

How Unfair Is the Inequality of Wage Earnings in Russia?

Estimates from Panel Data

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Abstract

This paper attempts to determine the extent to which inequality in wage earnings in the Russian Federation is unfair. Unlike other similar attempts that can, at best, produce a lower bound on the estimate of the share of inequality that is unfair, this paper exploits the longitudinal nature of the data to come up with a lower bound as well as an upper bound. The upper bound is further refined to take into account the indirect effect of circumstances at birth (gender, parental wealth, etc.) on effort. Results show that the upper

bound on the inequality of opportunity may be three to four times the measured lower bound and significantly higher for females than males in the sample. Finally, comparison with the United States and Germany show that although total inequality is lower in Russia, the share of unfair inequality is distinctly larger. The markedly large explanatory role of extraneous factors, such as gender and parental characteristics, in wage inequality calls for a close examination of governments' efforts to address inequities in the labor market.

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How Unfair Is the Inequality of Wage Earnings in Russia? Estimates from Panel Data

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1. Introduction

The relationship between inequality and long-term economic development has been a subject of considerable debate in the economic literature. The issue has become all the more salient at a time when the political economy discourse in several parts of the world is dominated by widespread perceptions of rising inequality, diminishing opportunity for economic mobility (through, for example, jobs) and the apparent inability or unwillingness on the part of incumbents in power to do much about it through public policy. As important as this issue is, empirical evidence on the topic has been disappointingly ambiguous: there are almost as many empirical papers that find inequality to have a positive effect on growth as there are that find the effect to be harmful. The reason for this ambiguity has been variously attributed to inadequate data quality, inconsistent nature of inequality measures, incomparability of the econometric methods used or the set of countries and their stages of economic development (Erhart, 2009).

Recently, there have been a number of efforts to examine if the empirical ambiguity in the relationship between inequality and growth has been due to the fact that the measure of inequality that is often used in the analysis is a composite of two different types of inequality, with (arguably) opposing effects on growth. In particular, a country where a large share of the overall inequality is associated with inequality of *opportunity*, namely inequality arising due to differing circumstances at birth (such as parental background, gender and ethnicity), is likely to have different constraints on growth than a country where inequality of *effort* dominates.² In the former, high inequality is likely to perpetuate over time, trapping entire segments of the population in a cycle of low income and opportunities across generations, thereby retarding growth.

While empirical work on this front is still at a nascent stage, some emerging evidence suggests that such inequality has an adverse impact on aggregate growth and economic development. Marrero and Rodriquez (2013), using state-level data on the United States, find a negative relationship between inequality of opportunity and economic growth. Inequality of opportunity in education among children seems to have a negative impact on the level of economic development in a cross-country setting (Molina and others 2012). *Inequality* in health, proxied by the gradient in child mortality over mothers' education groups, has a significant negative impact on economic growth, possibly explained by how health inequality affects average labor productivity (Grimm, 2011).³

Findings from several micro-level studies help corroborate this aggregate relationship. There is strong evidence linking interventions to equalize opportunities earlier in life to better outcomes in adult life, and

² Effort constitutes choices that are within the individual's responsibility and for which society holds him/her responsible. Examples are schooling and labor supply decisions.

³ Measured this way, the proxy for health inequality, in effect, measures inequality of opportunity since mother's education is a strong proxy for socio-economic circumstances of a child. The paper uses a cross-national panel data set of 62 low and middle-income countries between 1985 and 2007. A reduction in health inequality, equivalent to a 5 percent reduction in the mortality rate of children (under-5 years of age) born to mothers with a low education level, is estimated to lead to an almost 8 percent increase in GDP per capita after a period of 10 years. Impact of health inequality on labor productivity is identified as a possible channel. Microeconomic evidence suggests that labor productivity rises with health but at a decreasing rate (see, for example, Thomas and Strauss, 1997), which would imply that a more unequal distribution of health would result in lower average productivity and therefore, lower economic growth.

that early interventions are significantly more cost-effective and successful than those attempted later in life. Research shows that preschoolers with low levels of cognitive development have lower school achievement and earn lower wages in adulthood (Currie and Thomas, 1999; Case and Paxson, 2006); and that early childhood education has substantial long-term impacts, ranging from adult earnings to retirement savings (Chetty and others, 2010). Moreover, lost opportunities during childhood cannot always be compensated for. Child malnutrition, for example, can generate life-long learning difficulties, poor health and lower productivity and earnings over a lifetime (Alderman and others, 2006 and Hoddinott and others, 2008). The weight of evidence seems to imply that high inequality of opportunity in a society would likely lead to lower incomes and growth among the less well-off. Research on the causal impact of inequality of opportunity on income growth at the lower end of the distribution is at a nascent stage. However, Skoufias and others (2014) finds some evidence to suggest a robust negative relationship between inequality of opportunity and income growth of the bottom 40% of the income distribution across provinces (changwats) in Thailand.

