Inequality and growth in Portugal:

a reappraisal for the period1986-2017

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Abstract

This paper investigates the inequality-growth nexus for Portugal over the period 1986-2017. Portugal is a country that has recorded a decelerating growth trajectory together with high levels of inequality, coupled with relatively low levels of human capital and productivity. We compute different measures of earnings inequality using microdata from the *Quadros de Pessoal* database and use them to estimate VAR and SVAR A-B models with four variables (human capital, inequality, investment and output) to empirically assess the sign of the relationship between inequality and growth, as well as the underlying mechanisms. The results from the impulse response analysis indicate that a shock to inequality has a negative impact on growth and on human capital availability, and an initial negative impact on investment which eventually becomes positive. The evidence found highlights the human capital, savings, and domestic demand channels as good candidates to explain the relationship between inequality and growth in Portugal.

Keywords: Inequality, Human Capital, Investment, Growth, VAR, SVAR, Portugal

Introduction

Previous studies on the relationship between inequality and growth have often found conflicting results, not surprising given theoretical arguments supporting the existence of both positive and negative influences (Aghion et al. 1999, Voitchovsky 2012, Neves et al. 2016, Berg et al. 2018, Brueckner and Lederman 2018, and Gründler and Scheuermeyer 2018)[1].

One strand of the literature highlights the positive effects of inequality on incentives to work, incentives to invest and incentives to take risks, promoting faster growth. For instance, the savings mechanism posits that with more inequality, the rich, who have a higher propensity to save (Kaldor 1955), will have a higher share of income which will foster aggregate savings, capital accumulation, and growth. A positive link can also arise from higher inequality acting as an incentive for individuals to take risks, work harder, and invest in education to benefit from the higher returns to innovation and risk-taking.

Others suggest a series of mechanisms through which more inequality can hamper growth. One potential channel of influence is human capital accumulation: higher inequality, coupled with financial markets imperfections, will result in the poor underinvesting in human capital. For example, a poor individual might not invest in his/her tertiary education with the associated higher returns due to budget constraints and lack of collateral[2]. Higher inequality hence results in less human capital

[1] Reducing income inequality has also been considered a means for poverty alleviation, Naschold (2002). Understanding how inequality influences growth can help explain what makes countries improve the standards of living of their citizens, reducing poverty and promoting social inclusion. Lakner et al. (2020) provide evidence on the link between lower inequality and poverty alleviation.

[2] From the opposite perspective, Nakamura (2020) develops a model to show how higher public spending on education can reduce income inequality and contribute to poverty alleviation.

accumulation and slower growth. Another mechanism states that higher inequality is accompanied by demand for more redistribution, introducing distortions in savings and investment decisions due to the associated increase in taxes, again resulting in less growth. Yet another argument poses that the adoption of new technologies is dependent on a certain level of domestic aggregate demand. If inequality adversely affects aggregate demand, because the rich have a lower marginal propensity to consume than the poor, higher inequality will sap growth. In a context of increasing inequality, investors and entrepreneurs do not face enough demand to justify innovating and expanding production, which slows growth.

At the empirical level, Neves and Silva (2014) suggest that different results encompassing both positive, negative and non-significant estimates may be the result of the use of different methods, data sources, geographies and time periods. The contrasting evidence from empirical studies that adopt a linear specification can also be due to the non-linear nature of the relationship between the two variables, as argued by Grigoli and Robles (2017) who show that the sign of the relationship is positive for low levels of inequality and negative for high ones. Similarly, Barro (2000) and Brueckner and Lederman (2018) show that the effect may differ between rich and poor countries. It could also be the case that the impact of inequality on economic growth is dampened or amplified by some other factor, such as institutional quality, intergenerational mobility and equality of opportunities, or the level of redistribution.

Previous studies that examine specific mechanisms as drivers of the relationship between inequality and growth (see e.g. Perotti 1996; Barro 2000; Cingano 2014; Berg et al. 2018; Gründler and Scheuermeyer 2018), are scarce when compared to the literature that investigates the sign of the relationship by estimating reduced-form equations that directly relate the two variables. Dominicis et al. (2008), Neves et al.

(2016), Brueckner and Lederman (2018). Neves et al. (2016) also conclude that specific country contexts can influence which mechanism prevails. Additionally, this influence is not time-invariant, potentially changing depending on whether it is analyzed from a short-run or a long-run perspective. These conclusions are in accordance with the work of Gobbin and Rayp (2008) that highlighted the need for a country-specific approach, after obtaining quite different results for Belgium, the US and Finland. The former provides a strong case for studying the inequality-growth link for Portugal using a time-series approach as in Andrade et al. (2014) and Simões et al. (2015).

A candidate explanation for the existence of a country-specific nexus between inequality and growth relates to the welfare state regime adopted by different countries (Tridico and Paternesi Meloni (2018). Several types of welfare states coexist and may thus influence the impact of inequality on growth. This mediating role of welfare state regimes can be taken into account by investigating the inequality-growth link for specific countries, such as Portugal, that belongs to the Mediterranean or southern welfare state regime (Hay and Wincott 2012)[3].

Economic growth also influences income inequality (Kuznets 1955). Initially, for relatively low income levels, as a country income increases there is a rise in inequality; however, beyond a certain income level further increases are accompanied by a decrease in inequality. The former implies an inverted U relationship between income and inequality. This also poses the problem of endogeneity due to reverse causality. Sims (1980) suggested the use of Vector Auto-Regressive (VAR) models since it is

[3] Valls Fonayet et al. (2020) investigate the efficiency of social expenditure in poverty alleviation in the EU (2007-2015) and identify four groups of countries, corresponding to different welfare state regimes. The group formed by the Mediterranean welfare states shows low efficiency in reducing poverty through social expenditure.

possible to treat all variables as endogenous and consider more flexible dynamic adjustment mechanisms (Gobbin and Rayp 2008 and Frank 2009).

Previous studies that use VAR models to study the inequality-growth nexus include Assane and Grammy (2003), Frank (2009) and Atems and Jones (2015) for the USA, and Risso and Carrera (2012) and Chan et al. (2014) for China, with varying results in terms of the direction of causality and duration of the effects, highlighting the importance of looking at specific countries. For Portugal, Andrade et al. (2014) estimate Near-VAR and SVAR models for the period 1985-2007 with three variables, GDP per capita, earnings inequality and educational attainment. The authors concluded that a shock to inequality had a negative impact on output but a positive impact on human capital accumulation.

The main aim of this study is to add to the foregoing debate on the inequality-growth link by re-examining the relationship for Portugal, extending the analysis in Andrade et al. (2014) to the period 1986-2017 and considering an additional mechanism of transmission through physical capital accumulation (e.g. more inequality may imply less investment due to the indivisibility of some investment projects and lack of collateral). Portugal’s decelerating growth trajectory and high levels of inequality, coupled with relatively low levels of human capital and productivity and the relatively recent emergence of a true welfare state make it an interesting and relevant case study. We compute a set of earnings inequality measures using data from *Quadros de Pessoal* database and use them to estimate VAR and SVAR A-B models with four variables (human capital, physical capital accumulation, real GDP and inequality) to assess the impact of inequality on growth, both directly and through the operation of different transmission channels.

The remainder of the paper is set out as follows: the next section presents the data; the third section describes the empirical strategy in terms of VAR and SVAR models; the fourth section presents and discusses the results from the estimation of the associated impulse-response functions; and the fifth section concludes.

Data overview

We consider inequality in the distribution of earnings of Portuguese employees working in the private sector computed with data retrieved from *Quadros de Pessoal* (QP) database, an annual survey compulsory for Portuguese firms, conducted by the Ministry of Labor, Solidarity and Social Security (MLSSS) since 1985. The information includes base salary, total salary and educational attainment, among others. The workers included are employees working in the private sector, employers who have a job in their own firm, non-paid family workers and active members of a production cooperative. The number of workers covered has steadily increased over the years, starting at about 1.9 million in 1986 and covering over 3 million workers in 2017. The database does not include public servants or the military, and was not conducted in the years 1990 and 2001. The lack of information on civil servants for the calculation of earnings inequality does not bias the results since the structure of earnings of civil servants has not changed much over the years and, most importantly, it does not respond to the business cycle. Observations for the years 1990 and 2001 were obtained through univariate interpolation applying Kalman smoothing to an automatically generated ARIMA process selected based on the AIC criteria using the R package “imputeTS”, Moritz and Bartz-Beielstein (2017). Using simulated data, these authors show that this method is one of the better performing for imputing univariate missing data. Since in the years

1990 and 2001 there were no relevant macroeconomic and fiscal changes in Portugal, biased imputations are not likely. Additional features of our database can be found in the appendix.

For the distribution of earnings we computed the Gini index and three generalized entropy inequality indexes (GEs), Theil (1967): GE(α=0)=TheilL; GE(α=1)=TheilT and GE(α=2)=GE(2) using R package "ineq", Zeileis (2014).

The Gini index varies between zero (all workers earn the same) and one (all earnings go to one worker). Figure 1 presents the Gini index of earnings over the period 1986-2017, showing that the respective dynamics can be divided into three separate periods, described by an inverted U shaped curve. During the first period (1986-1994) inequality increased (from 0.259 to 0.322), and at a fast pace (average annual growth rate 2.8%). The second period (1995-2007) is characterized by fluctuations in earnings inequality, starting at 0.318 and ending at 0.319. In the third period (2008-2017), the Gini changes from 0.318 to 0.288 corresponding to a negative trend (average annual growth rate -1.1%). At the beginning of the first period inequality was low as the Portuguese economy was still not very developed. In 1986 Portugal became a member of the European Economic Community (now EU), after a period of political turmoil and economic hardships that resulted in two IMF interventions. The period of rapid growth that followed joining the EU was accompanied by an increase in inequality (Gini=0.32 in 1994), but as the economy converged to the richer member states this increase slowed down and was eventually reversed (Gini=0.323 in 2005). Another candidate explanation for the inverted U behavior of earnings inequality is the 2007-08 crisis and the subsequent sovereign debt/euro area crisis. During this period, the rich suffered higher income losses, while growing unemployment mostly affected low-income workers which were no longer included in QP since it only covers employees. To gain further insights on these dynamics, the Appendix provides an analysis of the statistical measure kurtosis and earnings percentiles' ratios (see Figures A.1 and A.2).

