INEQUALITY AND GROWTH IN PORTUGAL: A TIME SERIES ANALYSIS

DESIGUALDADE E CRESCIMENTO EM PORTUGAL: UMA ANÁLISE DE SÉRIES TEMPORAIS

João A. S. Andrade
jasa@fe.uc.pt
GEMF – Group for Monetary and Financial Studies; Faculty of Economics, University of Coimbra

Adelaide P. S. Duarte
maduarte@fe.uc.pt
GEMF – Group for Monetary and Financial Studies; Faculty of Economics, University of Coimbra

Marta C. N. Simões
mcsimoes@fe.uc.pt
GEMF – Group for Monetary and Financial Studies; Faculty of Economics, University of Coimbra

ABSTRACT/RESUMO

Following the recent resurgence of interest on the relationship between inequality and growth and the considerable debate that remains on its sign, we examine this nexus for Portugal during the period 1985-2007 using different time series approaches. The results suggest that earnings inequality has a negative impact on output thus confirming the view that inequality is detrimental to growth. Moreover, according to the results from the impulse response functions based on the preferred trivariate structural VAR (SVAR) model, these effects last in some cases for three years after the inequality shock. As far as education is concerned, the third variable considered in our SVAR models, the evidence does not support the theoretical prediction that more inequality reduces human capital accumulation, pointing in fact in the opposite direction: an increase in earnings inequality leads to more educated workers. Thus, the evidence of a negative influence of inequality on output seems to be explained by the fact that it implies more redistribution, with the associated distortionary effects from taxes on investment.

Keywords: Output, Inequality, Education, Hendry-Krolzig Methodology, Causality, SVAR

JEL Codes: O15, O52

Em linha com o interesse recente e renovado sobre a relação entre desigualdade e crescimento, e o importante debate que subsiste sobre o sinal desta relação, analisamos esta questão para Portugal no período de 1985-2005 usando diferentes metodologias de séries temporais. Os resultados sugerem que a desigualdade de ganhos tem um impacto negativo no *output*, confirmando assim o ponto de vista de que a desigualdade é nociva ao crescimento económico. Além disso, e segundo os resultados decorrentes da análise das funções impulso-resposta baseadas no modelo preferido, um VAR estrutural (SVAR) trivariado, estes efeitos duram, nalguns casos, três anos após o choque de desigualdade. No tocante à educação, a terceira variável considerada nos nossos modelos SVAR, não se confirma a predição teórica de que mais desigualdade reduz a acumulação de capital humano; ao invés, os resultados apontam na direção oposta: um aumento da desigualdade de ganhos conduz a trabalhadores com mais educação. Assim, a confirmação de uma influência negativa da desigualdade sobre o *output* parece ser explicada porque implica mais redistribuição, com os efeitos distorcionários decorrentes dos impostos sobre o investimento.

Palavras-chave: Produto, Desigualdade, Educação, Metodologia de Hendry-Krolzig, Causalidade, SVAR

Códigos JEL: O15, O52

1. INTRODUCTION

The relationship between inequality and economic growth has been comprehensively analyzed in the theoretical and empirical literature and still generates considerable amount of debate among economists. This debate revolves around two competing views or theories on the impact of inequality on growth. Earlier theories predicted a positive influence due to a higher propensity to save of the richer, with higher inequality leading to more physical and human capital accumulation and thus growth, and because it provides an incentive to the appearance of entrepeneurs/inventors expecting to belong to the wealthier part of the society, thus enhancing growth when innovation is the driving force of long run performance, as well as promoting higher effort by workers and thus efficiency (see e.g. Perotti (1996b); Aghion et al. (1999); and Barro (2000)). More recent theories associated with new growth theory claim that inequality is detrimental to growth. For developed countries, the negative effect of inequality on growth is justified on the basis of two main arguments or mechanisms of transmission. The credit market imperfections channel argues that these lead to lower levels of human capital investments and thus slower growth, since only initially rich individuals have the collateral to gain access to the credit necessary to invest in human capital (see e.g. Galor and Zeira (1993)). According to the fiscal policy channel, in more unequal economies the level of redistribution demanded from the government by the population will be higher, which in turn leads to higher levels of taxation that affect investment decisions, resulting in less investment and growth (see e.g. Alesina and Perotti (1994), and Persson and GuidoTabellini (1994)).

Empirical analyses of the impact of inequality on economic growth include, among others, Perotti (1996a), Chen (2003), and Balisacan and Fuwa (2003). The general picture from the former cross-country studies is that initial inequality reduces future growth. The message from panel data studies is however not clear. For instance, among the panel studies that consider wider samples of countries with both developing and developed countries, Deininger and Squire (1998) find that the sign of the relationship is ambiguous and even positive in some cases; Forbes (2000) detects a positive relationship that persists across different samples, variables definitions, and model specifications but not the length of period under consideration; Barro (2000) uncovers a negative relationship for poor countries, a positive relationship for rich countries, and an insignificant one for the whole sample; Banerjee and Duflo (2003) present evidence that it is a change in any direction, not the initial level of inequality that leads to slower future growth; and Voitchovsky (2005), using data on inequality for industrialized countries, concludes that top end inequality positively influences growth while the influence of bottom end inequality is negative. In face of the mixed evidence provided by empirical studies, Dominics et al. (2008) apply meta-analysis to a set of twenty-two studies, that give a total of 254 estimates for the coefficient of the inequality measure, with the results showing that the variation in the estimates of the income inequality-growth relation are systematically associated with differences in estimation methods, sample coverage and data quality.

Time series studies are scarcer. For instance, Gobbin and Rayp (2008) apply Johansen's cointegration methodology to the analysis of the relation between income inequality, education, social security and economic growth in Belgium, the US and Finland[1], finding quite different results in each case, which leads them to conclude that: "A country- specific estimation approach is needed since 'one-size-fits-all' does not apply in the field of growth empirics." (p. 892). Frank (2009) uses a time series approach to examine the relationship between income inequality, human capital attainment, and income growth in a sample of US states over the period 1929-2000. He finds evidence that a rise in the top income share has a negative impact on output growth and that this relationship is stronger in more densely populated states. Risso and Carrera (2012) study the long-run relationship between economic growth and income inequality in China using a cointegrated VAR approach. The results point to a positive and significant relationship between inequality and growth in the two periods under analysis, 1952-1978 and 1979-2007.

There is also considerable debate around whether the causality runs from inequality to growth or primarily the other way around. Since the seminal work of Kuznets (1955), that found an inverted U-shaped relation between per capita output and (income) inequality, several studies provide evidence of a reverse causal relationship from growth to inequality. For instance, Assane and Grammy (2003) use a trivariate VAR model comprised of per capita real GDP, the Gini coefficient of income, and human capital to assess the causal relationship between income inequality and growth in the US over the period 1960-1996 and find that it is growth that causes inequality, with inequality increasing as growth proceeds. However, Frank (2009) finds only weak evidence that income growth Granger-causes the top decile income share, and Risso and Carrera (2012) find a unidirectional causality from inequality to growth in China and only during the first period analyzed, 1952-1978.

Following this recent resurgence of interest in the relationship between inequality and growth, this paper examines this relationship for Portugal during the period 1985-2007 using a time series approach to characterize the dynamics of output in response to inequality shocks. In the period immediately after joining the European Union (EU) in 1986, Portugal grew at an encouraging growth rate of around 4% per annum, in per capita terms, but in a more recent period, 2000-2007, it has almost stagnated with an average annual growth of real GDP per capita around 0.6%. This dismal aggregate performance was accompanied by an increase in income inequality as measured by the Gini coef-

[1] In most cases for the period 1960-2000.

ficient of income distribution. This paper contributes to the literature by focusing on the experience of a single country, thus avoiding data comparability issues (see e.g. Knowles (2005)), and by exploring time series data that allows to overcome some of the problems of cross section (omitted variable bias) and panel data empirical growth studies (parameter heterogeneity and endogeneity), as pointed out by Gobbin and Rayp (2008). Additionally, it fills a gap in the empirical analysis of economic growth in Portugal by focusing on a growth determinant that is missing in previous studies (see e.g. Teixeira and Fortuna (2004); Teixeira and Fortuna (2010) and Pereira and St Aubyn (2009)) and might be extremely relevant for this specific country. The paper is also original in its application of a SVAR model to study the relationship between inequality, human capital and growth in a developed country, in this case Portugal, using inequality indicators computed by the authors and not from secondary sources. Moreover, inequality indicators based on earnings allow us to measure inequality in Portugal without considering the impact of redistribution policies. Thus these indicators are the most suited to portrait inequality before redistribution, e.g., to the empirical analysis of the fiscal mechanism explaining the relationship between inequality and economic growth.

