0.73	0.73
F	410.13	212.75	204.70
DW	2.38	2.35	2.38
AIC	6.01	5.99	6.02
SIC	6.05	6.05	6.08

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{pas}(t)$ – change in the volume of passenger transport in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3).
Source: Author's calculations based on SSSU and CGO data.

Table 4j. Estimated Weather Impact on Output: Freight Transportation

	$\Delta y_{cargo}(t)$		
	(1)	(2)	(3)
$\Delta y_{cargo}(t\text{-}1)$	0.84***	0.85***	0.84***
	(0.044)	(0.044)	(0.044)
$\Delta T^{Y}_{Dec,Jan,Feb}(t)$		0.33*	
		(0.190)	
$\Delta T^{Y}_{Mar,Apr,May}(t)$		-0.48**	
		(0.238)	
$\Delta T^{N}_{Dec,Jan,Feb}(t)$			-0.07
			(0.284)
$\Delta T^{N}_{Mar,Apr,May}(t)$			-0.41
			(0.334)
C	-1.96	-1.89	-1.73
N	155	155	155
R^2(adjusted)	0.70	0.71	0.70
F	357.90	125.47	119.38
DW	2.21	2.26	2.22
AIC	6.55	6.53	6.56
SIC	6.59	6.61	6.64

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{cargo}(t)$ – change in the volume of freight transport in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3).
Source: Author's calculations based on SSSU and CGO data.

Table 4k. Estimated Weather Impact on Output: Wheat Production

	$\Delta y_{wheat}(t)$		
	(1)	(2)	(3)
$Sown_{area}(cereals\&legumes)(t)$	6.72***	8.01***	6.99***
	(1.495)	(1.378)	(1.389)
$\Delta P^{Y}_{Oct,Nov}(t\text{-}1)$		1.22*	
		(0.709)	
$\Delta P^{Y}_{Apr,May}(t)$		0.53	
		(0.362)	
$\Delta P^{N}_{Oct,Nov}(t\text{-}1)$			2.12**
			(0.962)
$\Delta P^{N}_{Apr,May}(t)$			0.37
			(0.583)
C	40.70	42.06	31.09
N	17	17	17
R^2(adjusted)	0.55	0.66	0.63
F	20.17	11.45	10.08
DW	2.17	1.51	1.53
AIC	11.37	11.17	11.26
SIC	11.47	11.36	11.45

p-values $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{wheat}(t)$ – change in the volume of wheat production in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3); $Sown_{area}(cereals\&legumes)(t)$ – the growth rate of the sown area under cereals and legumes (excluding maize) in year t.
Source: Author's calculations based on SSSU and CGO data.

Table 4I. Estimated Weather Impact on Output: Maize Production

	$\Delta y_{maize}(t)$		
	(1)	(2)	(3)
$Sown_{area}(maize)(t)$	0.52***	0.69***	0.64***
	(0.183)	(0.132)	(0.195)
$\Delta T^{Y}_{Apr}(t)$		4.60	
		(2.859)	
$\Delta T^{Y}_{Aug}(t)$		-3.54**	
		(1.217)	
$\Delta P^{Y}_{Jun,July}(t\text{-}1)$		0.24*	
		(0.131)	
$\Delta T^{N}_{Apr}(t)$			6.87
			(5.411)
$\Delta T^{N}_{Aug}(t)$			-3.06
			(4.244)
$\Delta P^{Y}_{Jun,July}(t\text{-}1)$			0.44**
			(0.204)
C	11.01	7.70	9.66
N	17	17	17
R^2(adjusted)	0.31	0.72	0.47
F	8.03	11.16	4.57
DW	2.91	1.97	2.83
AIC	9.55	8.78	9.41
SIC	9.65	9.03	9.65

p-values $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01
Note 1. Standard errors are in parentheses.
Note 2. $\Delta y_{maize}(t)$ – change in the volume of maize production in month t, % yoy; $\Delta T(t)$ – change in the average monthly air temperature compared to the same month of the previous year $\Delta T^{Y}(t)$, column (2), and compared to the norm $\Delta T^{N}(t)$, column (3); $\Delta P(t)$ – change in the monthly amount of precipitation compared to the same month of the previous year $\Delta P^{Y}(t)$, column (2), and compared to the norm $\Delta P^{N}(t)$, column (3); $Sown_{area}(maize)(t)$ – the growth rate of the sown area under maize in year t, % yoy.
Source: Author's calculations based on SSSU and CGO data.

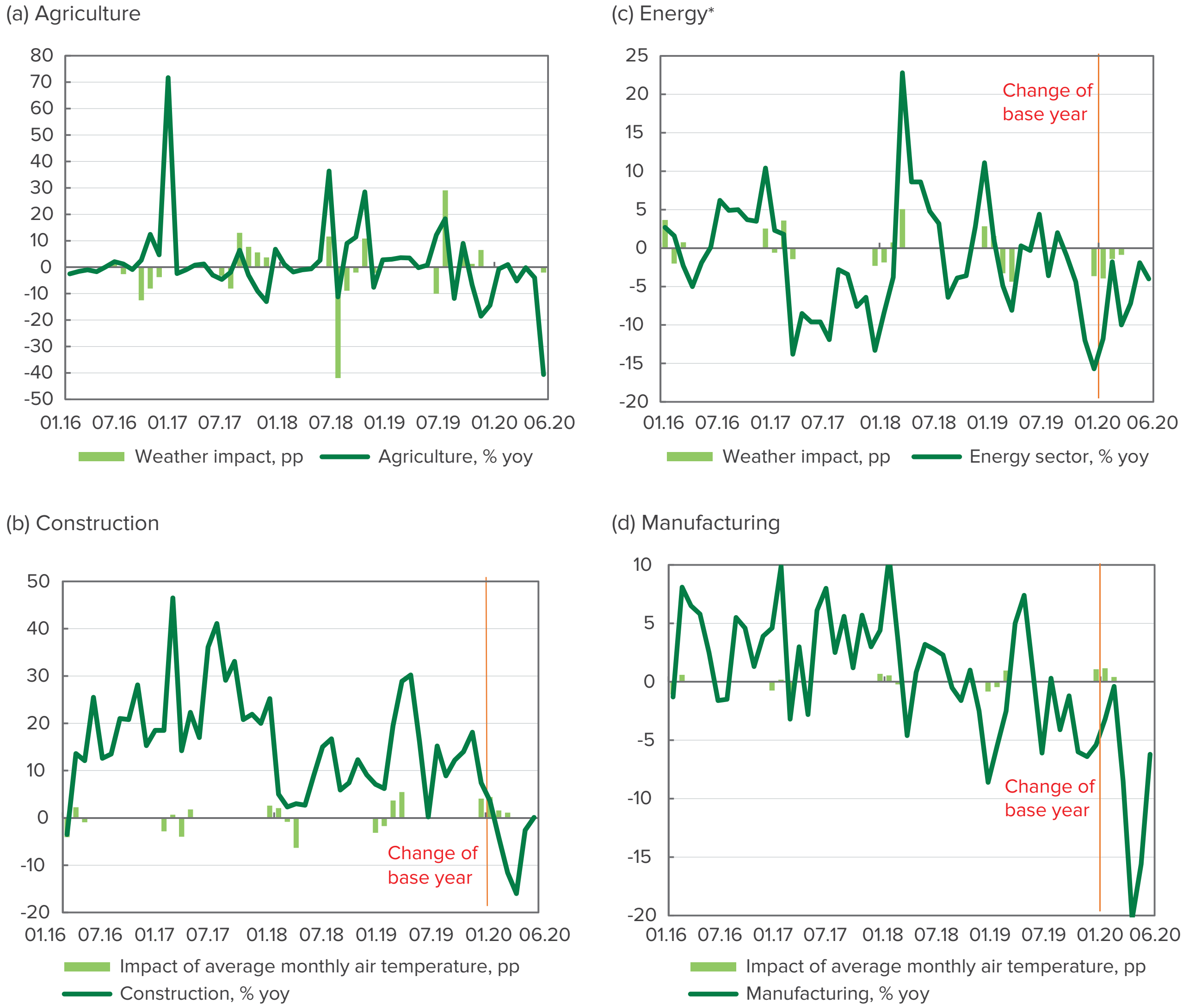

Figure 5. Production dynamics in selected sectors of Ukrainian economy, % yoy. (From January 2020, the base year i s 2016)
*Includes electricity, gas, steam, and air conditioning supplies.
Source: Author’s calculations based on SSSU and CGO data.

