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INVESTIGATING THE RELATION OF GDP PER CAPITA AND CORRUPTION INDEX

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Abstract. The paper is devoted to modelling the corruption perception index in panel data framework. As corruption index is bounded from below and above, traditional econometric multiple regression will produce a bad quality model. In order to correct that, we propose a mathematical framework for modelling bounded variables implementing a logistic function. It is shown that corruption is best explained by GDP per capita and all other major macroeconomic indicators cannot add any statistically significant improvement to the models' accuracy. Thus, we assume, that society wealthiness facilitates the reduction of corruption acts. Indeed, if some individual lives in a society that does not experiences almost any shortage of resources of whatever kind, the less interested this person is in getting wealthier by applying some corruption schemes. These methods are rather popular in less wealthy countries, where temptation to engage into corruption is higher, since it can drastically increase individual's utility function. Therefore, in this research we assert, that the growth of wealth in a society makes corruption recede and not the other way around (reducing corruption helps increase GDP per capita). However, the most counterintuitive finding of this research is the fact, that GDP per capita, adjusted by purchasing power parity, produces the model of a worse quality then just using plain GDP per capita. This fact can be tentatively explained by the flaws in the methodology of calculating these adjustments, since the basket of goods varies drastically across the countries.

Keywords: corruption; GDP per capita; purchasing power parity; macroeconomic indicators; modelling bounded variables; logistic curve; probability distribution

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JEL Classifications: D73, N10, C10

1. Introduction

Corruption is a broadly discussed and studied concept in economic and sociological scientific literature. Nevertheless, so far researchers didn't come to a unified opinion neither concerning its origin, nor about its effect on sustainable economic development, nor about how to combat this phenomenon in case its effect is rather negative. Early papers on corruption issue date back to Leff (1964) and Huntington (1968) and declare, that corruption positively affects the functioning of economic system since it reduces some bureaucratic delays and transaction costs. On the other hand, such authors as Kaufman and Wei (1999), Aidt (2009), Mauro (1995, 1997), Shleifer and Vishny (1993), Blackburn et al (2009), Barreto (1996), Tanzi and Davoodi (1997), etc. state, that corruption imposes a negative effect on economy.

In this paper we investigate in a panel data framework the relation between GDP per capita and corruption perception index, issued by Transparency International e.V., which defines corruption as "the misuse of public power for private benefit". Higher values of corruption index correspond to less corrupted countries, whereas lower values denote more corrupted ones. The central hypothesis that we utter is that corruption index variation is best explained by GDP per capita and inclusion of other most common macroeconomic indicators does not help increase the quality of the model.

In order to explain this statistically strong link, we assume, that the wealthier some society is, the easier it becomes for bureaucrats not to use their public power to obtain private benefits. Indeed, if one lives in a society that does not experiences almost any shortage of resources of whatever kind, the less interested this person is in getting wealthier by applying some corruption schemes. These methods are rather popular in less wealthy countries, where temptation to engage into corruption is higher, since it can drastically increase individual's utility function. In this paper we refer to utility as to a basic microeconomic concept of utility theory. If we consider a bureaucrat, deciding whether to engage into a corruption act, he or she would almost certainly consider a potential gain from this act and a potential punishment, which will occur with some probability. Thus, the bureaucrat will assess his or her utility of some corruption act given certain values of gain, punishment and its probability of occurrence. If this utility appears to be high enough, then, obviously, the decision is in favor of engaging into corruption. That is why in order to fight corruption one should consider either toughening the punishment, or decreasing the utility from financial gain, what can be only achieved by increasing the overall wealth of the society.

Therefore, in this research we assert, that the growth of wealth in a society makes corruption recede and not the other way around (reducing corruption helps increase GDP per capita), as stated in Mustapha (2014).

The paper has the following structure. Section 2 presents a quick literature review on the topic of corruption and its impact on economy. Section 3 presents a mathematical approach, that is proposed by the authors for modelling bounded indicators. In section 4 we present the results of our statistical modelling of corruption perception index in panel data framework. Section 5 is devoted to discussing the paper findings and pointing the directions for future research. Section 6 sums up the key points of the paper. Section 7 emphasizes scientific contribution of this paper.

