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IBS WORKING PAPER 5/2016
APRIL 2016

INEQUALITY OF OPPORTUNITY IN CENTRAL AND EASTERN EUROPE: ACCOUNTING FOR CHANGES OVER TIME

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INEQUALITY OF OPPORTUNITY IN CENTRAL AND EASTERN EUROPE: ACCOUNTING FOR CHANGES OVER TIME[1]

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Abstract

We study changes in income inequality and inequality of opportunity (IO) in seven Central and Eastern European (CEE) countries. Using EU SILC 2005 and 2011 data, we make a first attempt to apply inequality decompositions based on RIF regression to the problem of changes in IO over time. Our results indicate that there is considerable heterogeneity in levels of inequality and in the evolution of inequality over time in CEE countries, linked to both changes in the parental backgrounds of individuals and the effects of these changes on current incomes, and to micro-economic factors that correspond to the labour market status and educational attainment levels of households. Differentiating between the CEE countries, we provide evidence of a strong decrease in both overall income inequality and absolute IO in Poland; a decrease in absolute IO accompanied by modest changes in income distribution in Lithuania; and a relatively high and growing share of "unfair" inequality accompanied by a low levels of overall income dispersion in Hungary. We have found that the returns to circumstances (factors beyond individual control like parental education and occupation) were the major drivers of reduced absolute IO in Poland and Lithuania, with changes in the distribution of circumstances (e.g. improving distribution of parental education) playing a smaller role. The effects of other household characteristics (age structure, education, labour market status of households) on changes in absolute IO were negligible. The growing share of IO in total income inequality in Hungary and Slovakia was driven primarily by changes in the returns associated with having fathers with medium education (Hungary) and changes in wages across various groups defined by the same circumstances (Slovakia).

Keywords: inequality of opportunity, income inequality, RIF decomposition, Central and Eastern Europe

JEL codes: D31, D63, E24, O15

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[1] This paper was financially supported by the Network for Jobs and Development initiative under the auspices of the World Bank. We thank Francisco Azpitarte, Francisco Ferreira, Alexandra Killewald, the participants of the 2015 IBS Jobs Conference in Warsaw and the Population Association of America 2016 conference in Washington, DC for their helpful comments and suggestions. The usual disclaimers apply. All errors are our own.

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1. Introduction

In recent years, equality of opportunity (IO) has become one of the central concepts in the economic and philosophical literature concerned with the distribution of welfare, and research on IO has been growing and maturing. For example, comprehensive surveys of equality of opportunity have recently been published in the Handbook of Income Distribution (Roemer and Trannoy 2015a), the Oxford Handbook of Well-Being and Public Policy (Ferreira and Peragine 2015), and the Journal of Economic Literature (Roemer and Trannoy 2015b). In contrast to research on inequality of outcomes (e.g., incomes, consumption, or wealth), IO research seeks to separate the effects of circumstances and of effort on individual outcomes (Roemer 1993, 1998). Circumstances are defined as the factors for which the individual cannot be held responsible (e.g., biological characteristics, socio-economic background, place of birth, and ethnic origin), while effort refers to the variables that are within the realm of an individual's control (e.g., schooling choices and labour supply decisions). According to Roemer (1993, 1998), the goal of policies that promote equal opportunities is to eliminate unfair forms of inequality that result from the effects of socio-economic circumstances on outcomes, while still allowing for outcomes to be sensitive to effort.

Economists have developed social criteria and methods for measuring inequality of opportunity based on the dichotomy between circumstances and efforts. Recent overviews of this literature have been provided in Ferreira and Peragine (2015), Roemer and Trannoy (2015), and Ramos and Van de gaer (2015). In addition, economists have proposed a wide range of indices for measuring inequality of opportunity in different countries or at different times. However, because the ratio of specific (and thus not comparable) measurement approaches to actual empirical applications is high, it has so far been difficult to make a reasonably broad comparison of inequality of opportunity levels across countries (Brunori et al. 2013).

There are two major reasons why both researchers and policymakers are becoming increasingly interested in the issue of inequality of opportunity. First, in formulating policies, it is important to know to what extent IO contributes to overall inequality levels, and to the recent changes observed in these levels (Ferreira and Peragine, 2015). Second, researchers are trying to determine whether inequality of opportunity has a negative impact on economic growth (Marrero and Rodríguez 2013, Ferreira et al. 2014), especially if the inequality is driven by skill-biased technological change (Murphy and Topel 2016).

This paper is related to two strands of empirical literature on inequality. The first strand, which is smaller, has been investigating the determinants of IO and its changes over time. For example, using the ex-ante approach to measuring IO, Marrero and Rodríguez (2012) found that the effects of IO on income acquisition have been low in the Nordic, the continental European, and some of the Eastern European countries (the Czech Republic, Hungary, Slovakia, Slovenia); but have been high in the Mediterranean, the Atlantic, and some of the other Eastern European countries (Estonia, Latvia, Lithuania, Poland). They also showed that in a sample of European countries the absolute IO measure is negatively correlated with the level of GDP, the attainment of secondary education, and the level of social protection expenditures; but is positively correlated with long-term unemployment and the proportion of education dropouts. Institutional correlates of both ex-ante and ex-post IO indices were studied by Checchi et al. (2015). Using data from the intergenerational EU-SILC modules collected in 2005 and 2011, these authors applied a pseudo-panel approach to analyse the correlation between IO measures and a number of institutional features of European educational systems and labour markets. They found that both income inequality and ex-ante IO are positively correlated with pupil-teacher ratio in primary education and the share of secondary education students enrolled in vocational programmes, and that they are negatively correlated with parental leave opportunities. So far, however, the micro-economic determinants of IO measures and their changes have not yet been studied.

The second strand of inequality literature, which is related to our paper, has investigated changes in income inequality in CEE countries during the period when these countries were transitioning from having a centrally planned to a market economic system, and during the period that followed. This substantial body of literature has recently been reviewed by Alvaredo and Gasparnini (2015) and Perugini and Pompei (2016).[4] The collapse of communism in CEE had profound effects on the relatively egalitarian distributions of income in these countries (the Gini index was between 0.2 and 0.25). While income inequality increased in all of the CEE countries, the extent of the increase in inequality varied across the region. In the period between the late 1980s and 2010, the Gini index increased by 10 percentage points or more in Bulgaria, Estonia, Hungary, Latvia, Lithuania, and Romania (Tóth 2014). By contrast, the Gini coefficient rose by less than 10 percentage points in the Czech Republic, Poland, Slovakia, and Slovenia. Among the countries studied in this paper, the Baltic countries experienced the largest and the most rapid growth in inequality: e.g., the Gini index increased from under 0.25 to about 0.35 in Estonia and Lithuania between 1989 and 1993, and in Latvia between 1989 and 2004. Since then, the Gini coefficient has remained at around 0.35 in Latvia and in Lithuania, but had declined to about 0.3 around 2008 in Estonia. In Hungary, the Gini index increased steadily from about 0.2 in 1989 to about 0.3 around 2006, then decreased to about 0.24 in 2010, and rose again to 0.28 in 2014. In Poland, the Gini ratio increased steadily from about 0.25 in 1989 to about 0.35 in 2005, and then fell to around 0.31 in 2010. The Czech Republic and Slovakia experienced the smallest inequality shocks: in these countries, the Gini index was around 0.2 in 1989, grew slowly to about 0.25-0.27 around 2005, and has remained roughly unchanged since then. The Great Recession and its aftermath had relatively little impact on income inequality in the CEE countries, except in Estonia (the Gini coefficient grew from 0.31 to 0.36 in 2008-2014) and Hungary (the Gini index increased from 0.25 in 2008 to 0.28 in 2014). The major factors responsible for the growth in inequality levels in the CEE countries as they transitioned from having a centrally planned to having a market economy were processes of privatisation, liberalisation, and the decentralisation of wage setting, which resulted in an increase in wage dispersion (Ferreira 1999, Milanovic 1998, Mitra and Yemtsov 2007). These developments were accompanied by the rise of earnings premiums for highly qualified workers employed in highly skilled occupations. Milanovic (1999) has also stressed the importance of the "hollowing-out" of the state-sector middle class: while some of these workers entered the relatively well-paid private sector, others moved into low-income employment or became unemployed. Additional factors that may have contributed to the increase in inequality levels in the CEE countries during this period are that most of these countries had weakly redistributive tax-and-transfer systems (Ivanova, 2007) and relatively low levels of social in-kind benefits (e.g., education, health) (Flemming and Micklewright, 2000); and that a number of CEE countries suffered from hyperinflation and deindustrialisation (Ivaschenko, 2002).

[4] See also Binelli et al. (2015) for an analysis of inequality in CEE countries in terms of capabilities-based index that aggregates disparities in income, education, health status as well as in perceived access to health care and education.

The aim of our study is to investigate the changes in the levels of inequality of opportunity in Central and Eastern European countries (CEE), and to identify the drivers of these changes. We seek to answer the question of whether the cumulated economic growth recorded in these countries in the second half of the 2000s helped the poor by reducing the inequalities that arise from differences in family background, or harmed the poor by consolidating or even adding to these inequalities. Our investigation covers a six-year period between 2004 and 2010. This period is interesting for two reasons: first, during these years the CEE countries experienced very rapid economic growth, particularly after they joined the EU in 2004 (the rates of cumulated GDP growth in 2004-2010 ranged from 8% in Hungary to 41% in Slovakia); and, second, most of these countries were severely hit by the crisis in 2007-2009, and some experienced a severe recession (especially the Baltic states, where GDP fell 15% in 2009).

Our aim in this paper is to contribute to both the empirical and the methodological dimensions of the research on inequality of opportunity. First, we provide evidence for seven CEE countries on changes in the magnitude of IO over time, using comparable data and approaches. Despite the important changes in inequality levels that have recently occurred in these countries, IO has been less studied in CEE than in other countries. (See Perugini and Pompei 2015 for a recent comprehensive analysis of inequality changes in CEE countries during and after the transition from socialism). Second, using decompositions we identify micro-economic factors that affect income inequality and IO, and thus fill a gap in the current research. Third, from a methodological perspective we derive influence functions for selected measures of IO and apply them in Recentered Influence Function (RIF) regression-based decompositions (Firpo et al. 2007, 2009) of changes in IO over time. We use this approach to investigate how various micro-economic factors (demographic and educational characteristics, labour market status, etc.) account for the evolution of IO in CEE countries. To the best of our knowledge, this is the first application to the IO indices of the inequality decomposition method based on RIF regression.

This article is structured as follows. In section 2 we review the existing literature on inequality of opportunity and provide a conceptual framework for our analysis. We discuss our methodological approach in section 3, and describe the data in section 4. We present our results in section 5, and conclude in section 6.

2. Conceptual framework[5]

In contrast to the traditional concept of inequality of outcomes (e.g., incomes, consumption, or wealth), the aim of theories of equality of opportunity is to distinguish the effects on individual outcomes of circumstances (factors for which the individual is not responsible) and of efforts (factors for which the individual is responsible) (Roemer 1993, 1998). An individual's circumstances are typically measured by various aspects of his/her childhood and family environment, while the person's efforts are measured by, for example, his/her years of schooling or work intensity.[6] According to inequality of opportunity theories, inequalities that arise due to an

[5] In this section, we provide only a short overview of the theories of inequality of opportunity. See Roemer and Trannoy (2015a, b), Pignatoro (2012), Ramos and Van de gaer (2015), and Ferreira and Peragine (2015) for comprehensive reviews of the theory and empirical approaches to IO.

[6] According to the standard definition, circumstances are factors for which the individual cannot be held responsible. Some aspects of childhood environment can be therefore considered circumstances (e.g., parental level of education), while

individual's circumstances are considered unfair, while those that are the product of a person's efforts are considered ethically acceptable. Thus, the goal of policies designed to equalise opportunities is to compensate individuals who are subject to unfair inequalities (*compensation principle*), while allowing people's outcomes to be sensitive to effort (*reward principle*). Within this general framework, two main approaches to measuring IO have been developed. In the *ex-ante* approach, IO is measured as inequality between *types* (that is, groups of individuals who have the same circumstances). All of the differences in individual outcomes that remain after the impact of circumstances has been accounted for are assumed to be due to effort. For this reason, in measuring outcomes the *ex-ante* approach defines effort broadly: i.e., as comprising all of the factors that affect individual outcomes other than circumstances, including variables such as luck, talent, and error in measuring the outcome. By contrast, the *ex-post* approach to conceptualising IO measures inequality among individuals who have exerted the same degree of effort, regardless of their circumstances. In other words, according to the *ex-post* view, equality of opportunity is established if and only if people who exert the same level of effort end up with the same outcome. As these two approaches to conceptualising of IO are different in a number of ways, they may be expected to generate different rankings of IO. The possible clash between the *ex-ante* and *ex-post* perspectives on IO has been studied in detail by Fleurbaey and Peragine (2013).

