



Essays on Inequality and Growth: A bibliometric
approach, two time series analyses and a theoretical
contribution

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Doctoral Thesis in Economics

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“Don’t only practice your art, but force your way into its secrets, for it and knowledge can raise men to the divine.”

– Ludwig van Beethoven, Letter to Emilie M., at H., 1812

Biographical Note

Pedro Gil Gonçalves Lima was born on the 21st of February, 1993. He got a Bachelor's degree in Economics from the University of Aveiro, his hometown, in 2014. After a gap year dedicated to learning German and Chinese, in 2015, he enrolled at the School of Economics and Management of University of Porto in the Master of Economics and Business Administration. He defended his Master's dissertation in 2017. It was entitled "Fama-French models application to the Analysis of FTSE4GOOD, MSCI ESG and STOXX ESG Indices: Do SRI Indices have biases?" and was supervised by Professor Abel Fernandes.

He enrolled at the same institution in the Doctoral program in Economics in 2018. Before that, during the school year 2017-2018, he worked as a high school math tutor in a tutoring center and prepared an application for an individual Ph.D. scholarship from Fundação Ciência e Tecnologia (FCT). He proposed conducting a Ph.D. thesis focused on the relationship between inequality and growth under the supervision of Professors Sandra T. Silva and Óscar Afonso. His application was successful, and the corresponding working plan was completed during the Ph.D. course, culminating in the present Thesis.

He has been invited multiple times as a Teaching Assistant of Macroeconomics I and II (BSc in Economics) at the same institution. Moreover, he actively participated in the realization of research articles that included analyses beyond the scope of this thesis dedicated to Directed Technical Change, the Skill Premium, Labor Share, and automation, among other topics. Altogether, when this Thesis was submitted, four articles had been accepted for publication in the following international peer-reviewed journals: *Applied Economics*, *Economic Systems*, *Journal of Evolutionary Economics*, and *International Journal of Finance & Economics*. Moreover, a fifth paper is also a discussion paper on IZA.

Finally, besides Economics, he shares an active interest in Music. In 2014, he completed the Secondary Musical Course in Piano at the Conservatory of Aveiro.

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Abstract

This Thesis consists of four essays that provide different contributions to the inequality-growth literature.

In the first essay, we develop a systematic analysis of the inequality literature published in economic journals since 1950. We identify the main streams of research by mapping the most important references into clusters through a quantitative bibliometric analysis using the VOSviewer software and a categorization process based on a qualitative analysis of the content and citation context of each reference. Additionally, we characterize each cluster considering the latter analysis and the most influential journals, authors, *Almae Matres*, affiliations, and the corresponding countries. We identify seven clusters, broadly focused on (1) theoretical issues related to the measurement of inequality, (2) inequality and development, (3) inequality and growth, (4) theoretical and empirical analyses of the wealth distribution, (5) heterodox perspectives, (6) the rise of Inequality since 1980 and (7) Inequality, Education and Environment. The inequality-growth is the third largest cluster, with the most average number of citations per reference. Its emergence in the nineties was due to the development of endogenous growth models and increased data availability.

The second and third essays are complementary time series analyses of the inequality-growth relationship and its transmission channels. The second essay is focused on the United States and France during 1962-2018 and uses an approach that innovates by (i) adopting a SVAR approach that accounts for variables that simultaneously affect both variables, (ii) employing model reduction strategies to reduce the parameter space and applying bootstrap methods to diagnostic and causality tests and (iii) designing some of these methods. We find that (a) inequality decreases growth contemporaneously in the United States and in the medium run in France, with and without controlling for transmission variables, (b) it does not affect enrollment rates and increases redistribution intensity, with the latter not affecting economic growth, (c) in the United States, the negative effects of inequality on growth occur essentially after the year 1989.

The third essay is focused on 27 European Union members (as of 2021) during 2001-2019 and uses a structural panel VAR econometric approach. We find that inequality does not affect growth. Regarding transmission channels, it does not affect human capital; it decreases investment and increases redistribution, with the latter not affecting investment, human capital, or growth directly. These effects are stronger in laggard EU countries and are robust to accounting for variables that potentially determine inequality and growth simultaneously and the global financial and European sovereign Debt crises, as well as different model specifications and alternative identification assumptions concerning structural shocks.

This fourth essay is a theoretical analysis of the effects of inflation on inequality (Skill Premium) and growth, conducted in the context of a Directed Technical Change model (DTC) with cash-in-advance (CIA) constraints specific to the unskilled and skilled sectors. Calibrating with data from 36 countries, we find that the presence of

more stringent CIA constraints in the unskilled sector causes inflation to affect the skill premium positively. Moreover, it also increases the negative impact of inflation on the growth rate concerning the baseline scenario of homogeneous CIA constraints.

Keywords: inequality, growth, transmission channels, redistribution, human capital, investment, bibliometrics, time series, SVAR, panel VAR, Directed technical change, Inflation, CIA constraints, bootstrap, model reduction, crises, US, France, EU.

JEL Codes: B2, C32, C33, C61, D31, E24, C32, O10, O11, O15, O31, O38, O40, O47, O52, J31; E41.

Resumo

Esta Tese consiste em quatro ensaios com diferentes contribuições para a literatura da desigualdade-crescimento económico.

No primeiro ensaio, desenvolvemos uma análise sistemática da literatura da desigualdade publicada em revistas científicas desde 1950. Identificamos as principais correntes de investigação com um mapeamento em *clusters* das referências mais importantes com uma análise bibliométrica quantitativa, recorrendo ao software VOSviewer e a um processo de categorização baseado numa análise qualitativa do conteúdo e contexto de citação de cada referência. Adicionalmente, caracterizamos cada cluster tendo por base a análise referida e as principais revistas, autores, *Almae Matres*, afiliações e países correspondentes. Identificamos sete *clusters*, focados de uma forma geral em: (1) problemas teóricos com a mensuração da desigualdade, (2) desigualdade e desenvolvimento económico, (3) desigualdade e crescimento económico, (4) análises teóricas e empíricas da distribuição de riqueza, (5) perspetivas heterodoxas, (6) o crescimento da desigualdade desde 1980, (7) Desigualdade, educação e ambiente. O *cluster* dedicado à relação entre desigualdade e crescimento é o terceiro maior, com o maior número de citações médias por referência. O seu surgimento nos anos 90 deveu-se ao desenvolvimento de modelos de crescimento endógeno e à maior disponibilidade de dados.

O segundo e terceiro ensaios são análises complementares de séries temporais da relação entre desigualdade e crescimento económico e dos seus canais de transmissão. O segundo ensaio foca-se nos Estados Unidos da América e França durante 1962-2018 e utiliza uma abordagem que inova (i) pela adoção de uma abordagem SVAR que considera variáveis que afetam ambas simultaneamente, (ii) pelo emprego de estratégias de redução de modelos para reduzir o espaço de parâmetros e de métodos *bootstrap* no contexto de testes de diagnóstico e de causalidade, (iii) pelo desenvolvimento de alguns dos métodos mencionados. Verifica-se que (a) desigualdade tem um impacto negativo sobre o crescimento económico contemporaneamente nos Estados Unidos e a médio prazo na França, (b) não afeta a participação no ensino superior e aumenta a intensidade de redistribuição, sem que a última exerça efeitos no crescimento económico, (c) nos Estados Unidos, os efeitos negativos da desigualdade no crescimento ocorrem essencialmente após 1989.

O terceiro ensaio foca-se em 27 estados-membros da União Europeia (em 2021) durante 2001-2019 e utiliza uma abordagem econométrica VAR estrutural em painel. Verifica-se que a desigualdade não afeta o crescimento económico. No que diz respeito aos canais de transmissão, não afeta o capital humano, diminui o investimento e aumenta a intensidade redistributiva, sem que esta afete o investimento, capital humano ou crescimento económico diretamente. Estes efeitos são mais fortes em estados-membros menos avançados e são robustos à consideração de variáveis que potencialmente afetam a desigualdade e o crescimento económico simultaneamente, bem como das crise financeira e crise europeia da dívida soberana, a diferentes especificações do modelo e a pressupostos alternativos de identificação dos choques

estruturais.

O quarto ensaio é uma análise teórica dos efeitos da inflação sobre a desigualdade (Prémio Salarial) e o crescimento económico, no contexto de um modelo de *Directed Technical Change* com restrições *cash-in-advance* (CIA) específicas ao setor não qualificada e qualificado. Calibrando com dados de 36 países, a presença de restrições CIA mais elevadas em setores não qualificados leva a que a inflação tenha um impacto positivo no prémio salarial e exacerba o impacto negativo da inflação no crescimento económico em relação a uma especificação onde se consideram restrições homogéneas.

Palavras-chave: desigualdade, crescimento, canais de transmissão, redistribuição, capital humano, investimento, bibliometria, séries temporais, SVAR, VAR em painel, *Directed Technical Change*, Inflação, restrições CIA, *bootstrap*, redução de modelos, crises, EUA, França, União Europeia.

Classificação JEL: B2, C32, C33, C61, D31, E24, C32, O10, O11, O15, O31, O38, O40, O47, O52, J31; E41.

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Chapter 1

Introduction

The inequality-growth relationship has been studied extensively in the literature, both empirically and theoretically. Nonetheless, analyses of this topic remain crucial in current times, not only due to the increasing inequality trends that continue both within developing and advanced economies but also due to its complexity in general, which has kept the literature from reaching a consensus concerning its nature and the transmission channels through which it operates. Bearing this in mind, this Doctoral Thesis consists of four related essays that provide different and pertinent contributions to this literature, including innovative methodological approaches. The four essays are in chapters 2 to 5, and chapter 6 contains the main conclusions of the Thesis.

The first essay (chapter 2) is entitled “Major Streams in the Economics of Inequality: A Qualitative and Quantitative Analysis of the Literature since 1950” and consists of an analysis of the most relevant streams of research in the economic inequality literature since the 1950s. The essay analyzes the most influential papers in this literature and identifies the different streams of research to which they belong, with a methodology that innovates by combining a quantitative bibliometric co-citation analysis using the VOSviewer software and a qualitative analysis based not only on the context of each reference but also the context in which they are cited. We find seven distinct clusters, among which the inequality-growth strand of the literature, which is the most influential. Therefore, although the main focus of this essay is on the economic inequality literature in general, it is also an essential contribution to the inequality-growth literature by highlighting its importance within this broad literature and contextualizing within it and identifying the most influential papers.

The second essay (chapter 3) is entitled “The inequality-growth relationship in the US and France: A SVAR approach with bootstrap and model reduction techniques”. It consists of a time series analysis of the inequality-growth relationship and the transmission channels through which it operates using a structural vector autoregressive (SVAR) approach focused on the United States and France, in the period 1962-2018. This paper is motivated by the lack of consensus in the literature and the fact that there are few analyses focused on individual countries, despite the evidence over the years suggesting that this relationship is highly country-specific. We innovate in this essay due to our focus and the methodological approach we adopt, which, relative to the methodology usually adopted in the literature, allows us to obtain more information, more precise results and avoids specific issues, such as the quality problem of instruments. We also consider the importance of variables

simultaneously affecting inequality and growth, implement model reduction techniques where zero restrictions are applied to irrelevant coefficients and bootstrap methods to obtain more accurate results. This approach, to the best of our knowledge, has not yet been applied in the related literature. Moreover, we also provide novel contributions to the techniques we use. The first is a model reduction technique where restrictions are applied based on the results of causality tests conducted in the context of bivariate models. This approach innovates by providing information on bivariate models that is useful on its own and giving the researcher more flexibility and control over the applied restrictions. The second is a bootstrap method that can be used in the context of instantaneous causality tests. We found that inequality affects growth negatively in both countries, contemporaneously in the United States and in the medium run in France. An analysis of transmission channels shows that inequality does not affect human capital and increases redistribution, with the latter not affecting economic growth. Finally, we only found evidence of structural change in the relationship in the United States, where the negative effects of inequality on growth are present essentially after 1989.

The third essay (chapter 4) is entitled “How does inequality affect growth in the European Union? A structural panel vector autoregression analysis”. It corresponds to an analysis of the inequality-growth relationship and its transmission channels in 27 members (as of 2021) of the European Union (EU) in the period 2001-2019 using a panel VAR modeling approach. This essay shares some of the same reasons that motivated the previous one but also serves as a ‘back-to-back’ paper by compensating for its most important limitation, the reduced number of observations. The choice of the EU as the focus of our analysis is justified for two reasons. The first is the lack of studies of this relation in these countries despite the increased within-inequality trends that have characterized many European economies over time. The second is that EU member countries have a common set of institutions. Therefore, in relation to the approach usually adopted in the literature of considering highly heterogeneous countries, this analysis renders subsequent results more useful to the design of appropriate policies and avoids data problems due to the harmonization and quality of its sources. We find that inequality does not have a statistically significant impact on growth when no transmission variables are considered. However, when they are, we found that it affects redistribution positively and investment negatively, with the latter effect occurring only contemporaneously. Moreover, in an analysis of subgroups of countries with high and low GDP averages, we found that the previous negative

effects are more prevalent in the latter. These results are robust to the addition of control variables that potentially simultaneously affect inequality and growth, the inclusion of dummy variables to account for the effects of the global financial and European sovereign debt crises, and alternative estimation specifications and identification assumptions.

Finally, the fourth essay (chapter 5), entitled “Effects of Monetary Policy on the Skill Premium and the Growth rate in a Directed Technical Change model with heterogeneous Cash-in-Advance constraints”, is a theoretical contribution already published in the *International Journal of Finance & Economics*. In it, we consider a Directed Technical Change model with cash-in-advance constraints specific to skilled and unskilled sectors in the economy that are potentially heterogeneous. We conclude that the presence of heterogeneous constraints causes inflation to have a more substantial impact on the Skill Premium and economic growth comparing to a baseline scenario with homogeneous constraints. This essay is important because it provides a new perspective on how inequality, measured by the Skill Premium, and growth can be related to one another by being simultaneously affected by inflation when there are differences in certain restrictions faced by different sectors of the economy. Moreover, in doing so, it provides a theoretical justification for considering the role of this variable in empirical analyses of the inequality-growth relationship, namely those conducted in the second and third essays of this Thesis.

Chapter 2

Major Streams in the Economics of Inequality: A qualitative and quantitative analysis of the literature since 1950

A preliminary version of this chapter was published in 2021 in IZA as Discussion Paper No. 14777 .

2.1 Introduction

When the first volume of the Handbook of Income Distribution was published in 2000, the subject of income inequality was not in the mainstream of economic debate – despite the long history of engagement with this issue by earlier leading economists. Fifteen years later, inequality has become very much center stage. Rising income inequality has attracted the attention of the U.S. President, of international bodies such as the IMF and the OECD, and of participants in the Davos meeting. (A. B. B. Atkinson & Bourguignon, 2015, p. xvii)

In recent years the topic of inequality has attracted the attention of many economists and policymakers, as the epigraph points out. Following the success of the work by Piketty and others, several economists have been arguing that such renewed interest was only taking place after years of neglect (Alacevich & Soci, 2017; Cook, 2019). The topic of inequality has been a major issue in modern economic thought (and during most of the twentieth century). However, its academic visibility has often been shaped by the broader political and social context and the attention these circles have devoted to inequality. After a period, in the latter part of the twentieth century, when inequality was less visible in policy debates (A. B. Atkinson, 1997), the beginning of the twentieth-first century began showing a growing interest in academic and political circles on the topic, which has clearly intensified since the last great recession. Despite the importance of this literature, to the best of our knowledge, there has yet to be a systematic attempt to identify the main streams of research in this field and to explain how they evolved.

Considering this, we conduct a systematic analysis of the literature on inequality focused on the period after 1950. This objective can be accomplished by conducting traditional types of qualitative analysis (*e.g.*, textual analysis) or quantitative methods, namely bibliometric analysis. However, the literature has increasingly relied upon the latter. One of the main reasons is the massive increase in the number of publications over the years that make the former not only increasingly unfeasible but prone to biases of researchers (Claveau & Gingras, 2016). Moreover, quantitative methods are also particularly relevant when the emphasis is on magnitudes of interactions and dissemination or when it comes to studying the organizations producing, circulating and applying economic ideas (Claveau & Dion, 2018). Thus, several recent studies have used bibliometric tools to study the evolution of subject areas in economics (Kelly & Bruestle, 2011) and map developments in fields such as

finance (Borokhovich, Bricker, Brunarski, & Simkins, 1995, 1998; Borokhovich, Bricker, & Simkins, 1994, 2000); risk, insurance, and actuarial studies (Colquitt, 1997, 2003); health economics (Rubin & Chang, 2003); agricultural economics (Hilmer & Lusk, 2009); national systems of innovation (Teixeira, 2014); structural change (E. G. Silva & Teixeira, 2008); evolutionary economics (S. T. Silva & Teixeira, 2009); industrial relations (Casey & McMillan, 2008); environmental economics (Kube, Löschel, Mertens, & Requate, 2018); and behavioral economics (Geiger, 2017). These studies have illustrated the relevance of bibliometric tools in characterizing the intellectual and institutional networks and the dissemination flows established in several important areas of research in economics.