2. Literature review

In the paper by Leff (1964) it is stated that corruption helps spur up economic growth, as corrupt bureaucrats can make the government promote economic activities, what facilitates investments growth. Kaufman and Wei (1999) investigate the relation between bribe payment, management time wasted on bureaucrats and cost of capital. The main finding of that paper is that companies that pay more bribes are also likely to spend more (not less) time on negotiating with bureaucrats what leads to higher (not lower) cost of capital. Mauro (1995, 1997) states that high level of corruption causes a decrease in economic growth by decreasing investment attractiveness. Rahman et al. (2000) capitalize on the previous research and, using Bangladesh data set, study the impact of corruption on economic growth and investment flows. Their findings propose that in order to combat corruption, governments

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should drastically alter the incentives system and strengthen domestic institutions (Lopatin, 2019b; Meynkhard, 2019a; Meynkhard, 2019b; Meynkhard, 2020).

Aidt (2009) wrote that while corruption in a very narrow sense can be seen as a lubricator that may speed things up and help entrepreneurs getting on with wealth creation in specific instances, in a broader sense, corruption must be considered as an obstacle to development", as the author finds a strong negative correlation between corruption and economic development.

Mauro (2004) tries to understand the reason of why corruption persists in spite of its negative impact on the economic growth. The author's models are based upon multiple equilibria. In the final analysis the paper outlines, that when corruption is widely spread individuals have little stimuli to combat this phenomenon even though everybody would be better of without it. The paper by Blackburn et al. (2009) investigates the fact that in some countries corruption imposes stronger negative effect than in the others. Authors use general dynamic equilibrium framework to show that countries with organized corruption networks have higher chances for lower bribes level and faster economic growth.

The paper by Rock and Bonnett (2004) analyze four different data sets in order to prove the connection between corruption and economic growth. Authors conclude that the corruption effect on economic growth depends on the level of current economic state: corruption tends to slow down economic growth for developing countries of smaller size, whereas it spurs up economic growth for East Asian newly industrialized economies.

Li and Wu (2010) studied statistical data of 65 countries and say that trust in a corruption network facilitates economic growth and mitigates its negative effect on the economy. Finally, Mustapha (2014) runs several statistical tests in a panel data framework to display, that GDP per capita is negatively affected by corruption index.

The link between GDP per capita and corruption revolves around the need for a fair distribution of GDP between present and future generations through sustainable use of resources (Lisin, 2020c; Denisova et al, 2019). Each generation should take care of the following: as share of GDP from the previous generation arrive, it should retain a fair amount of capital for generations, while financing its own activities to an appropriate extent (Lopatin, 2019a; Lopatin, 2020; Lisin, 2020a; Lisin, 2020b).

3. Materials and methods

Let $\{y_t, X_t: t = 1, \dots, n\}$ be a set of considered variables, where y_t – corruption perception index, $X_t = (x_{0t}, x_{1t}, x_{2t}, \dots, x_{kt})$ – a set of explanatory variables. Since we consider a case, where tolerance range of a target variable is bounded from above and below, we propose to use a multivariate logistic regression to obtain a point forecast of considered indicator. The formula of the logistic curve is given below:

$$y_t = \frac{1}{1+e^{-z(t)}}, \tag{1}$$

where $y_t \in [0,1]$ represents a scaled corruption perception index, $z(t) \in (-\infty;+\infty)$.

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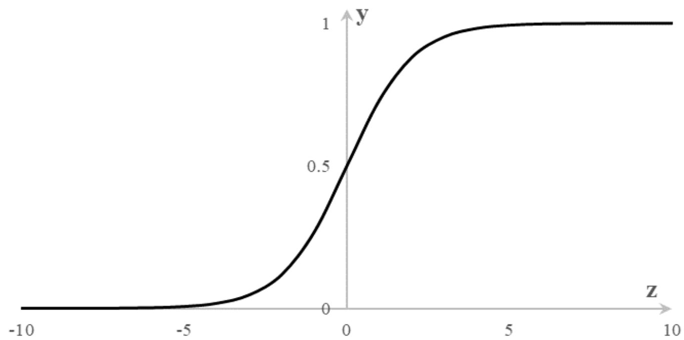

Fig. 1. Logistic curve
Source: author

It is worth noticing that $z(t)$ can be either linear or non-linear function of explanatory variables X_t. Parameters of such model are estimated by using OLS for which we previously conduct an inverse logarithmic transformation of the target variable, as shown below:

$$z(t) = -\ln\left(\frac{1}{y_t} - 1\right). \tag{2}$$

Thus, linear model can be presented as follows:

$$z(t) = X_t B + e_t, \tag{3}$$

where $B = (b_0, b_1, \dots, b_k)'$ is a column-vector of estimators for true model's parameters β, which is independent of any realization of vector X_t, e_t – "white" noise, which is assumed to be subject to normal distribution.

