UNIVERSIDAD COMPLUTENSE DE MADRID
FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

TESIS DOCTORAL

Inequality, growth and opportunity: the case of Russia

Desigualdad, crecimiento y oportunidad: el caso de Rusia

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

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Madrid

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FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

Programa de Doctorado en Economía

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[1]*These regions are not used in the study.

AGRADECIMIENTOS

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RESUMEN

La tesis estudia la relación entre desigualdad, crecimiento y oportunidades para el caso de Rusia en la época moderna, entre los años 2000-2015. Se ha realizado un estudio empírico exhaustivo para estimar la relación entre estos tres elementos.

En el Capítulo 1, estimamos el efecto del nivel de desarrollo económico sobre la desigualdad. Intentamos determinar si la hipótesis clásica de la curva de Kuznets (1955) es aplicable a Rusia. La idea de Kuznets era que la desigualdad de ingresos primero aumenta con el crecimiento económico en las etapas bajas de desarrollo y luego disminuye a medida que la economía madura. Hemos encontrado la evidencia empírica de la curva aplicable a las regiones rusas. También hemos tomado en consideración el problema de la causalidad inversa utilizando el metodo de variables instrumentales basado en los instrumentos externos. Además, para la robustez adicional hemos usado el método System GMM, que implica dos regresiones: una en las primera diferencias y otra en los niveles. Para los instrumentos externos, hemos utilizado la exportación neta de petróleo per cápita y el volumen de comercio per cápita como instrumentos. Si no implicamos el término cuadrático, nuestras estimaciones muestran un efecto positivo robusto significativo del desarrollo económico sobre la desigualdad. Por lo tanto, asumimos que sucede debido al hecho de que Rusia todavía se encuentra en el primer alza de la curva y aún no ha alcanzado niveles suficientes de desarrollo para bajar la desigualdad.

En el Capítulo 2, estimamos la relación inversa entre desigualdad y crecimiento. Analizamos el efecto de la desigualdad tanto en el crecimiento económico total de 5 años como en el crecimiento de los ingresos por quintiles. Aquí, también utilizamos el método de variables instrumentales para la estimación de modelos de datos de panel dinámicos teniendo en cuenta el problema de endogeneidad. Usamos el Gini residual no debido a los cambios en el PIB per cápita obtenidos en el Capítulo 1 para instrumentos externos y utilizamos System GMM nuevamente para el modelado de instrumentos internos para el análisis de robustez. Hemos descubierto un fuerte efecto positivo significativo de la desigualdad en el crecimiento total, así como en el crecimiento de todos los grupos de ingresos, incluso los más pobres. Estos hallazgos corresponden a la hipótesis de Galor y Tsiddon (1997) que afirma que la desigualdad es de hecho útil para el crecimiento en economías subdesarrolladas, mientras que es perjudicial para el crecimiento de las economías ricas.

En el Capítulo 3, estimamos hasta qué punto los ingresos de un individuo dependen de factores macroeconómicos regionales que están fuera de su control. Milanovic (2013) argumentó que casi dos tercios de los ingresos de un individuo dependen únicamente del Índice de Gini y del PIB per

cápita del país de residencia. Hemos realizado el mismo tipo de investigación, pero a nivel regional para datos traversales para el año 2015. Hemos descubierto que aproximadamente una cuarta parte de los ingresos personales depende de la región en la que reside. Otro resultado importante de este capítulo es que, para Rusia, la desigualdad total está más correlacionada con las desigualdades entre regiones que con la desigualdad intraregional, ya que casi toda la variación en el ingreso personal se debe al PIB per cápita regional.

Todos estos hallazgos generalmente nos proporcionan dos conclusiones importantes principales. Primero, la mayoría de las regiones rusas todavía están situadas en las etapas más bajas del desarrollo, por lo que la desigualdad se relaciona positivamente con el crecimiento en ambos sentidos. Segundo, los ingresos en Rusia están altamente concentrados tanto a nivel regional como individual.

ABSTRACT

The thesis covers the relation triad between inequality, growth and opportunity based on the case of modern Russia in 2000-2015. A comprehensive empirical study has been conducted in order to estimate the relationship between these three elements.

In Chapter 1, we estimate the effect of the level of economic development on inequality. We try to determine whether the classical Kuznets curve hypothesis (1955) is applicable to Russia. The idea of Kuznets was that income inequality first rises with economic growth on the low stages of development and then falls as the economy matures. We have found the empirical evidence of the curve applicable for the Russian regions. We have also taken into consideration the reverse casualty problem by using the instrumental variables (IV) method. For the external instruments, we have used the net oil export per capita and trade per capita as instruments. For the additional robustness we have also used the System GMM method, which implies two functions – one in first difference and the other one in levels. If we do not imply the quadratic term, our estimations show a significant robust positive effect of economic development on inequality. Thus, we assume that it happens due to the fact that Russia is still on the first upbeat of the curve and it has not yet reached sufficient levels of development to tear down inequality.

In Chapter 2, we estimate the reverse relation between inequality and growth. We analyse the effect of inequality both on the total 5-year growth and on the income growth by income quintiles. Here, we also imply the instrumental variables (IV) method for dynamic panel data models taking into consideration the endogeneity problem. We use the residual Gini not due to the GDP per capita changes obtained in Chapter 1 for external instruments, and once more, we use System GMM again for internal instruments modelling for the robustness checks. We have found out a robust significant positive effect of inequality on total growth as well as on the growth of all income groups, even the poorest ones. These findings correspond to Galor and Tsiddon's (1997) hypothesis that states that inequality is in fact helpful for growth in underdeveloped economies, while it is harmful for the growth of rich economies.

In Chapter 3, we estimate the extent to which one's personal income depends on regional macroeconomic factors beyond one's control. Milanovic (2013) argued that almost two thirds of one's personal income depends uniquely on the Gini Index and the GDP per capita of the country of residents. We have conducted the same type of research, but on the regional level for cross-sectional data for the year 2015. We have found out that around one fourth of one's income depends on the region in which one resides. Another important result of this chapter is that, for Russia, the total inequality is more correlated to between regional inequalities than to within

regional inequality, as almost all the variance in personal income is due to the regional GDP per capita.

All these findings generally provide us with two main important conclusions. First, most of the Russian regions are still situated on the lower stages of development, which is why inequality is positively related to growth both ways. Second, income in Russia is highly concentrated both on the regional and individual levels.

INTRODUCTION

Inequality has always been one of the most discussed topics on the economic, political, social and philosophical agenda. It is no surprise, as it is highly related with the concepts of justice and fairness, which are inseparable from the human nature itself. Throughout the ages philosophers from Aristoteles to Slavoj Zizek and economists from Adam Smith to Thomas Piketty have been trying to provide a comprehensive answer to a lot of questions related to this delicate issue. What is inequality? How many types of inequality are there? Is it justified by the right of birth or is it a moral duty for us all to fight against it? Is total equality absolutely desirable within society, and if not, where are the limits of 'good' inequality? And so on.

Economists were the ones who took a more practical approach to the issue focusing primarily on income and wealth inequality. Apart from simply measuring inequalities between or within countries, they also concentrate on relating it to other concepts, such as economic development, education level, market openness, technology or the quality of institutions.

Thus, the debate on the relationship between income inequality and growth is once more on the agendas of pundits and policy-makers. Despite the fact that income inequality and growth were at the centre of the economic debate for decades, the presence of many unresolved questions brought this debate to a dead-end street. However, the financial crisis of 2007-2008 and the Great Recession which followed, with the subsequent rise in inequality in many countries all over the world, and the recent theoretical and empirical developments in this field have prompted a renovated discussion on the influence of income and wealth inequality upon economic growth and vice-versa.

This thesis covers different theoretical aspects of income inequality employing Russian economy on the regional level as a case study to conduct econometric estimations. Before we start, we find it useful to provide in the introduction various important remarks on the Russian economy as well as the general economic outlook. Then in the first chapter, we discuss whether the Kuznets curve hypothesis, which connects inequality and growth, is valid for the case of Russia. In the second chapter, we investigate the reverse relation of how inequality affects the subsequent economic growth. Finally, in the third chapter, we analyse how much of Russians' personal income depends on the macroeconomic factors of their region of residence beyond their control. In the end, we make general conclusions based on the whole work as well as provide some insight on the possible future lines of research.

Introductory Remarks

In this section we provide some remarks and clarifications for a better and clearer understanding of our investigation. First, we give a short outlook on the Russian economy after the collapse of the Soviet Union and on the main economic indexes involved in this work. Second, we clarify some peculiarities of the Russian fiscal system, as the issues related to the redistribution through taxes are inseparable from almost any inequality-growth debate. Third, we comment on the issue of the massive migration which took place after the fall of the Soviet Union, which could affect our models' estimations. Then we provide some information on the regional structure of the Russian Federation through the years of study and, finally, we give a short literature review on the inequality-growth and opportunity studies on the modern Russia (1990-2015).

Russia's Economic Outlook

The Russian Federation, with a territory of 17.1 million square kilometres and a population of 143.8 million people in 2014, is the largest and the ninth most populous country in the world; besides, with the total GDP at market prices of $1.861 trillion in 2014, it is the tenth largest world economy (World Bank, 2015). Although in terms of GDP per capita of $13.220, Russia is only the 46th country in the world, the World Bank describes the country as 'high-income non-OECD'. Still, 11.2% of its population lived below the national poverty line in 2014.

After the fall of the Soviet Union and the central planned economic system in 1991, Russia has experienced a dramatic economic and political transformation, which hugely affected the country's economic development, social structure and economic and political opportunities for its citizens. During the last 25 years, it has suffered three huge crises, the first one in 1998, when the government announced bankruptcy, the second one in 2009 following the global financial crisis and the Great Recession which followed and the last one in 2014 due to the political and military conflict with Ukraine and the successive economic crises.

Figure 1 shows the average GDP per capita PPP in constant 2011 international dollars for the Russian Federation, OECD members and world's global average for 1995-2015. We can see that the dynamics of this index for Russia during these years has been much better as the global mean, although in 1995 it started very close to it. However, it is still a long way to go to reach the OECD countries numbers, where GDP per capita is almost twice as high.

Figure 1 GDP per capita 1995-2015

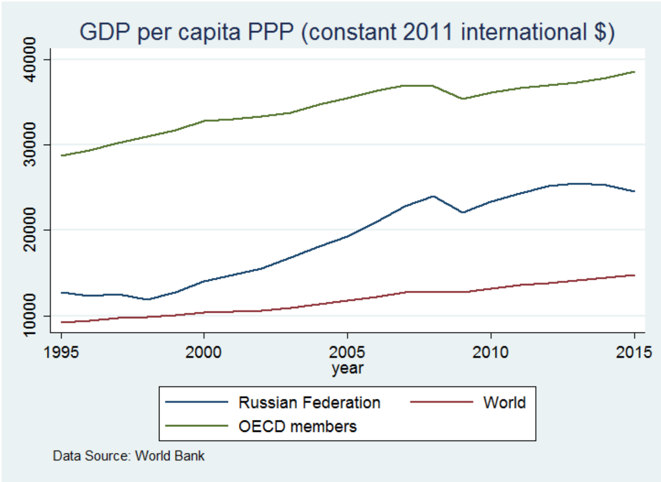
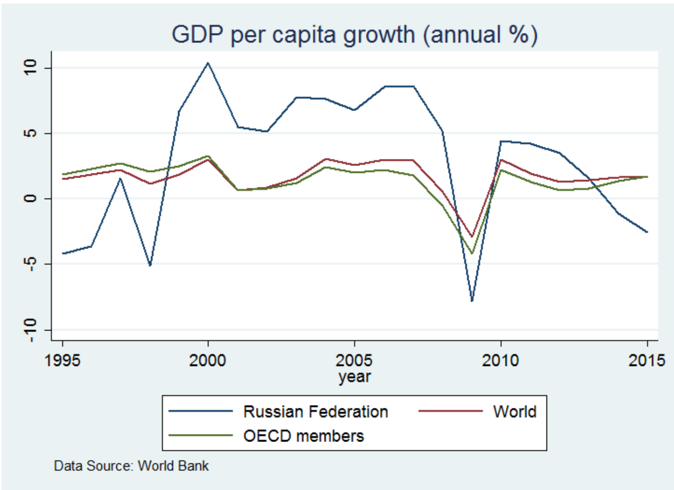


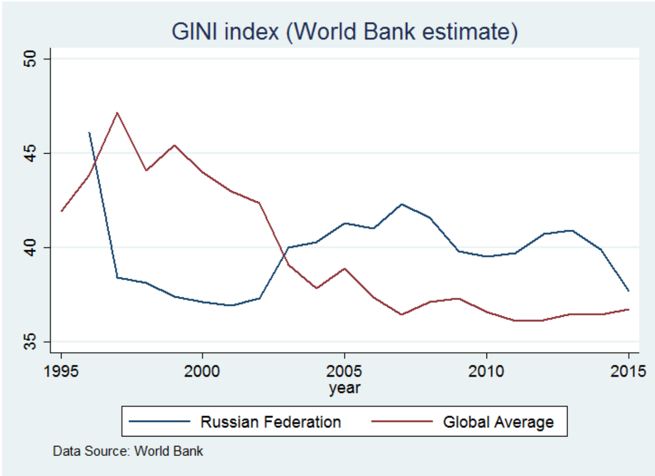
Figure 2 shows that the annual GDP growth rates have been very volatile over the course of these years. However, after the crisis of 1998, being a resource-based economy due to high oil and gas prices, Russia experienced a high-rate growth during the first decade of the 2000s (about 5 percent points higher than the global average and OECD countries), which ceased only with the global crisis of 2008. After the three years of recuperation (2010-2013), the growth rates started to decrease once more due to the political crisis of 2014 and following international economic sanctions.

Figure 2 GDP Growth 1995-2015



As for inequality measured by the Gini Index, Figure 3 shows that it has been also quite volatile throughout the years. The World Bank does not have any data available for 1995, but surprisingly, in 1996, just five years after the fall of communism with the believed extremely low levels of inequality, on the contrary, the country's inequality was considerably high. Then, it had been going down steadily until 2002, when it started to be going up again achieving its peak in 2007. After that, it went down and up again, when in 2013 it started to drop, almost achieving its historically lowest levels.

Figure 3 Gini Index 1995-2015



Regional Structure of the Russian Federation

Currently Russia consists of eighty-three regions or federal subjects. However, throughout the period of our research 2000-2015, the regional structure of Russia has been modified several times by grouping some regions (in the beginning of observation, there were 89 of them). For the research goal, we consider these regions as one from the very beginning of observation by summing the data. Besides, there is very little data only on a few variables on the Chechen Republic due to two military conflicts that have taken place during the period, so we have decided to drop this region, so that leaves us only with 82 regions.

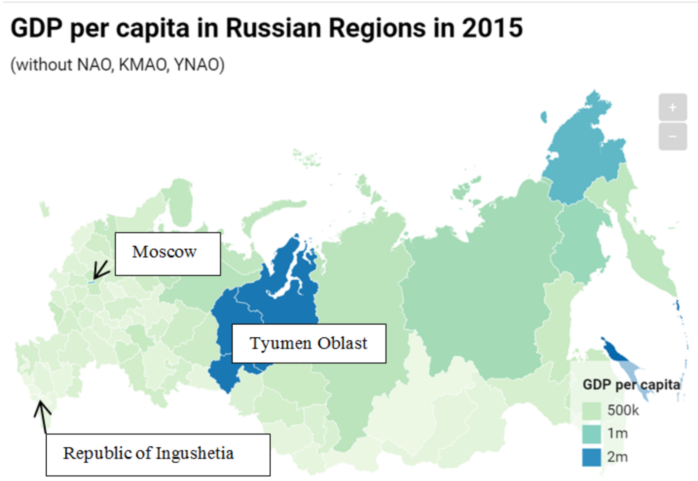
Moreover, due to a peculiar organisational structure of the Autonomous Okrugs of Russian Federation, which are pretty large territorial divisions but with the extremely small population (less than 50.000 people) within a larger federal subject and in fact are semi-autonomous. In the official statistics, the larger regions to which they belong do not even have the data without taking into the consideration this small sub-division. Thus, we also drop these three Okrugs (Nenets Autonomous Okrug – NAO , Khanty-Mansi Autonomous Okrug – Yugra - KMAO, Yamalo-Nenets Autonomous Okrug - YNAO), but without actually losing the information because this information counts within larger regions (Arkhangelsk Oblast and Tyumen Oblast). So finally, it leaves us with 79 regions[2].

All these federal subjects are very diverse economically, demographically, climatically, and even culturally and ethnically. Figure 4 shows the regional GDP per capita in roubles which is in fact a proxy for between-regions inequality. For example, in 2009, the average GDP per capita of $57,175 PPP in the Tyumen Oblast, the richest region of Russia, can be compared with that of

[2] See List of the Regions of the Russian Federation for the full list.

Norway, while the average GDP per capita of $3,494 PPP in the Republic of Ingushetia, the poorest Russian region, can be compared with that of Iraq (Auzan, 2011).

Figure 4 GDP per capita in roubles in Russian Regions in 2015 (map, without NAO, KMAO, and YNAO)



Speaking about growth, out of eighty-three Russian regions, only a few oil and gas extracting ones, such as Tyumen Oblast, Khanty-Mansi Autonomous Okrug, Yamalo-Nenets Autonomous Okrug and the Republic of Tatarstan, and Moscow due to its administrative status, as the capital city where all the main Russian oil and gas producers have the headquarters, have benefited from this unprecedented growth (Remington, 2015), while all remaining regions stayed highly subsidised. Figure 5 shows the regional GDP per capita in roubles for all regions, if we consider NAO, KMAO and YNAO separately.

Figure 5 GDP per capita in the Russian Regions in 2015 (map, with NAO, KMAO, and YNAO)

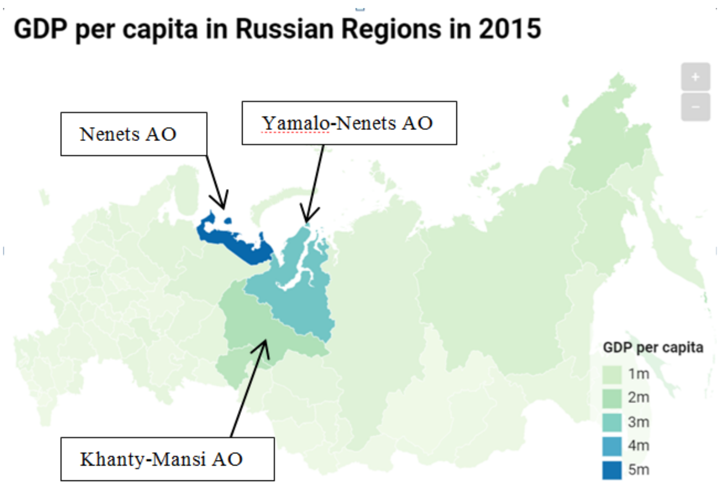


Figure 6 shows the disparities in the regional Gini index, which measures within-region inequality. We can see that there is no clear pattern here; however the regions with highest GDP per capita seem to be the regions with the highest within inequality as well.

Figure 6 Gini Index in Russian Regions in 2015 (map)

Fiscal System and Redistribution

Currently, Russia has a three-level tax system (federal, regional and local taxes), which makes it possible to redistribute federal revenues among the regions. The distinction between federal, regional and local taxes depends on the level of legislature that is entitled to establish rates for that kind of tax. Federal rates are explicitly set by the Tax Code, while regional tax rates are set by regional laws but limited by the Code.

According to the Article 13 of the Tax Code of the Russian Federation, federal taxes are VAT, excise taxes, personal income tax, corporate income tax, mining tax, water tax, custom duties, and state duties. Article 14 of the Tax Code states that corporate property tax, gambling tax and transport tax are regional taxes. Finally, Article 15 of the Code states that land tax, personal property tax and commerce fee are local taxes.

In such a way, revenues from the most important taxes go to the central federal budget opening to the federal government vast financial possibilities to redistribute both *between* regions and *within* regions between different individuals and groups. The inefficient way of some regions to spend the federal transfers and subsidies, for example, the well-known case of the Chechen Republic provokes a lot of social irritation and even public demonstrations (Yashin, 2016).

Thus, redistribution through the fiscal system in Russia is a very complex issue to be studied. Moreover, due to the high level of corruption, the official data on expense and income items of all the three levels of budgets does not provide clear and well-structured information on how many resources are actually redistributed or simply taken out from the federal budget. These issues are beyond the scope of this thesis that is why all the data we use are *before taxes*. However, these topics can be considered for the future investigation in the field.

Migration

Moreover, the issue of migration, both within Russia and between Russia and neighbour countries is also very important to analyse in the light of the topic of inequality, as the country has a huge potential for geographical labour reallocation. Due to the central planned economy of the USSR, before the 1990s the initial allocation of labour was not equilibrated, as soviet labour and industrialisation policies pursued geopolitical aims rather than economic ones (Guriev, 2015). In the 1990s and 2000s, a massive migration took place to compensate for this disequilibrium.

Besides, as Russia maintains one of the world's most liberal immigration policies, after the collapse of the Soviet Union, huge cities, such as Moscow, Saint Petersburg or Krasnodar have become centres of immigration of unqualified workers, both from the former Soviet Republics, primarily from underdeveloped Uzbekistan and Tajikistan, and from rural areas and underdeveloped regions of the Russian Federation itself. The affluence of illegal migration also took place provoking social debate and conflicts, including some burst of violence because of the xenophobic reasons. On the contrary, low-income regions, especially, their rural areas have become almost abandoned causing a huge decline in rural population and economic activity.

In our study we add net migration in the augmented models to pursue our secondary goal of analysing whether it has any significant effect both on inequality and growth. However, we consider that this issue may need some deeper investigation in a separate study.

Database

For the most of the estimations the data we use is macroeconomic and proceeds from the Rosstat Database. Rosstat is the Russian Federal State Statistics Service, the governmental statistics agency in Russia, which was created on the base of Goskomstat after the collapse of the Soviet Union.[3] Goskomstat was created in 1987 to replace the Central Statistical Administration, while maintaining the same basic functions in the collection, analysis, publication and distribution of state statistics, including economic, social, and population statistics.

In 2007, the Unified Interdepartmental Information and Statistical System (EMISS) was created in the framework of the implementation of the federal target program ‘Development of Russian State Statistics in 2007-2011’. The EMISS is operated by the Ministry of Communications and Mass Communications of the Russian Federation, but is coordinated by Rosstat. The purpose of

[3]Russian: Федеральная служба государственной статистики, Federal'naya sluzhba gosudarstvennoi statistiki
Russian: Государственный комитет по статистике, Gosudarstvennyi komitet po statistike, or, in English, the State Committee for Statistics

this system is to provide access to official statistical information, including metadata generated in accordance with the federal statistical work plan, using the data of state authorities, local governments, legal entities and individuals. Access to official statistical information is free of charge and non-discriminatory. This system allows an easy online access to the most of the Rosstat information.

The main source of data for our particular research comes from the Rosstat Publication 'Regions of Russia. Socio-Economic Indicators' for the years 2002-2016.[4] The data for the publication is obtained by state statistical agencies, from enterprises, organisations and the general public in the course of statistical observations, censuses, and sample surveys. Additionally, it contains the data of the ministries and departments of the Russian Federation. The data has been accessed through EMISS.[5] More detailed information on the data and variables are provided separately for each chapter.

Earlier Research on Inequality, Growth and Opportunity in Russia

In 2000s and 2010s, there have been some attempts to investigate these issues in Russia, although none of them have had the same focus as we have. One part of the research has been focused on regional income disparities. For example, Fedorov (2002) concentrates on regional inequality in 1990-1999 by calculating Estaban-Reay, Wolfson and Kanbur-Zhang indexes of polarization. He concludes that regional polarization is driven by structural differences between regions rather than geographic or political ones, while Litvintseva (2007) who investigated on regional inequalities in Russia in 2000-2004 attributes them to regional differences in the purchasing power of the national currency - rouble. Remington (2015) considers that regional differences in Russia and China and the lack of their convergence are attributed to both countries' communist institutional legacies.

Another group of researchers, on the contrary, analyse Russia as a whole without taking into consideration possible regional differences. Dang et al (2018) discovers rising income levels and decreasing inequality in Russia in 1994-2015, with the latter being mostly caused by pro-poor growth rather than redistribution. Also he investigates occupational mobility issues and concludes that transition to the formal sector, a full-time job, or a higher-skills job is statistically associated with higher income levels. Novokmet, Piketty and Zucman (2017) conduct a very peculiar research on income and wealth inequality in Russia between 1990 and 2015 and find out

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[4] These publications are available in its digital version on http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/publications/catalog/doc_1138623506156. [2019, June]
[5] The data can be found on https://fedstat.ru/organizations/.[2019, June]

that official measures severely underestimate the rise of inequality since 1990. They estimate that top income shares are now similar to (or higher than) the levels observed in the United States. They relate it to the fact that 'the wealth held offshore by rich Russians is about three times larger than official net foreign reserves, and is comparable in magnitude to total household financial assets held in Russia' (Novokmet, Piketty, Zucman, 2017).