[Insert Figure 1 here]

Figure 2 contains the evolution of *TheilL*, *TheilT* and *GE(2)* indexes of earnings inequality. These inequality measures take the value zero in the case of perfect equality in the earnings distribution. As the earnings distribution becomes more unequal all the three measures increase, varying until infinity, or unity if normalized. The three measures differ in their sensitivity to changes at the bottom of the earnings distribution (*TheilL* more sensitive to low earnings) relative to changes at the top (*GE(2)* more sensitive to higher earnings). Their evolution is similar to that of the Gini index but the faster growth of *GE(2)* in the period of rising inequality, going from 0.140 in 1986 to 0.258 in 1994, suggests that this increase is most likely due to an increase in top earnings. Several potential causes have been identified in the literature, such as skill-biased technological change, the number of routine and non-routine tasks in occupations, globalization and trade, minimum wage law changes, or unions' loss of bargaining power (see e.g. Centeno and Novo 2014).

[Insert Figure 2 here]

We use *GE(2)* in the estimation of our VAR and SVAR models since it is suitable to test transmission mechanisms, i.e. the channels through which inequality influences economic growth, related to savings and investment as savings increase when earnings at the top rise more than earnings at the bottom. *GE(2)* also captures better mechanisms related with incentives to work harder: higher income differences between top earners and the remaining workers imply stronger incentives to work harder in order to benefit from the relatively higher earnings at the top. In the specific context of the Portuguese economy, it additionally makes sense to use it to test the human capital channel as in the earlier part of the period under analysis the percentage of workers with 12 years of schooling was quite low (9% in 1986 and 18% in 1997). This suggests that inequality at the bottom should not be particularly relevant to explain secondary educational attainment, nor do we expect that it is explained by secondary educational attainment in these early years. *GE(2)* also does not ignore the remaining parts of the distribution, making it suitable to examine the human capital mechanism, even if for the second half of the period inequality at the bottom probably played a bigger role.

Besides earnings inequality, we also include human and physical capital in our empirical models as key factors of production, allowing this to shed additional light on the transmission mechanisms from inequality to growth. According to the literature, Perotti 1996; Barro 2000; Cingano 2014; Berg et al. 2018; Gründler and Scheuermeyer 2018, the human capital, the savings, and the domestic demand channels are candidate explanations of the inequality-growth nexus acting through human and physical capital accumulation. Human capital is measured as the log of the percentage of workers with at least secondary education and was computed with data from QP. Physical capital accumulation is measured as the log of gross fixed capital formation (2016 prices, thousands of million euros). As a proxy for economic growth our model includes output measured as the log of real GDP (2016 prices, thousands of million euros). Both are from PORDATA, the Database of Contemporary Portugal, organized and developed by the Francisco Manuel dos Santos Foundation, that reports statistics for Portugal on multiple areas of society derived from official and certified sources. We also carried out variance-decomposition analysis to support the choice of the four variables included in our VAR and SVAR models. This analysis showed that a shock to any of the variables contributes to the explanation of an important part of the behavior of the remaining variables. This analysis and the figures depicting the behavior of the different series can be found in the Appendix, Table A.1 and Figures A.3-A.5, respectively.

Empirical strategy[4]

To study the relationship between inequality and growth in the Portuguese economy, we first use a Vector Auto-Regressive (VAR) model. This model corresponds to a system of equations in which all variables are considered as potentially endogenous. Additionally, the VAR allows for the analysis of dynamic relationships by including lags and thus testing whether the effects of inequality on growth are only short-term or also longer lasting. The estimation of the associated impulse response functions (IRFs) describes the response of an endogenous variable to a shock in any other variable in the system over time. We focus our analysis on inequality shocks.

We consider a VAR model of order 1 (optimal number of lags is equal to one, see Table A.2 in the Appendix) given-by the system of equations (1) to (4):

$$HC_t = c_1 + \beta_{11}HC_{t-1} + \beta_{12}INEQ_{t-1} + \beta_{13}Kap_{t-1} + \beta_{14}YR_{t-1} + u_{1t} \quad (1)$$

$$INEQ_t = c_2 + \beta_{21}HC_{t-1} + \beta_{22}INEQ_{t-1} + \beta_{23}Kap_{t-1} + \beta_{24}YR_{t-1} + u_{2t} \quad (2)$$

$$Kap_t = c_3 + \beta_{31}HC_{t-1} + \beta_{32}INEQ_{t-1} + \beta_{33}Kap_{t-1} + \beta_{34}YR_{t-1} + u_{3t} \quad (3)$$

$$YR_t = c_4 + \beta_{41}HC_{t-1} + \beta_{42}INEQ_{t-1} + \beta_{43}Kap_{t-1} + \beta_{44}YR_{t-1} + u_{4t} \quad (4)$$

where *HC* is human capital; *INEQ* is inequality; *Kap* corresponds to physical capital accumulation and *YR* is output. Each variable is described by an equation that models the respective behavior over time as depending on its past values and the lagged values of the

[4] All computations were done with R using the packages “vars”, Pfaff (2008), “aTSA”, Qiu (2015), “generalCorr”, Vinod (2019), and “svars”, Lange et al. (2019).

other variables so that each variable in the system of equations (1)-(4) is assumed to influence every other variable. Our variables are considered in levels regardless of their level of integration, as suggested by Sims (1980) and the stationarity of our VAR model is guaranteed by the values obtained for the respective characteristic roots.

Obtaining the IRFs using the Cholesky decomposition implies ordering the variables according to their degree of exogeneity, from the most exogenous to the least exogenous. Considering that some of the variables might be *I(1)*, Granger causality tests cannot be used and, therefore, an alternative approach is needed. We apply the methodology proposed by Vinod (2017), based on kernel causality.

Consider the generalized measure of correlation between the variables Y and X, *GMC(Y|X)*, corresponding to the R^2 of the Nadaraya-Watson nonparametric Kernel regression given by:

$$Y = g(X) + \epsilon \qquad (5)$$

where *g(X)* is a non-parametric unspecified function.

Vinod (2017) suggests defining a δ equal to the difference between the *GMC* with one variable as the dependent variable and the *GMC* for the same pair of variables in reverse order, with $\delta = GMC(Y) - GMC(X)$. If $\delta > 0$, *Y* is the kernel cause of *X*; if $\delta < 0$, *X* is the kernel cause of *Y*. Using the R package "generalCorr", Vinod (2019), a matrix of GMC's was computed for the series in our VAR model. The results are presented in Table 1 where the columns contain the variable that potentially causes the row variable. For example, the value in the first column, second row is 0.996, while the value in the second column, first row is 0.975. Since 0.996 is higher than 0.975 we conclude that *HC* is a kernel cause of *INEQ*. We conclude that *HC* is a kernel cause of *INEQ*, *Kap* and *YR* since 0.996 > 0.975, 0.996 > 0.930 and 0.999 > 0.950, respectively. Applying the same reasoning, *INEQ* is a kernel cause of *Kap* and *YR* and *Kap* is a kernel cause of *YR*. A clear hierarchy of exogeneity can thus be established: *HC* → *INEQ* → *Kap* → *YR*, from the most exogenous to the least exogenous. This ordering represents a plausible description of the functioning of the Portuguese economy with human capital, inequality, investment and output, where human capital/schooling is less dependent on the remaining variables since it is determined to a greater extent by institutional (education system, compulsory schooling laws,…) and cultural factors, not included in our model; human capital is a main determinant of productivity and thus earnings; the former two variables are also an important determinant of the choices of firms in terms of the production technology used and thus investment; finally, all the former variables determine the level of output since human and physical capital are the two main inputs in production.[5]

[Insert Table 1 here]

VAR models explain the behavior of endogenous variables based solely on their own past values, while structural autoregressive (SVAR) models additionally consider the contemporaneous interdependencies. In this way, SVAR models go one step further since they allow for the identification of structural relations between the variables that should correspond to theoretical relations (Gottschalk 2001 and Lütkepohl 2004). In a VAR model we estimate the dynamic response of each variable to a shock in any of the other variables. For instance, a shock to inequality corresponds to an unexpected change in this variable that will affect the remaining variables. A SVAR model is estimated based on a VAR model to which we add contemporaneous relationships between the variables and impose constraints confirmed by adequate econometric tests to arrive at a

[5] We also run diagnostic tests to check the validity of our VAR model with the results confirming that the model is correctly specified. Moreover, all the characteristic roots of the VAR model have absolute values smaller than 1, indicating that the model is stationary and therefore the impulse-response analysis is valid. These results are available from the authors.

set of structural relationships. The economic meaning of these structural relationships has also to be justified on theoretical grounds. The “errors” for these structural relationships are true stochastic variables and are therefore not directly associated with the model's variables when we think of the former in terms of policies. Bernanke (1986) calls them primitive exogenous shocks. For example, a shock to "distribution" does not have to be a shock to the variable that we associate with distribution in the VAR, *INEQ*, but is a shock that in any way affects the distribution of earnings, e.g. an unexpected change in unions’ bargaining power. Two analogous examples apply to a shock to “education” since this does have to correspond to a shock to the variable representing human capital in the VAR. For instance, a change in compulsory schooling laws and the social and cultural environment that influence an individual’s decision to continue in the education system, for instance to obtain a higher education diploma, are examples of “education” shocks. Unexpected changes in future medium to long term interest rates is an example of a “supply” shock, i.e. does not originate directly in a change in investment (*Kap*). While unanticipated changes in future oil prices or a firm’s tax regime are two examples of “output” shocks. Summing-up, SVAR models are used to identify: a) contemporaneous structural relationships between the variables; and b) the impact of structural shocks on the behavior of the variables in the model. To define our SVAR model we tested the stability of the VAR model (Lütkepohl 2004), and also tested for the presence of volatility shifts in the dynamics of the residuals according to the identification method proposed by Rigobon (2003) and Lanne and Lütkepohl (2008). The results of these tests are available in the Appendix, Tables A.3 and A.4. They favor the use of a SVAR A-B model.

Our starting point was a VAR model that can be taken as a “reduced form” model as it allows us to summarize the dynamics of the variables included (Cooley and LeRoy

1985). Equation (6) represents our model with contemporaneous relations considering one lag, k endogenous variables and no deterministic variables (constant and trend), for convenience:

$$Ay_t = A_t^* y_{t-1} + B \in_t \tag{6}$$

The usual pre-multiplication by A^{-1}gives:

$$y_t = A_1 y_t + \mu_t \text{ with } \mu_t = A^{-1}B \in_t \text{ and } A_1 = A^{-1}A^* \tag{7}$$

Sims (1986) and Bernanke (1986) propose non-recursive identification thus allowing instantaneous/contemporaneous effects, and so $A \neq I_k$.

Following the classification of Amisano and Giannini (1997), we will estimate a SVAR A-B model imposing adequate restrictions which allow for structural shocks (ϵ_t) and not only reduced-form disturbances (μ_t) . The vector of structural shocks which are uncorrelated across equations and over time has mean zero and unit covariate matrix, $\epsilon_t \sim HD(0, I_k)$. The structural shocks cannot be recovered from reduced form estimates and so the effects of ϵ_t on the endogenous variables, y_t, cannot be identified without further assumptions. The number of elements of the structural matrices A and B is $2k^2$, and the restrictions that we should impose to identify the full model are $2k^2 - \left[\frac{k(k+1)}{2}\right] = k^2 + \frac{k(k-1)}{2}$.