The paper proceeds as follows. The next section provides a description of the variables used and identifies the respective data sources. In section 3 we present the econometric methodology and results. Section 4 offers some concluding remarks.

2. DATA OVERVIEW

We apply time-series analysis to examine the relationship between inequality and growth in Portugal. For this purpose we use annual data for the period 1985-2007 for three variables: output, y; inequality, I; and human capital/levels of education, E. The choice of the time period was essentially dictated by data availability concerning the earnings distribution measure we use to proxy for inequality in Portugal. The earnings and education data are computed from the *Quadros de Pessoal* (QP) database[2], a rich Portuguese dataset with detailed and comprehensive information on workers and firms, which during this period was the result of an annual compulsory survey conducted by the Ministry of Solidarity and Social Security (MSSS) where firms were required to provide information about their workers on items such as monthly compensation, highest schooling level attained, age, and monthly hours worked. This data was first collected for the year 1985 and continued to be collected by MSSS until 2009. However, we do not include the years 2008 and 2009 in our analysis since these are the years when the global financial and economic crisis started and the consequences on output were particularly serious, especially in 2009. By excluding these two years from our analysis we try to avoid considering years when the evolution of output was dictated by particular events that could hurt the identification of the true long-run influence of inequality on output.

Output, y, is measured as the log of GDP per capita at 2000 prices taken from the European Commission's AMECO database. We analyze the impact of inequality on real output per capita (in logs) and thus on long-term growth, since the latter corresponds to the behavior/growth rate of real output (total – extensive growth; or per capita – intensive growth, the living standards measure more widely used). According to Herzer and Vollmer (2012), one of the problems of previous empirical studies using cross-section or panel data to analyze the relationship between inequality and economic growth is the fact that they consider the output growth rate as the dependent variable and the level of inequality as an explanatory variable. While in most countries the output growth rate tends to remain relatively constant, inequality measures show significant and persistent changes over time. In empirical terms this means that it is not possible to find a long-term relationship between the growth rate of output and the level of inequality over time. Considering stationary and non-stationary variables can lead to misleading results, so it is most appropriate to analyze the relationship between the level of the output (in logs) and the level of inequality. In theoretical terms, the main implication in case of the existence of a relationship between the level of output and the level of inequality is that a change in the level of inequality will have a permanent level effect (on output), but a transitory growth effect that, however, can last for a long time (see e.g. Rao (2010) and Rao, Gounder and Loening (2010)).

Our study considers two variables out of a large number with the potential to influence economic growth (see e.g. Brock and Durlauf (2001)): inequality and human capital, in the form education. The number and type of variables considered is justified for different reasons. First, since the main objective of the paper is to analyze the relationship between inequality and economic growth, given the different transmission channels identified in the theoretical literature (see e.g. Aghion, Caroli and García-Penalosa (1999); Perotti (1996); Barro (2000)), the one that acts through the accumulation of human capital is probably the most relevant for the Portuguese economy based on the historically low levels of schooling of the Portuguese population. Our strategy is thus similar to that of previous studies such as Assane and Grammy (2003), Gobbin and Rayp (2008) or Frank (2009). Furthermore, we analyze a more recent period of the Portuguese economy, during which growth based on diminishing returns to inputs already had produced the bulk of its effects, thus human capital should play an increasingly important role in accordance with the predictions of endogenous growth models, in particular technological diffusion models (see e.g., Teixeira and Fortuna (2004; 2010) and Pereira and St. Aubyn (2009)) that argue that human capital is a crucial input in the creation

[2] Data provided by GEP-MSSS.

of new ideas (inventions), and for the imitation and absorption of existing technologies. Additionally the relatively small number of observations that can be used in the analysis does not recommend the introduction of a large number of variables. Finally, it is difficult to include all relevant variables and estimate with confidence their individual contribution to the level of output due to the high probability of multi-collinearity between variables.

We measure earnings as average full earnings of the employees that performed complete working hours during the month of October of the corresponding year. We excluded workers that earned less than the minimum wage, which corresponds to considering a minimum of 1,424,415 workers in 1985 and a maximum of 2,234,500 in 2007, across 308 geographic units and 17 economic activities. Earnings values were deflated by the harmonized consumer price index (HCPI)[3] for Portugal. Inequality, *I*, is proxied by three different measures of inequality in the distribution of earnings: *G*, the Gini coefficient; *Q*_10_90, the ratio of percentile 10% over percentile 90% of employees earnings; and *Q*_25_90, the ratio of quartile 25% over percentile 90% of employees earnings. A rise in the Gini coefficient is thus equivalent to more inequality, while a rise in each of the percentiles ratios means less inequality. The Gini coefficient captures the impact of changes in the overall earnings distribution; the *Q*_10_90 ratio concentrates on the impact of changes in the left tail of the distribution capturing better the influence of inequality upon growth through the credit markets imperfections channel; and the *Q*_25_90 ratio focuses on the middle of the distribution (it can be considered as a proxy for the size of the middle class) capturing better the growth impact of inequality through the demand for more redistribution predicted by the fiscal policy channel.

The human capital proxy, *E*, corresponds to the logarithm of the Portuguese workforce with at least 12 years of schooling. This proxy was computed based on the statistical information on educational attainment of employees recorded by QP, from where we retrieved the total number of employees with at least 12 years of schooling. Afterwards, we adjusted this value multiplying it by the ratio of the Portuguese total civilian employment (from AMECO database) relative to the total number of employees (from QP data base). This adjustment allows us to control for the effects of a steady increase in the number of firms included in the QP database, assuming that the proportion of the Portuguese workforce with at least 12 years of schooling is similar to the same ratio computed for the employees registered in QP.

The human capital proxy used is considered in levels to which we then applied logarithms. In this way, its impact on output corresponds to an elasticity. Measures of human capital based on the level of education of the workforce used in empirical growth studies are usually defined as a ratio (relative to the working age population). We consider the variable in levels (logs) since this is a country specific study and not cross-country, and so the effects associated with differences in scale between countries are not relevant. On the other hand, we want to emphasize the role of human capital in explaining the behavior of output through technological progress, thus focusing on the effects of the availability of workers with high levels of education (12 years or more), finding it less relevant to control for the composition of the human capital of the workforce according to schooling levels. Furthermore, by introducing the variable in log levels, and not in relative terms, we expect it to present greater variability, which will allow us to capture better the impact of this variable on output.

Finally, concerning our choice of the proxy for the stock of human capital based on educational attainment, this can be considered as representing the human capital available at an aggregate level for current use as an input into production, in line with the importance that growth literature attributes to human capital as a driver of growth and education as its main source (see e.g. Nelson and Phelps (1966), Abramovitz (1986), Lucas (1988), Romer (1990a;1990b); and Jones (1995; 2005)). In this case, the literature on human capital and growth (see e.g. Barro and Lee (2013), Hanushek and Woessmann (2011), Woessmann (2002)), argues that the conceptually more appropriate human capital measures (when it is not possible to control for the quality of education) refer to the schooling levels of the working age population rather than measures such as enrollment rates.

Even though our data refers to Portugal as whole, we believe that it also reflects to some extent regional dynamics. In Andrade, Duarte and Simões (2014) we show, using the same data source for earnings, that the dynamics of earnings inequality in Portugal is determined by its evolution in coastal regions, and so the relationship at the aggregate level between inequality and economic growth is likely to reflect these regional dynamics. A more direct way to consider the regional dimension in the analysis of the relationship between inequality and growth would be to carry out the analysis at the NUTS2 or NUTS3 levels. However, to the best of our knowledge, comparable GDP data at this level of disaggregation is only available from 1995 onwards. Thus, this strategy would allow us to increase the number of observations, but the period covered would be shorter, making inference in terms of the analysis of the long-run relationship between inequality and economic growth in Portugal less robust.