Parameters vector for such class of models is then estimated as below:

$$B = \left(X^T X\right)^{-1} X^T Z, \tag{4}$$

where $X = \begin{pmatrix} X_n \\ X_{(n-1)} \\ \vdots \\ X_1 \end{pmatrix}, Z = \begin{pmatrix} z_n \\ z_{n-1} \\ \vdots \\ z_1 \end{pmatrix}.$

We also suppose that all OLS prerequisites hold, i.e.

$$E\left(e_t \middle| X_t\right) = 0, \tag{5}$$

$$E\left(e_t^2 \middle| X_t\right) = \sigma^2, \tag{6}$$

$$\operatorname{cov}(e_i; e_j) = 0, \forall i \neq j. \tag{7}$$

In case $z(t)$ is a non-linear function of X_t, the model will look as follows:

$$z(t) = h(X_t, B) + e_t, \tag{8}$$

where h is a continuously differentiable function.

If prerequisites (5-7) hold, then the vector of parameter estimators for (8-9) is computed by numerical minimization of the following target function:

$$S(B) = \frac{1}{2}\sum_{t=1}^{n}\left(z(t) - h(X_t, B)\right)^2 \to \min \tag{9}$$

To analyze the probability distribution of model's errors we derive the probability density function for y_t. For this we start with the following calculations:

$$y_t = \frac{1}{1+e^{-(\hat{z}(t)+\varepsilon)}} = \frac{1}{1+e^{-\hat{z}(t)}e^{-\varepsilon}} = \frac{1}{1+\alpha e^{-\varepsilon}} \tag{10}$$

where $\hat{z}(t) = X_t B$, $\alpha = e^{-\hat{z}(t)}$ and $\alpha \in (0;+\infty)$.

Thus, the probability distribution of random variable y_t is a function of parameters α and σ. In the first step we derive the cumulative distribution function as shown below:

$$cdf_Y(y) = P(Y < y) = P\left(\frac{1}{1+\alpha e^{-x}} < y\right) = P\left(x < -\ln\left(\frac{1-y}{\alpha y}\right)\right) = \frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{-\ln\left(\frac{1-y}{\alpha y}\right)} e^{\frac{-x^2}{2\sigma^2}}dx. \tag{11}$$

Here σ denotes standard deviation of "white" noise ε. In order to derive the probability density function, we differentiate the obtained function with respect to y.

$$pdf(y) = cdf_Y(y)' = \left(\frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{-\ln\left(\frac{1-y}{\alpha y}\right)} e^{\frac{-x^2}{2\sigma^2}}dx\right)'_y = \frac{1}{\sqrt{2\pi}\sigma}e^{\frac{-\ln^2\left(\frac{1-y}{\alpha y}\right)}{2\sigma^2}}\left(-\ln\left(\frac{1-y}{\alpha y}\right)\right)'_y. \tag{12}$$

From the previous equation it is easy to obtain the analytical form of the probability density function for y, what is shown below:

$$pdf(y) = \frac{1}{\sqrt{2\pi}\sigma y(1-y)}e^{\frac{-\ln^2\left(\frac{1-y}{\alpha y}\right)}{2\sigma^2}}. \tag{13}$$

Probability density function (10-13) can take up different shapes depending on parameters (see fig. 2). In case parameters $\alpha = 1, \sigma = 0.5$, then distribution is close to normal, in case when $\alpha = 0.3, \sigma = 0.7$ and

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$\alpha = 3,\ \sigma = 1.3$ distribution is clearly skewed, and if $\alpha = 1, \sigma = 3$ it has a parabolic shape. It is worth noticing, that in the latter case, the model is uninformative because the confidence intervals will cover almost the entire tolerance range of the target variable. Therefore, while constructing the model, researchers should pay attention to the standard deviation of model's residuals, since if its value is greater than 2, the model can be considered as uninformative.