Finally, it is to be noted that there is no study on inequality of opportunity in Russia or on which extend the region of birth as a circumstance beyond one's control can affect individual income outcomes. Thus, although there are several recent studies on Russia in the field of inequality and economic development, they are focused on exclusively on the reasons of regional income differences or in inequality patterns in Russia is a whole. There is no research which connects both elements in one system and analyse how they affect each other on the macroeconomic level and how they affect the individual outcomes.

CHAPTER 1. INCOME INEQUALITY IN RUSSIA: *IS THE KUZNETS CURVE A VALID HYPOTHESIS?*

I. Introduction

The link between inequality and economic development is one of the most debated topics in inequality studies. How does economic development affect inequality? Does it make it go down, as the nation becomes richer, or on the contrary, does it push it up benefiting the rich? The most known hypothesis that connects these concepts is the Kuznets curve hypothesis, developed by Simon Kuznets back in 1955. It suggests the inverted-U relation between the two, i.e. on the earlier stages of development, the inequality goes up, as the national income grows, then it reaches a certain turning point and starts to go down, while the economy continues to grow.

There is a plenty of research investigating the empirical existence of the curve, but the conclusions are still ambiguous. Most researchers use the cross-sectional country-level data and a set of control variables to see, whether it is the development itself that makes the inequality to go down at a certain point in time, or whether there are other factors outside to create such an effect. However, even the most certain results are still left open for interpretation due to the endogeneity problem. There are two possible explications of the endogeneity of the variables: the reverse causality, i.e. it is the inequality that affects development; or the existence of another variable or variables that affects both.

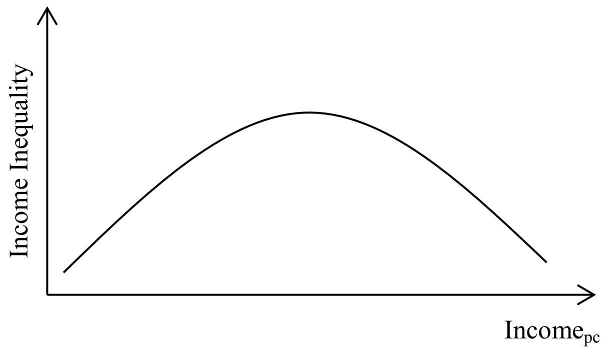
In this study, we try to deal with this problem using the available econometric methods. We analyse not only the 'classic' static model, but also the dynamic model and instrumental variables model. We start with the literature review, which sums up not only classical studies, but also the newest advances in inequality-development studies, then we proceed to explain all the models we employ in the study and the related econometric issues. Afterwards, we present our results with the extensive robustness checks and, finally, we present the discussion and some conclusions.

II. Literature Review and Contribution

The main theoretical approach to assessing the way how growth affects income inequality is the Kuznets curve (1955), later mathematically developed by Robinson (1976), who suggests that inequality first rises and then falls forming an inverted-U shape as the economy develops. This approach is based on the assumption that, initially, the national economy consists of just two sectors – agriculture and industry, and that the development is associated with the employees' movement from the former to the latter.

At the beginning, the income per capita is low, as well as the inequality, due to the fact that the huge majority of the population is employed in the agriculture sector, associated with low wages and low productivity of labour. As the industrialisation and subsequent urbanisation are considered the main sources of the initial economic development, more and more citizens start to move to urban areas to work in the industry, where wages are higher in comparison with the agricultural ones; the inequality begins to go up. Later, as the size and the importance of the agricultural sector diminish, so that the majority of the population works in high-wages industries, inequality starts to go down as well, and an inverted-U curve appears (Figure 7).

Figure 7 Kuznets Curve (1955)



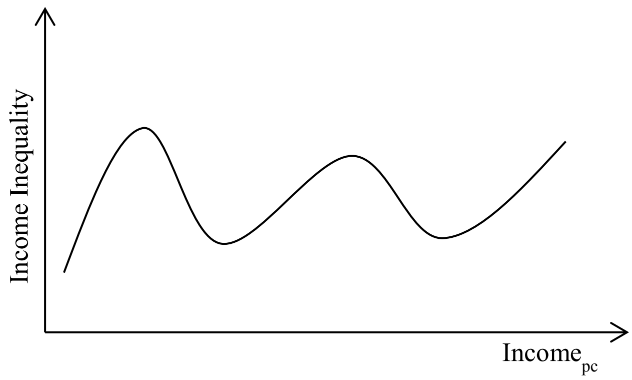
A huge number of scholars use this approach in the studies (Fields, 2001). More recent theoretical models, although assume the existence of the Kuznets' curve, propose different reasons for this change. For instance, Greenwood and Jovanovic (1990) argue that this shift occurs due to the change from financially unsophisticated systems to the modern inclusive and complex ones. Furthermore, Milanovic (1994) claims that besides purely economic factors, as the level of per capita income, the decrease in inequality in developed countries is mainly caused by the social-choice factors, such as the size of social transfers and the level of employment in the public sector.

In another approach, Galor and Tsiddon (1997) argue that it is the composition of human capital that is an important factor in the determination of the inequality and the economic development pattern. The polarisation of investment in human capital in the early stages of development is crucial to enhance growth, which will later pull the inequality down by a more equal distribution of human development.

Moreover, through the decades, a number of empirical investigations have been conducted, and although these generally confirm the hypothesis (Anand and Kanbur, 1993; Li, Squire and Zou, 1998), the results are still ambiguous, as other economists have not found any evidence of the existence of the curve (Gallup, 2012).

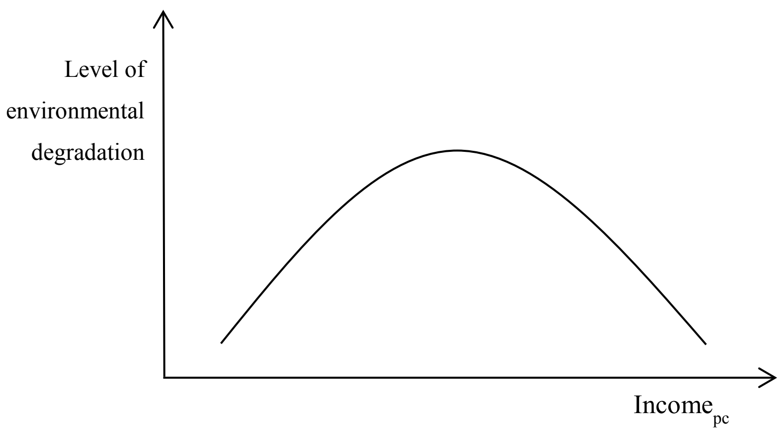
Besides, over the past twenty years, some inequality researchers have begun to empirically detect the second rise in inequality in rich countries (List and Gallet, 1999), which once more provoked a lot of academic discussion. One of the possible reasons for that is another structural switch from manufacturing to services economy and crucial technological changes. Finally, Milanovic (2016) suggests that in the very long term, Kuznets' curve converts into Kuznets' waves, or cycles, characterised by alternating increases and decreases in inequality (Figure 8).

Figure 8 Kuznets Waves (2016)



Another related concept to be mentioned here is the environmental Kuznets curve that first emerged in the early 1990s, when the 1992 World Bank Development Report was published. Basically, the environmental Kuznets curve suggests that indicators of environmental degradation first rise, and then fall with the increasing income per capita (Figure 9).

Figure 9 Environmental Kuznets Curve (1992)



Due to the lack of data, early empirical studies on the Kuznets curve were conducted on country-level cross-section data (Randolph and Lott, 1993; Anand and Kanbur, 1993), although there is a plenty of recent research that employs the panel data for a set of countries (Barro, 2000; Forbes, 2000; Gallup, 2012; Desbordes and Verardi, 2012; Jovanovic, 2017) or time-series data for the same country (Prados de la Escosura, 2008; Gunaydin, 2015).

However, in our case, regional data for the same country across time (79 regions and 21 years) is used. We consider that this choice gives us an important set of advantages. First, as the problem of data comparability across countries is very prominent in various research papers (Milanovic, 1994), if we use the data on inequality and development only for one country, we end up with the set of comparable data for each variable from the same database. That happens because we do not need to adjust the price levels or make conversions to another currency. Besides, the data-collecting process, sampling method and calculations are the same for all the regions. Second, the data on such a large and heterogeneous country as Russia with diverse levels of development allows us to have sufficient dispersion to make an analysis possible. Third, using panel data helps us to see the actual pattern of inequality changes, as the economy develops. As Gallup (2012) points out: ‘None of this research tested Kuznets hypothesis directly: that income inequality would increase and then decrease as income grew within countries’. But to our consideration, among all this reasons, the most important one is that we can finally answer the question whether pure market economic powers per se can change the inequality patterns through time. It is possible because of the existence of a set of factors, specific for every country, that are unobserved or are difficult to calculate, but can hugely affect overall inequality, are more or less equalised for the same county. Among these factors are labour and tax regulations, institutional quality, market legislation and others.

Besides, as we mentioned in the introduction, the vast majority of studies do not take into consideration the possible endogeneity problem in the regressions. Dollar and Kraay (2002), Lundberg and Squire (2003), and Brueckner, Norris and Gradstein (2014) are some of the few papers which employ various instruments to try to diminish the problem. In this research, we employ both internal and external instruments in our models, contributing significantly to the existing literature.

III. Data: Russia (2000-2015)[6]

As for the time-span of the research, it is to be said that as not all the variables are available for the whole period of twenty years, many of them are available only form 2000 or even 2005, so not all the regressions are run for the complete period. Although the data on regional GDP per capita and Gini Index are available prior to 2000, unfortunately, the data on the instruments (net oil export per capita in international dollars and services per capita in logs) are available only form 2000. That is why we are obliged to start with this particular year and run our regression for 15 years period.

Throughout the research of this chapter we use the variables described in the Table 1.[7] First variable that we use is regional Gini Index. Rosstat provides us with only before-tax Gini Index, which we use throughout the study. We assume that due to the fact that Russia lacks the progressive tax scale (for example, the personal income tax is 13% for all income levels), the difference between before-tax and after-tax would too insignificant to affect the results.[8]

Table 1 General Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini Index	1,264	37.86	3.49	27.6	59.50
ln (GDP pc)	1,264	3.72	0.61	1.51	5.66
Fertility	1,262	1.52	0.32	0.93	3.49
Life Expectancy	1,262	66.92	3.58	53.8	80.05
Unemployment	1,264	8.58	5.79	0.80	64.90
Labour	1,264	61.47	2.92	53.73	71.28
Prof. School	1,264	7.40	6.09	0.07	34.50
College	1,255	15.00	26.04	0	275.40
Migration	1,264	-9.82	102.51	-704.20	2522.50
ln (Services pc)	1,264	9.05	0.76	6.65	11.00
ln (Oil Export pc)	1,048	2.14	3.31	-5.26	10.74
Decile Index	1,264	12.64	3.79	6.10	48.70

One of the most important variables for our estimations is the regional GDP per capita, but we cannot use it in the original state without any transformation, because of the inflation as well as price level differences that can severely disturb our estimations. Fortunately, Rosstat calculates the special Index of Physical Volume of Production, which depicts the actual growth of GDP without the effect of interregional price changes and inflation. We recalculate all the GDP per capita levels in 2000 basic prices, as we see it more convenient to use this year as a benchmark.

[6] For the database description see Introduction.
[7] For the panel data descriptive statistics see Appendix 1.
[8] For more information on the Russian Fiscal System see Introduction.

For other variables, which should be used without inflation (Services per capita), we use the inflation index, which is calculated separately for each region as well.

Figure 10 Income inequality in Regions 2000-2015

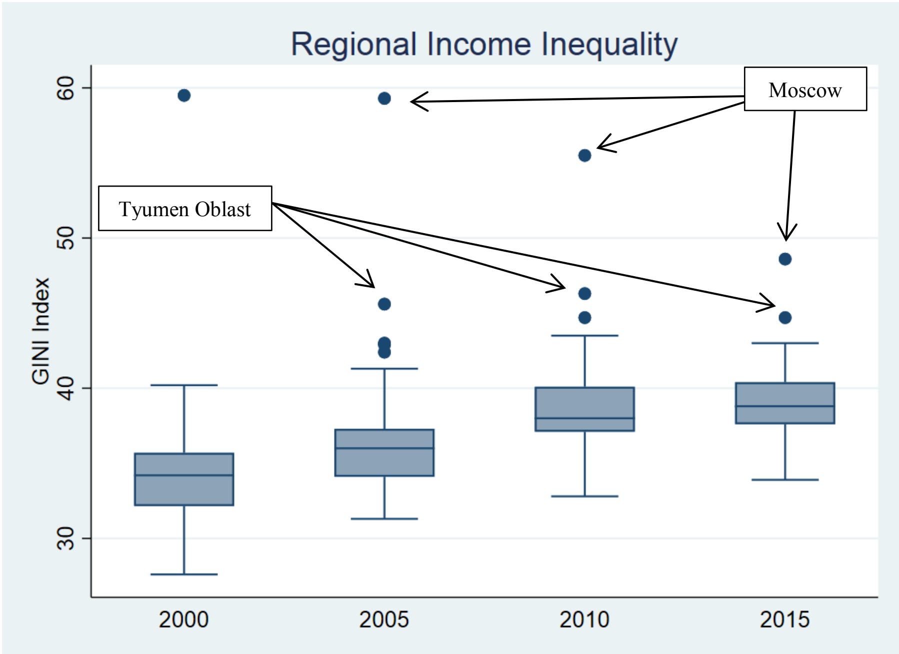


Figure 10 shows us regional Gini Index dynamics from 2000 to 2015. The outlier with the highest inequality is Moscow; the second highest inequality index is of Tyumen Oblast. It can be seen that while inequality in other regions had been going up and down with no particular trend, the inequality in Moscow dropped down dramatically during this period and finally converged with the rest.[9]

IV. Model and Econometric Issues

Basic and Augmented Models

The intuitive model to analyse the Kuznets curve in its pure state for panel data would be:

$$ini_{\ it} = \alpha_0 + \alpha_1 DP\ \ pc_{it} + \alpha_2 DPp\ \ c_{it}^{\ 2} + \varepsilon_{it}, (1)$$

where $Gini_{it}$ is the Regional Gini Index before taxes for the *i* region in the *t* year, $GDPpc_{it}$ is the Regional Gross Domestic Product per capita in 2000 prices (in logs) for the *i* region in the *t* year, ${GDPpc_{it}}^2$ is its quadratic term and $\varepsilon_{it}$is an error term. We use natural logarithm of GDP per capita to mitigate the effect of possible outliers in the regression.

[9] Graphs of Time Series and Heterogeneity on Gini Index and regional GDP per capita are in the Appendix 1.

The quadratic function is used in the model as we assume that, mathematically speaking, the inverted-U form is actually a concave parabola, as Kuznets (1955) suggested. Thus, in order to have a concave form, the coefficient before the explicative variable without a square is to be positive, while the coefficient before the square of this variable is to be negative. The maximum of the function represents a turning point where inequality starts to go down as the income continues to rise.[10]

Besides looking for the simple quadratic relation between development and inequality, we are to include various explicative variables and controls that, according to the literature, can have a significant influence on inequality in our estimations. So we use the following augmented model that we assume to be the best fit:

$$\mathrm{ini}_{it} = \alpha_0 + \alpha_1 \mathrm{DP\ \ pc}_{it} + \alpha_2 \mathrm{DPp\ \ c}_{it}{}^2 + \alpha_3\, \mathrm{Fert}_{it} + \alpha_4\, \mathrm{Life}_{it} + \alpha_5\, \mathrm{Unempl}_{it} + \alpha_6\, \mathrm{Prof\ pc}_{it} + \alpha_7\, \mathrm{College\ pc}_{it} + \alpha_8 \mathrm{Migr\ pc}_{it} + \varepsilon_{it}\ , (2)$$

where, again, ini_{it} is the Regional Gini Index before tax, $\mathrm{DP\ \ pc}_{it}$ is the Regional Gross Domestic Product per capita in 2000 prices (in logs) and $\mathrm{DPp\ \ c}_{it}{}^2$ is its quadratic term and $\varepsilon_{it}$is an error term[11], but now we add a set of controls, which corresponds to the most important demographic indexes. $Fert_{it}$ is the Fertility rate for the *i* region in the *t* year (children per woman in reproductive age), $Life_{it}$ is the Life expectancy for the *i* region in the *t* year (in years), $Unempl_{it}$is the Unemployment rate for the *i* region in the *t* year (in percent), $Prof_{it}$is the number of professional school students for each ten thousand habitants for the *i* region in the *t* year (people), $College_{it}$is the number of college students for each ten thousand habitants for the *i* region in the *t* year (people) and Migr_{it} which is the Net Migration for each 10 thousand habitants.

We add education variables, because it is assumed that education has a huge impact on inequality as it affects the composition of human capital. For example, Galor and Tsiddon (1997) argue that it is an important factor in the determination of the inequality and the economic development pattern. The polarisation of investment in human capital at the early stages of development is crucial to enhance growth, which will later pull the inequality down by a more equal distribution of human development. So in our case we believe that education will have a negative impact on inequality. Having two variables for two different stages of education helps us to distinguish the effect between the two.

[10] Data Summary Statistics, Tests and Preliminary Estimations are in Appendix 1.
[11] Multicollinearity Tests are in Appendix 1.

Also, we include the variable of Net Migration to take into the account the effect of immigration and emigration on overall inequality. According to the empirical findings of McKenzie and Rapoport (2007), emigration increases inequality at lower levels of migration stock and then reduces inequality at higher migration levels. This happens due to the fact that, initially, only individuals from the middle of the asset wealth distribution can afford to migrate, which washes out the middle levels of income distribution, and later when these people send remittances back home, it reduces inequality. On the contrary, the effect of immigration on inequality is seen as positive in the most of the research (Card, 2009), as it widens the gap between high- and low-skilled workers.

Life expectancy and fertility variables are demographic factors that also represent the development of the economy, because it is assumed that the more developed the economy is, the higher the life expectancy and the lower the fertility. Life expectancy is a good proxy for population health as well.

Unemployment and the share of people of working age are important control variables as well because they represent labour market conditions. In some economies, such as Spain, the high unemployment rate is the main channel of inequality. The share of people of working age can affect inequality due to the fact that the lower this share is, the higher the social pressure on the working population to maintain children and elderly people. Thus, by adding all these variables, we control not only for economic, but also for demographic and social development.

Instrumental Variables Method (IV)

Not taking into the consideration the endogeneity problem can bias significantly the regression coefficients as it violates the exogeneity assumption of the Gauss-Markov theorem. In broad terms, endogeneity exists in models in which an independent variable is correlated with the error term. Endogeneity is provoked by the existence of endogenous variables, that is, variables that are determined by the model itself on the contrary of exogenous variables, which are predetermined.

In our case, the possible reason can be the reverse causality, when it is actually inequality that provokes growth changes. Indeed, a large amount of literature exists that investigates this very correlation. In addition, there is the possibility of the existence of an omitted variable or even variables that in fact accounts for both growth and inequality. That concern implies the necessity of an exogenous variable that impacts the GDP to see its impact on inequality, or in the case of a lack thereof, the need for internal instruments for the equation.

Nevertheless, although the question of reverse causality may seem quite philosophical, Granger (1969) tried to solve it with the econometric method, which is now known as the Granger Causality Test. The premise of Granger is that the future is not able to cause the present or the past. If one event occurs after the other, we assume that the former cannot cause the latter. However, if something occurs beforehand, it does not automatically imply that it causes something that occurs latter. For examples, if the weather prediction happens before the snowfall, we cannot say it actually causes the snowfall. In our case, do changes in the GDP per capita precede changes in inequality, or is it vice-versa or are the changes simultaneous and caused by some other event? We suppose that in fact this process goes both ways in spiral.

In reality, the standard Granger causality test was developed for times-series, but not panel data. However, afterwards, a test for Granger non-causality in heterogeneous models was developed by Dumitrescu and Hurlin (2012), and later adopted for Stata by Lopez and Weber (2017).

To alleviate the endogeneity problem we concern that the best method to use in that case is the instrumental variable method (IV). Broadly speaking, an instrumental variable is a variable that is uncorrelated with the error term but correlated with the explanatory variable in the equation. The concept of instrumental variables was first derived by Philip G. Wright, in the context of simultaneous equations in his 1928 book 'The Tariff on Animal and Vegetable Oils'. This method is massively used for solving not only the endogeneity problem, but also measurement errors in the variables or the omitted variable problem.

One computational method, which can be used to calculate IV estimates, is the two-stage least squares (2SLS). In the first stage, each explanatory variable that is an endogenous covariate in the equation of interest is regressed on all of the exogenous variables in the model, including both exogenous covariates in the equation of interest and the excluded instruments. In the second stage, the regression of interest is estimated as usual, except that in this stage each endogenous covariate is replaced with the predicted values from the first stage.

The most important part of this method is the selection of valid and strong instruments. That means that the instrument should be both exogenous itself and strongly correlated to the endogenous variable. Normally, the precision of IV estimates is lower than that of the OLS estimates. In the presence of weak instruments (excluded instruments only weakly correlated with included endogenous regressors), the loss of precision will be severe, and IV estimates may represent no improvement over the OLS. Many researchers conclude from their work that if the first-stage F statistic exceeds 10, their instruments are sufficiently strong. More tests

During the selection of instruments for our model, we have based on the logic of Brueckner (2015). In his paper, where he estimates the effect of national income on inequality using a panel data for 144 countries between 1960 and 2007 for each 5-year interval, he employs to instruments for the log of GDP per capita. The first instrument is oil price shocks (OSP), which he himself constructed earlier (Brueckner, 2012) and the second instrument is trade-weighted world income (TWWI) constructed by Acemoglu et al (2008).

In a similar manner, we use two instruments in our model. First instrument is net oil and gas exports per capita (in logs). We assume that due to the fact that the Russian Economy in general largely depends on this type of exports, so there is no surprise that the most developed Russian regions are those having the highest oil and gas exports. We have calculated it the following way: in our database we have information on exports and imports of oil and gas (and other products) in international dollars for each region separately beginning from 2000. First, we calculate exports and imports per capita, then we calculate their logs and finally we calculate the difference between the log of exports and the log of imports.

We use net oil and gas export instead of total exports because of the two main reasons. First, we consider it crucial to take into the consideration the regions which are obliged to *import* oil and gas, and there are a number of them. Due to a high volatility of oil price, at same point it can hugely harm the economy of these regions, as the vast majority of them are underdeveloped. Second, if we have used only oil-exporting regions in our data, we would have lost a lot of observations due to a simple fact that not all the regions in Russia are oil-exporters. Moreover, although the final variable is in logs, we calculate it from the data in dollars and not in roubles on purpose. By doing this, we are taking into the consideration international oil and gas prices and dollar-roubles exchange rate – two factors which significantly affects the oil and gas export revenues and consequently, the Russian GDP, but have no significant effect on within regional inequality.

Second instrument is the volume of services per capita in 2000 basic prices. In 1955, Kuznets considered the economic developed to be associated with the industrialization and the change from the employment in agriculture to the employment in industry. Nowadays, this logic can be applied to the change from industrial economy to the service economy with the correspondent employment changes. So, we believe that the most developed regions are those that have the highest volume of services per capita and vice a versa. By applying a simple OLS (Figure A6), we can see that it is actually so. Moreover, we consider that the volume of service can effect within regional inequality only through its impact on GDP per capita.

So, the corresponding first-stage equation for two-stage least squares (2SLS) estimation is[12]:

$$\mathrm{DPpc}_{\mathrm{it}} = \alpha_{\mathrm{it}} + \mathrm{OilExport\ pc}_{\mathrm{it}} + \mathrm{Services\ pc}_{\mathrm{it}} + \varepsilon_{\mathrm{it}}, (4)$$

where $GDPpc_{it}$ is the Regional Gross Domestic Product per capita in 2000 prices (in logs) for the i region in the t year and $OilExport\ pc_{it}$ is the Net Oil Export per capita in current US dollars per capita for the *i* region in the *t* year, $Services\ pc_{it}$ is the volume of services per capita in roubles in 2000 basic prices (in logs) and ε_{it} is an error term.

V. Results

Preliminary Estimations

First of all, we conduct some preliminary estimation. The results for Pooled OLS and Fixed Effect models are shown in the Table 2[13]. If we run simple Pooled OLS regression, it can be seen that in the basic regression the relation between GDP per capita and Gini Index is positive and significant, but if we run a quadratic regression, in fact the U-shape is not inverted. It also can be seen in the graph in the appendix. In the augmented Pooled OLS regression the quadratic term loses its significance and the relation between two variables is again positive. Meanwhile, all the control variables have a positive and significant effect on inequality.

However, in the FE model the situation is different. When we control for regional fixed effects and time effects simultaneously, the Kuznets curve appears, although in the augmented model the quadratic term again is not significant. In the augmented FE model the only variable which has negative effect on inequality is college education.

[12] See OLS Graphs in Appendix 1.
[13] Specification tests are in the Appendix 1.

