PSYCHOLOGICAL TRAITS AND INCOME INEQUALITY AT THE COUNTRY LEVEL

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Abstract

This study explores the relationship between personality traits (measured by the NEO-PI-R) and income inequality (measured by Gini coefficient). It finds a statistically significant relationship between these variables and via this relationship predicts selected levels of pathological behavior in society – for example, the rate of economic and violent crime. These predictions have been hypothesizing to be linked with the reality of the labor market. Therefore, an analysis of the basic labor market indicators in relation to the above is also included.

This paper shows the importance of understanding potential psychological sources both to public policy and business viewpoints. If certain countries exhibit psychological traits that support income inequality, the psychological set-up of people themselves may be the reason why some countries are not achieving economic growth in even in long run.

On these bases, it is argued that understanding the relationship between personality traits, which were found in all cultures, and income inequality have significant policy implications. It suggests that there are strong differences in egalitarian believes and perception of pathological behavior between countries.

JEL classification: C44, C91, C93

Keywords

Gini coefficient, NEO-PI-R, pathological behavior, labor market, behavioral economics

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Introduction

The relationship between crime and economic output of the country has been detailly investigated in the past. These investigations show that hypothesis about poverty as the driving force of crime is simply not acceptable. Moreover, we can safely conclude from researchers as from Fajnzylber (2002) that the strongest predictor of crime is income inequality.

This has a great impact towards possible public policy. With a major goal to stabilize society in the long run, public policy might be designed to lower income inequalities and through this lower the crime rate. Although, this is not the only possible strategy towards social stability (and not sufficient condition) but compares to other options this way could be much more peaceful than many other possibilities.

From purely economic perspective the motivation for a crime would be simple. In every consideration of crime, the agent would make cost-benefit analysis with risk involvement and by the result, he/she would decide to commit or not to commit a specific crime. This way of thinking describes, for example, Becker (1974). According to Becker, crime rates depend on the risks and punishment associated with apprehension and on the difference between the potential gains from crime and the associated opportunity cost. These gains have been represented theoretically by the wealth differences or as the income differences between the rich and poor.

Becker's (and many others) viewpoint has been constructed purely through neoclassical economy approach. Unfortunately, this manner of economic thinking has two major issues that withstand the rising criticism - the homo economicus assumption and the ceteris paribus assumption. This paper will not cover details of limitations which these two assumptions bring, but as Kahneman and Tversky (1992) or van Benthem (2007) shows the high level of rational decision-making capacity of hommo economicus and the system stability via ceteris paribus are too demanding conditions for most cases.

As stated, an earlier analysis of the crime phenomenon with relationship to economic indicators took crime rates as a variable independent on the nature of the society. But as we can conclude from researchers like Hofstede (2010) or Allik (2017) sociological or psychological characteristic on society level play a huge role as an influence towards human behavior. The pathological behavior might be considered a subset.

In this paper, I choose opposite strategy from Becker's viewpoint and propose statistical models with purely psychological explanatory variables. Since neoclassical economics does not include this character of variables, I use a behavioral economy framework to formulate conclusions.

1 Data, variables and statistical method

As was noted, lab experiments usually study very simple decisions from limited possibilities. This section will briefly present the data and statistical method used for analysis of the

relationship between Income inequality, crime rate, labor market and mean profiles of the NEO Personality Inventory (NEO-PI). The chapter is divided into subsections for better clarity.

1.1 Sample of observations, data

The sample includes 47 countries. This sample has been made based on data availability. For 47 countries it has been possible to collect data for all variables. This makes the sample slightly biased. However, compared to some other research in this area, the analyzed dataset is not based only on WEIRD countries (= Western, Educated, Industrialized, Rich, Democratic).

Variables from databases and from NEO-PI has been analyzed in static view – most actual accessible level of variable has been used (which has been in all cases year 2017 or 2016). This approach enables to analyze more countries. If time series approach would be used, some countries would not be added due to short time series of data.