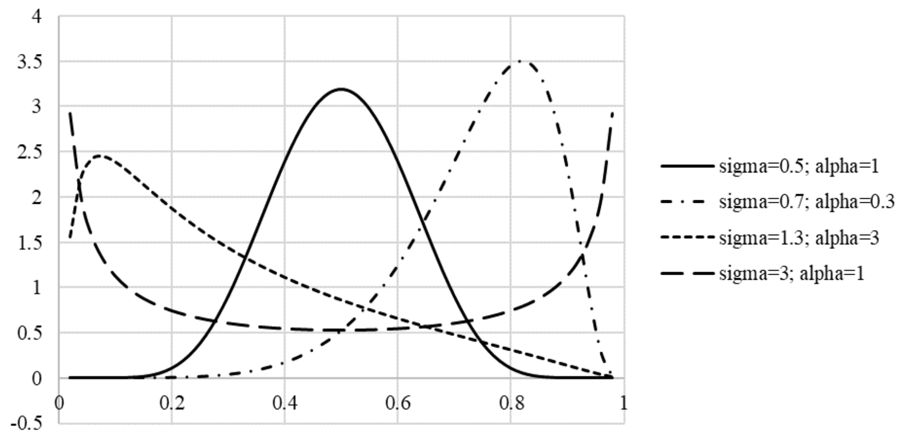

Fig. 2. Probability density of *y* given different parameters' values
Source: author

In order to compute the interval forecast, we calculate explicitly the expected mean square forecast error (MSFE). It is well-known, that MSFE consists of two components: the variance of "white" noise and the variance of the regression line. This can be presented as follows:

$$MSFE_{t+1} = Var(\hat{z}_{t+1} - z_{t+1}) = \sigma^2 + Var(\hat{z}_{t+1} - E(\hat{z}_{t+1})). \tag{14}$$

Hence, we do a quick recap of the derivation for the regression line variance.

$$\begin{aligned} Var(\hat{z}_{t+1} - E(\hat{z}_{t+1})) &= E(\hat{z}_{t+1} - E(\hat{z}_{t+1}))^2 \\ &= E\left(X_{t+1}(B-\beta)(B-\beta)^T X_{t+1}^T\right) \\ &= E\left(X_{t+1}\left(X^T X\right)^{-1} X^T \varepsilon\varepsilon^T X \left(X^T X\right)^{-1} X_{t+1}^T\right) \\ &= X_{t+1}\left(X_i^T X_i\right)^{-1} X_i^T E\left(\varepsilon\varepsilon^T\right) X \left(X^T X\right)^{-1} X_{t+1}^T \\ &= \sigma^2 X_{t+1}\left(X^T X\right)^{-1} X^T X \left(X^T X\right)^{-1} X_{t+1}^T \\ &= \sigma^2 X_{t+1}\left(X^T X\right)^{-1} X_{t+1}^T. \end{aligned}$$

4. Results

In this section we investigate the relation of corruption perception index and GDP per capita for 45 biggest economies. Considered data set covers a time frame from 2012 to 2018 and the following countries: Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Egypt, Finland, France, Germany, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands,

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Nigeria, Norway, Pakistan, Philippines, Poland, Romania, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Thailand, Turkey, United Arab Emirates, United Kingdom, United States, Vietnam.

Since corruption perception index ranges from 0 to 100, in order to model it we resort to the method, described in the previous section. The final model in this case will look as follows:

$$corruption_{ti} = \frac{100}{1+e^{-\left(b_0+b_1GDP_{ti}+b_2GDP_{ti}^2+e_{ti}\right)}}. \tag{15}$$

In order to apply OLS method, we apply the inverse logarithmic transformation on corruption index to get z-score, which can be modelled by traditional regression tools.

$$-\ln\left(\frac{100}{corruption_{ti}}-1\right) = z-score = b_0 + b_1GDP_{ti} + b_2GDP_{ti}^2 + e_{ti}. \tag{16}$$

Table 1 displays the summary of regression parameters estimation for model (16). As it can be clearly seen, considered z-score is very well modelled by constructed model. Durbin-Watson statistics is equal to 1.79, what testifies that selected analytical equation is rather correct. Intercept, first and second coefficients are highly significant as well as overall model's quality, what can be seen by extremely high value of F-statistics. Coefficient of determination as well as adjusted R-squared display values close to 1, what is interpreted as a model of a very good fit.