Table 2 The effect of GDP pc on Gini Index (Preliminary Results)

	Pooled OLS			Fixed Effects		
VARIABLES	Linear	Square[14]	Augmented	Linear	Square	Augmented
ln (GDP pc)	3.16***	-2.41***	2.89***	5.00***	9.56***	5.18***
	(0.12)	(0.81)	(1.04)	(0.43)	(1.11)	(1.42)
ln (GDP pc)^2		0.73***	-0.06		-0.61***	0.04
		(0.11)	(0.13)		(0.14)	(0.17)
Fertility			1.72***			0.42
			(0.31)			(0.42)
Life Expectancy			0.09***			0.17***
			(0.03)			(0.06)
Unemployment			0.05***			0.05**
			(0.02)			(0.02)
Prof. School			0.11***			0.05***
			(0.01)			(0.02)
College			0.04***			-0.07***
			(0.00)			(0.01)
Migration			0.00			0.00
			(0.00)			(0.00)
Constant	24.06***	34.28***	7.81**	17.97***	9.77***	-5.81
	(0.50)	(1.55)	(3.53)	(1.45)	(2.34)	(5.16)
Observations	1,264	1,264	1,253	1,264	1,264	1,253
R-squared	0.48	0.50	0.69	0.64	0.65	0.70
Number of Regions				79	79	79

Time dummies are included in all regressions. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

IV Results

First of all, we show the first stage results for the IV model (Table 3). Together with regional fixed effects and time effects, two instruments account for 99% of the variance in the regression. Both variables have a positive effect on the log of GDP per capita on 1% significance level.

Table 3 First Stage Effects of Net Oil Export pc and Services pc in logs on regional GDP pc

Variables	ln (GDP pc)
Net Oil Export pc	0.01***
	(0.00)
ln (Services pc)	0.19***
	(0.02)
Constant	1.50***
	(0.15)
Observations	1,048
R-squared	0.99

The method of estimation is Pooled OLS. Time and regional dummies are included, but not shown. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[14] See Figure A7 in the Appendix 1.

In our estimations we use Driscoll-Kraay Errors, fixed effects estimations and time dummies.[15] The instrumental variables regression results show us the existence of the Kuznets curve both in simple and augmented quadratic models (Table 4). The Hansen J tests whether the restrictions implied by the existence of more instruments than endogenous regressors are valid. The underidentification Kleibergen Paap test checks whether your instruments are relevant. So, our instruments are valid and relevant.

As for other independent variables, only college education has a negative significant effect on inequality, all the rest variables have a positive significant effect on inequality, except for fertility which has no significant effect.

Table 4 The effect of GDP pc on Gini Index (2SLS)

	Gini Index		
Variables	Basic	Square	Augmented
ln (GDP pc)	9.68***	20.72***	17.91***
	(2.15)	(3.98)	(6.46)
ln (GDP pc)^2		-1.35***	-0.97*
		(0.33)	(0.54)
Fertility			0.76
			(0.82)
Life Expectancy			0.26**
			(0.10)
Unemployment			0.13***
			(0.05)
Prof. School			0.04*
			(0.02)
College			-0.07***
			(0.01)
Migration			0.01*
			(0.00)
Observations	1,045	1,045	1,039
R-squared	0.57	0.59	0.65
Number of regions	76	76	76
Hansen J, p-value	0.243	0.940	0.727
Kleibergen Paap F-Stat	39.201	55.096	42.463

The method of estimation is 2SLS Fixed Effects. The instruments are Net Oil Export per capita and Services per capita in logs. Driscoll-Kraay Errors are shown in parentheses. Singleton groups are detected and 3 observations are not used. Time Dummies are not shown. *** p<0.01, ** p<0.05, * p<0.1

[15] See Appendix 1 for the explication of the method and specification tests.

Robustness Checks

Now we are to conduct some robustness checks of our model. First, we use the lag of one year of the independent variables, as we can assume that their effect is lagged in time (Table 5). It barely changes our results – the coefficients stay the same, except for professional school education and migration which lose its significance. Then we run the same kind of estimation, but for 5-year averages for each variable (Table 6). The Kuznets curve persists. In all the regressions the instruments are strong and valid.

Table 5 The effect of GDP pc on Gini Index (2SLS) Lagged

	Gini Index		
Variables	Basic	Square	Augmented
ln (GDP pc) (lag)	7.71***	23.47***	19.55***
	(1.89)	(4.10)	(5.73)
ln $(GDP\ pc)^2$ (lag)		-1.92***	-1.37***
		(0.30)	(0.47)
Fertility (lag)			0.61
			(1.07)
Life Expectancy (lag)			0.24***
			(0.07)
Unemployment (lag)			0.11*
			(0.05)
Prof. School (lag)			0.03
			(0.03)
College (lag)			-0.06***
			(0.01)
Migration (lag)			0.01
			(0.00)
Observations	975	975	969
R-squared	0.56	0.56	0.64
Number of Regions	76	76	76
Hansen J, p-value	0.515	0.684	0.725
Kleibergen Paap F-Stat	34.362	64.017	35.216

The method of estimation is 2SLS Fixed Effects. The instruments are Net Oil Export per capita and Services per capita in logs. Driscoll-Kraay Errors are shown in parentheses. Singleton groups are detected and 3 observations are not used. Time Dummies are not shown. *** p<0.01, ** p<0.05, * p<0.1

Table 6 The effect of GDP pc on Gini Index (2SLS, 5-year periods)

	Gini Index		
Variables	Basic	Square	Augmented
ln (GDP pc) (5 years)	8.14***	19.53***	16.33**
	(1.83)	(4.09)	(6.78)
ln $(GDP\ pc)^2$ (5 years)		-1.34***	-0.94*
		(0.44)	(0.52)
Fertility (5 years)			0.40
			(0.58)
Life Expectancy (5 years)			0.19
			(0.17)
Unemployment (5 years)			0.11***
			(0.03)
Prof. School (5 years)			0.05
			(0.06)
College (5 years)			-0.08***
			(0.03)
Migration (5 years)			0.01*
			(0.00)
Observations	231	231	230
R-squared	0.68	0.68	0.76
Number of Regions	77	77	77
Hansen J, p-value	0.188	0.285	0.295
Kleibergen Paap F-Stat	19.93	16.87	16.87

The method of estimation is 2SLS Fixed Effects. The instruments are Net Oil Export per capita and Services per capita in logs. Driscoll-Kraay Errors are shown in parentheses. Time Dummies are not shown. *** p<0.01, ** p<0.05, * p<0.1

The curious thing happens, when we run the same regression, but without Moscow (Table 7). In that case that Kuznets curve disappears, so does the significance of college education and migration. As we saw previously in the preliminary data analysis, Moscow is the region with the unique pattern of inequality-income development through the years. Actually, it is almost the only region, where inequality drops dramatically with the rise of income per capita.

Moreover, Moscow has the highest number of college students and the highest migration inflow. Nonetheless, we suggest that Moscow cannot be considered as an outlier and simply taken out of the regression without following research, because it has almost 10% of Russian population and accounts for almost 20% of total Russian GDP.

Table 7 The effect of GDP pc on Gini Index (2SLS, without Moscow)

	Gini Index		
Variables	Basic	Square	Augmented
ln (GDP pc)	6.69***	8.96**	11.19**
	(1.67)	(4.39)	(4.97)
ln (GDP pc)^2		-0.21	-0.52
		(0.44)	(0.43)
Fertility			0.06
			(0.70)
Life Expectancy			0.30***
			(0.09)
Unemployment			0.08**
			(0.04)
Prof. School			-0.03
			(0.02)
College			0.02
			(0.01)
Migration			0.01
			(0.00)
Observations	1,030	1,030	1,024
R-squared	0.65	0.67	0.74
Number of Regions	75	75	75
Hansen J, p-value	0.489	0.791	0.814
Kleibergen Paap F-Stat	41.114	41.083	36.327

The method of estimation is 2SLS Fixed Effects. The instruments are Net Oil Export per capita in logs and Services per capita in logs. Singleton groups are detected and 3 observations are not used. Time Dummies are not shown. Driscoll-Kraay Errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Finally, we estimate our model with System GMM as an alternative approach (Table 8)[16]. The Kuznets curve persists, although the coefficients are much lower. Interestedly enough, in that case education and migration change their signs.

Table 8 The effect of GDP pc on Gini Index (Two-Step System GMM)

	Gini Index		
Variables	Basic	Square	Augmented
ln (GDP pc)	0.94**	5.13***	8.37***
	(0.37)	(0.29)	(1.19)
ln (GDP pc)^2		-0.30***	-0.70***
		(0.04)	(0.13)
Fertility			1.77***
			(0.24)
Life Expectancy			0.38***
			(0.03)
Unemployment			0.01
			(0.01)
Prof. School			0.16***
			(0.02)
College			0.02***
			(0.00)
Migration			-0.01***
			(0.00)
Constant	29.95***	21.11***	-13.24***
	(1.43)	(0.70)	(4.48)
Observations	1,264	1,264	1,253
Number of Regions	79	79	79
Number of Instruments	42	83	83
AR (1) p-value	0.152	0.217	0.982
Hansen p-value	0.074	0.759	0.499

Time dummies are included in all models. Estimations are by two-step System GMM, reducing the number of lags to two. The AR (1) test is for the first-order correlation in the first-differenced residuals. It is above 0.5, so even the t-1 instruments are valid. The p-value for the Hansen over-identifying restriction test is above 0.5 for the base and augmented equations, so we assume that the instruments are strong. It is above 0.5 for the quadratic equation, but it can occur due to the multicollinearity problem because of the usage of the quadratic term. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[16] See the explication of the method and related issues in the Appendix 1.

VI. Conclusions

In this chapter, we have analysed the inequality-development link on the basis of the well-known Kuznets curve hypothesis and tried to answer the question, whether or not it is applicable for the Russian regions' economy for the period of 2000-2015. After running the IV model for the panel data and plenty of robustness checks we can sum up our principal findings:

First, we have found strong evidence that *in the Russian Federation economic growth increases inequality*. That is quite different from the results in other papers, where the estimation was conducted on the state level (Brueckner et al., 2014). That can happen due to the fact that Russia is not a highly developed country and it, as a whole, is still situated in the upbeat of the first Kuznets wave, according to Milanovic (2016). In the vast majority of the Russian regions, the average income is still on the level of the developing world.

Second, in general, *the inverted-U relation between the two exists on the regional level in the Russian Federation*. However, one more important result is that if we do not introduce the quadratic term in the regression, the relation between the development level and inequality is positive and significant. A few regions which are 'the engine' of the Russian economic growth (regions with the high net oil export per capita) are the ones that pull down the inequality pattern in it downbeat. That contradicts to hypothesis of other researchers who argue that inequality eventually goes down due to other factors, such as redistributive social policies.

Third, one peculiar pattern that we detected in the most of the regression is *the impact of higher education on inequality together with GDP per capita. Its negative effect* on inequality shows its significance in almost every regression. That may mean that it is in fact the level of education that tears the inequality down through the GDP per capita, but it requires further exhaustive research.

Fourth, we are also to *highlight the case of Moscow*, as it has its unique pattern of inequality in comparison with all the other regions: it starts with an extremely high level of inequality and then it drastically declines throughout the years. It is notable that Moscow also has the highest number of college students and the most drastic increase in its number as well. That is why, if we drop Moscow, the significance of the higher education on inequality disappears as well.

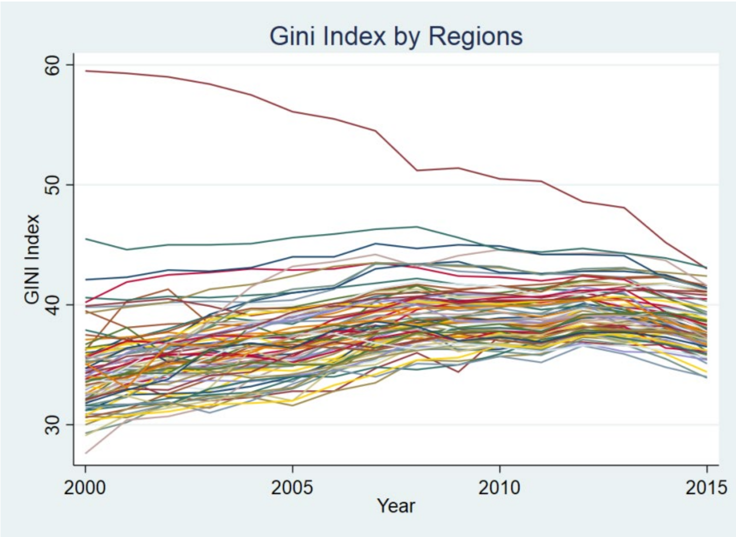
In the Russian media, Moscow is often referred to as 'a state within the state' meaning its unique economic structure, human developments indexes and cultural life. This is the issue for further investigation.

APPENDIX 1.

Table A 1 Panel Data Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
Gini Index	*overall*	37.86	3.49	27.6	59.5	N = 1264
	between		2.84	33.89	53.01	n = 79
	within		2.05	27.85	44.35	T = 16
ln (GDP pc)	*overall*	3.72	0.61	1.51	5.66	N = 1264
	between		0.57	1.84	5.53	n = 79
	within		0.23	2.86	4.24	T = 16
Fertility	*overall*	1.52	0.32	0.93	3.49	N = 1262
	between		0.25	1.13	2.68	n = 79
	within		0.21	0.67	2.33	T-bar = 15.97
Life Expectancy	*overall*	66.92	3.58	53.80	80.05	N = 1262
	between		2.69	58.57	75.58	n = 79
	within		2.37	62.15	72.23	T-bar = 15.97
Unemployment	*overall*	8.58	5.79	0.80	64.90	N = 1264
	between		5.26	1.63	46.31	n = 79
	within		2.49	-7.92	27.18	T = 16
Prof. School	*overall*	7.39	6.09	.07	34.50	N = 1264
	between		5.55	.23	24.58	n = 79
	within		2.57	-9.69	17.31	T = 16
College	*overall*	15.00	26.04	0	275.40	N = 1255
	between		25.33	.04	211.44	n = 79
	within		6.43	-70.63	78.95	T-bar = 15.89
Migration	*overall*	-9.82	102.51	-704.20	2522.50	N = 1264
	between		56.70	-186.90	141.93	n = 79
	within		85.62	-578.38	2470.01	T = 16
ln (Services pc)	*overall*	9.05	0.76	6.65	11.00	N = 1264
	between		0.43	8.05	10.42	n = 79
	within		0.62	7.37	10.01	T = 16
ln (Oil Export pc)	*overall*	2.14	3.31	-5.26	10.74	N = 1048
	between		2.62	-3.26	7.55	n = 79
	within		1.95	-5.27	10.50	T-bar = 13.27
Decile Index	*overall*	12.64	3.79	6.1	48.7	N = 1264
	between		3.28	9.32	34.49	n = 79
	within		1.93	-4.15	26.85	T = 16

Figure A 1 Gini by Region (Time Series)



As we can see in Figure A1, there was a large dispersion of the Gini Index in 2000, but it has been shrinking through the time to reach conversion, which is known as the 'shrinkage' effect.

Figure A 2 Regional GDP per capita (Time Series)

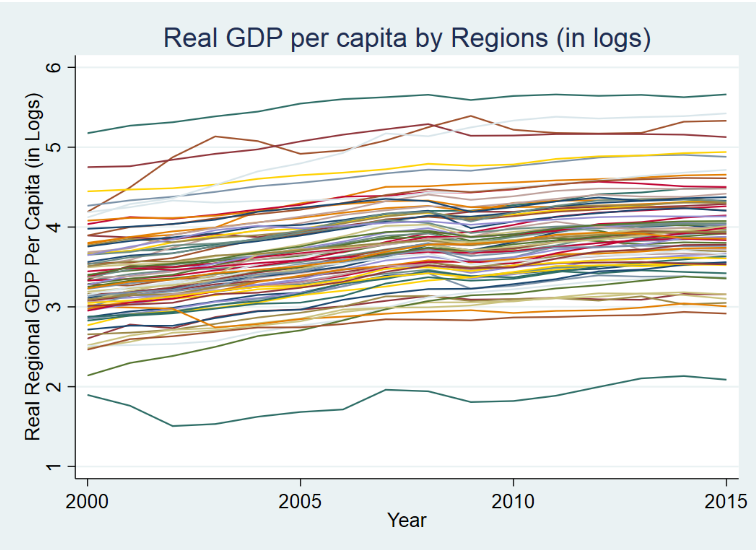


Figure A2 shows us a solid trend in regional GDP per capita growth between 2000 and 2015.

Figure A 3 Heterogeneity across Regions (GDP pc)

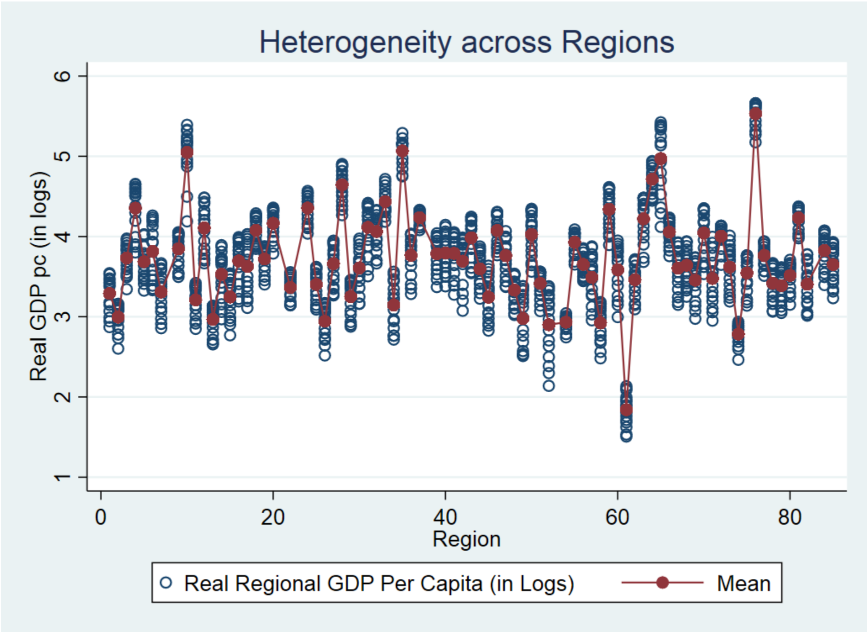
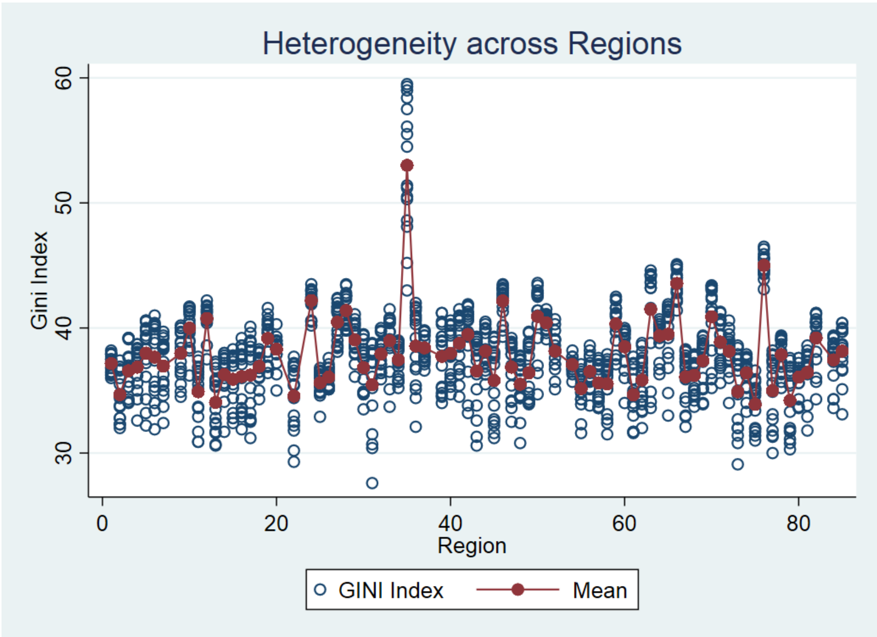


Figure A 4 Heterogeneity across Regions (Gini Index)



Figures A3 and A4 show the heterogeneity across regions, where we can see little or almost none of the homogeneity of the Russian regions.

Figure A 5 Regional GDP pc vs Net Oil Export pc (OLS)

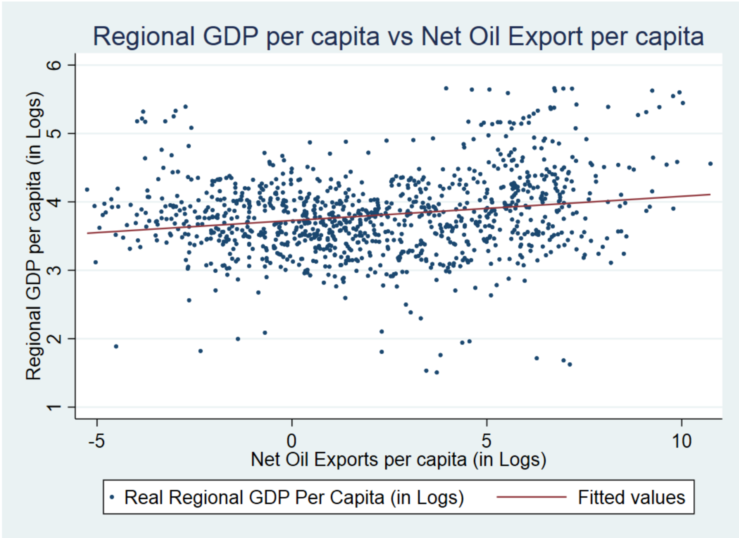
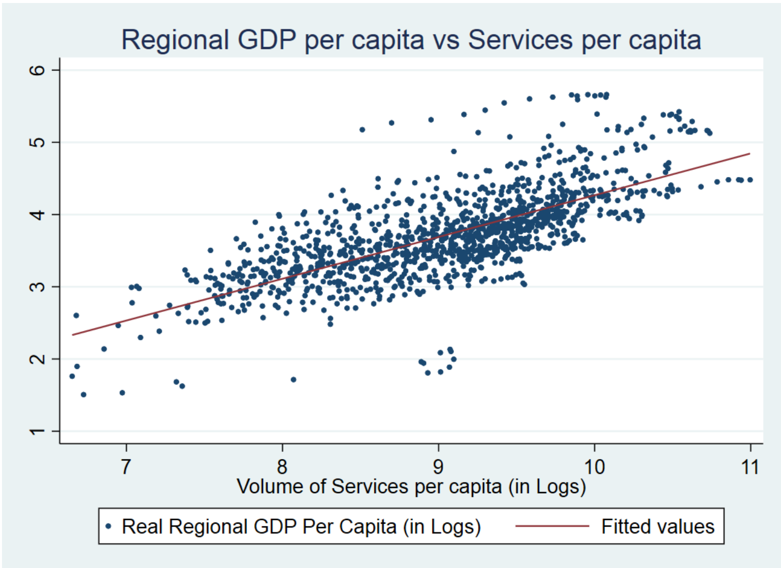
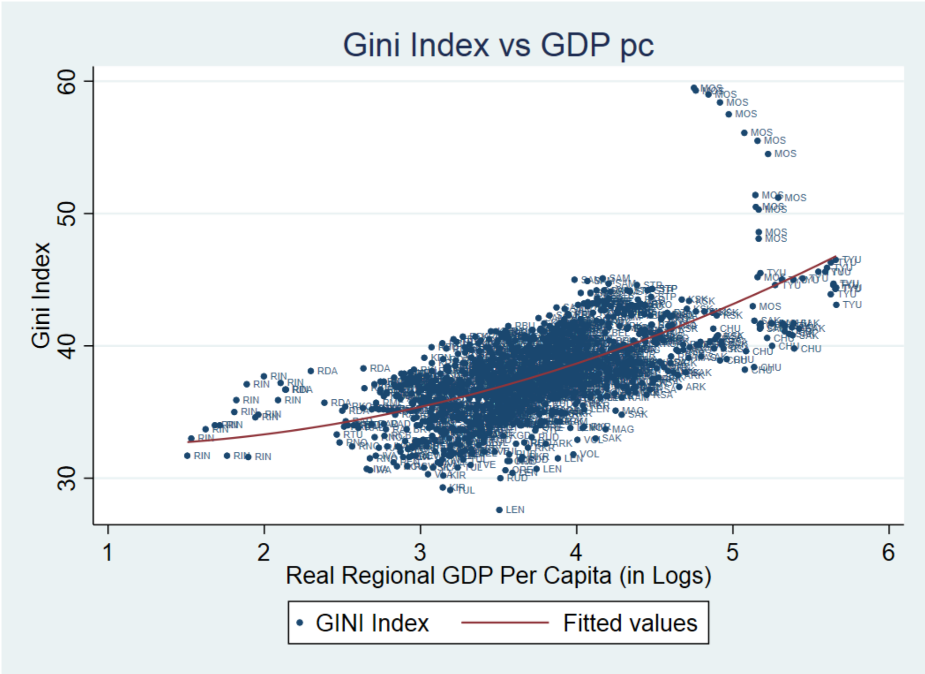


Figure A 6 Regional GDP pc (in logs) vs Services pc (in logs)



Figures A5 and A6 show fitted values of first stage regression for instruments.