1.2 National Income inequality statistic

This study uses well defined Gini coefficient as a proxy for Income inequality. Gini index measures the extent to which the distribution of income among individuals or households within an economy deviates from a perfectly equal distribution. The Gini index measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest individual or household. Thus, a Gini index of 0 represents perfect equality, while an index of 100 implies perfect inequality (World Bank, 2015).

1.3 National crime statistic

In this study are examined Violent crime and Property crime. As a proxy variable is used the number of homicides and robberies per 100,000 people. In this case study face common problem of cross-country studies of crime - most official crime data are not easily comparable across countries because each country suffers from its own degree of underreporting and defines certain crimes in different ways (Fajnzylber, Lederman, & Loayza, 2002). Underreporting is worse in countries where the police and justice systems are not reliable, where the level of education is low, and perhaps where inequality is high. Country-specific crime classifications, arising from different legal traditions and different cultural perceptions of crime, also hinder cross-country comparisons. The type of crime that suffers the least from underreporting and idiosyncratic classification is homicide. It is also well documented that the incidence of homicide is highly correlated with the incidence of other violent crimes (UNODC, 2017). These reasons make the rate of homicides a good proxy for crime, especially violent crime (Fajnzylber, Lederman, & Loayza, 2002).

Although data on robberies are less reliable than homicide data for cross-country comparisons, they are likely to be more reliable than data on lesser property crimes such as theft. This is so because robberies are property crimes perpetrated with the use or threat of violence; consequently, their victims have a double incentive to report the crime, namely, the physical and psychological trauma caused using violence and the loss of property. Robbery's close connection with property crimes, to which economic theory is more readily applicable, makes its study a good complement to that of homicide (Fajnzylber et al., 2002).

Both the number of homicides and robberies per 100,000 people used in the analysis are from the United Nations World Crime Survey (UNODC, 2017).

1.4 The Revised NEO Personality Inventory

The Revised NEO Personality Inventory (NEO-PI-R, Costa & McCrae, 1992) and its latest version, the NEO-PI-3, were designed to measure 30 distinctive personality traits, which are grouped into Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness domains (Allik et al., 2017). The study reports the mean scores of the NEO-PI-R/3 for 71 334 participants from 76 samples and 62 different countries, but in statistical analysis in this paper, data from only 47 countries were used (due to mentioned restrictions). Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness are coded in regression equations as Big5.N, Big5.E, Big5.O, Big5.A, Big5.C.

1.5 Other economic data

GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. World Bank national accounts data, and OECD National Accounts data files (OECD & World Bank, 2017b). This variable is used only as a control in regression analysis.

For analyzing labor market, the unemployment rate has been chosen as a proxy. The unemployment rate is the number of persons who are unemployed as a percent of the total number of employed and unemployed persons (i.e., the labor force) (ILOSTAT, 2017).

In one of the analyses, the annual percentage growth rate of GDP is used as a control. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources (OECD & World Bank, 2017a).

1.6 Multiple regression analysis

Multiple regression analysis is a statistical tool for evaluating the dependence of the dependent random variable on more independent variables. The most advantageous situation is that all variables involved are measurable (quantitative and continuous), but experience with the use of regression-type models shows that almost all types of variables are used in various research areas. The general objective of a regression analysis is to determine or at least estimate a regression function that would predict the values of the dependent variable by setting the values of independent variables. The functional relationship between those variables is never perfect (unless something obvious is studied or due to mistake) therefore some noise in prediction will always appear (random deviations from the relationship - ε).

$$D.V. = f(I.V.) + \varepsilon \tag{1}$$

In multiple regression approaches, the I.V. represents more than one variable.