We build a SVAR model with one over-restriction with the appropriate LR test not rejecting this restriction, LR test: $\chi^2(1) = 0.12$ (0.7). The estimated coefficient matrices $\tilde{A}$ and $\tilde{B}$ can be found in the Appendix, Tables A.5 and A.6. We also tried to include other contemporaneous effects related to inequality mechanisms, such as the borrowing constraints to investment in education (contemporaneous coefficients different from zero relating inequality to human capital and human capital to output), but those effects were not statistically significant. In what follows we present the vector of estimated residuals, $\mu_t = A^{-1}B\epsilon_t$, as a system of equations (8) to (11), to analyze in the next section the impulse response from the four structural shocks: Education (EDU), Distribution (DIST), Supply (SUP) and Output (OUT).

$$\mu_{HC,t} = 0.0406.\epsilon_{EDU,t} - 0.0231.\epsilon_{DIST,t} + 0.0000.\epsilon_{SUP,t} + 0.0000.\epsilon_{OUT,t} \quad (8)$$

$$\mu_{INEQ,t} = -0.0032.\epsilon_{EDU,t} - 0.0272.\epsilon_{DIST,t} - 0.0127.\epsilon_{SUP,t} - 0.0063.\epsilon_{OUT,t} \quad (9)$$

$$\mu_{KAP,t} = 0.0000.\epsilon_{EDU,t} - 0.0000.\epsilon_{DIST,t} + 0.0741.\epsilon_{SUP,t} + 0.0000.\epsilon_{OUT,t} \quad (10)$$

$$\mu_{YR,t} = 0.0043.\epsilon_{EDU,t} + 0.0030.\epsilon_{DIST,t} + 0.0181.\epsilon_{SUP,t} + 0.0085.\epsilon_{OUT,t} \quad (11)$$

The system of equations (8)-(11) describes the contemporaneous structural relationships between the variables in our model. Notice that the residual μ_{HC} is a component of the human capital equation in the SVAR, so a contemporaneous shock (ϵ_{EDU}; $\epsilon_{DIST;}\epsilon_{SUP}$; ϵ_{OUT}) on that residual will have an impact on human capital. The same reasoning applies to the remaining residuals.

According to equation (8), an *EDU* shock has a positive effect of magnitude 0.0406 on human capital. The sign confirms theoretical predictions since a quantitative/qualitative increase in the supply of education matched by higher demand for education will translate into more educated employees engaged in the private sector. A *DIST* shock has a negative impact (-0.0127) on human capital. This results confirms predictions related to the human capital mechanism since, in the presence of credit market imperfections, an increase in inequality will prevent lower income individuals from investing in human capital. Human capital is not contemporaneously affected by *SUP* or *OUT* shocks since it takes time for these shocks to have an impact on schooling decisions.

According to equation (9), earnings' inequality will react negatively to *EDU* (-0.0032) since human capital dispersion is expected to react positively to such a shock, as well as to *SUP* (-0.0127) and to *OUT* (-0.0063). The latter suggest that new technologies demand more qualifications/skills (human capital) thus reducing the demand by firms for less skilled workers after carrying out new investment projects. *DIST* on the other hand has a positive effect (0.0272) on inequality because a more uneven income distribution will result in higher earnings inequality.

The results patent in equation (10) suggest that risk taking by firms and entrepreneurs as far as investment decisions are concerned is exogenous as investment is only affected by *SUP* (0.0741) thus by shocks related to physical capital accumulation.

According to equation (11), output is positively affected by any of the structural shocks considered, *EDU* (0.0043), *DIST* (0.0030), *SUP* (0.0181) and *OUT* (0.0085). Since human and physical capital are the main inputs in production a shock that increases the respective availability is expected to increase production. The sign for *DIST* suggests the savings mechanism applies: more inequality increases the aggregate income share of the richer, who have a higher propensity to save, which results in higher aggregate savings that foster capital accumulation and growth.

Results

The estimated IRFs for the VAR model indicate how a variable is affected by a one standard deviation shock to another variable or to itself. We have the following impulse responses: a shock to *HC* has contemporaneous effects on all the variables; a shock to *INEQ* affects all variables contemporaneously except *HC*, which will be affected one year after the shock; a shock to *Kap* affects itself and *YR* immediately and the remaining variables one year later; finally, a shock to *YR* affects itself immediately and all the other variables one year later. Figures 3(a)-(b) show the response to inequality shocks 10 years after. Figure 3(c) shows results for 20 years after the shock to capture a potential change in the sign of the effect that might be relevant for our analysis.[6] See also Figures A.7 and A.8 in the Appendix.

According to Figure 3.a, a shock to inequality has a negative effect on output: a 1% increase in the inequality index leads to a 0.155% decrease in output after 10 years, a result in line with previous literature (Andrade *et al.* 2014). Besides this direct impact, Figure 3.b shows that a shock to inequality has an increasingly negative impact on human capital of up to -0.49% after 10 years. This seems reasonable since there is a lag between the time when an individual decides to invest in education and the time he/she enters the labor market. That investment has an impact on the respective earnings, implying that a shock to inequality takes some time to produce effects on human capital. These findings suggest that the human capital mechanism is an important channel of influence from inequality to growth. Less inequality probably makes the budget constraints that prevent some individuals from investing in education less binding, so more people are able to attain higher levels of education, resulting in more human capital and an increase in output (see also Figure A.7).

The interpretation of the results presented in Figure 3.c is not as straightforward since the impact of a shock to inequality on investment starts out as negative but ends up positive 12 years after the shock. A possible explanation could be that two mechanisms of opposite signs are at work. Over the short run, an increase in inequality causes aggregate demand to decrease and in turn there is less adoption of new technologies by firms implying a decrease in investment. On the other hand, with more

[6] The results of the estimation of all the impulse-response functions are available from the authors.

inequality, aggregate savings are higher due to the higher marginal propensity of the rich to save, leading to more investment. With some delay, the savings mechanism becomes stronger than the aggregate demand mechanism and the sign of the relationship between inequality and investment is reversed: 20 years after the shock a 1% increase in inequality results in a 0.17 % increase in *Kap*. Since *Kap* has a positive effect on output (see also Figure A.8), an increase in inequality initially decreases output but eventually leads to an increase. However, this increase is not strong enough to offset the overall negative impact of inequality on growth when all channels of transmission are accounted for. In any case, the confidence intervals do not exclude the hypothesis that the impact of the associated shock is zero.[7]

[Insert Figure 3.a here]

[Insert Figure 3.b here]

[Insert Figure 3.c here]

We next present and discuss the results of the estimation of the effects of the structural shocks based on the IRFs for our SVAR model. This allow us to gain further insights on the sign and magnitude of the influence of inequality on output (impact of DIST on *YR*). Additionally, we want to confirm (or not) the evidence from our VAR model on the human capital (impact of *DIST* on *HC*), savings and aggregate demand (impact of DIST on KAP) channels. We computed the (normalized) effects from the

[7] We estimated all the IRFs with the alternative measures of inequality, TheilL, TheilT and the Gini index. The results remain basically the same and all the models passed the diagnostic tests. These results are available from the authors.

shocks (for instance *HC*→ *YR* = (*HC*→ *YR*(kth year))/(*HC*→ *HC*(1st year)). In the SVAR model the first effects of the different shocks occur according to the following: an Education shock as well a Distribution shock will immediately affect the variables *HC*, *INEQ* and *YR* while *Kap* will be affected one year later; a Supply shock will affect *HC* one year later and all the other variables immediately after the shock; and an Output shock will immediately affect *INEQ* and *YR* and *HC* and *Kap* one year after the shock.

Table 2 summarizes and compares the effects of the shocks in the VAR and SVAR models. The results of the estimation of the IRFs for the SVAR model are presented in Figures 4.1-4.3 (see also Figures A.9 and A.10 in the Appendix). Overall, the shocks have similar effects in the VAR and SVAR models as far as the sign is concerned, except in the case of the *INEQ* and *DIST* shocks on *KAP*, negative and positive, respectively.

[Insert Table 2 here]

According to the results presented in Figures 4.1-4.3, the impact of *DIST* on *HC* is always negative (Figure 4.1); the effect on *KAP* is negative in the first four years but becomes positive from then onwards (Figure 4.2); and the effect on *YR* is positive for the first six years (Figure 4.3) and turns negative in the subsequent period. Overall, the results from the SVAR model in terms of the sign of the relationship between inequality and growth and the different transmission mechanisms are in line with the results obtained with the VAR model. Similar also to the VAR model, the effects of most of the shocks are not statistically significant.

[Insert Figure 4.1 here]

[Insert Figure 4.2 here]

[Insert Figure 4.3 here]

Conclusion

We revisited the inequality-growth nexus for Portugal using annual time-series data from 1986 to 2017 and estimating VAR and SVAR models with four variables (human capital, inequality, investment and output) to investigate how and why income inequality influences growth.

The results from the impulse-response analysis support the hypothesis that income inequality is detrimental for growth in Portugal, in line with the recent findings in a panel data context of Atems and Jones (2015), Grigoli et al. (2016), Castells-Quintana and Royuela (2017), Brueckner and Lederman (2018), Berg et al. (2018) and Gründler and Scheuermeyer (2018). Our estimates additionally show that more inequality reduces the availability of human capital and initially reduces investment although after some years this impact becomes positive, thus shedding additional light on the functioning of two of the transmission channels described and tested in the literature (see e.g. Castells-Quintana and Royuela 2017, Berg et al. 2018 and Gründler and Scheuermeyer 2018), and presenting evidence that the sign of the relationship might change over time (Halter et al. 2014). The overall effect of inequality on the macroeconomic performance of the Portuguese economy is thus the result of the positive and negative influences identified, with a higher relative strength of the effects that retard growth.

As such, policies aiming at the redistribution of income will result in faster growth. Given the variety of instruments available to achieve a more equal distribution, from the tax mix to the design of social policy programmes, our work paves the way for future research on the most effective and efficient mix of redistributive policies from the perspective of reducing income inequality in Portugal. The negative sign of the relationship between inequality and growth seems mostly due to the human capital channel with less inequality enabling talented individuals from lower-income households to have access to the collateral necessary to invest in their human capital. Policies are thus likely to work mostly through reducing inequality at the bottom of the income distribution, although public spending on education can attenuate this negative growth effect of inequality. Bearing also in mind how the human capital channel operates, through the existence of credit market imperfections, policies directed at the financial sector could also promote growth through human capital accumulation. In addition, in the short run an increase in inequality also negatively impacts investment, which in turn demands more efficiency in the allocation of capital to compensate for the former effect. Also, if poorer individuals are not able to implement relatively more productive investment projects due to credit markets imperfections, policies that make credit constraints less binding can stimulate growth.

