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Abstract

Is the relationship between inequality of opportunity (IOp) and economic growth different from the relationship between inequality of outcomes and economic growth? I answer this question using System GMM regressions applied to data for 27 European countries covering the period 2005-2011. I find that a one-standard deviation increase in IOp results in a statistically significant decrease in growth rates, ranging from 0.65 to 1.03 percentage points. On the other hand, inequality of outcomes has no statistically significant effect. The estimates are robust to the choice of instrumental variables and estimation approach. Additional analysis reveals that human capital levels partly explain this relationship, and that the effect is stronger for inequality indexes that are sensitive to changes in the middle of the distribution, with Ôbottom-sensitiveÕ indexes having almost no effect.

Keywords: Economic growth, equality of opportunity, gross national income.

JEL Classification: D31, D63, O47.

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1 Introduction

The question of whether and how inequality affects growth has motivated theoretical and empirical research over the last 25 years. This question has also been at the core of many policy discussions, as the idea of a trade-off between growth and inequality is often referred to whenever redistributive policies are discussed. Despite this interest, it is still not clear whether there is a trade-off between equality and growth.

The effect of inequality and growth is an important research question, as shown in review articles such as Bertola (2000), Voitchovsky (2009) or Quadrini and Ríos-Rull (2015). These reviews show how estimates differ both in size and direction, which Voitchovsky (2009) attributes to how particular components of inequality have different – and sometimes opposed – effects on growth. If we look at inequality of outcomes as a whole, we are combining these different effects, and depending on what component is being prioritised, we obtain different estimates of the effect of inequality on growth. For example, Voitchovsky (2005) shows opposite effects for inequality from the top and bottom ends of the income distribution, and Bagchi et al. (2016) shows how wealth inequality reduces growth when that inequality stems from political connections, but not in other cases. The estimates appear to be the most robust when research focuses on particular components of inequality.

In order to better understand the interaction between growth and inequality, researchers have looked at different components of inequality, each playing a different and sometimes opposed role. When looking at its effects on growth, inequality can be thought of as cholesterol: some inequalities might harm growth, while others might promote it.[1] According to Marrero and Rodríguez (2013), harmful inequality is embodied by inequality of opportunity, which reduces growth by limiting opportunities due to involuntarily inherited factors. On the other hand, beneficial inequality captures the role of autonomous choices and effort. In light of this dis-

[1] See the feature story "*Inequality of Opportunity: New Measurements Reveal the Consequences of Unequal Life Chances*" on the World Bank website (March 28th, 2019).

tinction, the ambiguity of the effects of inequality on growth can be explained by the different roles that inequality of opportunity and inequality of efforts might play.

Inequality of opportunity captures the differences in life outcomes in relation to factors we cannot control, for example the place we were born, the time our parents spent with us when we were children and our gender, among others. Roemer (1998) coins the term 'circumstances' to refer to these involuntarily inherited factors. Inequality of opportunity differs from inequality of effort, which represents differences in outcomes related to autonomous choices that are not influenced by circumstances. Inequality of opportunity has a negative effect on growth because inequality in life outcomes is driven by circumstances rather than effort.

In this paper I estimate the effect of inequality of opportunity on the growth rate of GNI per capita and contrast these estimates with the effect of inequality of outcomes. My outcome measure is individuals' household equivalised income. The estimates of IOp and inequality of outcomes are based on data for 27 European countries for the period 2005-2011 derived by Carranza (2020). Using System GMM regression I find that, while inequality of outcomes has no effect on growth, an increase in inequality of opportunity reduces growth. A decrease of one standard deviation in inequality of opportunity increases growth between 0.65 and 1.03 percentage points. This is a relatively large effect compared to that found in previous papers, which are closer to the lower part of this range.

I also examine this relationship in greater detail. First, the estimates appear to be robust to the choice of inequality index, except for those indices that focus on the bottom part of the distribution. I conclude that differences at the middle and – to a lesser extent – the top part of the distribution show the strongest effect of inequality of opportunity on growth. In other words, the effect of circumstances is not symmetrical. Circumstances that predict a 'good' outcome matter more when looking at the effect on growth than those predicting a 'bad' outcome. Second, the relationship between IOp and growth can be partly explained by variables that link productivity and distributional issues, particularly average human capital levels.

This paper is distinctive because it uses upper bound estimates of inequality of opportunity when examining the relationship between IOp and growth effect on growth. Researchers have almost always estimated lower bound estimates of inequality of opportunity. But the number of observable circumstances is typically limited in the available data sources, with most surveys missing potentially relevant circumstances such as time spent by parents with their children (playing, helping them with homework, etc.), bequests, or innate abilities, to name a few. As circumstances such as these affect growth, using lower bound estimates can be problematic when estimating growth regressions. Upper bound estimates capture all circumstances as well as other time-invariant factors that might not be considered circumstances. Thus, I contribute to the literature by using upper bound estimates to provide a new perspective on the relationship between inequality of opportunity on growth.

My paper confirms the 'cholesterol hypothesis', the idea that inequality of outcomes can have both 'good' and 'bad' effects on growth. Inequality of 'efforts' appears to have no relevant effect (thus explaining the small effect of inequality of outcomes), while an increase in inequality of opportunity results in a decrease in economic growth. This paper also looks in greater detail at this relationship, understanding some of the channels that explain it, particularly the importance of human capital and also of inequality of opportunity at the bottom of the distribution.

2 Measuring Inequality of Opportunity

Suppose the outcome of an individual i is represented by Y_i. Inequality of outcomes is the inequality of Y, summarised by an inequality index, in this case the Mean Log Deviation (MLD). In contrast, inequality of opportunity (IOp) refers to the inequality of Y_i related to factors over which we have no control, called circumstances. The standard model of IOp focuses on the role played by circumstances C_i and efforts E_i, plus an unobserved random term u_i, in determining Y_i.

In this context, efforts are partly determined by circumstances.

$$Y_i = f(C_i, E_i(C_i), u_i). \tag{1}$$

Typically, we use a reduced form of equation 1, represented as $Y_i = \phi(C_i, u_i)$, which accounts for both the direct effect of C_i, and the indirect effect through $E_i(C_i)$. This equation is traditionally estimated as a linear function of the log of Y_i, which is known as the parametric approach to estimating IOp, shown in Bourguignon et al. (2007) and Ferreira and Gignoux (2011).

$$\log(Y_i) = \beta C_i + u_i. \tag{2}$$

I follow standard practice and use the estimates of 2 to construct a counterfactual distribution where only differences in C explain differences in the outcome.[2]

$$\hat{\mu}_i = \exp(\hat{\beta} C_i). \tag{3}$$

The counterfactual distribution of $\hat{\mu}_i$ captures inequalities that are explained by differences in the circumstance vector C_i. The estimate of IOp for a given inequality index I is the inequality of the counterfactual distribution, $I^O = I(\{\hat{\mu}_i\})$.

In order to estimate the effect of IOp on economic growth I follow Ferreira et al. (2018) by decomposing total inequality into inequality of opportunity, and a residual term usually referred to as inequality of 'efforts'. If I_{jt} represents total inequality, then $I_{jt} = I^O_{j,t} + I^E_{j,t}$. The additive decomposition captures 'within' and 'between' group differences. $I^O_{j,t}$ represents IOp, the between group component, while $I^E_{j,t}$ represents inequality of efforts, the within group component, derived as the residual between total inequality and IOp.

[2] I estimate equation 2 using Poisson regressions to avoid the need for 'smearing' or adjusting for the $\hat{\mu}_i$ when going from the predicted log of income, to predicted income (Duan, 1983).

2.1 Upper bound estimates of IOp

My measure of IOp should account for all (or at least most) circumstances. This is not always possible, as most IOp estimates are derived from survey data, which has limited information about circumstances. These circumstances typically include self-reported education and occupation of the respondent's parents, place of birth and gender. Other important circumstances that are not included are parental interactions, innate abilities, and inheritances and gifts received at some point. As standard estimates of IOp only account for observed circumstances, they provide a lower bound estimate of IOp (Ferreira and Gignoux, 2011). The use of lower bound estimates of IOp has implications when estimating growth regressions. A biased estimate of IOp can result in a biased estimate of the relationship between IOp and growth. Carranza (2020) derives both lower bound and upper bound estimates of IOp for several European countries. I use these upper bound estimates of IOp in this paper to analyse the relationship between IOp and growth.

By using an upper bound approach, it is possible to estimate IOp for many more years as it does not require circumstance variables to be available in the dataset. This means that high quality datasets that could not been used to estimate the effect of IOp on growth using lower bounds, such as the EU SILC, can now be used. The use of a more exhaustive measure of IOp and for more years of data allows for the use of modern estimation techniques on comparable cross country data, such as System GMM. The appendix includes a detailed description of how to obtain upper bound estimates of IOp.

3 The effect of Inequality and Inequality of Opportunity on Growth

3.1 Understanding the relationship between IOp and growth

Inequality of opportunity (IOp) captures inequalities explained by inherited factors that are beyond our control, which are called circumstances. In contrast, inequalities of ‘effort’ represent inequalities stemming from autonomous choices. If circumstances determine a large part of inequality of outcomes, higher inequality will result in lower growth rates. In other words, IOp is not only morally illegitimate – as discussed by Roemer (1998) – it is also inefficient. This idea has been discussed by Marrero and Rodríguez (2013, 2019), among others. Higher IOp means intergenerational transmission disadvantages and that privilege plays a bigger role in determining life outcomes, which in turn reduces economic potential by excluding people from occupational and professional opportunities.

