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Abstract

Is the relationship between inequality of opportunity (IOp) and short-term economic growth different from the relationship between inequality of outcomes and short-term 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 decrease in growth rates ranging from 1.2 to 3.1 percentage points. Inequality of outcomes also has a statistically significant effect on growth, albeit much less robust. These estimates suggest that while all income inequalities might hinder growth, IOp is particularly harmful.

1 Introduction

The question of the effect of inequality on growth can be traced to the seminal work of Galor and Zeira (1993) and Galor and Tsiddon (1997). In this line of work, this relationship is mediated by human capital accumulation which is hampered by imperfections in the credit market. In the presence of credit market imperfections, only those with access to wealth can invest in human capital. Higher human capital investments are accompanied by higher intergenerational mobility, expansion of high-skilled sectors, and ultimately, economic growth. Underlying these models is the idea that inequality constraints the access to opportunities, particularly access to education, restricting access to productive positions in which people can contribute to economic growth.

The notion that unequal opportunities constrain growth has been picked up in recent years, specially following the work on inequality of opportunity measurement Roemer (1998); Fleurbaey (2008). 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] Following 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 distinction, 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

[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).

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.

When studying the relationship between inequality and growth, most studies focus on medium to long term economic growth, sometimes referred to as 'secular trends'. Among the papers reviewed in Voitchovsky (2009), all focus on long growth spells of 5, 10 or more years. Indeed, researchers looking at the relationship between inequality and opportunity and growth (Marrero and Rodríguez (2013); Ferreira et al. (2018); Marrero and Rodríguez (2019); Aiyar and Ebeke (2019), to name a few) have also looked at medium to long growth spells. While these papers are concerned with 'structural' determinants of growth, such as human capital or aggregate productivity, in this paper I focus on short-term growth and the role that inequality of opportunity plays in attenuating or accentuating these fluctuations.

I focus on a set of European countries in particular period of time. I study the 2005 to 2011 period, that includes both the Great Recession (2007-2009) and the European debt crisis (starting in late 2009). Jenkins et al. (2012) argue that the Great Recession is more of a 'structural break' rather than a standard business cycle shock, thus making it hard to extrapolate conclusions beyond this specific context. However, that does not mean that we should not pay attention to this period. This period of time – for this set of countries – provides a insightful look into how inequality of opportunity interacts with growth in the context of financial crises in high income economies.

In this chapter I estimate the effect of inequality of opportunity on the annual growth rate of GNI per capita and contrast these estimates with the equivalent effect of inequality of outcomes. The estimates of IOp and inequality of outcomes are based on household equivalised data for 27 European countries between 2005 and 2011 derived in the previous chapter. The present inequality of opportunity estimates address the 'lower bound' problem of most estimates, where inequality of opportunity only accounts the influence of observed circumstances. My estimates follow the method discussed in the previous chapter, where I use panel data to capture a summary measure of all time-invariant circumstances, thus providing 'upper bound' estimates of inequality of opportunity.

Using System GMM regression I find that an increase in inequality of outcomes reduces economic growth, albeit with a small and non-robust effect. An increase in inequality of opportunity also reduces growth, but this effect is robust to multiple functional forms, estimation approaches, and control variables. A decrease of one standard deviation in inequality of opportunity increases growth between 1.2 and 3.1 percentage points. Compared to previous studies, these effects are substantially larger, which could be explained by the use of 'upper bound' estimates in contrast to 'lower bound' estimates or by the focus on short-term economic growth. Future research will require to better disentangle the impact of each of these departures.

This chapter contributes to the literature of inequality of opportunity and growth in two ways. First, by using upper bound estimates of IOp, which provide a more exhaustive measure of the influence of circumstances. Second, by focusing on short-term dynamics in the context of financial crises. In this context, increases in inequality of opportunity result in decreases in economic growth. However, increases in inequality of 'efforts' also report a negative relationship with economic growth, albeit not statistically significant in most cases.

This chapter is consistent with previous research in that inequality of opportunity drives most of the overall effect of inequality of outcomes. However, my estimates differ from previous studies where increases in inequality of efforts promote (or do not influence) long growth spells (Marrero and Rodríguez, 2013, 2019). In the short term, both inequality of opportunities and inequality of effort are negatively correlated with economic growth, although the bulk of the overall effect is driven by the former. I draw insights from the literature on inequality and macroeconomic instability to discuss these results (van Treeck (2013), among others).

2 Measuring IOp

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, 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 resid-

[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).

ual term usually referred to as inequality of 'efforts'. If I_{jt} represents total inequality, then inequality of effort is defined as the residual $I^R_{j,t} = I_{jt} - I^O_{j,t}$. $I^O_{j,t}$ represents IOp, the between group component, while the interpretation of the residual $I^R_{j,t}$ depends on whether the inequality index is additively decomposable.

I use the Gini index to measure inequality, which is not additively decomposable. However, it less susceptible to extreme values at the top than indexes such as the Theil or the MLD (Cowell and Victoria-Feser, 1996; Cowell and Flachaire, 2007), having a simpler and well-established interpretation. As a result, the residual $I^R_{j,t}$ cannot be interpreted as solely within-type inequality because it also includes a term quantifying the overlap between types (Lambert and Aronson, 1993).

2.1 Upper bound estimates of IOp

Upper bound estimates of IOp capture the influence of time invariant determinants of income. They capture circumstances typically included in surveys such as parental education or occupation, place of birth and gender, but also other important circumstances that are not typically included such as parental interactions or innate abilities. However, they also capture time invariant efforts such as personal 'attitudes' (e.g., being hard-working or punctual). The formal derivation of these estimates is detailed in the Appendix.[3]

Just like with any IOp estimate, inequality of effort is constructed the difference between inequality of outcomes and IOp and it is therefore a residual term. In this case, given that the upper bound estimate includes all time invariant efforts, inequality of effort is a measure of the influence of factors that vary over time. Given that some efforts might be time invariant, this measure of inequality of efforts can be be interpreted as 'lower bound' estimates of effort.

[3]It could be argued that there are time-invariant circumstances, for example having a new roommate or colleague, as they still lie outside of individual control. However, here – as in most IOp exercises – I focus on childhood circumstances, what Dworkin (1981a,b) calls 'initial brute luck', in contrast to 'later brute luck'.

Given that EU-SILC dataset includes circumstance variables only for 2005 and 2011 (and soon, for its 2019 version), lower bound estimates have only been estimated for those two years (see, e.g., Yalonetzky (2010)). Because upper bound estimates are based on panel data rather than on the availability of circumstance variables, this approach allows the estimation of IO for many more years. The use several years of data allows for the use of modern estimation techniques on comparable cross country data, such as System GMM.