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FOREIGN ASSISTANCE AND CONSUMPTION INEQUALITY: DOES THE STRUCTURE OF AID MATTER?

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Abstract This paper uses a dataset of 75 countries covering 1960-2010 to examine whether foreign aid has any effect on consumption inequality. The variable of assistance is split into grants and loans – the central hypothesis being different non-linear impact of each on inequality – with the impact of loans being hump-shaped and grants “U”-shaped. The results corroborate the direction and the type of impact that foreign assistance has on inequality. In addition, the outcomes for quartile data subsets show that the relationships between foreign assistance and inequality differ depending on a country’s GDP per capita. However, the hypothesis regarding the influence of coup d’états hasn’t been confirmed.

JEL Codes F35, D63, O50, H81

Keywords foreign aid, grants, loans, consumption inequality, government overthrow

1. INTRODUCTION

It is well-established that income inequality is harmful to development and prosperity. Income inequality has detrimental effects on the credit markets (Aghion and Bolton, 1997), may cause economic crises (Piketty and Saez, 2003), and slows down recovery after crises (Stiglitz, 2012). Attempts to reduce poverty and income inequality intensified in 2000 with the establishment of the Millennium Development Goals (UN, 2005) as one of the main instruments of the international community being foreign aid.

The importance of foreign assistance in combatting poverty cannot be overestimated. The Organization of Economic Cooperation and Development (OECD) suggests that foreign aid is the primary way in which developed countries can help to alleviate poverty in the developing world (OECD, 2006) and the official rhetoric of donor organizations states that economic growth is a direct consequence of poverty reduction (Keeley, 2012). Due to these assumptions, for the last two decades, the international community has poured its resources into foreign aid in hopes of alleviating poverty, prompting the amount of external development assistance (ODA) distributed to developing countries to more than double (Figure 1). Despite the best efforts of the international community, income inequality has persisted in the developing world (Ravallion, 2014).

However, empirical studies are inconclusive as to the direct connection between economic growth and poverty reduction. According to Basu and Stiglitz (2016), the claim that development causes a decrease in inequality is doubtful. This “straightforward” view was challenged in 2006 when the World Development Report on Equity and Development was published. The report concludes that the

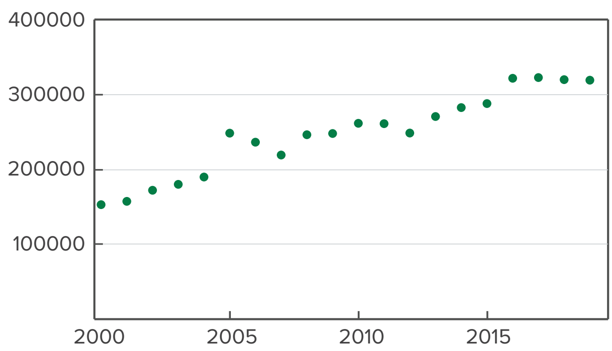

Figure 1. Total Yearly ODA Sent to Developing Countries in 2015 USD
Sources: OECD https://data.oecd.org/oda/net-oda.htm#indicator-chart.

reduction of inequality isn’t necessarily a consequence of economic growth and that inequality matters when it comes to improving economic efficiency (World Bank, 2006). The abovementioned arguments suggest that the impact on income distribution remains a relatively new avenue of studies that should be explored in depth.

The other avenue that has not been explored in the available literature is the differing effect of loans and grants on income inequality. Fiala (2018) finds that when comparing the influence of microfinancing via loans and grants in Uganda, only loans increase the sales of a firm. These findings imply that when faced with the condition of repayment, entrepreneurs allocate their investments more efficiently. Morrissey et al. (2006) reach a different conclusion when studying the effects of grants and loans. They conclude that grants are preferred to loans as they don’t impose an obligation to repay them in the future as

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loans do. Bulow and Rogoff (2005) also find that borrowing from development banks encourages more lending by the developing countries, which retards development. Though the current literature mostly looks into the effect on economic growth, their methodology may be used for studying the effect on income inequality.

This article studies the efficiency of foreign aid in alleviating income inequality of emerging economies depending on the foreign aid type. The hypothesis is that the impact of foreign assistance is ambiguous and depends on the type of aid being sent to the recipient country. If the aid is given with the condition of returning the credit at a later date, it will have an inequality-reducing effect as the money will be allocated more efficiently. On the other hand, if there is no constraint of returning the money, it will only temporarily boost the household's consumption, but will not have a significant effect on income distribution. Some previous research by Sanford (2002) shows that the influence of grants and loans is indeed different, and the question as to which form of aid is more efficient is still open.

The main contribution of the article is the deconstruction of foreign aid's influence on income inequality by studying the simultaneous effects of foreign loans and grants, the addition of the variable for the cases of violent regime changes and the use of a new dataset on income inequality.

The use of the regime change variable is interesting as existing studies (e.g., Masaki, 2016, Haggard and Kaufman, 2012, etc.) confirm the existence of the relationship between episodes of violent regime change and foreign aid and income inequality. Hence, the addition of this variable to the regression may help eliminate the omitted variable bias of the dependent variables.

Concerning the data, this work uses the Global Consumption and Income Project inequality database, which hasn't been used in the literature yet. This dataset allows for evaluating models based on the data from 75 countries in 1961-2010 (see Appendix A1 for the full list of countries). The main advantage of this dataset over others used in the literature is the availability of more country years and fewer gaps in the data. These data are also available for both consumption and income-based Gini; this feature allows for additional robustness checks.

The main issue with the full dataset is gaps in the periods that are also aligned with episodes of violent regime changes. In many cases, some observations were not collected due to the overthrow of the government in the country of interest. These gaps may prove to be an issue for the model itself and the role of the variable of violent regime change in particular. Another issue is the fact that the model doesn't consider the effects of grants and loans that are given based on the condition of a particular reform (i.e., loans are broken up into tranches and given only when the country implements a set of reforms that is required to receive the next installment). Unfortunately, such data are unavailable for the current dataset, and the article leaves this aspect of foreign aid's influence for future research.

The methodology is based on the works of Bandyopadhyay et al. (2013) and Hansen et al. (2009) in advancing the deconstruction of foreign aid from the former article, its control variables specification, and estimation procedure from the latter one. As for the model itself, the main specification follows Hansen et al. (2009) in removing the fixed effects from each country to account for the country-specific characteristics.