In all cases in this paper, the log-log model is used. Since it is no reason to assume that examined variables are linear, logarithmization is used to provide a linear course of variables and possibly linear relationship (natural logarithm has been used). Since logarithmization cannot guarantee a linear relationship, the condition of linear link function still needs to be checked.

$$\ln(D.V.) = f(\ln(I.V.)) + \varepsilon \tag{2}$$

Since I.V.s in following analyses are mean profiles of the NEO-PI we can specified regression equation.

$$\ln(D.V.) = \beta_0 + \beta_1 \ln(big5.O) + \beta_2 \ln(big5.C) + \beta_3 \ln(big5.E) + \beta_4 \ln(big5.A) + \beta_5 \ln(big5.N) + \varepsilon \tag{3}$$

In all cases, in this paper, first order error is accepted at the 5% level, which is applied both to the statistical analysis itself and on checking the model assumptions as well. The significance level is therefore set at 0,05.

2 Hypotheses

Gini – homicides Hypotheses in this paper are quite straightforward. Since relationships between

1. *Gini coefficient* and mean profiles of the *NEO Personality Inventory*
2. *the amount of violent crime* and mean profiles of the *NEO Personality Inventory*
3. *the number of reported robberies* and mean profiles of the *NEO Personality Inventory*
4. *unemployment* and mean profiles of the *NEO Personality Inventory*

are analyzed null hypotheses are:

$H1_0$: There is no relationship between *Gini coefficient* and mean profiles of the *NEO Personality Inventory*. Therefore $\beta_0: \beta_5 = 0$ in this regression equation.

$H2_0$: There is no relationship between *the amount of violent crime* and mean profiles of the *NEO Personality Inventory*. Therefore $\beta_0: \beta_5 = 0$ in this regression equation.

$H3_0$: There is no relationship between *the number of reported robberies* and mean profiles of the *NEO Personality Inventory*. Therefore $\beta_0: \beta_5 = 0$ in this regression equation.

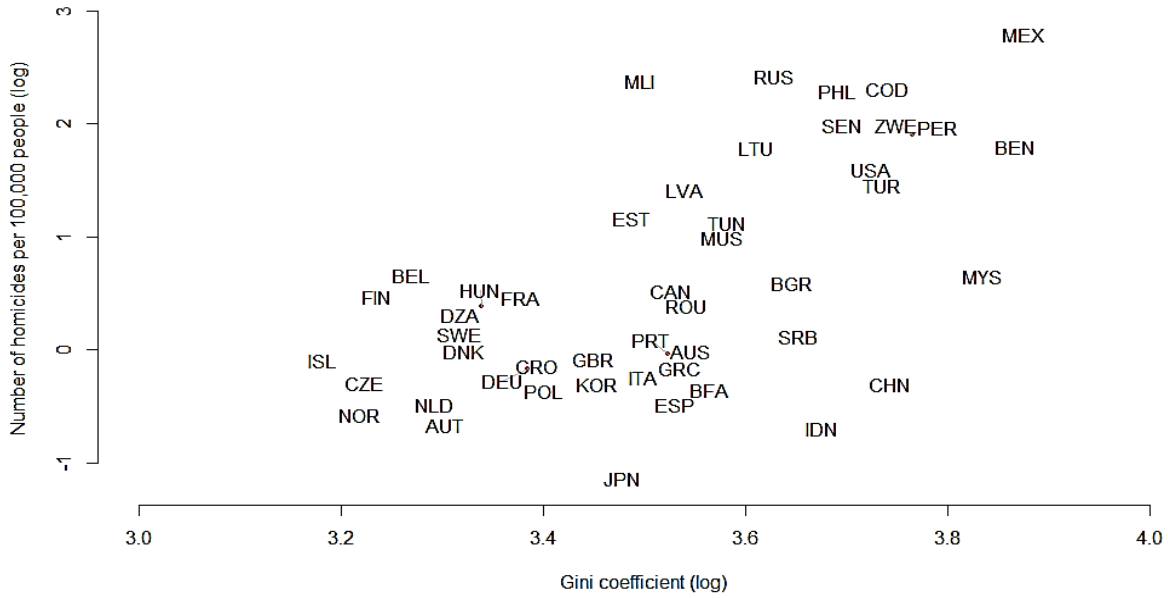
$H4_0$: There is no relationship between *unemployment* and mean profiles of the *NEO Personality Inventory*. Therefore $\beta_0: \beta_5 = 0$ in this regression equation.