3 The effect of inequality and IOp on growth

3.1 Understanding the relationship between IOp and growth

The idea behind decomposing inequality of outcomes and looking into the effect of IOp and inequality of efforts is that the former is not morally illegitimate but also inefficient. Higher IOp means that 'privilege' – for example, having highly educated parents – shape the distribution of rewards (concretely, household income) while providing no contribution to overall economic growth. This argument provides an instrumental rather than an intrinsic motivation to reduce IOp. The following section discusses the empirical approaches to study this relationship, and the expected effects.

This is the first paper to study this relationship using upper bound estimates of IOp. Contrary to lower bound estimates of IOp that suffer from omitted variables issues, upper bound estimates err on the side of including too many determinants of income, some of which can be construed as efforts. The overall effect on economic growth thus depends on the what is captured by the upper bound estimate of IOp. Based on the 'cholesterol hypothesis', if the upper bound estimates captures new circumstances then we would expect a larger effect than with a lower bound estimate, on the other hand, if the upper bound captures mostly efforts, then we would expect a smaller effect.

Beyond the measure of IOp, there are two important departures from previous studies. First, I focus on annual growth rates rather than medium-term (i.e., 5 or more years) growth spells, studying the impact of inequality on short term responses rather than in more structural or 'secular' trends. Short term variations in inequality (both of outcomes and opportunity) mostly reflect changes in labour income rather than in capital income or wealth.[4] As such, Royuela et al. (2018) suggest that higher inequality can have a substantial short term effects on household spending, particularly among those with liquidity constrains, reducing aggregate consumption and thus economic growth.

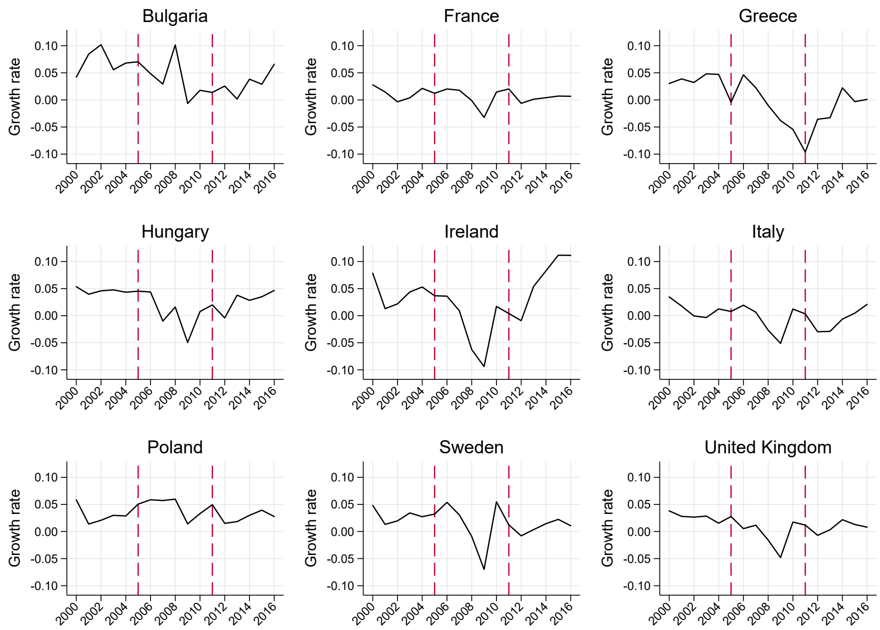
While the previous discussion is about inequality of outcomes, these effects might be stronger when driven by IOp. For example, if liquidity-constraint households are also those suffering from poor circumstances. Galor and Tsiddon (1997) propose a model of economic growth in periods of technological inventions. In the short term, a new technology will benefit (the few) who can use it, likely to be those that grew up with better circumstances. This increases the skill-premium gap and wage inequality, while reducing growth as the rest of the work forces 'catches-up' in the form of on-the-job-training. That association might dissipate (or even revert) in the medium to long term, depending on how the use of the new technology evolves. To the extent that IOp represents these mechanisms such as differences in skills or credit constraints, it should have a stronger effect on economic growth than inequality of outcomes.

The second departure relates to the specific time period I study. I study the 2005 to 2011 period, that includes both the Great Recession (2007-2009) and the European debt crisis (2009 onwards). This is a very specific context, as shown for nine countries in Figure 1. There are large drops in GNI per capita growth around 2009 and 2011, with very different trends to both before and after that period. Indeed, when refering to this period, Jenkins et al. (2012) talk about "structural changes" rather than short term volatility or business-cycle fluctuations. This particular

[4] There might be changes in capital income, but the probability of receiving capital income is unlikely to change. Moreover, labour income comprises around 80% of total income, having a bigger income on household inequality (Jenkins et al., 2012).

context might have changed the (short-term) relationship between inequality and growth.

Figure 1: Annual GNI per capita growth rates



Note: GNI per capita growth rates for nine countries in the sample, between the years 2000 and 2016. The red vertical dashed lines cover the period of study of this chapter (2005-2011). GNI per capita data from World Bank.

Recent studies have shown a negative association between inequality of outcomes and growth in the context of the Great Recession. Royuela et al. (2018) finds a negative association between inequalities and growth for OECD countries in the 2003-2013 period, particularly in urban regions. Similarly, Lewin et al. (2017) finds that US counties with higher income inequality entered the recession earlier than those with lower inequality. Cynamon and Fazzari (2015) argue that this negative association in the US is due to increased borrowing constraints among the bottom 95% of the income distribution, reducing aggregate demand. The Great Recession appears to have created a particular context where higher economic inequality (i.e., inequality of outcomes) reduces economic growth.

Income inequality has also been suggested as a cause of the Great Recession. In his review, van Treeck (2013) discusses the effect of inequality on economic growth in the context of the Great Recession. He argues that this relationship can be explained by the 'relative' income hypothesis (in contrast to the 'permanent' income hypothesis). Under this hypothesis, households react to their relative position in the income distribution. Higher inequality increases the consumption gap between the top income earners and the rest of the distribution, who attempt to 'catch up' to the former through higher debt. Along the same line, Wisman (2013) discusses three ways in which inequality made the economy vulnerable to systemic shocks, two of which relate to constrains in consumption that triggered higher debt (the third being wealth concentration and its impact on politics). These arguments highlight how inequality, independent whether it arises from differences in efforts or in circumstances, has created a context of low consumption, high debt, and ultimately, lower economic growth.