The article shows that both forms of aid are characterized by a significant nonlinear relationship with inequality. At low inflow-to-GDP ratios, grants are inequality-reducing, but become inequality-enhancing after a point. Then the relationship reverses itself for grants. One may argue that these relationships may partially cancel each other out. So as a way of verifying the economic significance of the article's findings, a model of the total aid's influence on inequality is also presented. The model shows that foreign aid has a significant, albeit small, negative impact on consumption inequality. As a final form of a check for robustness, the article breaks down the effects of foreign aid depending on the country's GDP per capita. The data are split into four quantiles and the effects of aid on inequality are studied for each of these groups. The relationships remain significant for the most part, but such a breakdown illustrates the complexity of aid's effect on inequality. As for the variable of episodes of violent regime change, it is shown to be insignificant in all of the models independent of the specification. One may conclude that this is most likely due to the missing country-year data during the years when the overthrow was occurring.

The article's structure consists of section 2 reviewing the current and historical literature on the subject of the foreign aid's effect, section 3 describing the methodology and the econometric model that is going to be run, section 4 describing the data, section 5 discussing the results of the estimations, and section 6 presenting conclusions and policy implications.

2. LITERATURE REVIEW

Overall, the literature on the economic effect of foreign aid can be divided into four methodological generations. The first generation is concentrated on simple Keynesian Harrod-Domar-like models, which linked foreign aid to economic growth via aid's link to savings and consumption. The second generation started in the 1970s and concentrated on the direct effect of foreign aid on the investment. The third generation of studies began in 1996 with Peter Boone's paper, "Politics and the effectiveness of foreign aid", which was the first to develop aid models with the variables of institutional and policy environments. The fourth generation of research moved away from the growth theory and concentrated on the effects of foreign aid on social factors, such as health, education, etc.

The first models describing the influence of foreign aid on the economy were developed in the 1960s and concentrated mostly on the added productivity of international assistance. These models assumed that every dollar of foreign inflows in the form of assistance should be followed by a one-dollar increase in investment and imports (Rosenstein-Rodan, 1961). Further models got more complicated – the assumption of the fixed capital-output ratio was forgone, while a country's import capacity, as well as domestic savings, were included (Chenery and Carter, 1973). All of these models assumed that aid inflows added to local investment and imports, dollar for dollar.

The third wave of aid research began in 1996 with the abovementioned paper by Peter Boone. This paper is revolutionary in the sense that it was the first to address the range of factors that may affect the effectiveness of foreign aid (e.g. political regime) (Boone, 1996).

The latter course of foreign aid literature strayed from looking into the direct effect of foreign aid on growth. Instead, these papers investigated the consequences of the inflow of foreign assistance on social indicators. Some of the most prominent examples of the literature from this period include Burnside and Dollar (1998), who link foreign aid to infant mortality and conclude that when a country has fixed property rights, open trade regimes, and macroeconomic stability, the assistance serves to reduce infant mortality. Collier and Dollar (2001) develop a poverty reduction model showing that aid can only be effective in reducing poverty in an appropriate policy environment. Fielding et al. (2006) show that foreign aid has a positive effect on development outcomes, including health, education, and fertility.

The first studies that link foreign aid to income inequality appear in this period. One of the most prominent papers written in this period was Chong et al. (2009). In this paper, the authors argue that using a simple cross-sectional estimation when evaluating the effect of foreign aid leads to the bias of the estimators due to the problems of simultaneity and reverse causality. The solution proposed is the use of dynamic panel data modeling. The particularity of the effect of foreign aid on income inequality is the presence of autoregressive errors, implying the need to use an estimator with uncorrelated disturbances. Taking this into account, the authors used the GMM-IV model. It showed that when the quality of a country's institutions is taken into account, foreign aid has a positive effect on income inequality, albeit not robust. A similar model is used in Pham (2015), though it's a simple GMM. This paper found that foreign aid exhibited an inequality increasing effect, though a small one.

Bourguignon et al. (2009) reach a similar conclusion when looking into the impact of trade and foreign aid on income inequality. While in their model aid is statistically significant, it isn't economically. However, while the effect is small, it is still helpful for the most deprived decile of the population. Following this stream of results, Shafiullah (2011) finds that the variable of foreign aid causes a small reduction in inequality when fixed and random effect models are used to analyze the data.

The other stream criticizes foreign aid, concluding that it may have an inequality increasing effect. Layton and Nielson (2008) show that, depending on the model specification, foreign assistance either enhances the impact on inequality, or an insignificant one. For the estimation, they use the instrumental variable approach to tackle the issue of endogeneity of the relationship between aid and inequality.

Bjørnskov (2010) shows that the interaction term between democracy and foreign aid has a positive effect on the share of income held by the upper quintile of the population. This result holds for democratic societies only, as the effect is negligible in authoritarian ones. These results were later disproven in Hansen et al. (2009), who address the issue of regression models with non-constant partial effects and conclude that foreign assistance has no significant impact on income inequality.

Another approach to the problem can be seen in Herzer and Nunnenkamp (2012), who argue that foreign aid and income inequality are cointegrated in the same order. Hence, a panel cointegration model can be built. This model shows that foreign aid exhibits an adverse effect on the distribution of income.

Another type of debate that exists in foreign aid literature concerns the ambiguity of its effect on the economy depending on the kind of aid. These debates originate in the report of the International Financial Institution Advisory Commission in 2000. This report argued that international grants were the preferred instrument for alleviating poverty in developing countries as opposed to loans. Somewhat repeating the argument of Mosley et. al (1987), the report concludes that when the loans given by the IMF and the World Bank are in the hands of the politicians of developing countries, the funds are typically spent on policies that can hardly be called growth-inducing (e.g., tax-reduction) (IFIAC, 2000).

Grants were viewed as preferable to loans based on three main arguments. Firstly, grants are more suited for social projects such as the development of the education or healthcare infrastructure, as they do not produce the returns needed to return the loan in the short run. Secondly, grants do not place more of a debt burden on the developing countries as loans do. Lastly, as grants do not need to be repaid, the donors can place more control on how the funds are spent to uphold the requirements of the UN's development goals and prevent the recipients' governments from squandering the assets, Sanford (2002)

Bulow and Rogoff (2005) reach a similar conclusion as they find that borrowing from development banks encourages more lending by the developing countries, which ultimately retards development.

On the other hand, one can find persuasive arguments regarding why loans should be preferred to grants. The core of this argument lies in the aid's influence on the fiscal behavior of the recipient: unlike loans, grants do not need to be repaid and hence may induce inefficient spending of the funds. Gupta et al. (2004) build a panel model investigating the fiscal response to decomposed aid inflows. The model shows that loans have a positive effect on tax revenues, while grants' impact is negative. This relationship may imply that grants cause inefficient policymaking. In the limited sample of highly corrupt countries, grants were fully offset by a decrease in tax revenues.

These results were later criticized by Morrissey et al. (2006), who show that when long-run effects are considered, this relationship disappears. Their findings suggest that there should be no consistent long-run relationship between decomposed foreign aid and tax revenues. Bandyopadhyay et al. (2013), on the other hand, show that the relationship is not as straightforward. In their paper, they examine a non-linear relationship between economic growth and foreign aid. Using the quadratic links and modeling simultaneous effects of both loans and grants, they find that grants are better for growth on the low levels of funding as the relationship between growth and financing via grants is hump-shaped. Furthermore, the relationship between growth and loans tends to be U-shaped, implying that high-level loans are highly effective in assisting with a country's growth.

As for the more recent literature, Fiala (2018) finds that when comparing the effect of microfinancing via loans and grants in Uganda, only loans increase the sales of a firm. These findings imply that when faced with the condition of repayment, entrepreneurs allocate their investments more efficiently.