3. ECONOMETRIC METHODOLOGY AND RESULTS[4]

3.1. UNIT ROOT TESTS

As a preliminary step to investigate the link between inequality and growth in Portugal, we test for the order of integration of variables. We examine the unit root properties of

[3] Base year 2000.

[4] In all estimations we follow Pfaff (2008).

the variables in Table 1 that presents the results of the augmented-Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests, since the ADF-tests are known to have low power for highly persistent series. As far as *y* is concerned, the ADF and KPSS tests do not allow for an unambiguous classification. Nevertheless, the KPSS test for the first difference of *y* around a constant and around a constant and a trend does not reject the null of stationarity indicating in this way that *y* is integrated of order one (*I(1)*). As for the inequality measures, *G*, *Q*_10_90 and *Q*_25_90, both tests indicate that they are integrated of order one, *I(1)*. Finally, the proxy for human capital, *E*, can be considered as stationary, in levels, around a trend[5].

TABLE 1. RESULTS FOR THE ADF AND KPSS UNIT ROOTS TESTS

Variable	D	l	t_α	$F_{\alpha,D}$	$KPSS_\tau$	$KPSS_\mu$
y	c,t	1	-2.90	7.27**	0.19*	
y	c	1	-3.21**	6.40**		0.81
dy	c,t	0	-2.91	4.25	0.06***	
dy	c	1	-1.86	2.06		0.47*
G	c,t	0	-3.30*	5.54	0.13**	
G	c	0	-2.04	2.17		0.57*
dG	c,t	0	-5.44***	14.90***	0.05***	
dG	c	0	-5.59***	15.63***		0.08**
*Q*_10_90	c,t	1	-2.56	3.43	0.13**	
*Q*_10_90	c	1	-1.31	1.07		0.54*
*dQ*_10_90	c,t	0	-5.98***	17.97***	0.05***	
*dQ*_10_90	c	0	-3.68**	6.79**		0.12***
*Q*_25_90	c,t	0	-3.18	5.28	0.13**	
*Q*_25_90	c	0	-1.92	1.92		0.52*
d*Q*_25_90	c,t	0	-6.01***	18.13***	0.05***	
d*Q*_25_90	c	0	-6.15***	18.92***		0.11***
E	c,t	2	-5.03***	13.22***	.06***	
E	c	2	0.22	3.93		0.87
dE	c,t	1	-6.68***	23.37***	0.06***	
dE	c	1	-6.92***	24.37***		0.08***

Notes: *d* is the first difference of the variable. Column "D" contains the deterministic components – constant and trend (c,t) and constant only (c). "l" is the number of lags in the ADF equation necessary to eliminate AR errors. t_α is the usual t-test for the null of a unit root and $F_{\alpha,D}$ is an F test for the null of α and the deterministic part. The appropriate critical values are reproduced in Hamilton (1994). "*", "**" and "***" mean rejection at the 10%, 5%, and 1% significance levels, respectively, of the null hypothesis. For the KPSS test we use the short lag determination $(4\dot{n}/100)^{1/4}$, which is equal to 2. "*", "**", and "***" mean it is not possible to reject the null of stationary at the 1%, 5% and 10% significance levels, respectively. *KPSS*τ is the KPSS test with a constant and around a trend and *KPSS*μ is the KPSS test with a constant.

[5] Since the unit root tests show that some series display trending patterns, we allowed for these trends in the econometric analysis. However, the trend was not statistically significant so we dropped it from the analysis.

3.2. EQUATION DYNAMIZATION AND THE LONG-RUN EQUILIBRIUM OF Y

We begin our empirical study of the relationship between inequality and growth by the dynamization of *y*, considering that *y* depends only on one of the inequality measures considered in this paper and education, and restricting this dependency to a maximum of three lags given the limited number of observations. We also derive the corresponding long-run equation.

Table 2 contains the results of applying the Hendry-Krolzig methodology of general-to-specific modelling[6] to the behaviour of *y*. In all three equations, Eq_1, Eq_2, and Eq_3, the relation between output and inequality is negative, conditioned on the positive influence of the level of human capital on output[7].

TABLE 2. DYNAMIC ESTIMATIONS FOR *Y*

	Eq_1	Eq_2	Eq_3
Constant	0.378*** (0.042)		
y_{t-1}	0.660*** (0.056)	0.846*** (0.047)	0.833*** (0.050)
G_{t-2}	-0.841*** (0.200)		
G_{t-3}	-0.657***		
E_{t-1}		0.034** (0.015)	
E_{t-2}	0.042** (0.016)		0.034** (0.016)
E_{t-3}	0.075*** (0.075)		
$Q\_10\_90_{t-1}$		0.401*** (0.068)	
$Q\_25\_90_{t-2}$			0.407*** (0.063)
σ	0.010	0.015	0.014
BIC	-8.594	-8.160	-8.230
AR(1)	1.399	0.878	0.771
ARCH(1)	0.437	0.646	2.031
RESET	1.319	0.299	0.374

Notes: in parenthesis are the coefficients' standard errors. BIC is the Schwarz information criteria; AR(1) is the $\chi^2(1)$, ARCH(1) represent the value of F(1,18), respectively for the LM test of auto-correlation and ARCH; RESET, from power 2 to 3, the test value of F(2,12), F(2,15) and again F(2,15), respectively. "*", "**" and "***" mean rejection at the 10%, 5%, and 1% significance levels, respectively, of the null hypothesis of each coefficient being equal to zero.

[6] See e.g. Campos et al. (2003), Hendry and Krolzig (2003), and Hendry and Krolzig (2005).

[7] The usual CUSUM test allows us to reject the possibility of structural change during the period under analysis in all the equations. See e.g. Ploberger and Krämer (1992). These results are available from the authors.

Table 3 contains the long-run equations corresponding to the dynamic equations in Table 2, confirming the short-run results of a negative influence of inequality on output, whatever the inequality measure used, and a positive impact for education. This last result is in line with the predictions of growth models known as endogenous, in which the main source of growth is technological change, and human capital is considered fundamental for knowledge production. In the models of Romer (1990) and Jones (1995; 2005), for instance, human capital is essential for the production of new ideas, while in the models of Nelson and Phelps (1966), Abramovitz (1986), and Barro and Sala-i-Martin (1997) human capital is a key determinant of the ability to absorb new technologies by economies more distant from the technological frontier. For these economies to be able to carry out imitation activities and thus overcome their technological backwardness, they need a workforce that can incorporate, adapt and use new technologies. For the specific case of Portugal, Teixeira and Fortuna (2004; 2010) and Pereira and St. Aubyn (2009) also confirm the importance of human capital in the form of education for growth, and in the case of the first two authors specifically through the technological improvement channel.

The negative impact of inequality on growth obtained is consistent with three main arguments. The fiscal or political economy approach channel is based on the interplay of two mechanisms, the political mechanism and the economic mechanism (see e.g. Bertola (1993); Alesina and Rodrik (1994), and Persson and Tabellini (1994)). The political mechanism states that in more unequal societies the median voter will vote for higher levels of taxation and government expenditure. These introduce distortions which will in turn discourage private investment, hindering in this way economic growth – the economic mechanism. The credit markets imperfection approach, also known as the borrowing constraints in human capital investments channel, explains the relationship between inequality and growth based on the analysis of investments in human capital, that foster growth, when there are imperfections in credit markets. Only those individuals that have a high enough initial level of wealth are able to invest in human capital because borrowing is costly and difficult. Thus, an economy with a less unequal wealth distribution will register faster growth because it invests more in human capital (see e.g. Galor and Zeira (1993)). The social-political instability channel argues that in more unequal societies individuals are more likely to be involved in activities that act as a disincentive to private investment, such as violent protests against the regime, coups or criminal activities, which in turn hinders capital accumulation and thus growth (see e.g. Alesina and Perotti (1996) and Perotti (1996)). We believe however that for the period under analysis this channel was less likely to occur in Portugal.