3.2 Estimating the effect of inequality 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, this line of research is far from resolved.

One of the explanations for the diversity of estimates 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 chapter, 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.[5]

System GMM is prone to instrument proliferation, a problem described in detail in 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

[5] The need for lagged observations as instruments can result in a trade-off between sample length and lag length, particularly when one needs lagged differences. However, this is not a problem for 'GMM-style' instruments, as missing observations (i.e., the unavaiable lags) are substituted for zeros in the final instrument matrix. Roodman (2009b, pp.107–108) discusses the process in detail.

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 estimates are equal to the biased OLS estimates. 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 chapter, 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.[6]

3.2.1 Growth regressions and dynamic panel data models

My growth regression specification follows from previous estimates for the effect of IOp and growth, such as Ferreira et al. (2018); Marrero and Rodríguez (2019). Particularly, it follows the latter in not including additional control variables be-

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

yond the GNI per capita level. The intuition being that the coefficient for IOp (and equivalently, the coefficient for inequality of effort) is capturing its direct and indirect effect. Where, as Barro (2000) puts it, the direct effect represents the effect of inequality beyond its effects on potential covariates such as education or investment. The specifications are shown in equation 4 and 5.

$$g_{j,\{t-1,t\}} = \beta_0 \log(y_{j,t}) + \beta_1 I_{j,t} + \alpha_j + \eta_t + u_{jt}. \tag{4}$$

$$g_{j,\{t-1,t\}} = \gamma_0 \log(y_{j,t}) + \gamma_1 I^O_{j,t} + \gamma_2 I^R_{j,t} + \alpha_j + \eta_t + u_{jt}. \tag{5}$$

I define growth ($g_{j,\{t-1,t\}}$) as the annual growth rates of GNI per capita from year $t-1$ to year t, where $t = 2005, \ldots, 2011$. GNI per capita (from World Bank Open Data) is measured in 2010 USD. I focus on GNI per capita rather than GDP per capita because it focuses on people living in the territory by including includes factor income earned by foreign residents, which also feature on my inequality estimates (For a detailed discussion on the relationship between household income in surveys, and GDP/GNI see Nolan (2020)).

Equation 4 studies the effect of inequality of outcomes ($I_{j,t}$), whereas equation 5 decomposes it into an upper bound estimate of IOp ($I^O_{j,t}$) and the residual, interpreted as inequality of efforts ($I^R_{j,t}$). I also include the log of GNI per capita for country j in year t (in constant 2010 USD), a country-level fixed effect (α_j), a time fixed-effect (η_t), and the residual (u_{jt}).

This specification follows Marrero and Rodríguez (2019) in that I do not include other covariates. This is done to capture the direct and indirect effect of inequality. That is, the coefficient for inequality of opportunity γ_1 will account for all 'channels' or 'paths' through which it can influence economic growth, either directly or through its influence on other covariates. In the robustness section I use two specifications that allow for covariates, one based on the model proposed by Forbes (2000) and later used in Ferreira et al. (2018), and another to account for determinants of growth in the context of the Great Recession.

4 Data

4.1 Upper bound estimates of IOp

All data for the inequality estimates comes from the EU-SILC. I take IOp and inequality of outcomes estimates for 27 countries in the period 2005-2011 from the previous chapter and expand that sample to include an estimate for 2012. I do not include this additional year of data in the previous chapter as I focus on the period bounded by the two lower bound estimates (2005 and 2011). Given that all countries except for Ireland and the United Kingdom report income from the previous year, I lag their estimates to represent the 2004-2011 period.

IOp is measured over household equivalised income (using the OECD equivalence scale) for all individuals aged 25 to 55. Inequality is measured using the Gini index. 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 to countries with over 4,000 observations.

I do not use the lower bound estimates of inequality of opportunity describe in the previous section. These estimates include two data points per country (2005 and 2011) and 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. 20 countries have complete data for the period 2004-2011 (2005-2012 for Ireland and the UK) and 7 have missing data for particular years. Bulgaria, the Czech Republic, Lithuania, Malta and Slovenia enter the SILC survey in 2006 (reporting 2005 income), Romania enters in 2007, and Ireland does not have data for the 2007 and 2008 waves. I do not include Iceland as it does not have GNI per capita data in constant USD on the World Bank Open Dataset. For each country, I have between 6 and 8 years of data, with an average of 7.7 years per country.

My income of interest, the annual growth rate of GNI per capita (measured in constant 2010 US dollars), was downloaded from the World Bank Open Database. Table A1 reports descriptive statistics for this variable as well as for inequality of outcomes and IOp. The average growth rate was 1.6%, with high heterogeneity, mostly accounted for by within country differences, as one would expect from a period of two economic crises. Average inequality of outcomes (measured through the Gini) is 28.4 points and average IOp is 23.1 points. In both cases the largest share of the variance is explained by between country differences.

In addition to GNI and inequality, I include additional covariates in some robustness exercises. These variables come from different sources. The share of the population over 25 with at least completed upper secondary (ISCED 0 to 4), separate for men and women, comes from Eurostat. The price level of capital formation (in PPP) relative to the United States exchange rate, as well as the average annual hours worked by persons engaged (converted into weekly hours) were downloaded from the Penn World Table (version 9.1). The annual growth rate for per capita consumption (for households and NPISHs) and the domestic credit to private sector by banks (as a share of GDP) come from the World Bank Open Database. Table A2 report descriptive statistics for these variables.

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, among which I include a few covariates that might shine a light on potential drivers of my main estimates. Together, my analysis contribute to a comprehensive examination of the effect of both inequality and IOp on short-term economic growth.

5.1 Main estimates: 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 4 using for inequality of outcomes as their dependant variable, and columns 5 to 8 using IOp. All estimates use System GMM with Windmeijer-corrected cluster–robust errors (i.e., two-step corrected standard errors) clustered at the country level.