For policy makers grappling with the reality and perception of rising inequality in their countries, there is also a strong interest in identifying the link between circumstances at birth and *overall* inequality of outcomes (such as income, wealth or employment status). Opportunity-equalizing investments in children are likely to yield dividends over time and across generations. These have the characteristics of what Heckman (2012) calls “*pre-distribution*”, which many societies find to be unambiguously desirable. However, the extent to which a society may find *ex post* redistributive policies (such as tax/subsidies or affirmative action) palatable is likely to depend on the extent to which disadvantages at birth are held responsible for inequities in outcomes such as income or labor market status, *net* of the effects of (differences in) effort and innate talent on those outcomes. Societies tend to be more ambivalent about inequality arising from differences in effort and innate talent; while inequalities due to differences in endowments (including parental characteristics) determined by the lottery of birth are more likely to be regarded as unfair, demanding policy attention of the sort that seeks to “level the playing field”.

Empirical work on measuring inequality of opportunities has proceeded along many different tracks, as developed by a number of researchers. One widely used approach, developed by Barros and others (2010), involves the Human Opportunity Index (HOI) that is used to measure inequality in access to basic goods and services among children, where the advantage or opportunity is defined as a binary variable. Another popular approach, by Bourguignon and others (2007) and Ferreira and Gignoux (2011), defines the opportunity in question as a continuous variable (such as income or wealth of individuals) and develops a measure known as Inequality of Economic Opportunity (IEO). In both these methodologies, the complete set of all circumstances at birth that could matter for inequality of opportunity is unlikely to be fully observable in data. Due to this handicap, the calculated scalar measure of inequality of opportunity is often interpreted as a *lower bound* estimate. While useful to document the baseline level of inequality of opportunity, the lower bound estimate may lead to severe underestimation of the degree of equalization required to make the distribution of opportunities fair. This problem is particularly aggravated in the latter methodology as it is often applied to incomes of adults. Unlike in the case of children for whom individual agency is assumed to be minimal, an underestimate of inequality of opportunity in adult outcomes automatically implies an over estimation of inequality attributable to effort.

In this paper, we use panel data from the Russian Federation to address the lower-bound problem in the calculation of inequality of opportunities in wage earnings. We closely follow the methodology developed

by Nieheus and Peichl (2012), which essentially entails the use of individual fixed effects as a superset of all relevant circumstances and allows us to compute an upper bound, or the maximum level of inequality of opportunities. The methodology also allows us to extend this further and refine the upper bound to take into account the indirect effect of circumstances on effort. Finally, we juxtapose the results from Russia against the results from US and Germany presented in Nieheus and Peichl (2012) to see if there are interesting conclusions that can be drawn from the comparison.

Issues of inequality have never been too far from the political economy discourse in Russia. The transition to a market economy during the decade of the 1990s was tumultuous: declining living standards and rising poverty were the key characteristics of this period. A large amount of intellectual capital during this time was devoted to understanding these emerging trends as well as the characteristics of the winners and the losers. As the country entered a relatively stable and prosperous period during the 2000s, two things happened. First, despite declines in monetary poverty, subjective poverty and perception of relative deprivation increased. Second, some global crises – particularly the food, fuel and financial crisis and the global economic slowdown that followed quickly – demonstrated that vulnerability to poverty remains an issue. (World Bank, 2009, Ovcharova et al 2010)

Taking a longer view of the reforms that have taken place in Russia during the course of its transition from a planned to a market economy, one of the most salient features is the growing importance of access to employment opportunities as a fundamental vehicle for economic mobility: to move out of poverty, to protect oneself against vulnerability and to enter the coveted middle class. Given widespread perception that only a few have benefitted from the economic transition, the extent to which labor market opportunities represent legitimate opportunities for economic betterment in Russia is an important question. This paper attempts to make a modest contribution also on this front.

The rest of the paper is organized as follows. Section 2 outlines the methodology in detail and Section 3 describes the data and its key features. Section 4 presents the key results and Section 5 summarizes and concludes with reflections on possible future work.

2. Empirical Strategy

Our method of measuring inequality of opportunity continuous variables was originally developed by Bourguignon and others (2007) and Ferreira and Gignoux (2011). We start from Roemer's (1998) model of advantages and define desirable labor market outcomes through three set of characteristics: circumstances (C), effort (E) and luck (u). Circumstances include all variables that are beyond the control of the individual, whereas “effort” refers to characteristics over which the individual has some control and which may also be correlated with circumstances. Finally, there are completely random variables that may affect an individual outcome. These we refer to as luck. Thus,

$$y = f(C, E, u) \tag{4}$$

As Ferreira and Gignoux (2011) note, the definition of equality of opportunity could be expressed as $F(y|C) = F(y)$ where $F()$ is the cumulative distribution function of the advantage of interest. To measure inequality of opportunity could then amount to measuring the extent that $F(y|C) \neq F(y)$. To do this, we

employ the ex-ante approach⁴ of equality of opportunity and partition the population of agents into mutually exclusive groups or types, i.e., subgroups of the population that are homogeneous in terms of their circumstances. We then construct a hypothetical smooth distribution (Foster and Shneyerov, 2000) where each individual outcome (y) is replaced by the group-specific mean for her type. Based on this distribution, we compute any inequality index $I(\cdot)$ the absolute inequality of opportunity level (IOL) defined as

$$\theta_a = I(\{\mu_i^k\}) \quad (5)$$

where μ_i^k represents the mean income of type k . We also calculate the share of total inequality of outcomes explained by the inequality of opportunity, that is, the share that can be attributed to circumstances. This relative inequality of opportunity (IOR) measure is defined as:

$$\theta_r = \frac{I(\{\mu_i^k\})}{I(\{y_i\})} \quad (6)$$

We will use mean log deviation as our inequality measure given the several desired properties.⁵ We closely follow Nieheus and Peichl (2012) and use a parametric approach to estimate the IOL and IOR of interest. Furthermore, we take advantage of the longitudinal nature of the RLMS and estimate the lower and upper bounds of the share of wage inequality explained by inequality of opportunity.