The current article contributes to the literature by exploring the effects of aid, both constrained and unconstrained by repayment. It also introduces the variable of violent regime changes to eliminate the potential bias on the variable of foreign aid. Lastly, it splits the dataset into four quantiles to explore the relationship between grants, loans, and consumption inequality depending on the country's GDP per capita. This paper takes inspiration from the models presented by Bandyopadhyay et al. (2013) and Hansen et al. (2009) by joining some elements of their models (i.e., the aid deconstruction and estimation methodology) and extending them.

3. METHODOLOGY

The article estimates a model of the simultaneous influence of each type of aid following the methodology of Bandyopadhyay et al. (2013). The specification of the empirical model and the estimation method is similar to Hansen et al. (2009).

$$\begin{aligned} GINI_i^{t+1} &= \beta_0 + \beta_1 * Loan_i^t \\ &+\beta_2 * (Loan^2)_i^t + \beta_3 * Grant_i^t \\ &+\beta_4 * (Grant^2)_i^t + \beta_5 Coup_i^t \\ &+ \beta_6 Polity_i^t + \beta_j X_i^t + \mu_i + \varepsilon_i^t \end{aligned} \tag{1}$$

In this specification, $GINI$ is the consumption-based income inequality index, while $Loan$ and $Grant$ are the variables of the international assistance provided with and without the constraint of returning the money respectively. The $Loan$ and $Grant$ are expressed in relative terms as the percentage of real GDP in 2016 USD. This is done to normalize the amounts of aid between the countries in the sample. As the countries in the sample differ in the sizes of their economies, populations, and territories, the model estimated on absolute values would be flawed. The issue would be caused by neglecting the relative importance of the assistance for the country's economy, which can be eliminated with the use of relative measures.

I use consumption as a measure of inequality because traditional income inequality measures do not reflect the asset availability of the population (e.g., housing), while this is reflected in the consumption inequality measure. The other issue with income as the primary measure of inequality is that it ignores the shadow economy – the income of the people on the bottom of the income distribution is often underreported in developing countries for the sake of tax evasion, making the income inequality measure imperfect. It is worth noting that the income measure is used in the robustness check portion of the article.

$Polity$ is the Polity IV index created by Center for Systemic peace; it ranges from -10 to 10, and is determined by the country's overall level of democracy, press freedom, transparency of the governing bodies, and the general process of electing of the government.

The $Coup$ is an indicator of a violent political regime change. This variable is expected to have a significant effect on the model's structure as it was shown to influence the aid variable and the inequality variable. Its influence on the foreign aid is negative and proven by the literature (Masaki, 2016, Haggard and Kaufman, 2012). As for the impact on regime changes, it's positive but not as straightforward. According to the literature, the relationship is backward – income inequality causes regime changes. The variable of regime changes concerns the coup d'etat's influence on income inequality. If one supposes that regimes become more egalitarian after change, the income inequality should decline (Galbraith 2010). However, it is expected that a period of political instability would come after the overthrow, hence causing a decrease in equality. Understandably, this relationship is not straightforward and should be explored in depth. But since it's not our variable of interest and is only added to the model to eliminate a part of the bias, it shouldn't matter all that much.

The problem with the $Coup$ variable, however, is that the episodes of violent regime change usually cause abrupt breaks in the data. This trend is especially evident in the 1970s-1980s, which were historically characterized by many coup d'etats. But unfortunately, the data for the response variable and independent ones is not available for these years. This issue is not supposed to cause much trouble. Most of the time, the indicator is positive for a year after the coup ends, and hence, matches the existing data. The dummy at the end of such structural breaks should be enough to soften the impact of the breaks.

The control variables are standard for the income inequality literature such as Burnside and Dollar (1998), Hansen and Tarp (2000) Arndt et al. (2010). The set of control variables includes the index of human capital, trade openness, the share of government expenditures of GDP and the share of population living in rural areas.

As suggested by Shafiullah (2011), all variables are taken with a lag of one year as it is expected that the foreign assistance's effect will not be immediate. As a way of checking the robustness of the findings, models with three- and five-year lags are also estimated. The lag also alleviates a potential endogeneity problem. While foreign aid affects income inequality, the reverse can also be true. Hence, by forwarding the response variable by one-year, we may limit its effect as inequality in the future period is quite unlikely to have a significant influence on the amount of foreign aid in the present one. Including μ I further control for unobserved individual country effects, while ε denotes the error term.

4. DATA

The inequality measure is taken from the Global Consumption and Income Project (GCIP), which presents a dataset containing measures of inequality based on income and consumption spanning 1960-2015 and covering more than 160 countries. This dataset was chosen over the other inequality datasets (WIID, SWIID, EHII, etc.) due to its country-year coverage. As it covers more country-years, it allows running models on more observations. While the merged datasets for the other income inequality measures allowed running the final regression on a mere amount of 400-600 observations, the GCIP allows for almost 3,000 observations in the merged dataset (this is especially helpful considering that the independent variables are estimated with a lag, which already reduces the number of observations by a large margin).

The data for the dependent variable of international loans and grants are taken from the OECD's Geographical Distribution of Financial Flows to Developing Countries annual publication. The full dataset covers over 150 different countries during 1960-2018. It contains the data on all of the aid funds flowing into the developing countries from both country and supra-national level donors. The final model uses the measure of net loans instead of gross loans because net loans more accurately show how much aid money the country has at a given moment. This choice may also capture the effects of political violence more accurately (i.e., states are more likely to receive a loan after a government overthrow and less likely to return old loans (Haggard and Kaufman, 2012), as well as partially serve as an indicator for the quality of governance in the country.

To measure the level of democracy in the country, the model uses the Polity index from Polity IV Annual time series covering 167 countries from 1800-2017. Polity IV is a combined index consisting of indices measuring democracy and autocracy. They are constructed using the measures of the governance selection process and its openness, regulation of the participation in political processes, etc. The Polity IV index ranges from -10 to 10, depending on the level of the democracy in the country. The index was normalized to the range of 0 to 20 during the process of data preparation.

To account for the possible structural breaks in the inequality distribution, the data on the adverse political regime changes are taken from the PITF State Failure Problem Set. It covers episodes of regime changes in 85 countries from 1955 to 2017.

Other control variables should also be added to the model to reduce the endogeneity. These variables include the index of human capital that is based on years of study taken from Barro and Lee (2013) and the assumed rate of return to education, which is calculated using the Mincer equation Psacharopoulos (1994); trade openness measured as the ratio of exports and imports to GDP; and government expenditures as the share of GDP. The data for human capital, trade openness, and government expenditures are taken from Penn World Tables (Feenstra et al., 2015), while the data on the rural share of the population can be found in World Development Indicators. Some additional dummy controls are added: the continent of the origin country, and whether the state is a post-Soviet one.

As one can see from Table 1, grants are far more preferable to loans when it comes to foreign aid. Judging by the averages, the total quantity of loans is more than three times smaller than the grants given by the international community. These data are presented for net loans, but even if we consider gross loans, the grants are still twice as large as the loans (see Figure 2).