Although our analysis of the relationship between inequality and growth in the Portuguese economy is limited to some of the channels identified in the literature, we believe that it represents a useful roadmap for policy making. We have also not tested for the possibility of nonlinearities in the relationship, namely whether it depends on the existence and quality of certain institutions (e.g. the welfare state) which remains an open question for future research.

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Appendix

The distribution of earnings is computed for the total salary that equals the base salary (the amount in money and/or goods, before taxes and transfers, paid to the worker on a monthly basis, in the month of October, based on the number of normal hours worked) plus all regular bonuses and subsidies and earnings from overtime work. Adjustments to the database include: i) removing every worker whose base salary was below the minimum salary for that year; this eliminated observations/employees that had a zero salary and potential mistakes that might have occurred along the process of collecting and assembling the original data, since no worker can receive an amount below the minimum wage for a full-time job; as a consequence many of the part-time workers were thus removed, but these are not directly comparable to full-time workers; ii) removing the highest 0.5% of total salaries in order to eliminate extreme outliers and errors that could taint the analysis; and iii) deflating salaries using the CPI (base=2010).

To gain further insights on the dynamics of earnings inequality over the period 1986-2017 we also computed and analysed the behaviour of the statistical measure kurtosis and earnings percentiles’ ratios (see Figures A.1 and A.2)

The kurtosis measures the “tailedness” of the distribution relative to the normal distribution: an increasing kurtosis indicates that there are more employees with low (bottom/left tail) and high (top/right tail) earnings and fewer employees with middle ones. It is especially sensitive to changes in top earnings since lower earnings (left tail) are typically much closer to the average. Figure A.1 contains the values of kurtosis for the earnings distribution over the period 1986-2017, where it is possible to see that until 1995, similar to the Gini index, kurtosis increases (from 5.04 to 11.03). However, kurtosis briefly decreases and then stagnates, albeit with some fluctuations for the most recent years. This suggests that while the increase in inequality during the period 1986-

1994 was driven by top earnings, the decrease after 2008 is not driven by an opposite movement in top earnings. Therefore, it must be the result of a lower earnings share for the middle and/or upper-middle class.

[Insert Figure A.1 here]

To corroborate the former hypothesis, Figure A.2 contains the ratio of all the earnings percentiles, from 1 to 99%, in year 2016 relative to the same percentile in year 1991. These two years were chosen because the Gini index is very similar for both, 0.2964 and 0.2959 respectively, but the behaviour of inequality should not be the same based on the kurtosis values, which are higher in 2016. Figure A.2 clearly shows the phenomenon of earnings polarization: earnings at all percentiles increased from 1991 to 2016 (all the ratios are higher than one), with the higher gains occurring at the top (28.1% for the richest 10%) and at the bottom of the distribution (34.4% for the poorest 10%). For percentiles 7% and 95% a gain close to 35% is observed. The lowest gains are observed between the 40th and the 88th percentiles (never higher than 25%).

[Insert Figure A.2 here]

The behaviour of the different series (except inequality) used in the VAR and SVAR models is shown in figures A.3 to A.5.

[Insert Figure A.3 here]

[Insert Figure A.5 here]

[Insert Figure A.4 here]

The variance decomposition analysis based on the VAR model described by equations (1) to (4) allow us to examine whether shocks to one variable are good predictors of the behaviour of the other variables and in this way give support to our choice of variables. The analysis was performed for 10 years after a shock to each of the variables. Each value in Table A.1 indicates the amount of the forecast error variance of a variable that can be explained by exogenous shocks to itself or to any of the other variables. The columns represent the variable that his hit by the exogenous shock and the rows the variable that is affected, therefore each row sums 1 (100%). The results show that all the variables play a role in the explanation of the behaviour of the other variables. The behaviour of human capital is mainly driven by its own inertia and by output (45% and 43% of the *HC* variance is explained by shocks to *HC* and *YR*, respectively); inequality has a smaller influence on human capital (8%), and about 4% of the *HC* variance is explained by shocks to *Kap*. Inequality is mostly explained by human capital (49%) and its own inertia (40%), followed by a shock to investment (8%), while a shock to output explains 2% of the variance of inequality. Interestingly, over 20% of the variance of *Kap* is explained by a shock to inequality, supporting the inclusion of investment in a parsimonious VAR model such as ours to better understand the mechanisms of transmission from inequality to growth. Finally, the behaviour of output is explained mostly by a shock to investment (68%) with the remaining 32.5% explained by a shock to inequality (17%) and output´s own inertia (14%), while a shock to human capital accounts for 2% of the variance of output.

[Insert Table A.1 here]

To select the optimal number of lags included in our VAR model that eliminates residual serial correlation, Table A.2 presents the results for the different information criteria corresponding to the estimation of the VAR model imposing a maximum number of lags of four since we are working with annual data with a relatively short time span (32 annual observations). Although the results for the AIC, HQ and FPE criteria indicate 3 or 4 lags, taking into account the parameter penalty imposed by the SIC and the size of our sample, we chose the optimal number of lags of one year.

[Insert Table A.2 here]

To define our SVAR model we started by testing for the stability of the VAR model, Lütkepohl (2004), which was never rejected except in the case of the CHOW break-point test for the year 2000 (see Table A.3 and Figure A.6). Considering these results, we tested for the presence of volatility shifts in the dynamics of the residuals according to the identification method proposed by Rigobon (2003) and Lanne and Lütkepohl (2008). Since the null hypothesis of proportional variance shifts was not rejected (see Table A.4), the selection of the SVAR B characterized by volatility change of the parameters was ruled out in favour of a SVAR A-B model.

[Insert Table A.3 here]

[Insert Figure A.6 here]

[Insert Table A.4 here]

For the SVAR model, tables A.5 and A.6 contain the estimated coefficient matrices $\tilde{A}$ and $\tilde{B}$. Matrix $\tilde{A}$ emphasises the relationship between inequality and output, which is fundamental for our analysis.

[Insert Table A.5 here]

[Insert Table A.6 here]

Figures A.7 and A.8 present the response of output to shocks to inputs (human capital, Figure A.7, and physical capital, Figure A.8) to highlight the potential role of the human capital and the savings mechanisms, respectively.

According to the results presented in Figures A.7 and A.8, exogenous shocks to either *HC* or *Kap* have a positive impact on output (YR). A 1% increase in the percentage of employees with at least secondary education leads to a 0.046% increase in output after 10 years. A 1% increase in gross fixed capital formation leads to a 0.107% increase in output after 10 years. These results are important for the analysis of the impact of inequality on growth in Portugal since most of the transmission mechanisms considered in this work assume that both human capital and investment positively influence growth.

[Insert Figure A.7 here]

[Insert Figure A.8 here]

Table A.7 summarises and compares the effects of shocks associated with inputs (human and physical capital) on output in the VAR and SVAR models as the channels of influence from inequality to growth considered in our analysis pose that both human capital and investment exert a positive influence on growth. Figures A.9 and A.10 contain the results of the estimation of the IRFs pertaining to the impact of education and supply shocks on output, respectively, for the SVAR model

[Insert Table A.7 here]

[Insert Figure A.9 here]

[Insert Figure A.10 here]

Table 1 Matrix of the generalized measures of correlations (GMCs)

	HC	*INEQ*	*KAP*	*YR*
HC	1	0.975	0.930	0.950
INEQ	0.996	1	0.761	0.967
KAP	0.996	0.960	1	0.458
YR	0.999	0.993	0.934	1

Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output. Each value represents a generalized correlation coefficient (GMC), δ. The variable in each column is the cause of the variable in the corresponding row. $\delta = GMC(Y) - GMC(X)$ where *Y* and *X* are the causes, respectively, if $\delta > 0$, *Y* is the kernel cause of *X*; if $\delta < 0$, *X* is the kernel cause of *Y*.

Source: own computations using R package "generalCorr"

Table 2: Non-structural and structural shocks: a comparison between VAR and SVAR models results

VAR model shocks	**1% shock effect after 10 years**	**SVAR model shocks**	**1% shock effect after 10 years**
INEQ → YR	-0.179%	*DIST→ YR*	-0.031%
INEQ → HC	-0.560%	*DIST→ HC*	-0.413%
INEQ→ KAP	-0.116%	*DIST→ KAP*	0.167%

Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output; *DIST* – distribution shock. X→Y represents how the variable Y reacts to a shock to variable X. * effect of the shock after three years.

Source: own computations.

Table A.1 Results of the variance decomposition analysis for the VAR model

	HC	*INEQ*	*KAP*	*YR*
HC	0.4479905	0.0834984	0.0417870	0.4267242
INEQ	0.4938232	0.4037304	0.0821255	0.0203209
KAP	0.0144885	0.2056899	0.7347249	0.0450966
YR	0.0201200	0.1655092	0.6751175	0.1392533

Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output. The columns contain the variables that are hit by the shock. The rows contain the variables that are affected by the shock. The values should be read as percentages, each representing how much of each variable's forecast error variance is explained by a shock to one of the other variables or to itself. Each row adds up to 1 or 100%.

Source: own computations

Table A.2 Selection of the optimal number of lags in the VAR model

	1	2	3	4
AIC	-0.28285	-0.28572	-0.29192	-0.29372*
HQ	-0.27994	-0.28048	-0.28436*	-0.28383
SIC	-0.27333*	-0.26859	-0.2.6718	-0.26137
FPE	5.28226e-13	4.2915e-13	2.85618e-13*	3.81609e-13

Notes: The different information criteria are identified in the first column. AIC is the Akaike information criterion, HQ is the Hannan-Quinn criterion, SIC is Schwarz criterion. FPE is the final prediction error criterion. The lowest value of each criterion indicates the optimal number of lags to include in the VAR model to eliminate residual serial correlation, identified with a *.

Source: own computations

Table A.3 Sample-split test for parameter instability (1000 boot trials)

Year	Test Value	p-value
2000	32.05	0.885
2009	32.94	0.341

Notes: the sample-split test for parameter instability was performed by bootstrap using 1000 trials. H0: parameter stability. A Chow break-point test to assess the existence of stability problems concerning the HC and INEQ variables in the year 2000 (test value of 215.11) was also performed and rejects the null of constant parameters. However, the Chow sample-split test does not reject parameter stability according to the values presented in this Table A.1.

Source: own computations.