A recent study by Herzer and Vollmer (2012), applying panel cointegration techniques to a sample of 46 countries over the period 1970-1995, concludes also for a negative long-run relationship between inequality and per capita income, a result that remains unchanged regardless of the consideration of different sub-samples: rich vs. poor countries and democracies vs. non-democracies.

TABLE 3. LONG-RUN ESTIMATIONS FOR Y

	Eq_1	Eq_2	Eq_3
Constant	1.110*** (0.169)		
G	-4.402*** (0.623)		
E	0.343*** (0.025)	0.221*** (0.036)	0.203*** (0.038)
Q_10_90		2.595*** (0.763)	
Q_25_90			2.445*** (0.647)
Long Run σ	0.030	0.095	0.085
Wald	188.03***	4989.5	6346.9***

Notes: in parenthesis are the coefficients' standard errors. Wald is the value of the χ^2 statistic for the Wald test of the null of the coefficients. "*", "**" and "***" mean rejection at the 10%, 5%, and 1% significance levels, respectively, of the null hypothesis of each coefficient being equal to zero.

3.3. VAR AND SVAR MODELLING OF THE INEQUALITY-GROWTH RELATIONSHIP

The previous analysis considers a model with just one equation to describe the relationship between inequality, education and growth. This kind of specification suffers from a serious drawback: it does not take into account the interdependency among variables. It is widely accepted that empirical growth studies suffer from endogeneity problems and the difficulty of finding adequate instruments (see e.g. Durlauf, Jonhson and Temple (2005)). Suitable external instruments are hard to find given the variety of possible growth influences and the explanatory variables may be highly persistent so that the use of the respective lagged values as instruments (internal instruments) makes them weak instruments. As Gobbin and Rayp (2008) argue, VAR models are a suitable framework to address these issues since they do not require the identification of exogenous/endogenous variables and consequently they are most adequate to model interdependent variables. However, although classical VAR models are useful when we want to take into account interdependencies and dynamic relationships between variables, they lack an underlying economic structure, so VAR models evolved in the sense of incorporating *a priori* information on the behavior of the variables under analysis. While VAR models explain the behavior of endogenous variables by their own past values, SVAR models allow for the presence of contemporaneous interdependencies between endogenous variables (see Breitung et al. (2004)).

A structural form of a VAR (SVAR) model of order k can be defined as,

$$AX_t = A_1^* X_{t-1} + ... + A_p^* X_{t-p} + Be_t \quad (1)$$

where X_t is a vector of k variables, comprised in this case of the variables y, I, and E; A_i, $i = 1,\ldots,p$ is the coefficient matrix; A_t are the structural coefficients and ε_t the structural errors, assumed white noise.

We can pre-multiply (1) by A^*, with $A_i = A^{-1} \cdot A^*$, to get:

$$\mu_t = A^{-1} B \varepsilon_t \quad (2)$$

where μ_t is a vector of order k with expected value $E(\mu_t)' = 0$ and the covariance matrix $E(\mu_t \cdot \mu_t^T) = \sum_\mu$ is time invariant positive definite.

Equation (2) is in turn equivalent to:

$$A \cdot \mu_t = B \cdot \varepsilon_t \quad (3)$$

where the elements of A and B are defined as $a_{i,j}$ and $b_{i,j}$, respectively.

We consider a SVAR model where the structural shocks are assumed to be independent, so $B = I_k$ [see Pagan (1995)]. The number of restrictions for exact identification is $\frac{k \cdot (k-1)}{2}$.

The parameters are estimated by minimization of the negative of the concentrated log-likelihood function, equation (4):

$$\ln Lc(A,B) = \frac{-kT}{2}\ln(2\pi) + \frac{T}{2}\ln|A|^2 - \frac{T}{2}\ln|B|^2 - \\ -\frac{T}{2} tr(A^T (B^{-1})^T B^{-1} A \Sigma_\mu) \quad (4)$$

where Σ_μ is an estimate of the reduced form covariance matrix of the error process.

We consider the following structural prior information for the analysis of output (y), inequality (I) and levels of education (E), in order to identify the structural residuals:

$$\mu^y = a_{1,2} \cdot \mu^I + a_{1,3} \cdot \mu^E + b_{1,1} \cdot \epsilon^y \quad (5)$$

$$\mu^I = b_{2,2} \cdot \epsilon^I \quad (6)$$

$$\mu^E = a_{3,2} \cdot \mu^I + b_{3,3} \cdot \epsilon^E \quad (7)$$

where ϵ^y, ϵ^I and ϵ^E will be defined as supply, distribution and human capital shocks, respectively, in order to distinguish them from the shocks in the reduced-form VAR models. The structural residuals are thus obtained by imposing the following restrictions: output is dependent on a supply (structural) shock, on inequality and on education shocks (see e.g. Galor and Zeira (1993), Alesina and Perotti (1994; Alesina and Perotti (1996), and Galor (2000)); inequality is assumed to depend only on a distribution (structural) shock, an assumption based on the specificities of the Portuguese economy during the period under analysis when changes in inequality were due mainly to institutional shocks[8]; and education is dependent on a human capital (structural) shock and on inequality, based on the predictions from growth models that analyze the impact of inequality on output through its effects on human capital briefly reviewed in the introduction[9]. The system composed of equations (5), (6) and (7) is exactly identified[10].

The different estimated VAR models are identified as M1, M2 and M3, respectively, when considering the variables y, G and E (M1); y, Q_10_90 and E (M2); and y, Q_25_90 and E (M3). Due to our relatively short data sample (1985-2007) and the well-known problem of over-parameterization in VAR models, we also estimate Near-VAR models where the variables retained are selected based on the estimated parameters t-values[11]. The corresponding restricted Near-VAR models are thus represented by M1R, M2R and M3R, respectively. All models include a constant term.

We have to guarantee[12] that we select a correctly specified VAR (or Near-VAR) model in the three variables y, I and E, that is a VAR with the right properties in terms of stability[13], adequate behavior of residuals in terms of normality, ARCH and serial correlation, and also one for which we can reject the hypothesis of a structural change in the parameters values.

Table 4 presents the results of the different specification tests based on the errors of each estimated equation. The roots of the companion matrix of the different VAR and Near-VAR models are in the unit-circle[14] except for model

[8] For instance, still associated with the political revolution of April 1974 following which the minimum wage was first set in May 1974.

[9] Important institutional changes affected Portugal over the period 1985-2007. For instance, in 1986 it became mandatory for children to have the first 9 years of the formal education system. These are reflected in the structural shock or human capital shock.

[10] We tested other restrictions but these were the ones that produced the best results. Results are available from the authors upon request.

[11] We retain the variables for which the estimated coefficients present a t-value greater than or equal to 2.0.

[12] We first tested for the optimal lag order of the VAR using the Schwarz Bayesian criterion (SBC). The results point to an optimum lag order of the VAR and Near-VAR models of four. These results also point to model M3R, that uses Q_25_90, as the best model, based also on the inspection of the actual and fitted values of the variables (very similar), and the behaviour of the errors (no autocorrelation). This result makes it more likely that the inequality-growth relationship in Portugal is mainly explained by the fiscal approach according to which the median voter (proxied by Q_25_90) plays an essential role leading us to expect a negative impact of inequality on output. Nevertheless, the SBC values for model M2 are the best across the three VAR models and the values for the Near-VAR models M2R and M3R are very similar, an indication that the credit markets imperfection channel might also be a relevant mechanism in the explanation of the inequality-growth relationship in Portugal. All these results are available in the working paper version of this article, Andrade, Duarte and Simões (2011).

[13] The VAR (Near-VAR) is stable if the absolute values of all eigenvalues of the system matrix lie on or inside the unit circle (see equation (2)).

[14] For economy of space reasons these results are not presented in the paper but are available from the authors.

M1R. We detect no serious problems for the VAR and Near-VAR models in terms of auto-correlation, ARCH process, functional misspecification and normality. In any case, for model M1R we reject the null hypothesis of correct specification at the 10% significance level in the inequality equation. For model M2, we cannot reject the null hypothesis of auto-correlation of the residuals in the inequality equation at the 10% significance level and also the null hypothesis of the presence of ARCH in the output equation at the 5% significance level. As for model M2R, we cannot reject the null hypothesis of the presence of ARCH in the education equation at the 5% significance level. For model M3, we cannot also reject the null hypothesis of auto-correlation of the residuals in the inequality equation at the 5% significance level. Finally, for model M3R we cannot reject the null hypothesis of auto-correlation of the residuals in the education equation at the 10% significance level, and also the null hypothesis of the presence of ARCH at the 5% significance level in this same equation[15].