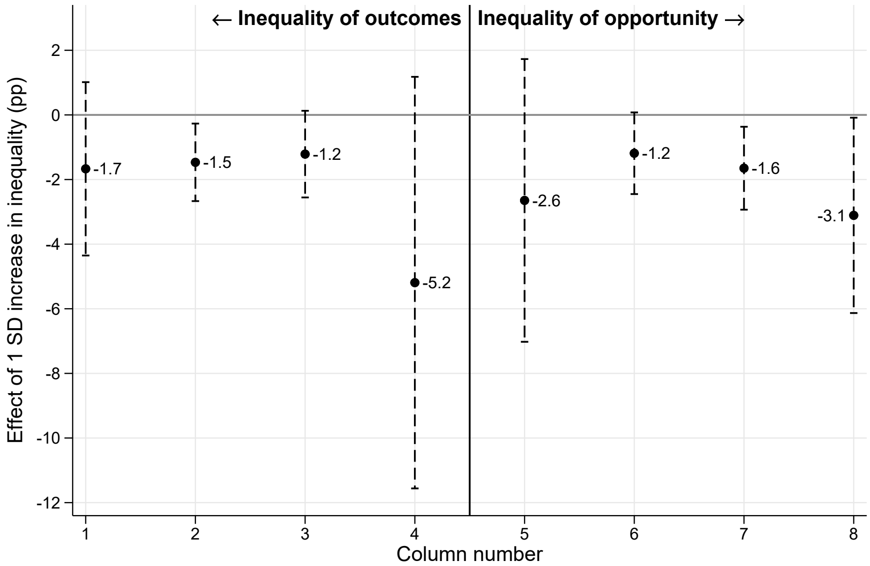
I use the same specifications for inequality of outcomes and for IOp. That is, columns 1 and 5 use the same estimation approach, and the same holds for columns 2 and 6, 3 and 7, and 4 and 8. The first column provides a System GMM estimation without any major restrictions. It includes all available lags as well as the complete 'GMM-style' instrument matrix. As result, the number of instruments is quite large (82 for inequality of outcomes and 117 for IOp, as I also instrument the residual inequality term). The second column caps the number of lags at 1, thus using only the first available lag for each of the instrumented variables. The third column collapses the instrument matrix, in contrast with the 'uncollapsed' matrix that uses one column for each instrument (see page 108 in Roodman (2009b)). Finally, the fourth column uses PCA to reduce the instrument matrix based to a few principal components, based on their correlation. Figure 2 summarises the coefficient for inequality of outcomes or IOp in terms of a one-standard deviation change in the particular inequality measure.

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

VARIABLES	(1) Ineq	(2) Ineq	(3) Ineq	(4) Ineq	(5) IOp	(6) IOp	(7) IOp	(8) IOp
Inequality	-0.370	-0.326**	-0.269*	-1.152				
	(0.304)	(0.136)	(0.152)	(0.722)				
IOp					-0.613	-0.275*	-0.382**	-0.720**
					(0.517)	(0.149)	(0.152)	(0.357)
IR					-0.883	-0.144	-0.280**	-0.406
					(0.727)	(0.231)	(0.124)	(0.406)
Log GNI	-0.040***	-0.038***	-0.031*	-0.057*	-0.035**	-0.024	-0.034*	-0.041**
	(0.013)	(0.012)	(0.018)	(0.030)	(0.016)	(0.017)	(0.019)	(0.019)
Constant	0.521**	0.490***	0.407**	0.946*	0.545*	0.318*	0.463**	0.631**
	(0.214)	(0.149)	(0.187)	(0.511)	(0.306)	(0.178)	(0.180)	(0.284)
Observations	207	207	207	207	207	207	207	207
Number of countries	27	27	27	27	27	27	27	27
Instruments	82	40	25	25	117	54	33	28
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All lags	Yes	No	No	Yes	Yes	No	Yes	Yes
PCA	No	No	No	Yes	No	No	No	Yes
Collapsed instrument	No	No	Yes	No	No	No	Yes	No
Sargan Test	0.000	0.047	0.722	0.145	0.008	0.035	0.926	0.341
Hansen Test	1.000	0.967	0.577	0.162	1.000	1.000	0.959	0.343
AR(1) Test	0.172	0.176	0.167	0.110	0.125	0.170	0.176	0.166
AR(2) Test	0.236	0.245	0.240	0.321	0.279	0.237	0.246	0.284
KMO measure				0.900				0.891

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Windmeijer-corrected standard errors, clustered at the country level. The dependent variable is the annual growth rate of GNI per capita (in constant 2010 US dollars). All estimations include 27 European countries for the years 2004 to 2011 (2005-2012 for the UK and Ireland). The main independent variable for columns 1 to 4 is the level of income inequality, and the upper bound estimate of inequality of opportunity (IOp) for columns 5 to 8. Both using the Gini index. System GMM use the inequality estimates and log GNI per capita as 'GMM style' instruments (making use of multiple lags). The years fixed effects are included as regular 'IV style' instruments. Columns differ in the number of lags. For both inequality of outcomes and IOp I include, respectively: all lags, only the first lag, a collapsed instrument matrix, a reduced instrument matrix based on PCA. 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 when using PCA. As a rule of thumb, a KMO measure below 0.5 is unacceptable and above 0.8 is desirable.

Figure 2: Effect of a 1sd increase in inequality on growth (pp)



Note: Graph includes all coefficients for IOp obtained from table 1, multiplied by the standard deviation of the corresponding inequality index. Coefficients are in percentage points of the annual growth rate of GNI per capita. 95% confidence intervals.

5.1.1 Inequality and economic growth

The coefficient for inequality of outcomes on growth rates ranges from -0.37 to 0.03 percentage points. The collapsed instrument matrix (column 3) and the PCA approach (column 4) reduces the number of instruments below the rule of thumb – fewer instruments than countries, 27 in this case. However, in the PCA case the coefficient is not statistically significant. The Arellano-Bond tests for autocorrelation and the Hansen and Sargan tests of overidentifying restrictions suggest no issues in any of the specifications. In sum, column 3 provides a reasonable estimate for the effect of inequality of outcomes on economic growth, that satisfy the required number of instruments as well as not rejecting the statistical tests.

The coefficient for inequality of outcomes on economic growth in column 3 is -0.27, and it is statistically significant at the 90% confidence level. We can also interpret this coefficient in terms of a change in one standard deviation. The standard deviation for inequality of outcomes is 4.5 points of the Gini (as shown in Table A1). A one standard deviation is equivalent to moving from a country with low inequality such as Norway or Denmark, to a country in the middle of the ranking such as France or Austria. From Figure 2 we see than an increase of a one standard deviation in inequality of outcomes is associated with a decrease in 1.2 percentage points of the growth rate.

To compare these estimates with previous papers, I look at the effect in terms of changes of one standard deviation of inequality of outcomes. Using a set of income and expenditure surveys and the MLD index to measure inequality, Ferreira et al. (2018) report an effect of -1.8 percentage points.[7] Using the same set of surveys as Ferreira et al. (2018) and measuring inequality using the Gini index, Marrero and Rodríguez (2019) report a coefficient of -0.7 percentage points.[8] My estimate lies between the two, however, both estimates are statistically non-significant. My results hint at a potential short-term effect of inequality of outcomes on economic growth that does not hold when studying medium to long term dynamics.