Figure A 7 Gini Index vs GDP pc in logs (OLS)



Econometric Issues

Panel data takes advantage of the cross-section variability, the identification and estimation of the parameters of a response function exploiting this variation of the included variables. If the variables do not show excessive time variability but a cross-sectional one, the approximation with panel data would provide extra capacity for that estimation.

$$Y_{it} = \alpha + \beta_1 X_{1it} + e_{it} \,,$$

where i means the i^{th} cross unit and t time t (year). This formulation allows the combination of multiple individual and temporal parameters.

Among the many models of panel data the most used are:

- Fixed effects model
- Random effects model

The difference between fixed or random effects does not lie in the morphology of the model, which is always the following:

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + e_{it} \,,$$

where $\alpha_i = \alpha + u_i$. That is, instead of considering a as fixed, we assume that it is a random variable with a mean value and a random deviation from this mean value. Substituting $\alpha_i = \alpha + u_i$ in $Y_{it} = \alpha_i + \beta_1 X_{1it} + e_{it}$ we obtain:

$$Y_{it} = \alpha + \beta_1 X_{1it} + u_i + e_{it},$$

where:

- u_i represents unobservable cross-sectional heterogeneity.

This modelling is a useful way to avoid that the inadvertent difference between the individuals in the sample had to be excluded by omission, but the omission of relevant variables may cause the estimators to be biased and therefore inconsistent, an effect of panel data modelling. Unidirectional fixed effects are very useful to mitigate the bias associated with the time of the invariant and unobservable effects.

But first we will try to include in our model the relevant variables, and then decide which of these models best fits our database – a fixed effects model or a random effects model. Also we suggest that the best method for estimating this kind of relationship is the fixed effects model, because we suppose that the constant term is fixed for all the regions.

Although our research goal is to estimate models (1) and (2), in the first place, we run various tests on the data to be sure that the method that we are to use is the best fit to our data-set. To do this, we start with the simple linear model. As for the methods, we start out with estimating our linear basic model with Pooled OLS, Fixed Effects and Random Effects.

Table A 2 Pooled OLS, Fixed Effects and Random Effects Comparison

	Gini Index		
Variables	OLS	FE	RE
ln (GDP pc)	3.64***	6.78***	6.30***
	(0.12)	(0.17)	(0.16)
Constant	24.33***	12.64***	14.41***
	(0.46)	(0.63)	(0.65)
Observations	1,264	1,264	1,264
R-squared	0.41	0.57	
Number of regions		79	79

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

As we can see from the table, our initial analysis shows that the Regional GDP per capita has a positive and significant effect on the Gini index. However, we need to conduct some tests to choose the best econometric methods from the three that we have used.

First of all, we compare Pooled OLS with Random Effect. To decide which model has better statistical properties, whether the RE model or the pooled data, we use the test known as the Breusch and Pagan Lagrangian Multiplier Test for Random Effects. The null hypothesis of this test is that H0: $\sigma_u^2 = 0$

If the test is rejected, there is a difference between the Pooled OLS model and the RE model, and it is preferable to use the random effects method.

Breusch and Pagan Test

```
Breusch and Pagan Lagrangian multiplier test for random effects

        GINI[id,t] = Xb + u[id] + e[id,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                    GINI |   15.83314       3.979088
                       e |   2.840359       1.685336
                       u |   5.636046       2.374036

        Test:   Var(u) = 0
                             chibar2(01) =  5049.65
                          Prob > chibar2 =   0.0000
```

With which we reject the Ho. Since its Prob> is less than 0.05, so the random effect estimators are better than the ordinary least squares estimators (Pooled).

Now the next step is to decide which model is better between FE and RE. To do this, we use the Hausman Test. The Hausman test evaluates the consistency of the RE estimator. The null hypothesis can be interpreted as these estimates being consistent, that is, the requirement of orthogonality of model errors and repressors is satisfactory.

Hausman Test

```
                      ──── Coefficients ────
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      FE           RE          Difference          S.E.
-------------+----------------------------------------------------------------
    LN_GDP00 |   6.816969     6.187671        .6292975        .0542083
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      134.77
                Prob>chi2 =      0.0000
```

As we can see, the p-value is less than 5% of fixed significance, so the random effects estimator is inconsistent, therefore, we will use the fixed effects estimator.

The Kuznets Curve Static Model Estimations

The Breusch and Pagan test and the Hausman test allow us to choose between traditional models, but these models are not effective in the case of detecting or modelling in the presence of autocorrelation and heteroscedasticity, for which we will use formal tests to identify what kind of problems are present in our model.

Table A 3 Panel Data Tests

Test	H_0		Result in our model (FE)
Testing for cross-sectional dependence/contemporaneous correlation	The null hypothesis is that residuals are not correlated	Frees' test of cross sectional independence = 12.047 |--| Critical values from Frees' Q distribution alpha = 0.10 : 0.1612 alpha = 0.05 : 0.2116 alpha = 0.01 : 0.3125 Pesaran's test of cross sectional independence = 52.276, Pr = 0.0000 Average absolute value of the off-diagonal elements = 0.422	We have cross-sectional dependence.
Testing for serial correlation.	The null is no serial correlation.	Wooldridge test for autocorrelation in panel data H0: no first order autocorrelation F(1, 81) = 152.733 Prob > F = 0.0000	We have presence of autocorrelation type ar (1)

Unit root for panels LN_GDP00		Fisher-type unit-root test for LN_GDP00 Based on augmented Dickey-Fuller tests Ho: All panels contain unit roots Number of panels = 82 Ha: At least one panel is stationary Avg. number of periods = 18.89 AR parameter: Panel-specific Asymptotics: T -> Infinity Panel means: Included Time trend: Not included Drift term: Included ADF regressions: 3 lags Statistic p-value Inverse chi-squared(164) P 545.1253 0.0000 Inverse normal Z -14.9514 0.0000 Inverse logit t(414) L* -15.7906 0.0000 Modified inv. chi-squared Pm 21.0441 0.0000 P statistic requires number of panels to be finite. Other statistics are suitable for finite or infinite number of panels.	No test shows the presence of unit roots.
Unit root for panels Gini		Fisher-type unit-root test for GINI Based on augmented Dickey-Fuller tests Ho: All panels contain unit roots Number of panels = 83 Ha: At least one panel is stationary Avg. number of periods = 20.48 AR parameter: Panel-specific Asymptotics: T -> Infinity Panel means: Included Time trend: Not included Drift term: Included ADF regressions: 3 lags Statistic p-value Inverse chi-squared(164) P 533.1326 0.0000 Inverse normal Z -14.6604 0.0000 Inverse logit t(414) L* -15.4937 0.0000 Modified inv. chi-squared Pm 20.3819 0.0000 P statistic requires number of panels to be finite. Other statistics are suitable for finite or infinite number of panels.	No test shows the presence of unit roots.
Testing for heteroscedasticity	The null hypothesis is homoscedasticity (or constant variance)	Modified Wald test for groupwise heteroskedasticity in fixed effect regression model H0: sigma(i)^2 = sigma^2 for all i chi2 (82) = 4834.87 Prob>chi2 = 0.0000	We have the heteroscedasticity.

As we can see, we have several problems with our data which put at risk the asymptotic properties of the estimators. Ignoring such kind of problems in the estimation of panel models can lead to severely biased statistical results.

Augmented Model

As we are going to add a set of additional variables to construct our basic and augmented models, first, we are to check, whether the explanatory variables we suggest do not have a multicollinearity problem.

To start, we check out correlation coefficients between explanatory variables, although according to Maddala and Lahiri (2009), ‘high intercorrelations among the explanatory variables are *neither necessary nor sufficient* to cause the multicollinearity problem'. They add, that 'the best indicators of the problem are the *t*-ratios of the individual coefficients'.

Table A 4 Correlation Table

	LN_GDP00	FERT	LIFE_EXP	UNEMPL	LABOUR	PROF_SCH	COLLEGE	MIGR
LN_GDP00	1.0000							
FERT	0.0491	1.0000						
LIFE_EXP	0.0603	0.2411	1.0000					
UNEMPL	-0.5894	0.2073	0.0055	1.0000				
LABOUR	0.4770	-0.0512	-0.2535	-0.1288	1.0000			
PROF_SCH	0.2455	-0.2721	0.0875	-0.2549	0.0875	1.0000		
COLLEGE	0.3691	-0.1079	0.3340	-0.2676	0.1317	0.5675	1.0000	
MIGR	-0.0684	-0.0869	0.2393	-0.0851	-0.2570	0.2287	0.2357	1.0000

Then we are finding VIF factors. As the rule of thumb, if the mean VIF is less than 10, we conclude that there is no multicollinearity in the model.

Table A 5 Collinearity Diagnostics

Variable	VIF	1/VIF
LN_TRADE	5.65	0.176999
FONDS	3.93	0.254391
LN_GDP00	3.46	0.288725
COLLEGE	3.06	0.326667
LIFE_EXP	2.93	0.341792
UNEMPL	2.57	0.389755
FERT	2.49	0.401404
LABOUR	1.98	0.505509
PROF_SCH	1.75	0.572097
MIGR	1.62	0.616232
LN_EXP	1.47	0.682377
Mean VIF	2.81	

Fixed Effects Regression with Driscoll and Kraay Standard Errors

There are several methods that are commonly used in econometrics to address the violation of classic linear model assumptions. To address the heteroscedasticity problem, heteroscedasticity-consistent or so-called "White" standard errors are used (White, 1980). Developing White's work, Arellano (1987), Froot (1989), and Rogers (1993) came up with generalized estimator that produces consistent standard errors if the residuals are correlated within, but uncorrelated between clusters. However, according to Reed and Ye (2011), the best method for estimating models with heteroscedasticity, contemporaneous cross-section correlation and autocorrelation of type AR (1) is Panel-Corrected Standard Error (PCSE) estimation suggested by Beck and Katz (1995), but that is only viable for OLS estimation.

On the contrary, Hoeckle (2007) argues that in the case of panel's cross-sectional dimension N is large compared to the time dimension T, the best way to estimate that kind of data is to use

Driscoll and Kraay (1998) standard errors. This method can be used both for Pooled OLS and FE estimators.

DK Standard Errors for FE are implemented in two steps. First of all, all model variables $z_{it} \in \{y_{it}, \mathrm{x}_{it}\}$ are within-transformed as follows:

$$\widetilde{z}_{it} = z_{it} - \overline{z}_i + \overline{\overline{z}}, \quad \text{where} \quad \overline{z}_i = T_i^{-1} \sum_{t=t_{i1}}^{T_i} z_{it} \quad \text{and} \quad \overline{\overline{z}} = \left(\sum T_i\right)^{-1} \sum_i \sum_t z_{it}$$

As the within-estimator corresponds to the OLS estimator of $\widetilde{y}_{it} = \widetilde{\mathrm{x}}_{it}'\theta + \widetilde{\varepsilon}_{it}$, the second step is to estimate the transformed regression model by Pooled OLS with DK SE.

In the table below we show the difference of estimation conducted by these four methods in our basic and quadratic models.

Table A 6 Comparison of standard error estimates for FE regression for basic model

Variable	FE	White	Rogers	DriscollKraay
LN_GDP00	6.8169688***	6.8169688***	6.8169688***	6.8169688***
_cons	12.141957***	12.141957***	12.141957***	12.141957***
N	1543	1543	1543	1543
r2	.54653498	.54653498	.54653498	

legend: * p<0.05; ** p<0.01; *** p<0.001

Table A 7 Comparison of standard error estimates for FE regression for quadratic model

Variable	FE	White	Rogers	DriscollKraay
LN_GDP00	11.058718***	11.058718***	11.058718***	11.058718***
SQRLN_GDP00	-.57358786***	-.57358786	-.57358786	-.57358786**
_cons	4.6183484**	4.6183484	4.6183484	4.6183484
N	1543	1543	1543	1543
r2	.55356422	.55356422	.55356422	

legend: * p<0.05; ** p<0.01; *** p<0.001

As we can see from the tables, application of DK SE did not change the coefficients and only changes the significance of the quadratic term in quadratic regression from 0,1% to 1%. Moreover, our hypothesis about the coefficients is confirmed and the relationship between inequality and development has the inverted-U form, at least in the basic model and in the basic quadratic model.

System GMM

One of the ways to estimate this kind of models is to apply the Difference GMM developed by Arellano-Bond (1991) and System GMM developed by Arellano-Bover (1995) and Blundell-Bond (1998). Both are generalised methods of moments estimators designed for ‘small T, large N’ panels. In other words panel data consisting of observation for many individuals, but just for a few time periods, where the dependant variable is dynamic, that is, it depends on its own past realisations. It can be used in dynamic models, where independent variables are not strictly exogenous, or correlated with the past or current error term, as well as in the models with heteroscedasticity and autocorrelation within individuals.

It is to be noted that these methods do not concern cross-sectional dependency and structural breaks. The Difference GMM estimator developed by Arellano-Bond (1991) transforms all regressors by differencing them and then uses the Generalised Method of Moments designed by Hansen (1982). The System GMM estimator (Arellano-Bover, 1995; Blundell-Bond, 1998) augments the Difference GMM estimator by making an additional assumption, which is that the first differences of instrument variables are uncorrelated with fixed effects. It dramatically improves efficiency by allowing the introduction of more instrumental variables. It is named System GMM, because it in fact builds a system of two equations – the original one and the transformed one.

We should mention that normally these methods are used for linear fixed effects models and we assume that our model is quadratic. Thus, we introduce the quadratic term as a separate variable assuming that it would cause the multicollinearity problem.

Basic and Augmented Models Estimations

As we already mentioned, the main problems of Difference GMM and System GMM is that it does not take into account cross-sectional dependency. That is why we need to perform cross-sectional independency tests to make sure we can apply these methods. According to Sarafidis and Robertson (2006), while dealing specifically with short dynamic panel-data models show that if there is cross-sectional dependence in the disturbances, all estimation procedures that rely on IV and the generalized method of moments (GMM)—such as Arellano and Bond (1991), and Blundell and Bond (1998)—are inconsistent as *N* (the cross-sectional dimension) grows large, for fixed *T* (the panel’s time dimension).

That is why we run some tests on cross-sectional dependence on our data. However, as these tests are based on FE and RE models, first of all we'll run these regressions together with Pooled OLS to see the difference (time dummies included).

In our case we cannot use Lagrange multiplier, also known as the LM test statistics proposed by Breusch and Pagan (1980), as it is developed for cases when T>N, and in the case of N>T it is not valid. In these cases we should test the hypothesis of cross-sectional independence in paneldata models by implementing two semi-parametric tests developed by Friedman (1937) and Frees (1995, 2004), together with the parametric testing procedure proposed by Pesaran (2004). According to De Hoyos and Sarafidis (2006), in dynamic panels, Pesaran's test remains valid under FE/RE estimation (even if the estimated parameters are biased) and therefore it may be the preferred choice, since the properties of the remaining tests in dynamic panels are not yet known.

Cross-sectional Dependence Tests

```
. xtcsd, pesaran abs


Pesaran's test of cross sectional independence =    -1.615, Pr = 0.1064

Average absolute value of the off-diagonal elements =     0.428

. xtcsd, frees abs


  Frees' test of cross sectional independence =     2.384
|--------------------------------------------------------|
  Critical values from Frees' Q distribution
                    alpha = 0.10 :   0.4892
                    alpha = 0.05 :   0.6860
                    alpha = 0.01 :   1.1046

Average absolute value of the off-diagonal elements =     0.457

. xtcsd, friedman abs


Friedman's test of cross sectional independence =     0.507, Pr = 1.0000

Average absolute value of the off-diagonal elements =     0.457

.
```

We run all three tests in Stata and see that, except Frees' test that produces the error due to insufficient time periods, the other two tests show that we do not have any cross-sectional dependency, as the p-value is much above 0.05. So we can proceed with Difference and System GMM estimations.

CHAPTER 2. GROWTH IN RUSSIA: *HOW DOES INCOME INEQUALITY AFFECT IT?*

I. Introduction

Economic development and growth have always been the key issues on the agenda of economists and policy-makers. Economic growth is largely determined by the accumulation of capital, both physical and human, and knowledge usable in the production of goods and services. However, there are a lot more social and economic factors that affect it, and one of them is income inequality.

Still, in the academic debate there is no consensus, whether the effect of inequality on growth is negative or positive. However, intuitively, a high inequality level is considered as 'a bad thing' to happen; in fact sometimes it can even stimulate growth on the initial stages of development. There are just too many factors to enter the game: initial income, level of development, level of inequality, inequality of opportunity and inequality of effort, etc.

In this chapter, we aim to investigate this very relation using panel data for Russian regions for the last fifteen years. We develop a dynamic econometric model and focus our estimations on instrumental variables (IV) method, although additionally, we estimate it both with 'traditional' panel methods and dynamic panel data method based on internal instruments (Difference GMM and System GMM). Moreover, we differentiate the effect of inequality on the growth of different income level groups (in total we have five of them).

To achieve that, first of all, we give a brief literature review on the advances of the inequality-growth research including the most recent development, and then we provide a detailed description of the data we use. We proceed with formulating our models and explaining the econometric issues related to them. Finally, we present the results together with the robustness checks, provide some discussion based on them and draw our conclusions.

II. Literature Review and Contribution

There is plenty of both theoretical and empirical literature on the issue. Interestingly enough in the early theoretical literature, higher inequality was believed to have a positive effect on growth. For instance, Kaldor (1956) considered higher income inequality necessary, because he believed that if the resources were scarce, only the rich were able to save in order to accumulate capital, invest and boost the subsequent growth. Moreover, such an income polarization can provide certain social incentives to the population in order to succeed. These arguments are supported by empirical studies of Forbes (2000) and Li and Zou (1998). However, it is very important to mention that in the case of Forbes's study (2000), the results hold only for 5-year time spans and changed their sign to negative for 10-year spans.

Afterwards, other research began to question this idea of positive correlation. There are a number of empirical papers, which appeal to the Meltzer-Richard's (1981) median voter hypothesis (Tabellini, 1991; Persson and Tabellini, 1994; Alesina and Rodrik, 1995, and Perotti, 1996). The idea is that if a median voter is relatively poor, he or she tends to vote for high tax rates, which in turn reduce incentives for investment activity and cause lower growth.

The later theoretical literature deals with the purely economic as well as complex politico-economic channels through which the actual inequality can affect the subsequent growth. As Ehrhart (2009) summarises it, the suggested three main economic channels are credit-market imperfections, domestic market size and endogenous fertility, while the two politico-economic channels are political instability and endogenous fiscal policy.

Summing up, the main idea of an 'imperfect capital market' approach is that the higher the income inequality is, the lower the number of individuals having access to credit markets and, consequently, to the opportunity to conduct a productive investment activity, that in the long run results in the reduction of growth rates (Aghion and Bolton, 1992, 1997; Banerjee and Newman, 1993; Galor and Zeira, 1993; Piketty, 1997).

The 'smaller domestic markets' approach deals with the hypothesis that the higher income inequality leads to smaller domestic markets, which do not allow taking advantage from the economies of scale and thus negatively affect subsequent growth (Murphy, Shleifer and Vishny, 1989; Falkinger, 1994; Mani, 2000, Zweimuller, 2000).

The last purely economic approach supposes that the more unequal distribution provokes that poorer and less educated households to raise their fertility rates and reduce their investments in human capital, which in its turn, reduces the future growth rates (Perotti, 1996; Galor and Zang, 1997; Dahan and Tsiddon, 1998; Morand, 1998; Kremer and Chen, 2002).

As for politico-economic reasons, first of all, widening income inequality can cause political instability, social unrest that in its turn is harmful for private investments (Alesina and Perotti, 1994, 1996; Perotti, 1996) and property rights (Alesina, Ozler, Roubini and Swagel, 1992; Keefer and Knack, 2000).

Such inconclusiveness in the theoretical and empirical literature provoked the creation of various 'differentiating' approaches: the researchers started to divide countries and people into different income groups that could explain the differences in sing of the effect of inequality on growth. For example, Barro (2000) split his sample into a low income- and a high-income sample, the results revealed a negative relationship for low income countries and a slightly positive, if any, relationship between inequality and growth for high income countries.

Here, we need to mention that one more important contribution of Galor and Zeira's (1993) and Galor and Tsiddon (1997) papers to the subsequent discussion on the issue is that their theoretical model predicts that the effect of inequality on transitional growth differs depending on the average wealth in the economy. This means that income inequality is beneficial for transitional growth in poor countries but it is harmful for growth in high-income economies.

Moreover, there is a myriad of empirical research which deals not only with the effect of inequality on total growth, but also on the growth of different income groups (Dabla-Norris et al., 2015; Milanovic, 2014; Van der Weide and Milanovic, 2018). Generally, they conclude that inequality is only detrimental for the growth of the poor, but it is actually beneficial for the growth of the rich.

Voitchovsky (2005) develops this idea and estimates inequality among the poor (the 50/10 ratio) and inequality among the rich (the 90/50 ratio) separately. Her conclusion is that bottom inequality is negative for growth due to the fact it impedes the poor to acquire education. Meanwhile top inequality is beneficial for growth as supported by the classical theoretical argument (Kaldor, 1956) that it promotes savings and subsequent investments and growth.

Marrero and Rodriguez (2013) decompose total inequality into inequality due to inequality of opportunity (to the circumstances outside one's control such as parental education and race) and the residual, assumed to be due to effort and luck. They found strong evidence that levels of inequality of opportunity are negatively correlated with growth while the residual ('good inequality') helps growth. However, it is to be noted that other studies failed to provide the same robust results. For instance, Ferreira et al. (2014) found a negative association between inequality and growth, their data did not permit robust conclusions as to whether inequality of opportunity is detrimental for growth.

Recent developments in the research of the effect of inequality on growth are related to the use of internal (Forbes, 2000; Banerjee and Duflo, 2003; Halter et al., 2014) and external (Galor et al., 2008) instruments to deal with the endogeneity problem and reverse causation. One of latest papers is by Brueckner and Lederman (2015) who provide panel estimates of the within-country effect that income inequality has on the GDP per capita by using the IV method. Their empirical results provide support for the hypothesis that income inequality benefits economic growth in developing countries, while it is harmful for economic growth in advanced economies.

In this chapter, we estimate the effect of inequality on the subsequent total growth of the GDP per capita, as well as the growth of the GDP per capita, which corresponds to a different income group. We use the data on the regions of the Russian Federation as a case study. There is some state-level research for panel data, for example, Panizza (2002) who uses state-level panel data for the United States during 1940-1980. By using GMM estimates, Panizza (2002) has found out a significant negative effect of the Gini Index on the transitional GDP per capita growth. But will it be negative for Russia? According to the World Bank (2018), the USA is a high-income country, while Russia is an upper-middle income country. As Galor and Zeira (1993) and Galor and Tsiddon (1997) hypothesised, the results can be different for poorer economies.

III. Data: Russia (2000-2015)

As in the previous chapter, all the data we use is macroeconomic and proceeds from the Rosstat Database and is accessed from the EMISS (Unified Interdepartmental Information and Statistical System) [17]. It was created in 2007 and it is operated by the Ministry of Communications and Mass Communications of the Russian Federation, but is coordinated by Rosstat.

The main source of data for our particular research comes from the Rosstat Publication 'Regions of Russia. Socio-Economic Indicators' for the years 2002-2016.[18] The data for the publication is obtained by state statistical agencies from enterprises, organisations and the general public in the course of statistical observations, censuses, and sample surveys. Additionally, it contains the data of the ministries and departments of the Russian Federation.

Before estimating our models, we prepare our data-set and make transformations of some variables to better suit our needs. One of the most important variables for our estimations is the regional GDP per capita, but we cannot use it in the original form without any transformation, because of the inflation as well as the price level differences that can severely disturb our estimations. Fortunately, Rosstat calculates the special Index of Physical Volume of Production, which depicts the actual growth of GDP without the effect of interregional price changes and inflation. We recalculate all the GDP per capita levels in 2000 basic prices, as we see it more convenient to use this year as a benchmark. For other variables, which should be used without inflation, we use the inflation index, which is calculated separately for each region as well.

[17]The data can be found on https://fedstat.ru/organizations/ [2019, June]
[18] This publications are available in their digital version on http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/publications/catalog/doc_1138623506156 [2019 June]

Additionally, we calculate five-year growth (three-year growth for robustness checks) of the regional GDP per capita for the corresponding period.