3.2 The effects of inequality and inequality of opportunity on growth

Empirical techniques to study the effect of inequality on growth have developed tremendously over recent years. The first papers to study the relationship between inequality and growth used OLS (or 2SLS) applied to cross-sectional data. For example, Alesina and Rodrik (1994) study several countries and explain how an increase in inequality reduces growth with reference to tax: higher inequality increases demands for redistribution, which in turn reduces growth. The estimates of Deininger and Squire (1998) show that an increase in land inequality results in a decrease in the growth rate, highlighting the importance of productive investments to promote both less inequality and higher growth. Other papers have used panel data and fixed effect regressions to control for time-invariant unobserved factors.

Both Li and Zou (1998) and Forbes (2000) find that an increase in inequality results in an increase in growth rates. Overall, we see that this line of research is far from resolved.

One of the explanations for the diversity of results is the presence of other sources of bias in the estimation, even when using a country-year. Particularly relevant in the context of growth regressions using panel data is dynamic panel bias, otherwise known as 'Nickell bias' (Nickell, 1981). Nickell bias arises because the lagged dependent variable is correlated with the error term, as the lagged regressor includes observations for all previous periods, which include past errors. Nickell bias is not eliminated by increasing N (in this case, the number of countries), which is why it becomes a large problem under 'small T, large N' settings. When T is small, as is the case in this paper, Nickell bias can be an important source of distortion (Cameron and Trivedi, 2005, pp.763-5). I address this problem by estimating growth regressions using System GMM (Arellano and Bover, 1995; Blundell and Bond, 1998).

System GMM uses both equations in levels and in first differences, using lagged first-differences as instrument variables in the former case and lags of the dependent variables in levels in the latter. System GMM estimates the dynamic panel mode by creating a system of equations – levels and first differences – with relevant instrumental variables for each case. These instruments satisfy the exclusion restriction, that is, they are not correlated with the error term (as they precede the error), while being correlated with the endogenous variable (in this case, the lagged dependent variable). System GMM has become the most commonly used method for estimating regressions under panel data, particularly when looking at the effect of inequality.

Because of the way System GMM works it is prone to instrument proliferation, a problem described in detail by Roodman (2009a). Because these methods use lags of each variable as instrumental variables for each endogenous variable, the number of instruments potentially grows quadratically with each additional year of data. A large number of instruments may result in overfitting problems, as well as a weaker test of overidentifying restrictions. This problem is particularly acute when the number of observations (e.g., countries) is small. Using 2SLS as an analogy, if the first stage regression is overfitted due to a large number of instruments, then its R^2 is close to 1 and the predicted value of the endogenous variable is close to its original value (i.e., $\hat{X}_i = X_i$). If that is the case, then the second stage results are equal to the biased OLS results. If all possible instruments are included, our estimations using System GMM will provide no additional more information compared to a standard OLS estimate.

As a rule of thumb, Roodman (2009a) suggests using at most as many instruments as there are countries in the data. He proposes using several techniques to satisfy this rule. One is to simply cap the number of lags. Another approach is to 'collapse' the instrument matrix, in other words, to go from having one first stage regression for the instrumental variable to having fewer regressions that include several instruments at the same time (see equation 11 in Roodman (2009a)). Another option is to only use the first differences of each variable as instruments, or to only use the variables in levels. However, these approaches limit the instrument count in arbitrary ways because they do not take into account the information that each instrument can provide, potentially leaving out relevant information. A fourth alternative is to use Principal Component Analysis to group instruments while aiming to minimise the loss of information conveyed in them (Bontempi and Mammi, 2015). All of these approaches limit the number of instruments but, in this paper, I focus on the PCA method for the previously described reasons. By reducing the number of instruments using PCA I can estimate the model with 27 less instruments, while preserving a larger part of the informational content of the original instrument matrix.[3]

[3]Despite choosing one specific approach to reduce the number of instruments, I provide robustness checks for alternative approaches in section 5.2.

3.2.1 Growth regressions and dynamic panel data models

My growth regression specification is shown in equation 4.

$$g_{j,\{t,t+5\}} = \beta_0 \log(y_{j,t}) + \beta_1 I^O_{j,t} + \beta_2 I^R_{j,t} + \gamma X_{j,t} + \alpha_j + \eta_t + u_{jt}. \quad (4)$$

I define growth ($g_{j,\{t,t+5\}}$) as the average yearly growth rates of GNI per capita over a 5 year period from year t to year $t+5$. t goes from 2005 to 2011. GNI per capita (from World Bank Open Data) is measured in 2010 USD and the yearly growth rate is calculated one year ahead in order to look at the effect of inequality in the following period. Equation 5 shows how my measure of growth is calculated.[4]

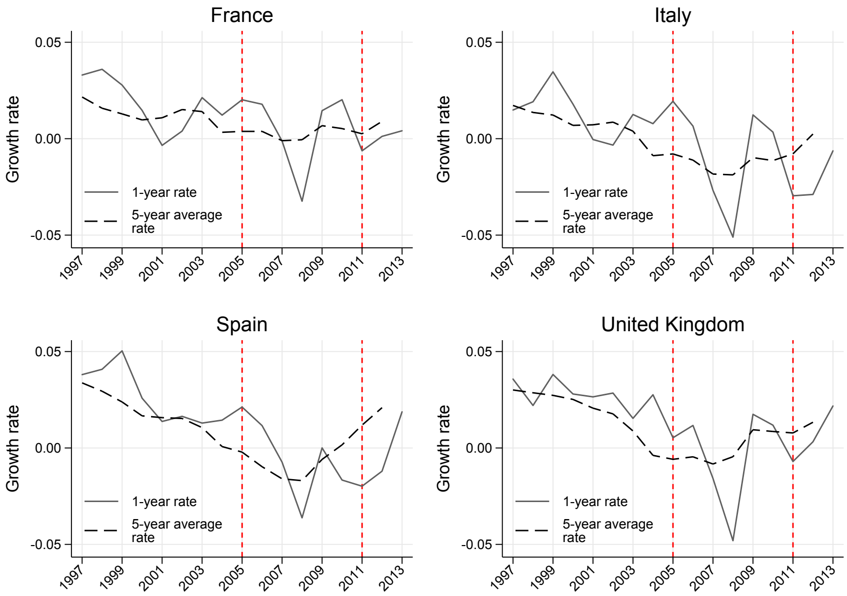
$$g_{j,\{t,t+5\}} = \frac{1}{5}\sum_{k=1}^{5}\left(\frac{y_{t+1+k} - y_{t+k}}{y_{t+k}}\right) \quad (5)$$

The yearly growth rates are averaged across 5 years to smooth out volatility, a particularly salient problem for the period 2005-2011, which includes the subprime and European crises. By averaging out the extreme changes in this period, I look at the effect of inequality of outcomes and IOp over a more stable trend, as shown in Figure 1 for four countries in the sample. Averaging also allows me to test whether inequality of outcomes or IOp have an effect on medium term growth, as I look at the effect of inequality in period t over growth calculated over a 5-year period, and not only for the next year .

The explanatory variables include the level of income and inequality measures, as well as other controls. $y_{j,t}$ is GNI per capita for country j in year t (in constant 2010 USD). $I^O_{j,t}$ is the measure of IOp from equation 13, while $I^R_{j,t}$ is the residual level of inequality and can be interpreted as a lower bound of inequality of 'choices'. $X_{j,t}$ includes the female and male unemployment rates and the value added of the service sector as a percentage of GDP, all for country j in year t. The value added of the service sector is a proxy of complexity and development, as the service sector

[4]GNI per capita is also used in Ferreira et al. (2018). In contrast to GDP that includes all people living within the national territory, GNI includes net receipts from abroad, which are included in my inequality estimates (see e.g., Nolan (2020)).

Figure 1: Relationship between inequality and growth



Note: The graphs show GNI per capita growth rates for 4 countries in the sample, between the years 1997 and 2013. Note that growth is calculated one year ahead, $y_{t+1} - y_t$, so that the large drop of the subprime crisis is shown in 2008 instead of 2009. The vertical dashed lines cover the period of study of this paper (2005-2011). The solid grey line is the yearly growth rate for each specific year, while the dashed and darker line is the 5 year average of the former, from year t to year $t + 5$. GNI per capita data from World Bank.

tends to grow when economies become more complex (Buera and Kaboski, 2012). The unemployment rate gives an idea of the short-term status of the economy, while decomposing it by gender allows me to account for different patterns that can be linked to IOp. I also include country level fixed effects (α_j) and year fixed effects (η_t) to account for unobserved time invariant and country invariant factors.