5.1.2 IOp and economic growth

Columns 5 to 8 in table 1 show the estimates of the effect of IOp on growth. The coefficients range from -0.72 to -0.28. All point estimates are negative, consistent with an increase in IOp resulting in a decrease in the growth rate. The Arellano-Bond tests for autocorrelation and the Hansen and Sargan tests of overidentifying restrictions suggest no issues in any of the specifications. Going from column 5 to column 8 we see an important drop in the number of instruments, highlighted by the Hansen test of 1 at the first two columns. Despite the last column reducing the number of instruments to 28, it is still one above the rule of thumb proposed

[7] I compute the standard deviation for total inequality in Ferreira et al. (2018) using Table A.1. in the online Appendix. The relevant coefficient is in Table 1, column 5.

[8] Marrero and Rodríguez (2019) report their standard deviation in Table 1. The relevant coefficient is found in Table 3, column 9.

by Roodman (2009a).[9]

The coefficient for IOp on economic growth in column 8 (the PCA adjusted instrument matrix) is -0.72, and it is statistically significant at the 95% confidence level. The standard deviation for IOp is 0.043 (see Table A1). Similar to inequality of outcomes, this is equivalent to going from the bottom of the ranking (Norway or Denmark) to the middle (the Netherlands or Austria). As a result, a one standard deviation increase in IOp is equivalent to a decrease of 3.1 percentage points in the annual growth rate for GNI per capita. Taking only the statistically significant coefficients, from Figure 2 we see that the effect of a one standard deviation in IOp ranges between -1.2 and -3.1 percentage points.

My estimates have some overlap with previous studies. Given a one standard deviation increase in IOp, Ferreira et al. (2018), using the MLD index and system GMM, find a non-significant effect of -1.3 percentage points of the growth rate. Using the same dataset and the Gini index, Marrero and Rodríguez (2019) report a statistically significant effect of -2.5 percentage points. Both their estimates fall within the range of estimates provided in Table 1 but are below my preferred estimate for the effect of IOp, in column 8. While there appears to be some overlap between short and medium term effects (both in size and statistical significance), the former are somewhat larger than the latter.

Contrary to previous estimates, the coefficient for residual inequality ('inequality of efforts') is also negative. Based on columns 6 to 8 in Table 1, an increase in one standard deviation of the residual term (equal to 0.02 points of the Gini) results in a decrease of growth rates ranging from 0.3 to 0.9. This is not consistent with the 'cholesterol hypothesis', that suggests that there are two components underlying inequality of outcomes. These components have significant but opposite effects on economic growth, cancelling out each other and resulting in inequality of outcomes having an ambiguous effect. In the context of short-term growth and the Great Recession, higher inequality of outcomes, opportunity, or 'effort' results in lower

[9]For that reason I include among the robustness check a set of regressions using PCA and capping the number of instruments. Results do not vary substantially from those in column 8.

growth rates.[10]

Despite the coefficients for IOp and for residual inequality being negative, the former is larger in absolute value in columns 6 to 8. This is consistent with what Ramos and Van de gaer (2020) call the 'weak hypothesis' about the effects of opportunity and efforts on economic growth. That is, that the effect of IOp is more negative than the effect of effort inequality. My estimates show that, everything else constant, higher inequality of outcomes reduces growth, and that an increase in IOp is more detrimental to economic growth that an increase in inequality of effort.

5.2 Robustness Checks

In this section I report several robustness checks. The first two deal with the issue of instrument proliferation. First, I modify the number of instruments by capping the number of lags to be considered by the System GMM estimation. Second, I cap the number of instruments by forcing the PCA algorithm to select fewer principal components. The third check involves an instrumental variable approach that addresses potential issues of reverse causality. Fourth, I use alternative dynamic panel models estimators that also address Nickell bias. Finally, I study the effect of including additional covariates. Overall, these checks are consistent with the main results.

5.2.1 Different choice of instruments

Bazzi and Clemens (2013) discuss several issues frequent in growth regression. Regarding System GMM, the discuss the need to 'unpack' the black box that

[10]It could be argued that this not because of the context but rather because of the use of an 'upper bound' estimate of IOp. However, the fact that inequality of outcomes as a whole has a negative effect suggests that this is not the case.

is the instrument matrix of internal instruments. For that reason, in my first check U unbundle the system GMM instruments to allow for different number of instruments for the different covariates, as well as differences in the the level and difference equations.

I provide estimates for the effect of inequality of outcomes and for IOp. For the latter I also include the same regressions without instrumenting for the residual component of inequality. 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 A3 in the appendix presents the estimates when unpacking the GMM instrument matrix. The main conclusions do not change from those in Table 1. Inequality of outcomes has a negative coefficient and it is statistically significant in two of the three specifications. Both IOp and the residual inequality term have negative coefficients, albeit only the former is statistically significant (in 4 of the 6 specifications). The coefficient for IOp tends to be larger than the one for residual inequality. Excluding the residual inequality term as an instrument makes little difference in the coefficient for IOp. The point estimate for the effect of inequality of outcomes ranges from -0.75 to -.46, while the coefficient for IOp ranges from -0.84 to -0.51. However, all specifications fail to satisfy the Sargan test of overidentifying restrictions which, together with the very large value for the Hansen test suggests the presence of too many instruments.

None of the specifications in Table A3 manage to reduce the number of instruments to be equal or below the number of countries (the rule of thumb in Roodman (2009b)). Which is why I repeat the estimation in column 8 of Table 1 by reducing the number of instruments using PCA, but also capping to the number of instruments to satisfy this rule of thumb. The estimates are reported in Table A4 and show that the main results do not change substantially when including 27, 26, or 25 instruments, if anything, the coefficients show a small decrease in absolute value when including fewer instruments.