TABLE 4. SPECIFICATION TESTS RESULTS

	M1	M1R	M2	M2R	M3	M3R
AR1						
y	2.24	0.97	1.40	1.08	1.32	0.25
I	2.96	0.99	4.50*	1.75	10.12**	1.44
E	0.00	0.03	3.93	3.73	2.03	4.17*
ARCH						
y	1.23	0.29	5.68**	0.16	0.65	0.85
I	1.21	1.93	0.37	0.31	0.98	0.01
E	2.25	0.97	2.26	4.77**	0.96	5.39**
RESET						
y	2.83	1.23	2.22	1.30	1.55	1.06
I	0.88	3.06*	1.33	0.27	0.91	1.27
E	2.15	1.21	0.31	0.34	0.57	0.21
Normality						
y	1.47	4.17	2.37	1.83	1.62	1.16
I	0.80	1.42	0.02	1.89	0.77	2.09
E	3.38	1.43	0.02	0.12	0.25	1.45

Notes: AR1, ARCH and RESET from powers 2 to 3 are F statistics and Normality (Jarque-Bera) is a χ^2 statistic.

We next tested for the presence of Granger and instantaneous causality between the variables since, when testing for Granger causality, in the case of non-stationarity the usual asymptotic distribution of the test statistic may not be valid under the null hypothesis. The test for Granger causality is a *F*-type test for block exogeneity. The test for instant causality is a Wald-type test for nonzero correlation between the error processes of the cause variable and effect variables in the model. The null hypothesis in both tests is non-causality. Table 5 presents the results of both tests. As far Granger causality is concerned, with the exception of model M1, for which output does not Granger-cause inequality and education, every variable in the different models has a role causing the other variables involved in that same model. As for instantaneous causality, in model M1 education does not instantaneously cause output and inequality and in model M2 output does not cause inequality or education. In all the other models causality between the different variables applies.

TABLE 5. GRANGER AND INSTANTANEOUS CAUSALITY TESTS

	Non Causality	Granger	Instantaneous
M1	$y \nRightarrow G, E$	1.45	5.27*
M1	$G \nRightarrow y, E$	3.75***	6.53**
M1	$E \nRightarrow y, G$	8.19***	4.12
M2	$y \nRightarrow Q\_10\_90, E$	4.36**	2.88
M2	$Q\_10\_90 \nRightarrow y, E$	7.05***	5.70**
M2	$E \nRightarrow y, Q\_10\_90$	6.08***	6.20**
M3	$y \nRightarrow Q\_25\_90, E$	3.69**	4.97*
M3	$Q\_25\_90 \nRightarrow y, E$	9.27***	6.80**
M3	$E \nRightarrow y, Q\_25\_90$	8.39***	6.99**

Notes: For the Granger causality test we have a F(8,18) statistic value and for the instantaneous causality test a χ^2 (2) statistics value.

In order to shed additional light on the relationship and forecasting ability of the variables in our model we also perform a variance decomposition analysis. The variance decomposition indicates how much of the forecast error variance of each variable can be explained by exogenous shocks to the variables in the same VAR or Near-VAR models with innovations to an individual variable having the possibility to affect both own changes and changes in the other variables. Analysing the decomposition of the variance (Table 6) the idea retained is that all variables have a significant role on the different models. However, education has a minor role on the explanation of y and I (see e.g. models M2, M2R, M3 and M3R). The results do not change much when considering VAR relative to Near-VAR models. Taking into account the gains associated with the extra degrees of freedom obtained with the Near-VAR models we are convinced that the costs associated with the relatively small number of observations of our sample are in this way mitigated.

[15] We also tested for the stability of the regression coefficients according to the test proposed by Ploberger and Krämer (1992). The respective OLS-CUSUM test results do not allow us to reject the null hypothesis of no-structural change in any of the equations of the different models. These results are available in the working paper version of this article.

TABLE 6. VARIANCE DECOMPOSITION (%) FOR THE VAR AND NEAR-VAR MODELS TWENTY YEARS AFTER A SHOCK

	M1			M2			M3		
Equations:	y	I	E	y	I	E	y	I	E
y	63	31	5	58	41	2	56	42	2
I	46	39	15	37	59	4	45	51	4
E	30	23	47	37	50	13	42	43	15
	M1R			**M2R**			**M3R**		
y	49	45	6	59	40	1	55	44	1
I	31	52	16	37	60	3	46	49	5
E	23	34	43	41	52	7	43	45	12

Notes: The equations are presented in the first column.

To determine and better understand the relationship between inequality and growth with our empirical model we have to estimate it in order mainly to identify the sign and the significance level of the coefficients $a_{1,2}$ and $a_{3,2}$, that give the impact of inequality on output and education, respectively, and the response of the different variables to shocks, especially distribution shocks. In order to do this we estimate structural VAR (SVAR) models based on the corresponding VAR and Near-VAR models and identify these models with the suffix "S". The structure of the errors is given by equations (7), (8) and (9). In some situations we can restrict certain structural parameters to equal zero and present a LR test of these restrictions.

Table 7 presents the results for the models with the Gini coefficient and is divided in two parts. The first part of the table presents the estimated coefficients of matrix *A* and the corresponding asymptotic t-values (see equation (5)). In the second part of the table we present the estimates of the coefficients of matrix $A^{-1}\cdot B$ (see equation (4)[16]). As we can see, a distribution shock has a negative impact on output and a positive impact on the level of education. These same conclusions apply for both VAR and Near-VAR based SVAR models. In model SM1 and model SMIR we find a positive impact of a human capital shock on output. Since the *t*-values of coefficient $a_{1,3}$ in the VAR and Near-VAR models are quite low we restrict the coefficient in both models to equal zero. This restriction is not rejected ($\chi^2(2)$=0.451 and 1.856, respectively) and so we present the corresponding estimated structural coefficients as the values of A^1 in Table 8[17]. The previous conclusion of a negative impact of a distribution shock on output is confirmed. We also detect in model M1O a positive impact of a human capital shock on output, but in model SM1RO there is no impact. The positive growth impact of a human capital shock confirms the predictions of endogenous growth models on its importance for knowledge production in the Portuguese economy. The negative impact of distribution on output supports the need for less inequality in Portugal as a means to promote economic growth and is again consistent with both the fiscal approach and the credits market imperfections channels described before. In order to get a clearer idea on which one is more likely to apply, in what follows we consider in our estimations the two alternative inequality measures we computed, the ratios *Q*_10_90 and *Q*_25_90. The first ratio concentrates on inequality at the bottom of the distribution that can be especially harmful for human capital accumulation, preventing poor but talented individuals from investing in education. The second ratio proxies for the size of the middle class, the median voter in political economy models that influences the size of redistribution.

TABLE 7. STRUCTURAL PARAMETERS FOR THE MODELS WITH THE GINI COEFFICIENT

SM1 (A)			SM1R (A)		
169.46	56.85	-2.37	250.84	81.20	-6.91
(6.16)	(2.87)	(0.67)	(6.16)	(3.05)	(1.36)
0	65.61	0	0	81.01	0
	(6.16)			(6.16)	
0	-38.89	15.27	0	-59.68	21.58
	(2.38)	(6.16)		(2.85)	(6.16)
SM1 (100xA^{-1})			**SM1R (100xA^{-1})**		
0.590	-0.457	0.091	0.399	-0.306	0.128
0	1.524	0	0	1.234	0
0	3.880	6.546	0	3.414	4.63

TABLE 8. STRUCTURAL PARAMETERS FOR THE OVER-IDENTIFIED MODELS WITH THE GINI COEFFICIENT

SM1O (A)			SM1RO (A)		
167.46	50.22	0	238.88	59.12	0
(6.16)	(2.93)		(6.16)	(2.83)	
0	65.61	0	0	81.01	0
	(6.16)			(6.16)	
0	-38.89	15.27	0	-59.68	21.58
	(2.38)	(6.16)		(2.85)	(6.16)
SM1O (100xA^{-1})			**SM1RO (100xA^{-1})**		
0.597	-0.457	0.091	0.419	-0.305	0
0	1.524	0	0	1.234	0
0	3.880	6.546	0	3.414	4.634

Table 9 presents the results for the VAR and SVAR models that use the ratio *Q*_10_90 as the inequality measure. These results correspond to the over-identified models, respectively SM2O and SM2R1O, since for both VAR and

[16] Since *B* is an identity matrix this is the same as A^{-1}.