The model shown in equation 4 is the standard approach to studying the effect of inequality on growth (see, e.g., Forbes (2000)). There are three main departures from previous papers. First, the data is different. I look at 27 European countries, while other papers have looked at the US (e.g., Marrero and Rodríguez (2013) or Bradbury and Triest (2016), both for IOp), or have merged different datasets to look at a global context (as in Banerjee and Duflo (2003) for inequality or Marrero and Rodríguez (2019) for IOp). Second, the set of explanatory variables is different from other papers. For example, while Marrero and Rodríguez (2019) includes no control variables to capture the direct and indirect effect of inequality on growth, Ferreira et al. (2018) includes male and female education as measures of the human capital stock, and the ratio of investment goods prices at PPP to prices at market exchange rates, as a proxy of market distortions. My choice lies somewhat in between these two papers, as I control for certain characteristics of the economy – unemployment and investment – but not for human capital, which I control for in an extension of my model described in section 5.3. The third and main difference is my measure of inequality of opportunity. While all other papers have looked at lower bound estimates of IOp, this is the first paper to look at upper bound estimates of IOp. These three departures – particularly the last – highlight the contribution of my paper to the study of the relationship between inequality and growth[5]

4 Data

4.1 Upper bound estimates of IOp

All data for the inequality estimates come from the EU-SILC. I take IOp and inequality of outcomes estimates for 27 countries in the period 2005-2011 from Carranza (2020). Table A3 (in the appendix) shows total income inequality and the upper bound estimates of IOp for all available countries and years. IOp is measured over household equivalised income (using the OECD equivalence scale) for all individuals aged 25 to 55. Inequality is measured using the MLD index, which allows for an additive decomposition. When estimating IOp, sample sizes vary significantly between countries. On average, I use around 1,800 observations per country to estimate IOp, ranging from countries with 350 to 400 observations

[5]Other papers have used proxies of IOp to look at their effect on growth, for example, using a measure of absolute and relative mobility as in Bradbury and Triest (2016) or using inequality adjusted by the intergenerational elasticity of income, as in Aiyar and Ebeke (2019).

to countries with over 4,000 observations.[6]

Carranza (2020) also has lower bound estimates of IOp. However I do not use them in the growth regressions as there are two data points per country (2005 and 2011). System GMM needs at least three time periods in order to work, as it uses both levels and first differences. The fact that only two years of data are available when looking at lower bound estimates of IOp is the main reason why previous research on Europe has not used estimates from the EU-SILC.

My analysis includes an unbalanced panel of 27 countries. 23 countries have complete data for the period 2005-2011 and 4 have missing data for particular years. The original sample considered in Carranza (2020) is comprised of 24 countries. However, the World Bank Open Dataset has no GNI per capita data (in constant USD) for Iceland, one of the 24 countries. On the other hand, I include four other countries with incomplete data. These countries are Bulgaria and Malta, which enter the sample in 2006; Ireland, with no data in 2007 and 2008; and Romania, which enters the sample in 2007. For each country, I have between 5 and 7 years of data, with an average of 6.78 years per country.

4.2 Growth rates and other macroeconomic variables

I obtained all of the macroeconomic variables from the World Bank Open Database. Economic growth is measured as the yearly average percentage change in Gross National Income (GNI) in constant 2010 US dollars, averaged over a 5-year period, starting in the present year. The values for each year and country are shown in Table A1 in the appendix. The remaining covariates are also included in the table. Table A2 in the appendix summarises growth, total inequality and IOp. The

[6] The two closest papers to this, Ferreira et al. (2018) and Marrero and Rodríguez (2019), use the same dataset, which attempts to maximise comparability between different data sources. For that reason they include as many individuals as possible (all individuals aged 15 or above). When measuring inequality, a part of the sample uses income per capita and the rest uses consumption per capita.

average 5-year annual growth rate is 0.6%, with growth rates going from -6.4% to 7.9%. Average IOp is almost two-thirds of average inequality, and in both cases the between country variance is higher.

5 Results

I start by showing the effect of both total inequality and IOp on growth. In the second part I look at some robustness checks related to the estimation approach. Lastly, in the third part I explore some factors behind the effect of IOp on growth. Together, these three parts contribute to a comprehensive examination of the effect of both inequality and IOp on growth.

5.1 Main results: The effects on economic growth of inequality and IOp

The main estimates are shown in table 1. All columns use the same specification, with columns 1 to 3 controlling for inequality of outcomes, and columns 4 to 7 controlling for IOp, all estimated via System GMM with Windmeijer-corrected cluster–robust errors, i.e., two-step corrected standard errors, clustered at the country level.

Columns 1 and 4 limit the number of instruments to the first three (that is, $t-1,\ t-2,\ t-3$). Columns 2 and 6 use PCA to reduce the instrument matrix to a few instruments. The specifications using IOp include column 5, in which I do not instrument for the level of inequality of efforts, the residual between total inequality and IOp, in order to further reduce the number of instruments. Figure A2 in the appendix summarises the coefficient for inequality of outcomes or IOp in terms of a one-standard deviation change in the particular inequality measure.[7]

[7]Table A4 in the appendix includes the specification with all available instruments. As ex-

Table 1: Effect of inequality on GNI per capita growth rate (System GMM)

VARIABLES	(1) Ineq	(2) Ineq	(3) IOp	(4) IOp	(5) IOp
Inequality	-0.119	0.063			
	(0.104)	(0.225)			
IOp			-0.246***	-0.177**	-0.282*
			(0.095)	(0.069)	(0.165)
IR			-0.149	-0.201	-0.178**
			(0.104)	(0.123)	(0.089)
Unemp. (F)	-0.002	-0.006***	-0.001	-0.003	-0.005
	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)
Unemp. (M)	0.003*	0.007***	0.004***	0.004**	0.007*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)
Services	0.000	0.000	-0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log GNI	-0.022***	-0.024***	-0.020***	-0.019***	-0.017**
	(0.007)	(0.009)	(0.006)	(0.006)	(0.007)
Constant	0.232***	0.213***	0.233***	0.225***	0.266***
	(0.050)	(0.069)	(0.063)	(0.052)	(0.093)
Observations	183	183	183	183	183
Number of countries	27	27	27	27	27
Instruments	49	19	70	61	20
Year FE	Yes	Yes	Yes	Yes	Yes
All lags	No	Yes	No	Yes	Yes
PCA	No	Yes	No	No	Yes
Instrument for IR	-	-	Yes	No	Yes
Sargan Test	0.000	0.000	0.000	0.000	0.004
Hansen Test	1.000	0.227	1.000	1.000	0.421
AR(1) Test	0.459	0.536	0.124	0.160	0.111
AR(2) Test	0.601	0.443	0.496	0.546	0.509
KMO Measure		0.831			0.853

Note: *** p<0.01, ** p<0.05, * p<0.1. Windmeijer-corrected standard errors, clustered at the country level. All estimations include 27 European countries for the years 2005 to 2011. The main independent variable for columns 1 to 3 is the level of income inequality, and the upper bound estimate of inequality of opportunity (IOp) for columns 4 to 7. Both using the MLD index. System GMM use the inequality estimate and log GNI per capita as 'GMM style' instruments (making use of multiple lags), plus the years fixed effects, which are included as regular 'IV style' instruments. Columns differ in the number of lags (either all of them or first to third), whether I use PCA to reduce the number of instruments, and for IOp, whether I instrument the residual inequality (IR). The Sargan and Hansen statistics are tests of overidentifying restrictions, the null being the joint validity of all instruments. The AR(1) and AR(2) statistics are tests of autocorrelation of order 1 and 2, the null being no autocorrelation of the residuals. The KMO measure is the Kaiser-Meyer-Olkin test for sampling adequacy for the use of Factor Analysis. As a rule of thumb, a KMO measure below 0.5 is unacceptable and above 0.8 is desirable.

5.1.1 Inequality and economic growth

The coefficient for inequality of outcomes on growth rates ranges from -0.12 to 0.06 percentage points. The PCA approach (column 2) reduces the number of instruments below the rule of thumb – as many instruments as countries, 27 in this case – but just like in column 1, the estimates do not differ significantly from zero in this case.

In order to compare these estimates with previous papers, I look at the effect in terms of changes of one standard deviation of inequality of outcomes. These estimates are shown in figure A2. A one standard deviation increase in inequality, 0.05 points of the MLD (see table A2) – which is equivalent to going from the inequality level of Finland or the Netherlands to that of Ireland or Spain – is associated with a change in the 5-year average of GNI per capita growth rate from -0.62 to 0.33 percentage points. These estimates lie within the range of previous studies that use a similar methodology. Using a set of income and expenditure surveys and for an equivalent estimation, Ferreira et al. (2018) report a nonsignificant effect of -0.18. Using the same set of surveys but measuring inequality using the Gini index, Marrero and Rodríguez (2019) report an effect of -0.74 percentage points. My estimates are similar to theirs when I use the Gini rather than the MLD (results available on request), with an effect ranging from -0.67 to -0.55 percentage points. Overall, my point estimates for the effect of total inequality on growth are consistent with previous studies.

Regarding the other covariates, the log GNI per capita coefficient is negative and significant, consistent with conditional convergence (i.e., as countries with a higher income have lower growth rates). An increase in male unemployment increases growth rates, while an increase in female unemployment decreases growth rates by roughly the same amount. Albanesi and Şahin (2018) reports how male and female unemployment rates depart during recession periods such as this one. The

pected, this specification suffers from instrument proliferation: Estimates for the second-stage are biased towards OLS as the first-stage suffers from overfitting (Roodman, 2009a).

share of the service industry shows a non-significant and very close to zero effect on growth rates.