The basic theoretical framework that can be used to explain differences between the *ex-ante* and *ex-post* approaches to IO can be formalised in the following way. Let the outcome variable y be income and consider a population of individuals indexed by $i \in \{1, \ldots, N\}$ with incomes, y_i, being determined only by the effort level, e_i, and the set of discrete circumstances, C_i. It is assumed that circumstances are exogenous, while efforts can be affected by circumstances and other factors. Hence, individual income is given by: $y_i = f[C_i, e_i(C_i)]$. The population is divided into M mutually exclusive and exhaustive *types*, $\Gamma = \{T_1, \ldots, T_M\}$, which are groups of individuals who have the same circumstances. Individuals within types are identical with respect to their circumstances, but different with respect to the level of effort they exerted. For a given set of socio-economic policies, the type-specific cumulative distribution of income, differentiated by varying levels of effort, is given for type k by $F^k(y)$.

According to the influential theory proposed by Roemer (1993, 1998), absolute individual effort is generally affected by circumstances. For example, it may be assumed that the number of years an individual spends in school will be heavily influenced by the levels of effort and of educational attainment of his/her parents. Therefore, Roemer proposed the use of an accountable *degree of effort* measure to rank an individual in the effort distribution of the individual's type. Moreover, since the outcomes y are assumed to be strictly monotone increases in efforts, an individual will be ranked in the same way in the distribution of y as in the distribution of e. Following this view, effort is measured as the percentile of the distribution of y within each type. This approach allows us to divide the population into *tranches*, or sets of individuals who expend the same degree of effort. In other words, tranches group together all of the individuals who are at the same percentiles of the type-conditional distribution of y.

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others can be treated as efforts or can be harder to classify (e.g., school achievement). Hufe et al. (2015) have recently argued that all of the behaviours and achievements of children before the age of consent should be considered circumstances.

Given this framework, the calculation of IO indices involves two steps. First, we construct a counterfactual distribution of outcome, which eliminates all fair inequality and reflects only unfair inequality between individuals. Second, we apply a chosen inequality measure to the counterfactual distribution in order to calculate a numerical value of an IO index. The first step looks different in the *ex-ante* approach than it does in the *ex-post* approach. In the *ex-ante* approach, the counterfactual distribution should reflect the *ex-ante* principle of compensation, which argues that all inequality attributable to circumstances should be eliminated. This approach replaces in the counterfactual distribution an outcome for each individual with the value of his/her opportunity set (defined as the set of all possible outcomes available to a person with a given set of circumstances). In many empirical applications, the value of opportunity set for individuals in a given type is assumed to be the mean of the outcome distribution for this type.[7] This counterfactual or smoothed distribution removes all inequality within types. IO is then measured as inequality between types.

The *ex-post* approach to constructing the counterfactual distribution relies on the *ex-post* principle of compensation: i.e., all inequalities among individuals who exert the same degree of effort should be eliminated. This approach is therefore concerned with removing all inequality between tranches that is attributable to differential efforts, and leaving only inequality within tranches. The counterfactual distribution is obtained by dividing for each tranche the outcomes within this tranche by the mean outcome for the tranche. An inequality index applied to this counterfactual distribution will capture only unfair inequality that is due to circumstances.

The second building block of the IO paradigm is the reward principle, which demands that inequalities that arise from exerting different levels of effort should be preserved. This principle has been formulated in many different ways (see, e.g., Ferreira and Peragine 2015 for a review), but the two most influential versions are the *liberal reward* and the *utilitarian reward* principle. According to the liberal reward principle, redistribution related to different levels of effort exerted by individuals within a type should be minimised; thus, these individuals are entitled to receive equal transfers as postulated by the principle of compensation. Under this principle, there is also no need for any additional redistribution based on the level of effort exerted. In contrast, the utilitarian reward principle aims at maximising the sum of the outcomes of individuals within types, which may require some redistribution in favour of people who exert more or less effort depending on the marginal return of their efforts with respect to their individual outcomes. As Fleurbaey and Peragine (2013) have shown, both the liberal and the utilitarian reward principles are incompatible with *ex-post* compensation, but are compatible with *ex-ante* compensation.

Empirical approaches to measuring IO have usually relied on the *ex-ante* view of IO (see, e.g., Bourguignon et al. 2007, Checchi et al. 2010, Lefranc et al. 2008, 2009, Marrero and Rodríguez 2012, Ferreira and Gignoux 2011, Brunori et al. 2013), as it does not require the researcher to measure the absolute or the relative efforts of individuals.[8] Roemer and Trannoy (2015a, b) argued that since the measurement of efforts usually involves

[7] Lefranc et al. (2008) have used the mean multiplied by one minus the Gini index as the measure of the value of opportunity set.

[8] See, however, Checchi and Peragine's (2010) and Checchi et al. (2015), who consider both *ex-ante* and *ex-post* IO measures.

significant error, it is better to rely on circumstances than on efforts when implementing policies aimed at alleviating inequality of opportunity. On the other hand, circumstances are usually only partially observable, as we cannot measure all of the uncontrollable (e.g., genetic) factors that influence individual outcomes.

In this paper, we follow most of the literature in using the *ex-ante* approach to IO.

3. Research methods

a. IO measurement methodology

As proposed by Bourguignon *et al*. (2007), the strong criterion of equality of opportunity requires that the within-types distribution of outcomes are identical across types. Using the notation introduced in the previous section, this criterion can be stated as follows:

$$F^k(y) = F^l(y), \forall l, k \mid T_l \in \Gamma, T_k \in \Gamma. \quad (1)$$

Lefranc *et al*. (2008) verified whether criterion (1) is fulfilled using stochastic dominance techniques applied to distributions of outcomes conditional on sets of circumstances defining types. However, as Ferreira and Gignoux (2011) observed, stochastic dominance techniques cannot be meaningfully used when the number of circumstances is high and the number of observations within some types is small. In such a setting, it appears sensible to apply a weaker criterion for equality of opportunity; i.e., a criterion that seeks to compare the mean levels of outcome across types rather than the complete conditional outcome distribution. This weaker criterion of equality of opportunity used by Ferreira and Gignoux (2011) can be defined as:

$$\mu^k(y) = \mu^l(y), \forall k, l \mid T_k \in \Gamma, T_l \in \Gamma, \quad (2)$$

where $\mu = (\mu^1, \ldots, \mu^M)$ is the vector of mean outcomes for types. The criterion (2) is implied by (1), but not vice versa. When criterion (2) is used to verify equality of opportunity, inequality of opportunity can be measured as a departure from the equality of mean outcomes across types. Ferreira and Gignoux (2011) proposed measuring IO on the basis of criterion (2) by applying an inequality index (I) to the counterfactual distribution obtained by replacing the outcomes of individuals with their type-specific means: $I(\mu)$.

In order to estimate the mean incomes for types, Ferreira and Gignoux (2011) introduced a parametric procedure that works well even when the number of circumstances is large and some types are represented in the available samples by a small number of observations.[9] The parametric specification uses the fact that the circumstances are exogenous by definition, while the effort can also be affected by circumstances: $y_i = f(C_i, e_i(C_i))$. A log-linearised version of this equation can be estimated by OLS:

$$lny = C\psi + \varepsilon, \quad (3)$$

[9]The alternative is a non-parametric method, which relies on the direct computing of mean outcomes for each type (Checchi and Peragine 2010). However, when the number of types is high, the level of precision of the estimates for type-specific means may be unsatisfactory due to the small number of sample observations per type.

where ε is a random term and ψ captures both the direct effect of circumstances on income, and the indirect effect of circumstances through their impact on effort.[10] Using estimates of coefficients ψ, a parametric estimate of the smoothed distribution can be obtained:

$$\tilde{\mu}_i = \exp[\hat{\psi} C_i], \tag{4}$$

where $\tilde{\mu}_i$ is the counterfactual income level for individual *i* and $\hat{\psi}$ is a vector of parameter estimates from the OLS regression. Obviously, the counterfactual incomes $\tilde{\mu}_i$ will be identical for individuals with the same circumstances. IO can be then measured in absolute terms, *A*, as the inequality of $\tilde{\mu}_i$, $A = I(\tilde{\mu}_1, \dots . \tilde{\mu}_N)$; and in relative terms, *R*, as the share of IO in total income inequality, $R = I(\tilde{\mu}_1, \dots . \tilde{\mu}_N) / I(y)$. The two measures of IO provide a different, but complementary, ranking of societies just like absolute and relative measures in the standard poverty and inequality measurement. In particular, while *A* measures only the distance between various types defined by circumstances, *R* captures the contribution of this between-type inequality to the total income inequality. Therefore, *R* can fall (rise) when either *A* is falling (rising) or when income inequality is increasing (decreasing).

Based on desirability from an axiomatic point of view, Ferreira and Gignoux (2011) chose the mean logarithmic deviation (MLD) as the preferred inequality measure, *I*. This index fulfils the most basic postulates proposed in the theoretical literature on inequality, such as symmetry, the Pigou-Dalton transfer principle, scale invariance, population replication, and additive decomposability. All of these properties are satisfied by a positive multiple of a member of the Generalized Entropy (GE) class of inequality indices. However, the MLD is the only measure among the GE indices (it is a member of the GE class, with its sensitivity parameter set to zero) that satisfies a further requirement of path-independent decomposability (Foster and Shneyerov 2000).[11] In some of the other applications, the Gini index, the Theil index, and variance have also been used (see Ferreira and Peragine 2015).

The log-linear specification (3) used in the parametric calculation of IO indices has recently been scrutinised by Van de gaer and Ramos (2015). They proved that none of empirical measures of IO obtained parametrically using a log-linear specification is consistent with the basic principles that underlie equality of opportunity theory: i.e., *ex-post* compensation and utilitarian reward. On the other hand, using linear least squares (3) or the non-parametric approach to estimate a type specification leads to measures that are consistent with utilitarian reward. However, a log-linear specification (3) is often preferred because it is a better fit for the highly skewed income data, while a non-parametric method is not suitable when a number of circumstance variables are available, and the number of types is high. Given these difficult choices, Van de gaer and Ramos (2015) have suggested that the outcome that should be considered is not income, but logarithms of income. IO indices can

[10] Marrero and Rodríguez (2011) and Hufe and Peichl (2015) have considered alternative specifications of equation (3), which allow for type-dependent heterogeneity in the influence of circumstances on income. This is obtained by introducing interactions between circumstances as additional independent variables in equation (3). However, in our empirical analysis, most of the interaction terms were found to be insignificant. Therefore, we have stayed with the simple regression specification given by (3). Notice also that equation (3) shows that the approach to IO used in this paper reduces to intergenerational income elasticity when the set of circumstances includes only parental income (see e.g. Piraino 2015).

[11] The advantage of using an additively decomposable index is that the total income inequality can be decomposed into between-type (interpreted as IO) and within-type (interpreted as inequality due to efforts) components.

be then measured on the distribution of the counterfactual logarithms of incomes.[12] Computed in this way, IO indices would be consistent with the principle of utilitarian reward.

In this paper, we follow the advice of Van de gaer and Ramos (2015) in computing IO measures on the predicted values obtained using log-linear specification (3):

$$\tilde{v}_i = \hat{\psi} C_i. \tag{5}$$

We calculate the IO indices on the distribution of $\tilde{v}_i$. The absolute IO index A = $I(\tilde{v}_1, \ldots . \tilde{v}_N)$, while the relative index measuring the share of IO in total income inequality is R = $I(\tilde{v}_1, \ldots . v_N)/ I$. As the preferred inequality index, *I*, we choose the variance.[13] Doing so allows us to measure regular income inequality using variance of logs, which is the standard inequality measure in labour economics. The standard inequality index used in *ex-ante* IO modelling, the MLD, seems to be less suitable for assessing inequality in the distribution of logarithms of income, because the MLD is already defined as the logarithm of mean income divided by income. The variance has been previously used to measure IO with imperfect data or in the context of education (Ferreira et al. 2011, Ferreira and Gignoux 2014). We also calculate the standard errors and the confidence intervals of all of the inequality indices using the bootstrap.[14]

The practical estimation of IO suffers from the problem of omitted circumstance variables, as real-world data sets contain only a sub-set of all possible circumstances, some of which are even unobservable. However, as Ferreira and Gignoux (2011) have stressed, following the IO estimation procedure described above ensures that the obtained estimates are lower-bound estimates of the true IO.[15] This means that adding any additional circumstance variables will have a non-decreasing effect on the IO estimates obtained using the approach of Ferreira and Gignoux (2011).