Despite the attractiveness of quantitative methods over traditional ones when analyzing large bibliographic data sets, several authors have emphasized the importance of complementing them with analytical approaches to understand major developments in economics (see Cherrier & Svorencík, 2018; De Vroey, 2016; Jovanovic, 2018). Hence, we combine a quantitative and qualitative approach to identify, characterize and contextualize the main streams of research on the inequality literature since 1950. Specifically, we use VOSviewer software to group the most important references into distinct clusters using a co-citation analysis, which quantifies the number of documents that cite each pair of references. We complement it with a categorization process that identifies each reference’s research streams through a qualitative analysis of its main focus and context of citation. We then characterize and contextualize the emergence and development of main clusters. This is done by considering the previous categorization and identifying top authors, affiliations, *Alma Matres*, and corresponding countries. Although there have been quantitative analyses of the literature on inequality (*e.g.*, Korom, 2019), we consider that these aspects make our approach a significant and innovative contribution.

The remaining structure of this article is as follows: Section 2.2 presents a brief overview of Inequality debates in the Twentieth Century; Section 2.3 describes the methodology used in more detail; Section 2.4 characterizes the network and each cluster; finally, Section 2.5 presents the main concluding remarks, some limitations and suggestions for further work on our study.

2.2 A brief overview of Inequality debates in the Twentieth Century

Inequality has been a major topic of interest in economics throughout the twentieth century, though the attention it has received has been uneven. The debates about it have often oscillated between theoretical discussions about the importance of inequality as an economic phenomenon and empirical controversies about how to measure inequality, its magnitude and its underlying factors. Since the early twentieth century, following the debates about the so-called Pareto's Law, one major issue has been how stable (or changeable) inequality was and how effective could different policy approaches be in tackling inequality. Moreover, these debates about policy and social changes have tended to interact with academic research on the topic, being nurtured by economists' contributions and also stimulating further research.

The topic of personal income distribution has attracted significant attention since the early twentieth century due to the so-called Pareto's law (Pareto, 1896). This analysis indicated that the distribution of wealth was stable in different historical and geographical contexts, which caused great perplexity and controversy as it suggested that the attempts to redress inequality were doomed to fail. Hence, a large part of research on income distribution in the early decades of the twentieth century focused on testing it in different geographical and historical contexts (*e.g.*, Bresciani-Turroni, 1905; Stamp, 1914). Although the initial results indicated that Pareto's views seemed to be empirically supported, subsequent research produced more ambiguous results and highlighted the fragility of the data (Bresciani-Turroni, 1939; Crum, 1935; Macgregor, 1936; Shirras, 1935).

This strengthened the view among many economists of the early twentieth century that social and economic policies could significantly impact inequality, especially many influential British economists, who had been investigating the factors underlying the distribution of personal income and wealth (see, among others, Cannan, 1914, 1917; Dalton, 1920; Stamp, 1926). Notable among these was Pigou (1920), who considered that the current distribution of income could be changed either by policies that changed the proportion between earned income and other (inherited) income or that created opportunities for social mobility (primarily through education and training).

If Pareto's approach was criticized in Britain mainly due to its implications regarding inequality, on the other side of the Atlantic, it was criticized for its

empirical and statistical shortcomings. These criticisms coincided with a growing concern among American economists about data limitations, especially within scientific contexts with a stronger empirical tradition or interest in the topic, such as the so-called old institutionalism (Rutherford, 2011). With the creation of the National Bureau of Economic Research (NBER) in the early twenties, the statistics related to inequality received a significant boost. It is noteworthy that the first study developed by the NBER was devoted to the quantification of American income and its distribution (Mitchell, King, & Macaulay, 1922), which was followed by several others in the 1920s and 1930s (Ingalls, 1922; King, 1930; Leven, Moulton, & Warburton, 1934). Another vital step to promote empirical research was the establishment by the NBER in 1936 of the Conference on Research in Income and Wealth, which aimed at stimulating cooperative research on these topics to contribute to a consensus in terms of concepts, terminology, and methods of exposition.¹

The growth in empirical studies about income and wealth distribution brought other problems. The available studies were quite heterogeneous concerning methods and data, which raised problems of comparability, reliability, and continuity of sources and types of income distribution data. There were also specific problems concerning concepts (especially income), the recipient units, the coverage of income groups, geographic dispersion, class intervals, and accessibility of data. Moreover, the lack of an extensive socioeconomic characterization of the income recipients, in particular the omission of the education factor, was seen as one of the most severe gaps affecting the generality of the studies. This scarcity of information prevented the discovery of the determinants of the income distribution (such as education, age, gender, religion, or ethnicity) and the assessment of their impact, thus requiring further work.

The significant improvements in data, especially in the postwar period, created new possibilities for empirical work that lead to two directions. Some authors took a macroeconomic approach and explored links between income inequality and macroeconomic variables. In this regard, Simon Kuznets was especially important. The author focused on relationship between economic growth and income inequality and such interest was reflected not only by his seminal contribution (Kuznets, 1955), but also the presidential address at the 1954 meeting of the American Economic Association (AEA).

Other authors focused on the possible factors determining the existing

¹These meetings gathered many economists that would provide essential contributions such as Simon Kuznets, Morris Copeland, Milton Friedman, Dorothy Brady, and Margaret Reid.

distribution. In this regard, Milton Friedman (1953) emphasized the role of individual decisions and challenged both the exogenous hypothesis of ability and the quasi-exogenous hypothesis of institutional arrangements (such as inheritance rules). By the late fifties, in a context of expanding statistical evidence and stronger theoretical emphasis, the exploration of socioeconomic characteristics associated with inequality (*e.g.*, education and training) gained increasing visibility. This was crucial for the emergence of human capital theory in the later part of the decade (as in Jacob Mincer’s Ph.D. dissertation, 1957). Henceforth, education and training became increasingly regarded as major forces shaping the personal distribution of income and wealth and dominated most inequality debates in the 1960s and 1970s.

Whereas human capital research emerged in a period characterized by great hopes in the potential role of public policies in promoting social mobility, notably in improving the traditionally disadvantaged groups such as women or ethnic minorities, by the end of the 1970s these hopes had given way to profound skepticism. Propelled by poor results in terms of social mobility and economic growth, many started to question the real economic effect of schooling and other policies aiming at reducing inequality (Jencks, 1972). Together with the reduction of the role of the state in several policy areas, this has led to declining attention in academic and policy circles to inequality in the last quarter of the twentieth century.

In recent decades, inequality has again come to the forefront of economic debates. This revival of interest is the result of a complex web of factors. One major factor has been the impact of technology on the labor market and the changing structure of employment (Autor, Katz, & Kearney, 2008; Card & DiNardo, 2002). Another important issue in recent decades has been the growing attention to issues of intergenerational transmission of inequality (Bowles & Gintis, 2002; Piketty, 2001). Finally, the debates about globalization have also given particular visibility to issues of inequality in the work of many economists (A. B. Atkinson, 2014; Bourguignon, 2015; Milanovic, 2016; Piketty, 2014).

In the following sections, we will analyze this large body of literature through a bibliometric approach. This will allow us to identify major clusters of themes, authors and publications in economics devoted to the study of inequality.

2.3 Methodology

In this section, we explain the methodology employed concerning the type of analysis and the reference selection process to achieve the main goal of this paper: to identify, characterize and contextualize the main streams of research in the inequality literature since 1950.

2.3.1 Type of Analysis

The identification of the main streams of research requires a suitable method to analyze the degree of similarity between the various references. This analysis can be done using informal inside knowledge of the field's authors or bibliometric methods (Claveau & Gingras, 2016). The first approach has the disadvantage of leading to biases and being increasingly unfeasible, considering the exponential growth of the literature in general. Therefore, a bibliometric approach is more appropriate.

The bibliometric literature has developed various types of analysis based on different measures to assess the degree of similarity between references. Some of the most popular are co-citations analyses, which are based on the number of times references are cited in the same documents (*e.g.*, Korom, 2019), bibliographic coupling analysis, which groups references based on the overlap degree of bibliographic references between documents (*e.g.*, Claveau & Gingras, 2016), and co-authorship analysis, which can consist of a network of authors, authors' countries or authors' affiliations grouped by the number of co-authored documents (*e.g.*, Park, Yoon, & Leydesdorff, 2016).

We opt for a co-citation analysis because it is the approach capable of providing the most relevant information. Focusing on bibliographic references permits analyzing in detail not only the authors that are most commonly co-cited together but also the particular context where such citations appear.

We conduct this bibliometric analysis with the VOSviewer software, which constructs a network of references grouped by clusters determined by the relatedness of the references. The clustering process of this software is based on a unified approach developed by Van Eck and Waltman (2014), Waltman and Van Eck (2013), Van Eck and Waltman (2010) and Waltman, Van Eck, and Noyons (2010). It consists of assigning cluster numbers to the references that minimize a value function that depends on two elements: The first is the association strength between different references, which is calculated automatically based on the number of links of the

references and their strength. The second is the distance between references, which, for different references, is equal to the inverse of the resolution parameter. Therefore, the higher it is, the less the distance between each pair of references and the final number of clusters.²

The researcher can set the resolution parameter and, therefore, maintains some control over the final number of clusters in the network. This permits conducting a qualitative analysis to determine an adequate division of clusters that considers aspects beyond the scope of a quantitative approach. Considering this, the final resolution parameter is determined using the following iterative algorithm: (i) divide the network into different clusters using the VOSviewer software for a given resolution parameter; (ii) categorize each reference based on a qualitative analysis of the summary and the context of citation. In this regard, particular attention is given to the reasons justifying the citation that are also congruent with other references in the same cluster; (iii) analysis of the similarity of the different streams of research within each cluster;³ (iv) if at least one cluster contains very different streams of research, increase the resolution parameter by a discretionary value and repeat the process from steps (i) to (iv). Otherwise, finish.

In the first iteration of this process, we considered the default resolution parameter, 1. This resulted in a network of five clusters but a closer analysis led us to revise this division as it contained quite heterogeneous streams of research. We successively increased the resolution parameter until we obtained sufficiently homogeneous clusters. This occurred when we obtained seven clusters with a resolution parameter of 1.17. We further increased this parameter to determine whether a higher number of clusters resulted in an even more adequate division. However, we concluded that a higher number of clusters was excessive as some clusters were not sufficiently heterogeneous to justify being separated. Therefore, we concluded that the most adequate division of clusters was seven.

We then characterized and contextualized the emergence of each cluster by focusing on the most important categories determined in step (ii) and the

²We must note that the resolution parameter is a technical parameter without an intuitive interpretation in itself. For more details, please consult Waltman et al. (2010) and the other references cited above.

³We must make a few notes. First, in some cases, the theme of a reference is not directly connected to its categorization. Second, we consider that many references belong to more than one stream of research because they are cited for multiple reasons. Third, although each reference is assigned a specific cluster, as can be readily seen by the map produced by VOSviewer, there is a close connection between many references belonging to different clusters. Therefore, we should not interpret the clusters as mutually exclusive groups due to their complex interconnections.

corresponding qualitative analysis. We additionally identified and analyzed the profile of the most influential authors, including aspects such as the journals where they have published, their academic affiliations and their *Alma Matres*, and the corresponding countries. In doing so, we have also considered relevant literature that provided additional personal, economic, political, and academic explanations for the development of the various streams of research.

2.3.2 Dataset

We first obtained 2510 references from a search on the Web of Science conducted on the 5th of April 2021 of english written articles published since 1950. We sought to retrieve articles that contained in their title and topic a combination of words related explicitly to the type of inequality we are studying, income and wealth inequality. This was accomplished by using the following search terms:

TI = (“income inequality” OR “inequality in income” OR “income distribution” OR “distribution of income” OR “wealth inequality” OR “inequality in wealth” OR “wealth distribution” OR “distribution of wealth”) AND TS = (“income inequality” OR “inequality in income” OR “income distribution” OR “distribution of income” OR “wealth inequality” OR “inequality in wealth” OR “wealth distribution” OR “distribution of wealth”) AND WC = economics,

where TI, TS and WC stand for Title, Topic, and Web of Science Category, respectively. With this strategy, we intended to minimize the risk of including unrelated references, which is especially important in a co-citation analysis. Since the focus is the bibliography of the retrieved references, each unrelated reference results in including potentially many unrelated bibliographic references in the analysis, which severely distorts it. The main limitation of this strategy is the exclusion of potentially important inequality references from the initial search. However, the most influential references are most likely part of the retrieved references’ bibliography, which minimizes this limitation.

We did not impose any restrictions based on the number of citations for two reasons. The first is that the high quality of the references we retrieved is already ensured by the Web of Science collecting articles from the most prominent academic journals in economics (Claveau & Gingras, 2016). The second is that this avoids

excluding important references with few citations due to their recent publication and, thus, facilitates discerning more recent lines of research in the literature.

The articles we retrieved contained 52730 unique bibliographic references, including journal articles and other reference types such as books. Using the VOSviewer software, we determined how many times each of these references were cited in the initial group of 2510 retrieved documents and, following previous studies (*e.g.*, Korom, 2019), we retrieved a sample of the most cited references, which we considered those with at least 15 citations. This resulted in a sample of 311 references.⁴

2.4 The clusters: a quantitative and a qualitative analysis

In this section, we characterize the network in general terms and then proceed to analyze each of the corresponding clusters in more detail.

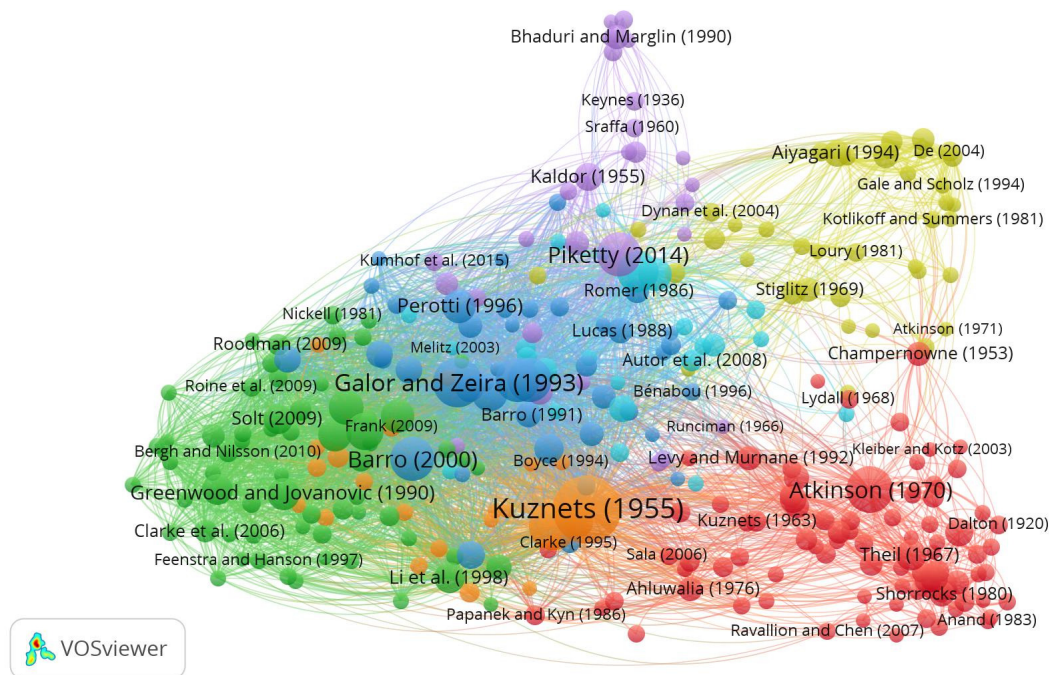
2.4.1 A generalized analysis of the network

Using the VOSviewer software, we obtained a network with seven clusters, visually represented in Figure 2.1.

We can see that there are very distinct clusters that, nonetheless, are quite close to each other, especially in the case of the clusters represented in blue (■), green (■), orange (■) and light blue (■). Moreover, in some cases, references from one cluster appear in the middle of others belonging to different clusters. As we will explain in more detail below, this reflects the presence of similar lines of research in the various references belonging to each cluster.

⁴We provide three appendices, available upon request, with information about the main analyses conducted in this paper. The first provides details of each of the network references concerning the identification of the streams of research as well the main elements used to justify them, namely the summary of the reference and the also relevant citing references. The second contains the authors' details of each of these references. The third has the complete Web of Science record of the references initially obtained that were used as citing references in the first appendix.

Figure 2.1: Network of 311 references obtained using the VOSviewer software



Source: Vosviewer software.