The Hansen J-test statistic shows that the null hypothesis, that the instruments are valid, has not been rejected. It is important to note that the Hansen test is weakened by too many instruments (getting close or being equal to 1). This can be seen in columns where the p-value equals 1. The Sargan test is inconsistent in the context of System GMM, as shown in Roodman (2009b), so I include it only for completeness. Regarding the remaining tests and checks, the Arellano-Bond test of second-order autocorrelation, AR(2), presents no significant evidence of serial correlation in the first-differenced errors. The KMO measure shows that the instrument matrix is appropriate for PCA analysis, and whether the factors are an efficient way to group the original variables (over 0.8 as a rule of thumb). System GMM methods under the PCA instrument reduction method show consistent estimates that fail to reject the nulls of exogenous instruments and of autocorrelation of the residuals, and – according to the KMO measure – do not lose too much information from the instrument matrix.

5.1.2 IOp and economic growth

Columns 3 to 6 in table 1 show the estimates of the effect of IOp on growth. According to all three columns, the coefficients range from -0.282 to -0.177, with only the coefficient in column 5 being not significant at 90%. All point estimates are negative, consistent with an increase in IOp resulting in a decrease in the growth rate. An increase in the estimate for the residual component of inequality, the component associated with efforts, also shows a decrease in the growth rate. The fact that both estimates are negative explains the negative coefficient for total inequality, while the non-significance for inequality of outcome is explained by the residual component of inequality.

Columns 3 to 5 all suffer from the problem of having too many instruments, i.e.

more than 27 (the number of countries). Column 4 shows the case where the instruments are capped at three, and column 5 shows the estimate when I do not include residual inequality as an instrument. These cases show significant estimates of -0.25 and -0.18, respectively. Lastly, when I use PCA to limit the number of instruments, satisfying the rule of thumb by only including 20 instruments, the estimate is -0.28, the largest among all of the columns.

To make these estimates comparable with previous studies, I examine the change in growth rate following an increase of one standard deviation in IOp as shown in figure A2. According to table A2, the standard deviation of IOp equals 0.037 points of the MLD index. This is equivalent to going from the bottom of the IOp ranking (i.e., Norway or Sweden in the 2011 ranking), to countries like France or Hungary in the middle of the same ranking. According my estimates, an increase of one standard deviation results in an increase in the growth rate from -1.03 to -0.65 percentage points. As for inequality of outcomes, the IOp estimates fall within the range suggested by previous papers. Based on their preferred estimates (instrumental variables, the Gini index, and their sample of income and expenditure surveys), Marrero and Rodríguez (2019) reports an effect of -0.68 percentage points. My estimates using the Gini index range from -1.05 to -0.65 (results available on request). On the other hand, Ferreira et al. (2018), using the same sample and system GMM, finds a non-significant effect ranging from -0.62 to -0.4 under different estimation approaches.[8] Previous estimates fall within the range of estimated coefficients in this paper, although they tend to be closer to the lower end of this range.

Overall, upper bound estimates of IOp show a larger effect (in absolute value) than their lower bound counterparts. In terms of absolute value, the coefficient for the lower bound estimates of IOp ranges between 0.4 and 0.7 percentage points, whereas the coefficients for the upper bound estimates range from 0.65 to 1 percentage points. Whatever is being captured by the upper bound estimates on top of the lower bound estimates (what Carranza (2020) calls the gap between the two bounds, which includes both unobserved circumstances and other time-invariant

[8] I calculated the standard deviation for IOp (0.06) using table A1 in their online appendix.

factors) reinforces the effect that the IOp estimate has on growth rates. By not including all possible circumstances, a lower bound estimate of IOp underestimates the importance IOp has for growth.

The rest of the coefficients and tests in Table 1's IOp regressions are similar to their counterparts in the inequality of outcomes regression table. An increase in male unemployment results in an increase in growth rates, while an increase in female unemployment results in a decrease. Increases in the share of the service sector and the log of GNI per capita result in decreases in the growth rate, but only the latter is statistically significant. The Hansen J-test does not reject the null hypothesis of valid instruments, but suggests the presence of too many instruments, being very close to 1. The Arellano-Bond test for AR(2) does not reject the null of no autocorrelation. All things considered, the main assumptions of System GMM are held, and the coefficients are consistent with previous literature on inequality and economic growth.

5.2 Robustness Checks

In this section I report three robustness checks. First, I use an even more limited set of instruments. By using a few key instruments I can avoid the problems of instrument proliferation to a larger extent. Second, I use a different identification strategy based on IV regressions to address potential issues of reverse causality. Last, I use other dynamic panel models estimators that also address Nickell bias.

5.2.1 Different choice of instruments

So far, I have chosen as many instruments as possible, and then limited their number to avoid issues of overfitting. However, Bazzi and Clemens (2013) shows that internal instruments tend to be weak, which can create problems for statistical inference. To partly address this issue , I unbundle the system GMM instruments into the levels and differences equations, in order to be able to treat each equation differently.

I report three sets of estimates for the effect of total inequality and three for IOp. In each case, the first model includes in differences – for the level equation – the first lag of log GNI per capita and the first three lags of inequality (i.e., if inequality in t is I_t, I include $I_{t-1} - I_{t-2}, \ldots, I_{t-3} - I_{t-4}$ as instruments). In levels – for the difference equation – I include the second and third lags, both for log GNI per capita and inequality (i.e., if inequality in t is I_t, I include I_{t-2} and I_{t-3} as instruments). These choices stem from the idea that these are the most important instruments to include: changes in inequality tend to be slower than changes in GNI per capita levels – for example – so additional lags need to be included. The first lag of inequality, on the other hand, is already included as it is already a part of the difference equation (which looks at $I_t - I_{t-1}$ as the outcome). The second set of estimates caps the number of instruments to two by only using the first two lags of inequality in the level equation. The third caps the number of instruments at one by only using the first lag of inequality in the level equation and the second lag for log GNI per capita and inequality in the difference equation. Cingano (2014) and Kraay (2015) follow similar approaches in their main estimations when studying the effect of total inequality, unbundling instruments and then capping the number of lags in each case.

Table A5 in the appendix presents the estimates with the reduced set of instruments. The main conclusions do not change from those in Table 1. Total inequality has no statistically significant effect on growth, while IOp has a significant and negative effect in all cases. Finally, the point estimate for IOp is higher than for total inequality (in absolute value). For total inequality the point estimate lies between -0.09 and -0.07, while that for IOp goes from -0.27 to -0.2, similar to the last two columns in table 1. In addition, these estimates better address the overfitting issue, as suggested by the Hansen test being below 1 in all cases. Overall, by using a very limited set of instruments, the estimates do not change substantially.

5.2.2 An IV approach to address reverse causality

System GMM addresses the reverse causality between economic growth and inequality by instrumenting the latter with lags of the independent variables, typically called internal instruments. But this is not the only way to address this issue. An alternative is to look for external instruments for inequality, i.e., factors that affect inequality but are independent of growth. One way to do this is to build a synthetic measure of inequality, one that captures changes that are not due to changes in GNI per capita or its growth rate. Brueckner and Lederman (2018) follow this approach. They estimate a model of inequality with GDP per capita as the only independent variable, and use the predicted residual as an instrument for their growth regression. This instrument identifies the variation in inequality that is not explained by changes in GDP per capita, thus 'shutting' the causal channel going from income to inequality. This approach has also been used by Marrero and Rodríguez (2019), who use it to look at IOp and its effect on growth.

The first step in this IV approach is to estimate the effect of income on inequality.

$$I_{j,t} = \alpha_j^1 + \delta_t^1 + \beta^1 \log(y_{j,t}) + \varepsilon_{it}^1 \quad (6)$$

$$I_{j,t}^O = \alpha_j^2 + \delta_t^2 + \beta^2 \log(y_{j,t}) + \varepsilon_{it}^2 \quad (7)$$

where $I_{j,t}$ is total inequality for country j in year t, and $I_{j,t}^O$ is the equivalent for IOp. $\log(y_{j,t})$ is the log of GNI per capita. The coefficients β^1 and β^2 are estimated using OLS, which are then used to construct the external instrument Z.[9]

$$Z_{j,t} = I_{j,t} - \hat{\beta}^1 \log(y_{j,t}) \quad (8)$$

$$Z_{j,t}^O = I_{j,t}^O - \hat{\beta}^2 \log(y_{j,t}) \quad (9)$$

The instruments $Z_{j,t}$ and $Z_{j,t}^O$ capture the variation in inequality that is not ex-

[9] To get a consistent estimate of β, equations 6 and 7 are estimated using 2SLS. Following Marrero and Rodríguez (2019) I use the first two lags ($t-1$ and $t-2$) of gross savings as a percentage of GDP and of GNI per capita growth rate as instruments. Data from the World Bank.

plained by the variation in log GNI per capita. Table A6 shows the estimations for this process in columns 2 and 4. As a reference, it also includes a naive OLS estimation that does not address the double causality problem in columns 1 and 3.

According to this IV approach, my earlier conclusions do not change. An increase in either inequality or IOp results in a decrease in growth rates – albeit a larger one for IOp. If I do not account for reverse causality (column 3), the point estimate is not statistically significant and roughly 50 percent smaller than the corresponding estimate in column 4. By not addressing the causal effect of income on inequality, the negative effect of IOp on growth is underestimated.

5.2.3 Different dynamic panel estimation methods

My third robustness check employs two alternative approaches to estimate dynamic panel models: Quasi–Maximum Likelihood (QML) and Bootstrap-Based Bias Correction with Fixed Effects (BCFE). Just like System GMM, these approaches address dynamic panel bias, making them useful when the time dimension is small.