The lower-bound estimates obtained in the *ex-ante* approach to measuring IO have recently been criticised by Kanbur and Wagstaff (2015). As these authors have suggested, and Balcázar (2015) has empirically shown, the lower bounds estimates can have substantial measurement error. For example, if the true relative IO, *R*, is 50%, but the observable circumstances are scarce, the estimated lower bound of IO can be only 10%. By using some additional circumstances, we could obtain a lower-bound estimate in the wide range of 10% to 50%. As a given set of observable circumstances may contribute relatively little to IO in some countries, but much more in other

[12] Van de gaer and Ramos (2015) have observed that defining outcomes in terms of the log of income may be justified if utility is a function of the log incomes.

[13] In a sensitivity analysis, we have also used the Gini index applied to the log incomes as the inequality measure (see Firpo et al. 2009 for the derivation of the Recentered Influence Function for the Gini index). The results of our decompositions based on the Gini index were quantitatively very similar to those obtained using the variance.

[14] The variance estimates are obtained through bootstrapping with 1000 replications. The critical values are taken from the standard normal distribution. The bootstrap accounts for the clustering of individuals within households. As shown by Goedemé (2013), this leads in most cases to the estimation of standard errors, which are close to those that take account of the full sample design in the EU-SILC.

[15] See Niehues and Peichl (2014) for an approach that estimates the upper bounds of inequality of opportunity using fixed effects models applied to panel data.

countries, it seems that the lower-bound estimates for different countries or samples may have different levels of measurement error. This would make comparisons of lower-bound IO estimates for various countries or samples inaccurate.

The criticism of the lower-bound IO estimates based on the *ex-ante* approach to IO seems to be valid, especially when applied to cross-country comparisons. However, in this paper we are primarily interested in studying the evolution of the lower-bound IO estimates over a relatively short period of time for each studied country separately. In this setting, it seems that the measurement error associated with lower-bound estimates is rather constant across the compared samples, and does not prevent us from making reliable IO comparisons.

b. Decomposition of IO indices based on RIF regression

In order to account for change in IO over time, we apply a decomposition methodology introduced by Firpo et al. (2007, 2009). This methodology is a generalisation of the well-known Oaxaca-Blinder decomposition (Blinder 1973, Oaxaca 1973), which is designed to decompose the overall difference in the unconditional mean outcome (e.g., wage or income) between two groups or two periods. The Oaxaca-Blinder approach assumes that the outcome variable *Y* is related in a linear way to the vector of covariates, *X*:

$$Y_{ti} = \beta_{t0} + \sum_{k=1}^{K} X_{ik}\,\beta_{tk} + \varepsilon_{ti}, t = 0{,}1, \tag{6}$$

where $E[\varepsilon_{ti}|X_i, t] = 0$. The overall change Δ_O^{μ} over time in mean outcome between period one and period zero can be decomposed into aggregate coefficient (or "unexplained", or "wage structure") effect (Δ_S^{μ}) and composition (or "explained") effect Δ_X^{μ} as follows:

$$\Delta_O^{\mu} = \mu_1 - \mu_0 = \Delta_S^{\mu} + \Delta_X^{\mu}. \tag{7}$$

The effects are defined in the following way:

$$\Delta_S^{\mu} = E[X|T = 1](\beta_1 - \beta_0), \tag{8}$$

$$\Delta_X^{\mu} = (E[X|T = 1] - E[X|T = 0]\beta_0.$$

The coefficient effect is related to the changes in the returns of the set of covariates *X*, while the composition effect accounts for the changes in the distribution of the covariates. The aggregate decomposition given in (7) can be supplemented by the detailed decomposition, which allows us to distinguish the contribution (in terms of both the coefficient and the composition effect) of each covariate.

Firpo et al. (2007, 2009) developed an extension of the Oaxaca-Blinder methodology that allows researchers to decompose not only the mean outcome, but any distributional statistics for which the so-called recentered influence function (RIF) can be computed. The *RIF* for the distributional statistics replaces *Y* as the left-hand side variable in (6). In the case of the mean, the *RIF* is simply *Y*.

The *RIF* for a given distributional statistic, *z*, is defined as the influence function for this statistic, *IF*(*y*,*z*), plus *z* itself: *RIF*(*y*,*z*) = *IF*(*y; z*) + *z*. The influence function, *IF*, is a statistical tool from robust statistics that is used to assess the influence of a particular observation on the value of the distributional statistics of interest (Hampel 1974).

The useful property of *RIF*(*y*; *z*) for statistic *z* is that its expected value coincides with the statistic itself, *z*. This allows us to write the conditional expectation of *RIF*(*y*; *z*) as a linear function of the covariates *X* – RIF regression:

$$z = E(RIF(y;z)) = E_X[E(RIF(y;z)|X)] = X\beta. \tag{9}$$

The parameters β in (9) obtained using OLS represent marginal effects of *X* on *z*. As in the standard Oaxaca-Blinder methodology, the estimated coefficients can be then used in performing aggregate and detailed decompositions. We obtain standard errors for the elements of the decompositions by bootstrapping the whole procedure of calculating IO indices and decomposing them according to equations (6)-(8).

c. The RIFs for IO indices

The RIF for variance is available in Firpo et al. (2007). It is defined simply as:

$$RIF(y;var) = (y-\mu)^2, \tag{10}$$

where μ is the mean income.

Since our absolute IO measure is variance in the distribution of the predicted values given by (5), $A = var(\hat{\psi}C_i)$, the *RIF* for *A* is given by:

$$RIF(y;A) = (\hat{\psi}C_i-\mu)^2, \tag{11}$$

The *RIF* for our relative IO measure, which is defined as $R = var(\hat{\psi}C_i)/var(y)$, can be derived in a straightforward way using the derivation rule for the influence function of a ratio (Deville 1999). The influence function for a ratio is given by:

$$IF\left[\frac{R(y)}{S(y)}\right] = \frac{IF[R(y)]S(y) - R(y)IF[S(y)]}{S(y)^2}. \tag{12}$$

Substituting the relevant terms into the above equation, the *RIF* for *R* can be derived as:

$$RIF(y;R) = \frac{(\hat{\psi}C_i-\mu)^2}{var(y)} + \left(1-\frac{(y-\mu)^2}{var(y)}\right)\frac{var(\hat{\psi}C_i)}{var(y)}, \tag{13}$$

4. Data

We use data from the European Union Survey on Income and Living Conditions (EU-SILC)[16], an annual survey that provides data that are comparable across countries on income distribution and social inclusion in the European Union. In 2005 and 2011, the EU-SILC contained additional ad hoc modules on the intergenerational transmission of disadvantages.[17] These modules collected extensive information about the respondents' socio-economic backgrounds that can be used to measure circumstances in IO empirical applications. In particular, the modules provide information on the educational levels and occupations of each respondent's parents, a qualitative variable on the financial situation of the respondent's household during his/her childhood, and information on the respondent's country of origin (i.e., whether s/he was born in the country where the survey was conducted, in another EU country, or a country in another part of the world). The EU-SILC also provides extensive information about the economic, demographic, and social characteristics of each respondent's household, which we use in our decomposition analyses.

In calculating the IO measures, we use a set of circumstance variables similar to those used by Marrero and Rodríguez (2012). In particular, for both the 2005 EU-SILC and the 2011 EU-SILC databases, we use the information on the educational levels of the respondent's parents, a variable that describes the occupation of the respondent's father (according to the ISCO classification at the one-digit level), and the information on the respondent's country of birth.[18] We were unable to include another circumstance variable that was used by Marrero and Rodríguez (2012)—namely, information on the financial situation of the household during the respondent's childhood—because the survey questions and the response scales related to this variable were defined differently for the two data modules considered, and these differences cannot be easily reconciled. However, this seems to be a rather minor problem given that the variable that describes the respondent's financial situation during childhood contributes relatively little to IO for our dataset; both the values of the IO measures and the ranking of countries were robust to the inclusion of this variable.

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[16] Cross sectional data from Eurostat, released in 2015. The responsibility for all conclusions drawn from the data lies entirely with the authors.

[17] The 2005 EU-SILC intergenerational module has been used to analyse inequality of opportunity in Europe by Checchi et al. (2010), Marrero and Rodríguez (2012), and Dunnzlaff et al. (2011). Recently, Andreoli and Fusco (2014) have used the 2005 and the 2011 EU-SILC intergenerational modules to study the evolution of IO in Europe over time. These authors introduced a new methodology for measuring IO based on a comparison of the gap curves between the distributions of advantages enjoyed by various types. In their empirical analysis, the authors used only one circumstance variable: the respondent's father's education.

[18] Parental education was measured on a six-point scale in the 2005 EU-SILC database, and on a four-point scale in the 2011 EU-SILC database. However, these differences can be reconciled by the appropriate reassigning of educational categories. In our empirical analysis, we measure parental education on a three-point scale, which is broadly consistent for both EU-SILC databases. The level of parental education was defined as low if the parent could neither read or write in any language, or if the parent had a pre-primary, primary, or lower secondary level of education. The level of parental education was defined as medium if the parent had an upper secondary or post-secondary non-tertiary level of education. Finally, the level of parental education was defined as high if the parent had a tertiary education.

We apply the following sample selection rules. Our main income variable is yearly equivalised household disposable income observed for individuals between 26 and 50 years old, expressed in real terms (2010 prices).[19] To avoid the age composition effect, which arises when the age distribution differs significantly between compared countries, we follow the literature (e.g., Marrero and Rodríguez 2012) in selecting individuals of prime working ages only. Observations of individuals with negative or zero income, as well as of individuals with an income 15 times higher than the mean income of their distribution, were removed from the sample. We use the EU-SILC intergenerational weights in all of the calculations. Our analysis is performed for seven Central and Eastern European countries: the Czech Republic (CZ), Estonia (EE), Hungary (HU), Lithuania (LT), Latvia (LV), Poland (PL), and Slovakia (SK).[20] For all of the countries in our sample, the income reference period in the EU-SILC is the calendar year preceding the survey year. Therefore, our estimates of IO based on the 2005 and 2011 EU-SILC databases actually refer to IO observed in, respectively, 2004 and 2010.

Our regression-based decomposition analyses are designed to explore the factors that account for the changes in income inequality and IO for income over time. Therefore, in the regression models we include several variables that can determine a household's income and opportunities for income acquisition. As our dependent variable is equivalised household disposable income, we measure most of the independent variables on the household level (see, e.g., Gradín 2015). Specifically, the independent variables are measured in a quasi-continuous way as within-household proportions. The first group of variables covers all circumstance variables that we use in calculating the IO indices. It includes the proportions of household members whose parents had attained low, medium, or high levels of education (defined independently for the respondents' fathers and mothers). Similarly, we use the shares of household members whose fathers had a given occupation, and the proportions of household members who were born abroad.

In order to account for the socio-demographic structure of the households, we use the proportions of household members who were females, children (aged 14 or under), and members of the following age intervals: 15-25, 26-29, 30-34, 35-39, 40-44, 45-50, and 51 and older. We also use variables that measure the shares of household adult members who were single, married, or no longer married (separated, widowed, or divorced). The health status of the household members is measured using the proportions of household members who rated their health as being good or better, fair, or bad or very bad. We account for the place of household residence by using indicator variables for densely populated areas, intermediate areas, and thinly populated areas.

The educational and the labour market characteristics of the households are measured using a number of variables. The household's level of education is measured by the proportion of the adult members (aged 16+) who had a low (primary or less), a medium (secondary), or a high (tertiary) level of education. We follow Gradín (2015) in defining the EU-SILC labour market variables in the following way. The labour market activity rate is measured as the ratio of the number of months during the income reference period the household members spent in the labour market to the total number of months in which the household members could have been

[19] The equivalence scale used in the standard Eurostat choice of the modified OECD scale.

[20] The 2011 EU-SILC database also provides data for Bulgaria and Romania. However, these countries were not included in the 2005 EU-SILC edition.

active in the labour market (i.e., the number of adult household members multiplied by 12). The full-time (part-time) employment rate is defined as the ratio of the number of months during the income reference period the household members spent in full-time (part-time) employment to the total number of months they spent in the labour force. The occupational structure of the households is measured using variables for the proportions of adult household members who were working in each occupation, according to the ISCO system of classification (measured at the one-digit level).