Note: This network contains 311 references, with more than 15 citations from the universe of 52730 cited references in 2510 journal articles published since 1950 and focused on the distribution of wealth, income or both, retrieved from the Web of Science on 5th April 2021. These references were selected and sorted into seven different clusters, identified by the following number and color: 1 , 2 , 3 , 4 , 5 , 6 , 7 . This was accomplished by using the VOSviewer software to group references based on the strength of their association, measured by the number of times each pair appears in the same document, and a resolution parameter (1.17), which determines the level of detail of the network. The individual importance of each reference is measured by the number of citations and represented by the size of the corresponding circle. The smaller the distance between each pair of references, the stronger the association between them. The latter is measured by the number of documents where each pair is jointly cited. The links between different references represent pairs that appear in the same documents. Therefore, the location of each reference in the network is only relevant in relation to the location of other references and not in itself.

Table 2.1 provides more details regarding each cluster. They are numbered by decreasing quantity of references, implying that cluster 1 is the largest and cluster 7 is the smallest. Clusters 3 and 7 are the most influential since they have the highest average number of citations. They also show the highest average number of links and strength per reference. These indicators represent, respectively, the number of references that were cited together with all the references of the cluster and the number of times each link is cited. Therefore they reinforce these clusters' importance and

suggest that they are quite homogeneous.

Table 2.1: Characterization of the number of references, number of citations and their strength in each and all clusters

Cl.	1 	2 	3 	4 	5 	6 	7 	311
N. Ref.	88	65	43	39	29	24	23	311
Cit. (per Ref.)	2383 (27)	1784 (27)	1795 (42)	896 (23)	819 (28)	699 (29)	914 (40)	9290 (30)
Links (per Ref.)	6432 (73)	7710 (119)	5798 (135)	2629 (67)	2126 (73)	2597 (108)	2690 (117)	29982 (96)
Str. (per Ref.)	12623 (143)	21988 (338)	21991 (511)	5830 (149)	4730 (163)	5568 (232)	8574 (373)	81304 (261)

Source: VOSviewer and authors' own compilation.

Notes: We identify each cluster by the corresponding number and color produced by VOSviewer software.

Legend: Cit. - Number of times each reference was cited. Links - The number of references that were cited together with all the references of the cluster or network. Str. - The number of times each link is cited. For example, if reference R1 is cited in document D1 with reference R2 and in document D2 with references R2, R3 and R4, this implies the existence of three links that include R1, R1-R2, R1-R3, and R1-R4, that are cited 2 times, 1 time and 1 time, respectively, implying that the total strength of R1 is $2 \times 1 + 1 \times 1 + 1 \times 1 = 4$.

In Table 2.2, we present the most important journals, authors, *Almae Matres*, affiliations, and corresponding countries of the entire network, measured by the number of citations of the corresponding references.⁵ The top 5 journals account for over 40% of the citations and they are *The American Economic Review*, *Econometrica*, *The Journal of Political Economy*, *The Quarterly Journal of Economics*, and *The Review of Economic Studies*, which also are the top 5 journals in economics in general (Heckman & Moktan, 2020).

Regarding authors, ten authors account for 20% of citations. This results from seminal contributions, namely of Anthony Atkinson, Thomas Piketty and Simon Kuznets.

⁵We also measured the relative importance of the attributes using the number of references instead of citations and the results are quite similar. Nonetheless, in some aspects, this better reflects the actual importance of the different journals by distinguishing between references with many citations from those with few, which is especially important in the case of authors.

Table 2.2: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding references of the entire network

Top 5 journals	46.11%: <i>The American Economic Review</i> (13.04%); <i>The Quarterly Journal of Economics</i> (9.41%); <i>The Review of Economic Studies</i> (8.25%); <i>Journal of Political Economy</i> (8.22%); <i>Econometrica</i> (7.19%)
Top 10 authors	20.18%: Atkinson A. (3.07%); Piketty T. (3.05%); Kuznets S. (2.43%); Saez E. (2.06%); Barro R. (1.97%); Squire L. (1.96%); Galor O. (1.58%); Alesina A. (1.41%); Deininger K. (1.36%); Shorrocks A. (1.29%)
Top 5 <i>Almae Matres</i>	49%: Harvard University (13.61%); MIT (12.11%); LSE (9.74%); University of Cambridge (8.14%); Columbia University (5.4%)
Top 5 countries (<i>Almae Matres</i>)	93.24%: US (68.3%); UK (19.25%); Israel (2.43%); Sweden (1.65%); France (1.61%)
Top 10 affiliations	42.26%: NBER (8.37%); World Bank (7.21%); CEPR (6.36%); Harvard University (5.83%); LSE (2.92%); The Hebrew University (2.77%); University of Chicago (2.37%); University of Pennsylvania (2.31%); MIT (2.19%); Nuffield College, University of Oxford (1.93%)
Top 5 countries (affiliations)	85.92%: US (54.82%); UK (18.82%); France (6.43%); Israel (3.53%); Canada (2.32%)

Source: Authors' own compilations.

Notes: The percentage of citations associated with each of these attributes is the sum of the citations of the references with the corresponding attribute divided by the sum of the total citations of all valid references in the entire network. In turn, the latter only includes references for which such attributes exist and were identified, excluding all others. We must note that some affiliations (*e.g.*, NBER, CEPR) do not have a permanent staff but are actually networks of researchers belonging to different institutions. Therefore, in most papers, the connection of authors to these institutions is not comparable to others as it is only mentioned to give recognition to the institutions. The *Almae Matres* are the institutions where the authors obtained their highest academic degree and were determined whenever possible using the official personal web pages of each author or an employer. Finally, the country corresponding to each institution is determined based on the corresponding official headquarters.

There is an even higher concentration of institutions. Almost half of the citations are attributed to references whose authors graduated from Harvard University, MIT,

LSE, University of Cambridge or the University of Chicago. These institutions also figure prominently as affiliations. Nonetheless, this ranking also includes non-academic institutions in top positions, namely the World Bank, NBER and CEPR.⁶ As a result, there is a prevalence of US institutions followed by the UK, which is consistent with patterns found in Economics research in general (Colander, 2005; Fourcade, 2006).

2.4.2 An individual analysis of each cluster

This section contains an individual analysis of each cluster, with the characterization of the corresponding Streams of Research summarized in Tables 2.10 to 2.16 from appendix 2.A.

Cluster 1: Theoretical issues related to the Measurement of Inequality

This cluster is identified by the color red - ■ - and is the largest in terms of number of references (88) and, as a result, it also has the highest number of unique Streams of Research, as it can be seen in Table 2.10.

The most relevant streams conduct positive and normative analyses of inequality measures' properties. The Pigou-Dalton Transfer Principle was one of the earliest that received substantial attention. This principle posits that transfers from the poor to the rich should result in higher inequality and lower welfare. Bearing this in mind, researchers sought to embody such property in inequality measures, such as the Gini coefficient, so that they could have a meaningful interpretation.

Researchers also sought to disaggregate them by the inequality within certain groups, weighted by their relative importance in the income distribution. This preoccupation with decomposing inequality was present in works that analyzed inequality trends and sought to explain its impacts. Some examples are the early works of Simon Kuznets and Arthur Lewis in the 1950s, who sought to determine the impacts of development on inequality by analyzing its effects on inequality within urban and rural workers. Other authors also decomposed inequality by other attributes, such as gender (Lydall, 1968) and race (Blinder, 1973).

This propelled the development of a literature devoted to conceiving sound decomposing techniques and inequality measures that embodied this property. One of the first researchers to contribute to this area was Vidyanand M. Rao, who, in 1969,

⁶This is justified primarily by some of these institutions being networks of researchers that belong to different institutions.

proposed two decomposition techniques of the Gini coefficient. Soon other researchers followed with more refined analysis and techniques, the most notable of which was Anthony Shorrocks, with its seminal papers published in the 1980s (*e.g.*, Shorrocks, 1980). Finally, we also find a closely related stream of papers that applied such techniques empirically.

Other research groups in this cluster centered their attention on issues related to the measurement of inequality, such as the choice of unit of analysis, and the development and estimation of appropriate functional forms to model the income distribution, for similar reasons. A group of authors proposed new inequality measures, such as the Theil Index (Theil, 1967), Atkinson Index (A. B. Atkinson, 1975), or the improvement of existing ones. Many of the mentioned theoretical discussions greatly influenced the latter's emergence. Additionally, in some cases, such as in the case of the Atkinson Index, normative analyses also played a significant role.

Other relevant groups in this cluster include those that followed the studies of Simon Kuznets and Arthur Lewis regarding the relationship between development and inequality and others that either constructed important databases subsequently used by other authors or analyzed important issues related to data quality and availability. The issue of the lack of appropriate data had a tremendous influence in shaping the development of many research lines in this cluster (*e.g.*, A. B. Atkinson, 1975; Kuznets, 1963; Kuznets & Jenks, 1953; Paukert, 1973). This problem only saw significant answers in the 1990s with the emergence of databases such as LIS, which resulted from the Luxembourg Income Studies (Buhmann, Rainwater, Schmaus, & Smeeding, 1988), Penn World Tables (Summers & Heston, 1991) and the dataset from Klaus Deininger and Lyn Squire (1996). Their development propelled analyses of the evolution of inequality in some advanced economies, mainly from the 1990s.

We also find streams centered on the relationship between inequality and other variables, namely education and macroeconomic variables, such as unemployment and inflation. One possible justification for the emergence of such studies and, specifically, those analyzing the connection between the development process and inequality was the growing importance given to variables other than income to measure well-being. Moreover, the necessity to “identify redistributive mechanisms which aid poverty reduction without hampering growth” (A. Shorrocks & Van der Hoeven, 2004, p. 1) was also influential. Tightly connected with this line of research are smaller streams dedicated to theoretical or practical issues associated with poverty measurement. In this regard, we highlight authors such as Sen and Foster.

Table 2.3: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding References of cluster 1 ■

Top 5 journals	59.41%: <i>Econometrica</i> (21.86%); <i>The Economic Journal</i> (12.38%); <i>Journal of Economic Theory</i> (10.64%); <i>The American Economic Review</i> (7.5%); <i>The Review of Economics and Statistics</i> (7.03%)
Top 10 authors	29.08%: Atkinson A. (7.8%); Shorrocks A. (5.82%); Sen A. (2.69%); Yitzhaki S. (2.16%); Theil H. (1.9%); Bourguignon F. (1.87%); Smeeding T. (1.84%); Kakwani N. (1.69%); Ahluwalia M. (1.67%); Milanovic B. (1.64%)
Top 5 <i>Almae Matres</i>	48.89%: University of Cambridge (18.07%); LSE (10.58%); Yale University (7.89%); Princeton University (6.77%); MIT (5.58%)
Top 5 countries (<i>Almae Matres</i>)	93.83%: US (47.98%); UK (36.05%); Canada (4.04%); Netherlands (3.02%); India (2.74%)
Top 10 affiliations	46.96%: LSE (9.42%); World Bank (8.85%); University of Cambridge (4.58%); Harvard University (4.14%); Cornell University (4.08%); Queen's University (3.63%); Yale University (3.35%); Université de Montréal (3.22%); Nuffield College, University of Oxford (2.94%); Princeton University (2.75%)
Top 5 countries (affiliations)	91.05%: US (52.97%); UK (19.75%); Canada (8.44%); France (5.21%); Israel (4.68%)

Source: Authors' own compilations.

Notes: See Table 2.2.

A small group of authors focused on documenting the evolution of inequality in transition economies, such as China and former members of the USSR. This was due to the collapse of Communism in the latter and the increased availability of information (Milanovic, 1998). The latter factor also determined the increased focus on the world income distribution in this period, despite the attention given before by Anthony B. A. B. Atkinson (1975).

The main characteristics of this cluster are summarized in Table 2.3. First, the most important journal, with one-fifth of total citations, is *Econometrica*, which reflects

the interest in the theoretical issues related to the measurement of inequality in this cluster, namely those belonging to the most important streams of research. In terms of the countries of affiliations and *Almae Matres*, although US institutions continue to occupy the first place in both rankings, the UK also ranks very high, especially in the case of the former. This reflects the contributions to the field of inequality by Atkinson and Shorrocks, who had strong ties to the University of Cambridge and LSE, respectively. Moreover, we can also see that the World Bank is a significant affiliation in this cluster due to the focus on the inequality-development relation from various researchers affiliated with this institution, especially in 1970s (Babb, 2009).

Cluster 2: The development process and inequality

The second largest cluster with 65 papers, identified with green - ■ - is also one of the most homogeneous, as seen by the strength indicator in Table 1, which is the second highest. This can be explained by the overall focus of most streams on how the development process affects inequality, as can be seen by analyzing the corresponding Streams of Research characterized in Table 2.11.

Nonetheless, there are different perspectives on the analysis of this relationship. One of the first to arise is centered on the hypothesis of Simon Kuznets in 1955 that inequality rises during the development process and decreases after a certain threshold.⁷ However, the most influential are focused on the impact of specific aspects of the development process on income or wealth disparities.

One line is mainly focused on determining and characterizing the relationship between the financial development of a country and inequality. In this group, the most cited reference is the work by Abhijit Banerjee and Andrew Newman (1993) with their theoretical model, where the existence of credit market imperfections can lead to a replication or worsening of an initial wealth distributions. This reference was cited along with many to justify a negative theoretical relationship between financial development and inequality (*e.g.*, Clarke, Xu, & Zou, 2006). Nonetheless, one of the first references to formalize a relationship between financial development and inequality was the work by Jeremy Greenwood and Boyan Jovanovic (1990). Moreover, this group also shares a strong connection with a smaller one represented by Raghuram Rajan and Luigi Zingales (2003), who have explicitly focused on

⁷However, the original reference, Kuznets (1955), is in cluster 7, which we explain in more detail in the corresponding section.

theoretically explaining a country's financial development process.

Another group focuses on the effects of trade openness and globalization on inequality. As countries developed and opened their frontiers to international trade, authors became interested in how such developments would affect the income distribution. Wolfgang Stolper and Paul Samuelson's article of 1941 is often cited in this context because the corresponding theorem offered one of several answers to this question, *i.e.*, that trade would increase the relative earnings of the owners of the more relatively abundant factors. The interest in this theme started with a contribution by François Bourguignon and Christian Morrison (1990), who considered that the literature dedicated to the Kuznets hypothesis neglected the effect of trade factors. Globalization reinforced the interest in this issue and extended the topic of openness to other areas, such as financial markets. As a result, there was a confluence between this stream and the previous one, which is reflected in the joint presence of several references, especially more recent ones (*e.g.*, Jaumotte, Lall, & Papageorgiou, 2013).

Two important groups also present in this cluster aggregate works often cited for having developed specific econometric techniques or databases. This suggests a significant role of such innovations in the empirical analyses in this cluster. Finally, we can find smaller lines of research dedicated to exploring the determinants of inequality in general and the role of specific variables, such as contribution, education or redistribution, in particular.

Table 2.4 summarizes the main characteristics of this cluster. There is a less-than-average concentration of publications in top 5 journals, which nonetheless account for almost 40% of citations. The indicator that stands out the most is that most authors are affiliated with the World Bank. This reflects the increased interest of this institution in inequality and development issues, which contributed significantly to the lines of research exploring the Kuznets hypothesis, in general, and the relation between finance and inequality, in particular.

This interest was brought about by a change in the political and academic landscape during this period and the growing criticisms of the so-called Washington Consensus.⁸ Government intervention was increasingly viewed as necessary for developing countries

⁸This designated a set of market-liberalization recommendations for developing countries from financial institutions such as the World Bank and IMF. It was motivated by shifts in the dominant political and ideological contexts and by empirical evidence that was critical of the magnitude of government intervention and its effects, especially in Latin America.

to prosper. Theoretically, this was justified by the idea that markets were imperfect in the absence of perfect information. This problem is especially severe in developing countries without solid institutions, where governments must intervene more intensely. Joseph Stiglitz, senior vice-president and chief economist of the World Bank from 1997 to 2000, was one of the most influential representatives of this perspective. A related issue that started receiving attention from the World Bank in the early 1990s due to the pressure of Civil Society was poverty (Babb, 2009). Amartya Sen, Nobel laureate in 1998, is one of the most influential economists in this area with many significant contributions. Moreover, he argued that development economists should expand their scope beyond the analysis of GNP growth.

The focus on poverty was accompanied by an interest in inequality, as illustrated by several anecdotal episodes. One occurred when *The World Development Report* of 2000 entitled “Attacking Poverty” was published. According to Babb (2009), at the time, it was deemed by the US Treasury as paying “too little attention to economic growth, too much to income inequality” (Babb, 2009, p. 178). This led to increased pressure on the then director Ravi Kanbur, appointed by Stiglitz, to revise it in line with these concerns. However, this only resulted in Kanbur resigning in protest and a revision “remarkably faithful to the original message” (Babb, 2009, p. 178). Another example was the appointment in 2003 of François Bourguignon as chief economist of the Bank, who was deeply interested in inequality, despite the administration at the time being ideologically conservative. This was facilitated by a passive attitude toward the research output of the World Bank in comparison with the previous presidency. This was primarily the result of the focus on other issues, such as the so-called “War on Terror” (Babb, 2009, p. 227).