Table 9 Descriptive Statistics[19]

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini Index	237	37.31	3.68	27.5	62.3
Decile Index	237	12.15	3.75	6	42.1
GDP pc	237	47.33	38.55	4.51	287.59
5-year Growth	235	8.97	10.25	-8.33	77.94
GDP pc (1 group)	235	13.95	9.25	1.74	70.46
GDP pc (2 group)	235	25.14	17.97	2.84	138.04
GDP pc (3 group)	235	36.57	27.55	3.86	209.94
GDP pc (4 group)	235	53.71	42.79	5.21	322.10
GDP pc (5 group)	235	107.18	97.05	8.91	737.52
5-year Growth (1 group)	235	2.39	2.34	-2.47	16.95
5-year Growth (2 group)	235	4.58	4.64	-4.47	36.80
5-year Growth (3 group)	235	6.82	7.14	-6.47	54.65
5-year Growth (4 group)	235	10.06	11.00	-9.58	85.83
5-year Growth (5 group)	235	20.30	26.01	-66.54	200.79
Investment	237	22.97	9.53	8.72	76
College	237	12.45	22.54	0	243
Prof. School	237	7.02	6.00	.1	34.1
Unemployment	237	9.59	6.34	.9	58.2
Labour	237	59.98	3.54	53.73	70.36
Life Expectancy	237	67.05	3.51	53.8	80.05
Migration	237	-9.86	83.63	-784.8	263.2
3-year Growth	316	5.46	8.18	-43.56	70.45
3-year Growth (1 group)	316	1.78	2.34	-15.72	23.38
3-year Growth (2 group)	316	3.46	4.33	-27.05	40.28
3-year Growth (3 group)	316	5.23	6.39	-37.94	57.54
3-year Growth (4 group)	316	7.86	9.42	-50.32	81.56
3-year Growth (5 group)	316	16.12	21.08	-86.76	149.47

Moreover, we needed to calculate the average GDP, which corresponds to each of the five 20%-income groups. Initially, we had the data on how much of the total income corresponds to each of the groups expressed as a percentage (from the minimum 2.5% for the bottom quantile to the maximum 68.7% for the top quantile). So we multiply the total GDP per capita by the coefficient that we obtained by dividing this share to 20% (perfect equality). With all these transformations we can proceed to our estimations. Table 9 shows the descriptive statistics for all the variables used.

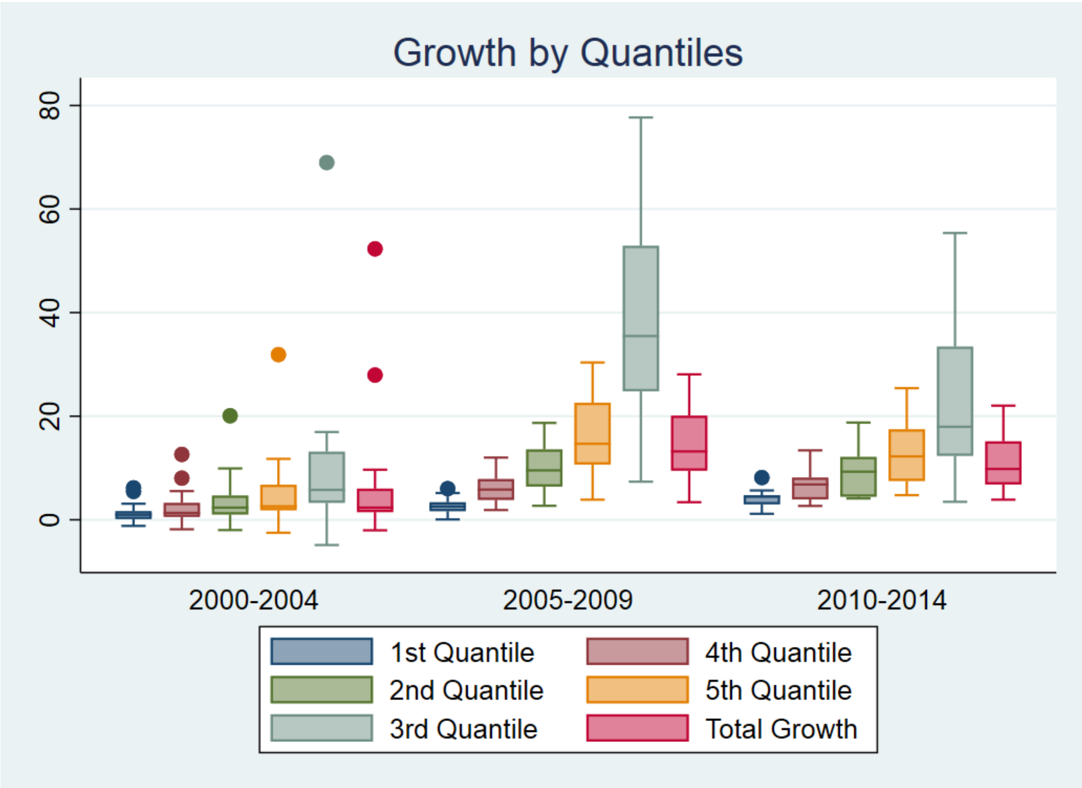
Figure 11 shows box plots for total growth and growth by quintiles for three time periods. We can see that although all the groups have positive growth, in every time period the richer the

[19] See Panel Data Statistics in the Appendix 2.

group is, the higher its growth is. The fourth and fifth groups' rates are higher than the average. That makes sense, as the inequality has been rising in Russia between 2000 and 2015.

In general, in 2000-2004 growth was pretty modest for all income groups and regions (some regions even had a decline in GDP per capita), except for a few outliers. The highest growth occurred between 2005 and 2009 (with no regions in decline) and then become to slow down.

Figure 11 Total Growth and Growth by Quantiles



IV. Models and Econometric Issues

The initial intuitive empirical model used in this study is as follows:

$$Growth_{it} = \alpha GDPpc_{it-s} + \beta Gini_{it-s} + \varepsilon_{it-s}, (1)$$

where $Growth_{it} = GDPpc_{it} - GDPpc_{it-s}$, which is the difference between the GDP per capita in the current *t* period and the previous *t-s* period for region *i*, $GDPpc_{it-s}$ is the Regional Gross Domestic Product per capita in 2000 prices in the previous *t-s* period for region *i*, $Gini_{it-s}$ is the Regional Gini Index in region *i* in the previous *t-s* period for region *i*, and $\varepsilon_{it-s}$is an error term.

In addition to the basic model, we estimate an augmented model by adding some controls:

$$Growth_{it} = \alpha GDPpc_{it-s} + \beta Gini_{it-s} + \gamma Invest_{it-s} + \delta College_{it-s} + \epsilon Prof.School_{it-s} + \theta Unempl_{it-s} + \vartheta Labour_{it-s} + \mu Life\ Exp_{\ it-s} + \rho Migr_{it-s} + \varepsilon_{it-s}, \quad (2)$$

where, again $Growth_{it} = GDPpc_{it} - GDPpc_{it-s}$, which is the difference between the GDP per capita in the current t period and previous *t-s* period for region i, $GDPpc_{it-s}$ is the Regional Gross Domestic Product per capita in 2000 prices in the previous *t-s* period for region *i*, $Gini_{it-s}$ is the Regional Gini Index for region *i* in the previous *t-s* period, $Invest_{it-s}$ is the share of investments in the total regional GDP (in percent) for region *i* in the previous *t-s* period, $College_{it-s}$ is the number of college students for each ten thousand habitants (people) for region *i* in the previous *t-s* period, $Prof.School_{it-s}$ is the number of professional schools students for each ten thousand habitants (people) for region *i* in the previous *t-s* period, $Unempl_{it-s}$ is the unemployment rate (in percent of economically active population) for region *i* in the previous *t-s* period, $Labour_{it-s}$ is the share of the economically active population (percent, between 15 and 60 for men, and between 15 and 55 for women) for region *i* in the previous *t-s* period, $Life\ Exp_{\ it-s}$ is life expectancy at birth (years) for region *i* in the previous *t-s* period, $Migr_{it-s}$ is the net migration (people for each ten thousand habitants) for region *i* in the previous *t-s* period, and $\varepsilon_{it-s}$is an error term. We use the same model for five income groups too.

For controls, we selected a set of variables that represents the population's health (life expectancy) and education (number of students graduated both from professional schools and colleges for every ten thousand habitants), and other economic factors (unemployment, share of economically active population, migration and investment rate) which are considered the most important and influential for growth (Forbes, 2000). Thus, we are taking in the consideration not only the economic development, but also human development in terms of health and education, and other important conditions.

The independent variables are measured at the beginning of each 5-year period and the dependent variable is economic growth in the ensuing five years (e.g. the regional GDP per capita growth during the period of 2000-2005 is regressed on variables measured at the 2000 levels). As for time spans, normally in this kind of research, the growth rates are measured every 5-year or 10-year periods (Partridge, 1997). For Russia, we have our panel data for the last fifteen years, so it allows us to conduct our analysis both for four 5-year spans and for 4 3-year spans. It is important to highlight that in this chapter, we are talking about the effect of the *initial inequality* of distribution of income on *subsequent growth.*

For different income groups (we have five of them) we use the same model:

$$Growth_{it}^{q} = \alpha GDP_{it-s}^{q} + \beta Gini_{it-s}^{q} + \varepsilon_{it-s}^{q}, (2)$$

where $Growth_{it}^{q} = GDPpc_{it}^{q} - GDPpc_{it-s}^{q}$, which is the difference between the GDP per capita (in logs) in the current t period and previous *t-s* period for region i , which corresponds to the income group q, $GDPpc_{it-s}^{q}$ is the Regional Gross Domestic Product per capita in 2000 prices in the previous *t-s* period in region i and income group q, $Gini_{it-s}^{q}$ is the Regional Gini Index in region i in the previous *t-s* period for region i and income group q, and $\varepsilon_{it-s}^{q}$is an error term.

As we are going to analyse the dynamic model, we add past realisations of the GDP per capita. The concept of dynamic panel data appears when we wish to estimate economic processes that are dynamic in nature, that is, for which the data generating process is a panel containing lagged dependent variables.

Instrumental Variables (IV) Model

Instrumental Variables (IV) is a method of estimation that is widely used in many economic applications when correlation between the explanatory variables and the error term is suspected (e.g. due to reverse causation, omitted variables or measurement error).

We suppose that in our panel data model $y_{it} = \beta x_{it} + u_{it}$, x_{it} is correlated with u_{it}. The basic idea is that if we can replace the actual values of x_{it} by predicted values of x_{it} that are to satisfy two main properties: to be correlated with the actual x_{it}, but to be uncorrelated with u_{it} ; we can obtain a consistent estimator of β. Predicted values are created by regressing x_{it} on a set of instrumental variables or 'instruments' with the above mentioned two properties. The general problem with the instrumental variables is that they have *both* these properties.

This is one more way to deal with the endogeneity problem, which is used by Brueckner and Lederman (2018). They use residual variation in inequality that is not due to the GDP per capita as an instrument for the Gini Index. Using an instrument for inequality ensures that the estimated β is not subject to a reverse causality bias.

One computational method that can be used to calculate IV estimates is the two-stage least squares (2SLS). In the first stage, each explanatory variable that is an endogenous covariate in the equation of interest is regressed on all of the exogenous variables in the model, including both exogenous covariates in the equation of interest and the excluded instruments. In the second stage, the regression of interest is estimated as usual, except that in this stage, each endogenous covariate is replaced with the predicted values from the first stage.

We use two specification tests. The Hansen J tests whether the restrictions implied by the existence of more instruments than endogenous regressors are valid. The underidentification Kleibergen Paap test checks whether your instruments are relevant.

We can use the same method by calculating the residual Gini Index not explained by GDP per capita level (Z_{it}) of the static IV model we estimated in Chapter 1:

$$\mathrm{ini}_{\ \mathrm{it}} = \alpha_0 + \alpha_1 \mathrm{DP}\ \ \mathrm{pc}_{\mathrm{it}} + \alpha_2 \mathrm{DPp}\ \ \mathrm{c}_{\mathrm{it}}^{\ 2} + \mathrm{Z}_{\mathrm{it}}, (3)$$

By simply mathematical transformation of we function we obtain:

$$\mathrm{Z}_{\mathrm{it}} = \mathrm{ini}_{\ \mathrm{it}} - \alpha_0 - \alpha_1 \mathrm{DP}_{\ \mathrm{it-s}} - \alpha_2 \mathrm{DP}_{\ \mathrm{it-s}}^{2}, (4)$$

Thus, our first-stage regression is:

$$Gini'_{it} = Z_{it} + \varepsilon_{it}, (5)$$

where Z_{it} is residual Gini index which is not due to GDP per capita. And we insert it in the main model to calculated Growth due to inequality:

$$Growth_{it} = \alpha GDPpc_{it-s} + \beta Gini'_{it-s} + \varepsilon_{it-s}\ (6)$$

V. Results

Preliminary Results

First of all, we run some preliminary estimation[20]. Table 19 shows the results for Pooled OLS and Fixed Effects basic and augmented models[21]. In all the regressions Gini Index has a significant positive effect on the subsequent growth, although the coefficient of the lagged GDP per capita changes from positive in the Pooled OLS to negative in the FE model. In the augmented version the only significant coefficient that held in both model is professional school education. We also would like to note that in the FE model the coefficient for Gini index are almost three times higher than in the simple Pooled OLS model.

[20] See all the specification tests in the Appendix 2.
[21] See FE model regressions for quintiles in the Appendix 2.

Table 10 Effect of Gini Index on Growth (Pooled OLS and FE)

	Pooled OLS		FE	
Variables	Basic	Augmeneted	Basic	Augmented
Gini (lag)	0.37**	0.36**	0.94***	0.92***
	(0.15)	(0.18)	(0.28)	(0.30)
GDP pc (lag)	0.11***	0.10***	-0.22***	-0.24***
	(0.02)	(0.02)	(0.05)	(0.05)
Investments		0.19***		0.12
		(0.07)		(0.08)
College		-0.04		0.09*
		(0.03)		(0.05)
Prof. School		0.17*		0.74***
		(0.10)		(0.23)
Unemployment		-0.23**		0.08
		(0.10)		(0.25)
Labour		0.09		0.29
		(0.26)		(0.54)
Life Expectancy		0.17		0.47
		(0.21)		(0.61)
Migration		-0.00		0.01
		(0.01)		(0.01)
Constant	-13.40**	-30.45	-22.66**	-77.83
	(5.22)	(20.73)	(10.10)	(58.41)
Observations	235	235	235	235
R-squared	0.49	0.53	0.56	0.61
Number of regions			79	79

Time dummies are included in all the models. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Instrumental Variables (IV) Model Results

First of all, we show the first stage results for the IV model (Table 11). Together with regional fixed effects and time effects, residual Gini Index accounts for 89% of the variance in the regression. It has a negative effect on the log of GDP per capita on 1% significance level[22].

Table 11 First-Stage Regression for Gini Index

Variables	Gini Index
Residual Gini Index	-0.32***
	(0.02)
Observations	235
R-squared	0.89

The method of estimation is Pooled OLS. Time and regional dummies are included, but not shown. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[22] See a graph for the Fitted OLS in the Appendix 2.

Finally, we present the results of the IV regression, both for basic and augmented models. We can see that, generally, the results stay intact: inequality has a positive effect on growth, while initial level of GDP per capita has a negative effect for all the groups. Interestedly enough, in the basic model inequality does not have a significant effect on the growth of the richest groups, while in the augmented model this effect is significant.

In the augmented model, we confirm that professional school education, college education and investments are beneficial to growth, although their effect is not equal for all the groups. College education has no significant effect on income growth of the riches quantile, while investments affect positively only two richest groups. That can be explained by the hypothesis that the main source of income for poorer groups are salaries and for the riches group is profit.

Table 12 Effect of Inequality on the Growth (by quantile) Basic IV Model

Variables	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini Index (lag)	0.92*	0.55***	0.80***	0.95**	0.85	1.91
	(0.51)	(0.16)	(0.27)	(0.38)	(0.58)	(1.41)
GDP pc (lag)	-0.22***					
	(0.04)					
GDP pc (lag) group 1 (lowest)		-0.14***				
		(0.04)				
GDP pc (lag) group 2			-0.13***			
			(0.04)			
GDP pc (lag) group 3				-0.17***		
				(0.03)		
GDP pc (lag) group 4					-0.20***	
					(0.04)	
GDP pc (lag) group 5 (highest)						-0.26***
Constant	-25.03	-18.34***	-26.05**	-28.93*	-21.46	-49.90
	(19.95)	(6.51)	(10.64)	(15.03)	(22.53)	(54.13)
Observations	235	235	235	235	235	235
Number of regions	79	79	79	79	79	79
R-squared	0.77	0.72	0.78	0.79	0.77	0.75
Hansen J, p-value	0.65	0.63	0.72	0.71	0.72	0.66
Kleibergen Paap F-Stat	44.20	55.10	42.46	43.20	46.08	42.46

The method of estimation is 2SLS FE. Time dummies are included in every regression. The instrumental variable for the Gini Index is residual variation in inequality that is not due to the GDP per capita. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 13 Effect of Inequality on the Growth (by quantile) Augmented IV Model

Variables	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini Index (lag)	1.14**	0.52***	0.82***	1.06***	1.28**	2.15*
	(0.47)	(0.14)	(0.23)	(0.33)	(0.52)	(1.28)
GDP pc (lag)	-0.24***					
	(0.04)					
Investments	0.12*	0.01	0.03	0.07	0.13*	0.37**
	(0.07)	(0.02)	(0.03)	(0.05)	(0.07)	(0.18)
College	0.11**	0.08***	0.12***	0.14***	0.22***	-0.03
	(0.05)	(0.01)	(0.02)	(0.04)	(0.06)	(0.14)
Prof. School	0.73***	0.12***	0.27***	0.46***	0.79***	1.99***
	(0.18)	(0.05)	(0.08)	(0.12)	(0.19)	(0.49)
Unemployment	0.06	0.01	0.02	0.03	0.06	0.21
	(0.20)	(0.05)	(0.09)	(0.14)	(0.22)	(0.55)
Labour	0.25	-0.25**	-0.22	-0.11	0.16	1.73
	(0.43)	(0.11)	(0.20)	(0.30)	(0.47)	(1.18)
Life Expectancy	0.51	0.11	0.24	0.33	0.56	1.35
	(0.49)	(0.13)	(0.23)	(0.34)	(0.54)	(1.32)
Migration	0.01	0.01	0.01	0.01	0.01	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
GDP pc (lag) group 1 (lowest)		-0.23***				
		(0.04)				
GDP pc (lag) group 2			-0.22***			
			(0.04)			
GDP pc (lag) group 3				-0.23***		
				(0.04)		
GDP pc (lag) group 4					-0.25***	
					(0.04)	
GDP pc (lag) group 5 (highest)						-0.24***
						(0.05)
Constant	-95.56*	-11.39	-33.84	-55.71	-98.86*	-288.6**
	(51.09)	(13.96)	(24.38)	(35.94)	(56.73)	(137.7)
Observations	235	235	235	235	235	235
Number of Regions	79	79	79	79	79	79
R-squared	0.77	0.72	0.78	0.79	0.77	0.75
Hansen J, p-value	0.69	0.70	0.65	0.66	0.72	0.66
Kleibergen Paap F-Stat	27.97	24.03	25.43	26.09	22.89	23.65

The method of estimation is 2SLS FE. Time dummies are included in every regression. The instrumental variable for the Gini Index is residual variation in inequality that is not due to the GDP per capita. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Robustness Checks

For the robustness checks, first, we change some model specifications and then we try an alternative method that implies internal instruments use – System GMM and Difference GMM. First, we run both basic and augmented regressions not for 5-year period growth, but for 3-year period growth. We see that it has not changed our results in any significant way.

Afterwards we eliminate Moscow from our group of regions and then we eliminate huge oil-exporting regions. We can see that it has not changed our results; only the significance of college education has gone both for the model without Moscow and for the model without huge oil-exporting regions. The instruments stay valid and strong.

Table 14 Effect of Inequality on the Growth (by quantile) Basic IV Model (3-year periods)

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini Index (lag)	1.31***	0.32	0.54	0.80*	1.35**	3.52***
	(0.50)	(0.21)	(0.34)	(0.45)	(0.58)	(1.16)
GDP pc (lag)	-0.45***					
	(0.03)					
GDP pc (lag) group 1 (lowest)		-0.50***				
		(0.05)				
GDP pc (lag) group 2			-0.47***			
			(0.05)			
GDP pc (lag) group 3				-0.46***		
				(0.04)		
GDP pc (lag) group 4					-0.44***	
					(0.03)	
GDP pc (lag) group 5 (highest)						-0.43***
						(0.03)
Observations	316	316	316	316	316	316
R-squared	0.60	0.38	0.42	0.50	0.58	0.65
Number of Regions	79	79	79	79	79	79
Hansen J, p-value	0.10	0.07	0.06	0.06	0.07	0.08
Kleibergen Paap F-Stat	57.841	40.565	45.961	49.795	55.178	62.653

The method of estimation is 2SLS FE. Time dummies are included in every regression. The instrumental variable for the Gini Index is residual variation in inequality that is not due to the GDP per capita. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 15 Effect of Inequality on the Growth (by quantile) Augmented IV Model (3-year periods)

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini Index (lag)	1.10**	0.38**	0.56*	0.76*	1.23**	2.54**
	(0.47)	(0.18)	(0.30)	(0.40)	(0.53)	(1.13)
GDP pc (lag)	-0.33***					
	(0.03)					
Investments	0.04	0.00	0.02	0.03	0.04	0.13
	(0.04)	(0.01)	(0.03)	(0.04)	(0.05)	(0.11)
College	-0.01	0.05***	0.08**	0.08*	0.04	-0.31**
	(0.05)	(0.02)	(0.03)	(0.04)	(0.06)	(0.13)
Prof. School	0.30**	-0.01	0.05	0.14	0.30**	0.99***
	(0.14)	(0.05)	(0.08)	(0.11)	(0.15)	(0.33)
Unemployment	0.03	0.02	0.04	0.04	0.05	-0.00
	(0.14)	(0.05)	(0.08)	(0.11)	(0.16)	(0.34)
Labour	0.10	-0.21*	-0.24	-0.17	0.04	1.10
	(0.37)	(0.12)	(0.21)	(0.30)	(0.41)	(0.91)
Life Expectancy	0.22	0.06	0.17	0.23	0.18	0.45
	(0.46)	(0.15)	(0.27)	(0.38)	(0.52)	(1.13)
Migration	0.01*	0.00*	0.01*	0.01*	0.01*	0.03*
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
GDP pc (lag) group 1 (lowest)		-0.35***				
		(0.05)				
GDP pc (lag) group 2			-0.35***			
			(0.04)			
GDP pc (lag) group 3				-0.34***		
				(0.04)		
GDP pc (lag) group 4					-0.33***	
					(0.03)	
GDP pc (lag) group 5 (highest)						-0.32***
						(0.04)
Observations	312	312	312	312	312	312
R-squared	0.55	0.24	0.30	0.40	0.52	0.65
Number of Regions	79	79	79	79	79	79
Hansen J, p-value	0.12	0.10	0.09	0.08	0.11	0.11
Kleibergen Paap F-Stat	62.404	42.205	50.908	55.270	60.326	65.439

The method of estimation is 2SLS FE. Time dummies are included in every regression. The instrumental variable for the Gini Index is residual variation in inequality that is not due to the GDP per capita. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 16 Effect of Inequality on the Growth (by quantile) Augmented IV Model without Moscow

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini Index (lag)	0.93**	0.57***	0.83***	0.98***	1.12**	1.22
	(0.47)	(0.14)	(0.22)	(0.33)	(0.51)	(1.28)
GDP pc (lag)	-0.24***					
	(0.04)					
Investments	0.11*	0.01	0.02	0.06	0.11	0.34**
	(0.06)	(0.02)	(0.03)	(0.04)	(0.07)	(0.17)
College	0.08	-0.01	0.01	0.03	0.08	0.27
	(0.07)	(0.02)	(0.03)	(0.05)	(0.08)	(0.20)
Prof. School	0.38**	0.10**	0.17**	0.27**	0.41**	0.95**
	(0.18)	(0.05)	(0.08)	(0.12)	(0.19)	(0.48)
Unemployment	0.07	0.02	0.03	0.04	0.08	0.16
	(0.19)	(0.05)	(0.09)	(0.13)	(0.20)	(0.51)
Labour	0.08	-0.23**	-0.24	-0.19	0.01	1.04
	(0.40)	(0.10)	(0.18)	(0.27)	(0.43)	(1.09)
Life Expectancy	0.27	0.06	0.12	0.14	0.26	0.79
	(0.45)	(0.12)	(0.21)	(0.31)	(0.49)	(1.23)
Migration	0.01	0.01	0.01	0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
GDP pc (lag) group 1 (lowest)		-0.22***				
		(0.04)				
GDP pc (lag) group 2			-0.21***			
			(0.03)			
GDP pc (lag) group 3				-0.23***		
				(0.03)		
GDP pc (lag) group 4					-0.23***	
					(0.04)	
GDP pc (lag) group 5 (highest)						-0.25***
						(0.04)
Constant	-56.19	-8.97	-21.98	-31.47	-56.93	-163.3
	(48.53)	(13.54)	(23.09)	(34.05)	(52.86)	(131.4)
Observations	231	231	231	231	231	231
R-squared	0.78	0.69	0.75	0.77	0.78	0.76
Number of Regions	78	78	78	78	78	78
Hansen J, p-value	0.77	0.61	0.79	0.72	0.72	0.73
Kleibergen Paap F-Stat	19.2341	17.2654	16.6519	16.3421	17.4319	17.3190

The method of estimation is 2SLS FE. Time dummies are included in every regression. The instrumental variable for the Gini Index is residual variation in inequality that is not due to the GDP per capita. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 17 Effect of Inequality on the Growth (by quantile) Augmented IV Model without Huge Oil-Producing Regions

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini Index (lag)	0.74**	0.56***	0.74***	0.83***	0.89**	0.83
	(0.34)	(0.17)	(0.21)	(0.28)	(0.39)	(0.83)
GDP pc (lag)	-0.20***					
	(0.07)					
Investments	-0.01	-0.01	-0.02	-0.02	-0.02	0.02
	(0.05)	(0.02)	(0.03)	(0.04)	(0.06)	(0.12)
College	0.10	-0.01	0.01	0.04	0.10	0.35*
	(0.08)	(0.03)	(0.05)	(0.06)	(0.09)	(0.19)
Prof. School	0.29**	0.11**	0.18**	0.25**	0.33**	0.59*
	(0.14)	(0.05)	(0.08)	(0.11)	(0.16)	(0.34)
Unemployment	0.09	0.01	0.03	0.05	0.09	0.27
	(0.14)	(0.05)	(0.08)	(0.11)	(0.16)	(0.34)
Labour	-0.17	-0.26***	-0.30*	-0.31	-0.24	0.22
	(0.30)	(0.10)	(0.17)	(0.23)	(0.34)	(0.73)
Life Expectancy	-0.35	0.02	-0.03	-0.17	-0.36	-1.16
	(0.35)	(0.13)	(0.21)	(0.28)	(0.40)	(0.85)
Migration	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
GDP pc (lag) group 1 (lowest)		-0.08				
		(0.11)				
GDP pc (lag) group 2			-0.13*			
			(0.08)			
GDP pc (lag) group 3				-0.16**		
				(0.07)		
GDP pc (lag) group 4					-0.19***	
					(0.07)	
GDP pc (lag) group 5 (highest)						-0.25***
						(0.07)
Constant	11.39	-4.97	-4.16	3.31	11.52	45.09
	(38.04)	(15.92)	(23.13)	(30.91)	(43.44)	(90.42)
Observations	203	203	203	203	203	203
Number of Regions	68	68	68	68	68	68
R-squared	0.75	0.58	0.65	0.70	0.74	0.78
Hansen J, p-value	0.55	0.58	0.55	0.50	0.54	0.58
Kleibergen Paap F-Stat	14.02	32.78	33.49	35.93	31.86	35.50

The method of estimation is 2SLS FE. Time dummies are included in every regression. The instrumental variable for the Gini Index is a residual variation in inequality that is not due to the GDP per capita. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 The regions that are excluded are Arkhangelsk Oblast, Chukotka Autonomous Okrug, Leningrad Oblast, Moscow, Novosibirsk Oblast, Tyumen Oblast, Republic of Tatarstan, Republic of Bashkortastan, Saint Petersburg, Sahklin Oblast and Samara Oblast.