[17] For instance, in the model identified as SM1RO, "S" stands for SVAR, "M1" for a M1 type model in terms of variables, "R" for a Near-VAR, and finally "O" because we have changed equations (7), (8) and (9) describing the errors of the model according to the restrictions imposed on the coefficients and the model is now over-identified.

SVAR models the *t*-values for the coefficients $a_{1,2}$ and $a_{1,3}$ are quite small and it was not possible to reject the null hypothesis that a_{12} and a_{13} are both equal to zero (the results of the LR test of the joint restriction are, respectively, $\chi^2(1)$=3.746 and 4.160). As we can see, both a distribution shock (corresponding to more inequality)[18] and a human capital shock have no impact on output. As before however, a distribution shock has a negative impact on education so that in this case less inequality (now corresponding to a rise in *Q*_10_90) leads to less education. Our preliminary idea that the credits markets imperfection channel might be a relevant mechanism to explain the influence of inequality on output in the Portuguese economy is thus not confirmed.

TABLE 9. STRUCTURAL PARAMETERS FOR THE OVER-IDENTIFIED MODELS WITH *Q_10_90*

SM2O (A)			SM2RO (A)		
132.75	0	0	203.52	0	0
(6.16)			(6.16)	(2.83)	
0	54.57	0	0	82.15	0
	(6.16)			(6.16)	
0	47.30	26.96	0	81.68	46.80
	(3.22)	(6.16)		(3.54)	(6.16)
SM2O (100xA^{-1})			**SM2RO (100xA^{-1})**		
0.753	0	0	0.491	0	0
0	1.832	0	0	1.217	0
0	-3.215	3.709	0	-2.125	2.137

Table 10 presents the results for the VAR and Near-VAR models, M3 and M3R, respectively that consider *Q_25_90* as the inequality measure, with some additional restrictions. For both VAR and SVAR models the *t*-values of the coefficients $a_{1,2}$ and $a_{2,3}$ are quite small but it was possible to reject the null hypothesis that $a_{1,2}$ and $a_{2,3}$ are both equal to zero at the 1.6% and 0.5% levels of significance for the VAR and the Near-VAR models, respectively. Since the restriction that $a_{1,3}$ alone equals zero is not rejected (the results of the LR test of the joint restriction are, respectively, $\chi^2(1)$=1.951 and 2.150, respectively), we estimate the corresponding SM3O and SM3RO over-identified models. These are the results presented in Table 10. The coefficient estimates show a negative impact of a distribution shock on output and a positive one on education, confirming the results obtained with the Gini coefficient (see Tables 7 and 8). The first result seems to confirm our preliminary idea that the fiscal channel is a relevant mechanism to explain the influence of inequality on output in the Portuguese economy.

TABLE 10. STRUCTURAL PARAMETERS FOR THE OVER-IDENTIFIED MODELS WITH *Q_25_90*

SM3O (A)			SM3RO (A)		
176.01	-27.96	0	294.41	-51.05	0
(6.16)	(2.51)		(6.16)	(2.87)	
0	44.37	0	0	68.62	0
	(6.16)			(6.16)	
0	47.84	25.42	0	84.85	43.31
	(3.74)	(6.16)		(4.07)	(6.16)
SM3O (100xA^{-1})			**SM3RO (100xA^{-1})**		
0.568	0.358	->0	0.340	0.253	->0
0	2.254	->0	0	1.217	->0
0	-4.241	3.934	0	-2.125	2.310

Notes: '->0' stands for infinitesimal values.

From the estimation of the SVAR models with the different inequality measures it is possible to highlight two results. A distribution shock corresponding to an increase in inequality has a negative impact on output (except for the models that use the *Q*_10_90 ratio, when it has no impact) and has a positive impact on education. The latter result indicates that inequality can be considered as a premium on education: at the individual level more earnings inequality means a higher opportunity cost of the no(more)-education decision[19]. The rationale for the first result might lie in the corrective policy measures aimed at reducing the rise in inequality that will influence decisions affecting labour supply[20] and reducing investment, since they are most likely financed by taxes with the associated distortionary effects. However, the results also point to a non-negative impact of education on output, as predicted by economic theory. We thus have to reconcile the results of a positive effect of inequality on education and this non-negative effect of education on output with the result of a negative effect of inequality on output. In order to get an idea of the global impact of inequality on output, the main goal of this paper, we conducted an impulse response analysis since it takes into consideration the interactions between all the variables.

3.4. IMPULSE RESPONSE ANALYSIS BASED ON THE NEAR-VAR AND SVAR MODELLING

The impulse response analysis shows how a one standard deviation innovation in one of the variables of the model

[18] Recall that when measuring inequality using the ratios *Q*_10_90 and *Q*_25_90, it is a decrease in either that corresponds to more inequality, contrary to what happens when using the Gini coefficient as the inequality measure. Thus the relevant estimated coefficients should have opposite signs in these cases in order to allow us to reach the same conclusion on the growth impact of inequality.

[19] This is also in line with the fact that, in the past, low qualified Portuguese workers recorded low unemployment rates and earnings differentials between workers that completed secondary schooling and those that did not were, in Portugal, comparatively low. Thus less educated workers did not recognize the true long-run value of investing in education (see Carneiro (2014)). If however earnings inequality rises this can constitute an incentive to invest in education in Portugal.

[20] For instance, individuals/workers will not invest as much in human capital since they will expect higher income taxes.

affects the contemporaneous and future values of all endogenous variables in that same model. In Figures 1 and 2 we present the impulse response functions for the Near-VAR model M3R and for the structural version of model M3, model M3RO. Both models use *Q_25_90* as the inequality measure.[21]. We only describe and analyze the results for model M3RO (Figure 2) since the results of the impulse response functions analysis are not substantially different across the two models.

FIGURE 1. RESPONSES TO SUPPLY, INEQUALITY AND HUMAN CAPITAL SHOCKS IN MODEL M3R (VAR ORTHOGONAL IMPULSE RESPONSES)