Table 2.4: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding References of cluster 2 ■

Top 5 journals	39.78%: <i>Journal of Econometrics</i> (10.42%); <i>Journal of Political Economy</i> (8.07%); <i>The Review of Economic Studies</i> (7.84%); <i>Journal of Economic Growth</i> (7.27%); <i>The Economic Journal</i> (6.18%)
Top 10 authors	29.87%: Bond S. (5.01%); Arellano M. (4.68%); Levine R. (3.22%); Zou H. (2.86%); Squire L. (2.6%); Solt F. (2.46%); Blundell R. (2.38%); Demirgüç-Kunt A. (2.35%); Beck T. (2.27%); Banerjee A. (2.04%)
Top 5 <i>Almae Matres</i>	46.2%: Harvard University (18.64%); LSE (11.94%); MIT (8.64%); University of California LA (3.65%); University of Rochester (3.33%)
Top 5 countries (<i>Almae Matres</i>)	93.25%: US (69.53%); UK (15.75%); Netherlands (3.59%); Sweden (2.38%); Italy (2%)
Top 10 affiliations	42.41%: World Bank (13.94%); IMF (4.86%); Institute for Fiscal Studies (4.21%); NBER (3.99%); LSE (3.41%); Harvard University (3.13%); CEPR (3.13%); University of Oxford (2.04%); Nuffield College, University of Oxford (1.85%); University College London (1.85%)
Top 5 countries (affiliations)	79.66%: US (47.73%); UK (19.57%); Netherlands (4.27%); France (4.08%); Spain (4.01%)

Source: Authors' own compilations.

Notes: See Table 2.2.

Cluster 3: Inequality and Economic Growth

The color blue - ■ - identifies the third largest cluster with 43 references and the corresponding streams of research are characterized in Table 2.12. It shows the highest average number of citations per reference (42) and strength (511), which suggests that this cluster is the most important and homogeneous.

One of the first authors that produced a seminal reference focused on this relationship was Arthur Okun, who, in 1975, published *Equality and Efficiency: The Big Tradeoff*, which established the hypothesis that equality and economic efficiency were incompatible. This tenet was not contested for a long time until some researchers in the 1990s conducted empirical analyses that contradicted it, namely Alberto Alesina, Roberto Perotti, Mark D. Partridge. These contributions were strongly influenced by the frameworks used in empirical analyses in the early 1990s focused on income convergence (Thewissen, 2014). One of several reasons was the realization of researchers dedicated to this topic that inequality had an important role in income convergence due to its impact on growth rates (Partridge, 1997). This justifies the presence of many works related to convergence in this cluster, namely by Robert Barro (*e.g.*, Barro & Sala-i Martin, 1992).

These results spurred interest in the literature. In 1996, Klaus Deininger and Lyn Squire, two researchers of the World Bank, established a new database that contributed to improving the quality and volume of inequality data. This led to more empirical analyses that were also more sophisticated due to the possibility of applying panel data estimation procedures. In turn, the conclusions of these new studies further stimulated interest in the topic due to the divergent conclusions from the previous authors (*e.g.*, Forbes, 2000).

There are also streams focused on developing and testing specific mechanisms through which inequality can affect economic growth. One of the most important was the fiscal policy channel, whereby inequality leads to more intense redistribution policies due to greater societal pressure that, in turn, harms growth by distorting incentives. This perspective was directly influenced by a stream dedicated to Political-Economy models. This is the second most cited stream of this cluster and is focused on theoretical models where economic and political outputs are endogenously determined. Another channel that also emerged at this time was the credit market imperfections channel. It posited that inequality would damage growth if the poorest were barred from the credit market since it would decrease human capital

accumulation. Similarly, contributions related to this theoretical mechanism were largely influenced by the development of economic models where agents face borrowing constraints, thanks primarily to the seminal contribution of Oded Galor and Joseph Zeira (1993).

One group tightly connected to both of these streams contains authors focused on comparing the economic effects of different education systems (public *vs.* private). Many of these authors employ Political-Economy models where redistribution takes the form of public education instead of taxes.

Most previous streams were largely influenced by the Endogenous Growth Theory, pioneered by Robert Lucas and Paul Romer and developed in the late 1980s and early 1990s. It consisted in theoretical models where the economic growth rate was the result of the internal decisions of the agents of an economy and not merely of exogenous factors, as it was, for instance, in the case of the seminal Solow model. Such models, and some of their attributes, such as the importance of human capital accumulation in generating economic growth, prompted the appearance of works such as Galor and Zeira (1993), which analyzed how inequality can affect this process and economic growth.

Finally, the remaining lines of research are mostly connected to other perspectives on this relation. One stream focused on exploring mechanisms whereby inequality can have a positive effect on growth, for instance, through technological progress improvements by rewarding risk (Inequality, Technological Progress and Growth) or the saving rate (Classical approach). Their relative unimportance can be attributed to the consecutive empirical pointing to a negative effect of inequality on growth. More recent lines explored the negative effects on growth through its effects on the fertility rate and how the relationship depended on structural conditions.

The main attributes of this cluster are described in Table 2.5. The three most important journals are *The Review of Economic Studies*, *The American Economic Review* and *The Journal of Economic Growth*, accounting for more than half of the publications in this cluster. The prestige of these journals confirms the importance of this topic. Moreover, the latter's importance is expected, considering its focus on economic growth. Robert Barro is the most influential author, followed closely by Oded Galor. Most authors attended Harvard or MIT, and these academic institutions also rank in the top 10 affiliations, reflecting the influence of new growth theories developed by researchers connected to these institutions. The latter ranking only includes three non-academic institutions that, nonetheless, are quite influential, namely CEPR and NBER.

Table 2.5: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding References of cluster 3 ■

Top 5 journals	75.58%: <i>The Review of Economic Studies</i> (19.97%); <i>The American Economic Review</i> (19.33%); <i>Journal of Economic Growth</i> (16.08%); <i>The Quarterly Journal of Economics</i> (13.29%); <i>Journal of Political Economy</i> (6.91%)
Top 10 authors	55.09%: Barro R. (8.43%); Galor O. (8.23%); Alesina A. (6.24%); Zeira J. (5.67%); Perotti R. (5.4%); Aghion P. (4.82%); Persson T. (4.42%); Tabellini G. (4.42%); Rodrik D. (4.39%); Forbes K. (3.07%)
Top 5 <i>Almae Matres</i>	69.41%: Harvard University (27.82%); MIT (19.78%); Columbia University (9.79%); The Hebrew University (7.52%); University of California LA (4.5%)
Top 5 countries (<i>Almae Matres</i>)	99.43%: US (79.07%); Israel (7.78%); Sweden (4.66%); UK (4.44%); France (3.48%)
Top 10 affiliations	67.89%: CEPR (14.72%); Harvard University (11.64%); NBER (9.93%); The Hebrew University (9.68%); Brown University (5.89%); MIT (3.62%); University of Chicago (3.34%); Columbia University (3.34%); European Bank for Reconstruction and Development (2.99%); Stockholm University (2.74%)
Top 5 countries (affiliations)	91.37%: US (46.66%); UK (21.3%); Israel (10.72%); France (7.21%); Italy (5.48%)

Source: Authors' own compilations

Notes: See Table 2.2.

Cluster 4: Theoretical and empirical analyses of the Wealth Distribution

The fourth largest cluster (39 references) is identified in light green - ■ - is one of the most heterogeneous, with the lowest average strength indicator per reference. Table 2.13 shows this stems from different perspectives on wealth distribution.

Some of the most important streams focused on developing dynamic general equilibrium models of wealth distribution with different assumptions, namely the existence of: (i) incomplete markets leading to uninsurable risks; (ii) several and possibly overlapping generations linked through the transmission of wealth and valuation of the utility of future generations; (iii) heterogeneous agents (*e.g.*, consumers, firms, and so forth); (iv); imperfections in the credit market leading to borrowing constraints.⁹ The seminal contribution by Joseph E. Stiglitz (1969) played a significant role in developing such streams of research, which focused on individuals rather than factors.

Other streams focused on empirical analysis related to the Wealth Distribution. One of the first contributions was made by Anthony A. B. Atkinson (1971), who empirically tested if the Life-Cycle Hypothesis could explain the upper tail of the wealth distribution in Britain in the 1960s. This Hypothesis was developed by Franco Modigliani and Richard Brumberg (Modigliani & Brumberg, 1954) and stated that individuals' consumption choices depended on expected income as well as earning and retirement span. Atkinson recognized that this theory implied that wealth inequality at any particular time could result from a greater proportion of older individuals that saved more and, consequently, had more assets. To address this issue, the author suggested using the inherited wealth distribution to measure wealth inequality since this approach was not affected by life-cycle factors, unlike the former. Using returns from Estate Duty as a proxy for this, the author concluded that life-cycle factors had a marginal effect on determining wealth distribution. A subsequent work by Lawrence Kotlikoff and Larry Summers in 1981 (Kotlikoff & Summers, 1981) also reached the same conclusion regarding the US. These results contradicted an empirical analysis previously conducted by Modigliani (1966). Using historical data for the United States, they concluded that the accumulation of assets implied by the Life-Cycle Hypothesis accounted for much of the observed distribution of wealth distribution. This spurred further interest in this issue.

⁹We also found a small group of authors that analyzed the adequacy of statistical distributions, namely Pareto, to fit the upper tail of the wealth distribution.

Finally, we also find streams focused on the empirical and theoretical relationship between income and consumption inequality. When faced with uncertain incomes, consumers seek to smooth consumption patterns by investing in assets and contracting debt (*e.g.*, Iacoviello, 2008), which affects their wealth position. This illustrates the connection to the broader topic of wealth distribution and also others focused on the permanent and transitory components of income.

Table 2.6: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding References of cluster 4 ■

Top 5 journals	71.05%: <i>Journal of Political Economy</i> (31.68%); <i>The Quarterly Journal of Economics</i> (13.24%); <i>Econometrica</i> (10.17%); <i>The Review of Economic Studies</i> (8.04%); <i>The American Economic Review</i> (7.92%)
Top 10 authors	38.12%: Becker G. (4.89%); Díaz-Giménez J. (4.56%); Ríos-Rull J. (4.56%); Quadrini V. (4.17%); Tomes N. (3.91%); Huggett M. (3.45%); De Nardi M. (3.39%); Aiyagari S. (3.13%); Perri F. (3.06%); Saez E. (3%)
Top 5 <i>Almae Matres</i>	67.35%: University of Minnesota (22.02%); University of Chicago (11.73%); MIT (11.66%); University of Pennsylvania (11.45%); Harvard University (10.49%)
Top 5 countries (<i>Almae Matres</i>)	99.99%: US (89.12%); UK (4.94%); Spain (3.74%); France (2.19%); Netherlands (0%)
Top 10 affiliations	65.44%: NBER (18.16%); CEPR (11.99%); FED (10.13%); University of Chicago (4.75%); New York University (4.71%); University of Pennsylvania (3.52%); Universidad Carlos III de Madrid (3.44%); University of Minnesota (3.16%); University of California at Berkeley (3.05%); Yale University (2.53%)
Top 5 countries (affiliations)	97.03%: US (72.75%); UK (13.92%); Spain (6.21%); Canada (2.37%); Sweden (1.78%)

Source: Authors' own compilations.

Notes: See Table 2.2.

The main characteristics of this cluster are described in Table 2.6. We highlight the importance of the University of Chicago, shown in the importance of the *Journal*

of *Political Economy*, its rank in the top affiliations and also reflected on the importance of authors such as Becker, Díaz-Giménez, and Ríos-Rull J. and the University of Minnesota as an *Alma Mater*. Many of these authors had as an advisor Edward Prescott (Nobel recipient in 2004) and Neil Wallace. Both had been colleagues of Robert Lucas at the University of Chicago and explored microeconomic foundations to macroeconomic theories, a topic explored by many streams of research in this cluster.¹⁰ We also highlight the importance of NBER, CEPR and the Federal Reserve Bank as affiliations.

Cluster 5: Heterodox Perspectives

The fifth cluster, identified by color purple - ■ - and described in Table 2.14, is the third smallest, with 29 references. It also shows the second lowest average strength indicators per reference. These indicators reflect the great diversity of research streams and the heterodox approach of many concerning the study of inequality.

The most influential streams congregate contributions with a new perspective on the effects and determinants of inequality. The notorious number of citations is attributed to specific seminal works, namely *Capital in the Twenty-First Century* by Thomas Piketty (2014) and *Price of Inequality* by Joseph Stiglitz (2012). Both attracted the attention of academics, policymakers and the public to the dramatic increase in inequality and its consequences.

Another important stream focused on the effects of inequality on growth through its effects on factors incomes and how the latter affected aggregate demand according to the prevailing demand regime (*e.g.*, Stockhammer, Onaran, & Ederer, 2009). For instance, a redistribution of income favoring workers instead of capitalists was expected to have two effects on aggregate demand. On the one hand, it increased consumption since it is usually assumed that workers have a higher propensity to consume. On the other hand, it decreased investment due to the dependence of the latter on profits (Onaran & Obst, 2016). In a wage-led demand regime, the first effect prevails, leading to an increase in aggregate demand, stimulating investment and economic growth.

These perspectives were primarily influenced by the so-called Cambridge growth

¹⁰Moreover, the interest in such topics was also prevalent at MIT and Harvard, where some authors also graduated. An example that we consider the general interest of these institutions is exemplified by the joint Harvard-M.I.T. Seminar held in 1971 dedicated to the topic of income distribution in which Alan Blinder, a MIT *alumnus*, had the opportunity to present his paper “A Model of Inherited Wealth”.

models, which extended Keynesian theories (Keynes, 1936) to long-run analyses. In this regard, we highlight the impact of the contributions of Michael Kalecki (*e.g.*, Kalecki, 1971). The author considered that business cycles and crises were unavoidable due to the impossibility of maintaining a steady level of investment over time. As investment contributes to increasing the capacity of utilization, even with depreciation, a steady level would create at some point an excess of capacity which would lower profits and, in turn, lower investment in a downward spiral that decreases aggregate demand (Dixon & Toporowski, 2013). Therefore, when the global financial crisis of 2007-2008 occurred, many authors revived this perspective and analyzed the role of inequality in exacerbating these destabilizing effects on the economy.

Most of the remaining contributions are also connected to this topic. For instance, some streams explore the relationship between inequality and savings, which is naturally related to Kaleckian models due to the assumption of different saving propensities between workers and capitalists. Others explore, empirically and theoretically, the extent to which consumers' utility depends on their condition, regarding income or wealth, compared to their peers and how this can lead to the emulation of consumption patterns.

The main attributes of this cluster are summarized in Table 2.7. We note the influence of the University of Cambridge, reflected both in the importance of the *Cambridge Journal of Economics* and the rank of this university as affiliation and *Alma Mater*, surpassed only by LSE in the case of the latter. The most influential author is Thomas Piketty, followed by Nicholas Kaldor, Allan Melzer and Scott Richard, which is justified by the corresponding seminal contributions.

Table 2.7: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding References of cluster 5 ■

Top 5 journals	76.87%: <i>Cambridge Journal of Economics</i> (21.2%); <i>The Review of Economic Studies</i> (18.42%); <i>Journal of Political Economy</i> (13.7%); <i>The Quarterly Journal of Economics</i> (11.99%); <i>The American Economic Review</i> (11.56%)
Top 10 authors	49.07%: Piketty T. (12.41%); Kaldor N. (7.04%); Meltzer A. (4.35%); Richard S. (4.35%); Solow R. (3.8%); Bhaduri A. (3.7%); Marglin S. (3.7%); Dutt A. (3.52%); Rajan R. (3.24%); Pasinetti L. (2.96%)
Top 5 <i>Almae Matres</i>	65.67%: LSE (20.49%); University of Cambridge (12.78%); EHESS (11.73%); MIT (10.95%); Harvard University (9.72%)
Top 5 countries (<i>Almae Matres</i>)	93.94%: US (54.58%); UK (31.58%); France (2.86%); Poland (2.63%); Turkey (2.29%)
Top 10 affiliations	70.04%: University of Cambridge (12.84%); Carnegie-Mellon University (11.18%); Harvard University (8.32%); Institut für Geld u. Fiskalpolitik Vienna (7.13%); Paris School of Economics (5.95%); NBER (5.23%); CEPR (5.23%); MIT (4.88%); Indian Institute of Management Calcuta India (4.76%); Cornell University (4.52%)
Top 5 countries (affiliations)	95.84%: US (53.27%); UK (22.95%); France (7.73%); Vienna (7.13%); India (4.76%)

Source: Authors' own compilations.