The results of the System GMM base model estimations are pretty similar to the ones of the IV. Inequality has a positive and significant effect on the growth of income of almost every quantile, except for the fourth one. And again, the richer quantiles are the ones that benefit more from the inequality. However, we need to mention that as p-value of Hansen test is quite low, especially in the augmented model, the estimation results are doubtful and we should hold to IV model results.

Table 18 Effect of Inequality on the Growth (by quantile) Basic System GMM Model

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
GDP pc (lag)	-0.04					
	(0.07)					
Gini (lag)	2.35*	0.84***	2.41*	4.41**	2.16	8.26***
	(1.35)	(0.27)	(1.30)	(2.25)	(1.70)	(2.94)
GDP pc (lag) group 1 (lowest)		-0.02				
		(0.06)				
GDP pc (lag) group 2			-0.21			
			(0.14)			
GDP pc (lag) group 3				-0.29*		
				(0.15)		
GDP pc (lag) group 4					0.01	
					(0.09)	
GDP pc (lag) group 5 (highest)						-0.17**
						(0.07)
Observations	235	235	235	235	235	235
Num. of Regions	79	79	79	79	79	79
Num. of Instruments	9	9	9	9	9	9
Hansen (p-value)	0.099	0.126	0.447	0.563	0.063	0.126
AR (1) (p-value)	0.006	0.346	0.742	0.581	0.012	0.008

A constant term and time dummies are included in all models. Estimations are by two-step System-GMM, reducing the number of lags to two. Standard errors are in parentheses. The p-value of Hansen over-identifying restrictions tests is for the null hypothesis of instrument validity. The AR (1) p-value is for first-order serial correlations.
Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 19 Effect of Inequality on the Growth (by quantile) Augmented System GMM Model

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini (lag)	0.22***	0.22***	0.35***	0.43***	0.20***	0.19
	(0.05)	(0.01)	(0.03)	(0.04)	(0.06)	(0.12)
GDP pc (lag)	0.09***					
	(0.01)					
Investments	0.28***	0.05***	0.12***	0.19***	0.32***	0.73***
	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.09)
College	-0.11***	0.01***	0.02***	-0.01	-0.06***	-0.51***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Prof. School	0.16***	-0.06***	-0.09***	-0.05	0.07	0.86***
	(0.05)	(0.01)	(0.02)	(0.03)	(0.05)	(0.14)
Unemployment	-0.32***	-0.07***	-0.16***	-0.24***	-0.36***	-0.79***
	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.10)
Labour	1.26***	0.03	0.35***	0.84***	1.27***	3.58***
	(0.11)	(0.03)	(0.06)	(0.09)	(0.11)	(0.30)
Life Expectancy	0.46***	0.17***	0.33***	0.41***	0.50***	1.24***
	(0.14)	(0.02)	(0.05)	(0.08)	(0.14)	(0.43)
Migration	0.03***	0.01***	0.01***	0.02***	0.03***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GDP pc (lag) group 1 (lowest)		0.14***				
		(0.01)				
GDP pc (lag) group 2			0.12***			
			(0.01)			
GDP pc (lag) group 3				0.10***		
				(0.01)		
GDP pc (lag) group 4					0.10***	
					(0.01)	
GDP pc (lag) group 5 (highest)						0.07***
						(0.01)
Observations	234	234	234	234	234	234
Num. of Regions	79	79	79	79	79	79
Num. of Instr-s	64	64	64	64	64	64
Hansen (p-value)	0.077	0.134	0.066	0.019	0.027	0.029
AR (1) (p-value)	0.021	0.034	0.035	0.063	0.059	0.118

A constant term and time dummies are included in all models. Estimations are by two-step System-GMM, reducing the number of lags to two. Standard errors are in parentheses. The p-value of Hansen over-identifying restrictions tests is for the null hypothesis of instrument validity. The AR (1) p-value is for first-order serial correlations. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 20 Effect of Inequality on the Growth (by quantile) Basic Difference GMM Model

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
GDP pc (lag)	-0.13					
	(0.12)					
Gini (lag)	5.48**	0.61**	1.31**	2.36**	7.30**	22.38*
	(2.48)	(0.25)	(0.55)	(0.99)	(3.24)	(12.72)
GDP pc (lag) group 1 (lowest)		-0.01				
		(0.10)				
GDP pc (lag) group 2			-0.08			
			(0.09)			
GDP pc (lag) group 3				-0.15*		
				(0.09)		
GDP pc (lag) group 4					-0.10	
					(0.13)	
GDP pc (lag) group 5 (highest)						0.04
						(0.31)
Observations	156	156	156	156	156	156
Num. of Regions	79	79	79	79	79	79
Num. of Instruments	6	6	6	6	6	6
Hansen (p-value)	.	.	.	.	.	.
AR (1) (p-value)	0.040	0.124	0.190	0.020	0.118	0.030

Time dummies are included in all models. Estimations are by one-step Difference-GMM, reducing number of lags to three. Standard errors are in parentheses. The p-value of Hansen over-identifying restrictions tests is for the null hypothesis of instrument validity. The AR (1) p-value are for first-order serial correlations. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

VI. Conclusions

In this chapter, we have analysed the effect of inequality on growth using a dynamic panel data model. We have used regional data for the Russian Federation for the last fifteen years and employ an instrumental variables (IV) model. We have also verified the effect of inequality on growth on different steps of the income ladder. For all these models we have conducted plenty of robustness checks. Here are our principal findings:

First, the main conclusion of our research is that for Russian regions *inequality generally has a significant positive effect on growth*. As we commented in the introduction, the results contradict the findings of Panizza (2012) in his similar research for the United States. To our minds, these results comply with the hypothesis that inequality is in fact beneficial to growth in low-income countries. Although according to World Bank, Russian is upper-middle income country, not exactly the low income country, the average income of the vast majority of regions corresponds to lower-middle income classes (including some of them to low-income countries).

Second, *the effect is positive even for the lowest income groups*. Of course, the higher the income group, the higher the positive effect of inequality. For example, a ten-point increase in the Gini index corresponds to more than 5.000 roubles of additional income for the lowest group and more than 20.000 roubles of additional income for the highest income group. But nevertheless it is still not negative for the poor.

Third, *our results prove to be robust to a battery of robustness checks*. We have used different estimation techniques, different time periods and control variables, as well as different variables to measure inequality. Besides, we have excluded some possible outliers and the results held.

Fourth, *we have also detected a significant positive robust result of investment, college and professional education on growth.* However, this effect of investment and college education is not the same for all the income groups. For example, investments are beneficial only for two riches groups, while college education is beneficial for all the groups, except of the riches one. We hypothesis that it can happen due to the fact that the main source of income for higher income groups are profits (which normally are positively correlated with investment activity), while the main source of income of lower income groups are salaries (with normally higher in higher educated societies).

APPENDIX 2

Preliminary Estimation

First of all, we are to conduct several standard specification tests on our model. We start with the estimation Pooled OLS, FE and RE basic model. We can see that according to our estimations, the Gini index has a significant positive effect on subsequent growth.

Table A 8 Pooled OLS, FE and RE

	Growth		
Variables	OLS	FE	RE
Gini Index (lag)	0.37**	0.94***	0.38**
	(0.15)	(0.28)	(0.17)
GDP pc (lag)	0.11***	-0.22***	0.14***
	(0.02)	(0.05)	(0.01)
Constant	-13.40**	-22.66**	-14.20**
	(5.22)	(10.10)	(5.67)
Observations	235	235	235
R-squared	0.49	0.56	
Number of Regions		79	79

Time dummies are included in all regressions. Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Breusch and Pagan Test

```
Breusch and Pagan Lagrangian multiplier test for random effects

        gln5[n_reg,t] = Xb + u[n_reg] + e[n_reg,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                    gln5 |   .0243337       .1559925
                       e |   .0068036       .0824839
                       u |   .0025148       .0501473

        Test:   Var(u) = 0
                             chibar2(01) =     2.39
                          Prob > chibar2 =   0.0612
```

Then we conduct the Breusch and Pagan Lagrangian Multiplier Test for Random Effects. The null hypothesis of this test is that H_0: $\sigma_u^2 = 0$. As P>0.05 we fail to reject the null hypothesis and conclude that the Pooled OLS estimation is better than RE.

Hausman Test

```
             ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      FE           RE           Difference          S.E.
-------------+----------------------------------------------------------------
        GINI |
         L5. |   .0045618     .0004327        .0041291        .0027695
   LN_GDP00  |
         L5. |  -.5563756    -.0368187       -.5195569        .0532896
        year |
        2008 |   .3404338     .2559832        .0844506        .0010546
        2015 |     .30103      .051782        .2492481        .0244386
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       96.28
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Now the next step is to decide which model is better between FE and RE. To do this, we use the Hausman Test. The Hausman test evaluates the consistency of the RE estimator. As we can see, the p-value is less than 5% of fixed significance, so the random effects estimator is inconsistent.

```
F test that all u_i=0: F(78, 152) = 3.34                     Prob > F = 0.0000
```

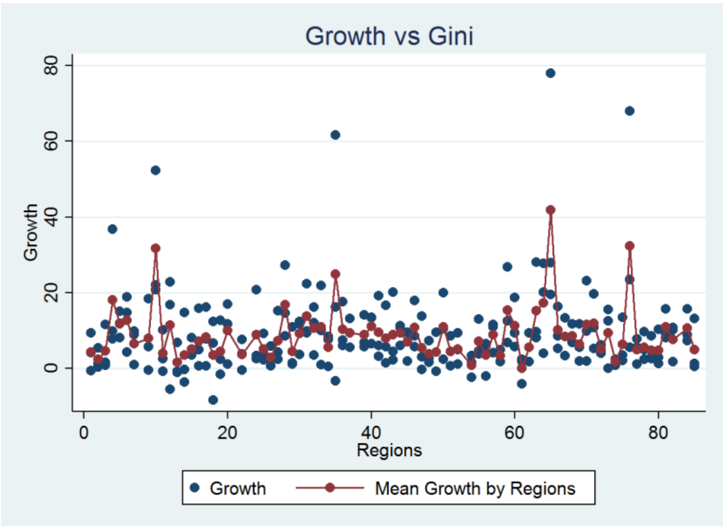
If this test is significant, i.e., all firm effects are equal to 0, you reject probability and opt for the fixed effects model. So, the conclusion is that the FE model is the most suitable one. Nevertheless, we should conduct more tests.

Table A 9 Statistic Tests

Test	H_0		Result in our model (FE)
Testing for cross-sectional dependence/contemporaneous correlation	The null hypothesis is that residuals are not correlated	Friedman's test of cross sectional independence = 0.114, Pr = 1.0000 Average absolute value of the off-diagonal elements = 1.000	We do not have cross-sectional dependence.
Testing for heteroscedasticity	The null hypothesis is homoscedasticity (or constant variance)	Modified Wald test for groupwise heteroskedasticity in fixed effect regression model H0: sigma(i)^2 = sigma^2 for all i chi2 (79) = 0.00 Prob>chi2 = 1.0000	We do not have the heteroscedasticity.

Figures A8 and A9 show the heterogeneity of growth of GDP per capita in roubles in 2000 basic prices by periods and regions. Figures A10 and A11show the heterogeneity of 5-year GDP per capita by periods and regions.[23]

Figure A 8 Heterogeneity of Growth by Regions



[23] See Chapter 1 for the same figures for Gini Index.

Figure A 9 Heterogeneity of 5-year GDP by regions

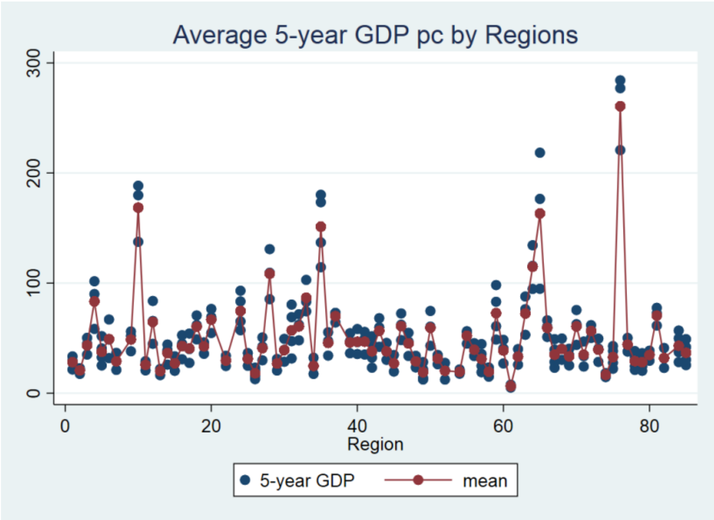


Figure A 10 Growth by years

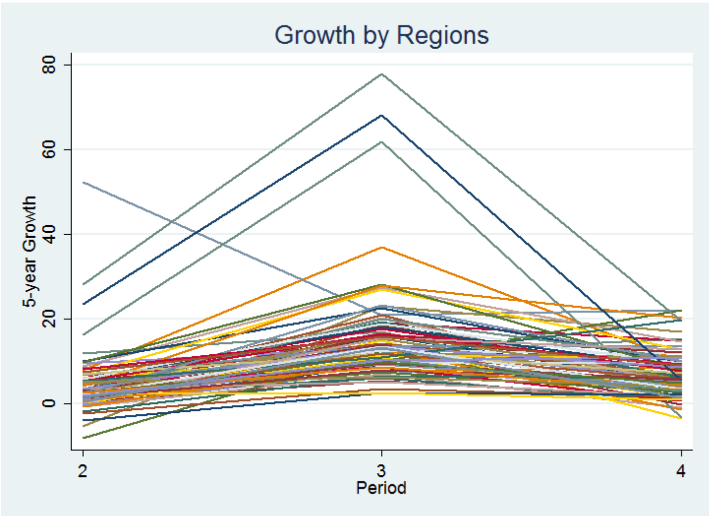


Figure A 11 5-year GDP pc by years

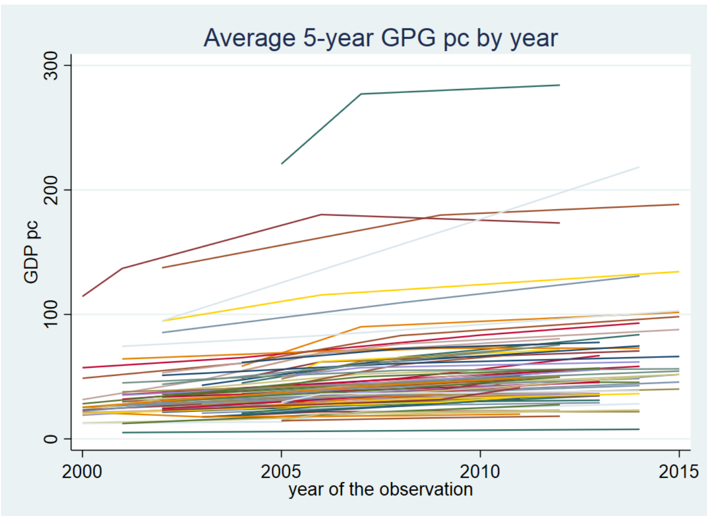


Figure A 12 OLS Fitted Values for Growth and Gini

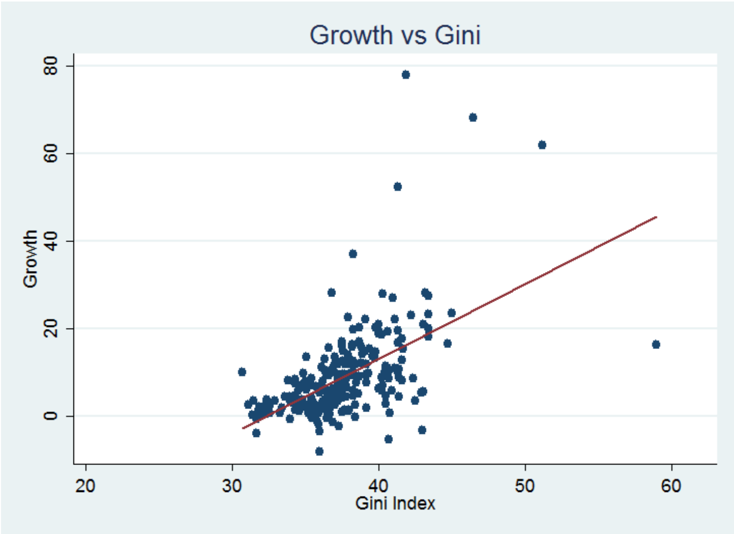
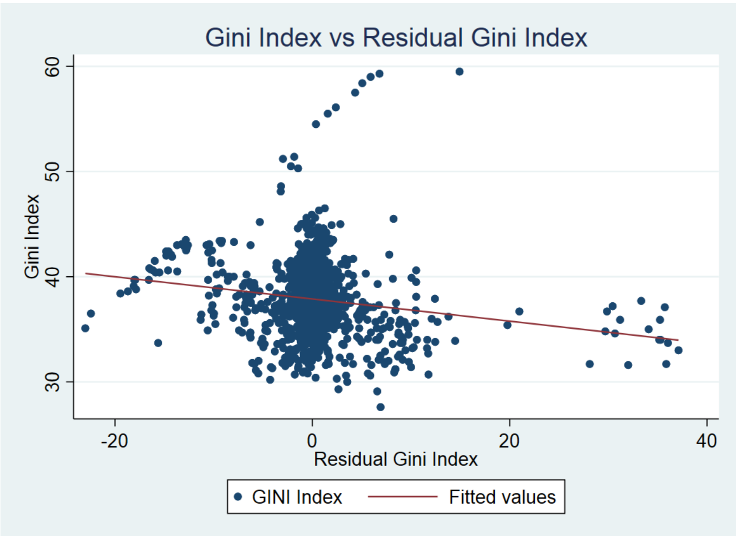


Figure A 13 Gini Index vs Residual Gini Index



Augmented Model

As we are going to add a set of additional variables to construct our basic and augmented models, first, we are to check, whether the explanatory variables we suggest do not have a multicollinearity problem.

To start, we check out correlation coefficients between explanatory variables, although according to Maddala and Lahiri (2009), 'high intercorrelations among the explanatory variables are *neither necessary nor sufficient* to cause the multicollinearity problem'. They add, that these are 'the best indicators of the problem are the *t*-ratios of the individual coefficients'.

Table A 10 Correlation Matrix

	GINI	GDP00	INVEST	COLLEGE	PROF_SCH	UNEMPL	LABOUR	LIFE_EXP	MIGR
GINI	1.0000								
GDP00	0.5882	1.0000							
INVEST	0.1732	0.1707	1.0000						
COLLEGE	0.5697	0.3851	-0.1052	1.0000					
PROF_SCH	0.3971	0.1826	-0.1490	0.5671	1.0000				
UNEMPL	-0.3171	-0.3394	-0.0380	-0.2667	-0.2519	1.0000			
LABOUR	0.3240	0.4385	0.1845	0.1314	0.0869	-0.1278	1.0000		
LIFE_EXP	0.3096	0.1034	0.1969	0.3333	0.0853	0.0098	-0.2546	1.0000	
MIGR	0.0775	-0.0284	-0.0130	0.2348	0.2267	-0.0811	-0.2581	0.2372	1.0000

Then we are finding VIF factors. As a rule of thumb, if the mean VIF is less than 10, we conclude that there is no multicollinearity in the model.

Table A 11 Multicollenearity Diagnostics

Variable	VIF	1/VIF
GINI		
L1.	2.93	0.341416
GDP00		
L1.	2.27	0.440502
INVEST		
L1.	1.45	0.690436
COLLEGE		
L1.	2.49	0.401303
PROF_SCH		
L1.	2.17	0.460448
UNEMPL		
L1.	1.81	0.552498
LABOUR		
L1.	3.16	0.316405
LIFE_EXP		
L1.	2.88	0.347454
MIGR		
L1.	1.71	0.585333
year		
2008	2.66	0.375822
2015	5.43	0.184033
Mean VIF	2.63	

Quantile FE Model Results

First, we have a look at the Fixed Effect results of the basic model and augmented models. In both models, inequality has a positive significant impact on growth in all the income groups, while the initial GDP per capita level has a negative effect. However, for richer income groups, this effect is much more prominent than for poorer income groups. For example, the rise of inequality by ten Gini points for the highest income group provokes the rise of income of almost 32.000 roubles in five years, while for the lowest income group, this is only for less than 1.400 roubles. On average, it raises the GDP per capita by almost 10.000 roubles.

When we add more control variables, this pattern remains, but the differences between groups are less dramatic. For the rise of 10 Gini points, the lowest group benefits by 2.400 roubles, while the highest group benefits by 15.500 roubles. The effect of investments is positive and significant for each regression.

That is worth mentioning that college education and life expectancy have a significant positive effect on the income of four lower income groups, while its impact is insignificant for the highest one. On the contrary, the share of labour force and professional schools education are significant only for the highest group. We imagine that may happen, because of the fact that the highest income group is represented by entrepreneurs who take advantage of these two factors. Migration benefits all groups except the lowest one. Again, that may happen due to the fact that migrants normally occupy the lowest-paid jobs that correspond to the first group.

Table A 12 Effect of Inequality on Growth (by quantile) Basic FE Model

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group 5 Growth
Gini (lag)	0.94***	0.14*	0.28**	0.52***	0.72**	3.17***
	(0.28)	(0.07)	(0.13)	(0.19)	(0.31)	(0.77)
GDP pc (lag)	-0.22***					
	(0.05)					
GDP pc (lag) group 1 (lowest)		-0.18***				
		(0.05)				
GDP pc (lag) group 2			-0.15***			
			(0.04)			
GDP pc (lag) group 3				-0.18***		
				(0.04)		
GDP pc (lag) group 4					-0.20***	
					(0.05)	
GDP pc (lag) group 5 (highest)						-0.27***
						(0.05)
Constant	-22.66**	-1.978	-5.162	-10.99	-14.41	-86.59***
	(10.10)	(2.72)	(4.77)	(7.08)	(11.31)	(27.71)
Observations	235	235	235	235	235	235
R-squared	0.557	0.369	0.445	0.514	0.539	0.572
Number of Regions	79	79	79	79	79	79

The estimation method is FE. Time dummies are included in all regressions. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A 13 Effect of Inequality on Growth (by quantile) Augmented FE Model

VARIABLES	Total Growth	Group 1 Growth	Group 2 Growth	Group 3 Growth	Group 4 Growth	Group Growth
Gini (lag)	0.65**	0.24***	0.36**	0.49**	0.69**	1.55*
	(0.30)	(0.08)	(0.14)	(0.21)	(0.33)	(0.79)
GDP pc (lag)	-0.36***					
	(0.05)					
Investments	0.20***	0.04**	0.09**	0.14***	0.23***	0.51**
	(0.08)	(0.02)	(0.04)	(0.05)	(0.09)	(0.20)
College	0.06	0.07***	0.10***	0.12**	0.19***	-0.17
	(0.06)	(0.02)	(0.03)	(0.05)	(0.07)	(0.16)
Prof. School	0.68	-0.05	0.01	0.20	0.53	2.77**
	(0.44)	(0.12)	(0.21)	(0.31)	(0.49)	(1.17)
Unemployment	0.28	0.05	0.11	0.19	0.31	0.72
	(0.25)	(0.06)	(0.12)	(0.17)	(0.28)	(0.65)
Labour	0.84	-0.05	0.15	0.41	0.85	2.73*
	(0.59)	(0.15)	(0.28)	(0.41)	(0.66)	(1.56)
Life Expectancy	1.01*	0.29*	0.55**	0.75*	1.16*	2.31
	(0.56)	(0.15)	(0.27)	(0.39)	(0.63)	(1.48)
Migration	0.04**	0.01	0.01*	0.02**	0.04**	0.10**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
GDP pc (lag) group 1 (lowest)		-0.36***				
		(0.06)				
GDP pc (lag) group 2			-0.30***			
			(0.06)			
GDP pc (lag) group 3				-0.32***		
				(0.05)		
GDP pc (lag) group 4					-0.37***	
					(0.05)	
GDP pc (lag) group 5 (highest)						-0.39***
						(0.06)
Constant	-135.4**	-21.34	-54.50**	-86.79**	-145.5**	-366.1**
	(53.54)	(14.09)	(25.56)	(37.70)	(59.96)	(141.1)
Observations	234	234	234	234	234	234
R-squared	0.660	0.493	0.540	0.607	0.645	0.698
Number of Regions	79	79	79	79	79	79

The estimation method is FE. Time dummies are included in all regressions. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

System GMM Model

According to Pesaran (2015), 'if lagged dependent variables appear as explanatory variables, strict exogeneity of the regressors does not hold, and the maximum-likelihood estimator or the within estimator under the fixed-effects specification is no longer consistent in the case of panel data models where the number of cross-section units, N, is large and T, the number of time periods, is small'. In this study, due to the nature of the dynamic panel data, we suggest using the System GMM method as well. It is widely used in growth models (Panizza, 2002) and was developed by Arellano and Bover (1995), and Blundell and Bond (1998).

They argue that this method is able to correct unobserved country heterogeneity, omitted variable bias, measurement error, and potential endogeneity that frequently affect growth estimation. This approach is based on the use of internal instruments (lagged levels of regressors) and estimates a system of equations in both first-differences and levels. The instruments for differenced equations are obtained from the values (levels) of the explanatory variables lagged at least twice, and the instruments for the levels equations are the lagged differences of the variable.

The consistency of the GMM estimator depends on the validity of the instruments. As suggested by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998), two specification tests are used. Firstly, the Sargan/Hansen test of over-identifying restrictions, which tests for the overall validity of the instruments and the null hypothesis is that all instruments as a group are exogenous. The second test examines the null hypothesis that the error term of the differenced equation is not serially correlated particularly at the second order (AR (2)). One should not reject the null hypothesis of both tests.

As the System GMM and Difference GMM are inconsistent with the presence of cross-sectional dependence, first of all, we run Friedman's test.

Cross-sectional Dependence Test