Lower bound. Based on the parametric approach of Ferreira and Gignoux (2011), we estimate the impact of our circumstance variables. Log linearization of an equation such as (4) would yield the following specifications:

$$y_i = \alpha C_i + \beta E_i + \vartheta_i \quad (7)$$

$$E_i = H C_i + \omega_i \quad (8)$$

where equation (8) represents the indirect effect of circumstances on the outcome through effort. To compute IOL and IOR as described above, we can estimate by OLS the reduced-form equation:

$$y_i = \varphi C_i + \varepsilon_i \quad (9)$$

where $\varphi = \alpha + \beta H$ and $\varepsilon_i = \beta \vartheta_i + \omega_i$. The estimates $\hat{\varphi}$ measure the overall effect of circumstances on outcomes, combining the direct and indirect effects. To construct the parametric estimate of the smoothed distribution, we then calculate the predicted outcome:

$$\hat{y}_{i,LB} = \hat{\varphi} C_i \quad (10)$$

⁴ An ex-post approach is based on identifying individuals with the same level of effort and then estimating the inequality in outcomes variables and then measure how outcomes vary by types. See (Ferreira and Gignoux, 2009)

⁵ Mean log deviation is defined as: $I_o = \frac{1}{N} \sum_i \ln\left(\frac{\mu}{y_i}\right)$ where μ is the overall mean of the outcome variable.

and replace each individual's outcome with their predictions.⁶ This necessarily means that all individuals with the same circumstances will have the same predicted outcome variables.

Upper bound. To implement the upper bound estimator, we explicitly deal with potential indirect effects of circumstances through effort on the outcome of interest. This will include, for instance, the indirect effect that father's education may have on wages *through* its positive impact on the educational attainment of the individual. There are two possible extremes: (1) no compensation for indirect effects or (2) full compensation, i.e. the indirect effects are also treated as circumstances. We follow the first approach.⁷

Under approach (1), we exploit the longitudinal data structure. To estimate the inequality of opportunity at time s , say the latest time period observed in our data, we define the following empirical specification for time periods t (with $t \neq s$):

$$y_{it} = \alpha C_{it} + \beta E_{it} + u_i + u_t + \vartheta_{it} \quad (11)$$

The time specific effects u_t take up serial effects such as inflation common for all individuals, while ϑ_{it} are idiosyncratic shocks that influence outcomes. The longitudinal design enables us to derive consistent estimates for the effort variables despite their endogeneity. A key assumption is that all time constant heterogeneity across individuals can be attributed to exogenous circumstances and will be captured by the fixed effect. We treat all circumstances as unobservable, and allow the individual specific unit-effect c_i to account for them as follows:

$$y_{it} = \beta E_{it} + c_i + u_t + \vartheta_{it} \quad (12)$$

In the final model we use the estimated unit effect from (12) as a circumstance variable which includes all unobservable and observable time-constant circumstances of an individual. In this approach, the indirect effects of circumstances on effort variables are captured by the beta coefficients in equation above and hence treated as effort. We estimate our model of interest using the outcomes of time point s as dependent variable:

$$y_{it} = \varphi \hat{u}_i + \varepsilon_{it} \quad (13)$$

where \hat{u}_i acts as the maximum extent of inequality which can be attributed to circumstances. As in the lower bound case, we construct a parametric estimate of the smoothed distribution by replacing individual earnings by their predictions ($\hat{y}_{i,UB} = \hat{\varphi} \hat{u}_i$). Based on the predicted counterfactual levels, we estimated IOL and IOR as in (5) and (6).

Upper bound with indirect effects. Alternatively, the upper bound can also be calculated by incorporating into the circumstances the indirect effect that these circumstances also have on effort. For example, being

⁶ For outcomes that are estimated in log linear form, we estimate the prediction as $\hat{y}_{i,LB} = \exp[\hat{\varphi} C_i + \frac{\sigma^2}{2}]$ where σ^2 is the estimated residual variance in the equation (Nieheus and Peichl, 2012).

⁷ Nieheus and Peichl (2012) labeled this as approach (1). Results using their second approach are very similar to those presented here.

born of a particular circumstance of disadvantage may induce despondency, helplessness and a fatalistic lack of belief in one's agency to achieve something and this may lower effort which may accumulate over the life cycle to affect outcomes in a meaningful way. Instead of treating differences in circumstance-induced effort as a matter of individual responsibility, some may be of the view that they should be accounted into the circumstances themselves in order to get a fuller picture of the true inequality of opportunity.