With this in mind, we can construct simple classifications for the countries in the sample to see whether there is a strict divide in the funding source specialization. Considering the relative weight of grants versus loans, one can view the country as loan-oriented if the relative importance of loans is higher than grants. The country is deemed to be grant-oriented if grants account for more than twice the percentage of loans in the economy. We end up having six states that are purely loan-oriented and 57 countries that are grant-oriented, with the rest falling somewhere in between (the full lists can be found in Appendix A2). The traditional role of loans in the loan-oriented countries of the sample cannot be overestimated, and it may have led to positive inequality outcomes. Some of those countries were allowed to take large amounts of loans due to the U.S.-sponsored regimes during the ’70s and ’80s (e.g., Chile, Indonesia). Others are countries that have historically been productive in the poverty-alleviation process (e.g., India, Turkey). Historical development of these countries and the growth associated with poverty reduction may become a focus of further research.

Some other interesting facts that can be derived from Table 1 include the importance of the government sector in developing economies. The role of government expenditures in the budget averages out to approximately 18%. A few African countries are most likely the cause of the high maximum value of the variable (mostly Nigeria and Madagascar).

Most of the countries in the sample are open economies and are considered to be
quite democratic, according to the polity index and their large rural population. The high rural population isn’t driven by the outliers, but by the inclusion of data for developing countries during the 1960s and 1970s. The other side of the distribution is exclusively produced by the data on Singapore.

As for the variable of violent political regime changes, it is only present in less than 3% of the sample. This is mostly due to coups being a rare political event and the unavailability of the data for the years in which the overthrow has occurred. This may cause further problems in the estimation stage of the article.

After merging the data, we end up with the dataset containing 2,994 observations during 1961-2010 and in 75 countries, with all of the countries with less than four country-year cells deleted. One of the peculiarities of the merged

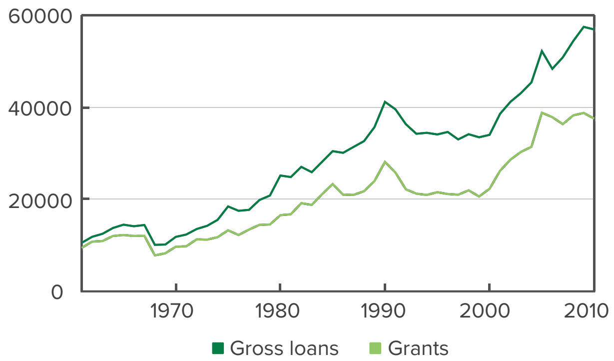

Figure 2. Total Yearly Aid Inflows in 2016 USD

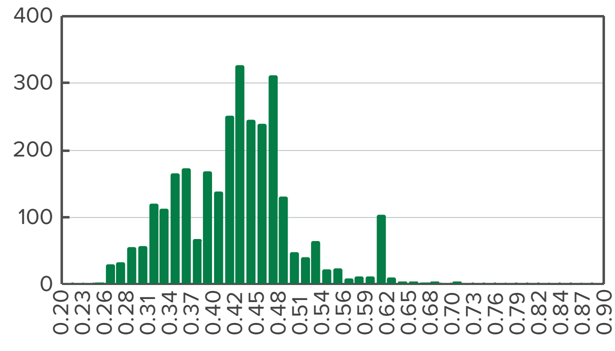

Figure 3. The Boxplot of Consumption Inequality

data is the presence of Singapore and Israel in the final sample. To avoid any inconsistencies with the data that may have arisen due to the presence of these countries in the sample, both countries were excluded from the final models.

Figure 3 presents the distribution of income inequality (consumption estimate). As one can observe the inequality has remained stable over the entire available period, though this might be explained by the composition of the sample (i.e., only developing countries are selected and China is out of the sample).

Initially, the variables of loans and grants were characterized by outliers that skewed both distributions. To normalize them, the outliers have been dropped. As a result, the sample has been reduced to 2,887 observations.

5. RESULTS

The following section is structured in the following way: the first subsection presents an overview of the estimation results of the primary model, the second subsection is dedicated to robustness checks of the models, and the last subsection is dedicated to the post-estimation tests.

5.1. The Main Results

As expected, both loans and grants have significant effects on income inequality in the final FE (fixed effects) model. However, the direction of their impact seems to be the opposite. For loans, the breakpoint at which they help to reduce inequality is 2.6% of GDP. This percentage of loans was at some point present in 33.3% of the countries in the sample. As for the grants, the breakpoint after which they start to enhance the inequality is 9.1%. It is quite interesting to note that the amount of grants at which they are helpful for the economy is quite significant in relative terms. This percentage was at one point present in 20% of the countries of the sample.

As for the violent episodes of political change, they don't seem to affect income inequality despite being one of the main reasons behind government overthrows. This insignificance may be due to the structural breaks in the data, which distort the results. Some ways of dealing with this issue are presented in the final chapter.

The coefficients on all the other control variables are consistent with the literature. Human capital, trade openness, the percentage of the rural population, and government expenditures all have an inequality enhancing effect, while the polity index shows reduced inequality, as was shown in Hansen et al. (2009). The full model can be found in Table 4.

5.2. Robustness Check

Table 5 presents the first robustness check of the model. The main claim behind the one-year lags in our main model is that the changes in inequality are not visible as soon as aid is given. We take the minimal lag following the suggestion presented in Shafiullah (2011), but one may argue that a one-year lag is too short. Sometimes, goverments in developing countries take years to invest funds. So to test for this, we take lags of three and five years to test the model's robustness.

It appears that grants affect income inequality in neither the 3rd nor 5th lag models. On the other hand, loans have a significant adverse effect on the third lag with a consistent non-linear relationship. That suggests they have a lasting impact on a country's economy and are essential to reducing inequality long after they came into the country. However, the effect of loans becomes insignificant with the fifth lag model, which suggests that the positive influence of this form of aid diffuses after some time. As for the coup d'état, it remained insignificant in all of the models above. Hausman test for 3-year lag model yielded p-value of 0.002, while the same test for 5-year lag yielded the value of 0.0027, meaning that fixed effects model is appropriate for both specifications.

The second robustness check of the model (Table 6) concerns the variable of net loans. As the argument of the article goes: net loans are a preferable measure to gross loans as they show the actual amount of aid that a country has at a given year. But the argument may also apply vice versa – one should look into how much money is given to a country per year to observe the results.

The term of gross loans is insignificant in this specification. This means that the total amount of aid that's pumped into the economy per year doesn't matter for income inequality. Only the real amount available is the value that determines the change in inequality.

Table 7 deals with the economic significance of the model. As the effects of both loans and grants are simultaneous, one may certainly argue that they cancel each other out and the cumulative effect of foreign aid is either insignificant or too small to matter. Table 5 presents the full aid model with the removal of the hump shape hypothesis. As the effects of the decomposed aid are inverse to each other, the U-shaped relationship is unlikely to hold. Moreover, the linear relationship is a standard specification for the current literature (Herzer and Nunnenkamp, 2012, Layton and Nielson, 2008, etc.)

The variable of the aid ratio is significant econometrically, though that's not the case economically. The change presented would mean that a 1% increase in total aid would result in approximately a 0.2% wealth transfer from the population above the median income to the population below it.

Table 6 deals with the separation of the influence of foreign aid types. The results of models of simultaneous influence may have been caused by the multicollinearity in the loan and grant variables. The following table presents separate models for both grants and loans. The results from this robustness check show that both variables are significant, and their magnitudes and directions of the effect remain virtually unchanged from the main model.

Table 7 is the last of the robustness check section of this chapter. It tests the consistency of the model under a different measurement of inequality. Instead of a consumption-based measure, the models use an income-based one.

The income-based models show results similar to those of the primary model, but less significant. This may be due to the noisiness of the income inequality measure as compared to the consumption inequality one. Both loans and grants still exhibit a significant negative and positive effect on income inequality, respectively.