Table A.4 Pairwise Wald tests for 2000 and 2009

	2000		2009	
Variance Shifts	Wald-test	p-value	Wald-test	p-value
$\omega\_1=\omega\_2$	1.66	0.20	2.37	0.12
$\omega\_1=\omega\_3$	2.58	0.11	3.89	0.05
$\omega\_1=\omega\_4$	1.01	0.31	3.66	0.06
$\omega\_2=\omega\_3$	3.20	0.07	3.35	0.07
$\omega\_2=\omega\_4$	2.77	0.10	1.43	0.23
$\omega\_3=\omega\_4$	1.55	0.21	2.62	0.11

Notes: H0: proportional variance shifts ($\omega_i = \omega_j$). We confirm that the ω_js are not different for the years 2000 and 2009 considering critical levels smaller than 5% for rejection of H0.

Source: own computations.

Table A.5 Matrix $\tilde{A}$ – SVAR model

	HC	*INEQ*	*Kap*	*YR*
HC	1.0000	0.0000	0.0000	0.0000
INEQ	0.0000	1.0000	0.0000	0.7339
st. dev.				*(0.256)*
Kap	0.0000	0.0000	1.0000	0.0000
YR	0.0000	-0.1213	0.0000	1.0000
st. dev.		*(0.075)*		

Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output. st. dev.- standard deviation; $\tilde{A}$ is the estimated *A* matrix for our SVAR model. The estimated coefficients represent the contemporaneous relationships between the variables, e.g. 0.7339, fourth column and second row, indicates the contemporaneous impact of YR on INEQ.

Source: own computations

Table A.6 Matrix $\tilde{B}$ – SVAR model

	HC	*INEQ*	*Kap*	*YR*
HC	0.0406	-0.0231	0.0000	0.0000
st. dev.	*(0.005)*	*(0.008)*		
INEQ	0.0000	0.0296	0.0000	0.0000
st. dev.		*(0.004)*		
Kap	0.0000	0.0000	0.0741	0.0000
st. dev.			*(0.009)*	
YR	0.0047	0.0000	0.1970	0.0012
st. dev.	*(0.002)*		*(0.003)*	*(0.001)*

Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output. st. dev.- standard deviation; $\tilde{B}$ is the estimated B matrix, the matrix of the components of structural shocks for our SVAR model.

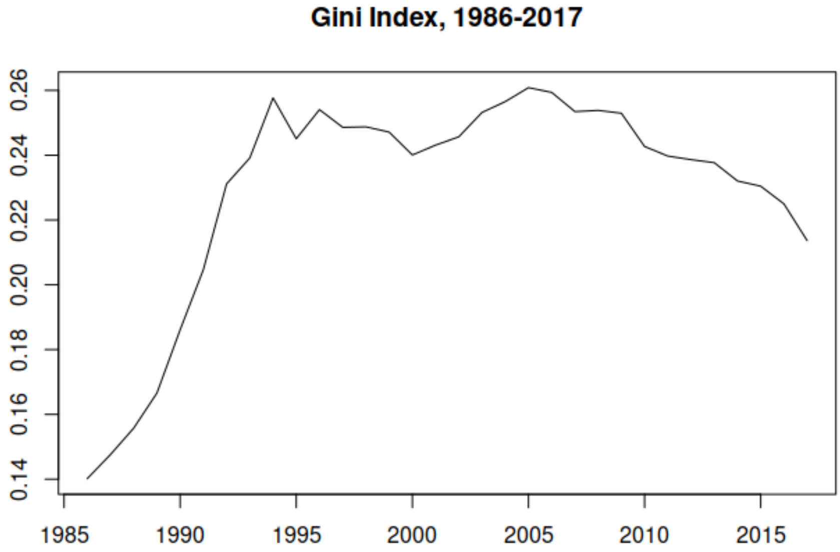
Source: own computations.

Table A.7 Non-structural and structural shocks to inputs and ouput: a comparison between VAR and SVAR models results

VAR model shocks	**1% shock effect after 10 years**	**SVAR model shocks**	**1% shock effect after 10 years**
HC→ YR	0.047%	*EDU→ YR*	0.108%* 0.068%
KAP → YR	0.124%	*SUP→ YR*	0.125%

Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output; *EDU* – education shock; *SUP* – supply shock. X→Y represents how the variable Y reacts to a shock to variable X. * effect of the shock after three years.

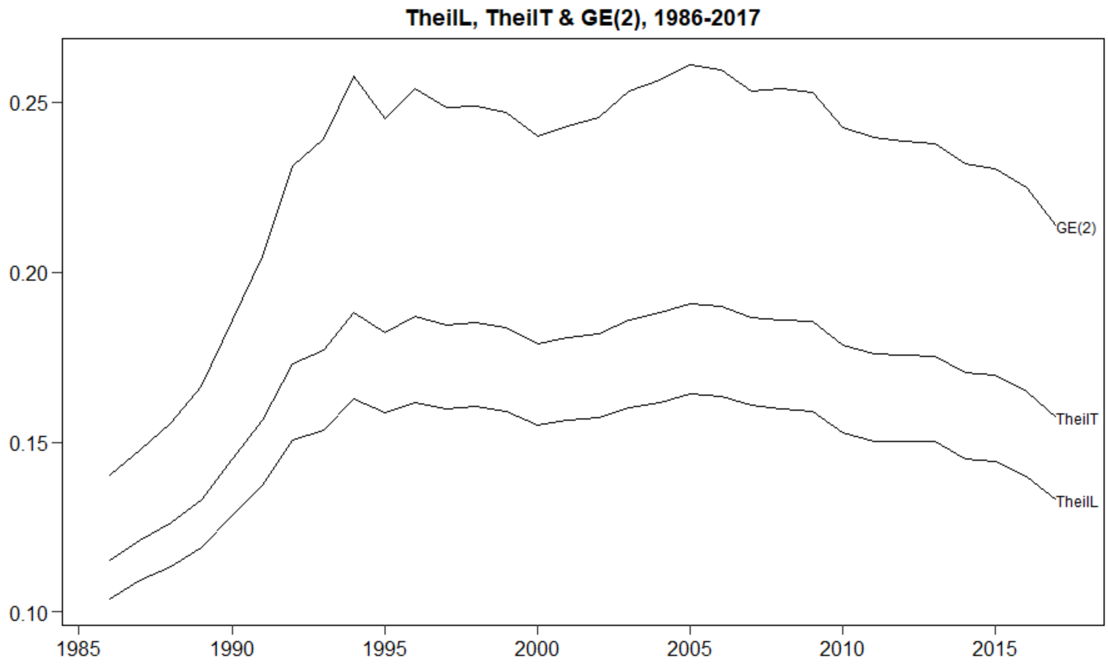
Figure 1 Gini Index, Portugal 1986-2017



Notes: Higher values of the Gini index correspond to more inequality in the distribution of earnings of employees working in the private sector before transfers and taxes.

Source: own computations based on data from *Quadros de Pessoal*.

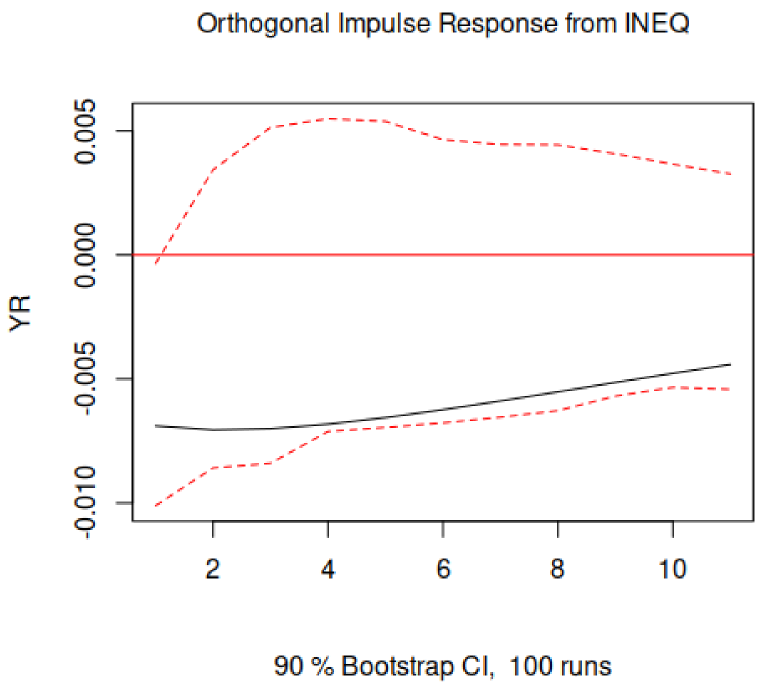
Figure 2 TheilL, TheilT and GE(2), Portugal 1986-2017

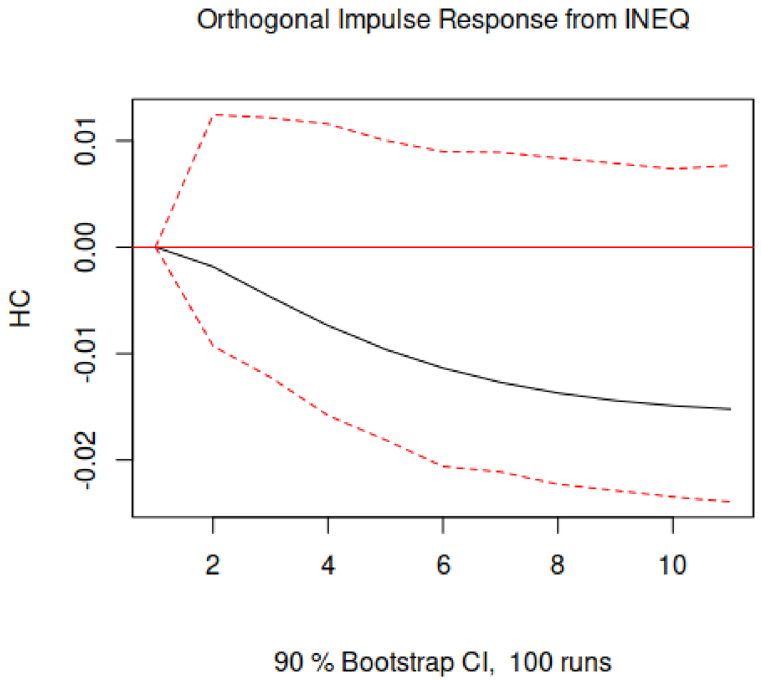


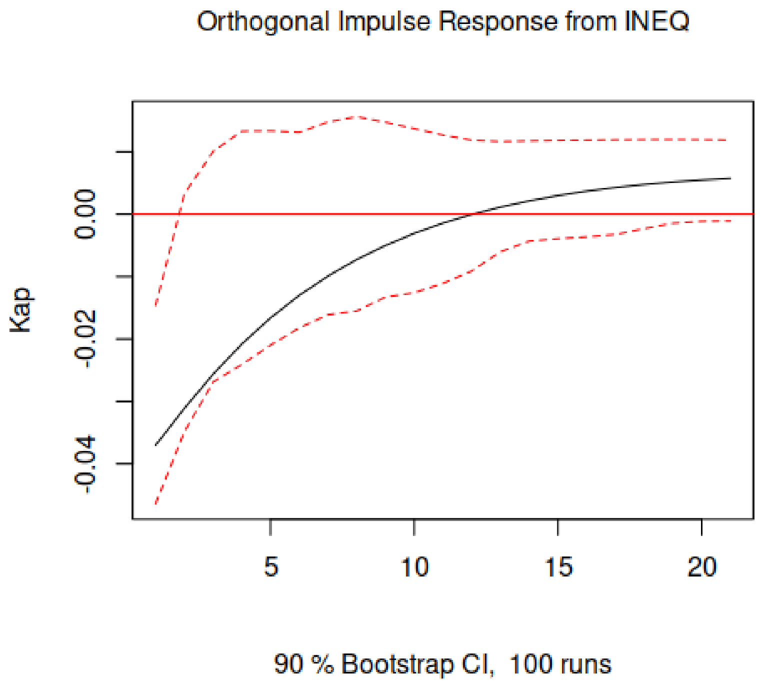
Notes: TheilL, TheilT and GE(2) are Generalised Entropy (GE) indices setting the entropy parameter α equal to 0, 1 and 2, respectively, corresponding to higher sensitivity to different parts of the earnings distribution. Lower (higher) values of α make the GE inequality measure more sensitive to changes in earnings at the bottom (top) of the distribution of earnings of employees working in the private sector before transfers and taxes. Higher values of the indices correspond to higher inequality.