5.2.2 An IV approach to address reverse causality

System GMM, through its use of internal instruments, is not the only way to address the issue of endogeneity. An alternative approach is to use external instruments for inequality, i.e., factors that affect inequality but are independent of growth. Brueckner and Lederman (2018) propose constructing a synthetic measure of inequality, one that captures changes that are not due to changes in GNI per capita or its growth rate. This approach is designed to explicitly address reverse causality, as, by construction, growth will have no impact on the synthetic measure of inequality, 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.

$$\begin{aligned} I_{j,t} &= \alpha_j^1 + \delta_t^1 + \beta^1 \log(y_{j,t}) + \varepsilon_{it}^1 && (6) \\ I_{j,t}^O &= \alpha_j^2 + \delta_t^2 + \beta^2 \log(y_{j,t}) + \varepsilon_{it}^2 && (7) \end{aligned}$$

where $I_{j,t}$ is total inequality for country j in year t, and $I^O_{j,t}$ 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.[11]

$$Z_{j,t} = I_{j,t} - \hat{\beta}^1 \log(y_{j,t}) \tag{8}$$
$$Z^O_{j,t} = I^O_{j,t} - \hat{\beta}^2 \log(y_{j,t}) \tag{9}$$

The instruments $Z_{j,t}$ and $Z^O_{j,t}$ capture the variation in inequality that is not explained by the variation in log GNI per capita. Table A5 shows the estimations for this process in columns 2 and 4. Columns 1 and 3, on the other hand, include a 'naive; OLS estimation that does not address the double causality problem in columns 1 and 3.

The IV approach is consistent with my previous estimates. 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 (columns 1 and 3), the point estimate is not statistically significant and 3 to 5 times smaller than the corresponding estimate in column 2 or 4. These IV estimates show that not addressing the causal effect of income on inequality underestimates the effect of IOp on growth.

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 and are particularly useful when the time dimension is small.

[11] 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 the second lag of GNI per capita growth rate ($t-2$) as instruments. Data from the World Bank.

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. Unlike System GMM, that simply omits missing instruments, these approaches drop one year of observations when using first differences as instruments. Therefore, these estimates not directly comparable with those reported earlier. This is particularly true for QML, as countries with interior gaps such as Ireland are dropped altogether.

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.

What stands out more than both coefficients being significant is that the point estimates for total inequality and IOp are very similar. Both approaches show negative coefficients for all three inequality terms (Inequality of outcomes, IOp and the residual term), with the coefficient for the residual term being higher than the one for IOp. BCFE estimates are not statistically significant (with the exception of the residual term, significant at the 90% level). While less robust than the main estimates, both the QML and BCFE approaches show negative coefficients for the effect of IOp on growth.

5.3 Including covariates

To better understand the relationship between IOp and growth, I complement the main estimates by including two set of covariates. The first one follows from Forbes (2000) and Ferreira et al. (2018), and considers medium to long-term determinants of growth, namely measures of human capital and market distortions. The second set of covariates includes short-term determinants of growth in the context of the Great Recession (van Treeck, 2013; Wisman, 2013). These covariates include consumption growth rates, worked hours, and the level of private debt. These variables are described in Table A2 in the Appendix.

Table A7 reports the estimations for inequality of outcomes (columns 1 and 3) and for IOp and the residual term (columns 2 and 4). All estimates use PCA to reduce the number of instruments. Columns 3 and 4 report fewer observations because the consumption growth rate does not have data for Malta and there is no private debt data for a few years of Lithuania, Latvia, and Slovakia. As a result, the second set of covariates estimates the effect of inequality on growth for 26 countries with 187 observations.[12]

Estimates show very little change when accounting for these covariates. When following the specification in Forbes (2000), the coefficients for inequality remain negative with a small decline in absolute value. The coefficient for inequality of outcomes becomes statistically significant at the 90% and the coefficient for IOp remains statistically significant at the 95% level. The coefficient for the residual inequality remains insignificant. None of the additional covariates is statistically significant. When comparing these estimates with those in Table 1, we see that coefficients are smaller (in absolute term). However, the main takeaways remain the same: higher inequality results in lower growth rates, with IOp having a larger effect than the residual term.

[12] When using the reduced sample, the estimates in columns 4 and 8 of Table 1 remain qualitatively unchanged (i.e., signs and statistical significance does not change).

Contrary to human capital and market distortions, short-term determinants of growth have a statistical significant effect in the IOp regression (column 4). Both the growth rate of per capita consumption and the number of hours worked in a week increase economic growth. In addition, both the coefficient for IOp and for the residual term are statistically significant. Moreover, while the coefficient for IOp does not change from the one in Table 1, the coefficient for the residual inequality almost doubles once we control for these variables. Once we hold consumption, worked hours and debt levels constant, an increase in the residual inequality term (i.e., inequality of 'effort') reduces economic growth, more so than IOp.

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 annual growth rate of GNI per capita. I study 27 European countries between 2004 and 2012. In contrast with previous studies, I use 'upper bound' estimates of IOp, which account for all time-invariant sources of inequality. My estimates show that an increase in IOp results in a decrease in economic growth. This is consistent with the idea that unequal circumstances can hamper growth. However, my estimates also show that inequality of outcomes has a negative coefficient, albeit a less robust one. IOp, on the other hand, is robust to choice and number of instruments, to alternative estimation approaches and the inclusion of covariates. Overall, increases in both inequality of outcomes and IOp result in lower growth rates, with a much stronger effect for the latter.

It is important to highlight the context in which I estimate the effect of inequality on growth. This period of time includes two very large financial crises, the Great Recession and the European Debt crisis. As such, and together with the focus on short-term growth rates, my estimates cannot be directly extrapolated to other context. These estimates shows whether IOp (and inequality of outcomes) hinders growth in the context of generalised private debt, low consumption, and high unemployment, a context in which the distinction between efforts and circumstances appears to become less relevant.

This is not to say that the differences between efforts and circumstances became irrelevant. In almost all specifications the coefficient for IOp is higher in absolute value than the residual term (the difference between inequality of outcomes and IOp, sometimes interpreted as inequality of efforts). This is not consistent with the 'cholesterol hypothesis' (see, e.g., Marrero and Rodríguez (2019)), the idea that IOp is harmful for growth while the inequality of efforts. My estimates are consistent with a weaker version of this hypothesis, discussed in Ramos and Van de gaer (2020), where the effect of IOp is stronger than the effect of the residual term.

To some extent, my findings could be driven by the use of an upper bound estimate of IOp, in contrast with the more widely used lower bound estimates. The stronger effect of IOp could be driven by time-invariant factors that might not be considered to be circumstances (a common example of such a factor is having a 'hard working attitude'). Unfortunately, given current data availability, it is impossible to decompose the role of the upper bound estimate from the context in which I estimate its impact on growth. However, the fact that inequality of outcome also reports a negative coefficient suggests the context matters more than the measurement of IOp. The 2019 wave of the EU-SILC will include circumstance variables, making it possible to get enough years of lower bound estimates to compare their effect on growth using similar estimation techniques to those used in this paper.