5.3. Post-Estimation Tests

To see whether the main model has any statistical issues, I've conducted three post-estimation tests for the following issues: multicollinearity, autocorrelation, and heteroskedasticity.

To test for multicollinearity, I've conducted a variance inflation factor test (VIF) with centered values of test's coefficients. The mean-variance inflation factor is 2.91, meaning that the model isn't characterized by multicollinearity.

The Inoue and Solo LM test was used to test the model for autocorrelation, of any order, with the null hypothesis of there being none. The test produced a p-value of 0.936, so it fails to reject the null hypothesis of the test.

Lastly, to test for heteroskedasticity, I've used a Modified Wald test for group-wise heteroskedasticity. With the null hypothesis of homoscedasticity, this test has shown a p-value of 0, meaning that one can reject the assumption of homoskedasticity.

To solve this issue, a linear regression was run, absorbing multiple levels of fixed effects with robust standard errors. The panel variable was chosen for the factor whose effects were specified to be absorbed by the model. It is an extension of the linear regression with a large dummy-variable set and is usually used for datasets with multiple levels of fixed effects. This model is preferable to the simple addition of robust standard errors to the fixed effects panel model when it comes to heteroskedasticity. This is due to the fact that it absorbs multiple levels of country-level effects. The results of the model are presented in Table 8.

As one can see, the issue of heteroskedasticity of the data isn't as critical as might seem at first glance. The model with the absorption of country-level fixed effects remains consistent with the article's previous findings in terms of variables' significance.

To test whether the asymmetry effect of GDP does matter I ran regressions for quantile subsamples. Table 9 show the estimation results obtained for the quantile groups, depending on the country's GDP per capita. The full sample were split into the following groups: GDP per capita below USD 1,350 – the 25th percentile, GDP per capita between USD 1,350 and 2,950 – the 50th percentile, GDP per capita between USD 2,950 USD and 6,175 – the 75th percentile, and GDP per capita above USD 6,175. After the split, all countries having less than three observations within a dataset were dropped.

Obtained outcomes show that loans and grants have different effects depending on the GDP per capita for the country. The relationship that we've explored in the earlier models is confirmed for the poorest quantile of our dataset. Both grants and loans are significant, albeit loans are at a 10% significance level. Here grants have an inequality reducing effect until they reach 9.7% of a country's GDP, after which they start to increase consumption disparity. Loans show us that, for this particular segment of our dataset, they have an inequality increasing effect until they reach 5.1% of GDP. After this point, loans reduce inequality.

The results for the second model show us a differing relationship between these variables. In this model, loans have a completely insignificant relationship with consumption inequality, while the relationship for grants is reversed. For these countries, grants have an inequality increasing effect until they reach 10.1% of GDP. After this point, grants start reducing it.

The third quantile shows similar results with loans being an insignificant factor in determining consumption inequality; however, here the relationship between grants and inequality is reversed once more. Now grants have an inequality reducing effect until they reach 6.6% of GDP, after which point they increase the consumption disparity in the country.

And for our final quantile, we can see that grants are insignificant for consumption inequality, though loans have a significant linear term. To make sure that what we're seeing is not the result of statistical noise, I've estimated one final model with loans as a linear term. This model shows that the estimated relationship holds true and that, while grants do not affect consumption inequality for these countries, loans are significant and have a considerable effect on consumption inequality. A 1% increase in the loans-to-GDP ratio will result in approximately a 2% wealth transfer from people above the median income to people below it.

6. CONCLUSIONS

Some important policy implications can be derived from the results above. The first one is that grants and loans are different in their effects on consumption inequality. These relationships may be caused by the difference in the repayment condition of both. As grants don't need to be repaid, the money is going to be used inefficiently because there's no direct incentive to use them properly. The relationship is reverse for loans.

Overall, foreign aid has a positive, albeit small, effect on income inequality. With the correct balance of loans and grants, a net inequality reduction effect can be reached. The last estimation of the previous chapter has shed some light on the differing effects of loans and grants. We have seen that loans work better for the poorest countries in the sample (by reducing their consumption disparity after reaching 5.1% of GDP), as well as for the richest countries in the sample, by having a linear effect on their consumption inequality. It is worth noting that grants can also help the poorest countries in the sample.

When it comes to the middle of wealth distribution, loans tend to be insignificant and have little to no influence on the inequality, while grants have strong and consistent effects on the dependent variable. Though, it is worth noting that the mechanism behind loans' and grants' differing effects should be studied in depth by researchers further.

Generally speaking, loans are well suited for a reduction in small quantities. A net point of 2% is needed for the loans to have an inequality-reducing effect. As for grants, they are only harmful when they constitute more than 9% of the economy, which may seem like a lot. But such values are indeed present in the sample, and they aren't as uncommon as they may appear at the first glance.

The article has shown that the question of the effect of foreign aid on income inequality is an important topic that deserves more attention in the literature than it currently gets.

Not only is income inequality a more appropriate measure of effectiveness when it comes to the alleviation of poverty, but it also helps to see what is the effect of international efforts to combat global poverty.

The decomposition of the aid sheds light on the mechanism behind its influence on the economy. In this regard, the article has shown that the effect is twofold – one form of assistance serves as an inequality redactor, while another kind is an inequality expander. This relationship is shown to be non-linear with its breakpoints and the appropriate strategies for each type of aid.

The model has passed most forms of the robustness check, though it is worth noting that loans were more consistent than grants. This result may have been due to how the loans were measured. In the models above, a measure of net loans was used. As such, it may have captured some degree of political confidence of government bodies, and caused the coefficient to be more stable over time.

Still, the research is just one small step on the way to fully understanding the nature of aid's influence on income inequality. Another avenue that may be studied in the future is further deconstruction of the loan variable into loans that are given on the condition of legislative reforms and loans that are given on the simple term of repayment. This may show an even more interesting result as reform-demanding loans are likely to have a larger magnitude of their effect on the inequality.

As for the variable of political violence, it was insignificant in all of our models. In further research, it may be worth focusing on an alternative measure of the political instability within countries. One of such indicators may be the percentage of the population fleeing the country as refugees or the rate of Internally Displaced Persons (IDP) in society. These ratios are likely to be correlated with both income inequality and the amount of foreign aid given to a country. Moreover, because the variable of coups was only binary, it has had a significant flaw in that it ignores the magnitude of the political violence in the country. The number of refugees is a lot more sensitive, and their emergence is more common, than the episodes of political overthrows, hence making it a better potential indicator.