In order to do that, we will need to purge the effort variable from any component that is correlated with circumstances. We begin by first implementing the following regression:

$$y_{it} = u_i + u_t + \varepsilon_{it} \quad (14)$$

which is a pure fixed effect regression of wages. From this regression we extract an estimate of individual effects, \hat{u}_i . In the next step, we run a regression of the effort on the estimated individual effects to extract the component of effort that is orthogonal to individual circumstances. To be precise, we run:

$$E_{it} = \hat{u}_i + u_t + e_{it} \quad (15)$$

and collect the residual of that regression. In the final step, we then run the following regression:

$$y_{it} = \beta \hat{e}_{it} + c_i + u_t + \varepsilon_{it} \quad (16)$$

which is a regression of log wages on an estimate of the component of effort that is orthogonal to circumstances and the individual fixed effects. Note that the difference between (12) used in the calculation of the first upper bound and (16) which is being used to calculate the second upper bound is that any component of effort that is likely to be correlated with circumstances is going to be captured by the individual effects in the latter.

3. Data

In this section, we discuss some key characteristics of the data. We use the Russia Longitudinal Monitoring Survey (RLMS) for this analysis. The RLMS is a nationally representative survey that is widely used to monitor the health and economic welfare of households and individuals in the Russian Federation. We focus on the rounds between 2006 and 2010. The survey contains detailed information about the demographic and economic characteristics of the surveyed individuals. Variables of interest include age, education, nation of birth of the individual, as well as labor force participation, wages and fringe benefits for those working. Given our focus on circumstance variables for inequality of opportunity, we use a key question included in the 2006 round that refers to the parents of the interviewee. In particular, we use the questions on father's education and the father's affiliation to the communist party before 1991.

The RLMS collected information for around 12,000 adults for the rounds of 2006-2009. In 2010, additional households were surveyed from a new batch of independent samples.⁸ The samples analyzed in our study cover adults of working age that belong to the labor force and who are looking for work. Roughly, these individuals account for 60% of the total sample. We also restrict the sample to individuals with information on all variables of interest. We include over 60% of the population of interest in the final sample. Table 1 presents the number of individuals included in our estimations.

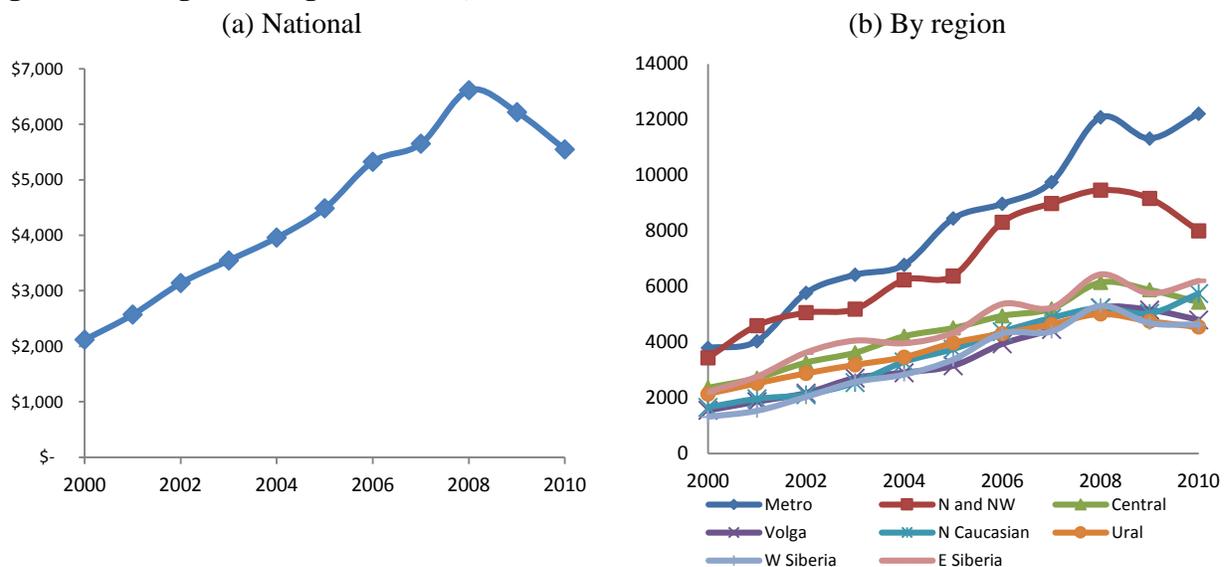
Table 1: RLMS sample used in this analysis

Round	Reference year	Adults surveyed	Adults in the labor force or looking for work ¹	Sample with complete data available ²	Proportion of sample of interest used in analysis
15	2006	12,490	7,371	5,916	80.30%
16	2007	12,301	7,229	4,942	68.40%
17	2008	11,864	6,946	4,446	64.00%
18	2009	11,816	6,916	4,249	61.40%
19	2010	17,810	9,771	3,706	37.90%

Notes: Own calculations using the RLMS-HSE survey.¹ The sample is also restricted to those in working age (male 16-59, female 16-54). ²Data restrictions include availability for region of residence, education, and father's characteristics.

During 2000-2010, it is evident that real wages as well as household income showed a positive trend. Based on the RMLS data, average real wages increased from around \$2,000 rubles to just over \$6,000 in the 2000-2008 period. After the financial crisis hit, wages broke this trend and started dropping, with the average real wage in 2010 being \$5,500 rubles. Household income per capita showed the same increasing trend as wages, but after the 2008 crisis, they appear to have regained their previous trend and moreover, to be above pre-crisis levels at just under \$5,000 rubles.