Source: own computations based on data from *Quadros de Pessoal*.

Figure 3 Selected impulse-response results from the VAR model



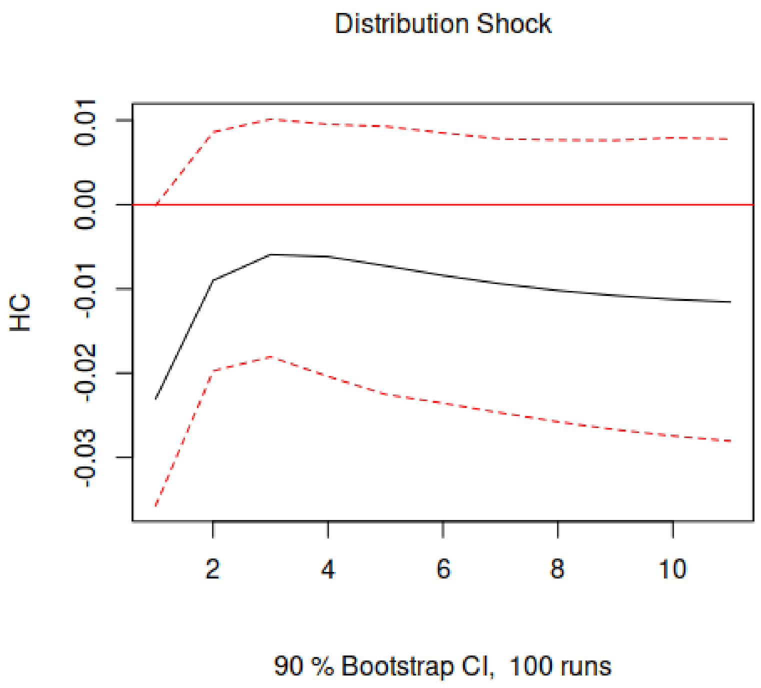


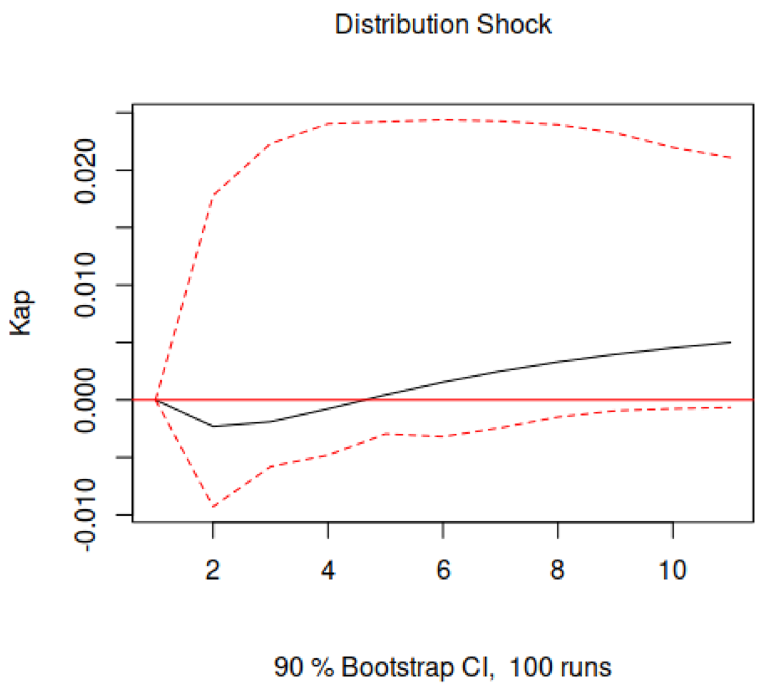


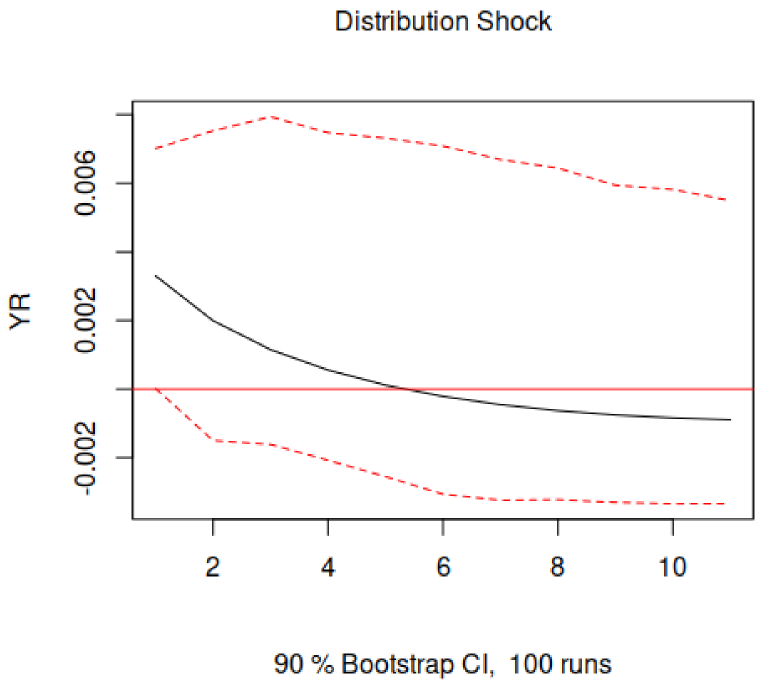
Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output. 3.a – response of *YR* to a one standard deviation shock/impulse to *INEQ* over a 10-years period; 3.b – response of *HC* to a one standard deviation shock/impulse to *INEQ* over a 10-years period; 3.c – response of *Kap* to a one standard deviation shock/impulse to *INEQ* over a 20-years period. The vertical distance between the dashed lines represents the 90% Confidence Interval (CI) computed with bootstrap, based on 100 runs.

Source: own computations based on data from *Quadros de Pessoal* and PORDATA

Figure 4 Selected impulse (structural shocks)-response results from the SVAR model



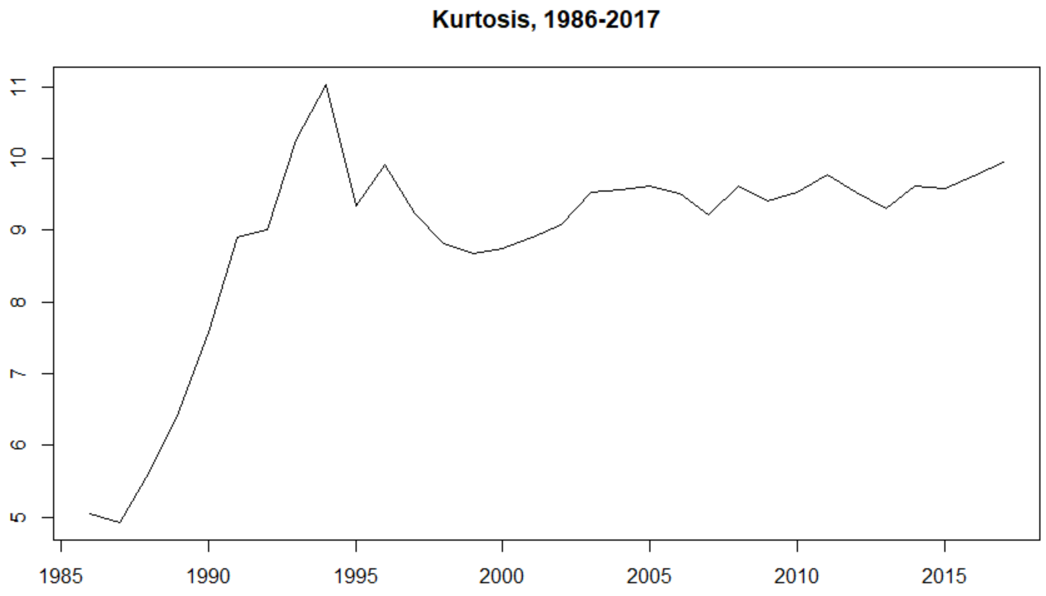




Notes: See notes to Figure 3. 4.1 – response of *HC* to a distribution shock (DIST) over a 10-years period after the shock; 4.2 – response of *Kap* to a distribution shock (DIST) over a 10-years period; 4.3 – response of *YR* to a distribution shock (DIST) over a 10-years period.