3 Regression models and relationship analysis

3.1 Relationship analysis - Gini coefficient and mean profiles of the NEO Personality Inventory

As already stated it has been stated rising inequality of income causes a higher number of pathological behavior. For this analysis, the relationship between those variables is verified. Pearson correlation indicate that there is a significant positive association between Gini coefficient and the number of homicides (to 100 000 people) *R = 0,6; n = 46; p << 0,001* (variables logarithmized – natural log has been used, see fig. 1). On the other hand, the GDP per capita has been shown as a nonsignificant predictor for the number of homicides. More specifically: there is a significant correlation between the GDP per capita and the number of homicides but it vanishes completely when Gini coefficient is included as a control variable.

Fig. 1: Gini coefficient (log) and the number of homicides to 100 000 people (log)



Source: data from World Bank, OECD, and UNDODC (UNODC, 2017; World Bank, 2015)

To analyze the relationship between Gini coefficient and mean profiles of the NEO-PI I used multiple regression analysis where I set Gini coefficient as dependent variable and means of personality traits as independent variables. Specifically, I use a log-log model to fit the data to produce a constant elasticity measurement.

A multiple linear regression was calculated to predict Gini coefficient based on mean profiles of the NEO-PI in countries. A significant regression equation was found *(F (5, 41) = 4,75, p < 0,002)*, with an *Adjusted R-squared 0,29*. Mean profiles of the NEO-PI predicted Gini coefficient as demonstrated in equation 4:

$$\ln(Gini) \sim 4{,}01 - 0{,}21\ln(big5.O) + 1{,}68\ln(big5.C) - 0{,}69\ln(big5.E) - 0{,}94\ln(big5.A) + 0{,}03\ln(big5.N) \quad (4)$$

The mean of the conscientiousness and agreeableness personality trait were significant predictors of Gini coefficient. All assumptions of multiple regression models have been met. Based on the statistical analysis we can reject $H1_0$ about the independence of Gini coefficient and mean profiles of the NEO-PI.

3.2 Relationship analysis - Homicides and mean profiles of the NEO Personality Inventory

To analyze the relationship between the amount of violent crime and mean profiles of the NEO-PI I used multiple regression analysis where I set the number of homicides to 100 000 people as dependent variable and means of personality traits as independent variables. Specifically, I use a log-log model to fit the data to produce a constant elasticity measurement.

A multiple linear regression was calculated to predict the amount of violent crime based on mean profiles of the NEO-PI in countries. A significant regression equation was found *(F (5, 41) = 2,56, p < 0,04)*, with an *Adjusted R-squared 0,15*. Mean profiles of the NEO-PI predicted the amount of violent crime as demonstrated in equation 5:

$$\ln(homicides) \sim 13{,}74 - 3{,}45\ln(big5.O) + 4{,}91\ln(big5.C) + 0{,}44\ln(big5.E) - 5{,}4\ln(big5.A) + 0{,}13\ln(big5.N) \quad (5)$$

The mean of the agreeableness personality trait was a significant predictor of the amount of violent crime. Also, the mean of the conscientiousness and openness were on the edge of significance, therefore its influence will be also considered. All assumptions of multiple regression models have been met. Based on the statistical analysis we can reject $H2_0$ about the independence of the amount of violent crime and mean profiles of the NEO Personality Inventory.

Table 1 summarizes both regressions analysis.