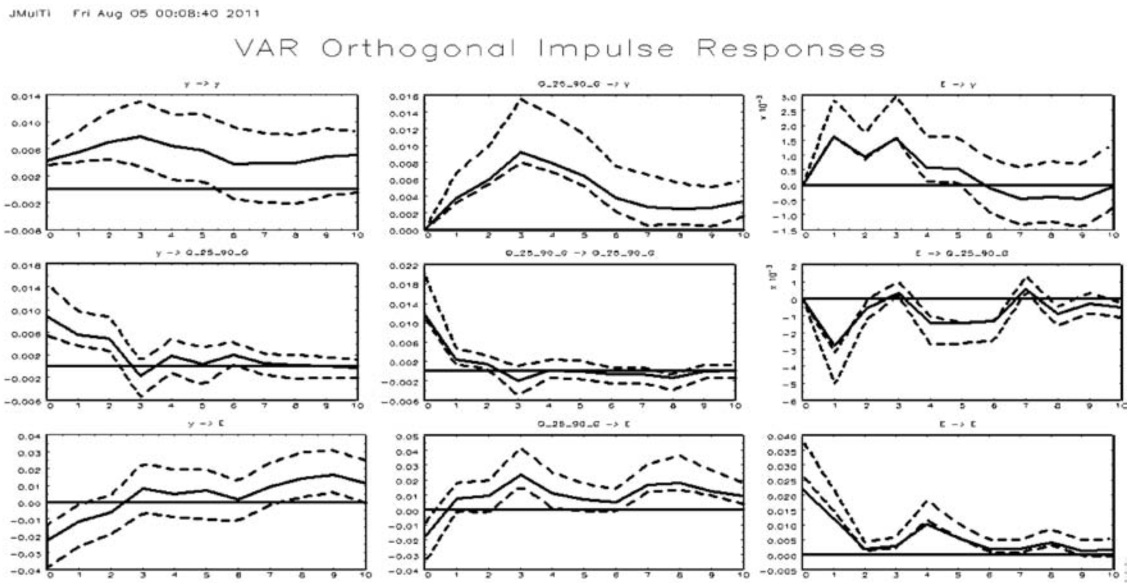
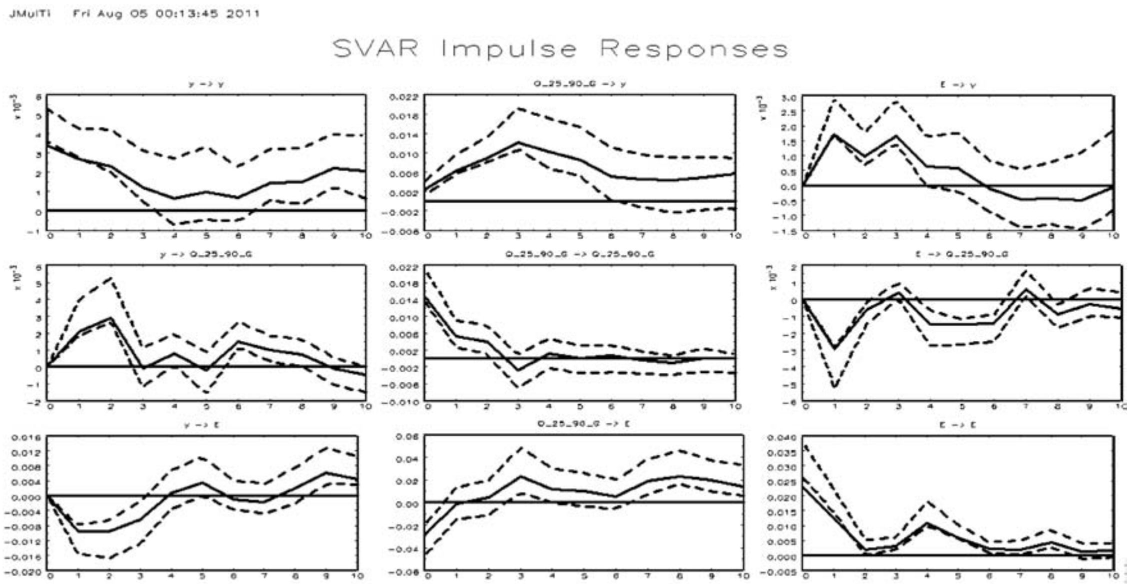


FIGURE 2. RESPONSES TO SUPPLY, INEQUALITY AND HUMAN CAPITAL SHOCKS IN MODEL SM3RO (SVAR IMPULSE RESPONSES)



The main results concerning the impact of each of the three possible structural shocks are:

a. a supply shock has: (i) a persistent positive impact on output, as expected; (ii) a negative impact on earnings inequality (*Q*_25_90 rises so there is less inequality) – according to the lower confidence interval (c.i.) this effect vanishes after 3 years but the response values shows that there is still a reduction in inequality 9 years after the shock; (iii) a negative effect on the level

[21] The 90% confidence intervals correspond to Hall's percentile interval calculated with 100 bootstrap replications (Hall (1992)).

of education during 1 to 3 years, but after 8 years it has an unambiguous positive effect[22];

b. a distribution shock, corresponding to a reduction in inequality, has: (i) a clearly positive effect on output for at least 8 years; (ii) a positive impact on *Q*_25_90 (inequality decreases) that vanishes right after 2-2.5 years; (iii) a negative impact on education during the first year, followed by a null effect (see the lower c.i.), but after 6 years it becomes positive and remains so for the next 4-5 years, which is probably a consequence of the effect of the distribution shock on output;

c. a human capital shock has: (i) a clearly positive impact on output during the first 4 years becoming null afterwards (see the lower c.i.); (ii) a clearly negative impact on *Q*_25_90 (inequality increases) during the 2 first years, and after a null effect during the third year, the effect becomes negative again for the next 6-7 years. The persistence of this human capital shock on education is obviously important, lasting for as long as 9 years, even though, as time goes by, the quantitative impact becomes much lower than the initial impact.

Taking into account the interdependency between the variables by analyzing the respective impulse response functions thus confirms the negative effect of a distribution shock (increased inequality) on output and a long run positive effect of a distribution shock on education.

4. CONCLUSIONS

This study examined the impact of earnings inequality on output in Portugal in order to contribute to the ongoing debate on the relationship between inequality and economic growth. To achieve this goal we conducted a time series analysis of the relationship between output, earnings inequality and education over the period 1985-2007, using different time series econometric methodologies: the Hendry-Krolzig general-to-specific reduction methodology; VAR and Near-VAR modeling; Granger and instantaneous causality; and the structural VAR approach with the associated impulse response analysis.

The results suggest that earnings inequality has a negative impact on output supporting in this way the view that inequality is detrimental to growth. This result does not seem to depend on the time series methodology applied. For instance, the long-run equation for output, obtained with the Hendry-Krolzig general-to-specific reduction methodology, shows a negative relationship between earnings inequality and output. Additionally, the VAR and Near-VAR analysis indicates that there is a high level of interdependency among the three variables in our models, output, earnings inequality and education. These results thus seem to support the use of this type of models to overcome endogeneity problems in empirical growth studies.

The analysis based on the corresponding structural models (SVAR analysis), found that in the models with the Gini coefficient and the *Q*_25_90 ratio there is a negative relationship between distribution shocks (increased inequality) and output and a positive relationship between distribution shocks and education. Only the latter conclusion applies in the model with *Q*_10_90. Finally, taking into account the interdependency between the variables by analyzing the respective impulse response functions, we confirmed the negative effect of a distribution shock (increased inequality) on output and a long run positive effect of a distribution shock on education. As for the direction of causality, this seems to run mainly from inequality to growth and not the other way around.

As far as education is concerned, the evidence does not support the theoretical prediction that more inequality reduces human capital accumulation, pointing in fact in the opposite direction: an increase in earnings inequality, corresponding in our models to a distribution shock, results in more educated workers, an indication that inequality acts as an incentive for individuals to belong to the richer parts of society, which can only be achieved by investing in human capital.

In summary, the results obtained point to a negative global influence of inequality on output, that however does not seem to be explained by the prediction of the credits markets imperfections channel which argues that more inequality leads to less human capital accumulation and thus slower growth. Our preferred explanation for this negative impact is thus that suggested by the fiscal policy channel: more inequality implies more redistribution, with the associated distortionary effects from taxes on investment. Corrective policy measures aimed at reducing the rise in inequality may thus influence decisions that will affect, in a negative way, investment and production opportunities.

Further research, as more data becomes available, should focus on extending the time period analyzed and considering alternative inequality measures relative to the distribution of income or the distribution of education.

ACKNOWLEDGEMENTS

We are grateful to two anonymous referees for excellent suggestions that considerably improved this paper and to conference participants at the 10th EEFS and 5th PEJ Annual Meetings for valuable comments. Any remaining errors are the sole responsibility of the authors. Financial support from the Fundação para a Ciência e a Tecnologia (FCT) of the Portuguese Ministry of Science under the project PTDC/ECO/71326/2006 is also gratefully acknowledged.

[22] We are convinced that the effect of the supply shock on inequality (a decrease) is responsible for the negative effect on impact on education.

REFERENCES

Abramovitz M. (1986). Catching up, forging ahead and falling behind. *Journal of Economic History*, vol. 46, pp. 385-406.

Aghion P., Caroli E., García-Penalosa C. (1999). Inequality and economic growth: The perspective of the new growth theories. *J Econ Lit* 37 (4):1615-1660. doi:10.1257/jel.37.4.1615

Alesina A., Perotti R. (1994). The political economy of growth: A critical survey of the recent literature. *World Bank Econ Rev* 8 (3): 351-371.

Alesina A., Perotti R. (1996). Income distribution, political instability, and investment. *Europ Econ Rev* 40 (6): 1203-1228.