QML (Kripfganz, 2016) is a special case of structural equation modelling. It fits a fixed effect model that accounts for Nickell bias without using instrumental variables by specifying the joint distribution of the outcome variable (both in levels and first differences) and the distribution of the error terms. BCFE (De Vos et al., 2015) addresses this bias using a two-step process: it first obtains a biased estimator, and then removes the bias using a bootstrap procedure. Unfortunately, as both of these approaches use first differences, a year of observations is lost, making the estimates not directly comparable with those reported earlier. This is particularly true for QML, as countries with interior gaps are dropped altogether, as is the case for Ireland.

The estimates from QML and BCFE show that an increase in either total inequality or IOp results in a statistically significant decrease in growth rates. One potential explanation for both estimates being significant could lie in their standard errors. Unlike the previous estimates, the software for these methods does not allow for the calculation of robust standard errors (e.g., with countries as clusters). QML uses the Huber–White estimator for heteroscedasticity-consistent standard errors, while BCFE uses standard errors that follow from the bootstrap distribution of the point estimate under a t-distribution. These estimators do not account for within-country error correlations, making the standard errors smaller than earlier estimators.

What stands out more than both coefficients being significant is that the point estimates for total inequality and IOp are very similar. In both QML and BCFE we still see that the coefficient for IOp is higher, but much less so than in previous cases. Nonetheless, my main results remain unchanged: an increase in IOp results in a statistically significant decrease in growth rates that is larger than for total inequality.

5.3 What explains the relationship between IOp and growth?

To better understand the relationship between IOp and growth, I complement the main results with two additional tests. First, I look at the role of productivity. Hai and Heckman (2017) report that both those constrained early in their life and those who remain poor and constrained underinvest in human capital and lower expected productivity. Along the same line, Aghion et al. (2005) reports how credit constraints can result in periods of low growth and less productive investments, further reducing growth. To explore whether productivity can explain the relationship between IOp and growth, I complement the main estimates by controlling for four different productivity measures.

Second, I look at additional inequality measures that are more sensitive to changes in the top or the bottom of the distribution. An increase of IOp at the top means a stronger transmission of privilege and advantage from one generation to the next. An example of this mechanism is described in Calarco (2014), as parents coach their children differently depending on their socioeconomic background, reinforcing existing inequalities. On the other hand, an increase in IOp at the bottom means that disadvantageous circumstances are transmitted over generations. For example, Cobb-Clark et al. (2017) show that individuals are almost twice as likely to receive social assistance if their parents did, and this relation is stronger for parents who themselves suffered disadvantageous circumstances. To carry out this analysis, I use the General Entropy family of inequality indexes and look at different values of the sensitivity parameter.

5.3.1 The role of productivity

In this section I explore whether productivity can help explain the effect that IOp has on growth. I expect productivity to be a mediator between IOp and growth. IOp reduces productivity by reinforcing the intergenerational reproduction of privilege and disadvantage; while higher productivity boosts growth by increasing output, lower productivity reduces growth.

To examine various dimensions of productivity, I use four measures derived from the Penn World Table database (v9.1). The measures are human capital, measured as a combination of years of schooling and their expected return, capital stock in 2011 U.S. dollars PPP, the share of labour compensation in GDP (in current prices), and total factor productivity or TFP in current PPP, relative to the U.S.A. (TFP for the U.S.A. equals 1).

To account for the role of each productivity measure, I follow research on mediation analysis (see, e.g., Hayes (2009)). I compare the coefficient for IOp from my previous estimates with the new estimate once I have controlled for productivity. If the coefficient for IOp changes once I have controlled for a productivity measure, then the total effect (from earlier estimates) is split into a direct effect (the new coefficient for IOp) and an indirect effect (the coefficient for the productivity measure).

Table A8 in the appendix reports the estimates when controlling for productivity. Column 1 is the benchmark, the same estimation as column 7 in table 1, which is derived using System GMM and PCA to reduce the number of instruments. Using the same estimation approach, I include each productivity measure separately in columns 2 to 5. Column 6 includes both TFP and capital stock, while column 7 includes all four together.

Table A8 shows that none of the productivity measures is statistically significant from zero. However, the effect of IOp becomes non-significant if I control for human capital only or for the labour share of GDP only. It remains statistically significant when we control for the capital stock or for TFP, and also when I control for both, as in column 6. The two potential mediators linking IOp, productivity, and growth are the labour share of GDP and human capital.

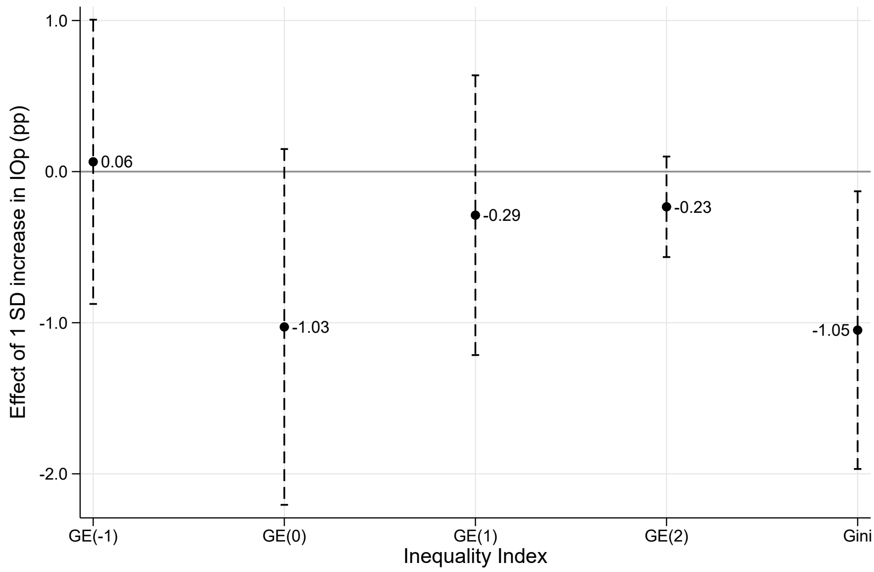
An additional component of mediation analysis is to verify that the mediator (productivity) is affected by the independent variable (IOp). Among the four productivity measures, IOp has a statistically significant effect only on human capital (robust to several specifications not reported in the paper). Human capital mediates the relationship between IOp and growth. An increase in IOp reduces human capital levels, which in turn reduce economic growth.

5.3.2 Measuring IOp with other inequality indexes

In this section I re-estimate my previous results using different inequality indexes. I examine the General Entropy Index using other sensitivity parameters, as well as the Gini index. In every case I control for both the level of IOp and the difference between inequality of outcomes and IOp, using the same inequality index. The goal of this exercise is to verify whether the relationship between IOp and growth holds for inequality measures that are relatively sensitive to different parts of the distribution.

Table A9 in the appendix shows the results for four generalised entropy (GE) indexes – the MLD is among them – and the Gini index. For the GE index, I look at GE(-1), GE(0) GE(1), and GE(2). The number in parenthesis is the sensitivity parameter, where a low number means an index that is sensitive to the bottom of the distribution, while a high number means an index that is sensitive to the top of the distribution. Figure 2 summarises these estimates and compares the change in growth rate following a one-standard deviation increase in each respective inequality index.

Figure 2: Effect of an increase of 1 SD of IOp on growth (pp)



Note: Graph includes all coefficients for IOp obtained from table A9, multiplied by the standard deviation of the corresponding inequality index. MLD estimation from table 1 column 7 is also included as GE(0). Coefficients are in percentage points of the 5-year average growth rate of GNI. 95% confidence intervals.

The coefficient for GE(0) is equivalent to column 5 in my main results. With the exception of the GE(-1), all of the point estimates report that an increase in IOp results in a decrease in growth rates. The Gini and the GE(0) – both relatively sensitive to changes in the middle of the distribution – show similar (and the largest) point estimates. A one-standard deviation increase in the Gini index results in a decrease of 1.05 percentage points in the GNI per capita growth rate (1.03 for the GE(0)). The GE(1) and GE(2) – relatively top sensitive inequality indexes – for a comparable increase in inequality show point estimates of -0.29 and -0.23, respectively. Table A9 reports that only the coefficients for GE(0) and the Gini index are statistically significant (at the 90% and 95% level, respectively).

The point estimates show a larger effect for 'middle-sensitive' inequality indexes, such as the Gini and MLD. These estimates are also the most robust to extreme values, either at the bottom or the top. 'Top-sensitive' indexes, such as the GE(1) and GE(2), show much smaller effects, while the GE(1) – a 'bottom-sensitive' index shows almost no effect. Changes at the middle and – to a lesser extent – at the top of the distribution drive the effect of IOp on growth.

6 Discussion

I use System GMM to estimate the effect of IOp on growth and show a negative effect of IOp on economic growth, measured as the 5-year average of the annual growth rate of GNI. Estimates show that it is IOp that drives the negative relationship between total income inequality and economic growth. A one standard deviation decrease in the upper bound estimate of IOp, which is equivalent to going from the middle of the ranking to the top, results in an increase in the growth rate of GNI per capita from 0.65 to 1.03 percentage points. Previous estimates – which have only used lower bound estimates of IOp – are close to the lower part of this range. The estimates are robust to the choice of instruments, alternative IV methods, or different estimation approaches.