Table 1. Regression summary for corruption perception index and GDP per capita

Regression Statistics	
Multiple R	0.923845
R Square	0.85349
Adjusted R Square	0.852551
Standard Error	0.375962
Observations	315

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	256.9057	128.4529	908.7742	7.5E-131
Residual	312	44.10038	0.141347		
Total	314	301.0061			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.576067	0.029486	19.53704	4.45E-56	0.518051	0.634083	0.518051	0.634083
GDP per capita	0.980353	0.023849	41.10676	5.7E-128	0.933428	1.027278	0.933428	1.027278
GDP per capita squared	-0.18142	0.020511	-8.84486	6.92E-17	-0.22177	-0.14106	-0.22177	-0.14106

Source: authors' calculations

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Thus, from table 1 we can conclude, that the variation of corruption perception index across analyzed countries at different time periods is well explained by the variation of GDP per capita. Table 2, on the other hand presents the regression summary for model (16), but instead of GDP per capita we used GDP per capita, adjusted by purchasing power parity. If we compare numbers form tables 1 and 2, we can conclude, that GDP per capita PPP, though producing a good quality model, still significantly underperforms in explaining the variation of corruption perception index. Standard error in the latter case is by almost 38% greater, than for model, based on plain GDP per capita.

Table 2. Regression summary for corruption perception index and GDP per capita PPP

Regression Statistics	
Multiple R	0.854034
R Square	0.729374
Adjusted R Square	0.727639
Standard Error	0.510969
Observations	315

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	219.5461	109.773	420.4417	2.82E-89
Residual	312	81.46002	0.26109		
Total	314	301.0061			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.562875	0.0377	14.93033	2.08E-38	0.488697	0.637054	0.488697	0.637054
GDP per capita PPP	0.875029	0.030253	28.92363	2.67E-90	0.815504	0.934555	0.815504	0.934555
GDP per capita squared PPP	-0.16822	0.02434	-6.91138	2.71E-11	-0.21612	-0.12033	-0.21612	-0.12033

Source: authors' calculations

This finding is counterintuitive, as it would be more logical, to orient on GDP per capita PPP rather than on plain GDP per capita, since purchasing power parity adjustment is supposed to help better understand the true living standard in a country. Indeed, when making a decision whether to engage into some corruption act an individual should consider his current living standard and compare it with his living standard after accepting a bribe, of course, corrected by the probability of being exposed to justice and corresponding penalties. In this case GDP per capita PPP should more accurately define the average living standard of citizens, working as a reference point for bureaucrats. However, our statistical analysis shows, that probably there is a flaw in methodology of calculating purchasing power parity adjustments. This flaw, in our opinion, is based on the fact, that purchasing power parity adjustment is calculated on some unified basket of consumer goods, which may not adequately assess the average living standard, since the effective structure of this basket varies drastically across the countries due to their geographical, climatic, political, cultural, economic, historical, gastronomical and other differences. Thus, we conclude, that plain GDP per capita is a more adequate predictor for corruption perception index as it, apparently, is a better proxy of a living standard across different countries.

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Moreover, we tried to include into model (15-16) different macroeconomic indicators, such as: consumer price index, current account, Gini income inequality index, government debt to GDP ratio, unemployment rate, GDP, population and government budget surplus. However, all these indicators failed to significantly improve the quality of the model, since all regression coefficients, associated with these factors happened to be statistically insignificant, compared to GDP per capita. This statement does not assert, that there are no other factors, determining the level of corruption other then GDP per capita or it is impossible to find a better fitted model, using already considered factors. Of course, since there is a high degree of multicollinearity among explanatory variables, it is probably possible to apply some sort of regularization in order to improve the quality of the model, but this procedure is beyond the scope of this paper.

Figure 3 presents the scatter plot of z-score for corruption index and standardized GDP per capita, computed as below:

$$GDP_{ti} = \frac{GDP_{ti} - \underset{i}{E}(GDP_{ti})}{\underset{i}{SD}(GDP_{ti})}. \tag{17}$$

Figure 4 displays the scatter plot for corruption perception index and standardized GDP per capita. Both figures also display regression lines and 95% confidence levels, computed by proposed in section 3 method of modelling bounded indicators.