Tab. 1: β coefficients of regression functions, significance, and standard deviation

Analyzed predictor	Impact of the predictor, *(st.deviation)* and its significance on Gini coefficient	Impact of the predictor, *(st.deviation)* and its significance on the number of homicides
(Intercept)	4,01	13,74
	(4,7)	*(28,35)*
ln(Big5.O)	-0,21	-3,45 .
	(0,33)	*(1,98)*
ln(Big5.C)	1,68 ***	4,91 .
	(0,44)	*(2,66)*
ln(Big5.E)	-0,69	0,44
	(0,44)	*(2,64)*
ln(Big5.A)	-0,94 *	-5,4 *
	(0,4)	*(2,42)*
ln(Big5.N)	0,03	0,13
	(0,46)	*(2,74)*

From the table 1 is clearly visible, that the mean of the conscientiousness and agreeableness personality trait are not only significant (or on the edge of significance) predictors to Gini coefficient and to the number of homicides but also the influence on both dependent variables is heading in the same direction (positive correlation for conscientiousness and negative correlation for agreeableness).

Negative correlation with agreeableness personality trait is easier to understand. A person with a high score on this personality trait tends to be more trusted, altruistic, modest and compliant (Costa & McCrae, 1992). We can assume that when whole society has tendencies shift to those attributes the inequality of income would tend to lower levels. Also, those attributes could be directly linked to the numbers of violent crimes – more altruistic and modest society would have fewer homicides.

Interestingly, if we analyze mean of agreeableness personality trait in relationship to culture dimensions we find that agreeableness is significantly negatively correlated with masculinity and uncertainty avoidance culture dimension (Hofstede & McCrae, 2004). Low level of masculinity dimension is defined as a preference for cooperation, modesty, caring for the weak and quality of life (Hofstede, Hofstede, & Minkov, 2010). This could be easily linked to lower levels of violent crime as well as tendency to reduce (income) inequalities.

The uncertainty avoidance culture dimension does not show clear reasoning how it should influence violent crime or tendency to (income) inequalities. Studies show that high level of uncertainty avoidance might be linked to adopting a rigid set of rules and developing strictly hierarchical organizations. But there are two factors required – low-level agreeableness (which is truly significant by statistical analysis) and high neuroticism (which has no significant relationship in the analysis) (Hofstede & McCrae, 2004). Therefore, a conclusion based on

cultural dimensions cannot be definitively established based on the relationship with uncertainty avoidance culture dimension.

With conscientiousness, personality trait is perhaps harder to find any connection between both dependent variables. Conscientious people tend to be more orderly and industrious. The crucial connection seems to be in orderliness. A society with tendencies towards higher orderliness produces more strict hierarchies with more boundaries and restrictions. The extremes of orderly societies are dictatures. Either the "soft" version of stricter hierarchical society or "hard" dictator regimes the circumstances produce higher income inequalities.

Crime is a consequence of this social structure. In societies which generate a large group of people with none or very little property while the luxurious and easy life is in sight, there is a high risk of instability. Why? The lowest class in these societies has very much to gain from the rich. But not very much to lose. Especially young men in these societies are the source of social unrests (Daly, 2016). These moods in society do not always immediately trigger riots, but they tend to create higher chances of violent outbreaks.

Perhaps a better angle of view on the relationship between conscientiousness, income inequalities, and violent crime could be seen through correlated culture dimension which is power distance. This dimension measures tendencies to the extent to which the less powerful members of organizations and institutions (like the family) accept and expect that power and sources are distributed unequally (Hofstede et al., 2010). The relationship to income inequalities follows from the definition. As mentioned this is reflected by orderliness but not in a straightforward way as in power distance culture dimension. The reasoning under relationship with violent crimes stands analogical.

3.3 Relationship analysis - Property crime and mean profiles of the NEO Personality Inventory

As stated, this paper use data on reported robberies (number of robberies of 100 000 people) as a proxy for property crime.

Contrary to Fajnzylber (2002) this analysis shows no significant correlation between property crime and income inequality. Analysis identifies relationship $R = 0,08; n = 46; p = 0,59$ which cannot be considered substantial in any way of interpretation. As shown, the dataset is, in this case, an inappropriate procedure for searching for the relationship between the variables. The dynamic dataset used in Fajnzylber (2002) shows a significant relationship between variables. A likely explanation may be that in less developed economies, state security

forces do not function effectively enough to be able to accept and record less serious crime reports. For this reason, more developed economies will have a long-term higher share of property crime - simply because state security forces work more efficiently.