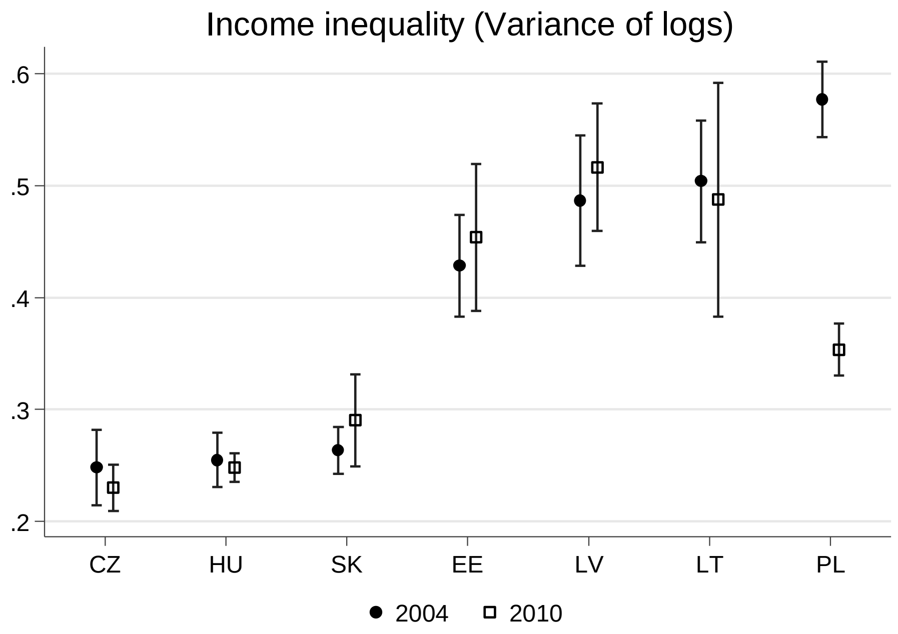
The descriptive statistics for the variables used in our empirical analysis are presented in Table A1 (see the Appendix). The sample sizes range from 2893 observations for Lithuania in 2011 to 15,802 observations for Poland in 2005. In most cases, the distributions of the explanatory variables did not change significantly between 2004 and 2010. For some countries, the most striking difference between the distributions observed in 2004 and 2010 is a sizable decrease in the proportion of parents who had a low level of education, coupled with increases in the proportion of parents who had a medium or a high level of education. In some cases, especially for the Czech Republic, the differences are so large that we assume that they must reflect some kind of measurement error. However, in other countries it seems that these differences are simply related to the increasing average levels of human capital in Europe over the second half of the 20th century, and also to the different degrees of access to education between people who were born either before World War II and those who were born during or after the war (cf. footnote 17). Among other variables, we see important changes in the labour market statistics that are primarily attributable to the economic crisis (which led to a sharp decline in employment rates, particularly in the Baltic states), or the lack of such changes coupled with strong improvements in the labour market after 2004 (which explains the changes observed in Poland); and the effects of the educational boom observed in CEE. Finally, we see a slight decline in the share of households with children; and an improvement in health status, as smaller shares of respondents reported being in bad or very bad health.

5. Results

Income inequality in the CEE displays a high degree of heterogeneity with respect to both the levels of and the changes in inequality over time. Measured by the variance of logs (Figure 1), the inequality levels were lowest in the three Visegrad countries (CZ, HU, and SK), and were highest in Poland and the three Baltic states. Between 2004 and 2010, the most important changes occurred in Poland, where income inequality decreased considerably. Over the same period, inequality levels also declined (slightly) in Lithuania, the Czech Republic, and Hungary; and increased (also slightly) in Slovakia, Estonia, and Latvia (although it should be emphasised that these changes have non-overlapping confidence intervals for Poland only[21]). Thus, the 2010 levels of inequality in CEE were less dispersed than they were in 2004.

[21] When the confidence intervals of estimates for 2004 and 2010 are non-overlapping, we conclude that the inequality changes were significant. In other cases, we conduct tests of statistical significance on inequality changes using a *t*-type statistic with variance estimates obtained using bootstrap. The statistic used for the hypothesis that an inequality index, I,

Figure 1: Changes in inequality in CEE, 2004- 2010



Note: The vertical bars denote 95% confidence intervals computed by bootstrap accounting for the clustering of individuals within households.

Falling (rising) levels of income inequality could have been driven by changes in the lower or the upper part of the income distribution, or by a combination of the two. Our results (Appendix Figure 1) show that the growth incidence curves (GIC, Ravallion and Chen 2003), which plot changes in real (per capita) disposable incomes between 2004 and 2010 along the income distribution, had very different patterns in the seven analysed countries. The GICs were rather flat for the Czech Republic, Lithuania, and Estonia (leading to small, insignificant declines in income inequalities in the first two countries and an increase in the third). Hungary experienced an increase in incomes at the low end of the distribution, but also strong income growth among households in the top half and the upper deciles in particular. A similar, albeit weaker, pattern is visible for Latvia. Slovakia saw the largest increases in income among households in the third and the 20th percentiles, but these increases did not fully offset the income declines at the very bottom of the distribution; thus, in Slovakia there was a small (albeit insignificant) increase in overall income inequality. Finally, Poland had a clear pattern of strong income growth at the bottom of the distribution, positive but lower income growth in the middle of the distribution, and a much slower income growth among the highest income deciles; thus, in Poland there was a sharp decline in income inequality.

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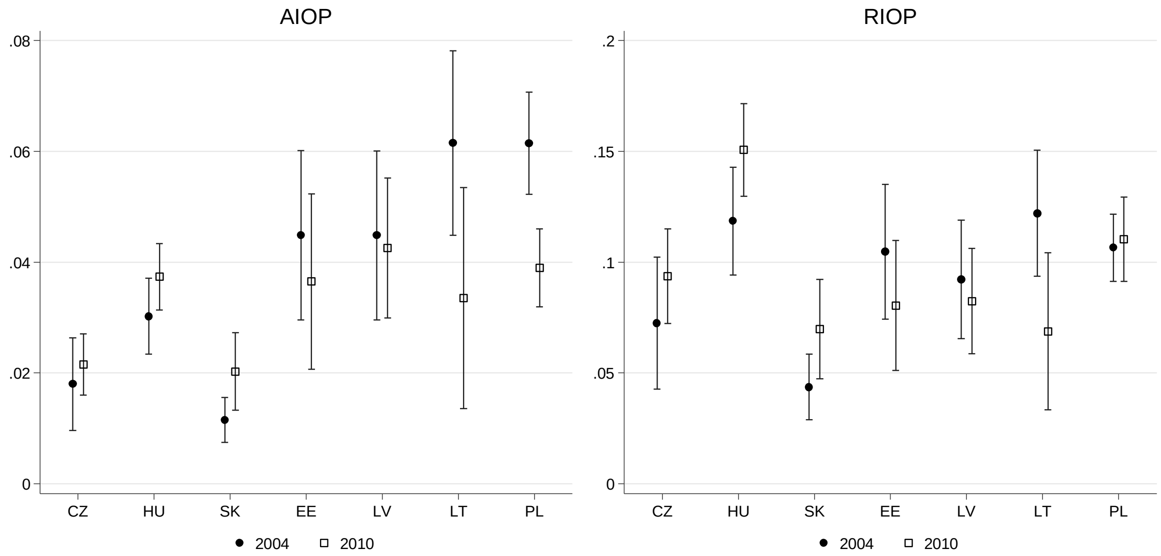
has the same value in 2004 and 2010, I_{2004}=I_{2010}, is $T = (\hat{I}_{2010} - \hat{I}_{2004})/[\hat{V}(\hat{I}_{2010}) + \hat{V}(\hat{I}_{2004})]^{1/2}$, where V denotes variance of an inequality measure and hats denote estimates of given quantities.

To what extent are the overall levels of inequality linked to inequality of opportunity? Absolute and relative inequality of opportunity in CEE also vary considerably in terms of both their levels and the extent to which they have changed over time (Figure 2). In 2004 Poland and Lithuania stood out as having the highest levels of absolute IO (as well as the highest levels of overall income inequality) in CEE, while absolute IO was three times lower in the Czech Republic and Slovakia (which also had low levels of overall income inequality). By 2010 these cross-country differences had diminished, and the trend towards convergence was driven in part by increasing IO in the countries where it was the lowest (CZ, HU, SK, with the last one being statistically significant with p-value=0.027), but primarily by considerable decreases in IO in LT and PL (both statistically significant, p-value=0.036 and 0.000, respectively).

Figure 2: Absolute and relative levels of inequality of opportunity, 2004 and 2010, CEE.



Note: The vertical bars denote 95% confidence intervals computed by bootstrapping the whole procedure of estimating IO indices, described in section 3.1. The bootstrap accounts for the clustering of individuals within households.

The levels of relative IO also vary significantly across CEE countries, and that large degree of heterogeneity was maintained over time. In 2004 in Slovakia inequality of opportunity accounted for less than 5% of the overall inequality level, while in HU and LT it accounted for 12%. No single pattern of change over time could be observed, with RIOP increasing even further in HU (reaching 15%, the highest level among the CEE countries), decreasing strongly in LT, and increasing slightly in SK (although it still had the lowest level among the analysed countries). All of these changes were statistically significant (with p-values of 0.049, 0.021, and 0.051; respectively).

Decompositions.

In the next step we use the RIF regression methods to investigate the changes in the distributional statistics we are interested in: i.e., the statistically significant changes in total income inequality (measured by the variance of logs) for Poland; absolute IO in Lithuania, Poland, and Slovakia; and relative IO in Hungary, Lithuania and Slovakia. Our aim is to investigate the role of changes in the composition and returns to factors that explain (part of) the observed inequality changes, such as circumstances, demographic factors, and the individuals' labour market positions. To this end, we use the Oaxaca-Blinder decomposition framework, and apply it to the Recentered Influence Functions of the inequality and IO measures. The RIF regressions coefficients are presented in Appendix Table A2.

Table 1 presents a summary of the decomposition of the substantial decline in income inequality in Poland (measured by the variance of logs). While in 2004 Poland had the highest level of overall inequality among the CEE countries we analysed, inequality had declined to median levels by 2010. Most of the observed decrease in inequality (about 64%) can be attributed to coefficient effects or "unexplained" factors that reflect changes in the economic returns to the characteristics we accounted for.[22] The overall composition effect contributed around one-third of the observed decline in income inequality.

Table 1: Decomposition of changes in income inequality (variance of logs) for PL

	Poland					
	overall		explained		unexplained	
	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error
Variance of logs in 2010	0.353***	0.013				
Variance of logs in 2004	0.577***	0.016				
difference	-0.22***	0.021				
explained	-0.08***	0.051				
unexplained	-0.14***	0.059				
Summary of detailed decomposition						
Circumstances			-0.006*	0.004	-0.057*	0.034
Demographic characteristics			-0.005	0.003	-0.002	0.148
Marital status			-0.000	0.001	-0.082	0.103
Degree of urbanisation			0.000	0.001	0.013	0.044
general health			-0.004	0.004	0.059**	0.026
Education			0.012***	0.004	0.096	0.099
Household's work intensity			-0.07***	0.010	-0.027	0.138
Job experience			-0.004	0.005	-0.258	0.263
Occupations			-0.005	0.004	0.057	0.093
_cons					0.066	0.394
Number of observations	21 177					

note: *** p<0.01, ** p<0.05, * p<0.1. Full set of details in Table A4 in the Appendix.

[22] Negative composition and coefficient effects should be in this case (negative difference between inequality measures observed in 2010 and 2004) interpreted as inequality decreasing, while positive effects as inequality increasing.

Compositional changes were of importance for some of the characteristics. In particular, changes in the structure of individuals with respect to their circumstances (parental background: parents' education and occupational structures) contributed to the observed decrease in income inequality (and inequality of opportunity, as shown above and discussed below), contributing 3% of the overall change (the coefficient of 0.006 in total change of 0.22). Although our analysis covers six years only, we can see that the parents of the cohorts born in 2010 were better educated than the parents of those who were born in 2004[23] (cf. Table A1 in the Appendix): the shares of individuals whose parents had low levels of education dropped by more than 10 percentage points (0.12 pp for fathers and 0.15 pp for mothers). While the impact of changes in the composition of individuals with respect to their circumstances was statistically significant, its contribution was much smaller than the impact of changes in the structure of households with respect to their work intensity. Thus, the substantial increase in the share of months spent in full-time employment between 2004 and 2010 (0.77 vs. 0.87 months spent in full-time employment) accounted for a sizeable share (around 30%) of the observed decline in inequality, as full-time employment is a strong determinant of income inequality (cf. RIF regression results in Table A2). In Poland, labour market conditions improved considerably between 2004 and 2008, with unemployment rates decreasing from 19% to 7% over the period. Moreover, Poland was the only EU country that did not experience an economic recession in 2008-2009; instead, the country saw only a slowdown of GDP growth. Overall, Poland's employment rate in 2010 was 59% (among adults aged 15-64), or seven percentage points higher than in 2004. Increasing work intensity, particularly among previously workless households, led to strong income growth and a decrease in income disparities (Lis & Potoczna 2013).