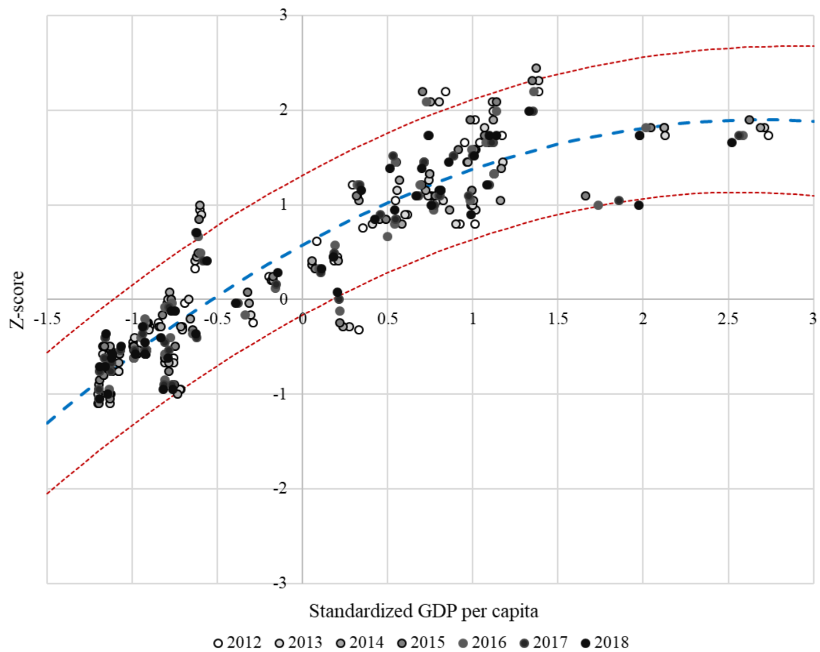

Fig. 3. Scatter plot for z-score and GDP per capita
Source: authors' calculations based on statistical data from Transparency International e.V. (https://www.transparency.org/) and World Bank (https://data.worldbank.org/indicator/)

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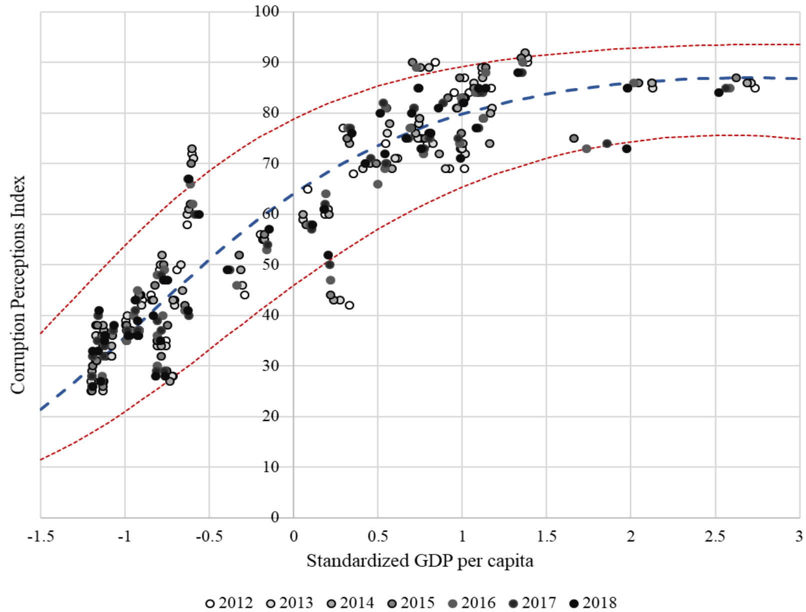

Fig. 4. Scatter plot for corruption perception index and GDP per capita
Source: authors' calculations based on statistical data from Transparency International e.V. (https://www.transparency.org/) and World Bank (https://data.worldbank.org/indicator/)

From figure 4 we can see that the relation between corruption index and GDP per capita is clearly non-linear, what requires some changes in traditional linear approach. Proposed model approximates data quite well and around 95% of all data points are lying within the confidence band. Exactly the same conclusions can be made, when modelling corruption index for each particular time period. R-squared remains stably around 0.83-0.87 and all coefficients are significant. Therefore, we can state, that constructed model is adequate and can be used for drawing economic conclusions, based on its statistics and features.