Figure 1. Average real wages in Russia, 2000-2010



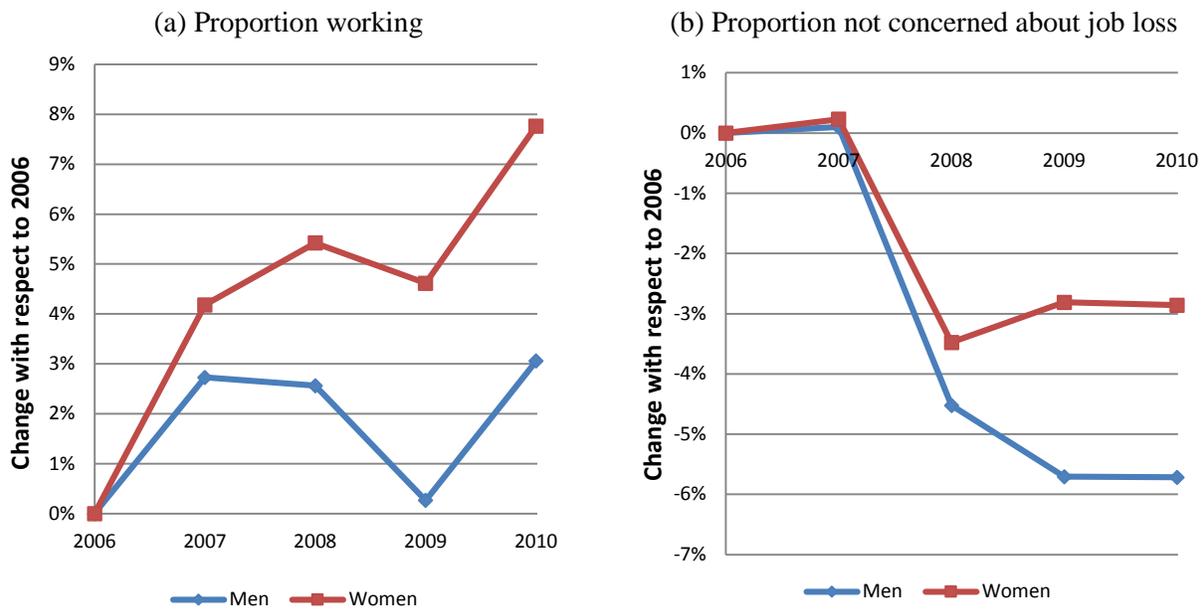
Notes: Authors' calculations

⁸ <http://www.cpc.unc.edu/projects/rlms-hse/project/sampling>

Figure 1 illustrates the evolution of real wages over time for the major regions of Russia. It is clear that all regions were experiencing sustained growth, with the Metropolitan and Saint Petersburg, as well as the North and North West, being the highest wage areas throughout the country. In the period 2000-2006, real wages appear to have doubled for all regions with MSTP and the Northern regions reaching \$8,000 rubles. There is evidence that the crisis affected the other regions and the North, with the former experiencing a flattening of the trend in real wages and the latter seeing its trend reversed. The MSTP seems to be the only region that was only temporarily affected by the crisis.

Different sectors of the working population also seem to be affected differentially by the 2008 crisis. Focusing on the period 2006-2010, Figure 2 shows the proportion of men and women that were working and among these, the share of individuals who were not concerned about losing their jobs. The share of women who worked increased almost in all years after 2006. Meanwhile, the share of working men increased in 2007 and 2008, but in 2009 this share dropped to the same level as 2006. Among the working population, the 2008 crisis seems to have increased men’s concern for losing their job, with this share being 4.5 higher in 2008 than in 2006, and 6 percentage points higher in 2010. Women saw a drop in 2008, but this share remained largely the same through 2010.

Figure 2. Changes in proportion of individuals working and proportion of individuals not concerned about job loss, 2006-2010