Demographic characteristics contributed less to the decrease in income inequality as the total effect of demographic factors is insignificant, although two points are worth noting. First, the increasing share of households made up of elderly people (who in Poland are, on average, less likely to be poor than other households, and thus have lower levels of income inequality, cf. Table A2), as well as the rising relative incomes of households in the prime age range (35-50, who are most likely to have labour market income) both contributed to the decline in the overall level of income inequality. Second, while less than good self-reported health was negatively related to income inequality in 2004, it has become an insignificant factor in 2010 (see Table A2 in the Appendix). Thus, the effect of changing returns to self-reported health have been inequality-increasing. This finding may reflect the indexation of disability pensions, which increased at a slower pace than labour market incomes. It is also interesting to note that rising educational attainment was associated with increased income inequality. The share of individuals with tertiary education (and higher incomes) rose from 17% in 2005 to more than 25% in 2011, which resulted in (a small, but statistically significant) increase in income dispersion. Finally, changing returns to circumstances account for about 26% (0.057 in 0.22) of the overall fall in income inequality. This is associated with the fact that having mother with medium or high education has become an inequality decreasing factor in Poland between 2004 and 2010 (see Table A2). Similarly, the role of

[23] This is likely strongly influenced by the fact whereas that the median year of birth of the mothers of the respondents analysed in 2004 was 1932, the median year of birth of the mothers of the respondents analysed in 2010 was 1940. Thus, because of the effects of World War II, the mothers in the former group would have had greater difficulties than the mothers in the latter group in accessing education.

having father working as a manager or in an elementary occupation played a greater role as an inequality-increasing factor in 2004 than 2010.

Table 2: Decomposition of changes in AIOP: Lithuania, Poland, and Slovakia.

	LT		PL		SK	
	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error
Absolute IO in 2010	0.033***	0.010	0.039***	0.004	0.020***	0.004
Absolute IO in 2004	0.061***	0.008	0.061***	0.005	0.012***	0.002
difference	-0.028**	0.013	-0.022***	0.006	0.009**	0.004
explained	-0.001	0.004	-0.003**	0.001	-0.004**	0.002
unexplained	-0.027**	0.012	-0.019***	0.006	0.012**	0.005

note: *** p<0.01, ** p<0.05, * p<0.1. Full set of details in Table A4 in the Appendix.

When we look at changes in absolute IO, we can see that there were statistically significant changes in three of the analysed countries: Lithuania, Poland, and Slovakia (cf. Figure 2, Tables 2-3). Between 2004 and 2010, Lithuania and Poland saw substantial declines in absolute inequality of opportunity, while Slovakia experienced a (slight) increase. Again, the majority of these changes can be ascribed to unexplained factors, reflecting changes in the economic returns of various individual characteristics to absolute IO, and in unobservables. Yet the change in the composition of individuals with respect to their parental background (there was a strong improvement in parents' educational levels in Poland, a smaller improvement in Slovakia, and an even smaller improvement in Lithuania) was associated with a decline in absolute levels of inequality of opportunity in the first two countries (a portion of the parental background variable was also statistically significant in Lithuania, cf. Appendix Table A4). Interestingly, changes in the households' labour market situation and in other characteristics had in general negligible impact on changes in the absolute IOP measures. In line with expectations, we find that circumstances variables have a significant impact on the measures of absolute inequality of opportunity in all three countries (cf. Appendix Table A3 with coefficients of RIF regressions and Table A4 with detailed decomposition results). In case of Poland, fast income growth for persons whose mother had at least medium education and for persons whose father worked in an elementary occupation account for about 77% of the fall in absolute IO.

Table 3: Decomposition of changes in absolute IO: Lithuania, Poland and Slovakia; details.

	Lithuania				*Poland*				*Slovakia*			
	explained		unexplained		explained		unexplained		explained		unexplained	
	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error
Circumstances	-0.001	0.00	0.017	0.04	-0.003**	0.00	-0.03***	0.01	-0.004**	0.00	0.001	0.02
demography	-0.000	0.00	0.014	0.01	0.000	0.00	-0.005**	0.00	-0.000	0.00	-0.001	0.00
education	-0.000	0.00	0.012	0.01	-0.000	0.00	0.002	0.00	-0.000	0.00	-0.004	0.01
health	-0.000	0.00	-0.001	0.00	-0.000	0.00	0.000	0.00	0.000	0.00	0.000	0.00
marital status	0.000	0.00	-0.001	0.00	-0.000	0.00	-0.003*	0.00	0.000	0.00	-0.001	0.00
urbanisation	-0.000	0.00	-0.001	0.00	-0.000	0.00	-0.001	0.00	0.000	0.00	-0.000	0.00
work intensity	0.000	0.00	0.007	0.01	0.000	0.00	-0.003	0.00	0.000	0.00	-0.003	0.00
occupation	0.000	0.00	0.002	0.01	0.000	0.00	0.002	0.00	0.000	0.00	-0.000	0.00
experience					0.000	0.00	0.002	0.01	-0.000	0.00	0.002	0.00
_cons			-0.08*	0.04			0.016	0.01			0.018	0.02
Observations:	5 598				21 177				8 949			

note: *** p<0.01, ** p<0.05, * p<0.1. Full set of details in Table A4 in the Appendix.

We now turn to the results for relative IO, which measures the share of income inequality attributed to IO. Statistically significant changes in relative IO over time are found for Hungary, Lithuania, and Slovakia. In 2004, Hungary and Lithuania had similar levels of relative IO, while Slovakia had much lower levels (Table 4). By 2010, the relative IO level had increased significantly in Hungary and Slovakia, but had declined sharply in Lithuania; thus, the Lithuanian relative IO was the same as the Slovakian level. Moreover, whereas in Hungary and Slovakia the increase in the share of inequality of opportunity is attributable to changes in coefficient effects, there is no obvious pattern that explains its decline in Lithuania (where, as discussed earlier, absolute inequality of opportunity fell strongly even though there were no significant changes in overall inequality; hence we assume that the changes in relative IO reflect the fall in IO).

Table 4: Decomposition of changes in relative IO: Hungary, Lithuania, and Slovakia

	Hungary		Lithuania		Slovakia	
	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error
Relative IO in 2010	0.151***	0.010	0.069***	0.018	0.070***	0.011
Relative IO in 2004	0.119***	0.012	0.122***	0.014	0.044***	0.008
difference	0.032**	0.017	-0.053***	0.023	0.026**	0.013
explained	-0.013**	0.006	-0.016	0.012	-0.014**	0.007
unexplained	0.046**	0.018	-0.037	0.028	0.041**	0.017

note: *** p<0.01, ** p<0.05, * p<0.1. Full set of details in Table A5 in the Appendix

Table 5: Decomposition of changes in relative IO: Hungary, Lithuania, and Slovakia, details.

	HU				LT				SK			
	explained		unexplained		explained		unexplained		explained		unexplained	
	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error
circumstances	0.002	0.01	0.016	0.05	-0.004	0.01	0.004	0.06	-0.009**	0.00	0.022	0.06
demography	-0.001	0.00	0.016	0.04	-0.000	0.00	-0.107	0.07	-0.002	0.00	-0.046	0.03
education	-0.004**	0.00	0.015	0.05	-0.000	0.00	0.152*	0.09	0.002	0.00	0.026	0.07
general health	0.002	0.00	-0.012	0.01	0.002	0.01	-0.001	0.02	-0.004	0.00	0.011	0.01
marital status	-0.000	0.00	-0.016	0.03	-0.002	0.00	-0.015	0.04	0.001	0.00	-0.043	0.03
degree of urbanisation	0.000	0.00	-0.008	0.01	-0.000	0.00	0.004	0.01	0.000	0.00	0.002	0.01
work intensity	-0.012***	0.00	0.036	0.06	-0.009*	0.01	-0.308***	0.08	-0.000	0.00	0.197***	0.05
occupation	-0.004**	0.00	0.015	0.05	-0.002	0.00	-0.054*	0.03	-0.002*	0.00	-0.027	0.03
job_experience									0.000	0.001	-0.039	0.048
_cons			0.008	0.105			0.287*	0.150			-0.063	0.103
Number of observations	12 175				5 598				8 949			

note: *** p<0.01, ** p<0.05, * p<0.1. Full set of details in Table A5 in the Appendix

Table 5 shows the summary of detailed decompositions for changes in relative IO. The unexplained factors behind the rise in relative IO in Hungary (where absolute IO increased, but the overall income inequality decreased slightly) are related mainly to a decreasing protective effect of having a father with a medium level of education (see Tables A5-A6 in the Appendix).[24] In other words, having a father with medium level of education was a much stronger relative IO-reducing factor in 2004 than in 2010. It seems therefore that rising differences in incomes between various types defined by father's education were a major contributor to increasing relative IO in Hungary. Overall, the coefficient effect for having a father with medium level of education accounts for about 66% of the increase in relative IO in Hungary.

Looking at the composition effects for Hungary, we can see that the overall increase in Hungarian relative IO was attenuated by changes in the composition of households with respect to labour market activity, which - were reducing the relative IO. This effect is due to the fact that full-time employment rate fell by about 3 percentage points in Hungary between 2004 and 2010, while the part-time employment rate grew by the same amount. The effect is sizeable as it accounts for about (-) 38% of the overall rise in relative IO. It can be explained by noting that full-time employment occurs relatively more frequently among the more opportunity-advantaged types in Hungary, while part-time employment is more often found among opportunity-deprived types. The increase in the share of individuals with tertiary education (which in Hungary is the single factor that accounts for the largest share of total inequality, see Fabian et al. 2014) as well as occupational changes led to small decreases in relative IO.

The increase in relative IO in Slovakia was mostly driven by considerable increases in returns to both full-time and part-time employment as relative IO-increasing factors (see Table A6 in Appendix). This suggests that the difference in wages between opportunity-deprived types and opportunity-advantaged types has risen significantly in Slovakia between 2004 and 2010. We can also observe a small relative IO-decreasing composition effect for occupation and a larger (35% of the overall growth in the relative IO) composition effect for circumstances. The latter is due to a significantly reduced proportion of Slovakians who had mothers having only low level of education (a fall by 9 percentage points).

Finally, our results for Lithuania suggest that falling returns to full-time employment had an important relative IO-decreasing effect, which was largely offset by large opposite effects for education and unobservable factors (accounted for by the intercept). The coefficient effect for full-time employment works through the reduced strength of full-time employment as an inequality-protecting mechanism, not through reducing absolute IO in Lithuania (see Table 3).[25] Growing returns to tertiary education (see Table A5 in Appendix) were relative IO-increasing factor (accounting for almost 90% of its change).

[24] While the overall coefficient effect for all circumstances taken together in Table 5 is statistically insignificant, the individual coefficient associated with having a father with medium level of education is significant at the 5% level (see Table A5 in Appendix).

[25] The decomposition results for changes in income inequality for Lithuania (not shown) indicate that the return to full-time employment as income inequality-reducing factor fell from -1.9 in 2004 to -1.1 in 2010.

6. Conclusions

The aim of this paper has been to improve our knowledge about inequality of opportunity (IO) in Central and Eastern European (CEE) countries, including evidence about the levels, patterns of changes, and drivers of developments in IO. Studying IO, which distinguishes between fair income inequality resulting from individual responsibility and unfair inequality due to factors beyond individual control, has received so far little attention in the context of the CEE countries. In order to identify drivers of IO changes over time, we extended the decomposition method based on Recentered Influence Function (RIF) concept (Firpo et al. 2007, 2009) that has so far been used mostly in labour economics to explain changes and differences in ordinary income inequality, and applied it to IO measures. This approach allowed us to investigate the factors behind changing inequalities at the micro level; i.e., to verify to what extent they were shaped by individuals' and households' demographic characteristics, educational attainment levels, labour market situations, and changes in socio-economic background.