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TABLES

Table 1. Summary Statistics

Variable	Observations	Mean	Standard deviation	Min	Max
Grants	2,994	0.017	0.024	0.000	0.181
Net loans	2,994	0.005	0.010	-0.048	0.171
GINI	2,994	0.425	0.077	0.247	0.875
Human capital	2,994	1.732	0.538	1.007	3.301
Govt. spending	2,994	0.178	0.089	0.016	0.687
Polity	2,994	0.538	6.874	-10.000	10.000
Trade openness	2,994	63.352	39.337	5.222	251.112
Rural pop.	2,994	0.598	0.218	0.000	0.978
Coup d’etat	2,994	0.026	0.159	0.000	1.000

Table 2. Foreign Assistance and Consumption Inequality: Estimation Results

GINI	RE	RE	RE	FE
	(1)	(2)	(3)	(4)
Loans	0.2838***	0.3191***	0.3341***	0.3362***
	(0.006)	(0.002)	(0.002)	(0.001)
$Loans^2$	-5.6236***	-6.1574***	-6.2562***	-6.3039***
	(0.004)	(0.002)	(0.001)	(0.001)
Grants	-0.3997***	-0.2989***	-0.3195***	-0.3201***
	(0.000)	(0.003)	(0.002)	(0.002)
$Grants^2$		1.6150**	1.7534**	1.7509**
		(0.025)	(0.015)	(0.015)
Openness		0.0071***	0.0067***	0.0068***
		(0.001)	(0.002)	(0.002)
Govt. exp.		0.0614***	0.0634***	0.0633***
		(0.000)	(0.000)	(0.000)
Human cap.		0.0166***	0.0217***	0.0215***
		(0.000)	(0.000)	(0.000)
Polity		-0.0004***	-0.0004***	-0.0004***
		(0.006)	(0.006)	(0.005)
Rural pop.		0.0247*	0.0377**	0.0375**
		(0.089)	(0.010)	(0.012)
Coup d’état		-0.0012	-0.0010	-0.0012
		(0.768)	(0.790)	(0.767)
Americas			0.0024	
			(0.896)	
Asia			-0.1091***	
			(0.000)	
Europe			-0.1809***	
			(0.000)	
Middle East			-0.0490	
			(0.283)	
Oceania			-0.1102*	
			(0.083)	
Post-Soviet			-0.1748***	
			(0.000)	
Hausman (χ^2)				31.29***
N	2,887	2,887	2,887	2,887

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3. Foreign Assistance and Consumption Inequality: Time Effect

GINI	3 year lag		5 year lag	
	RE	FE	RE	FE
	(1)	(2)	(3)	(4)
Loans	0.2631**	0.2666**	0.1289	0.1326
	(0.018)	(0.017)	(0.277)	(0.262)
$Loans^2$	-4.6402**	-4.7189**	-3.2510	-3.3458
	(0.021)	(0.019)	(0.121)	(0.111)
Grants	-0.1659	-0.1617	-0.0119	-0.0058
	(0.112)	(0.122)	(0.911)	(0.957)
$Grants^2$	0.6102	0.5787	-0.0140	-0.0610
	(0.418)	(0.444)	(0.985)	(0.936)
Openness	0.0086***	0.0088***	0.0100***	0.0102***
	(0.000)	(0.000)	(0.000)	(0.000)
Govt. exp.	0.0748***	0.0748***	0.0861***	0.0862***
	(0.000)	(0.000)	(0.000)	(0.000)
Human cap.	0.0234***	0.0233***	0.0241***	0.0240***
	(0.000)	(0.000)	(0.000)	(0.000)
Polity	-0.0005***	-0.0005***	-0.0006***	-0.0006***
	(0.001)	(0.001)	(0.000)	(0.000)
Rural pop.	0.0472***	0.0478***	0.0527***	0.0539***
	(0.002)	(0.002)	(0.001)	(0.001)
Coup d'état	-0.0012	-0.0013	-0.0040	-0.0041
	(0.765)	(0.736)	(0.315)	(0.297)
Americas	0.0080		0.0132	
	(0.658)		(0.484)	
Asia	-0.1060***		-0.1020***	
	(0.000)		(0.000)	
Europe	-0.1782***		-0.1725***	
	(0.000)		(0.000)	
Middle East	-0.0453		-0.0442	
	(0.317)		(0.344)	
Oceania	-0.1084		-0.1046	
	(0.087)		(0.107)	
Post-Soviet	-0.1831***		-0.1872***	
	(0.000)		(0.000)	
Hausman (χ^2)		32.01***		25.25***
N	2,738	2,738	2,590	2,590

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4. Foreign Assistance and Consumption Inequality: Impact of Gross Loans

GINI	RE	RE	RE	FE
	(1)	(2)	(3)	(4)
Gross loans	-0.0088	-0.1319	-0.2902	-0.2578
	(0.956)	(0.717)	(0.435)	(0.489)
Gross loans^2		9.2702	18.3400	17.4904
		(0.508)	(0.189)	(0.212)
Grants	-0.1308***	-0.3976***	-0.3150***	-0.3201***
	(0.003)	(0.000)	(0.003)	(0.003)
Grants^2		2.0701***	1.5147**	1.5338**
		(0.005)	(0.041)	(0.039)
Openness			0.0068***	0.0069***
			(0.002)	(0.002)
Govt. exp.			0.0661***	0.0661***
			(0.000)	(0.000)
Human cap.			0.0203***	0.0200***
			(0.000)	(0.000)
Polity			-0.0004***	-0.0004***
			(0.006)	(0.005)
Rural pop.			0.0371**	0.0370**
			(0.013)	(0.016)
Coup d’état			-0.0014	-0.0015
			(0.725)	(0.703)
Americas			0.0020	
			(0.913)	
Asia			-0.1089***	
			(0.000)	
Europe			-0.1803***	
			(0.000)	
Middle East			-0.0488	
			(0.286)	
Oceania			-0.1110*	
			(0.081)	
Post-Soviet			-0.1743***	
			(0.000)	
N	2,887	2,887	2,887	2,887

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5. Foreign Assistance and Consumption Inequality: Total Effect of Aid

GINI	RE	RE	RE	FE
	(1)	(2)	(3)	(4)
Total aid	-0.1130***	-0.0900**	-0.0932**	-0.0930**
	(0.002)	(0.014)	(0.011)	(0.011)
Openness		0.0071***	0.0068***	0.0068***
		(0.001)	(0.002)	(0.002)
Govt. exp.		0.0633***	0.0653***	0.0654***
		(0.000)	(0.000)	(0.000)
Human cap.		0.0143***	0.0187***	0.0190***
		(0.001)	(0.000)	(0.000)
Polity		-0.0004***	-0.0004***	-0.0004***
		(0.003)	(0.003)	(0.002)
Rural pop.		0.0180	0.0280*	0.0301**
		(0.208)	(0.050)	(0.043)
Coup d'état		-0.0011	-0.0010	-0.0011
		(0.773)	(0.798)	(0.772)
Americas			0.0029	
			(0.874)	
Asia			-0.1002***	
			(0.000)	
Europe			-0.1772***	
			(0.000)	
Middle East			-0.0497	
			(0.276)	
Oceania			-0.1103*	
			(0.082)	
Post-Soviet			-0.1708***	
			(0.000)	
Hausman (χ^2)				21.65***
N	2,914	2,914	2,914	2,914

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6. Foreign Assistance and Consumption Inequality: Estimation of On-Simultaneous Effects of Grants and Loans

GINI	RE	RE	FE	FE
	(1)	(2)	(3)	(4)
Loans		0.2971***		0.3001***
		(0.004)		(0.004)
Loans^2		-6.9030***		-6.9723***
		(0.000)		(0.000)
Grants	-0.3091***		-0.3105***	
	(0.002)		(0.002)	
Grants^2	1.5611**		1.5662**	
	(0.027)		(0.028)	
Openness	0.0066***	0.0070***	0.0066***	0.0070***
	(0.002)	(0.001)	(0.002)	(0.001)
Govt. exp.	0.0649***	0.0634***	0.0651***	0.0636***
	(0.000)	(0.000)	(0.000)	(0.000)
Human cap.	0.0188***	0.0209***	0.0192***	0.0213***
	(0.000)	(0.000)	(0.000)	(0.000)
Polity	-0.0004***	-0.0005***	-0.0004***	-0.0005***
	(0.005)	(0.001)	(0.005)	(0.001)
Rural pop.	0.0313**	0.0307**	0.0335**	0.0335**
	(0.028)	(0.031)	(0.025)	(0.025)
Coup d’état	-0.0012	-0.0004	-0.0013	-0.0005*
	(0.762)	(0.916)	(0.736)	(0.888)
Americas	0.0013			
	(0.943)	(0.753)		
Asia	-0.1024***	-0.0981***		
	(0.000)	(0.000)		
Europe	-0.1781***	-0.1767***		
	(0.000)	(0.000)		
Middle East	-0.0502	-0.0493		
	(0.274)	(0.280)		
Oceania	-0.1103*	-0.1089*		
	(0.084)	(0.086)		
Post-Soviet	-0.1726***	-0.1712***		
	(0.000)	(0.000)		
Hausman (χ^2)			25.70***	27.00***
N	2,914	2,914	2,914	2,914