Andrade, J. S., Duarte, A., Simões, M. (2011). Inequality and growth in Portugal: a time series analysis. *GEMF Working Papers Series* No. 2011-11.

Andrade, J. S., Duarte, A., Simões, M. (2014). Earnings and education in Portugal, 1985-1991. *Int J Soc Econ*, 41(7).

Assane, D., Grammy A. (2003). An assessment of the growth and inequality causality relationship. *Appl Econ Lett* 10 (14):871- 873. doi:10.1080/13504850310001635249

Balisacan, A. M., Fuwa, N. (2003). Growth, inequality and politics revisited: A developing-country case. *Econ Lett* 79:53-58. doi:10.1016/S0165-1765(02)00287-2

Banerjee, A. V., Duflo, E. (2003). Inequality and growth: What can the data say? *J Econ Growth* 8 (3): 267-299.

Barro, R. J. (2000). Inequality and growth in a panel of countries. *J Econ Growth* 5 (1): 87-120.

Barro, R., Lee, J.-W. (2013). A new dataset of educational attainment in the world, 1950-2010. *J of Dev Econ*, 104 (September): 184-198.

Barro, R. J., Sala-i-Martin, X. (1997). Technological diffusion, convergence, and growth. *Journal of Economic Growth*, vol. 2, pp. 1-26.

Breitung, J., Brüggemann, R., Lütkepohl, H. (2004). Structural vector autoregressive modelling and impulse responses. *In*: Lütkepohl, H., Krätzig, M. (eds.), *Applied Time Series Econometrics*. C.U.P., Cambridge, pp. 159-196. doi:10.1017/CBO9780511606885.005

Brock, W. A., Durlauf, S. N. (2001). Growth empirics and reality. *World Bank Econ Rev* 15(2): 229-72.

Campos, J., Hendry, D. F., Krolzig, H.-M. (2003). Consistent model selection by an automatic gets approach. *Oxford Bull Econ Statist* 65 (supplement): 803-819. doi:10.1046/j.0305-9049.2003.00092.x

Carneiro, P. (2014). A educação em Portugal numa perspetiva comparada: factos e prioridades de política. In Alexandre et al. (eds.). *A Economia Portuguesa na União Europeia: 1986-2010*, Coimbra: Almedina.

Chen BL (2003), An inverted-u relationship between inequality and long-run growth. *Econ Lett* 78 (2): 205-212. doi:10.1016/S0165-1765(02)00221-5

Deininger, K., Squire, L. (1998). New ways of looking at old issues: Inequality and growth. *J Devel Econ* 57 (2):259-287. doi:10.1016/S0304-3878(98)00099-6

Dominics, L., Groot, H., Florax, R. (2008). A meta-analysis on the relationship between income inequality and economic growth. *Scottish J Pol Econ* 55 (5): 654-682. doi:10.1111/j.1467-9485.2008.00470.x

Durlauf, S., Johnson, P. A., Temple, J. Growth econometrics. In *Handbook of Economic Growth*, Aghion, P. and Durlauf, S. (eds.), Chapter 8, 555-677. Amsterdam: North-Holland, 2005.

Forbes, K. (2000). A reassessment of the relationship between inequality and growth. *Am Econ Rev* 90 (4): 869-887.

Frank, M. W. (2009). Income inequality, human capital, and income growth: Evidence from a state-level VAR analysis. *Atlantic Econ J* 37: 173-185.

Galor, O. (2000). Income distribution and the process of development. *Europ Econ Rev* 44 (4-6): 706-712. doi:10.1016/S0014-2921(99)00039-2

Galor, O., Zeira, J. (1993). Income distribution and macroeconomics. *Rev Econ Stud* 60: 35-52.

Gobbin, N., Rayp, G. (2008). Different ways of looking at old issues: A time-series approach to inequality and growth. *Appl Econ* 40 (7): 885-895.

Hall, P. (1992). *The Bootstrap and Edgeworth Expansion*. Springer, New York.

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton University Press, New Jersey.

Hanushek, E., Woessmann, L. (2011), How much do educational outcomes matter in OECD Countries? *Econ Policy*, 26 (67): 427-491.

Hendry, D. F., Krolzig, H.-M. (2003). New developments in automatic general-to-specific modeling, chapter 16. *In*: Stigum, B. P. (ed.). *Econometrics and the Philosophy of Economics: Theory-Data Confrontations in Economics*. Princeton University Press, Princeton, pp. 379-419.

Hendry, D. F., Krolzig, H.-M. (2005). The properties of automatic gets modelling. *Econ J* 115 (502): C32-C61.

Herzer, D., Vollmer, S. (2012). Inequality and growth: evidence from panel cointegration. *J Econ Ineq* 10: 489-503.

Jones, C. I. (1995). R&D-based models of economic growth. *Journal of Political Economy*, vol. 103, pp. 759-784.

Jones, C. I. (2005). Growth and ideas. *In*: Aghion, P. & Durlauf, S. (eds.). *Handbook of Economic Growth*. Amsterdam: North-Holland.

Knowles, S. (2005). Inequality and economic growth: The empirical relationship reconsidered in the light of comparable data. *J Devel Stud* 41 (1): 135-159. doi:10.1080/0022038042000276590

Kuznets, S. (1955). Economic growth and income inequality. *Am Econ Rev* 45:1-28.

Lucas, R. (1988), On the mechanics of economic development. *J Mon Econ*, 22(1): 3-42.

Nelson, R. R., Phelps, E. S. (1966). Investment in humans, technological diffusion and economic growth. *American Economic Review*, vol. 56, pp. 69-75.

Pagan, A. (1995). Three econometric methodologies: An update. *In*: Oxley, L. T., George, D. A. R., Roberts C. J., Sayer, S. (eds.). *Surveys in Econometrics*. Basil Blackwell, Oxford, pp. 30-41.

Pereira, J., St. Aubyn, M. (2009). What level of education matters most for growth? Evidence from portugal. *Econ Educ Rev* 28 (1): 67-73. doi:10.1016/j.econedurev.2007.12.001

Perotti, R. (1996a), Democracy, income distribution and growth: What the data say. *Journal of Economic Growth* 1: 149-187.

Perotti, R. (1996b). Democracy, income distribution and growth: What the data say. *J Econ Growth* 1: 149-187.

Persson, T., Guido Tabellini (1994). Is inequality harmful to growth? *Am Econ Rev* 84 (3): 600-621.

Pfaff, B. (2008). VAR, SVAR and SVEC models: Implementation within {r} package {vars}. *J Statistical Software* 27 (4).

Ploberger, W., Krämer, W. (1992). The cusum test with ols residuals. *Econometrica* 60 (2): 271-285.

Rao, B. B. (2010). Time-series econometrics of growth-models: a guide for applied economists. *App Econ*, 42(1): 73-86.

Rao, B. B., Gounder, R., Loening, J. L. (2010). The level and growth effects in the empirics of economic growth: some results with data from Guatemala. *App Econ*, 42(16): 2099-2109.

Risso, W. A., Sánchez Carrera, E. J. (2012). Inequality and economic growth in China. *J Chinese Econ and Foreign Trade Stud*, 5(2): 80-90.

Romer, P. (1990a). Endogenous Technological Change. *J Pol Econ*, 98(5): S71-102.

Romer, P. (1990b). Human capital and growth: theory and evidence. *Carnegie-Rochester Conference Series on Public Policy*, vol. 32, pp. 251-286.

Teixeira, A., Fortuna, N. (2004). Human capital, innovation capability and economic growth in Portugal, 1960-2001. *Port Econ J* 3 (3): 205-225. doi:10.1007/s10258-004-0037-8

Teixeira, A. A. C., Fortuna, N. (2010). Human capital, R&D, trade, and long-run productivity. Testing the technological absorption hypothesis for the Portuguese economy, 1960-2001. *Res Pol* 39: 335-350. doi:10.1016/j.respol.2010.01.009

Voitchovsky, S. (2005). Does the profile of income inequality matter for economic growth? Distinguishing between the effects of inequality in different parts of the income distribution. *J Econ Growth* 10: 273-296.

Wößmann, L. (2002). *Schooling and the Quality of Human Capital*, Berlim: Springer.