The analysis produced a number of interesting findings. Despite being similar from a global perspective in terms of their economic development levels and institutional settings, the CEE countries displayed a large degree of heterogeneity in terms of their levels of income inequality and inequality of opportunity, and of how these levels evolved over time. Levels of income inequality in the CEE countries appear to have converged slightly between 2004 and 2010, a trend that was driven primarily by a strong narrowing of Poland's income distribution (as Poland displayed the highest level of inequality at the beginning of the period). The pattern in the development of absolute IO levels was similar: the levels declined mainly in the two countries that had the highest levels in 2004; i.e., Poland and Lithuania. Hungary, despite having low overall levels of income inequality and absolute IO, experienced the highest growth in relative IO (the ratio of absolute IO to income inequality).

The labour market situation (in particular rising employment rates) seems to have been the most important factor accounting for the significant reduction in income inequality in Poland. Ageing processes and rising educational levels were also associated with changes in income inequality, albeit to a lesser degree. With respect to reductions of absolute IO that occurred in Lithuania and Poland, we have found that they were mostly driven by returns to the factors beyond individual control (circumstances), with changes in the distribution of circumstances (e.g. improving distribution of parental education) playing a smaller role. The effects of standard economic and demographic characteristics (related to age structure, education, labour market status of households) on changes in absolute IO were negligible. We have also found that the major drivers of increases in relative IO in Hungary and Slovakia were related to changes in returns to having fathers with medium education (Hungary) or changes in wages across various more or less opportunity-deprived groups of individuals (Slovakia).

Finally, although the formal analysis of the relationship between GDP growth, income inequality, and IO was beyond the scope of our paper, we found it interesting that the observed changes in inequality appear to have been unrelated to GDP growth in CEE. Poland and Slovakia had similarly high rates of economic growth, but displayed completely different patterns of changes in both income inequality and IO. Lithuania's and Latvia's patterns of economic development were also quite similar over time (both countries experienced sharp recessions and spending cuts during the recent economic crisis), but their patterns of changes in inequality varied substantially. We believe that changes in the institutional settings and the overall targeting of social policies were likely more important determinants of inequality developments in CEE than GDP fluctuations.

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Appendix

Table A1: Summary statistics (in %).

	CZ		EE		HU		LT		LV		PL		SK	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Father's education														
low	0.13	0.63	0.34	0.24	0.38	0.56	0.54	0.50	0.48	0.37	0.45	0.33	0.28	0.25
medium	0.77	0.26	0.44	0.50	0.52	0.33	0.34	0.37	0.40	0.49	0.48	0.59	0.62	0.64
high	0.10	0.11	0.22	0.26	0.11	0.11	0.12	0.13	0.13	0.14	0.07	0.09	0.10	0.11
Mother's education														
low	0.29	0.59	0.33	0.19	0.52	0.58	0.54	0.38	0.44	0.29	0.51	0.36	0.42	0.31
medium	0.67	0.34	0.44	0.49	0.42	0.34	0.34	0.46	0.43	0.53	0.44	0.56	0.53	0.62
high	0.05	0.06	0.22	0.32	0.07	0.08	0.12	0.16	0.13	0.18	0.05	0.08	0.05	0.07
Father's occupation														
Manager	0.04	0.04	0.11	0.10	0.06	0.04	0.06	0.06	0.06	0.05	0.04	0.05	0.08	0.05
Professional	0.06	0.08	0.11	0.11	0.08	0.08	0.09	0.10	0.09	0.11	0.05	0.06	0.07	0.08
Technician	0.16	0.15	0.05	0.08	0.05	0.06	0.04	0.04	0.06	0.05	0.07	0.07	0.10	0.12
Clerk	0.03	0.03	0.01	0.02	0.03	0.02	0.02	0.02	0.01	0.01	0.03	0.03	0.03	0.03
Salesman	0.04	0.04	0.01	0.02	0.03	0.06	0.02	0.04	0.02	0.03	0.02	0.05	0.03	0.05
Skill agricultural	0.05	0.04	0.02	0.04	0.09	0.07	0.05	0.07	0.03	0.07	0.23	0.20	0.03	0.02
Craft trade	0.36	0.34	0.30	0.26	0.37	0.33	0.27	0.29	0.29	0.28	0.30	0.28	0.29	0.34
Machine operator	0.19	0.22	0.29	0.31	0.18	0.22	0.27	0.21	0.31	0.30	0.17	0.19	0.23	0.23
Elementary occup	0.06	0.05	0.07	0.05	0.09	0.11	0.18	0.17	0.12	0.09	0.08	0.07	0.14	0.08
Armed/military	0.01	0.02	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.00	0.01

Born abroad	0.04	0.04	0.14	0.09	0.03	0.01	0.05	0.04	0.13	0.07	0.00	0.00	0.01	0.01
Share of women	0.38	0.38	0.40	0.40	0.40	0.39	0.40	0.40	0.41	0.42	0.38	0.40	0.40	0.41
Age														
Age 0-14	0.19	0.18	0.16	0.19	0.18	0.18	0.20	0.18	0.16	0.16	0.18	0.18	0.17	0.14
Age 15-24	0.14	0.14	0.17	0.13	0.14	0.14	0.15	0.16	0.15	0.14	0.16	0.13	0.20	0.18
Age 25-29	0.12	0.09	0.10	0.12	0.10	0.10	0.08	0.08	0.09	0.10	0.10	0.10	0.09	0.09
Age 30-34	0.13	0.14	0.10	0.13	0.13	0.12	0.10	0.11	0.10	0.10	0.11	0.13	0.10	0.11
Age 35-39	0.10	0.13	0.12	0.11	0.11	0.13	0.11	0.10	0.11	0.11	0.09	0.11	0.08	0.11
Age 40-44	0.10	0.11	0.11	0.11	0.09	0.11	0.12	0.12	0.11	0.11	0.10	0.09	0.10	0.10
Age 45-49	0.13	0.13	0.15	0.14	0.14	0.13	0.15	0.16	0.15	0.14	0.14	0.12	0.14	0.14
Age 50+	0.09	0.08	0.10	0.09	0.11	0.10	0.10	0.10	0.13	0.14	0.12	0.14	0.12	0.15
Employment rate														
full time	0.87	0.90	0.87	0.81	0.88	0.86	0.83	0.81	0.86	0.78	0.77	0.87	0.86	0.86
Part time	0.03	0.02	0.04	0.06	0.05	0.03	0.06	0.03	0.03	0.03	0.05	0.04	0.02	0.02
Marital status														
single	0.26	0.34	0.40	0.44	0.31	0.34	0.21	0.22	0.28	0.35	0.24	0.23	0.28	0.33
married	0.62	0.53	0.45	0.41	0.54	0.52	0.66	0.62	0.51	0.45	0.65	0.66	0.66	0.56
other	0.12	0.12	0.13	0.12	0.15	0.11	0.12	0.12	0.20	0.19	0.08	0.07	0.06	0.09
Health status														
very good, good	0.69	0.65	0.70	0.59	0.62	0.76	0.55	0.55	0.46	0.62	0.67	0.71	0.65	0.75
average	0.16	0.11	0.23	0.16	0.28	0.16	0.37	0.24	0.42	0.29	0.21	0.19	0.27	0.16
bad, very bad	0.05	0.04	0.06	0.04	0.10	0.05	0.08	0.05	0.11	0.06	0.09	0.06	0.08	0.07
Education level														
primary	0.00	0.00	0.02	0.01	0.02	0.01	0.04	0.03	0.16	0.01	0.13	0.09	0.00	0.00
secondary	0.86	0.79	0.68	0.58	0.80	0.74	0.70	0.60	0.63	0.68	0.68	0.62	0.85	0.75
tertiary	0.14	0.19	0.29	0.38	0.17	0.22	0.25	0.33	0.20	0.28	0.17	0.25	0.15	0.22

Job experience														
less than 1	0.00	0.01	0.01	0.01	0.00	0.00	0.01	.	0.01	0.01	0.04	0.01	0.00	0.02
1-2 years	0.05	0.05	0.05	0.05	0.04	0.09	0.04	.	0.04	0.04	0.06	0.06	0.05	0.05
3-5 years	0.08	0.09	0.08	0.10	0.05	0.13	0.07	.	0.06	0.09	0.09	0.11	0.07	0.07
6-9 years	0.14	0.13	0.11	0.16	0.08	0.13	0.11	.	0.10	0.12	0.12	0.14	0.10	0.10
10+ years	0.73	0.73	0.75	0.67	0.82	0.66	0.78	.	0.79	0.74	0.69	0.68	0.79	0.77
Occupation														
Manager	0.05	0.05	0.13	0.11	0.10	0.05	0.08	0.08	0.08	0.07	0.04	0.06	0.05	0.04
Professional	0.09	0.11	0.12	0.18	0.10	0.13	0.16	0.17	0.09	0.16	0.13	0.13	0.11	0.10
Technician	0.20	0.21	0.11	0.14	0.11	0.11	0.07	0.09	0.13	0.13	0.09	0.10	0.15	0.19
Clerk	0.08	0.08	0.05	0.06	0.07	0.08	0.04	0.04	0.05	0.06	0.06	0.06	0.07	0.07
Salesman	0.13	0.12	0.11	0.10	0.12	0.13	0.12	0.11	0.12	0.12	0.12	0.12	0.12	0.12
Skill agricultural	0.02	0.02	0.03	0.02	0.03	0.03	0.06	0.03	0.03	0.02	0.10	0.09	0.01	0.01
Craft trade	0.19	0.15	0.15	0.12	0.19	0.14	0.17	0.14	0.15	0.12	0.17	0.15	0.16	0.14
Machine operator	0.09	0.10	0.13	0.10	0.08	0.11	0.09	0.09	0.11	0.08	0.08	0.09	0.12	0.11
Elementary occup	0.06	0.05	0.08	0.06	0.09	0.10	0.11	0.09	0.13	0.12	0.08	0.07	0.07	0.05
Residence:														
Dense	0.33	0.36	0.48	0.54	0.32	0.31	0.42	0.45	0.48	0.50	0.41	0.41	0.23	0.26
Intermediate	0.23	0.25	0.00	0.00	0.22	0.22	0.00	0.00	0.00	0.00	0.13	0.15	0.35	0.31
Thin	0.44	0.39	0.52	0.46	0.46	0.47	0.58	0.55	0.52	0.50	0.46	0.44	0.42	0.43
N	3435	6214	3689	3599	6076	8830	3983	2893	3079	4523	15802	10682	5513	4894

Table A2: RIF regression, variance of logs, Poland

	POLAND, varLog	
	2004	2010
Father education		
Medium	-0.014	0.0352
	(0.036)	(0.023)
High	0.135*	0.217***
	(0.08)	(0.043)
Mother education		
Medium	-0.014	-0.097***
	(0.036)	(0.023)
High	0.071	-0.185***
	(0.071)	(0.039)
Father occupation		
Manager	0.292***	0.113***
	(0.071)	(0.042)
Professional	0.139	0.082*
	(0.087)	(0.046)
Technician	0.0872	0.080**
	(0.058)	(0.037)
Clerk	0.096	-0.043
	(0.074)	(0.048)
Salesman	-0.027	0.085**
	(0.085)	(0.039)
Craft trade	0.070*	0.073***
	(0.038)	(0.025)
Machine operator	0.09**	0.011
	(0.041)	(0.026)
Elementary occup.	0.150***	0.023
	(0.049)	(0.033)
Armed/military	0.014	0.088
	(0.099)	(0.07)
Born abroad	0.788***	-0.082
	(0.231)	(0.182)
Share of females	-0.246***	-0.136***
	(0.07)	(0.046)
Age structure		
0-14	-0.586***	-0.305***
	(0.155)	(0.081)
15-24	-0.548***	-0.320***

	(0.106)	(0.067)
25-29	-0.136*	0.022
	(0.081)	(0.051)
35-39	0.297***	-0.026
	(0.086)	(0.049)
40-44	0.450***	0.06
	(0.087)	(0.054)
45-49	0.500***	0.031
	(0.083)	(0.052)
50+	-0.462***	-0.407***
	(0.107)	(0.065)
Activity rate	0.233***	-0.008
	(0.071)	(0.054)
Employment rate (full time)	-0.857***	-0.778***
	(0.054)	(0.047)
Employment rate (part time)	-0.142	-0.547***
	(0.092)	(0.075)
Marital status		
single	0.244***	0.081*
	(0.071)	(0.048)
married	0.113**	0.041
	(0.057)	(0.039)
Health status		
average	-0.114***	0.0356
	(0.044)	(0.029)
bad	-0.213***	0.089
	(0.0703)	(0.055)
Educational attainment		
secondary	-0.075	0.073*
	(0.056)	(0.044)
tertiary	0.378***	0.187***
	(0.086)	(0.055)
Job experience		
1-2 years	0.212*	-0.328***
	(0.126)	(0.113)
3-5 years	0.044	-0.266**
	(0.119)	(0.107)
6-9 years	0.077	-0.191*
	(0.116)	(0.106)
10+ years	-0.009	-0.214**
	(0.108)	(0.103)

Occupation		
Professional	-0.004	-0.013
	(0.092)	(0.052)
Technician	-0.129	-0.280***
	(0.089)	(0.051)
Clerk	-0.232**	-0.415***
	(0.099)	(0.061)
Salesman	-0.365***	-0.217***
	(0.088)	(0.054)
Skill agricultural	0.228**	0.012
	(0.095)	(0.060)
Craft trade	-0.294***	-0.290***
	(0.085)	(0.055)
Machine operator	-0.392***	-0.425***
	(0.099)	(0.059)
Elementary occup	-0.124	-0.125**
	(0.097)	(0.061)
Place of residence's density		
medium density	0.037	0.062***
	(0.038)	(0.023)
thin density	0.004	-0.007
	(0.037)	(0.022)
_Constant	1.609***	1.584***
	(0.193)	(0.141)
N	12559	8618

Note: Coefficients, standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: RIF regression, Absolute IO measures.