Source: own computations based on data from *Quadros de Pessoal* and PORDATA

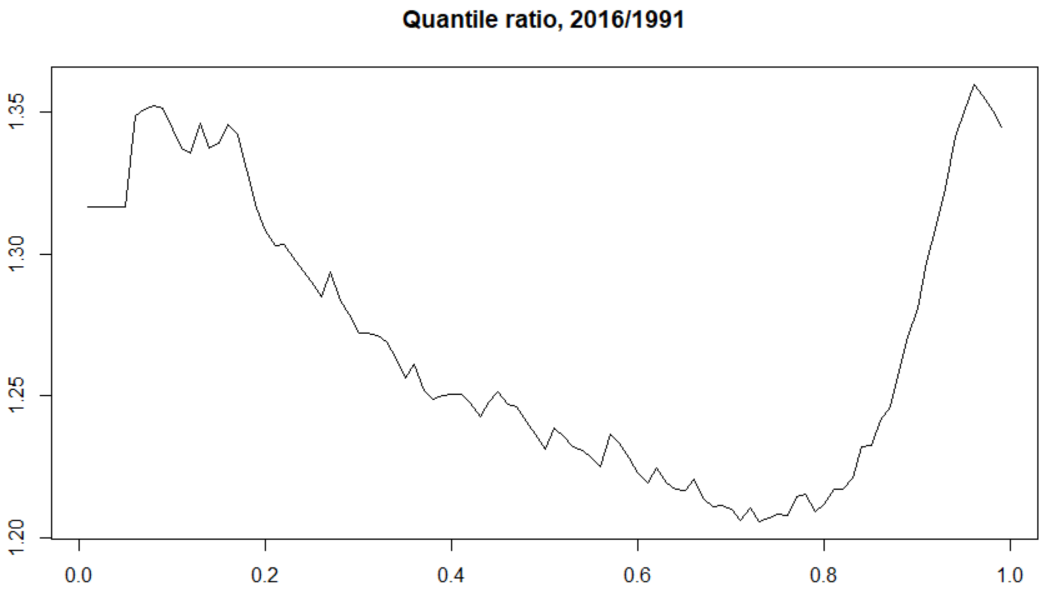
Figure A.1 Kurtosis, Portugal 1986-2017



Notes: a higher value for kurtosis indicates an increase in earnings at the top of the distribution (a fat right tail) relative to the remaining parts of the distribution of earnings of employees working in the private sector before transfers and taxes.

Source: own computations based on data from *Quadros de Pessoal*.

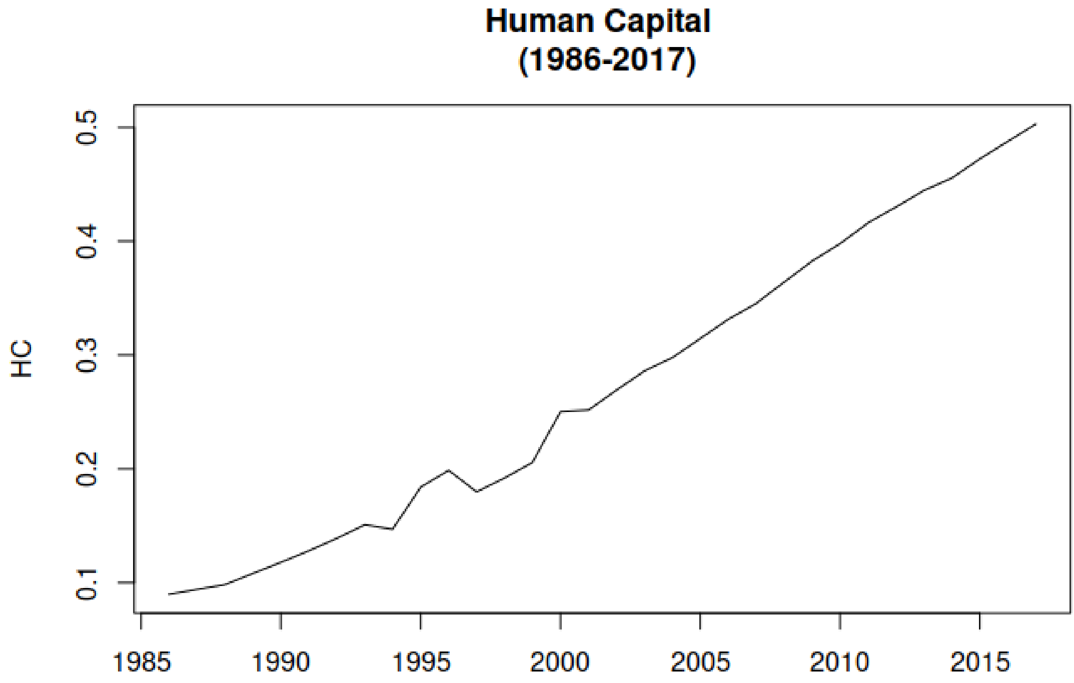
Figure A.2 Quantiles ratios, Portugal 2016 relative to 1991



Notes: ratio between the earnings percentiles 1% to 99% in 2016 relative to 1991. A ratio higher than one implies that between the two years, from 1991 to 2016, there was an increase in earnings for the percentile in question.

Source: own computations based on data from *Quadros de Pessoal*.

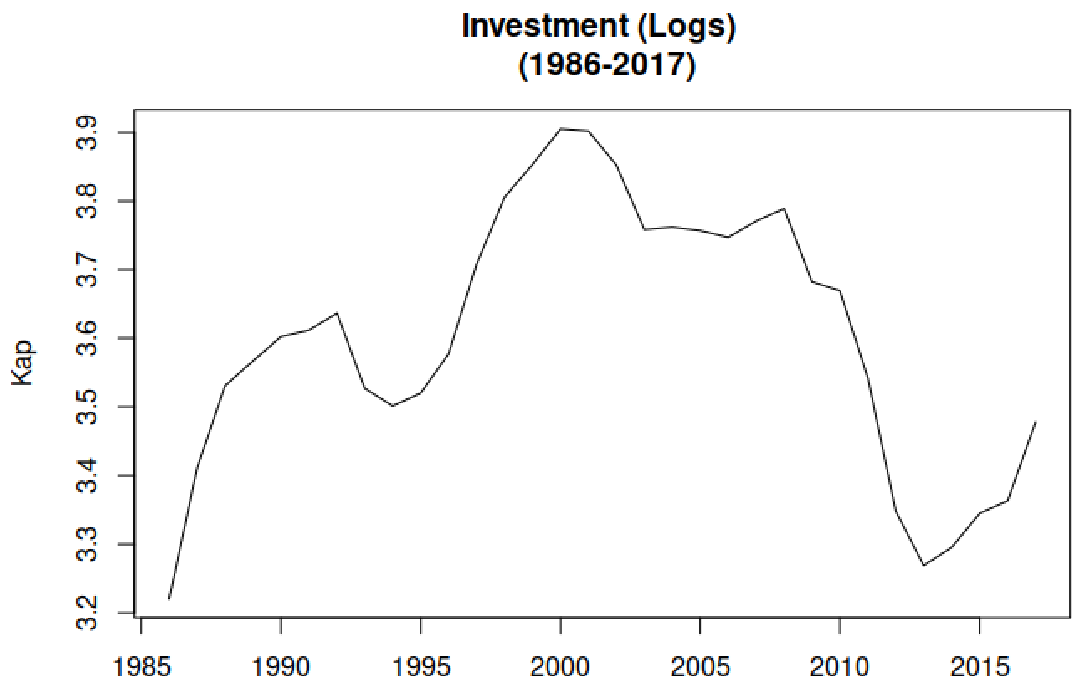
Figure A.3 Human capital, Portugal 1986-2017



Notes: human capital (*HC*) is the log of the percentage of employees that have attained at least secondary education.

Source: own computations based on data from *Quadros de Pessoal*

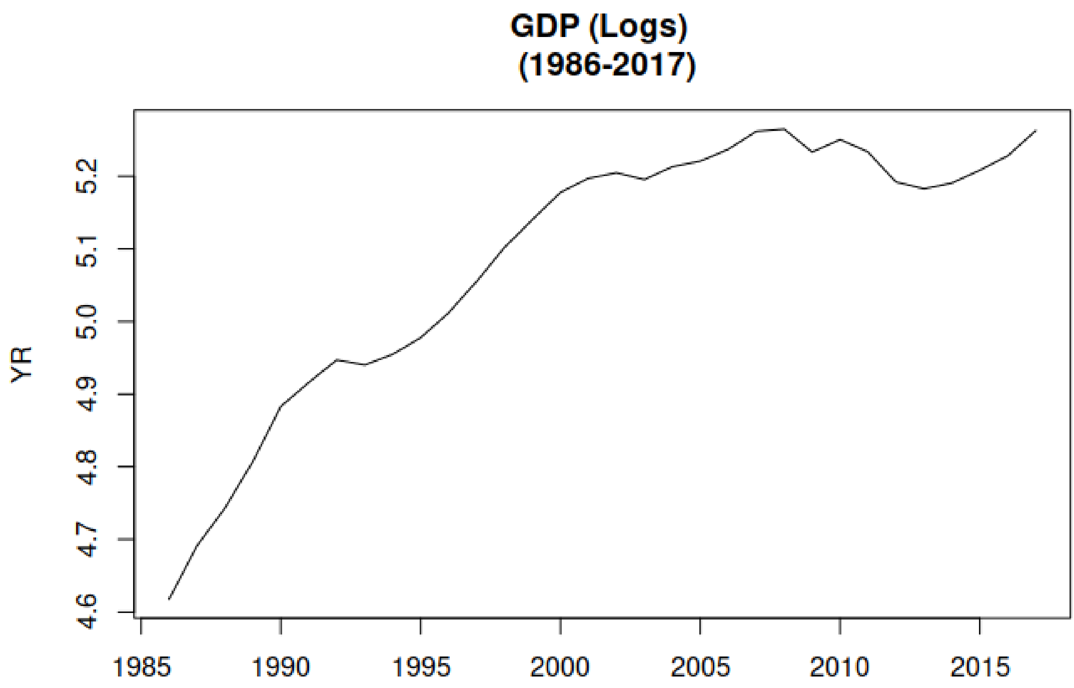
Figure A.4 Investment (logs), Portugal 1986-2017



Notes: investment (*Kap*) is measured as the log of gross fixed capital formation (2016 prices, thousands of million euros).