Notes: Authors’ calculations

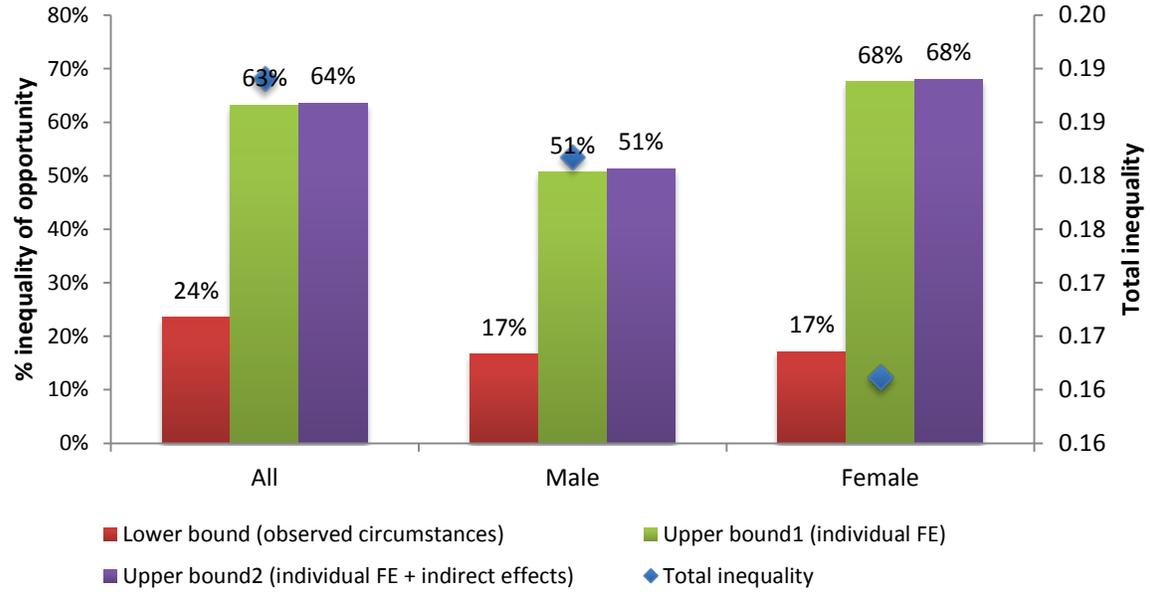
4. Results and Discussion

In this section, we describe the main results of our estimation based on the methodology described in Section 2. Figure 3 shows the total inequality in labor earnings as well as the shares of the inequality

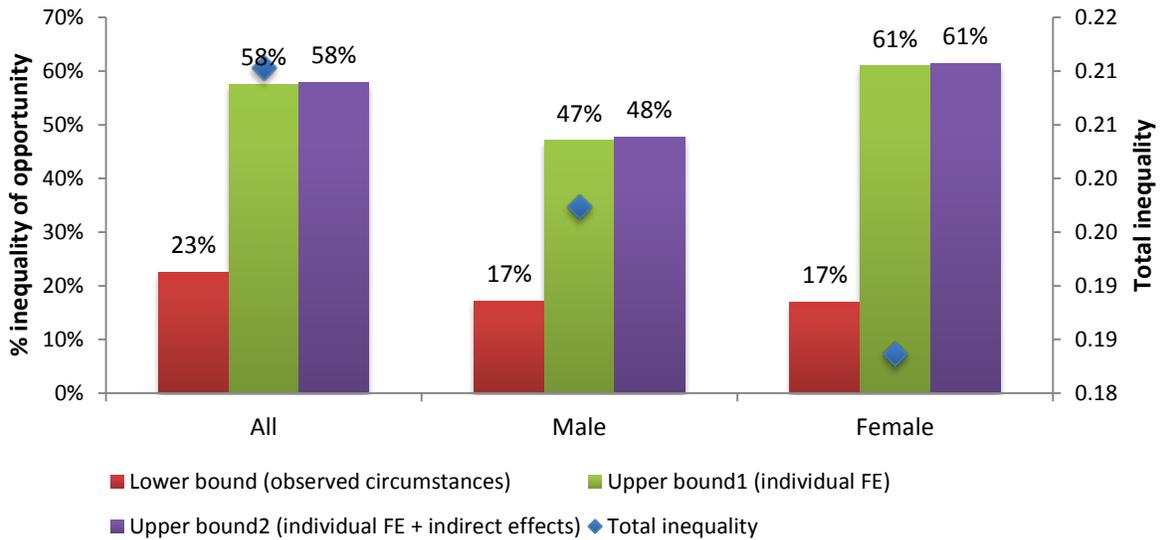
attributable to circumstances. We show results for GE(0) in panel (a) and GE(1) in panel (b). The analysis is presented for the whole sample as well as separately by males and females.⁹

Figure 3. Total inequality in wage earnings and the share due to inequality of opportunity, GE(0) and GE(1)

(a) GE(0) – Mean Log Deviation



(b) GE(1)



Notes: Authors' calculations

⁹ Full results of the underlying estimations of the OLS and FE regressions are presented in the Appendix.

Overall, we find that the inequality levels of wage earnings are relatively low in all samples studied. The mean log deviation (i.e. $GE(0)$) is estimated to be 0.189. Men's wages seem to be more unequal than women's. The results for the share of inequality of opportunity show that for the full sample, at least 24% of this observed inequality is due to circumstances of the individual that should be orthogonal to wages. Once we account for the fact that the observed set of circumstances is by no means the complete list of all the relevant circumstances and use individual fixed effects as the superset of all circumstances that characterize an individual using the methodology described in Section 2, the share explained by inequality of opportunity jumps up to 63%. Furthermore, recognizing the fact that circumstances may have an indirect effect of effort itself and accounting for that bumps up the total share of inequality of opportunity in total earnings to 64%.