```
Friedman's test of cross sectional independence =     7.911, Pr = 1.0000
Average absolute value of the off-diagonal elements =     1.000
```

It shows that we do not have any cross-sectional dependency, as the p-value is much above 0.05. So we can proceed with the Difference and System GMM estimations.

CHAPTER 3. OPPORTUNITY IN RUSSIA: *HOW MUCH OF RUSSIANS' INCOME IS DETERMINED AT BIRTH?*

I. Introduction

In this chapter, we are moving from estimating purely macroeconomic factors to investigating inequality and economic development from the individual point of view. To be precise, we are going to see to what extent the economic factors over which a separate individual has no control affect one's personal wellbeing. We are estimating how much of individuals' personal income depends on two main regional macroeconomic factors in focus – inequality and GDP per capita.

To do that, we employ microeconomic data for personal income from the Microcensus 2015 Data Base and go on using our macroeconomic data base for the Gini Index and GDP. Thus, we have a cross-sectional data-set for the year 2015. Working with the microeconomic database allows us to calculate a huge variety of variables, which opens a lot of possibilities for the research. We will see how the reginal GDP per capita and Gini Index affect income not only for the whole sample, but also the income of different income groups with high precision.[24]

When we were formulating the model, our main assumption is that these two macroeconomic variables cannot be significantly affected by one's individual effort, so econometrically speaking, they are exogenous. And this idea is crucial for our research. In other words, they are one's 'circumstances'. The conceptual difference between the inequality caused by circumstances in comparison with the inequality caused by individual efforts leads to the concept called 'inequality of opportunity', which gives impetus to the new wave of inequality studies. We will develop on this concept in detail in the literature review part.

So, first, we will provide a quick review of the related literature, and then we will describe our data and specify how various variables have been calculated. In its turn, it will lead to the discussion on the econometric model implied in the research and related econometric issues. Finally, we will present our results together with the necessary robustness checks for the main model y for the model by 20 income groups and finish with the discussion on the whole issue and subsequent conclusions.

[24] We will give more details on the database in the Data part of this chapter.

II. Literature Review and Contribution

As the research on income inequality was accumulating new data and new methods, the results were becoming increasingly ambiguous. That provoked the appearance of the inequality of opportunity concept mainly developed by Roemer (1993) and Van de Gaer (1993). The economics literature on inequality of opportunity builds explicitly on a few key contributions from philosophy, including Dworkin (1981), Arneson (1989) and Cohen (1989). The idea is that the total inequality actually consists of two elements – inequality of opportunity and inequality of effort.

The first element, inequality of opportunity, refers to factors beyond an individual's control and responsibility, or circumstances. On the microeconomic level, that can be gender, race, ethnicity, family wealth or parents' education; on the macroeconomic level, this is the place of birth or residence, economic, demographic and social development factors in the country or region, etc. The second element, inequality of effort, represents the factors of individual choice and control, for example, professional development or hours spent on education and working. According to some of the research (Marrero and Rodriguez, 2013), these two elements can affect other variables, such as growth, in opposite directions.

It is worth mentioning that this concept still provokes plenty of philosophical, political and economic discussion. As the IO is considered unjust, and IE is viewed as just, in order to create a fairer society, we are to create a level playing field, or to give the same opportunities to everyone. However, the border what is beyond individual control that we should equalise and what not is not so clear. Besides, IE are no independent from IO (for example, children of well-educated parents, on average tend to exercise more effort in the studies than ones of poor-educated parents).

Recently, a vast amount of empirical literature has been dealing with this very issue. The authors try to estimate, whether opportunities are equally distributed on the national level by measuring the extent of inequality of opportunity (Almas et al., 2011; Bjorklund et al., 2012; Bourguignon et al., 2007; Checchi and Peragine, 2010; Devooght, 2008; Lefranc et al., 2008). However, the measurement of equality of opportunity entails many methodological questions that are often difficult to resolve. There is no standard methodology to calculate IO that is why methodological differences have so far prevented meaningful international comparisons.

However, Brunori, Ferreira and Peragine (2013) tried to collect and summarize the results of empirical applications of two measures of inequality of opportunity - ex ante inequality of economic opportunity and the Human Opportunity Index (HOI)[25]. They also intend to describe correlations between these two indexes and GDP per capita, overall income inequality, and intergenerational mobility. At the same time Ramos and Van de Gaer (2012) try to put together conceptual issues in measuring IO as well as suggest a few new possibilities to measure it. They also list in one table all the empirical research available to them according to the measurement methodology implied (for example, direct and indirect ex-ante and ex-post, etc).

The development of this concept provoked the discussion about global inequality of opportunity, an idea suggested by Milanovic (2008). He argues that two thirds of one's individual income depends only on two variables beyond one's control – the average income of the country and the inequality of income distribution. In his paper of 2013, Milanovic states: 'Assignment to country is fate, decided at birth, for approximately 97% of the people in the world: less than 3% of the world's population lives in countries where they were not born. (…) By being ''allocated'' to a country, a person receives at least two ''public'' goods—average income of the country and inequality of income distribution—that are unalterable by one's own effort.' One of the conclusions of Milanovic is that when individual effort cannot significantly affect one's income, another solution will be to migrate to another country to improve one's well-being. Moreover, he develops the concept of the so-called 'location premium' – additional income explained only by differences in the GDP per capita between countries.

However, this statement proved to be true on the state-level, is it true on the regional level in the same country? Does one's income depend not only on the country in which one is born, but also on the region in which one is born? We assume that in a large heterogeneous country such as Russia with huge disparities of regional GDP and other development variables between regions per capita that can in fact be true.

Thus, we consider that the main contribution of this chapter is to determine, whether the concept of location premium works on the regional level, something that at that point has not been covered in the literature. We argue that not only the country of one's residence matters, but also *the region of residence within the country*. That influence on income may be insignificant for small homogeneous countries, but for large heterogeneous countries, such as Russia, China, Brazil or the United States *within country regional income* differences can be even more overwhelming than both the differences *between countries average income* differences and the difference *between individuals within one country*.

[25] They note that HOI, which is the measurement of children's access to basic services adjusted for differences related to circumstances, 'is not a measure of inequality of opportunity per se; it is better seen as a development index that is designed to be sensitive to inequality of opportunity' (Brunori, Ferreira and Peragrine, 2013).

To put it in simple words, in income terms it may be ‘better’ to be born in a middle-income country, but in a high-income region than to be born in a high-income country but in a lower-middle income region. As for migration, in case of being born in a poor region in a large country, it would be much easier and more beneficial to migrate to the richer region of the same country than to change one’s country of residence. We believe that we should always take into consideration these differences, in addition to the simple average-income differences between countries.

III. Data: Russia (2015)

As we mentioned before, to conduct the research, we employ both microeconomic and macroeconomic data for the year 2015. We get microeconomic data from the Russian Microcensus 2015 and we get macroeconomic data from Rosstat, the Russian Federal State Statistics Service, governmental statistics agency in Russia[26].

The sample population of the Russian Microcensus 2015 is a set of counting general census plots in which the population of private households satisfies the following requirements: territorial representation in a sample of urban and rural population; reflection of the main structural features of the population, composition and types of private households; the possibility of obtaining representative results for generalising the demographic and socio-economic characteristics at the level of the subjects of the Russian Federation and their centres; relevance and non-crossover with selected aggregates of other population surveys conducted by Rosstat. A sample of the microcensus is generated for all subjects of the Russian Federation on the basis of the information array of the All-Russian population census 2010. As a result of the microcensus, the survey covered 2154.2 thousand people (1.5% of the population of Russia as for January 1, 2016). Rosstat provides free access to the microdata of this census.

There are two sets of data – household data and individual data. For our research, we use the household set of data for several reasons. First, we are more interested in how the macroeconomic situation affects the financial well-being of individuals in general, not specifically the ones who have a direct source of income, such as salary or profit. Second, in the individual set of data all the population is included, that means, children from zero years of age and elderly people who do not have their own labour income. That is why in the case of using the individual data we should have dropped these observations. These selection criteria can significantly bias the estimations.

[26] Please see the introduction for more information on the database.

Moreover, it provides different types of income; we find it convenient to choose the disposable income after all the subsidies and transfers. In comparison with previous chapters, where we used exclusively before-tax data, here we use after-tax data for the first time. That has its logic and corresponds to our current research goal, that is, how much one's *personal* situation is affected by the factors, which one does not have control upon. An individual in Russia cannot either affect the redistributional policies of the federal government, regardless whether they benefit him or her or not in terms of personal income.

In general, the data base has 160,008 observations, so to render the analysis manageable we calculate the mean income for each of one hundred income groups from the poorest to the richest. The income differences between the individuals within these groups are almost indistinguishable, so we will not lose a lot of information. Besides, we calculate the mean income for twenty groups as well to run the regression by groups.

As for the macroeconomic variables, as we have cross-sectional data, we use the GDP per capita in current 2015 prices, not in basic ones. For our main regression, we use the Gini index from the macroeconomic database, but for robustness checks, we use the Gini Index calculated from the data itself (it is a bit lower than the first one). As we use weighted regression, we also use the information about the total population of the region from the macroeconomic database.

Finally, it is to be mentioned that we only have data for 77 and not for 79 regions as previously expected due to the fact that there is no data on the Komi Republic and Republic of Ingushetia for the GDP per capita and Gini Index for 2015. Number of observations, means, standard deviations and minimum and maximum values can be consulted in Table 21.

Table 21 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Percentile Income	7,700	264476.7	171190	7460.634	2074817
GDP pc	7,700	420665.8	337086.7	139908.7	1716734
Gini Index	7,700	38.17	2.23	33.9	43.1
Gini Index (alternative)	7,700	26.19	3.17	21.6	40.4
ln (GDP pc)	7,700	12.76	0.55	11.85	14.36
ln (Percentile Income)	7,700	12.32	0.58	8.92	14.55
Population	7,700	1870247	1795457	50540	1.22e+07
Decile Index	7,700	12.65	2.13	9.3	17.8

In order to better understand the income disparities between regions, we have created Figure 12with three representative regions – Moscow (the capital of Russia), Tyumen Oblast (oil-producing region) and Tuva Republic (one of the poorest regions)[27]. From this figure, we can see that the average income of the lowest percentile in Moscow corresponds approximately to the 20th percentile of Tyumen Oblast and the 60th percentile of Tuva Republic. We can also see that the differences in income between the lowest percentiles between regions are larger than the differences between higher percentiles.

Figure 12 Income by Percentiles by Regions

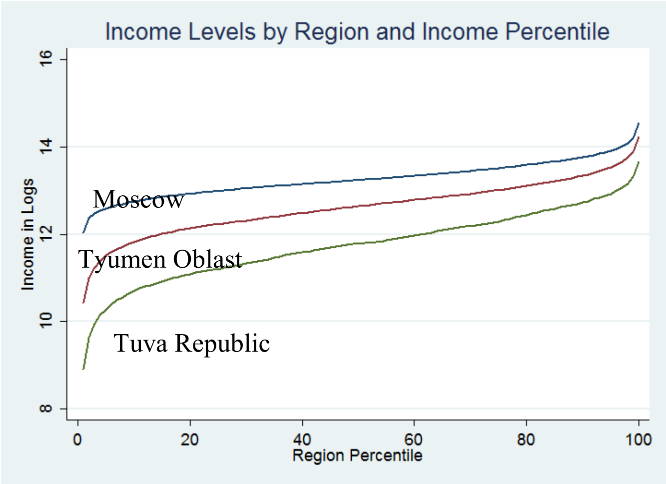
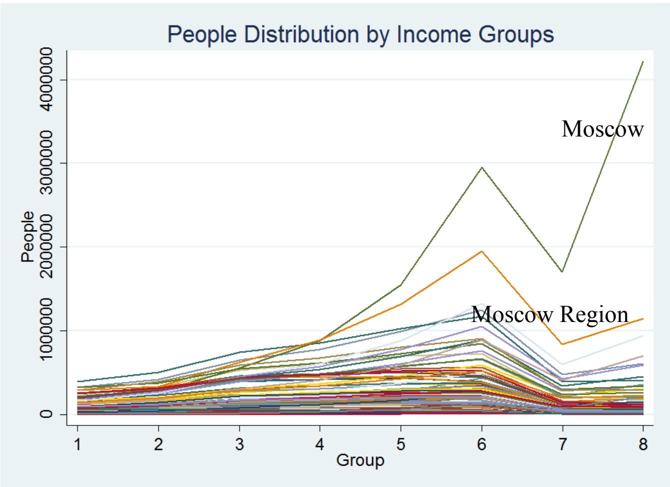


Figure 13 shows the distribution of people by regions according to the average monthly income (there are eight groups). Again, it confirms high income concentration in just a few Russian regions. For example, from approximately 15 million Russians who have 60 thousand roubles or more income per month (about 1.000 dollars), more than 4 million live in Moscow, more than 1 million in the Moscow region, almost 1 million in Saint Petersburg, 700 thousand in Tyumen Oblast, more than 600 thousand in Krasnodar Krai, almost 600 thousand in Sverdlov Oblast.

Figure 13 Population Distribution in Income Groups by Regions



[27] See Appendix 3 for the same figure for all the regions.

Taking all the above mentioned into account, it becomes obvious that personal income depends not only on *the country* of residence (a citizenship rent, according to Milanovic, 2013), but in case that you live in a huge highly populated heterogeneous country such as Russia, *the region* is also a contributing factor (let us call it a regional rent). And in some cases the regional rent can be even more significant than the citizenship rent.

IV. Model and Econometric Issues

Using the data described above, we formulate our econometric model as follows:

$$PI_{iq(1-100)} = \alpha_{iq} + \beta Gini_i + \gamma GDP_i + \varepsilon_{iq}, \text{(1)}$$

where PI_{iq} is the annual average household per capita income in roubles for percentile q in region *i*, $Gini_i$ is the inequality measured by the Gini Index in region *i*, GDP_i is the regional GDP per capita in region i, and ε_{iq} is the error term. Both independent variables are strictly exogenous. This happens because individuals cannot change with their individual efforts any macroeconomic variables such as the GDP per capita or Gini Index.

It is very important to highlight that we use right-hand variables from the macroeconomic database and not calculate them from the initial data to avoid collinearity (although in the robustness checks we will use this method as well). Moreover, we run two types of this model – unweighted and population-weighted. Additionally, we run a similar model, but for personal income groups (twenty of them) separately to see, whether the results change for different income groups.

$$PI_{iq(1-20)} = \alpha_{iq} + \beta Gini_i + \gamma GDP_i + \varepsilon_{iq}, \text{(2)}$$

Although our basic regression is unweighted and both personal income and regional GDP per capita are without natural logarithm, we will run additional regressions to double check the validity of the results. We consider it important to use population-weighted regression, because although from the individual point of view, the population size of the region of residence does not matter, on the macroeconomic level it does, because of the significant disparities in population sizes between regions (from several hundred people to several millions of people).

Besides, we run the so-called LSDV (least square dummy variable) regression, where we replace both the Gini index and regional GDP per capita with simply regional dummies. The coefficient on each region's dummy provides a regional location premium or penalty with respect to a baseline region. We are also interested, whether this kind of simply regression explains enough variability of individual income percentiles across regions.

V. Results

Basic Model Results

First, we look on the results of the unweighted model for the logarithm, level and LSDV models in the Table 22[28]. On average, they explain around 20% of the income variance between regions. As expected, the coefficient before the GDP per capita is positive and the coefficient before Gini is negative. Although if in the case of GDP per capita the coefficient does not lose its significance if we do not use logs, the coefficient of the Gini index is insignificant with no logs. In the case of LSDV, the regression explains 23.4% of the variance.

Table 22 The Dependent Variable is the Household per Capita Income in Roubles for each Region and Percentile (Unweighted)

VARIABLES	Logs (1)	No Logs (2)	Dummies (3)
ln(GDP pc)	0.53***		-
	(0.06)		
Gini Index	-0.03***	-2,883	-
	(0.01)	(3,701)	
GDP pc		0.26***	
		(0.07)	
Constant	6.52***	271,640**	12.14***
	(0.75)	(134,396)	(0)
Observations	7,700	7,700	7,700
Regions	77	77	77
R-squared	0.174	0.167	0.234

The regressions are run with the cluster option to adjust for the correlation of within-country observations. Individual coefficients for regions in regression (3) are not shown here. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If we weigh the regression by population size, the results generally hold, however, Gini loses its significance even in logarithmic regression (Table 23). Thus, the significance of Gini Index is highly sensitive to the model specification. Interestingly, in the population-weighted regression, the model explains a higher percent of variance – almost 25% in the case of the first two regressions and almost 35% in the case of the LSDV regression.

[28] See preliminary specification test in the Appendix 3.

Table 23 The Dependent Variable is the Household per Capita Income in Roubles for each Region and Percentile (Weighted by Population Size)

VARIABLES	Logs (1)	No Logs (2)	Dummies (3)
ln(GDP pc)	0.61***		-
	(0.13)		
Gini Index	-0.02	4,403	-
	(0.01)	(5,808)	
GDP pc		0.29**	
		(0.13)	
Constant	5.06***	-11,376	12.90***
	(1.58)	(201,240)	(0)
Observations	7,700	7,700	7,700
Regions	77	77	77
Population Weight (millions)	141.27	141.27	141.27
R-squared	0.247	0.239	0.345

The regressions are run with the cluster option to adjust for the correlation of within-country observations. The weights are the population size of each region. The individual coefficients for regions in the regression (3) are not shown here. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Robustness Checks

We start our robustness checks using an alternative measure of inequality. First, we use the Decile Index. This index is the coefficient between the average income of the richest 10% of the population and the poorest 10% of the population.

Table 24 The Dependent Variable is the Household per Capita Income in Roubles for each Region and Percentile (Decile Index as an Alternative Measure of Inequality)

VARIABLES	Logs (1) unweighted	No Logs (2) unweighted	Logs (3) weighted	No Logs (4) weighted
ln (GDP pc)	0.53***		0.60***	
	(0.06)		(0.12)	
Decile Index	-0.02**	-2,577	-0.01	5,615
	(0.01)	(4,335)	(0.01)	(6,484)
GDP pc		0.25***		0.28**
		(0.07)		(0.13)
Constant	5.91***	194,782***	4.83***	87,827
	(0.69)	(50,934)	(1.55)	(69,758)
Observations	7,700	7,700	7,700	7,700
R-squared	0.173	0.167	0.246	0.240
Population Weight (millions)			141.27	141.27

The regressions are run with the cluster option to adjust for the correlation of within-country observations. The weights are the population size of each region. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

As may be observed in the Table 24, it has almost not changed our results: the regressions describe around 20-25% of variance, the effect of GDP per capita is still positive and significant, and the coefficient for Gini and its significance is sensitive to the model specification.

Then we proceed with running the same regressions, but with the alternative Gini index. Instead of using the Gini index from the macroeconomic database we possess, we calculate it directly from the microdata. That gives us slightly lower Gini indices for all the regions due to the fact, that we use the after-tax income, not before-tax as in the initial Gini (see Table 21 Descriptive Statistics). Here again, generally, the results do not change, however logically, the Gini index is more significant than in other models (Table 25).

Table 25 The Dependent Variable is the Household per Capita Income in Roubles for each Region and Percentile (Alternative Calculation of the Gini Index)

VARIABLES	Logs (1) unweighted	No Logs (2) unweighted	Logs (3) weighted	No Logs (4) weighted
ln(GDP pc)	0.48***		0.58***	
	(0.05)		(0.08)	
Gini (Alternative)	-1.03*	-224,140	-3.66**	-1.506e+06**
	(0.53)	(202,909)	(1.41)	(697,274)
GDPpc		0.25***		0.32***
		(0.06)		(0.08)
Constant	6.52***	222,529***	5.92***	526,032***
	(0.69)	(57,542)	(1.07)	(184,678)
Observations	7,700	7,700	7,700	7,700
R-squared	0.171	0.168	0.268	0.272

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results by Income Groups

Now we proceed to estimate the effect of the GDP per capita and Gini on the income of separate income groups (from poorest to the richest). To be able to do it, we see it as more reasonable to use only 20 income groups, not 100. Thus, previously, we separated our observations to 20 income groups according to the income and then we calculated the new mean of income of each of these groups. We consider 20 groups the right number to estimate this kind of relations, because they give us enough variability between groups and enough observations within group to have possibly different results for each of them. Although that is also so with fewer groups, be in that case the analysis would not be equally precise.

Twenty Income Groups Statistics

Figure 14 shows the income distribution for each of 20 income groups.[29] By looking at it, we can notice that the richer the group is, the larger is the difference between the same group in different regions. The poorer groups tend to converge.

Figure 14 Household per Capita Income by Quantiles

Equally to the previous part, we run four types of regressions to add additional robustness to the results: unweighted model with income and GDP per capita calculated in logarithms (Table 26), unweighted model with income and GDP per capita calculated in levels (Table 27), weighted by the population size model with these two variables in logarithms (Table 28) and the same model but in levels (Table 29).

First of all, we need to mention that R^2 has increased significantly in that case (from 0.317 for the lowest income groups to 0.767 for the highest income groups). Interestingly enough, the higher the income, the more it is explained by simple variation in the GDP per capita and Gini index.

The results for the effect of GDP per capita on the personal income for each income group are positive and significant in all the models, expect for the level weighted model (Table 29), where it is insignificant for the three lowest income groups. So we can conclude that the high GDP per capita is beneficial for everyone independently of their level of income.

As for the Gini index, we have relatively inconclusive results. However, in regressions where its effect is significant, it is always negative. We suggest that as its contribution to the explanation of variance is almost insignificant, it is highly sensitive to specification tests.

[29] See Descriptive Statistics in the Appendix 3.

Table 26 Dependant Variable: Log of Household Per Capita Income in Roubles (unweighted)

VARIABLES	(1)	(2)	(3)	(4)	(5)
ln (GDP pc)	0.55***	0.56***	0.54***	0.53***	0.52***
	(0.10)	(0.08)	(0.07)	(0.07)	(0.07)
Gini Index	-0.03*	-0.03**	-0.02**	-0.02**	-0.02**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	5.18***	5.50***	5.82***	6.06***	6.26***
	(1.29)	(1.07)	(0.98)	(0.91)	(0.88)
Observations	77	77	77	77	77
R-squared	0.491	0.612	0.652	0.680	0.694
VARIABLES	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
ln (GDP pc)	0.52***	0.52***	0.51***	0.51***	0.51***
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Gini Index	-0.03**	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	6.42***	6.52***	6.63***	6.70***	6.75***
	(0.86)	(0.82)	(0.78)	(0.75)	(0.73)
Observations	77	77	77	77	77
R-squared	0.702	0.718	0.732	0.741	0.747
VARIABLES	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
ln (GDP pc)	0.52***	0.52***	0.52***	0.52***	0.53***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Gini Index	-0.02***	-0.02***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	6.76***	6.79***	6.80***	6.83***	6.85***
	(0.72)	(0.71)	(0.70)	(0.70)	(0.69)
Observations	77	77	77	77	77
R-squared	0.752	0.753	0.754	0.752	0.751
VARIABLES	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**
ln (GDP pc)	0.53***	0.54***	0.56***	0.56***	0.56***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Gini Index	-0.03***	-0.03***	-0.03***	-0.03***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	6.87***	6.85***	6.79***	6.83***	7.14***
	(0.67)	(0.67)	(0.67)	(0.64)	(0.60)
Observations	77	77	77	77	77
R-squared	0.749	0.747	0.743	0.735	0.711

Robust standard errors in parenthesesb*** p<0.01, ** p<0.05, * p<0.1

Table 27 Dependant Variable: Household Per Capita Income in Roubles (unweighted)

VARIABLES	(1)	(2)	(3)	(4)	(5)
GDP pc	0.06**	0.10***	0.12***	0.13***	0.14***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)
Gini Index	635.8	165.2	84.68	-222.8	-463.8
	(1,785)	(2,232)	(2,402)	(2,538)	(2,699)
Constant	27,780	69,396	87,406	110,602	130,235
	(67,325)	(82,957)	(88,785)	(93,672)	(99,204)
Observations	77	77	77	77	77
R-squared	0.317	0.415	0.451	0.478	0.488
VARIABLES	(6)	(7)	(8)	(9)	(10)
GDP pc	0.15***	0.17***	0.18***	0.19***	0.21***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Gini Index	-848.3	-1,203	-1,492	-1,833	-2,081
	(2,886)	(2,991)	(3,088)	(3,252)	(3,372)
Constant	154,046	175,302	193,735*	213,742*	229,823*
	(105,765)	(109,560)	(113,029)	(118,806)	(122,773)
Observations	77	77	77	77	77
R-squared	0.494	0.512	0.531	0.543	0.557
VARIABLES	(11)	(12)	(13)	(14)	(15)
GDP pc	0.22***	0.24***	0.26***	0.28***	0.30***
	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)
Gini Index	-2,256	-2,605	-3,041	-3,393	-3,739
	(3,506)	(3,653)	(3,836)	(4,033)	(4,285)
Constant	242,951*	263,033*	286,949**	308,575**	331,465**
	(127,249)	(132,284)	(138,560)	(145,470)	(154,276)
Observations	77	77	77	77	77
R-squared	0.570	0.579	0.587	0.594	0.600
VARIABLES	(16)	(17)	(18)	(19)	(20)
GDP pc	0.33***	0.37***	0.42***	0.50***	0.73***
	(0.09)	(0.09)	(0.10)	(0.12)	(0.15)
Gini Index	-4,379	-5,190	-6,313	-7,489	-11,579
	(4,622)	(5,006)	(5,496)	(6,176)	(8,834)
Constant	366,595**	410,068**	468,192**	543,027**	803,745**
	(166,489)	(180,233)	(197,250)	(221,561)	(319,945)
Observations	77	77	77	77	77
R-squared	0.608	0.617	0.627	0.637	0.659

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 28 Dependant Variable: Household Per Capita Income in Roubles (weighted by population)

VARIABLES	(1)	(2)	(3)	(4)	(5)
GDP pc	0.10	0.13	0.15	0.16*	0.18*
	(0.07)	(0.08)	(0.09)	(0.09)	(0.10)
Gini Index	3,726	4,503	4,748	4,727	4,822
	(3,201)	(3,805)	(4,085)	(4,318)	(4,494)
Constant	-98,789	-102,489	-96,806	-84,317	-77,616
	(112,356)	(132,931)	(142,580)	(150,447)	(156,430)
Observations	77	77	77	77	77
R-squared	0.459	0.502	0.523	0.536	0.547
VARIABLES	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
GDP pc	0.19*	0.20*	0.21*	0.23**	0.24**
	(0.10)	(0.11)	(0.11)	(0.11)	(0.12)
Gini Index	4,799	4,670	4,513	4,422	4,374
	(4,714)	(4,882)	(5,024)	(5,174)	(5,341)
Constant	-67,484	-54,683	-41,369	-30,725	-21,944
	(163,926)	(169,606)	(174,431)	(179,596)	(185,396)
Observations	77	77	77	77	77
R-squared	0.552	0.561	0.572	0.582	0.592
VARIABLES	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
GDP1 pc	0.26**	0.27**	0.29**	0.31**	0.34**
	(0.12)	(0.12)	(0.13)	(0.13)	(0.14)
Gini Index	4,397	4,351	4,230	4,234	4,246
	(5,525)	(5,726)	(5,951)	(6,276)	(6,628)
Constant	-16,170	-7,123	5,393	13,440	21,499
	(191,786)	(198,628)	(206,293)	(217,499)	(229,773)
Observations	77	77	77	77	77
R-squared	0.602	0.610	0.617	0.621	0.630
VARIABLES	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**
GDP pc	0.37**	0.40**	0.45**	0.52***	0.74***
	(0.15)	(0.16)	(0.17)	(0.19)	(0.25)
Gini Index	4,120	3,944	3,802	3,920	5,776
	(7,015)	(7,527)	(8,117)	(8,917)	(11,941)
Constant	35,962	55,093	78,252	106,585	144,240
	(243,198)	(260,727)	(280,749)	(307,810)	(412,134)
Observations	77	77	77	77	77
R-squared	0.639	0.646	0.655	0.662	0.688

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 29 Dependant Variable: Log of Household Per Capita Income in Roubles (weighted by population)

VARIABLES	(1)	(2)	(3)	(4)	(5)
ln (GDP pc)	0.66***	0.63***	0.61***	0.60***	0.59***
	(0.22)	(0.18)	(0.16)	(0.15)	(0.15)
Gini Index	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	3.02	3.86*	4.30**	4.60**	4.81***
	(2.702)	(2.183)	(1.998)	(1.889)	(1.800)
Observations	77	77	77	77	77
R-squared	0.536	0.612	0.642	0.660	0.675

VARIABLES	(6)	(7)	(8)	(9)	(10)
ln (GDP pc)	0.58***	0.58***	0.58***	0.58***	0.58***
	(0.14)	(0.14)	(0.13)	(0.13)	(0.12)
Gini Index	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	4.99***	5.12***	5.22***	5.31***	5.37***
	(1.75)	(1.70)	(1.63)	(1.58)	(1.53)
Observations	77	77	77	77	77
R-squared	0.683	0.694	0.705	0.715	0.722

VARIABLES	(11)	(12)	(13)	(14)	(15)
ln (GDP pc)	0.59***	0.59***	0.59***	0.60***	0.61***
	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)
Gini Index	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	5.38***	5.42***	5.44***	5.45***	5.43***
	(1.49)	(1.45)	(1.41)	(1.39)	(1.37)
Observations	77	77	77	77	77
R-squared	0.731	0.736	0.742	0.745	0.750

VARIABLES	(16)	(17)	(18)	(19)	(20)
ln (GDP pc)	0.62***	0.63***	0.64***	0.64***	0.63***
	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)
Gini Index	-0.02*	-0.02*	-0.02*	-0.02*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	5.41***	5.39***	5.40***	5.50***	5.81***
	(1.34)	(1.31)	(1.27)	(1.18)	(1.06)
Observations	77	77	77	77	77
R-squared	0.755	0.759	0.763	0.761	0.767

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Robustness Checks

We run some additional robustness checks on inequality. Now we are going to use an alternative measure of inequality for both unweighted and weighted regressions. We use the Decile Index, which is the coefficient between the average income of the 10% of the richest population and 10% of the poorest population. As we can see, in the unweighted regression the effect thereof is negative (Table 30), but in the weighted regression it is insignificant (Table 31). We consider that the population size of the regions has more effect on one's personal well-being than the actual regional Gini Index.

While using other specifications of the same model (without logarithms, weighted by population, etc.), we see that the coefficient and the sign of the GDP per capita stay significant, while they are highly sensitive in the case of the Gini index.

Surprisingly, we have not found any significant differences between income groups while analysing the effect of GDP per capita and Gini on them, the only differences is R^2 or to what extent one's personal income is affected by macroeconomic factors. But there are no changes in sign or significance of the coefficients depending on group.

Table 30 Dependant Variable: Log of Household Per Capita Income in Roubles Alternative Measurement of Inequality is the Decile Index (Unweighted)

VARIABLES	(1)	(2)	(3)	(4)	(5)
ln (GDP pc)	0.55***	0.55***	0.54***	0.53***	0.52***
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
Decile Index	-0.03	-0.03*	-0.02*	-0.02*	-0.02**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	4.53***	4.87***	5.24***	5.48***	5.67***
	(1.19)	(0.10)	(0.9)	(0.85)	(0.82)
Observations	77	77	77	77	77
R-squared	0.489	0.610	0.649	0.676	0.690
VARIABLES	(6)	(7)	(8)	(9)	(10)
ln (GDP pc)	0.52***	0.51***	0.51***	0.51***	0.51***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
Decile Index	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	5.82***	5.91***	6.03***	6.10***	6.16***
	(0.81)	(0.77)	(0.72)	(0.70)	(0.70)
Observations	77	77	77	77	77
R-squared	0.698	0.713	0.727	0.736	0.742
VARIABLES	(11)	(12)	(13)	(14)	(15)
ln (GDP pc)	0.51***	0.51***	0.52***	0.52***	0.52***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Decile Index	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	6.17***	6.21***	6.21***	6.24***	6.25***
	(0.67)	(0.67)	(0.66)	(0.66)	(0.65)
Observations	77	77	77	77	77
R-squared	0.747	0.748	0.749	0.747	0.747
VARIABLES	(16)	(17)	(18)	(19)	(20)
ln (GDP pc)	0.53***	0.54***	0.55***	0.56***	0.55***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Decile Index	-0.02**	-0.03**	-0.03**	-0.03**	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	6.26***	6.23***	6.15***	6.20***	6.56***
	(0.65)	(0.65)	(0.66)	(0.65)	(0.64)
Observations	77	77	77	77	77
R-squared	0.744	0.742	0.738	0.730	0.706

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 31 Dependant Variable: Log of Household Per Capita Income in Roubles Alternative Measurement of Inequality is the Decile Index (Weighted by Population)

VARIABLES	(1)	(2)	(3)	(4)	(5)
ln (GDP pc)	0.65***	0.62***	0.60***	0.59***	0.58***
	(0.21)	(0.17)	(0.16)	(0.15)	(0.14)
Decile Index	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.012)	(0.01)	(0.01)	(0.01)
Constant	2.97	3.81*	4.24**	4.49**	4.68***
	(2.66)	(2.15)	(1.97)	(1.86)	(1.77)
Observations	77	77	77	77	77
R-squared	0.536	0.612	0.642	0.660	0.674
VARIABLES	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
ln (GDP pc)	0.58***	0.58***	0.58***	0.58***	0.58***
	(0.14)	(0.13)	(0.13)	(0.12)	(0.12)
Decile Index	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	4.84***	4.93***	5.01***	5.01***	5.13***
	(1.72)	(1.66)	(1.60)	(1.54)	(1.49)
Observations	77	77	77	77	77
R-squared	0.682	0.693	0.703	0.713	0.721
VARIABLES	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
ln (GDP pc)	0.58***	0.58***	0.59***	0.59***	0.60***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Decile Index	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	5.14***	5.16***	5.16***	5.15***	5.12***
	(1.44)	(1.41)	(1.37)	(1.35)	(1.33)
Observations	77	77	77	77	77
R-squared	0.729	0.735	0.740	0.743	0.748
VARIABLES	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**
ln (GDP pc)	0.61***	0.62***	0.63***	0.63***	0.63***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Decile Index	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	5.07***	5.02***	5.00***	5.11***	5.51***
	(1.30)	(1.28)	(1.24)	(1.16)	(1.07)
Observations	77	77	77	77	77
R-squared	0.753	0.757	0.761	0.759	0.765

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

VI. Conclusions

In this chapter, we have estimated how and to what extent one's personal income is affected by the region one inhabits. So, our main finding can be summed up in the following way:

First, in our research we have found out that *approximately from 20% to 25% of one's income is determined by the region one lives*. This difference contributes a lot to the general level of global inequality of opportunity, as we mentioned in the introduction.

Second, it is worth mentioning that on the regional level, *the inequality within the regions seems to have very small effect on one's income*; actually, most of the variance is explained only by one variable – regional GDP per capita. That may happen due to the fact that the differences between the regions' Gini indices are not as significant as the differences between regional GDP per capita levels.

Third, *the positive effect of the GDP per capita on the income of all income groups is robust to all kinds of robustness checks*. While *the negative effect of inequality disappears while we weight the regression by population size.* That may contribute to our initial idea that general inequality in Russia is caused more by inequality between the regions, than by inequality within the regions.

Fourth, *there is almost no difference in how the general GDP per capita and Gini index affect various income groups*. When we ran regressions for twenty different income groups, we noticed that the GDP per capita always affects personal income significantly and positively, while the Gini index, if it is significant, affects it negatively throughout the whole distribution.

This research is based on Milanovic's (2013) paper, where he estimated how much of one's income depends on the country in which one lives. We tried to extrapolate this theory on the regional level, because we suggest that in huge heterogeneous countries (for example, Russia, China, Brazil or India) there are a lot of regional variations in income levels. The average income in some rich regions can be comparable with the one of a developed OECD state, while the average income in the poorest regions can be compared to the poorest states in Asia or Africa.

In his paper Milanovic discovered that approximately two thirds of one's income is explained only by two variables – the country's GDP per capita and its distribution or Gini index. That means that it is determined only by one's residence. In our case, only around one fourth of individual income is explained by the region one resides in Russia. It is considerable lower than in case of Milanovic's paper, but it also quite logical. First, in any case, within regional dispersion of income and inequality is lower than between countries globally. Second, we assume that this 20-25% if regions inequality is not the part of this 60-70% of global inequality, but in fact it sums up to this global level of inequality, that makes the things even worse from the individual point of view.

APPENDIX 3

As we have cross-sectional data, we perform a simple OLS analysis, although first of all we should run several standard tests to make sure we have normally distributed data and our estimations are not biased.

Breusch -Pagan Test for the Baseline Regression

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ln_pct_income

         chi2(1)      =    26.89
         Prob > chi2  =   0.0000
```