Source: owncomputations based on data from PORDATA

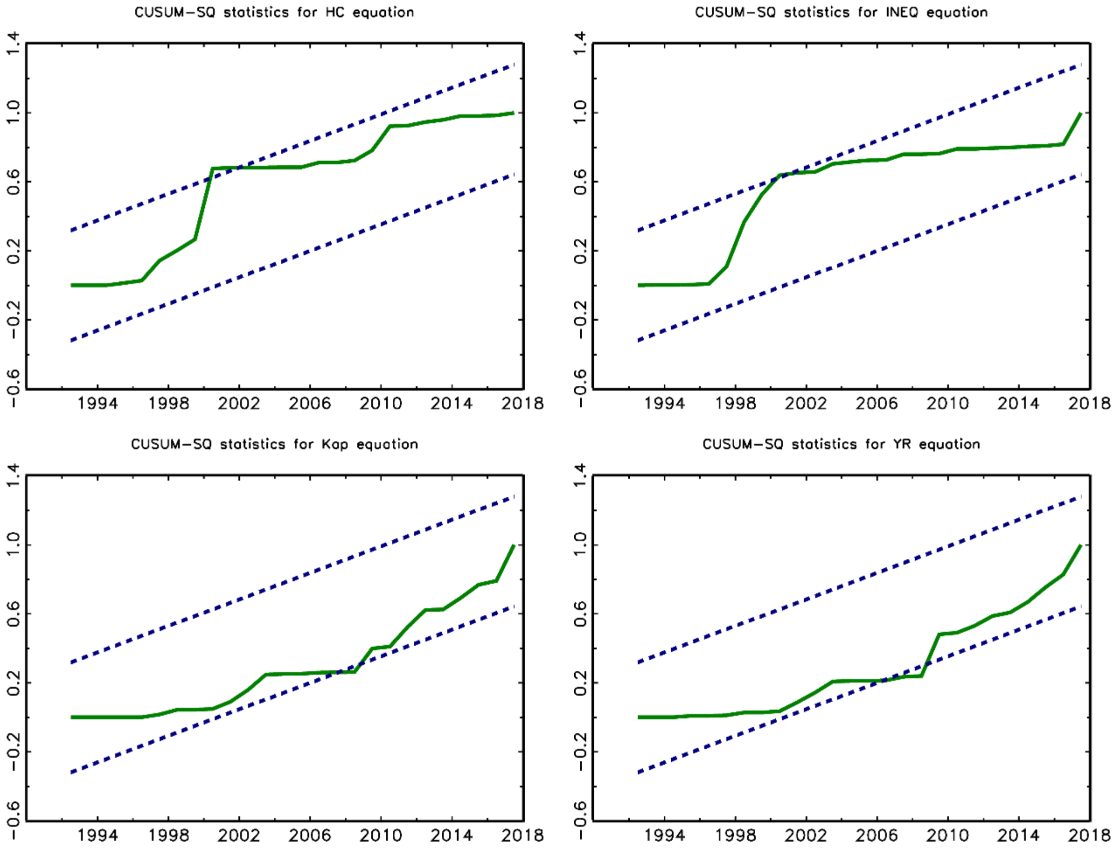
Figure A.5 Real GDP (logs), Portugal 1986-2017



Notes: output (*YR*) is measured as the log of real GDP (2016 prices, thousands of million euros).

Source: own computations based on data from PORDATA

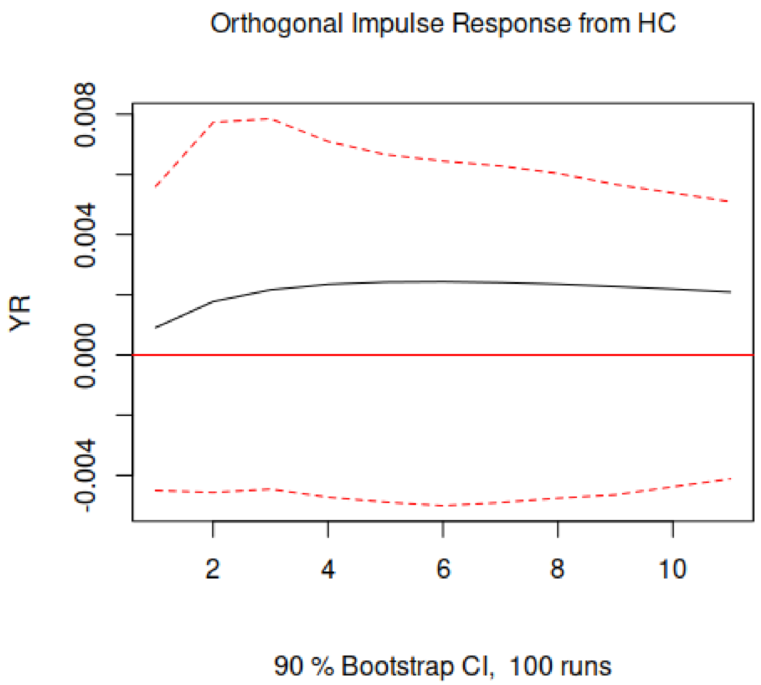
Figure A.6 CUSUM squared test results



Notes: *HC* – human capital; *INEQ* – inequality; *Kap* – investment; *YR* – output. Each figure describes the cumulative sum of the squared scaled recursive residuals (full line) for each of the VAR equations over the period under analysis. The null hypothesis of the CUSUM squared test of parameter stability is rejected at the 5% level if the cumulative sum of the forecast scaled recursive residuals lays outside the 95% confidence interval (dashed lines).

Source: own computations based on data from *Quadros de Pessoal* and PORDATA

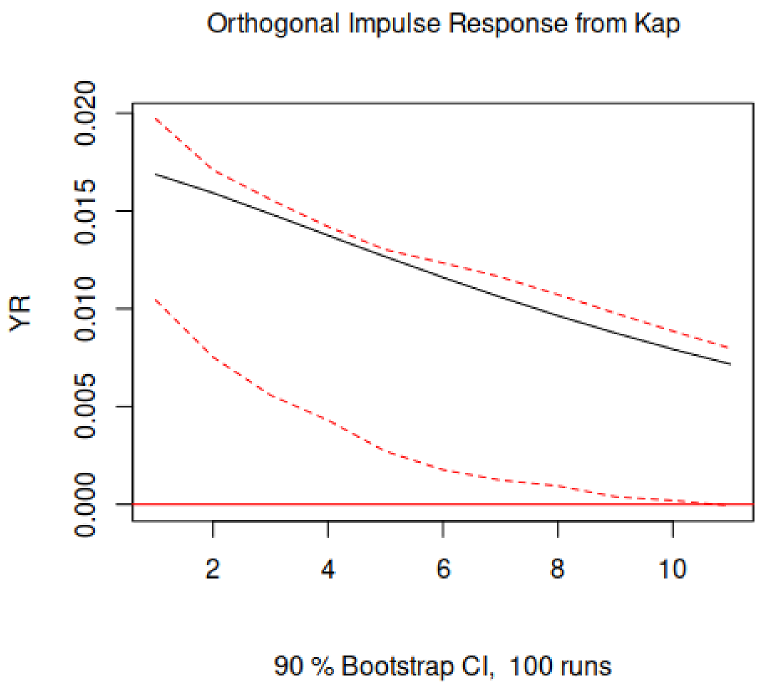
Figure A.7 Response of output to a human capital shock in the VAR model



Notes: *HC* – human capital; *YR* – output. Response of *YR* to a one standard deviation shock/impulse to *HC* over a 10-years period after the shock. The vertical distance between the dashed lines represents the 90% Confidence Interval (CI) computed with bootstrap, based on 100 runs.

Source: own computations based on data from *Quadros de Pessoal* and PORDATA

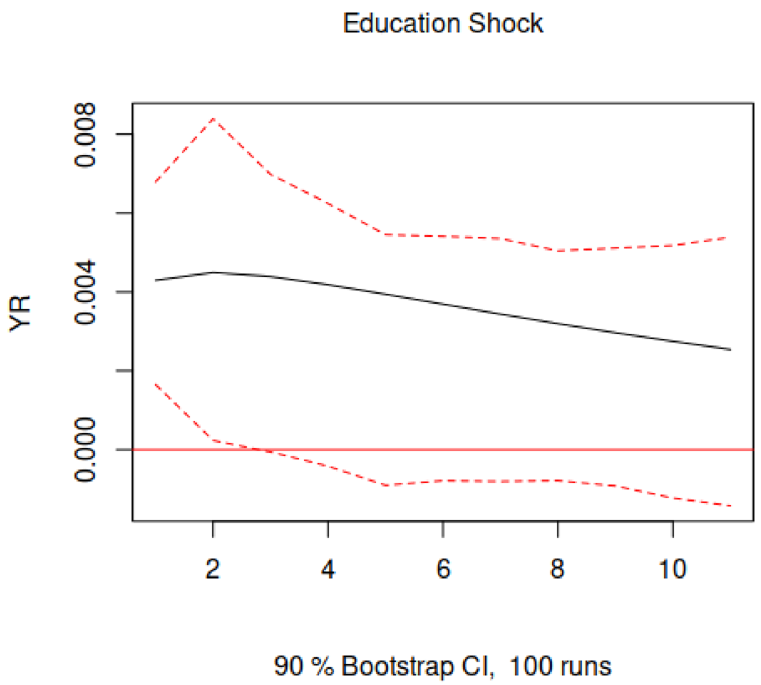
Figure A.8 Response of output to an investment shock in the VAR model



Notes: *Kap - investment*; *YR* – output. Response of *YR* to a one standard deviation shock/impulse to *Kap* over a 10-years period. The vertical distance between the dashed lines represents the 90% Confidence Interval (CI) computed with bootstrap, based on 100 runs.

Source: own computations based on data from *Quadros de Pessoal* and PORDATA

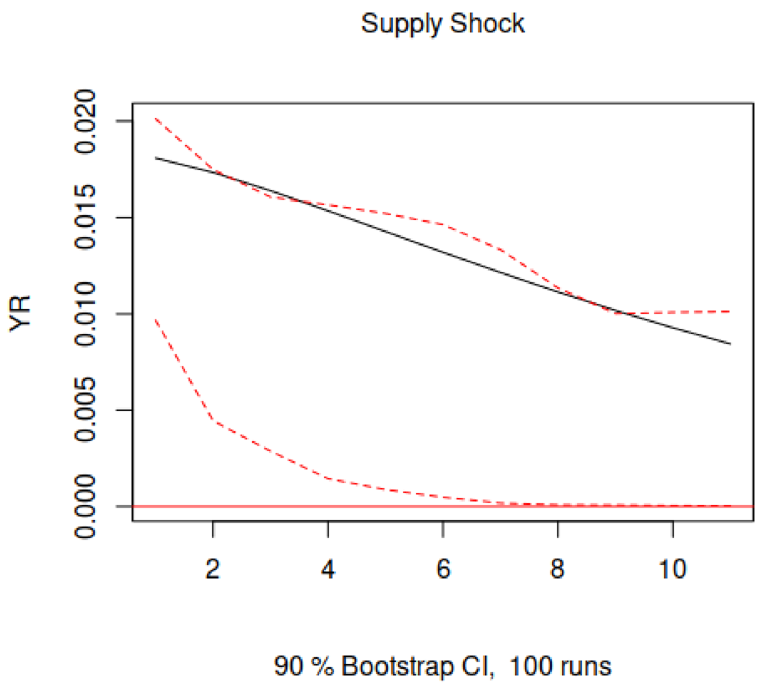
Figure A.9 Response of output to a education shock in the SVAR model



Notes: *YR* – output. Response of *YR* to an education shock (EDU) over a 10-years period.

Source: own computations based on data from *Quadros de Pessoal* and PORDATA

Figure A.10 Response of output to a supply shock in the SVAR model



Notes: *YR* – output. Response of *YR* to a supply shock (SUP) over a 10-years period.

Source: own computations based on data from *Quadros de Pessoal* and PORDATA