I explore two paths to better understand the relationship between IOp and growth. First, productivity measured through average human capital partly mediates the relationship. IOp reduces human capital on average, which in turn reduces growth.

Second, the relationship between IOp and growth is strongest when using inequality indexes that are sensitive to the middle part of the distribution, while the relationship disappears when using 'bottom-sensitive' measures such as the GE(-1).

There are some policy implications of my results. First, there is no trade-off between inequality and growth if inequality is IOp rather than inequality of outcomes. There are policies that can promote both equal opportunities and economic growth. The OECD and other international agencies have done a substantial amount of work in that direction, as discussed in OECD (2018a,b). Second, policies aimed at reducing IOp by investing in human capital can promote economic growth. Examples of such policies are a minimum inheritance for every adult (Atkinson, 2015, pp.170-172) or the improvement of education systems (Elliot Major and Machin, 2018, pp.183–192).

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Appendix

Upper bound estimates of inequality of opportunity

Upper bound estimates use predicted fixed effects instead of a vector of circumstance variables, following a two-step process. The first step is a fixed effect regression for income, including both individual (η_i) and time fixed effects (u_t). This regression uses all years except the first, which in this case means three years (Carranza, 2020). For example, to get the upper bound estimate of IOp of 2008 we need to estimate a fixed effect regression for years 2009, 2010, and 2011.[10]

$$\log(Y_{it}) = \alpha + \eta_i + u_t + \varepsilon_{it} \quad \text{for } t = \{2, 3, 4\}. \tag{10}$$

The second step uses the predicted fixed effect from the first step ($\hat{\eta}_i$) as a measure of circumstances. Using the first year for each respondent ($t = 1$).

$$\log(Y_{it}) = \delta + \psi\hat{\eta}_i + \omega_{it} \quad \text{for } t = \{1\}. \tag{11}$$

From equation 11, we build a counterfactual distribution that is only determined by changes in the circumstance variable:

$$\widehat{\log(Y_i)} = \hat{\delta} + \hat{\psi}\hat{\eta}_i. \tag{12}$$

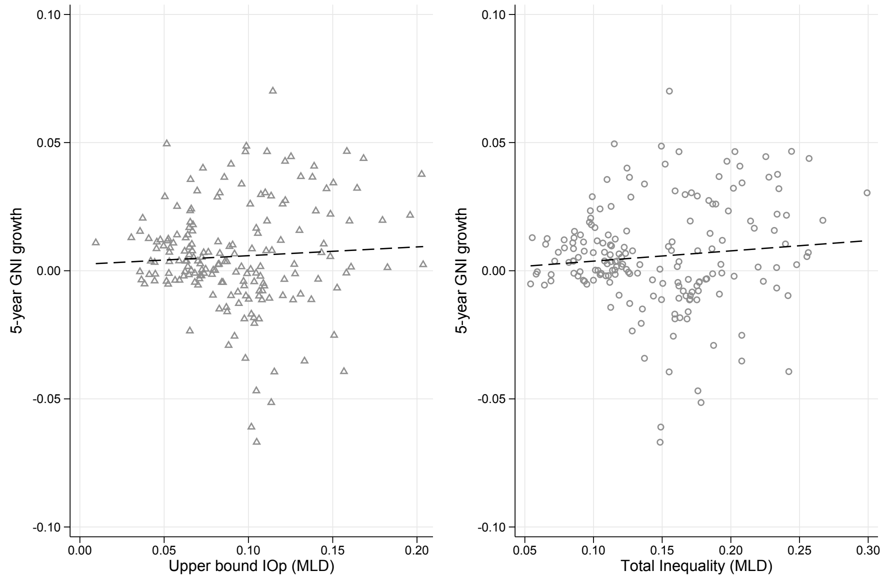
If we measure inequality over the counterfactual distribution of earnings $\hat{Y}$ – in this case using the MLD index – we get the Inequality of Opportunity Level, or IOL.

$$\text{IOL} = I(\{\hat{Y}\}). \tag{13}$$

[10] The complete methodology, including the departures from the method described in Niehues and Peichl (2014), as well as estimates and robustness checks are described in detail in Carranza (2020).

Descriptive statistics by country

Figure A1: Relationship between inequality and growth



Note: The graphs compare inequality (X-axis) and 5-year average GNI per capita growth (Y-axis) for 27 European countries between 2005 and 2011. The left panel uses the upper bound estimate of IOp, while the right panel uses total inequality, both measured through the MLD index. Source: Author's calculations, detailed in Carranza (2020). GNI per capita data from World Bank, inequality and IOp estimated using EU-SILC.

Table A1: Five-year GNI per capita growth average by country

Country	2005	2006	2007	2008	2009	2010	2011
Austria	0.012	0.010	0.004	-0.001	0.008	0.001	0.000
Belgium	0.011	0.004	0.000	-0.004	0.006	-0.004	0.003
Bulgaria	–	0.031	0.030	0.010	0.019	0.022	0.032
Cyprus	0.007	0.004	-0.015	-0.039	-0.023	-0.010	-0.010
Czech Rep.	0.014	0.007	-0.001	-0.005	0.010	0.017	0.019
Denmark	0.000	-0.006	-0.005	-0.001	0.013	0.011	0.010
Estonia	-0.001	-0.003	-0.004	0.011	0.042	0.046	0.037
Greece	-0.007	-0.035	-0.047	-0.051	-0.039	-0.029	-0.010
Spain	-0.002	-0.010	-0.016	-0.017	-0.006	0.002	0.012
Finland	0.007	0.001	-0.011	-0.014	0.000	-0.005	-0.001
France	0.004	0.004	-0.001	-0.001	0.007	0.005	0.003
Hungary	0.002	-0.003	-0.002	0.002	0.018	0.023	0.029
Ireland	-0.019	-0.025	–	–	0.030	0.049	0.070
Italy	-0.008	-0.011	-0.018	-0.019	-0.010	-0.011	-0.008
Lithuania	0.027	0.023	0.015	0.017	0.046	0.047	0.041
Luxembourg	-0.034	-0.026	-0.067	-0.061	-0.005	-0.011	-0.002
Latvia	0.016	0.007	-0.004	0.006	0.022	0.044	0.037
Malta	–	0.015	0.009	0.008	0.036	0.040	0.034
Netherlands	0.014	0.007	0.000	0.000	0.004	0.003	-0.001
Norway	-0.002	-0.004	-0.004	-0.002	0.008	0.011	0.013
Poland	0.045	0.043	0.034	0.026	0.029	0.030	0.026
Portugal	0.001	0.001	-0.011	-0.009	-0.001	-0.003	0.003
Romania	–	–	0.020	0.002	0.019	0.032	0.038
Sweden	0.012	0.004	-0.004	-0.001	0.015	0.009	0.009
Slovenia	0.013	0.004	-0.013	-0.021	0.002	-0.001	0.005
Slovakia	0.050	0.036	0.021	0.012	0.025	0.024	0.029
UK	-0.006	-0.005	-0.008	-0.005	0.009	0.009	0.008

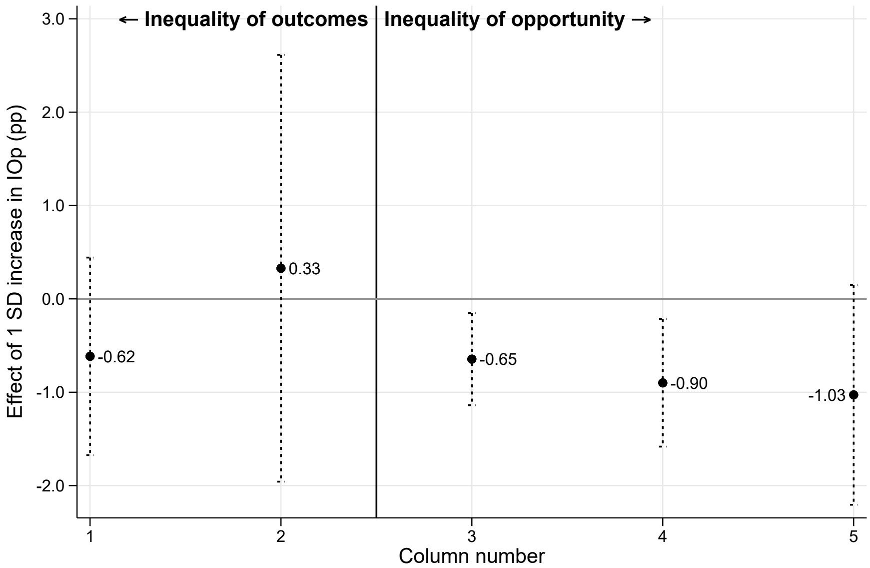
Table A2: Descriptive statistics: Within and between country differences

		Mean	Std. Dev.	Min	Max	Observations
Growth	Overall	0.006	0.021	-0.064	0.079	Total = 183
	Between		0.017	-0.032	0.036	Countries = 27
	Within		0.013	-0.043	0.061	Avg. = 6.78
Ineq.	Overall	0.147	0.052	0.054	0.299	Total = 183
	Between		0.050	0.063	0.241	Countries = 27
	Within		0.018	0.082	0.222	Avg. = 6.78
IOp	Overall	0.093	0.037	0.009	0.204	Total = 183
	Between		0.034	0.042	0.182	Countries = 27
	Within		0.017	0.037	0.163	Avg. = 6.78