5. Discussion

Corruption by most scientists is believed to have a negative impact on economic growth and sustainable society development. Indeed, it undermines concepts of justice and equality, since rich individuals can escape punishment for crimes they actually committed or get an advantage in business environment. Corruption facilitates an outgoing cash flow, as bureaucrats try to launder the illegal income through some offshore accounts. These facts obviously hinder country's investment attractiveness, ease of doing business and free market concept. Lack of investments flow seriously damages growth potential compared to the level a country could reach, had there been a lower level of corruption (Chiabaut and Barcet, 2019; Nguyen et al., 2019; Bešinović and Goverde, 2019; Enayatollahi et al., 2019; Mohri and Akbarzadeh, 2019; Sun and Apland, 2019; Jevinger and Persson, 2019; Czioska et al., 2019).

However, combating corruption in order to spur up economic development can appear to be suboptimal, as it may require more resources, than a country will actually gain from a reduced corruption level. In this paper we show that corruption is in a very close relation with the average living standard in a country, which in our case is represented by GDP per capita. Indeed, for a bureaucrat it is much easier to resist the temptation to engage into some act of corruption if his utility from the bribe is not high, what can happen either if the punishment is severe enough, or bureaucrat's value for money is not that high. The latter can only happen if bureaucrat's living standard is pretty high, compared to the average in the world, what is supported by decreasing marginal utility

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theory. That explains, why poor countries tend to have higher level of corruption and rich ones, on contrary, low. (Heyken Soares et al, 2019; Habib and Hasnine, 2019; Malucelli and Tresoldi, 2019; Downward et al., 2019; Candelieri et al., 2019).

That means, that probably economic growth helps reduce corruption as well as low corruption level increases economic growth. We suppose that it is more important to concentrate on some economic reforms, that would facilitate economic growth, rather than combat corruption. First of all, these reforms are supposed to be made by bureaucrats, which are usually the most corrupted society group (Veynberg and Titov, 2017; Veynberg and Popov, 2016; Veynberg et al., 2015; Mikhaylov, 2015).

Secondly, one of the social constructs in the new knowledge economy is the technology of leading indicators that is widely used today, which allows managers in corporations and public administration to anticipate economic events in planning before the appearance of relevant statistics and to set real tasks in resolving conflicts of interest in a working order.

That is why, reforms or laws, aimed at combating corruption will not meet a joyful approval from policymakers. But reforms, aimed at economic development will unlikely meet resistance in the government. On contrary, corrupted policymakers greet faster pace of economic growth as his or her “services” become more expensive. This, obviously, happens because if the corporate sector becomes richer it can afford to give more expensive bribes (Szlosarek et al., 2019; Covic and Voss, 2019; Dorantes-Argandar et al., 2019; Iliopoulou et al., 2019).

Thus, we emphasize the point that corruption is a social phenomenon, that is self-annihilating as economy develops at a higher pace, than the average growth rate across the world. That is why, it is important to try to focus on economic development, what will eventually reduce the corruption level in a country (Huang et al., 2019; Hadiuzzaman et al., 2019; Jasti et al., 2019).

6. Conclusion

In this research we propose a mathematical approach to modelling bounded economic indicators, that is based on logistic curve and ordinary least squares and developed within a parametric framework. With the help of this approach we investigate and model the relation between the corruption perception index and GDP per capita. It is shown that corruption perception level is best modelled by GDP per capita and not by GDP per capita, adjusted by purchasing power parity. This counterintuitive result we explain by the flaw in the methodology of computing these adjustments, since the basket of goods varies drastically across countries. Moreover, other major macroeconomic indicators, such as: consumer price index, current account, Gini income inequality index, government debt to GDP ratio, unemployment rate, GDP, population and government budget surplus could not significantly improve the quality of the model, based on GDP per capita.

We suppose that in order to reduce corruption, a government should focus more on ensuring a faster sustainable economic development, rather than on directly constraining corruption activities. Such an approach is believed to be more effective, since reforms and laws, which are aimed at economic development, will not meet such a resistance as, for instance, introducing flexible tax rate, or aggravate penalties for acts of corruption.

7. Contribution to the Body of knowledge

This paper is devoted to working out a mathematical approach to modelling bounded economic indicators and investigating the relation between corruption and GDP per capita. This research makes at least three important contributions to the body of knowledge. The first contribution is the method modelling bounded from below and above economic indicators. The second contribution is constructed econometric model for corruption perception

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index depending on GDP per capita, which explains the variation of dependent variable better, than any other major macroeconomic indicator. The third one is the conclusion, that increasing overall wealth of the society helps combating corruption and not the other way around, as it was previously believed.

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