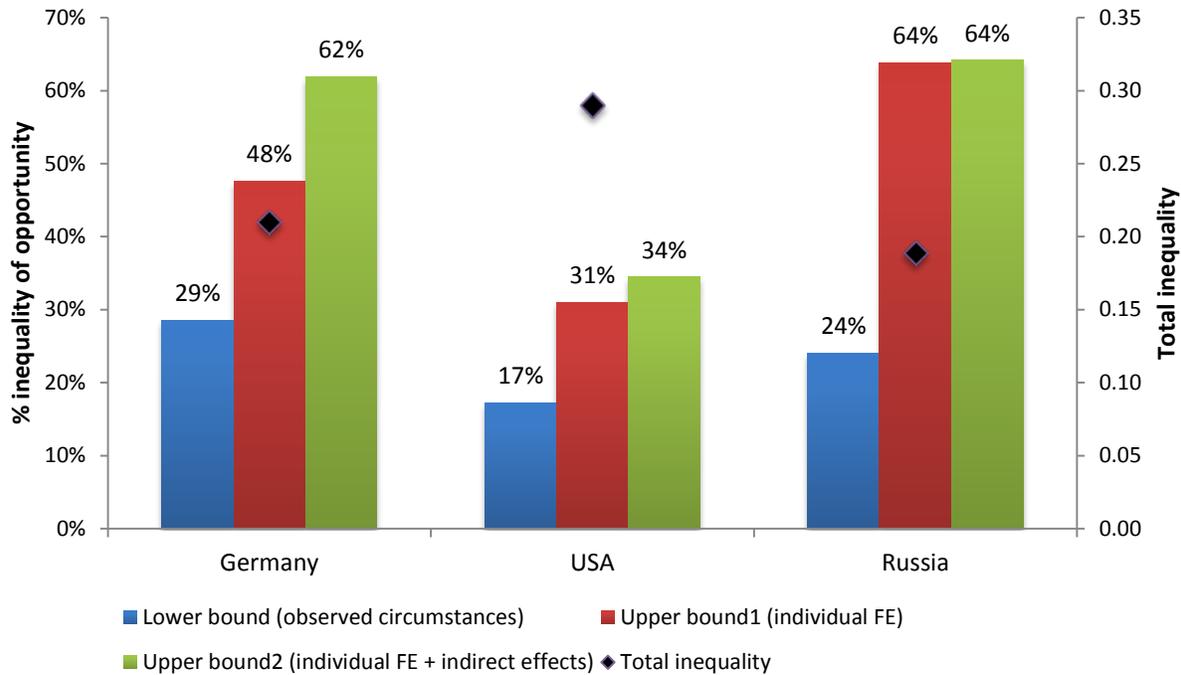
Breaking down the sample and treating males and females separately reduces the overall inequality – as it should because gender no longer remains a discriminant – as well as the shares explained by circumstances but the broad pattern is roughly similar. Total inequality for males and females are 0.18 and 0.16 respectively and the bounds on inequality of opportunity range from 17% to 51% for males and 17% to 68% for females. This suggests that even if the lower bounds are identical, the upper bound for wage inequality that is attributable to circumstances in Russia is higher for female workers than their male counterparts. In the second panel of Figure 3, we present the same results using $GE(1)$ instead of $GE(0)$ and confirm that the results are very similar.

What does all this mean? Any attempt to calculate inequality of opportunity is in some ways an attempt to parse out the component of inequality that an individual faces due to the circumstances endowed to him/her by the accident of birth versus the inequality that may emerge as a result of differential choices such as effort. The empirical distinction of these two is of paramount importance for policy because the scope and indeed even public appetite for policy action that attempts to redress such inequality is likely to be higher if a larger share of the inequality is due to components that are universally acknowledged to be unfair. Thus, from this point of view, all the attempts that have been made to make such an empirical distinction have been constrained in their ability to fully account for the unfair inequality because of the lack of data sets that allow all possible set of circumstances to be observed. What we show here is that, if one is talking about wage inequality in Russia and one were to work with any of the cross-sections of the RLMS surveys and use the same set of circumstances we use, the estimated inequality of opportunity would be severely underestimated: the upper bound may be higher by a factor of three to four.

A methodological note is also in order on what exactly individual fixed effects capture in this context and whether all of what is captured can be regarded as being outside of the realm of individual responsibility. In this methodology, individual fixed effects capture all of the time invariant attributes of individuals which society agrees should not influence wages, and more. They also capture other aspects of the individual such as unobserved ability, aptitude or intelligence. Should ability be something an individual is held accountable for? Or is it the society that should be faulted for inequalities that are attributed to such traits? This is indeed a hotly debated question that touches upon, among other things, genetics: for example, what is the exact extent to which cognitive abilities are transmitted through generations? The original Barros et al. (2009) formulation is predicated on the argument that inequality emanating from differences in talent is fair: the argument goes that “success in life should depend on people's choices, effort and talents, not on their circumstances at birth”. So by the Barros (2009) framework, the upper bound we have estimated by treating unobserved ability, talent and aptitude etc. to

be outside the domain of individual responsibility, is in fact higher than the true upper bound. But if we recognize the fact that talent (or ability) is be a function of cultivated talent just as well as innate talent and that the ability to cultivate and develop talent or skills over a lifetime may, in turn, depend on birth circumstances, then the upper bound we report here will be closer to the what would be the true upper bound of the inequality due to circumstances along the lines argued by, for example, Kanbur and Wagstaff (2014).

Figure 4. Total inequality and the bounds on inequality of opportunity in Russia, Germany and the United States



Notes: Authors’ calculations for Russia. Numbers for Germany and the USA are from Niehaus and Piechl (2012).