Notes: See Table 2.2.

Cluster 6: The rise of inequality since 1980

The sixth cluster is identified by light-blue - ■ - and the main streams of research are described in Table 2.15. It is the second smallest, with 24 references, but is, nonetheless, relatively homogeneous, with the fourth largest average strength indicator per reference. These indicators reflect the presence of the most recent streams, as shown by the substantial share of papers published after 2000 and the focus on analyzing possible explanations for the inequality increase since 1980 in most advanced economies, especially the US.

There are three streams with different perspectives on this subject. The first related this increase to the rise of the so-called skill premium, the ratio of wages of workers with a college degree to those without one, and developed in great part thanks to the seminal contributions of Daron Acemoglu, Kevin Murphy and Lawrence Katz. The authors advanced several hypotheses to explain this phenomenon, among which the most popular was the Skill Biased Technological Change Hypothesis. It posited that the relative increase in the labor supply of skilled workers increased the market size for technologies complementary to such workers, increasing its relative demand and, thus, their relative wage.

The second comprises contributions from Anthony Atkinson, Thomas Piketty, Emmanuel Saez, Facundo Alvaredo and Michael Veall concerning the increase of top incomes and wealth shares. The authors considered that the available data had significant problems, namely heterogeneity and few observations per country. Therefore, they sought to improve its quality and extension by building upon the work of Simon Kuznets and using income tax and other sources. The data showed an extraordinary evolution of the income share of the top 1%, which, according to the authors, could not be explained adequately by theories aimed at explaining the skill premium. Its origins can be traced back to Piketty's paper of 2001 (Piketty, 2001), which was focused on France. It played a prominent role in stimulating other authors to pursue similar analyses in other countries, namely Atkinson (England) and Saez (US), which ultimately led to the development of the WID.world database (Alvaredo, Atkinson, Chancel, Piketty, & Zucman, 2016).

A third stream, represented by Loukas Karabarbounis and Brent Neiman (2014), analyzed the decrease in the income share of workers, *i.e.*, the labor share. This functional perspective of inequality reflected the structure of most macroeconomic models, most of which divided agents between workers and capitalists. Finally, we can

find other smaller streams of research dedicated to analyzing how inequality was determined by some variables, such as tax policy, monetary policy or trade, and affected others, such as intergenerational mobility.

Table 2.8 indicates that five economic journals account for over 80% of the citations, with approximately half attributed to publications in *The Quarterly Journal of Economics*. Most top authors were already mentioned and graduated and were affiliated with American and British Universities, such as MIT and LSE. Piketty also attended EHESS in France. The NBER also figures highly among affiliations.

Table 2.8: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding References of cluster 6 ■

Top 5 journals	83.77%: <i>The Quarterly Journal of Economics</i> (40.75%); <i>Journal of Economic Literature</i> (19.43%); <i>The American Economic Review</i> (13.21%); <i>The Review of Economics and Statistics</i> (5.85%); <i>Journal of Political Economy</i> (4.53%)
Top 10 authors	76.76%: Piketty T. (22.83%); Saez E. (19.71%); Atkinson A. (8.41%); OECD (6.67%); Katz L. (5.94%); Murphy K. (3.7%); Acemoglu D. (3.33%); Autor D. (2.25%); Kearney M. (2.25%); Bound J. (1.67%)
Top 5 <i>Almae Matres</i>	84.09%: MIT (26.45%); LSE (22.79%); EHESS (19.89%); University of Cambridge (8.46%); Harvard University (6.5%)
Top 5 countries (<i>Almae Matres</i>)	100%: US (75.37%); UK (18.87%); France (3.77%); Serbia (1.99%); Netherlands (0%)
Top 10 affiliations	86.05%: NBER (21.07%); Harvard University (10.95%); University of California at Berkeley (10.85%); Paris School of Economics (9.13%); EHESS (7.16%); Nuffield College, University of Oxford (5.97%); CEPREMAP (5.92%); LSE (5.76%); MIT (4.83%); University of Chicago (4.41%)
Top 5 countries (affiliations)	100%: US (62.07%); France (23.25%); UK (13.75%); Canada (0.93%); India (0%)

Source: Authors' own compilations

Notes: See Table 2.2.

Cluster 7: Inequality, Education and Environment

The seventh cluster is identified in orange - ■ - and the corresponding streams are described in Table 2.16. It is the smallest, with only 23 references, but it also has one of the highest number of average citations per reference (40) and strength indicators (373).

This results from two factors. The first is the inclusion in this cluster of the seminal contribution of Simon Kuznets in 1955, “Economic growth and income inequality”, which postulated the famous inverted U-relationship between inequality and growth and is the focus of the most influential stream in this cluster.

The second is the overall focus of the remaining streams of research on the relationship between particular aspects of the development process and inequality, which makes it quite similar in scope to cluster 2. Nonetheless, this cluster differs in some aspects, namely the greater focus on education and the environment. Regarding the first, multiple analyses explore the role of education in reducing inequality at the final stages of the process of development by contributing to the equalization of the distribution of skills (Ahluwalia, 1976). Regarding the second, there is a particular focus on the so-called environmental Kuznets curve. This hypothesis postulates that, during the development process, pollution increases at earlier stages only to decrease afterward, in similarity to the trajectory of inequality in the original curve (*e.g.*, Torras & Boyce, 1998).

Table 2.9 shows a high concentration of journals, with *The American Economic Review* accounting for more than one-third of total citations. Moreover, the top *Almae Matres* and affiliations show that Columbia University and the University of Pennsylvania were important. These indicators reflect Kuznets’s importance as an individual author, who accounts for one-fifth of the total citations in this cluster, published mainly in this journal and is closely related to the mentioned universities. Klaus Deininger and Lyn Squire are other authors that rank highly due to the database they developed, which was used extensively. The importance of the latter also explains the presence of the University of Minnesota in the Top 5 *Almae Matres* and the World Bank as the most important affiliation.

Table 2.9: Most important journals, authors and their *Almae Matres*, affiliations and corresponding countries in terms of number of citations of the corresponding References of cluster 7 ■

Top 5 journals	73.2%: <i>The American Economic Review</i> (37.64%); <i>World Bank Economic Review</i> (16.96%); <i>Journal of Econometrics</i> (7.77%); <i>Journal of Economic Literature</i> (5.69%); <i>Journal of Applied Econometrics</i> (5.14%)
Top 10 authors	66.6%: Kuznets S. (20.94%); Deininger K. (10.61%); Squire L. (10.61%); Pesaran M. (6.57%); Atkinson A. (3.56%); Brandolini A. (3.56%); Shin Y. (3.56%); Smith R. (2.67%); Boyce J. (2.4%); Im K. (2.12%)
Top 5 <i>Almae Matres</i>	68.7%: Columbia University (27.56%); University of Cambridge (16.83%); University of Minnesota (12.6%); University of Oxford (7.4%); University of Chicago (4.31%)
Top 5 countries (<i>Almae Matres</i>)	100%: US (68.12%); UK (30.56%); Denmark (1.32%); Netherlands (0%); India (0%)
Top 10 affiliations	68.99%: World Bank (23.13%); University of Pennsylvania (19.77%); University of Cambridge (5.04%); Nuffield College, University of Oxford (3.36%); Bank of Italy (3.36%); University of Edinburgh (3.36%); University of Massachusetts Amherst (3.29%); National Taiwan University (2.84%); University of California San Diego (2.71%); NBER (2.13%)
Top 5 countries (affiliations)	95.28%: US (67.44%); UK (19.06%); Italy (3.36%); Taiwan (2.84%); Chile (2.58%)

Source: Authors' own compilations.

Notes: See Table 2.2.

2.5 Concluding Remarks

In this paper, we provide an overview of the field of inequality since 1950 with a new method that combines quantitative bibliometric techniques with an innovative qualitative analysis. Therefore, our analysis adds to the extant literature on the topic and is also innovative due to the methodology we consider.

We identified several clusters. The first and largest contains some of the oldest lines of research since 1950. These were mainly devoted to analyzing theoretical issues related to the measurement of inequality, especially decomposition by factors or sources. The second focuses on the relationship between the development process and inequality and specific aspects concerning financial development and openness. The third is the most influential and analyzes the relationship between inequality and growth empirically and theoretically. It emerged thanks to increased data availability and the development of endogenous growth theories. The fourth focuses on theoretical and empirical analyses related to the wealth distribution from different perspectives. The fifth aggregates more heterodox approaches influenced by Michael Kalecki focused on the growth impacts of inequality through changes in aggregate demand. The sixth cluster concentrated on the increased inequality trends in advanced economies since the 1980s. Finally, the seventh cluster is dedicated to the relationship between inequality, education and the environment.

Many streams emerged thanks to particular seminal contributions and further developed due to interesting empirical and theoretical results. Some clusters were largely influenced by particular academic departments and schools of thought. For instance, clusters 4 and 5 were largely influenced, respectively, by the University of Chicago and the University of Cambridge.

We acknowledge that our new method of analysis has its limitations. The categorization of the streams of research relies on citations chosen by the researcher. Thus this process is not immune to subjective considerations, especially when references are cited for multiple reasons. The tractability of the analysis prevents analyzing every relevant reference. Therefore, we cannot guarantee that we cover all streams of research exhaustively. However, we consider these were addressed by our approach. Subjective considerations are minimized through the application of the algorithm of the VOSviewer software, which is objective and considers well-established similarity criteria (*e.g.*, Van Eck & Waltman, 2010; Waltman et al., 2010). Moreover, the most important references in the inequality literature that comprised the network

of clusters we analyzed were chosen from an extensive universe of over 50000 bibliographic references.

Our work opens several interesting venues for future research to explore. In particular, studies in the future could adopt this methodological approach in bibliometric analyses of other fields in economic and to each cluster we uncovered in this paper to obtain more relevant details. Finally, in the field of inequality, it would be pertinent to complement the co-citation analysis with other types of bibliometric analysis to obtain and analyze additional information.

2.A Tables with main Streams of research in each cluster

Table 2.10: Main Streams of Research of References in cluster 1 ■

Streams of Research	Description	TC NR: Ref.
Inequality decomposing techniques	Analyzes or develops techniques for decomposing inequality by different subgroups or factor components or sources.	446 15: Rao (1969); Pyatt (1976); Fei et al. (1978); Bourguignon (1979); Cowell (1980); Fields (1980) (*); Pyatt et al. (1980); Shorrocks (1980); Mookherjee and Shorrocks (1982); Shorrocks (1982) ; Shorrocks (1983); Shorrocks (1984); Lerman and Yitzhaki (1985); Juhn et al. (1993); Morduch and Sicular (2002)
Inequality Measures	Proposes, corrects, or characterizes one or various inequality measures	430 10: Theil (1967) (*); Atkinson (1970) ; Sen (1973) (*); Atkinson (1975) (*); Paglin (1975); Kolm (1976); Pyatt (1976); Kakwani (1980) (*); Anand (1983) (*); Atkinson (1983) (*)
Properties of Inequality Measures	Describes and discusses the desirability of properties of inequality measures.	361 8: Dalton (1920); Atkinson (1970) ; Gastwirth (1972); Dasgupta et al. (1973); Sen (1973) (*); Kolm (1976); Kakwani (1980) (*); Cowell (1995) (*)
Data	Constructs a database or discusses data related issues.	308 13: Kuznets (1963); Lydall (1968) (*); Paukert (1973) ; Atkinson (1975) (*); Jain (1975) (*); Kuznets (1976); Fields (1980) (*); Buhmann et al. (1988); Summers and Heston (1991); Atkinson and Mickelwright (1992) (*); Khan and Riskin (1998); Milanovic (1998) (*); Bourguignon and Morrisson (2002)
Income Distribution Model	Develops, estimates, or characterizes a particular or several functional forms used to model the income distribution.	277 13: Gibrat (1931) (*); Champernowne (1953) ; Aitchison and Brown (1957) (*); Lydall (1968) (*); Thurow (1970); Salem and Mount (1974); Kakwani and Podder (1976); Singh and Maddala (1976); Adelman and Robinson (1978) (*); McDonald (1984); Buhmann et al. (1988); Deaton (1997) (*); Kleiber and Kotz (2003) (*)

Growth and Inequality or Kuznets Hypothesis	Analyzes the relationship between growth and inequality, in general, or the Kuznets Hypothesis, in particular.	270 10: Lewis (1954); Kuznets (1963); Harris and Todaro (1970); Paukert (1973) ; Chenery (1974) (*); Ahluwalia (1976); Ahluwalia (1976); Robinson (1976); Adelman and Robinson (1978) (*); Papanek and Kyn (1986)
Empirical Decomposition of Inequality	Conducts an empirical analysis where inequality is decomposed by subgroups, factor components or both.	268 12: Lydall (1968) (*); Blinder (1973); Oaxaca (1973); Stark et al. (1986); Rozelle (1994); Jenkins (1995); Karoly and Burtless (1995); DiNardo et al. (1996) ; Kanbur and Zhang (1999); Milanovic (1999); Gustafsson and Shi (2002); Benjamin et al. (2005)
Determinants of Inequality	Identifies or analyzes determinants of inequality.	165 6: Thurow (1970); Tinbergen (1975) (*); Papanek and Kyn (1986); Wood (1994) (*); Atkinson (1997); Gottschalk and Smeeding (1997)
Measurement of Inequality	Analyzes or discusses issues inequality measurement issues.	158 7: Kuznets (1976); Shorrocks (1983); Buhmann et al. (1988); Atkinson and Micklewright (1992) (*); Atkinson (1995) (*) ; Deaton (1997) (*); Bourguignon and Morrisson (2002)
Evolution of Inequality in Advanced Economies	Describes the evolution of Inequality in Advanced Economies (<i>e.g.</i> , USA, UK).	124 4: Tinbergen (1975) (*); Levy and Murnane (1992) ; Jenkins (1995); Atkinson (1997)
Global Inequality	Describes or analyzes the inequality of the World Distribution of Income.	88 4: Atkinson (1975) (*); Bourguignon and Morrisson (2002) ; Milanovic (2002); Sala i Martin (2006)
Evolution of Inequality in Transition Economies	Describes the evolution of Inequality in Transition Economies (<i>e.g.</i> , former members of the USSR, China).	86 5: Milanovic (1998) (*); Milanovic (1999); Gustafsson and Shi (2002); Benjamin et al. (2005); Ravallion and Chen (2007)
Education and Inequality	Analyzes the relation between education related variables and Inequality.	70 3: Adelman and Morris (1973) (*) ; Mincer (1974) (*); Ahluwalia (1976)
Macroeconomic Variables and Inequality	Analyzes the relationship between inequality and one or various macroeconomic variables (<i>e.g.</i> , inflation, unemployment).	67 3: Salem and Mount (1974); Beach (1977); Blinder and Esaki (1978)

Normative Analysis	Conducts a normative analysis of the level of inequality in a society.	45	2: Rawls (1971) (*) ; Shorrocks (1983)
Poverty Measures	Develops a measure of poverty.	41	2: Sen (1976); Foster et al. (1984)
Econometric Techniques	Develops econometric techniques.	37	2: Heckman (1979) ; White (1980)
Poverty decomposing techniques	Analyzes or develops techniques for decomposing poverty by different subgroups, factor components or sources.	25	1: Foster et al. (1984)
Comparative analysis of Inequality	Compares the levels of inequality in different countries.	23	1: Lydall (1968) (*)
Statistical Techniques	Develops statistical techniques.	21	1: Silverman (1986) (*)

Source: Authors' own compilations.

Note: The details of each of the network references concerning the identification of the streams of research as well as the main elements used to justify them (the summary of the reference and relevant citing references), are available in an appendix upon request. The most cited reference is in bold.