To further explore the role of the financial crises in explaining these results I control for measures of private debt, worked hours and consumption growth. These variables have been highlighted as determinants of short-term growth as well as factors that reinforced the relationship between inequality and growth in high income countries (van Treeck, 2013). I find that worked hours and consumption growth are both predictors of short-term growth, and IOp remains a statistically significant predictor. Moreover, once I control for these variables, the coefficient for the residual term of inequality becomes larger (i.e., more negative) than IOp.

How to interpret the effect the residual component of inequality? In light of the upper bound measurement of IOp, this term includes all sources of income inequality that vary over time. In addition, as I use the Gini index to measure inequality, this measure accounts for both within-type inequality and the extent to each the different income types across types overlap. As a result, it cannot be directly interpreted as a measure of inequality of efforts, but rather as a 'catch-all' measure of inequality beyond that captured in the IOp.

In the context of two financial crises, I argue that this component accounts for the worsening economic climate as well as the efforts and individual choices taken by households, given this climate. Framed as an optimization problem, this measure captures both changing restrictions (access to liquidity, for example) and changing responses (in terms of consumption and work). If worked hours and levels of debt represent the latter, then they are proxies of 'efforts' (indeed, both have a positive coefficient on economic growth). Under that assumption, and once we control for these variables, the residual component of inequality becomes a measure of the worsening economic climate, which has a worse effect on economic growth than inequalities due to differences in childhood circumstances, represented by IOp.[13]

Future search should look into this relationship. Inequality of outcomes appears to be negatively associated with economic growth in the context of financial crises. What role does inequality of effort play in this context? Does the distinction between efforts and circumstances become less relevant as predictors of growth? Or does it depend on how we decompose inequality of outcomes. In a similar vein, Ramos and Van de gaer (2020) discuss how the effect of IOp (and inequality of efforts) on growth might not be robust to the measure of IOp. For example, the distinction between ex-ante or ex-post estimates of IOp, but also between upper and lower bound estimates. A better understanding of the relationship between growth and inequality in the context of financial crises can prove helpful in understanding the welfare implications in the context of high income inequalities,

[13]This distinction can also be framed using the work of Dworkin (1981a,b). IOp would represent initial brute luck, both socioeconomic and genetic, whereas the residual component (once we exclude efforts) could represent later brute luck (see Ferreira and Peragine (2015)).

even if they are driven by differences in effort rather than circumstances.

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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. 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.[14]

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

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.

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

[14] The complete methodology, including the departures from the method described in Niehues and Peichl (2014), as well as estimates and robustness checks are described the previous chapter.

Descriptive statistics

Table A1: Descriptive statistics (growth rates and inequality)

		Mean	Std. Dev.	Min	Max	Observations
Growth	Overall	0.016	0.050	-0.278	0.184	Total = 207
	Between		0.017	-0.011	0.051	Countries = 27
	Within		0.048	-0.258	0.205	Avg = 7.66
Ineq.	Overall	0.284	0.045	0.188	0.379	Total = 207
	Between		0.042	0.208	0.355	Countries = 27
	Within		0.017	0.239	0.338	Avg = 7.66
IOp	Overall	0.231	0.043	0.087	0.345	Total = 207
	Between		0.038	0.164	0.314	Countries = 27
	Within		0.022	0.150	0.309	Avg = 7.66

Note: Growth is the annual growth rate for GNI per capita. Inequality of outcomes (Ineq.) and inequality of opportunity (IOp) are measured using the Gini index.

Table A2: Descriptive statistics (covariates)

		Mean	Std. Dev.	Min	Max	Observations
Education (W)	Overall	72.8	9.4	54.2	90.0	Total = 207
	Between		9.3	58.1	87.2	Countries = 27
	Within		2.6	65.3	80.4	Avg = 7.66
Education (M)	Overall	76.4	7.6	60.5	89.9	Total = 207
	Between		7.5	66.6	88.4	Countries = 27
	Within		1.8	68.8	82.6	Avg = 7.66
Investment	Overall	0.84	0.19	0.45	1.41	Total = 207
	Between		0.18	0.53	1.25	Countries = 27
	Within		0.08	0.66	1.05	Avg = 7.66
Consumption	Overall	1.73	4.65	-16.5	19.8	Total = 200
	Between		1.84	-0.35	5.26	Countries = 26
	Within		4.30	-19.3	16.3	Avg = 7.69
Weekly hours	Overall	33.7	3.8	27.2	41.7	Total = 207
	Between		3.8	27.5	41.1	Countries = 27
	Within		0.5	31.5	35.4	Avg = 7.66
Bank debt	Overall	97.4	46.4	26.0	243.1	Total = 194
	Between		44.5	35.2	195.4	Countries = 27
	Within		13.7	49.3	145.0	Avg = 7.19

Education (W and M): The share of the population over 25 with at least completed upper secondary (ISCED 0 to 4), separate for women and men (Eurostat). Investment: The price level of capital formation (in PPP) relative to the United States exchange rate (Penn World Table). Weekly hours: Average weekly hours worked by persons engaged (Penn World Table). Consumption: The annual growth rate for per capita consumption for households and NPISHs (World Bank). Bank debt: The domestic credit to private sector by banks as a share of GDP (World Bank).

Table A3: Robustness check 1 - Different instrument choice

VARIABLES	(1) Ineq	(2) Ineq	(3) Ineq	(4) IOp	(5) IOp	(6) IOp	(7) IOp	(8) IOp	(9) IOp
Inequality	-0.463	-0.673**	-0.749**						
	(0.321)	(0.330)	(0.358)						
IOp				-0.513	-0.579**	-0.773*	-0.656	-0.702*	-0.842**
				(0.353)	(0.273)	(0.452)	(0.433)	(0.385)	(0.418)
IR				-0.660*	-0.302	-0.151	-0.660	-0.438	-0.334
				(0.361)	(0.319)	(0.619)	(0.512)	(0.363)	(0.547)
Log GNI	-0.048**	-0.045***	-0.046***	-0.049**	-0.041***	-0.045**	-0.055***	-0.051**	-0.047***
	(0.022)	(0.016)	(0.015)	(0.021)	(0.012)	(0.023)	(0.020)	(0.022)	(0.016)
Constant	0.635**	0.668***	0.706***	0.661**	0.587***	0.685*	0.765***	0.732**	0.726***
	(0.277)	(0.249)	(0.262)	(0.292)	(0.175)	(0.356)	(0.295)	(0.329)	(0.266)
Observations	207	207	207	207	207	207	207	207	207
Number of countries	27	27	27	27	27	27	27	27	27
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	53	45	36	68	60	42	53	45	36
Instrument IR	–	–	–	Yes	Yes	Yes	No	No	No
Lags growth in level	1st	1st	1st	1st	1st	1st	1st	1st	1st
Lags growth in diff	2 to 3	2nd	2nd	2 to 3	2nd	2nd	2 to 3	2nd	2nd
Lags ineq. in level	1 to 3	1 to 3	1st	1 to 3	1 to 3	1 to 3	1 to 3	1 to 3	1 to 3
Sargan Test	0.001	0.003	0.001	0.001	0.002	0.002	0.000	0.001	0.001
Hansen Test	0.998	0.995	0.987	1.000	1.000	0.971	1.000	0.990	0.945
AR(1) Test	0.179	0.168	0.164	0.161	0.167	0.153	0.167	0.179	0.154
AR(2) Test	0.248	0.274	0.294	0.265	0.273	0.297	0.273	0.277	0.316