Table A3: Inequality estimates using the MLD index (Carranza, 2020)

	Income Inequality							Inequality of Opportunity						
Country	2005	2006	2007	2008	2009	2010	2011	2005	2006	2007	2008	2009	2010	2011
Austria	0.116	0.113	0.162	0.116	0.128	0.148	0.103	0.053	0.050	0.053	0.078	0.067	0.075	0.066
Belgium	0.107	0.116	0.115	0.093	0.112	0.100	0.110	0.055	0.087	0.072	0.057	0.065	0.059	0.071
Bulgaria	–	0.159	0.299	0.240	0.170	0.240	0.235	–	0.070	0.083	0.145	0.111	0.196	0.146
Cyprus	0.108	0.113	0.136	0.155	0.128	0.144	0.119	0.076	0.086	0.083	0.115	0.065	0.106	0.079
Czech Rep.	0.111	0.100	0.105	0.095	0.112	0.101	0.097	0.064	0.073	0.074	0.052	0.091	0.065	0.065
Denmark	0.059	0.064	0.054	0.058	0.055	0.085	0.065	0.036	0.070	0.038	0.045	0.031	0.009	0.066
Estonia	0.193	0.169	0.177	0.157	0.152	0.162	0.191	0.158	0.121	0.103	0.082	0.090	0.098	0.131
Greece	0.233	0.208	0.176	0.178	0.242	0.187	0.242	0.153	0.133	0.105	0.114	0.157	0.088	0.120
Spain	0.202	0.171	0.169	0.159	0.162	0.161	0.194	0.107	0.090	0.087	0.102	0.109	0.107	0.119
Finland	0.119	0.124	0.150	0.113	0.114	0.112	0.126	0.092	0.101	0.137	0.087	0.080	0.084	0.099
France	0.117	0.108	0.106	0.125	0.123	0.120	0.121	0.070	0.063	0.053	0.093	0.083	0.072	0.083
Hungary	0.120	0.182	0.109	0.134	0.098	0.098	0.127	0.064	0.071	0.072	0.082	0.067	0.065	0.082
Ireland	0.168	0.208	–	–	0.167	0.149	0.155	0.106	0.151	–	–	0.107	0.099	0.114
Italy	0.165	0.170	0.163	0.159	0.167	0.175	0.176	0.107	0.100	0.103	0.098	0.098	0.108	0.108
Lithuania	0.184	0.198	0.185	0.217	0.203	0.244	0.207	0.122	0.140	0.106	0.105	0.111	0.158	0.139
Luxembourg	0.137	0.158	0.148	0.149	0.150	0.162	0.111	0.098	0.092	0.105	0.102	0.109	0.112	0.071
Latvia	0.232	0.256	0.224	0.255	0.234	0.257	0.228	0.130	0.143	0.097	0.149	0.149	0.168	0.138
Malta	–	0.124	0.122	0.157	0.126	0.124	0.137	–	0.067	0.065	0.114	0.086	0.073	0.096
Netherlands	0.090	0.074	0.090	0.101	0.085	0.082	0.086	0.058	0.053	0.062	0.079	0.059	0.044	0.068
Norway	0.105	0.143	0.093	0.089	0.093	0.093	0.066	0.065	0.037	0.051	0.062	0.062	0.046	0.041
Poland	0.225	0.197	0.208	0.189	0.176	0.171	0.187	0.125	0.122	0.150	0.101	0.113	0.110	0.120
Portugal	0.233	0.220	0.170	0.192	0.187	0.182	0.193	0.182	0.161	0.127	0.131	0.128	0.141	0.127
Romania	–	–	0.267	0.248	0.214	0.202	0.234	–	–	0.180	0.204	0.160	0.164	0.203
Sweden	0.079	0.072	0.069	0.069	0.086	0.079	0.085	0.048	0.042	0.044	0.041	0.036	0.054	0.045
Slovenia	0.086	0.085	0.126	0.135	0.117	0.132	0.089	0.063	0.063	0.094	0.104	0.096	0.105	0.067
Slovakia	0.115	0.110	0.098	0.103	0.113	0.105	0.099	0.052	0.066	0.037	0.052	0.058	0.066	0.050
UK	0.175	0.161	0.172	0.177	0.155	0.186	0.176	0.098	0.085	0.094	0.068	0.089	0.102	0.111

Figure A2: Coefficient for inequality of outcomes and IOp



Note: Graph includes all coefficients for IOp obtained from table 1, multiplied by the standard deviation of the corresponding inequality index. Values in the x-axis are the column number of each estimation. Columns 1 and 4 limit the number of instruments to the first three. Columns 2 and 6 use PCA to reduce the instrument matrix to a few instruments. Column 5 removes does not instrument for level of inequality of effort. Coefficients are in percentage points of the 5-year average growth rate of GNI per capita. 95% confidence intervals.

Table A4: Effect of inequality on GNI per capita growth rate (All instruments)

VARIABLES	(1) Inequality of outcomes	(2) Inequality of opportunity
Inequality	-0.096*	
	(0.056)	
IOp		-0.109
		(0.076)
IR		-0.028
		(0.075)
Unemp. (F)	-0.002*	-0.000
	(0.001)	(0.002)
Unemp. (M)	0.003*	0.003*
	(0.002)	(0.001)
Services	0.000	-0.001
	(0.001)	(0.001)
Log GNI	-0.018**	-0.015***
	(0.008)	(0.006)
Constant	0.196***	0.194***
	(0.059)	(0.058)
Observations	183	183
Number of countries	27	27
Instruments	61	88
Year FE	Yes	Yes
All lags	Yes	Yes
PCA	No	No
Instrument for IR	-	Yes
Sargan Test	0.000	0.000
Hansen Test	1.000	1.000
AR(1) Test	0.583	0.532
AR(2) Test	0.541	0.314

Note: *** p<0.01, ** p<0.05, * p<0.1. Windmeijer-corrected standard errors, clustered at the country level. All estimations include 27 European countries for the years 2005 to 2011. The main independent variable for column 1 is the level of income inequality, and the upper bound estimate of inequality of opportunity (IOp) for column 2. Both using the MLD index. System GMM use the inequality estimate and log GNI per capita as 'GMM style' instruments (making use of multiple lags), plus the years fixed effects, which are included as regular 'IV style' instruments. Columns differ in the number of lags (either all of them or first to third), whether I use PCA to reduce the number of instruments, and for IOp, whether I instrument the residual inequality (IR). The Sargan and Hansen statistics are tests of overidentifying restrictions, the null being the joint validity of all instruments. The AR(1) and AR(2) statistics are tests of autocorrelation of order 1 and 2, the null being no autocorrelation of the residuals. The KMO measure is the Kaiser-Meyer-Olkin test for sampling adequacy for the use of Factor Analysis. As a rule of thumb, a KMO measure below 0.5 is unacceptable and above 0.8 is desirable.

Table A5: Robustness check 1 - Different instrument choice

VARIABLES	(1) System GMM All lags	(2) System GMM All lags	(3) System GMM All lags	(4) System GMM All lags	(5) System GMM All lags	(6) System GMM All lags
Inequality	-0.091	-0.071	-0.091			
	(0.079)	(0.100)	(0.130)			
IOp				-0.205**	-0.214**	-0.268***
				(0.104)	(0.091)	(0.090)
IR				-0.162	-0.158	-0.106
				(0.155)	(0.141)	(0.146)
Unemp. (F)	-0.003**	-0.002*	-0.003***	-0.002	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Unemp. (M)	0.005***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Services	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log GNI	-0.015	-0.013	-0.017	-0.018	-0.014	-0.016
	(0.010)	(0.010)	(0.013)	(0.012)	(0.010)	(0.013)
Constant	0.171**	0.147*	0.193**	0.209**	0.174**	0.204**
	(0.083)	(0.086)	(0.099)	(0.083)	(0.077)	(0.085)
Observations	183	183	183	183	183	183
Number of countries	27	27	27	27	27	27
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	41	38	27	41	38	27
Sargan Test	0.000	0.000	0.000	0.000	0.000	0.000
Hansen Test	0.998	0.985	0.308	0.995	0.967	0.251
AR(1) Test	0.377	0.448	0.433	0.164	0.144	0.142
AR(2) Test	0.387	0.360	0.565	0.554	0.413	0.644

Note: *** p<0.01, ** p<0.05, * p<0.1. All equations use a reduced number of instruments. In differences: first lag of log GNI per capita and the first three lags of inequality. In levels: second to third lags of inequality and the first lag of log GNI. Windmeijer-corrected standard errors, clustered at the country level. All estimations include 27 European countries for the years 2005 to 2011. The main independent variable for columns 1 to 3 is the level of income inequality, and the upper bound estimate of inequality of opportunity (IOp) for columns 4 to 6. Both using the MLD index. Columns 1 and 4: In differences (i.e., for the level equation), I include the first lag of log GNI per capita and the first three lags of inequality. In levels (i.e., for the difference equation), I include the second and third lags, both for log GNI per capita and inequality. Columns 2 and 5 drop the third lag of inequality (level equation), and columns 3 and 6 additionally drop the third lag of both instruments (difference equation). The Sargan and Hansen statistics are tests of overidentifying restrictions, the null being the joint validity of all instruments. The AR(1) and AR(2) statistics are tests of autocorrelation of order 1 and 2, the null being no autocorrelation of the residuals. Hansen tests for each subset of instruments were estimated (not included), the null hypothesis is not rejected in any of the cases.