Legend: (*) non-article reference; TC - Total citations; NR - Number of references

Table 2.11: Main Streams of Research of References in cluster 2 ■

Streams of Research	of	Description	TC N. Ref.: Ref.
Finance Inequality	and	Analyzes the relationship between financial development, financial liberalization or both and inequality.	553 19: Greenwood and Jovanovic (1990); Banerjee and Newman (1993) ; King and Levine (1993); Mookherjee and Ray (2003); Clarke et al. (2006); Beck et al. (2007); Claessens and Perotti (2007); Chong and Gradstein (2007); Roine et al. (2009); Demirgüç Kunt and Levine (2009); Ang (2010); Beck et al. (2010); Gimet and Lagoarde Segot (2011); Kim and Lin (2011); Agnello et al. (2012); Jaumotte et al. (2013); Delis et al. (2014); Jauch and Watzka (2016); De Haan and Sturm (2017)
Econometric Techniques		Develops econometric techniques.	396 9: Hausman (1978); Nickell (1981); Arellano and Bond (1991) ; Arellano and Bover (1995); Blundell and Bond (1998); Wooldridge (2002) (*); Windmeijer (2005); Roodman (2009); Roodman (2009)
Openness Inequality	and	Analyzes the relation between the degree of openness of an economy, concerning trade, financial transactions, or both and inequality.	339 16: Stolper and Samuelson (1941); Bourguignon and Morrisson (1990); Richardson (1995); Feenstra and Hanson (1997); Edwards (1997); Spilimbergo et al. (1999); Reuveny and Li (2003); Dollar and Kraay (2004); Milanovic (2005); Anderson (2005); Goldberg and Pavcnik (2007); Dreher and Gaston (2008); Meschi and Vivarelli (2009); Bergh and Nilsson (2010); Jaumotte et al. (2013) ; Asteriou et al. (2014)
Data		Constructs a database or discusses data related issues.	215 9: Barro and Lee (2001); Alesina et al. (2003); Galbraith and Kum (2005); Lane and Milesi Ferretti (2007); Solt (2009) ; Barro and Lee (2013); Jenkins (2015); Feenstra et al. (2015); Solt (2016)
Growth Inequality or Hypothesis	and Kuznets	Analyzes the relationship between growth and inequality, in general, or the Kuznets hypothesis, in particular.	176 5: Greenwood and Jovanovic (1990) ; Bourguignon and Morrisson (1998); Ravallion (2001); Dollar and Kraay (2002); Lundberg and Squire (2003)
Determinants Inequality	of	Identifies or analyzes determinants of inequality.	121 4: Li et al. (1998) ; Bourguignon and Morrisson (1998); Hall and Jones (1999); Easterly (2007)

Macroeconomic Variables and Inequality	Analyzes the relationship between inequality and one or various macroeconomic variables (<i>e.g.</i> , inflation, unemployment).	42	2: Easterly and Fischer (2001) ; Albanesi (2007)
Theories of Financial Development	Analyzes and develops theories for the process of financial development of a country.	19	1: Rajan and Zingales (2003)
Fractionalization and Redistribution	Analyzes how the degree of ethnic, linguistic, and religious fractionalization affects redistribution policies.	18	1: Alesina et al. (2003)
Corruption and Inequality	Analyzes the relationship between corruption and inequality.	17	1: Gupta et al. (2002)
Education and Inequality	Analyzes the relation between education related variables and Inequality.	16	1: Sokoloff and Engerman (2000)
Redistribution and Inequality	Analyzes the relationship between redistribution Policies and inequality.	15	1: Musgrave and Thin (1959) (*)

Source: Authors' own compilations.

Note: See Table 2.10.

Legend: See Table 2.10.

Table 2.12: Main Streams of Research of References in cluster 3 ■

Streams of Research	Description	TC N. Ref.: Ref.
Inequality-Growth empirical analysis	Conducts an empirical analysis of the relationship between inequality and growth.	595 12: Clarke (1995); Alesina and Perotti (1996); Perotti (1996); Partridge (1997); Deininger and Squire (1998); Li and Zou (1998); Barro (2000) ; Forbes (2000); Panizza (2002); Banerjee and Duflo (2003); Partridge (2005); Voitchovsky (2005)
Political-Economy Models	Develops an economic model where both political and economic outcomes are endogenously determined.	441 9: Barro (1990); Glomm and Ravikumar (1992); Bertola (1993); Perotti (1993); Saint Paul and Verdier (1993); Alesina and Rodrik (1994); Persson and Tabellini (1994) ; Bénabou (1996); Bénabou (1996)
Model with Credit or Capital Market Imperfections	Develops an economic model where agents (<i>e.g.</i> , consumers, firms) face borrowing constraints in the credit market	332 5: Banerjee and Newman (1991); Galor and Zeira (1993) ; Bénabou (1996); Aghion and Bolton (1997); Aghion et al. (1999)
Inequality, Human Capital and Growth	Analyzes a transmission channel between Inequality and Growth through its effects on Human Capital	219 2: Galor and Zeira (1993) ; Galor and Moav (2004)
Inequality, Redistribution and Growth	Develops or analyzes a theoretical channel whereby inequality affects growth through its impacts on redistribution.	186 3: Bertola (1993); Perotti (1993); Alesina and Rodrik (1994)
Endogenous Growth Models	Develops models where the growth rate is endogenously determined as a result of the actions of the agents in the economy.	180 7: Romer (1986); Lucas (1988) ; Barro (1990); Grossman and Helpman (1991) (*); Aghion and Howitt (1992); Bertola (1993); Aghion and Howitt (1998) (*)
Convergence	Analyzes the rate of convergence of income per capita between developed and developing countries, with or without consideration of the parameters determining their steady-state values.	120 4: Barro (1991) ; Barro and Sala i Martin (1992); Mankiw et al. (1992); Barro and Sala i Martin (1995) (*)

Public versus Private Education Growth Models	Develops a growth model where the impacts on economic performance of a public and private education system are assessed and compared.	68	3: Glomm and Ravikumar (1992) ; Saint Paul and Verdier (1993); Bénabou (1996)
Determinants of Growth	Conducts an empirical analysis of the determinants of growth.	43	1: Barro (1991)
Model of Optimal Taxation	Develops or discusses a theory of optimal taxation.	29	1: Mirrlees (1971)
Inequality, Technological Progress and Growth	Develops an economic model where greater inequality, by rewarding risk and productivity, increases technological progress and, therefore, growth.	25	1: Galor and Tsiddon (1997)
Structural Changes	Develops a model where the relationship between inequality and growth is affected by structural changes (<i>e.g.</i> , rate of time preference, productivity, risk).	20	1: García Peñalosa and Turnovsky (2006)
Model with Hierarchic preferences	Develops an economic model where the preferences of consumers differ due to the existence of goods with different levels of desirability.	18	1: Murphy et al. (1989)
Classical approach	Develops a model that follows the classic approach according to which inequality increases savings, which is then applied by authors to analyze the inequality-growth relationship.	16	1: Bourguignon (1981)
Equality-Growth Tradeoff	Establishes the notion of a trade-off between Equality and Economic Efficiency or Growth.	16	1: Okun (1975) (*)
Inequality, Fertility and Growth	Analyzes a transmission channel between Inequality and Growth through the impacts of the former on fertility rates.	16	1: De La Croix and Doepke (2003)

Source: Authors' own compilations.

Note: See Table 2.10.

Legend: See Table 2.10.

Table 2.13: Main Streams of Research of References in cluster 4 ■

Streams of Research	Description	TC N. Ref.: Ref.
GE Models with idiosyncratic risk and incomplete markets	Develops a General Equilibrium Model where agents face uninsurable risks due to the absence of complete markets.	236 7: Huggett (1993); Aiyagari (1994) ; Huggett (1996); Krusell and Smith (1998); Quadrini (2000); Castañeda et al. (2003); Cagetti and De Nardi (2006)
GE Models with links between generations	Develops a General Equilibrium Model with multiple generations linked through the possibility of transmission of wealth and valuation of future utility.	177 7: Stiglitz (1969) ; Blinder (1973); Barro (1974); Becker (1974); Becker and Tomes (1979); Loury (1981); Becker and Tomes (1986)
GE Models with Heterogenous Agents	Develops a General Equilibrium Model where agents (<i>e.g.</i> , consumers, firms) differ in some respect (<i>e.g.</i> , endowments, preferences).	81 4: Chatterjee (1994); Caselli and Ventura (2000); De Nardi (2004) ; Benhabib et al. (2011)
Empirical analysis of the relation between Intergenerational Transfers and Wealth Inequality	Conducts an empirical analysis of the relative importance of Intergenerational Transfers in shaping the Wealth Distribution.	77 4: Atkinson (1971); Atkinson and Harrison (1978) (*) ; Kotlikoff and Summers (1981); Gale and Scholz (1994)
Relation between Income and Consumption Inequality	Conducts an empirical or theoretical analysis of the relation between consumption and income inequality.	77 4: Blinder (1975); Deaton and Paxson (1994); Krueger and Perri (2006); Heathcote et al. (2010)
Empirical analysis of the Wealth Distribution	Conducts an empirical analysis of the Wealth Distribution over time and of the degree of inequality.	48 2: Rodriguez et al. (2002); Saez and Zucman (2016)
Empirical Analysis of Mobility	Conducts an empirical analysis of the degree of mobility in the wealth distribution over time or across generations.	47 3: Solon (1992) ; Zimmerman (1992); Kopczuk et al. (2010)

Data	Constructs a database or discusses data related issues.	40	2: Atkinson and Harrison (1978) (*) ; Díaz Giménez et al. (1997)
GE model with credit market imperfections	Develops a General Equilibrium Model where agents (<i>e.g.</i> , consumers, firms) face borrowing constraints in the credit market.	36	2: Chatterjee (1994); Piketty (1997)
Transitory and Permanent components of Income	Analyzes the differences between the Transitory and Permanent components of income and their implications.	27	1: Friedman (1957) (*)
Empirical analysis of heterogeneous saving rates	Conducts an empirical analysis to determine whether saving rates vary with different groups.	25	1: Dynan et al. (2004)
Almost Ideal Demand System	Develops a system of demand equations derived from consumer theory.	17	1: Deaton and Muellbauer (1980)
Econometric Techniques	Develops econometric techniques.	16	1: Tauchen (1986)
Pareto of Wealth Distribution	Describes the adequacy of Pareto Models to describe the upper tail of the distribution of wealth.	15	1: Gabaix (2009)
Tax Progressiveness	Defines and characterizes a progressive income tax system.	15	1: Musgrave and Thin (1948)

Source: Authors' own compilations.

Note: See Table 2.10.

Legend: See Table 2.10.

Table 2.14: Main Streams of Research of References in cluster 5 ■

Streams of Research	of	Description	TC N. Ref.: Ref.
Determinants of Inequality	of	Identifies or analyzes determinants of inequality.	157 2: Stiglitz (2012) (*); Piketty (2014) (*)
Evolution of Inequality	of	Describes the evolution of inequality over time in particular a country or region.	151 2: Gollin (2002); Piketty (2014) (*)
Inequality, Aggregate Demand and Growth		Analyzes the effects of inequality on components of aggregate demand or growth.	137 6: Kalecki (1971) (*); Dutt (1984); Bhaduri and Marglin (1990) ; Dutt (2006); Hein and Vogel (2008); Stockhammer et al. (2009)
Classical approach		Develops a theoretical model where inequality increases aggregate savings.	108 3: Kaldor (1955) ; Kaldor (1957); Pasinetti (1962)
Median-voter hypothesis		Develops, empirically analyzes the Hypothesis that an increase in inequality worsens the position of the median voter, leading to stronger redistribution policies.	93 3: Meltzer and Richard (1981) ; Bénabou (2000); Milanovic (2000)
Interpersonal Dependency of Preference Theory	of	Develops, analyzes or empirically tests the Hypothesis that the happiness or utility of individuals is conditional on how they compare to other persons' income or wealth.	89 5: Veblen (1899) (*); Duesenberry (1949) (*) ; Runciman (1966) (*); Luttmer (2005); Frank et al. (2014)
Inequality Crisis	and	Analyzes the impacts of inequality on financial crises.	60 2: Rajan (2010) (*) ; Kumhof et al. (2015)
Inequality Saving Rate	and	Establishes a connection between inequality and the aggregate saving rate.	41 1: Solow (1956)
Inequality Health	and	Analyzes the relationship between inequality and health outcomes.	40 2: Wilkinson (1996) (*) ; Deaton (2003)
Keynesian Theories		Develops growth theories that extend Keynes focus on short-run phenomena to long-run outcomes and economic growth.	38 2: Keynes (1936) (*) ; Robinson (1956) (*)

Effects of Inequality	Describes or analyzes the effects of inequality on multiple dimensions.	23	1: Stiglitz (2012) (*)
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Source: Authors' own compilations.
 Note: See Table 2.10.
 Legend: See Table 2.10.

Table 2.15: Main Streams of Research of References in cluster 6 ■

Streams of Research	Description	TC N. Ref.: Ref.
Evolution of Inequality	Describes the evolution of inequality over time in a particular country or region.	512 15: Kuznets and Jenks (1953) (*); Bound and Johnson (1992); Katz and Murphy (1992); Card and DiNardo (2002); Piketty (2003); Piketty and Saez (2003); Saez and Veall (2005); Piketty and Saez (2006) ; Atkinson and Piketty (2007) (*); Autor et al. (2008); OECD (2008) (*); Atkinson et al. (2011); Alvaredo et al. (2013); OECD (2015) (*); Milanovic (2016) (*)
Top Shares	Describes and analyzes the evolution of top income and wealth shares.	367 10: Kuznets and Jenks (1953) (*); Piketty (2003); Piketty and Saez (2003) ; Saez and Veall (2005); Piketty and Saez (2006); Atkinson and Piketty (2007) (*); Autor et al. (2008); Atkinson et al. (2011); Alvaredo et al. (2013); Piketty et al. (2014)
Impacts of Inequality	Analyzes empirically or theoretically the impact of inequality on one or several variables.	180 3: Piketty (2003); Piketty and Saez (2003) ; OECD (2011) (*)
Skill Premium and SBTC Hypothesis	Analyzes empirically or theoretically the Skill Biased Technological Change Hypothesis	138 5: Bound and Johnson (1992); Katz and Murphy (1992) ; Acemoglu (1998); Acemoglu (2002); Card and DiNardo (2002)
Determinants of Inequality	Identifies or analyzes determinants of inequality.	118 6: Melitz (2003); OECD (2008) (*) ; Alvaredo et al. (2013); Piketty et al. (2014); OECD (2015) (*); Coibion et al. (2017)
Wealth to Income Ratio	Analyzes the concentration of wealth relative to income.	32 2: Piketty and Zucman (2014) ; OECD (2015) (*)
Measurement of Inequality	Analyzes or discusses issues inequality measurement issues.	18 1: Cowell (2011) (*)
Labor share	Documents or analyzes the decrease of the labor share	17 1: Karabarbounis and Neiman (2014)

Source: Authors' own compilations.

Note: See Table 2.10.

Legend: See Table 2.10.

Table 2.16: Main Streams of Research of References in cluster 7 ■

Streams of Research	of	Description	TC N. Ref.: Ref.
Growth and Inequality or Kuznets Hypothesis	and	Analyzes the relationship between growth and inequality, in general, or the Kuznets hypothesis, in particular.	366 4: Kuznets (1955) ; Ram (1991); Anand and Kanbur (1993); Partridge et al. (1996)
Data		Constructs a database that is used by the citing reference or discusses data related issues.	251 4: Deininger and Squire (1996) ; Atkinson and Brandolini (2001); Leigh (2007); Frank (2009)
Econometric Techniques		Develops econometric techniques that are used by the citing reference.	189 9: Engle and Granger (1987); Johansen (1988); Pesaran and Smith (1995); Maddala and Wu (1999); Pedroni (1999); Pesaran et al. (2001); Levin et al. (2002); Im et al. (2003) ; Pesaran (2007)
Education and Inequality	and	Analyzes the relation between education-related variables and Inequality.	77 4: Becker and Chiswick (1966); Knight and Sabot (1983) ; De Gregorio and Lee (2002) ; Leigh (2007)
Inequality and Environment	and	Analyzes the relation between Inequality and the Environment.	35 2: Boyce (1994) ; Torras and Boyce (1998)
Openness and Inequality	and	Analyzes the relation between the degree of openness of an economy, concerning trade, financial transactions, or both and inequality.	16 1: Partridge et al. (1996)
Macroeconomic Variables and Inequality	and	Analyzes the relationship between inequality and one or various macroeconomic variables (<i>e.g.</i> , inflation, unemployment).	15 1: Mocan (1999)

Source: Authors' own compilations.

Note: See Table 2.10.

Legend: See Table 2.10.

Chapter 3

The inequality-growth relationship
in the US and France: A SVAR
approach with bootstrap and model
reduction techniques

3.1 Introduction

Inequality has been increasing in many advanced economies (*e.g.*, Alvaredo, Chancel, Piketty, Saez, & Zucman, 2018). This has contributed to amplified attention both by researchers and policymakers to this phenomenon and its consequences on several dimensions, including economic growth (*e.g.*, Berg, Ostry, Tsangarides, & Yakhshilikov, 2018; Gründler & Scheuermeyer, 2018). The former have devoted much attention to this topic with empirical studies and theoretical analyses where some channels have been established through which inequality can affect growth. The effects of inequality can be negative, by increasing redistribution intensity and reducing investment incentives - Fiscal Policy channel -, reducing human capital in the presence of capital market imperfections - Credit Market Imperfections channel -, or positive, by increasing the aggregate saving rate - Savings channel. Nonetheless, no clear consensus has emerged yet concerning the nature of the effects of the former on the latter and the specific mechanisms through which such a relationship operates (Neves, Afonso, & Silva, 2016; Neves & Silva, 2014).