Given the nonsignificant relationship between variables, no further analysis was performed. $H3_0$ based on analyzed data cannot be resolved.

3.4 Relationship analysis - unemployment and mean profiles of the NEO Personality Inventory

To analyze the relationship between unemployment and mean profiles of the NEO-PI I used multiple regression analysis where I set unemployment as dependent variable and means of personality traits as independent variables. Specifically, I use a log-log model to fit the data to produce a constant elasticity measurement. Nevertheless, it is common knowledge that best predictor of unemployment is by far the economic growth. Therefore, the regression equation adds economic growth as a control variable. Moreover, the Gini coefficient is also included as a control to avoid overlapping in further conclusions which include previous analysis.

A multiple linear regression was calculated to predict unemployment based on mean profiles of the NEO-PI in countries. A significant regression equation was found ($F\ (7, 39) = 3{,}81$, $p < 0{,}003$), with an *Adjusted R-squared 0,30*. Mean profiles of the NEO-PI predicted unemployment as demonstrated in equation 6:

$$\ln(unemployment) \sim (-21{,}27) - 2{,}15\ln(big5.O) + 3{,}93\ln(big5.C) + 2{,}59\ln(big5.E) - 1{,}13\ln(big5.A) + 3{,}41\ln(big5.N) + controls \quad (6)$$

The mean of the openness, conscientiousness, extraversion and neuroticism personality trait were significant predictors of unemployment. Also, control variable *economic growth* has been shown as a significant predictor of unemployment (as expected). All assumptions of multiple regression models have been met. Based on the statistical analysis we can reject $H4_0$ about the independence of unemployment and mean profiles of the NEO Personality Inventory.

The openness and neuroticism personality traits seem to influence the rate of unemployment consistently with an intuitive assumption – higher openness would predict lower unemployment and higher neuroticism would predict higher unemployment. This finding is consistent with previous researches like from Uysal and Pohlmeier (2011).

The conscientiousness and extraversion traits not only have the opposite relationship than which could be intuitively expected but more importantly contradict previous finding in this field (Uysal & Pohlmeier, 2011). Because of this, no reliable explanation can be provided. One possible reason for this inconsistency is a quite low resolution of this analysis. We might

assume, that more heterogeneous groups are included under the aggregate unemployment rate, and with more detailed data, a less paradoxical relationship could be found by hierarchical analysis.

4 Conclusion

On current data from World Bank, OECD, ILOSTAT, UNODC and the mean scores of the NEO-PI traits, this paper analyzes possible relationship between income inequality, pathological behavior, unemployment and personality traits.

Even though used data has static character, analyze shows a significant positive relationship between Gini coefficient and conscientiousness personality trait. The possible reason could be found in orderliness (which is subdimension of conscientiousness), where more orderly society could produce more strict hierarchies with more boundaries and restrictions – thus higher income inequality. Also, significant negative correlation with agreeableness personality trait has been found. I proposed an explanation that society with higher agreeableness (as with higher agreeable person) is more trusted, altruistic, modest and compliant. Therefore, via that behavior, the inequality of income would tend to lower levels.

Same personality traits with same directions have been shown as predictors of violent crime. Similarly to Gini coefficient, more agreeable society - more altruistic and modest society - would generate fewer homicides. For conscientiousness, it is possible explanation through social structures. When society generates stricter "caste" system, with low chance to improve, the lowest class in these societies has very much to gain and not much to lose.

An analysis of the relationship between personality traits and unemployment and economic crime could not be concluded with reliable conclusions. In these two cases, data proved to be inadequate, whether due to its static character or low resolution. Although some relationships in the analysis of unemployment appear to be significant, some are paradoxical and there is a strong suspicion of a second order error.

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