Finally, we juxtapose our main results for Russia against corresponding numbers calculated for Germany and the United States by Niehues and Peichl (2012) to compare inequality of opportunity in wage earnings in the three countries. As can be seen in Figure 4, the overall inequality in labor earnings is lower in Russia than in both the US and Germany. However, once we start looking at the share of this inequality that is unfair in the sense that we have described in this paper, then the narrative reverses. The lower bounds are not strictly comparable here (as the circumstances used are different), however, if one looks at the first upper bound with the individual fixed effect, it is clear that the inequality of opportunity shares are markedly higher in Russia in comparison to both the US and Germany. To be precise, while 64% of the total wage earnings inequality in Russia is of the “unfair” kind, only 31% is unfair in the US and 48% in Germany. Another interesting observation that can be made in Figure 4 is the fact that the difference between the two upper bounds appears substantially smaller for Russia in comparison to the US and Germany. Recall that the difference is a measure of the extent to circumstances affect inequality indirectly through effort. While there are several factors relating to the comparability of the samples for the three countries, one possible and rather speculative reason for this difference could be that educational

attainments are far more “equal” in Russia across the circumstance groups in comparison to the US and Germany.

5. Conclusion

This paper has attempted to determine the extent to which inequality in wage earnings is unfair in Russia. Unlike other similar attempts at this exercise that can, at best, produce a lower bound on the estimate, this paper exploits the longitudinal nature of the data to come up with a lower as well as upper bound on the true extent of inequality of opportunity. The results show that the upper bound on the inequality of opportunity may be 3-4 times the measured lower bound. The upper bound on the inequality is also found to be markedly higher for females than males in the sample. Finally, a comparison with the United States and Germany shows that even though total inequality is lower in Russia, the extent of inequality of opportunity is distinctly larger. A fair labor market would be a marketplace where one is rewarded based on one’s talent, educational qualifications, aptitude and nothing else. If extraneous factors such as one’s gender or parental characteristics, or race and ethnicity determine success in the labor market, then a larger and more active role of the government may be called for to remedy the situation. Interventions can take a variety of forms, ranging from investment in early childhood education, particularly among the disadvantaged groups, to bolster the development of cognitive as well as non-cognitive skills during the formative years, to active interventions to eliminate discrimination in the workplace against particular social groups, such as the Roma, for example. While this paper does not disentangle the dimension along which wage inequality is highest, it does shed light on the fact that conventional methods of calculating unfair inequality may yield extremely low estimates for Russia and there might be a larger role for the government than what is widely perceived.

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Appendix Table 1. OLS reduced-form regressions – lower bound of inequality of opportunity
Dependent variable: Log wage earnings

VARIABLES	
Dummy =1 if individual is female	-0.244*** (0.037)
Education of father: Secondary	0.131** (0.051)
Education of father: Professional courses without secondary	0.038 (0.041)
Education of father: Vocational training	0.189*** (0.038)
Education of father: University or higher	0.377*** (0.048)
Father affiliated to communist party	-0.026 (0.034)
Region: North and Northwest	-0.217** (0.100)
Region: Other regions	-0.674*** (0.087)
Year of Birth	-0.000 (0.002)
Height (in cm)	0.010*** (0.002)
Foreign	0.107** (0.043)
Constant	8.018** (3.280)
Observations	1,626
R-squared	0.226

Notes: Data from RLMS 2010 round. Omitted category for education of father: less than secondary; omitted category for region: Metropolitan MOS and Saint Petersburg. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2. FE earnings regressions to get unit-effect

VARIABLES	
Experience	0.036*** (0.005)
Experience squared	-0.001*** (0.000)
Working hours	0.004*** (0.000)
Dummy =1 if worked under 1 hour/week	-0.805*** (0.118)
Dummy =1 if worked over 16 hours/day	-0.443** (0.188)
Education: High school	-0.015 (0.039)
Education: Professional course	0.030 (0.041)
Education: PTU with no secondary	-0.056 (0.042)
Education: PTU with secondary	-0.003 (0.040)
Education: Technical diploma	0.006 (0.042)
Education: University	0.029 (0.046)
Education: Graduate school or residency	0.035 (0.099)
Constant	6.887*** (0.098)
Observations	11,661
Number of unique individuals	1,638
R-squared	0.535

Notes: Data from RLMS rounds 2000-2009. Omitted category for education: less than secondary. Categorical dummy variables for years and type of occupation included in the regression. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3. Circumstances and controls used for HOI estimation

<i>Type</i>	<i>Circumstance/Control</i>	<i>Specification</i>
<i>Individual characteristics</i>	Gender	Dummy indicator if female
	Age	Age groups (16-25, 26-35, 36-45, 45 and over)
	Education	Categories: Less than High School, High school diploma, Professional course, PTU without secondary, PTU with secondary, Technical diploma, University, Graduate school or residency
	Nationality	Dummy indicator if born outside Russia
	Height	Self-reported height (cm)
	Region	Region of current residence; and Dummy indicator if currently living in a village
	<i>Father characteristics</i>	Father's affiliation to communist party
Father's education		Categories: Less than Secondary, Secondary, Professional or vocational courses without secondary, Vocational/Technical training, University or higher

Notes: Author's categorization using RLMS data.

Appendix Table 4: Circumstances and effort variables included in the estimations of Lower and Upper Bound inequality of opportunity

<i>Type</i>	<i>Variable</i>
<i>Circumstance</i>	Gender
	Father's education
	Region
	Year of birth
	Height
	Foreign status
<i>Effort</i>	Years of Experience
	Number of hours worked per week
	Education
	Type of occupation

Notes: Authors' categorization using RLMS data.