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Windmeijer-corrected standard errors, clustered at the country level. The dependent variable is the annual growth rate of GNI per capita (in constant 2010 US dollars). All estimations include 27 European countries for the years 2004 to 2011 (2005-2012 for the UK and Ireland). 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 9. Both using the Gini index. Columns 1, 4, and 7: 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, 5, and 8 drop the third lag of inequality (level equation), and columns 3, 6, and 9 also 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 A4: Robustness check 2 - Fewer instruments (PCA only)

VARIABLES	(1) IOp	(2) IOp	(3) IOp
IOp	-0.727*	-0.720*	-0.691*
	(0.411)	(0.385)	(0.385)
IR	-0.403	-0.403	-0.404
	(0.503)	(0.454)	(0.447)
Log GNI	-0.043**	-0.043**	-0.042**
	(0.019)	(0.020)	(0.019)
Constant	0.651**	0.647**	0.630**
	(0.309)	(0.306)	(0.294)
Observations	207	207	207
Number of countries	27	27	27
Instruments	27	26	25
Year FE	Yes	Yes	Yes
All lags	Yes	Yes	Yes
PCA	Yes	Yes	Yes
Collapsed instrument	No	No	No
Sargan Test	0.317	0.254	0.214
Hansen Test	0.340	0.280	0.221
AR(1) Test	0.164	0.164	0.165
AR(2) Test	0.288	0.289	0.284
KMO measure	0.891	0.891	0.891

Note: *** p<0.01, ** p<0.05, * p<0.1. Windmeijer-corrected standard errors, clustered at the country level. The dependent variable is the annual growth rate of GNI per capita (in constant 2010 US dollars). All estimations include 27 European countries for the years 2004 to 2011 (2005-2012 for the UK and Ireland). The main independent variable for columns 1 to 4 is the level of income inequality, and the upper bound estimate of inequality of opportunity (IOp) for columns 5 to 8. Both using the Gini index. System GMM use the inequality estimates and log GNI per capita as 'GMM style' instruments (making use of multiple lags). The years fixed effects are included as regular 'IV style' instruments. Columns differ in the number of lags. For both inequality of outcomes and IOp I include, respectively: all lags, only the first lag, a collapsed instrument matrix, a reduced instrument matrix based on PCA. 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 when using PCA. As a rule of thumb, a KMO measure below 0.5 is unacceptable and above 0.8 is desirable.

Table A5: Robustness check 3 - IV approach

VARIABLES	(1) Ineq	(2) Ineq	(3) IOp	(4) IOp
Inequality	-0.193	-0.644*		
	(0.194)	(0.354)		
IOp			-0.179	-1.011**
			(0.201)	(0.511)
IR			-0.258	-0.928**
			(0.210)	(0.442)
Log GNI	-0.254***	-0.259***	-0.258***	-0.259***
	(0.061)	(0.056)	(0.058)	(0.060)
Constant	2.800***	2.976***	2.840***	3.064***
	(0.653)	(0.615)	(0.626)	(0.664)
Observations	204	207	204	207
R-squared	0.597	0.581	0.597	0.529
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 Gini 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 A6: Robustness check 4 - Alternative estimation approaches

VARIABLES	(1) Ineq	(2) IOp	(3) Ineq	(4) IOp
Inequality	-0.422**		-0.277	
	(0.199)		(0.179)	
IOp		-0.460*		-0.266
		(0.238)		(0.165)
IR		-0.571**		-0.313*
		(0.291)		(0.186)
Lagged growth	0.183*	0.188*	0.280*	0.282*
	(0.111)	(0.109)	(0.144)	(0.144)
Log GNI	-0.321***	-0.323***	-0.333***	-0.335***
	(0.064)	(0.065)	(0.062)	(0.063)
Constant	3.376***	3.410***		
	(0.635)	(0.639)		
Observations	175	175	182	182
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 Gini index.

Table A7: Effect of IOp on Growth: Including covariates

VARIABLES	(1) Ineq	(2) IOp	(3) Ineq	(4) IOp
Inequality	-0.912*		-0.264	
	(0.495)		(0.233)	
IOp		-0.583**		-0.707***
		(0.247)		(0.214)
IR		-0.207		-0.914**
		(0.344)		(0.362)
Fem. second. educ.	0.002	-0.001		
	(0.007)	(0.004)		
Male second. educ.	-0.002	-0.001		
	(0.007)	(0.003)		
Price level of inv.	-0.326	0.057		
	(0.202)	(0.221)		
Consumption p/c (growth)			0.002	0.009***
			(0.005)	(0.003)
Weekly worked hours			-0.012	0.007**
			(0.008)	(0.003)
Domestic credit from banks			0.000	0.000
			(0.000)	(0.000)
Log GNI	0.009	-0.062	-0.048**	0.002
	(0.036)	(0.068)	(0.021)	(0.016)
Constant	0.467	0.916	0.948**	-0.045
	(0.441)	(0.739)	(0.445)	(0.200)
Observations	207	207	187	187
Number of countries	27	27	26	26
Instruments	25	28	24	29
Year FE	Yes	Yes	Yes	Yes
All lags	Yes	Yes	Yes	Yes
PCA	Yes	Yes	Yes	Yes
Collapsed instrument	No	No	No	No
Sargan Test	0.133	0.245	0.168	0.236
Hansen Test	0.352	0.303	0.263	0.789
AR(1) Test	0.095	0.185	0.223	0.160
AR(2) Test	0.393	0.255	0.213	0.313
KMO measure	0.900	0.891	0.894	0.871

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. The sample size is constrained in columns 3 and 4 due to the availability of covariates.