	Lithuania		Poland		Slovakia	
	2004	2010	2004	2010	2004	2010
Father's education						
Medium	-0.014***	-0.005***	-0.020***	-0.015***	-0.012***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
High	0.142***	0.033***	0.084***	0.027***	0.011***	0.049***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)
Mother's education						
Medium	-0.011***	-0.020***	-0.002***	-0.018***	-0.003***	-0.015***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)

High	0.066***	0.053***	0.203***	0.072***	0.017***	0.016***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Father's occupation						
Manager	0.047***	-0.007***	0.022***	-0.017***	-0.008***	-0.008***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Professional	-0.029***	0.034***	0.074***	0.031***	0.014***	0.001
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Technician	-0.021***	-0.018***	0.021***	-0.014***	0.004***	0.005***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Clerk	0.004	0.008**	-0.040***	-0.045***	-0.001**	-0.001
	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)
Salesman	0.053***	0.005*	-0.047***	-0.051***	-0.005***	-0.007***
	(0.005)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Craft trade	-0.047***	-0.001	-0.046***	-0.057***	-0.004***	-0.005***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Machine operator	-0.037***	0.008***	-0.048***	-0.058***	-0.004***	-0.006***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Elementary occup.	-0.015***	0.003*	-0.008***	-0.044***	0.005***	0.039***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Armed/military	-0.098***	0.097***	0.043***	-0.029***		-0.018***
	(0.007)	(0.005)	(0.002)	(0.002)		(0.002)
Born abroad	-0.002	0.012***	-0.029***	-0.001	-0.000	0.038***
	(0.003)	(0.002)	(0.005)	(0.005)	(0.001)	(0.002)
Share of females	-0.001	-0.002	-0.001	0.001	0.000	-0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age structure						
0-14	-0.022***	-0.003	0.005**	-0.002	-0.001	-0.002
	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)
15-24	-0.015***	0.002	0.002	-0.004**	-0.000	-0.000
	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)
25-29	-0.016***	0.008***	-0.001	-0.004**	-0.001	0.002
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
35-39	-0.009**	0.003	0.002	-0.001	0.000	0.000
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
40-44	-0.014***	0.001	0.004**	-0.004**	-0.000	-0.001

	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
45-49	-0.014***	-0.000	0.002	-0.004***	0.000	-0.003**
	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
50+	-0.014**	-0.005	0.004*	-0.008***	0.001	-0.002
	(0.006)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
Activity rate	-0.001	0.003	0.002	-0.001	0.000	-0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Employment rate_(full time)	-0.006**	-0.002	0.002*	0.001	-0.001*	-0.003***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Employment rate (part time)	-0.006	-0.001	0.002	0.000	0.000	-0.005**
	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)
Marital status						
single	0.000	0.001	0.006***	0.002	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
married	0.001	-0.002	0.003***	-0.000	0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Health status						
average	0.002	0.001	0.001	0.001	-0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
bad	0.001	-0.005	0.000	0.003	-0.001	0.001
	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Educational attainment						
secondary	-0.009*	0.004	-0.004***	-0.002*	0.006**	0.002
	(0.005)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)
tertiary	-0.005	0.005	-0.008***	-0.002	0.007**	0.002
	(0.006)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Occupation						
Professional	-0.002	0.002	0.002	0.001	0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Technician	-0.003	0.001	-0.001	0.002	0.000	0.001
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Clerk	-0.004	0.010***	-0.001	0.002	0.001	0.000
	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
Salesman	-0.000	-0.003	-0.002	0.003**	0.000	-0.001
	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)

Skill agricultural	-0.001	-0.001	-0.001	0.002	0.001	-0.002
	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)
Craft trade	-0.004	-0.002	-0.001	0.001	0.000	-0.000
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Machine operator	-0.006	-0.003	-0.004**	-0.000	0.000	0.000
	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Elementary occup	-0.004	0.003	-0.001	0.001	0.000	0.000
	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
Place of residence's density						
medium density	0.002	-0.000	0.002**	0.001*	0.000**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
thin density			0.001*	0.000	0.000	-0.000
			(0.001)	(0.001)	(0.000)	(0.000)
Constant	0.098***	0.022***	0.068***	0.084***	0.012***	0.030***
	(0.008)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
N	3086	2512	12559	8618	4677	4272

Note: Estimated coefficients, standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Decomposition of changes in Absolute IO: Lithuania, Poland and Slovakia, detailed (complements tables 2 and 3).

	Absolute IO, Lithuania				Absolute IO, Poland				Absolute IO, Slovakia			
	explained		unexplained		explained		unexplained		explained		unexplained	
	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error
Father's education												
Medium	-0.000	0.000	0.003	0.002	-0.002***	0.000	0.002	0.003	-0.000	0.000	0.000	0.004
High	0.000	0.001	-0.013**	0.007	0.000	0.000	-0.004	0.004	0.000	0.000	0.004**	0.002
Mother's education												
Medium	-0.002*	0.001	-0.003	0.004	-0.002***	0.000	-0.007***	0.002	-0.001***	0.000	-0.007***	0.002
High	0.002	0.001	-0.002	0.005	0.002***	0.001	-0.007**	0.003	0.000	0.000	-0.000	0.001
Father's occupation												
Manager	0.000	0.000	-0.003	0.003	-0.000	0.000	-0.002	0.001	0.000	0.001	-0.000	0.002
Professional	0.000	0.001	0.005	0.005	0.000	0.000	-0.002	0.003	0.000	0.000	-0.001	0.002
Technician	-0.000	0.001	0.000	0.003	0.000	0.000	-0.002	0.002	0.000	0.000	0.000	0.002
Clerk	-0.000	0.000	0.000	0.001	0.000	0.000	-0.000	0.001	0.000	0.000	0.000	0.001
Salesman	0.000	0.000	-0.001	0.002	-0.001***	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.001
Craft trade	-0.000	0.000	0.012	0.009	0.001	0.000	-0.003	0.003	-0.000	0.001	-0.000	0.005
Machine op	-0.000	0.001	0.012	0.010	-0.001***	0.000	-0.002	0.002	0.000	0.000	-0.000	0.004
Elementary occ	-0.000	0.000	0.003	0.008	0.000	0.000	-0.003*	0.002	-0.002	0.002	0.005	0.004
Armed/military	-0.000	0.001	0.002	0.002	0.000	0.000	-0.001	0.001	-0.000	0.000	(dropped)	
Born abroad	-0.000	0.001	0.001	0.004	0.000	0.000	0.000	0.000	-0.000	0.000	0.001	0.001
Share of females	0.000	0.000	-0.000	0.003	0.000	0.000	0.001	0.001	-0.000	0.000	-0.000	0.001
Age												
0-14	0.000	0.000	0.004	0.003	0.000	0.000	-0.001*	0.001	0.000	0.000	-0.000	0.001
15-24	0.000	0.000	0.003	0.002	0.000	0.000	-0.001*	0.001	0.000	0.000	-0.000	0.001

25-29	-0.000	0.000	0.002*	0.001	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000
35-39	-0.000	0.000	0.001	0.001	-0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000
40-44	-0.000	0.000	0.002	0.001	0.000	0.000	-0.001**	0.000	0.000	0.000	-0.000	0.000
45-49	-0.000	0.000	0.002	0.001	0.000*	0.000	-0.001*	0.000	-0.000	0.000	-0.000	0.000
50+	-0.000	0.000	0.001	0.001	-0.000***	0.000	-0.001***	0.000	-0.000	0.000	-0.000	0.000
Activity rate	0.000	0.000	0.003	0.007	-0.000	0.000	-0.002	0.002	0.000	0.000	-0.000	0.001
Employment rate full time	0.000	0.000	0.004	0.006	0.000	0.000	-0.001	0.001	0.000	0.000	-0.002	0.001
Employment rate part time	0.000	0.000	0.000	0.001	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
Marital status												
single	0.000	0.000	0.000	0.002	-0.000	0.000	-0.001	0.001	0.000	0.000	-0.000	0.001
married	0.000	0.000	-0.002	0.004	-0.000	0.000	-0.002	0.001	0.000	0.000	-0.001	0.001
Health status												
average	-0.000	0.000	-0.000	0.001	-0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000
bad, very bad	0.000	0.000	-0.001	0.001	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000
Educational attainment												
secondary	-0.000	0.001	0.009	0.008	0.000	0.000	0.001	0.001	-0.000	0.000	-0.004	0.008
tertiary	0.000	0.001	0.003	0.003	-0.000	0.000	0.001*	0.001	0.000	0.000	-0.001	0.001
Occupation												
Professional	0.000	0.000	0.001	0.002	0.000	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000
Technician	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Clerk	0.000	0.000	0.001	0.001	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000
Salesman	0.000	0.000	-0.000	0.001	0.000	0.000	0.001	0.000	-0.000	0.000	-0.000	0.000
Skill agricultural	0.000	0.000	0.000	0.001	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000
Craft trade	0.000	0.000	0.000	0.002	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000
Machine operator	0.000	0.000	0.000	0.001	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000
Elementary occup	-0.000	0.000	0.001	0.001	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000

Place of residence's density												
dense	0.000	0.000	-0.001	0.001	-0.000	0.000	-0.000	0.001	0.000	0.000	-0.000	0.000
thin	-0.000	0.000	0.000	0.001	-0.000	0.000	-0.000	0.001	-0.000	0.000	-0.000	0.000
Job experience												
1-2 years					-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3-5 years					0.000	0.000	-0.000	0.001	0.000	0.000	0.000	0.000
6-9 years					0.000	0.000	0.000	0.001	-0.000	0.000	0.000	0.000
10+ years					-0.000	0.000	0.002	0.004	-0.000	0.000	0.002	0.003
Constant			-0.077*	0.042			0.016	0.013			0.018	0.019

Note: *** p<0.01, ** p<0.05, * p<0.1

Table A5: Decomposition of changes in Relative IO: Hungary, Lithuania and Slovakia, detailed (complements tables 4 and 5). .