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7. Foreign Assistance and Consumption Inequality: Income Measure of Inequality

GINI	RE	RE	RE	FE
	(1)	(2)	(3)	(4)
Loans	0.2160	0.2852*	0.3004**	0.3035**
	(0.128)	(0.050)	(0.038)	(0.035)
Loans^2	-4.1431	-4.8522*	-4.8566*	-4.8686*
	(0.124)	(0.072)	(0.070)	(0.069)
Grants	-0.2983**	-0.2374*	-0.3017**	-0.3404**
	(0.028)	(0.084)	(0.027)	(0.013)
Grants^2	1.4172	1.0425	1.4483	1.6651*
	(0.146)	(0.288)	(0.137)	(0.090)
Openness		0.0155***	0.0137***	0.0136***
		(0.000)	(0.000)	(0.000)
Govt. exp.		-0.0002		0.0034
		(0.986)	(0.800)	(0.796)
Human cap.		0.0062	0.0121**	0.0145**
		(0.303)	(0.045)	(0.023)
Polity		-0.0002	-0.0002	-0.0002
		(0.296)	(0.332)	(0.388)
Rural pop.		0.0335*	0.0383**	0.0465**
		(0.082)	(0.043)	(0.024)
Coup d'état		0.0034	0.0042	0.0040
		(0.480)	(0.425)	(0.447)
Americas			-0.0899***	
			(0.000)	
Asia			-0.1614***	
			(0.000)	
Europe			-0.2560***	
			(0.000)	
Middle East			-0.1630***	
			(0.000)	
Oceania			-0.1441**	
			(0.020)	
Post-Soviet			-0.1650***	
			(0.000)	
Hausman (χ^2)				24.15***
N	2,949	2,949	2,949	2,949

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8. Foreign Assistance and Consumption inequality: Multiple Fixed Effects Absorbtion Model

GINI	FE	FE	FE
	(1)	(2)	(4)
Loans	0.0501	0.2830**	0.3332***
	(0.643)	(0.014)	(0.003)
$Loans^2$		-5.6100**	-6.2810***
		(0.014)	(0.002)
Grants	-0.1431***	-0.4206***	-0.3203***
	(0.005)	(0.001)	(0.008)
$Grants^2$		2.3370***	1.7462***
		(0.001)	(0.009)
Openness			0.0067***
			(0.007)
Govt. exp.			0.0634***
			(0.000)
Human cap.			0.0209**
			(0.000)
Polity			-0.0004**
			(0.010)
Rural pop.			0.0359***
			(0.008)
Coup d'état			-0.0010
			(0.822)
N	2,914	2,914	2,914

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9. Foreign Assistance and Consumption Inequality: Results for GDP per Capita Quartile Subsets

GINI	1st Quarter	2nd Quarter	3d Quarter	4th Quarter	FE 100th percentile
	FE	FE	FE	FE	FE
	(1)	(2)	(3)	(4)	(5)
Loans	0.4737**	0.0978	-0.0471	-1.2852**	-1.1109**
	(0.021)	(0.589)	(0.786)	(0.022)	(0.017)
$Loans^2$	-4.6312*	-2.4533	4.5905	29.1704	
	(0.079)	(0.497)	(0.446)	(0.504)	
Grants	-0.7331***	0.9975***	-0.4012**	-0.2576	-0.2301
	(0.001)	(0.000)	(0.015)	(0.441)	(0.494)
$Grants^2$	3.7567***	-4.5663***	3.0082***	2.1716	1.6458
	(0.001)	(0.004)	(0.001)	(0.709)	(0.779)
Openness	0.0191**	0.0103**	0.0100**	0.0075**	0.0072**
	(0.031)	(0.012)	(0.010)	(0.028)	(0.031)
Govt. exp.	-0.0212	0.0707***	0.0749***	-0.0476**	-0.0469**
	(0.479)	(0.000)	(0.000)	(0.016)	(0.017)
Human cap.	-0.0502**	0.0159**	0.0613***	0.0215*	0.0219**
	(0.024)	(0.049)	(0.000)	(0.053)	(0.045)
Polity	-0.0012***	-0.0008***	0.0001	0.0001	0.0001
	(0.006)	(0.003)	(0.530)	(0.752)	(0.765)
Rural pop.	-0.2302***	0.0677**	0.2220***	0.0788***	0.0778***
	(0.000)	(0.011)	(0.000)	(0.001)	(0.001)
Coup d'état	-0.0025	-0.0016	0.0056	-0.0019	-0.0020
	(0.805)	(0.708)	(0.434)	(0.682)	(0.661)
N	736	726	735	704	704

p-values in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

APPENDIX A

A1. List of Countries Used in the Models

Albania	Indonesia	Sierra Leone
Algeria	Jamaica	Slovenia
Angola	Jordan	South Africa
Argentina	Kazakhstan	Sri Lanka
Armenia	Kenya	Tajikistan
Bangladesh	Lesotho	Thailand
Benin	Liberia	Togo
Botswana	Madagascar	Trinidad and Tobago
Brazil	Malawi	Tunisia
Burkina Faso	Malaysia	Turkey
Burundi	Mali	Uganda
Cambodia	Mauritania	Ukraine
Cameroon	Mauritius	Uruguay
Central African Republic	Mexico	Zambia
Chile	Mongolia	
Colombia	Morocco	
Costa Rica	Mozambique	
Croatia	Namibia	
Cyprus	Nepal	
Dominican Republic	Nicaragua	
Ecuador	Niger	
El Salvador	Nigeria	
Ethiopia	Pakistan	
Fiji	Panama	
Gabon	Paraguay	
Ghana	Peru	
Guatemala	Philippines	
Haiti	Rwanda	
Honduras	Senegal	
India	Serbia	

A2. Aid Specialization Classification

Loan oriented	Grant oriented	
Brazil	Albania	Madagascar
Chile	Algeria	Mali
India	Angola	Mauritania
Indonesia	Argentina	Mauritius
Pakistan	Bangladesh	Mongolia
Turkey	Benin	Mozambique
	Botswana	Namibia
	Burkina Faso	Nepal
	Burundi	Nicaragua
	Cambodia	Niger
	Cameroon	Nigeria
	Central African Republic	Panama
	Costa Rica	Paraguay
	Croatia	Peru
	Cyprus	Philippines
	Ecuador	Rwanda
	El Salvador	Senegal
	Ethiopia	Serbia
	Fiji	Sierra Leone
	Gabon	South Africa
	Guatemala	Tajikistan
	Haiti	Thailand
	Honduras	Togo
	Jordan	Trinidad and Tobago
	Kazakhstan	Uganda
	Kenya	Ukraine
	Lesotho	Uruguay
	Liberia	Zambia