An extensive review of the inequality-growth literature covered by Neves and Silva (2014) concludes that one reason for such heterogeneity in results is the country-specific nature of this relationship. This aspect has been neglected by the overwhelming number of empirical studies that have been conducted. Most consist of panel and cross-section analyses that assume homogeneous parameters across different units of analysis, despite the lack of empirical and theoretical evidence to support such an assumption (Durlauf & Johnson, 1995). The importance of conducting country-specific analyses is further reinforced by the resulting conclusions being more useful in designing appropriate policies for specific realities (Forbes, 2000; Gobbin & Rayp, 2008).

Bearing this in mind, in this paper we seek to answer the research questions below by conducting a time series analysis using a Structural Vector autoregressive (SVAR) modeling approach:

1. What is the relationship between inequality and growth?
2. What are the channels through which the former affects the latter?

The analysis is focused on the United States and France during the period 1962-2018. These are two of the most advanced economies in the world that have, nonetheless, experienced some of the most significant increases in inequality, and for which is

available a sufficient number of time observations for the variables of interest to conduct an adequate time series analysis. The methodological approach and the focus of the analysis constitute important innovations in relation to the existing literature in several aspects.

First, we employ the VAR approach, which is the natural choice in analyses focused on aggregate time series analysis of individual countries (*e.g.*, Gobbin & Rayp, 2008) but also offers important advantages in relation to the methodological approach usually adopted in the literature. The latter consists of panel data models estimated by Difference or System GMM estimators (*e.g.*, Gründler & Scheuermeyer, 2018) to address the endogeneity of many variables of interest. This requires using lagged variables in levels as instruments for the endogenous variables in first differences and, in the case of the System GMM, also lagged first differences as instruments for variables in levels. Consequently, the validity of the results depends, to a large extent, on the appropriateness of the chosen instruments, which is often an issue in growth regressions (Bazzi & Clemens, 2013). By contrast, this is not an issue in VAR models, which can be estimated by OLS or maximum likelihood without using instruments. Another advantage is that it can lead to more precise results, by explicitly modeling the lagged dynamics of the endogenous variables. Finally, this approach can provide more information concerning the relationships between variables through impulse response analysis of shocks. These consider not only the lagged dynamics of the endogenous variables but also contemporaneous relationships, an aspect that is not usually considered in panel data models but can significantly affect the results (Huang, Lin, & Yeh, 2009; Lundberg & Squire, 2003).

Second, in the context of this time series approach, to the best of our knowledge, we are the first to consider variables that simultaneously affect inequality and growth. This is important to avoid reaching erroneous conclusions regarding the relationship between inequality and growth driven by the unaccounted effects of variables that simultaneously determine them (Lundberg & Squire, 2003).

Third, we employ techniques to obtain the most accurate results possible with the sample at hand. The first is a model reduction technique that permits excluding irrelevant parameters without the risk of distorting the analysis. This is motivated by two factors: the sample period, which, despite being long, is nonetheless limited, and the considerable number of variables that are analyzed compared with similar studies. The second is conducting all the statistical inference based on a bootstrap approach, which leads to more accurate results, especially in small samples. The greater

precision comes from approximating the distribution of the test statistics with a numerical distribution about which almost no assumptions are made, instead of using the asymptotic distribution to this effect.

Fourth, we made some innovations within the context of some techniques mentioned above. The first is the model reduction strategy we apply, which is novel and has advantages to the ones developed in the literature. In particular, it provides more valuable information with a pre-analysis of bivariate models and allows the researcher to decide what restrictions can be applied based on theoretical arguments and not just statistical criteria. The second is a straightforward bootstrap method that can be applied in the context of instantaneous causality tests.

Our results indicate a negative impact on economic growth in France over the medium run and the very short run in the United States. In both economies, it was found that inequality does not affect enrollment rates and increases redistribution intensity, with the latter not affecting growth directly or indirectly through its determinants. Moreover, we found a negative effect of inequality on growth even when controlling for the transmission channels. This suggests that the negative relation between inequality and growth might be explained by mechanisms different from those considered. We only found evidence for structural change in the United States in 1989. An analysis by subperiods resulting from dividing the sample period around this year confirmed that many of the previously mentioned effects occur throughout the period but also suggest that the negative effects of inequality on growth occur primarily after 1989. Moreover, inequality decreased enrollment rates during 1962-1989 and increased them during 1990-2018. The main results are robust to alternative assumptions concerning the short-run relations between variables.

The remainder of this essay is structured in the following manner: in section 3.2, we conduct a review of the literature; in section 3.3, we describe the data and its sources and conduct unit root tests of each time series that take into account the presence of structural breaks; in section 3.4, we describe the model, the identification approach and both the model reduction strategy and bootstrap method we employ; in section 3.5, we apply the model reduction strategy, present the main results and analyze the robustness of the results; in section 3.6, we conclude.

3.2 Review of the Literature

The inequality-growth relationship has been studied extensively in the literature, with numerous empirical studies and the proposal of theoretical channels through which the former affects the latter. In this regard, bearing in mind an extensive review of the literature of Neves and Silva (2014) and more recent developments (*e.g.*, Gründler & Scheuermeyer, 2018), three of the most relevant mechanisms are the following:

- Fiscal Policy (FP) (*e.g.*, Alesina & Perotti, 1996; Alesina & Rodrik, 1994; Persson & Tabellini, 1994) – Higher inequality can affect redistribution in two different ways. The classical view (CV) posits that it increases redistribution through a political process that presses policymakers in this direction. On the other hand, the new view (NV) considers that higher inequality may lead the richest to have more political power and exert it to further increase their economic and social position, which implies the opposite effect. In turn, a redistribution policy is financed through taxes, leading to distortions that reduce investment incentives and, therefore, growth.
- Credit Market Imperfections (CMI) (Galor & Moav, 2004; Galor & Zeira, 1993) – An increase in inequality leads a larger fraction of the population to be kept from carrying out the desired level of investment in human capital when credit markets are imperfect, which reduces growth;
- Savings (SA) (Kaldor, 1955) – An increase in inequality implies that resources become more concentrated on the richest that have a higher saving rate, which results in higher investment and growth rates.

Despite the attention this topic has deserved, a clear consensus has yet to emerge regarding the specific nature of this relationship. One of the findings of a meta-analysis of this literature conducted by Neves et al. (2016) is that including regional dummies substantially weakens the statistical significance of effects found in the context of analyses of this relationship that consider multiple countries. This suggests that this relationship is highly country-specific, but this has not been reflected in the literature. In the survey of Neves and Silva (2014), of the 34 studies reviewed by the paper, the authors were only able to find two studies that conducted a time series analysis focused on specific countries, Gobbin and Rayp (2008) and Frank (2009). In more recent years, numerous studies that favor the time dimension

have been published (*e.g.*, Atems & Jones, 2015; Halter, Oechslin, & Zweimüller, 2014; Henderson, Qian, & Wang, 2015), but, to the best of our knowledge, only Atems and Jones (2015) focused on a single country, the United States. Finally, another issue seldom addressed is the fact that variables that simultaneously determine inequality and growth need to be considered when analyzing the relationship between the two variables. The first authors to analyze this issue were Lundberg and Squire (2003) and, later, Huang et al. (2009). Both conducted analyses in the context of panels of countries and obtained statistically significant results of the effects of inequality on growth and vice-versa that, in the case of the former, were significantly different using this approach.

The focus of our analysis is the United States and France, which are two of the most advanced and influential economies in the world. Both belong to important international organizations in shaping international policy, such as the G-20, the G-7, and the World Trade Organization, and have figured systematically among the 10 largest economies in the world.¹ They have also experienced some of the largest increases in inequality among advanced economies, which, bearing in mind their importance, reinforces the importance of analyzing the potential economic impacts of such increases in disparities.

Notwithstanding their advanced economic status on the global stage, they have important differences. The most important one concerns the labor market, which is more tightly regulated in France than in the United States, exemplified by the existence in the former of the 35-hour working week, the minimum wage, and more stringent rules that affect the hiring and firing process (Howell & Okatenko, 2010). Many authors consider that most of these institutional differences are reflected in differences in wage inequality (*e.g.*, Koeniger, Leonardi, & Nunziata, 2007), which, as it will be shown further ahead, has been systematically higher in the United States than in France. Another important difference concerns the welfare state, which is also stronger in France, with higher welfare benefits and transfer programs (Geis, Uebelmesser, & Werding, 2011). This can explain the higher levels of redistribution found in France, as shown further in Figure 3.1.

They have also experienced different economic performances over time. Chappert (2007, p. 203) conducts a comparative analysis of the differences in the trajectory of

¹For example, in 2020, the United States and France were, respectively, the largest and seventh-largest economies in the world (Retrieved from “<https://www.worlddata.info/largest-economies.php>” on the 8th September 2022).

GDP per capita in both economies and finds that France had a satisfactory performance until the mid 1970s, beginning to decline in relation to the American economy after this period, which is consistent with Figure 3.1. The authors conclude that this results from differences in the growth rate of the labor force but also labor productivity. Some authors consider that such differences can be explained, at least partially, by some of the institutional differences described above. For example, Geis et al. (2011) considers that the welfare system and less selective immigration policy concerning the skills of immigrants contribute to European countries, including France, receiving a higher influx of lower-skilled and less productive workers compared with the US. Van Ark, O'Mahoney, and Timmer (2008) considers that the slowdown of productivity in Europe in general in relation to the United States between 1995-2006 and 1973-1995 is justified by the lower relative development in information and communication technologies (ICT) in the former, which, in turn, is considered a consequence of higher levels of labor market rigidities and product regulation.

In this paper, we intend to estimate VAR models focused on vector processes with a considerable number of variables in a limited period. In VAR models, the regressors of all equations are all assumed to be the same. This results in a large number of parameters to be estimated that grows significantly with each additional lag or variable that is added, which decreases the accuracy of confidence intervals for impulse responses. Moreover, there is also the risk of including many irrelevant variables and lag terms, which causes confidence intervals to be substantially distorted (Brüggemann, 2004, p. 10).

Therefore, we consider important the implementation of a strategy to remove the largest number of irrelevant parameters as possible to maximize the precision of the results. In the literature, some authors have adopted different strategies for this purpose, which can be broadly divided into two categories. The first consists of search path strategies whereby parameters are consecutively restricted to zero if some condition concerning a single equation or the whole system is satisfied. One example is the Top-Down strategy, where each parameter is checked individually to determine if its exclusion improves some information criteria such as AIC (Brüggemann, 2004, p. 21).² Another approach is the application of the Least Absolute Shrinkage and Selection Operator (LASSO), and has experienced some developments in more recent years. It consists of estimating a VAR model using a modified version of the usual

²For more details concerning this and other similar reduction strategies, the reader is referred to Brüggemann (2004).

OLS estimator, with the addition of a penalty term that results in irrelevant parameters being restricted to zero (Nicholson, Matteson, & Bien, 2017; Ren & Zhang, 2010).

One of the criticisms pointed to the first approach is that the model reduction is made along a specific path, which makes its reliability dependent on choosing the correct one (Brüggemann, 2004, p. 22). The second approach addresses this issue, but we consider that, in similarity to the first, it is inherently statistical in nature, leaving no room to choose what subset of parameters should be kept in the model and what should be excluded. While it could be argued that this feature renders such approaches objective, they can also lead to an excessive reduction of the number of parameters to be estimated, especially in small samples and medium-sized vector processes, such as in our case.

Bearing this in mind, we developed a different approach, explained in more detail in section 3.4, which we consider intuitive and straightforward, and is as follows. First, we determine the lag order of the VAR models of all pairs of variables in the vector process under analysis, estimate them, and conduct instantaneous and Granger causality tests. Then, we check for the existence of potentially irrelevant variables and remove them in case they exist, and estimate the intended VAR model. Finally, we test zero restrictions consistent with the information obtained from the bivariate models and impose those that are not rejected.

Our approach has several substantial benefits in relation to the existing ones in the literature. First, by analyzing bivariate models, we obtain information regarding the relations between each pair of variables and different lag structures, which is useful on its own and an advantage concerning both categories. Second, the zero restrictions that are imposed do not depend on specific search paths, as in the first category of model reduction strategies. Third, they minimize the risk of excluding important variables to the system due to the imposition of restrictions that are not rejected both as a whole and individually, in the context of the bivariate VAR models, and by allowing the researcher to choose what restrictions should not be imposed based on theoretical reasons, which is an advantage compared to the LASSO approach.

Our methodological approach also innovates by extending the application of bootstrap methods, which are techniques used to obtain a distribution of a test statistic or an estimator by repeated resampling processes with replacement of the original data or quantities obtained from it, such as residuals from econometric models. These methods are adequate in many circumstances by providing a better

approximation of the distribution of a quantity of interest than alternatives based on asymptotic theory (Horowitz, 2019) as a result of making no or weak assumptions, at most, regarding the Data Generating Process of the original data (Lütkepohl, 2005, p. 127). Therefore, they are particularly important for time series analysis focused on annual data due to the relatively small sizes and the large number of variables that are included. In this context, these methods are commonly used to obtain confidence intervals for impulse responses (Lütkepohl, 2005, p. 377). We innovate by using them for this purpose and conducting statistical inference regarding statistical tests. Moreover, in the process, we also design a novel bootstrap method to be applied in the context of instantaneous causality tests, as explained in detail in subsection 3.4.4.

3.3 Data

3.3.1 Description

This section provides details regarding the data we analyze in this paper.

Our data concerns the United States and France and spans the period 1962-2018, with the details described in Table 3.1 and the plots in Figure 3.1. Economic growth is measured using GDP per capita retrieved from the Penn World Table 10.0 (Feenstra, Inklaar, & Timmer, 2015), hereafter PWT. Aggregate inequality is proxied by the Gini coefficient, retrieved from the Standardized World Income Inequality Database, Version 9.3, June 2022 (Solt, 2020), hereafter SWIID. We opt for this inequality measure from this source to make our results comparable with the existing literature, which uses it extensively (*e.g.*, Berg et al., 2018; Gründler & Scheuermeyer, 2018).

We include proxies for the intermediate variables of each transmission channel under analysis. The intermediate variable of the fiscal policy channel, redistribution intensity, is proxied by the difference between the Gini coefficient of the market and net incomes, retrieved from the SWIID. We follow this approach following other authors in the literature that also analyze transmission channels (*e.g.*, Berg et al., 2018; Gründler & Scheuermeyer, 2018). Moreover, we consider this measure adequate and more complete than others, such as taxes, because it also includes the redistribution effects of subsidies and other welfare benefits. The savings rate is proxied by the investment share in aggregate output, as in Barro (2000), which is retrieved from PWT.

We proxy human capital with the gross enrollment rate. The corresponding time series for both countries were obtained from different sources and in different manners:

- In the case of France, we retrieved them from the World Bank Development Indicators Database (World Bank, 2020), hereafter WBDI. This source had missing values in 1962-1970 and 1984. In the case of the first period, we considered the values in Table V from Radica (1975), while the single missing observation in 1984 was imputed using linear interpolation between the actual observations of the surrounding years.³
- In the case of the United States, we calculated the gross enrollment rate directly from values obtained from Digest Education Statistics (DES) using the definition used by the WBDI database.⁴ Specifically, to calculate the gross enrollment ratio, we obtained (a) estimates for the resident population in the United States between 18 and 24 years old (the official age group of tertiary education in this country) and (b) total fall enrollment in degree-granting post-secondary institutions for the period of analysis (1962-2018) and divided (b) by (a) for each year. To obtain updated figures for both variables, the estimates of (a) for the entire period of analysis were retrieved from Table 303.10 of the 2021 edition (NCES, 2022). For (b), we were able to obtain figures from 1970 to 2021 from Table 101.10 from this edition as well. The values for 1963 to 1969 were obtained from Table 14 from the edition of 1996 (Snyder, Hoffman, & Geddes, 1996). We could not obtain a value for (b) for the year 1962 and therefore imputed it using linear interpolation from surrounding years.

We acknowledge that the gross enrollment rate has limitations. For example, a high indicator might result from additional factors other than a good education system, such as the presence of overaged individuals enrolled to repeat academic years. This problem could be mitigated by considering instead the corresponding net enrollment rate, which only measures the percentage of the population group corresponding to tertiary education enrolled in a higher education system instead of all individuals. However, we could not find a time series with observations for all the years of the

³We must note that there is a substantial increase in the enrollment rate from 12.92% in 1967 to 16.90% in 1968 due to the creation in the latter year of the University Institutes of Technology (IUC) (Radica, 1975, p. 13). For the years 1971-1973 we obtained enrollment rates of 18.55%, 19.57% and 20.78% in Radica (1975) and of 18.56%, 19.64% and 21.40% in WBDI, which are very similar. For these years, we opted for using the values from the WBDI database.

⁴We opted for this alternative instead of relying on the WBDI Database because this source exhibited missing observations in several periods for extended years. Replacing them using values from DES was not feasible since both sources resorted to different methodologies, which was reflected by substantially different values in years for which there were observations from both.

period of analysis for both countries.