	Relative IO, Hungary				Relative IO, Lithuania				Relative IO, Slovakia			
	explained		unexplained		explained		unexplained		explained		unexplained	
	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error	coefficient	stand. error
Father's education												
Medium	0.003	0.002	0.021**	0.011	-0.000	0.001	0.007	0.013	-0.001	0.001	0.006	0.014
High	0.001	0.002	0.003	0.012	0.000	0.002	-0.025*	0.014	0.001	0.001	0.014**	0.007
Mother's education												
Medium	-0.001	0.001	0.004	0.008	-0.006**	0.003	-0.015*	0.008	-0.004***	0.002	-0.021**	0.009
High	0.003**	0.001	-0.005	0.007	0.004	0.003	-0.004	0.010	0.001	0.001	-0.000	0.005
Father's occupation												
Manager	-0.000	0.002	-0.000	0.007	0.000	0.001	-0.006	0.007	0.002	0.003	-0.001	0.008
Professional	0.000	0.001	0.012	0.010	0.001	0.001	0.009	0.011	0.000	0.001	-0.001	0.006
Technician	-0.001	0.001	0.000	0.004	-0.001	0.002	-0.004	0.008	0.000	0.001	0.001	0.007
Clerk	0.001	0.001	-0.000	0.003	-0.000	0.000	0.000	0.002	-0.000	0.000	0.001	0.002
Salesman	-0.004***	0.001	-0.001	0.002	-0.000	0.001	-0.003	0.003	-0.000	0.001	0.000	0.002
Craft trade	0.005**	0.002	-0.019	0.021	0.000	0.001	0.020	0.017	-0.000	0.003	0.006	0.018
Machine op	-0.007***	0.002	-0.005	0.010	-0.001	0.002	0.019	0.018	0.000	0.001	0.002	0.015
Elementary occ	0.001	0.001	0.004	0.007	-0.000	0.001	0.007	0.014	-0.006	0.005	0.012	0.012
Armed/military	0.001	0.001	0.001	0.003	-0.000	0.001	0.002	0.003	-0.000	0.001	(dropped)	
Born abroad	0.000	0.001	-0.000	0.003	0.000	0.001	-0.002	0.006	-0.001	0.001	0.003	0.002
Share of females	-0.000	0.001	-0.001	0.020	0.000	0.000	-0.037	0.028	0.000	0.000	-0.009	0.015
Age												
0-14	0.002	0.001	0.002	0.013	-0.001	0.001	-0.027	0.018	-0.001	0.001	-0.005	0.008
15-24	-0.000	0.001	0.005	0.008	-0.000	0.001	-0.011	0.017	-0.002	0.001	-0.003	0.011
25-29	-0.000	0.000	0.002	0.004	-0.000	0.001	0.009	0.006	-0.000	0.000	-0.002	0.003

35-39	0.000	0.000	0.001	0.005	0.000	0.001	-0.008	0.010	-0.001	0.001	-0.006**	0.003
40-44	-0.000	0.001	0.002	0.007	-0.000	0.001	-0.006	0.009	0.000	0.000	-0.008*	0.005
45-49	-0.000	0.001	0.005	0.007	0.000	0.001	-0.013	0.011	-0.000	0.001	-0.012*	0.007
50+	-0.001**	0.001	-0.000	0.006	0.000	0.001	-0.014	0.009	0.002*	0.001	-0.001	0.004
Activity rate	0.000	0.000	-0.000	0.023	-0.001	0.002	-0.060	0.051	-0.000	0.001	0.016	0.024
Employment rate full time	-0.007***	0.002	0.036	0.053	-0.004	0.003	-0.234***	0.083	-0.000	0.002	0.178***	0.053
Employment rate part time	-0.004***	0.001	0.001	0.003	-0.004	0.002	-0.014**	0.007	0.000	0.001	0.003***	0.001
Marital status												
single	0.000	0.001	-0.010	0.015	0.000	0.001	-0.009	0.015	-0.002	0.002	-0.016	0.014
married	-0.000	0.000	-0.006	0.019	-0.002	0.002	-0.006	0.030	0.003	0.002	-0.027	0.018
Health status												
average	0.001	0.002	-0.007	0.007	-0.003	0.003	0.008	0.010	-0.002	0.003	0.006	0.008
bad, very bad	0.001	0.002	-0.006	0.005	0.004	0.004	-0.008	0.011	-0.001**	0.001	0.005*	0.003
Educational attainment												
secondary	0.002	0.002	0.014	0.039	-0.002	0.009	0.105	0.066	0.004	0.005	0.018	0.057
tertiary	-0.006***	0.002	0.001	0.010	0.002	0.006	0.047**	0.024	-0.003	0.003	0.008	0.010
Occupation												
Professional	0.001	0.001	-0.009*	0.005	0.000	0.001	-0.007	0.008	0.000	0.000	-0.010**	0.005
Technician	-0.000	0.000	-0.005	0.004	0.000	0.001	-0.008*	0.004	0.002	0.001	-0.004	0.006
Clerk	0.000	0.000	-0.003	0.003	0.000	0.001	-0.002	0.002	0.000	0.000	-0.002	0.003
Salesman	0.001	0.001	0.003	0.005	-0.000	0.001	-0.016**	0.007	-0.000	0.000	-0.008	0.005
Skill agricultural	-0.000	0.000	0.001	0.002	-0.000	0.001	0.005	0.004	-0.000	0.000	0.000	0.001
Craft trade	-0.005***	0.001	0.007	0.009	-0.001	0.002	-0.019*	0.010	-0.000	0.001	-0.009	0.008
Machine operator	0.002***	0.001	-0.003	0.003	-0.000	0.001	-0.007	0.006	-0.002*	0.001	0.004	0.005
Elementary occup	0.000	0.000	0.000	0.005	-0.002	0.001	-0.000	0.006	-0.002**	0.001	0.002	0.003
Place of residence's density												

dense	0.000	0.000	-0.003	0.007	0.000	0.001	-0.002	0.009	0.000	0.000	0.000	0.003
thin	0.000	0.000	-0.006	0.009	-0.000	0.000	0.006	0.006	0.000	0.000	0.002	0.005
Job experience												
1-2 years									-0.000	0.000	-0.001	0.003
3-5 years									-0.000	0.001	-0.004	0.004
6-9 years									0.000	0.000	-0.002	0.005
10+ years									0.000	0.001	-0.032	0.041
Constant			0.008	0.113			0.287*	0.150			-0.063	0.103

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A6: : RIF regression, Relative IO measures, Hungary, Lithuania and Slovakia.

	Hungary		Lithuania		Slovakia	
	2004	2010	2004	2010	2004	2010
Father's education						
Medium	-0.059***	-0.018**	-0.023*	-0.003	-0.043***	-0.033***
	(0.012)	(0.008)	(0.012)	(0.011)	(0.004)	(0.010)
High	0.197***	0.228***	0.268***	0.062***	0.031***	0.171***
	(0.025)	(0.016)	(0.022)	(0.020)	(0.007)	(0.019)
Mother's education						
Medium	0.003	0.013*	-0.009	-0.052***	-0.008**	-0.048***
	(0.011)	(0.008)	(0.012)	(0.012)	(0.004)	(0.010)
High	0.249***	0.166***	0.138***	0.103***	0.049***	0.039**
	(0.022)	(0.014)	(0.019)	(0.017)	(0.007)	(0.018)
Father's occupation						
Manager	0.015	0.009	0.101***	-0.006	-0.047***	-0.056**
	(0.025)	(0.020)	(0.028)	(0.025)	(0.010)	(0.028)
Professional	-0.116***	0.049**	-0.052**	0.053**	0.036***	0.022
	(0.029)	(0.020)	(0.026)	(0.023)	(0.010)	(0.027)
Technician	-0.095***	-0.087***	-0.019	-0.142***	0.007	0.014
	(0.024)	(0.017)	(0.030)	(0.025)	(0.010)	(0.025)
Clerk	-0.036	-0.039	0.015	0.038	-0.025**	0.009
	(0.027)	(0.024)	(0.036)	(0.034)	(0.011)	(0.030)
Salesman	-0.138***	-0.159***	0.122***	-0.006	-0.033***	-0.028
	(0.027)	(0.016)	(0.034)	(0.026)	(0.011)	(0.027)
Craft trade	-0.102***	-0.154***	-0.070***	0.004	-0.026***	-0.004
	(0.017)	(0.012)	(0.021)	(0.017)	(0.009)	(0.023)
Machine operator	-0.131***	-0.158***	-0.049**	0.023	-0.024***	-0.015
	(0.017)	(0.012)	(0.020)	(0.018)	(0.009)	(0.023)
Elementary occup.	0.000	0.040***	-0.020	0.017	0.015	0.098***
	(0.019)	(0.014)	(0.021)	(0.018)	(0.009)	(0.025)
Armed/military	-0.168***	-0.107***	-0.116**	0.185***		-0.041
	(0.034)	(0.027)	(0.052)	(0.051)		(0.042)
Born abroad	-0.022	-0.031	0.015	-0.028	-0.053***	0.146***
	(0.026)	(0.025)	(0.020)	(0.021)	(0.011)	(0.036)
Share of females	0.089***	0.087***	0.080***	-0.012	0.033***	0.011
	(0.022)	(0.016)	(0.024)	(0.023)	(0.009)	(0.019)
Age structure						
0-14	0.181***	0.194***	0.180***	0.040	0.077***	0.045
	(0.035)	(0.023)	(0.038)	(0.036)	(0.014)	(0.033)
15-24	0.131***	0.164***	0.075**	-0.003	0.094***	0.079***

	(0.030)	(0.023)	(0.037)	(0.036)	(0.012)	(0.030)
25-29	0.031	0.054***	-0.036	0.080***	0.036***	0.010
	(0.025)	(0.019)	(0.030)	(0.030)	(0.011)	(0.026)
35-39	0.005	0.010	0.046	-0.025	0.027**	-0.045*
	(0.026)	(0.017)	(0.029)	(0.028)	(0.011)	(0.025)
40-44	-0.047*	-0.023	0.072**	0.021	0.018	-0.060**
	(0.028)	(0.019)	(0.029)	(0.027)	(0.011)	(0.027)
45-49	-0.002	0.036**	0.082***	0.000	0.010	-0.075***
	(0.025)	(0.018)	(0.028)	(0.025)	(0.010)	(0.025)
50+	0.113***	0.110***	0.201***	0.055	0.059***	0.050*
	(0.032)	(0.022)	(0.039)	(0.034)	(0.012)	(0.029)
Activity rate	0.003	0.003	-0.016	-0.094***	-0.018**	0.003
	(0.020)	(0.014)	(0.023)	(0.023)	(0.008)	(0.018)
Employment_rate_(full time)	0.278***	0.319***	0.440***	0.158***	0.064***	0.270***
	(0.021)	(0.013)	(0.019)	(0.016)	(0.006)	(0.015)
Employment rate (part time)	0.259***	0.276***	0.346***	0.123***	0.033*	0.237***
	(0.033)	(0.027)	(0.029)	(0.037)	(0.017)	(0.040)
Marital status						
single	0.038*	0.005	0.071***	0.026	0.016	-0.041*
	(0.021)	(0.015)	(0.023)	(0.022)	(0.010)	(0.021)
married	0.031**	0.020*	0.054***	0.045***	0.013	-0.028*
	(0.016)	(0.012)	(0.016)	(0.016)	(0.008)	(0.017)
Health status						
average	0.016	-0.008	0.001	0.022	-0.002	0.021
	(0.013)	(0.011)	(0.013)	(0.014)	(0.005)	(0.015)
bad	0.040*	-0.018	-0.034	-0.138***	0.012	0.071***
	(0.024)	(0.021)	(0.026)	(0.030)	(0.009)	(0.025)
Educational attainment						
secondary	-0.054	-0.036	-0.126***	0.024	-0.065	-0.043
	(0.046)	(0.024)	(0.037)	(0.029)	(0.048)	(0.039)
tertiary	-0.155***	-0.148***	-0.157***	0.029	-0.090*	-0.039
	(0.050)	(0.026)	(0.040)	(0.031)	(0.049)	(0.039)
Occupation						
Professional	0.113***	0.028	0.065***	0.022	0.087***	-0.008
	(0.025)	(0.019)	(0.024)	(0.024)	(0.010)	(0.026)
Technician	0.109***	0.063***	0.129***	0.018	0.066***	0.037
	(0.024)	(0.019)	(0.029)	(0.026)	(0.009)	(0.023)
Clerk	0.109***	0.070***	0.128***	0.078**	0.063***	0.039
	(0.027)	(0.021)	(0.036)	(0.034)	(0.011)	(0.028)
Salesman	0.078***	0.100***	0.146***	0.011	0.071***	-0.001
	(0.024)	(0.018)	(0.027)	(0.026)	(0.010)	(0.026)

Skill agricultural	-0.011	0.020	-0.075**	0.013	0.072***	0.104*
	(0.037)	(0.028)	(0.032)	(0.036)	(0.022)	(0.063)
Craft trade	0.069***	0.104***	0.132***	0.024	0.070***	0.018
	(0.022)	(0.018)	(0.025)	(0.025)	(0.009)	(0.025)
Machine operator	0.127***	0.092***	0.166***	0.092***	0.077***	0.107***
	(0.026)	(0.019)	(0.029)	(0.030)	(0.010)	(0.026)
Elementary occup	0.036	0.040**	0.097***	0.096***	0.068***	0.094***
	(0.027)	(0.020)	(0.027)	(0.029)	(0.011)	(0.032)
Place of residence's density						
medium	-0.014	-0.022***	0.005	-0.010	0.003	0.005
	(0.012)	(0.008)	(0.009)	(0.009)	(0.004)	(0.009)
thin	0.021*	0.008			0.008***	0.012
	(0.011)	(0.007)			(0.003)	(0.008)
Constant	-0.202***	-0.194***	-0.389***	-0.0920**	-0.0429	-0.106
	(0.061)	(0.034)	(0.058)	(0.044)	(0.051)	(0.065)
N	4487	6984	3086	2512	4677	4272

note: *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Growth incidence curves, 2004-2010 real income change.