Table A6: Robustness check 2 - IV approach

VARIABLES	(1) Ineq	(2) Ineq	(3) IOp	(4) IOp
Inequality	-0.056	-0.107*		
	(0.052)	(0.060)		
IOp			-0.075	-0.148**
			(0.060)	(0.060)
IR			-0.039	-0.032
			(0.056)	(0.062)
Unemp. (F)	-0.002	0.002	-0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Unemp. (M)	0.003*	0.001	0.003*	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Services	-0.001	0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Log GNI	-0.124***		-0.121***	
	(0.021)		(0.022)	
Constant	1.387***	-0.036	1.365***	-0.021
	(0.220)	(0.070)	(0.232)	(0.070)
Observations	183	183	183	183
R-squared	0.885	0.827	0.886	0.832
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Estimation	OLS	2SLS	OLS	2SLS

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the country level. All estimations include 27 European countries for the years 2005 to 2011. The main independent variable for columns 1 and 2 is the level of income inequality, and the upper bound estimate of inequality of opportunity (IOp) for columns 3 and 4. Both using the MLD index. The 2SLS estimation (columns 2 and 4) requires a two steps process, done separately for total inequality and for IOp. The first step is an 2SLS estimation of inequality on time and year fixed effects, as well as the log of GNI (with lagged savings and growth rates as instruments). That estimation is then used to build the instrument $Z_{j,t} = I_{j,t} - \hat{\beta}\log(y_{j,t})$. The second step is a 2SLS estimation that uses said instrument to estimate the effect of inequality or IOp on growth.

Table A7: Robustness check 3 - Alternative estimation approaches

VARIABLES	(1) Ineq	(2) IOp	(3) Ineq	(4) IOp
Inequality	-0.042*		-0.059**	
	(0.022)		(0.028)	
IOp		-0.049*		-0.064**
		(0.028)		(0.030)
IR		-0.051**		-0.056*
		(0.023)		(0.030)
Lagged growth	0.369***	0.354***	0.410***	0.410***
	(0.083)	(0.080)	(0.097)	(0.105)
Unemp. (F)	-0.001	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Unemp. (M)	0.002***	0.002***	0.002**	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)
Services	0.001**	0.000	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Log GNI	-0.123***	-0.132***	-0.122***	-0.122***
	(0.018)	(0.018)	(0.020)	(0.022)
Constant	1.204***	1.327***		
	(0.204)	(0.210)		
Observations	152	152	154	154
Number of countries	26	26	27	27
Estimation	QML	QML	BCFE	BCFE
Repetitions	-	-	250	250

Note: *** p<0.01, ** p<0.05, * p<0.1. QML: Quasi–maximum likelihood estimation of linear dynamic models. BCFE: Bootstrap-based bias correction for dynamic Panels with fixed effects. As they all use first differences and control for the first lag of growth, these estimates include a lower number of observations. QML excludes Ireland, as countries with interior gaps are dropped. BCFE includes all countries. BCFE uses boostrapped standard errors, each with 250 repetitions. All estimations include 27 European countries for the years 2005 to 2011. The main independent variable for columns 1 and 3 is the level of income inequality, and the upper bound estimate of inequality of opportunity (IOp) for columns 2 and 4. All using the MLD index.

Table A8: Effect of IOp on Growth: Role of productivity

VARIABLES	(1) PCA All lags	(2) PCA All lags	(3) PCA All lags	(4) PCA All lags	(5) PCA All lags	(6) PCA All lags	(7) PCA All lags
IOp	-0.282*	-0.120	-0.299*	-0.218	-0.286*	-0.293*	-0.135
	(0.165)	(0.242)	(0.179)	(0.162)	(0.157)	(0.173)	(0.241)
IR	-0.178**	0.123	-0.141	-0.112	-0.175*	-0.138	0.155
	(0.089)	(0.359)	(0.137)	(0.122)	(0.098)	(0.137)	(0.469)
Unemp. (F)	-0.005	-0.010	-0.007	-0.006	-0.006	-0.008	-0.012
	(0.005)	(0.009)	(0.006)	(0.004)	(0.006)	(0.006)	(0.022)
Unemp. (M)	0.007*	0.012	0.009**	0.007**	0.008	0.009**	0.015
	(0.004)	(0.008)	(0.004)	(0.003)	(0.005)	(0.004)	(0.019)
Services	-0.001	0.001	-0.002	-0.001	-0.001	-0.002	0.001
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Log GNI	-0.017**	-0.018*	-0.010	-0.018**	-0.020*	-0.012	-0.016
	(0.007)	(0.010)	(0.016)	(0.008)	(0.011)	(0.017)	(0.015)
Labour share		0.255					0.313
		(0.312)					(0.565)
TFP			-0.041			-0.039	0.011
			(0.070)			(0.066)	(0.068)
Human capital				0.013			-0.010
				(0.015)			(0.087)
Capital stock					0.001	0.001	0.002
					(0.004)	(0.004)	(0.012)
Constant	0.266***	-0.009	0.278**	0.208	0.281***	0.280**	-0.058
	(0.093)	(0.337)	(0.130)	(0.133)	(0.107)	(0.119)	(0.287)
Observations	183	183	183	183	183	183	183
Number of countries	27	27	27	27	27	27	27
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	20	20	20	20	20	20	20
Sargan Test	0.004	0.016	0.014	0.003	0.004	0.007	0.001
Hansen Test	0.421	0.521	0.333	0.443	0.305	0.224	0.175
AR(1) Test	0.111	0.341	0.121	0.203	0.125	0.122	0.651
AR(2) Test	0.509	0.240	0.478	0.484	0.550	0.502	0.481
KMO Measure	0.853	0.853	0.853	0.853	0.853	0.853	0.853

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Windmeijer-corrected standard errors, clustered at the country level. All estimations include 27 European countries for the years 2005 to 2011. The main independent variable is the upper bound of inequality of opportunity. System GMM uses log GNI per capita and inequality variables as 'GMM style' instruments (making use of multiple lags), as well as the years fixed effects, which are included as regular 'IV style' instruments. The Sargan and Hansen statistics are tests of overidentifying restrictions, the null being the joint validity of all instruments. The AR(1) and AR(2) statistics are tests of autocorrelation of order 1 and 2, the null being no autocorrelation of the residuals. The KMO measure is the Kaiser-Meyer-Olkin test for sampling adequacy for the use of Factor Analysis. As a rule of thumb, a KMO measure below 0.5 is unacceptable and above 0.8 is desirable.

Table A9: Effect of IOp on Growth: Different inequality indices

VARIABLES	(1) S. GMM PCA All lags	(2) S. GMM PCA All lags	(3) S. GMM PCA All lags	(4) S. GMM PCA All lags	(5) S. GMM PCA All lags
GE(-1)	0.011				
	(0.085)				
GE(0)		-0.282*			
		(0.165)			
GE(1)			-0.079		
			(0.130)		
GE(2)				-0.037	
				(0.027)	
Gini					-0.233**
					(0.104)
Unemp. (F)	-0.004**	-0.005	-0.005***	-0.004***	-0.004
	(0.002)	(0.005)	(0.002)	(0.001)	(0.005)
Unemp. (M)	0.005***	0.007*	0.006**	0.006***	0.007*
	(0.002)	(0.004)	(0.002)	(0.001)	(0.004)
Services	-0.001***	-0.001	-0.000	-0.001***	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Log GNI	-0.008	-0.017**	-0.019***	-0.012*	-0.018**
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Constant	0.137	0.266***	0.219***	0.176**	0.255***
	(0.087)	(0.093)	(0.054)	(0.070)	(0.079)
Observations	183	183	183	183	183
Number of countries	27	27	27	27	27
Year FE	Yes	Yes	Yes	Yes	Yes
Instruments	27	20	20	27	20
Sargan Test	0.001	0.004	0.008	0.000	0.012
Hansen Test	0.711	0.421	0.591	0.426	0.359
AR(1) Test	0.375	0.111	0.200	0.207	0.196
AR(2) Test	0.501	0.509	0.468	0.400	0.417
KMO Measure	0.755	0.853	0.859	0.820	0.824

Note: *** p<0.01, ** p<0.05, * p<0.1. Windmeijer-corrected standard errors, clustered at the country level. All estimations include 27 European countries for the years 2005 to 2011. The main independent variable is the upper bound of inequality of opportunity, measured using different inequality indeces. Each estimation controls for the difference between inequality of outcomes and IOp, for each specific index. All columns are estimated via System GMM with PCA to reduce the number of instruments. System GMM uses log GNI per capita and inequality variables as 'GMM style' instruments (making use of multiple lags), as well as the years fixed effects, which are included as regular 'IV style' instruments. The Sargan and Hansen statistics are tests of overidentifying restrictions, the null being the joint validity of all instruments. The AR(1) and AR(2) statistics are tests of autocorrelation of order 1 and 2, the null being no autocorrelation of the residuals. The KMO measure is the Kaiser-Meyer-Olkin test for sampling adequacy for the use of Factor Analysis. As a rule of thumb, a KMO measure below 0.5 is unacceptable and above 0.8 is desirable.