Breusch-Pagan Test for Regression by Groups with Logarithms

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of ln_quant

         chi2(1)      =     5.14
         Prob > chi2  =   0.0234
```

Breusch-Pagan Test for the Regression by Groups without Logarithms

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of quant_inc

         chi2(1)      =   688.90
         Prob > chi2  =   0.0000
```

As Prob < 0.05, we reject the null hypothesis and conclude that there is the heteroscedasticity problem in the data, so we need to use robust errors.

Figure A 14 Income Levels by Regions and Income Percentiles

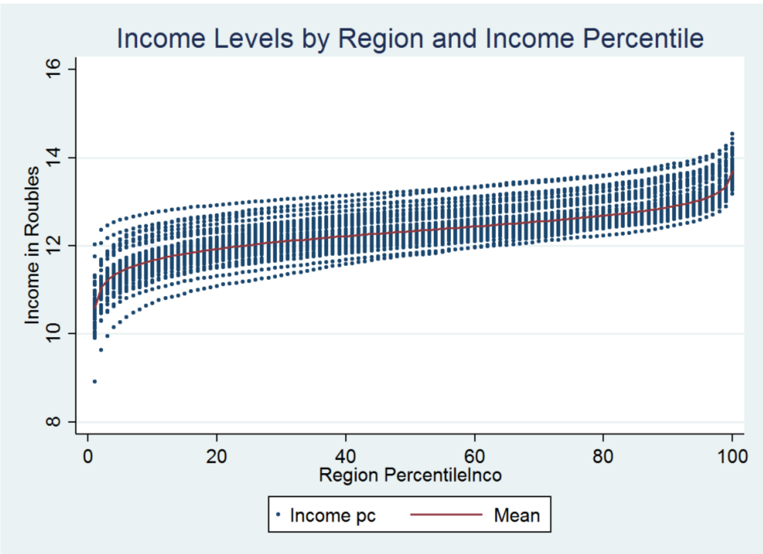


Table A 14 Group Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Group 1	75284.25	31600.54	19587.08	245808
Group 2	113618.5	43289.84	38530.96	324298.6
Group 3	135259.2	48634.41	50942.61	366577.9
Group 4	152520.6	52826.31	61457.73	398963.3
Group 5	167403.4	56513.56	70416.27	425995.6
Group 6	181403.8	60573.96	78834.2	452655
Group 7	194309	64188.98	89768.27	477603.2
Group 8	206579.7	67433.05	102275.8	500248.1
Group 9	218800.8	71354.34	114220.8	523391.3
Group 10	231310.6	75781.45	126549.4	548133.9
Group 11	244004.3	80694.22	136037.2	575866.8
Group 12	257706.4	86136.94	151723.9	603726.7
Group 13	272612.7	92220.37	162278.5	647320.4
Group 14	288850.9	98734.02	173482.2	695985.3
Group 15	307110.8	105789.7	187323.4	738148.6
Group 16	328691.7	114362.9	200510.5	783036.4
Group 17	355784.6	125890.1	215168.8	848791
Group 18	392397.7	143001.3	237548	963427
Group 19	450529.3	165903.2	273499.3	1104427
Group 20	644185.1	237429.9	381458.8	1499533

CONCLUSIONS

In this thesis, we have provided a vast analysis of inequality, growth and opportunity in Russia using regional data for 2000-2015. As for the main results obtained during the work, they are the following:

In the first chapter we have determined that the Kuznets curve hypothesis is applicable to the Russian economy. However, if we estimate the linear model, we can see a significant positive result of the GDP per capita on the rise of inequality. These results are robust to the battery of robustness checks and for controlling of the reverse causation by using instrumented variables.

In the second chapter, we have found out that inequality has a significant positive effect on the following growth. This result holds for each of the five income groups. Again, we have used instrumented variables to control for the endogeneity problem. These results are robust to diverse methods of estimations and specifications.

In the third chapter, we have found out that the main contributor to total inequality in Russia is between regions' inequality, not within. Macroeconomic differences between regions beyond one's individual control represented by only two variables which are regional GPD per capita and the regional Gini index explain about 25% of the variance.

In general, we can draw various interpretations of the results of the study. First, Russia is still situated on the lower level of development. That is why inequality and growth are positively correlated both ways. Second, income in Russia is highly concentrated both on the regional and individual levels: the highest incomes are in a few regions which are characterized by the highest GPP per capita and highest inequality all together. Third, the case of Moscow cannot be considered as outlier, because of its size and political and economic importance and is to be studies more in detail. We suggest that in comparison with other regions, Moscow is highly developed region, both in terms of incomes and human capital. Its economy is based on services and diversified. That is why the inequality there has shown the pattern of the downbeat of the Kuznets curve, as it was a developed 'state'. This hypothesis is also confirmed by the fact that if we take off Moscow from our observations and run the regression for the Kuznets curve, the quadratic term loses its significance.

All these findings go in consonance with the idea of 'Four Russias' proposed by a Russian economist Zubarevich (2013). She argues that economically speaking, Russia can be divided into four 'countries'. Each of them has their own average income, human capital index, economic structure and modernization level. ‘First Russia’ consists of huge urban centres with high living and educational standards, a developed university education system and mass Internet use. ‘Second Russia’ is smaller industrial cities which inherited most of their infrastructure from the Soviet era and are mostly monotowns and highly subsidies by the government.[30] ‘Third Russia’ is rural area or small towns, where population is low educated and work primarily in agriculture. The first three Russia are approximately equal-sized and corresponds to about 30% of population each. Finally, ‘fourth Russia’ consists of several underdeveloped republics of the North Caucasus and South Siberia, where almost 6 per cent of the country’s population lives. Extremely low level of development, ethnical and religious conflicts, debates on possible disintegration and rising terrorism create constant political tensions which are no help for development.

Contributions and Comparisons

First and the most straightforward one is that it’s the first comprehensive empirical study about the Russian economy on the link between inequality, growth and opportunity. Although there are a few separate studies on these elements (Federov, 2002; Litvintseva 2007; Novokmet, 2017; Dang, 2019), they are not systematic and each of them pursue their independent goals. This research can be a good base of following investigation which could lead to implementing various economic policies to lower income inequality and foster growth.

Second, we think that the results we obtain can throw some light on the regional economic situation not only in Russia, but in other countries with a similar geography and socio-economic development, for example, BRICS countries. It highlights the idea that regional differences within one country can be equally or sometimes even more important as between countries differences. We can hypothesis that while high inequality in small homogeneous countries can be attributed to *within individual*s’ differences in income, high inequality in huge heterogeneous countries is attributed more to *within regional* differences.

Second, one more contribution to the inequality-growth studies is the use of instrumental variables methods based both on external and internal instruments. Our research continues the line of implementing IV method lately developed by Brueckner (2018), who in his tern followed Castello-Climent (2010), Halter et al (2014), Ostry et al (2014) and Dabla-Norris et al (2015). In aggregate with panel data, it gives us more robust results and significantly alleviates the endogeneity problem in the estimates. Besides, we use the System GMM method, which to the best of our knowledge, has not been used in estimating the Kuznets Curve before. We also use

[30] Monotowns are towns and cities with the economic base dominated by a core enterprise or single industry.

traditional panel data estimation methods for the preliminary estimations in order to better understand the differences and possible estimation biases.

Fourth, it contributes to the list of countries where the same issues have been studied, for example, the United States (Panizza, 2002) or Spain (De la Escosura, 2008) and provides a lot of field for international comparisons between different development level countries.

Study's Limitations

Nevertheless, we should mention some of our study's limitations. For the first two chapters, unfortunately, we only had regional data from our Rosstat Database only he year 1995. Moreover, due to the fact that we do not have any data available for our instruments (net oil export and services per capita) prior 2000, we were obliged to sacrifice five more years and start from 2000. It would be ideal to make a study from 1991, the year of the collapse of the Soviet Union to see the total economic dynamics through all that years.

Also we possessed the data on regional economic structure only from the year 2005 and it was not sufficient to be able to use it for estimating the effect of economic sectoral structure both on growth and inequality.

As for inequality of opportunity, due to the lack of any longitudinal survey and microdata, we were not able to calculate the inequality opportunity in its straightforward form. We only could estimate the effect of some macroeconomic factors on the individual income.

Future Research

As we have mentioned a few times previously in the thesis, we have not taken into the consideration any fiscal or redistributive data. Rosstat possesses this data, but refining and analysing it goes beyond the scope of this study. We consider that investigating on the state redistribution among regions and within regions and its efficiency can contribute a lot to creating or modifying this kind of policies.

Although, there is a lot of research which decomposes inequality into 'good' and 'bad' in order to see how it affects growth, but the idea of decomposing 'good' and 'bad' growth and how it affects inequality seems to be a bit abandoned. High growth rates in Russia in early 2000s caused by the rise of oil and gas prices were extremely unstable; many economists even compare it to the Dutch disease. Intuitively, that could not be considered as 'good' growth, but is there any difference in how 'good' growth and 'bad' growth affects inequality? Maybe, the two-way positive relation between inequality and growth in Russia in 1997-2015 is not due to the fact that it is not a high income country, but because of the nature of its growth? And it may cause that Moscow has experienced a totally different inequality-growth pattern, because its growth has been ‘good’, that is, based on structural changes in the economy and increasing levels of population education and innovation.

Moreover, a study that makes international comparisons for this kind of relations can be of interest. We consider it useful to make comparison with BRICS countries, which have a lot of similarities or with former Soviet republics to see the difference in development patterns after the collapse of the Soviet Union.

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