Moreover, we also found that the alternative of using the human capital index time series available at PWT posed several problems related to how this variable is constructed, which is by linear interpolation from the corresponding five-year series from Barro and Lee (2013). First, most of the yearly observations of the human capital index time series are imputed rather than real values, with these only existing for years that are multiples of five. In contrast, it is possible to obtain real values of the gross enrollment rate for almost all years in the analysis period. Second, these values are obtained using linear interpolation. This assumes a linear evolution between existing data points, which might not be realistic. Third, this method leads to sudden changes in the slope of the human capital index that leads to artificial discontinuities in the data that create technical difficulties in the analysis.

Finally, we also include variables that can theoretically affect both inequality and growth since, as explained in detail further ahead, this is necessary in the context of our analysis. Bearing in mind the availability of data and the theoretical and empirical evidence in the literature, we consider in our analysis inflation (Afonso & Lima, 2022), education (Huang et al., 2009; Lundberg & Squire, 2003), government expenditures and openness (Huang et al., 2009).⁵ The proxy for education was already described. In the case of the remaining variables, as shown in Table 3.1, we use the conventional proxies in the literature (*e.g.*, Gründler & Scheuermeyer, 2018), namely a price index from PWT, the share of government expenditures and the sum of the shares of exports and imports.

⁵Another variable that theoretically also affects inequality and growth is financial development (*e.g.*, Clarke et al., 2006; Huang et al., 2009). However, we do not consider it here because both countries enjoyed a stable high level of financial development throughout the analysis period, as two of the most advanced economies in the world.

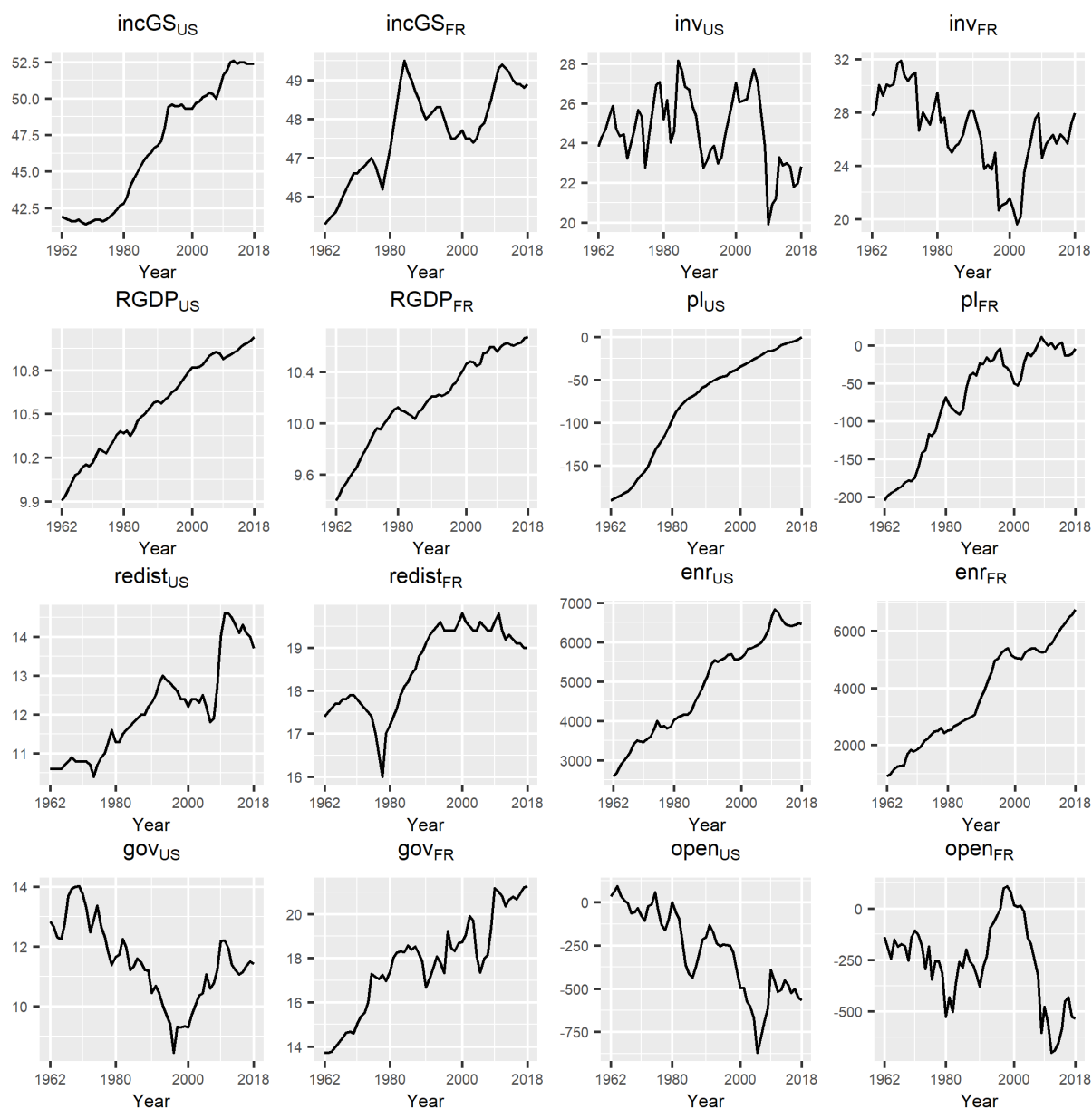
Table 3.1: Description of the data

Variable	Formula	Description of Unit of Measurement	Source
$rgdp^{(a)}$	$100 \times \log(\text{Real GDP per capita})$	GDP per capita at current PPP (in millions of 2017 international dollars).	PWT
$gini^{(b)}$	$100 \times \text{Gini coefficient of the income distribution}$	Gini of the pre-tax national income of the entire distribution of income.	SWIID
$redist^{(c)}$	$100 \times (\text{Pre-tax Gini} - \text{Post-tax Gini})$	Difference between the estimate of the Gini index of inequality in equivalized household market (post-tax) and disposable (pre-tax) incomes.	SWIID
$enr^{(c)(d)}$	$100 \times \text{Gross Enrollment Rate}$	Ratio of the resident population enrolled in tertiary education to the corresponding official group.	France: RA; WBDI US: DES
$inv^{(c)}$	$100 \times \text{Investment Shares}$	Share of investment in Real GDP at current PPP (in millions of 2017 international dollars).	PWT
$pl^{(d)}$	$100 \times \log(\text{Price Index})$	Price level of household consumption, with the benchmark being the price level in the US in 2017.	PWT
$open^{(d)}$	$100 \times \text{Investment Shares}$	Share of government consumption in Real GDP at current PPP (in millions of 2017 international dollars).	PWT
$gov^{(d)}$	$100 \times (\text{Import Shares} + \text{Export Shares})$	Sum of the absolute values of the shares of merchandise exports and imports in Real GDP at current PPP (in millions of 2017 international dollars).	PWT

Note: (a) Proxy for economic productivity; (b) Proxy for aggregate inequality; (c) Proxies for the intermediate variables of transmission channels; (d) Proxies for variables that can simultaneously affect inequality and growth.

Legend: PWT - Penn World Table 10.0 (Feenstra et al., 2015); WBDI - World Bank Development Indicators Database (World Bank, 2020); SWIID - Standardized World Income inequality Database, Version 9.3, June 2022 (Solt, 2020); RA - Radica (1975); DES - Digest Education Statistics (NCES, 2022; Snyder et al., 1996); PPP - purchasing-power-parity.

Figure 3.1: Plots of all the variables concerning the United States and France during the period 1962-2018



Source: See Table 3.1.

3.3.2 Unit Root and individual structural break tests

In this subsection, we analyze the presence of unit roots in the data to ascertain the degree of integration of the variables.⁶ This is important because the VAR model described further ahead is generally speaking applied to stationary variables (*e.g.*, Gobbin & Rayp, 2008).

A brief analysis of the plots of the different series in Figure 3.1 reveals that many appear to show structural shifts in their trajectories, such as the Gini coefficient and redistribution measures in both countries during the 1980s and 1990s. Bearing this in mind, we conduct the Kapetanios Unit Root (KPT) test (Kapetanios, 2005), which tests the null hypothesis that a time series has a unit root against the alternative that it is stationary with up to M^* structural breaks either in level or trend. The previous analysis suggests the possibility of multiple structural breaks, and, therefore, we opt for considering $M^* = 3$.⁷

We complement this test with a structural change test and two of the most common unit root tests in the literature, the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979; Wayne A. Fuller, 1995), and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). The first determines whether a stationary series has structural breaks or not. The second and third are used in combination with the KPT test to reach more robust conclusions, although the latter is more reliable in the presence of structural breaks than the ADF/KPSS approach by explicitly accounting for this possibility.

The results are in Table 3.2. In most of the time series in levels, in at least one of the versions of the KPT test, the null hypothesis of integration of order 1 is not rejected at the 5% level. The results of the ADF/KPSS tests almost always reinforce this conclusion. The only exceptions concern inv_{US} , where the null hypothesis of stationarity is not rejected by both KPSS tests, and $open_{US}$, where the ADF test rejects the null that the series is integrated. Nonetheless, we consider that these series are integrated based on the corresponding plots. Therefore we conclude that no variables are stationary in levels.

The results of the tests applied to the first differences are much more varied and

⁶A variable w_t is $I(p)$, *i.e.*, integrated of order p , iff $z_t = \Delta^p w_t$ is weakly stationary, *i.e.*, iff (i) $\mathbb{E}(z_t) = \mu < \infty$, (ii) $\text{var}(z_t) = \sigma^2 < \infty$ and (iii) $\text{cov}(z_t, z_{t-\tau}) = \gamma_\tau, \tau > 0$, where $\Delta w_t = w_t - w_{t-1}$ and $\Delta^p w_t = \Delta \Delta^{p-1} w_t, p > 1$.

⁷We opted for this approach instead of the Zivot-Andrews test (Zivot & Andrews, 2002) because the latter only assumes, at most, one structural break in a time series.

ambiguous. In almost all cases, the results of the constant version of the Kapetanios test lead to a rejection of the null hypothesis of integration of order 1, while the corresponding version of the KPSS test also does not reject the null hypothesis of stationarity at least at 5% significance level. The only exceptions concern enr_{US} , inv_{US} , pl_{US} , gov_{FR} but, in all cases, a closer analysis of the results and a graphical analysis leads to the conclusion that the first differences were stationary.

Therefore, we consider that all series are integrated of order 1. Finally, if we analyze the structural change tests applied to first differences in the majority of time series, we can see that the null hypothesis of no structural change is rejected at least at the 5% level, which suggests that many have structural breaks.

3.4 Methodology

3.4.1 The SVAR Model

In this essay we consider the following Vector autoregressive (VAR) model of a M dimensional vector process $\mathbf{y}_t$:

$$\mathbf{y}_t = \boldsymbol{\eta} + \sum_{l=1}^p \boldsymbol{\Phi}_l \mathbf{y}_{t-l} + \mathbf{v}_t, \quad (3.1)$$

where $\boldsymbol{\eta}$ is a vector of M constants, p is the lag order of the model, $\boldsymbol{\Phi}_l$ is the coefficient of the lag term l , $\mathbf{v}_t$ is a $M \times 1$ multivariate normal random disturbance with $\mathbb{E}(\mathbf{v}_t) = \mathbf{0}_{M \times 1}$, $\mathbb{E}(\mathbf{v}_t \mathbf{v}_t') = \boldsymbol{\Omega}$, and $\mathbb{E}(\mathbf{v}_t \mathbf{v}_{t-s}') = \mathbf{0}_{M \times M}$, $\forall s \neq 0$, where $\mathbf{0}$ is a zero matrix and $\boldsymbol{\Omega}$ is a $M \times M$ positive definite matrix. The estimation of the model requires that the stability condition below is satisfied (Lütkepohl, 2005, p. 15).

Definition 1 (Stability Condition). A VAR model is stable if the *moduli* of the eigenvalues λ of the companion matrix below of the VAR model, which is obtained by representing (3.1) in a VAR model of order 1, are all less or equal to 1:

$$\boldsymbol{\Phi}_{comp} := \begin{bmatrix} \boldsymbol{\Phi}_{p-1}^O & \boldsymbol{\Phi}_p \\ \mathbf{I}_{M(p-1)} & \mathbf{0} \end{bmatrix}, \quad \boldsymbol{\Phi}_{p-1}^O := [\boldsymbol{\Phi}_1, \dots, \boldsymbol{\Phi}_{p-1}]. \quad (3.2)$$

For $\mathbf{y}_t$, we will consider two groups of variables specific to each country $i \in \{US, FR\}$, justified in section 3.4.2 and defined below:

Table 3.2: Results of the Unit root and individual structural break tests with simulated p-values

	KPT		ADF	KPSS		SC Test	
	H_1 : Lvl Brk	H_1 : Tr Brk		H_0 : Lvl Sta	H_0 : Tr Sta	H_0 : No Tr	H_0 : Tr
$incGS_{FR}$	-7.246**	-6.070	-1.827	0.965***	0.170**	134.755***	57.847***
$\Delta incGS_{FR}$	-7.254**	-4.961	-2.000	0.108	0.057	10.716**	22.209***
inv_{FR}	-6.387	-4.905	-0.793	0.762***	0.201***	51.939***	84.832***
Δinv_{FR}	-8.224***	-8.135***	-2.300	0.115	0.086	3.140	5.725
$RGDP_{FR}$	-4.072	-3.652	-2.572	1.460***	0.190***	114.058***	186.774***
$\Delta RGDP_{FR}$	-7.231**	-6.115	-1.915	0.422*	0.096	15.918***	14.845**
pl_{FR}	-5.115	-4.197	-1.456	1.343***	0.315***	218.405***	194.753***
Δpl_{FR}	-7.361**	-5.939	-2.853	0.277	0.045	5.493	4.338
$open_{FR}$	-4.689	-5.293	-2.221	0.291	0.174**	63.927***	85.257***
$\Delta open_{FR}$	-9.774***	-9.440***	-1.854	0.097	0.078	2.542	5.989
gov_{FR}	-6.906*	-4.834	-2.544	1.307***	0.152**	107.206***	52.258***
Δgov_{FR}	-6.304	-5.572	-1.921	0.054	0.046	1.372	5.532
$redist_{FR}$	-2.878	-7.281**	-1.754	1.130***	0.170**	277.351***	66.041***
$\Delta redist_{FR}$	-11.818***	-7.412***	-1.982	0.147	0.114	6.538	54.428**
enr_{FR}	-5.551	-6.384*	-3.027*	1.497***	0.105	297.590***	70.496***
Δenr_{FR}	-7.724***	-5.593	-2.347	0.065	0.066	3.067	18.374***
$incGS_{US}$	-3.443	-5.319	-1.950	1.478***	0.151**	277.494***	71.668***
$\Delta incGS_{US}$	-7.470**	-5.322	-2.385	0.176	0.163**	7.736*	30.213***
inv_{US}	-5.234	-4.354	-2.145	0.285	0.130*	42.461***	40.216***
Δinv_{US}	-6.607	-6.296	-3.205*	0.062	0.033	1.485	4.650
$RGDP_{US}$	-6.046	-5.817	-1.113	1.519***	0.256***	178.722***	127.737***
$\Delta RGDP_{US}$	-7.321**	-6.320	-1.887	0.328	0.044	5.082	6.391
pl_{US}	-3.996	-7.659***	-1.843	1.441***	0.360***	238.176***	697.072***
Δpl_{US}	-6.967*	-7.666***	-2.206	0.674**	0.136*	42.239***	124.836***
$open_{US}$	-4.745	-5.580	-3.422**	1.258***	0.064	126.780***	32.067***
$\Delta open_{US}$	-8.635***	-6.389	-3.386**	0.041	0.040	4.028	13.520**
gov_{US}	-3.833	-5.968	-0.951	0.794***	0.261***	74.421***	119.000***
Δgov_{US}	-7.641***	-7.189**	-3.057*	0.144	0.084	5.356	10.991*
$redist_{US}$	-7.035*	-5.531	-2.610	1.294***	0.070	98.274***	50.925***
$\Delta redist_{US}$	-8.165***	-8.383***	-3.213*	0.043	0.042	3.683	39.956***
enr_{US}	-4.714	-4.170	-0.517	1.497***	0.131*	260.672***	51.619***
Δenr_{US}	-5.041	-4.851	-3.068*	0.184	0.058	13.877***	13.334*

Source: Authors' own computations.

Note: The Unit Root tests are the Kapetanios (Kapetanios, 2005), the Augmented Dickey-Fuller (Dickey & Fuller, 1979; Wayne A. Fuller, 1995) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) tests. The first tests the null hypothesis that a series is integrated of order 1 against the alternative that is stationary with a possible break, up to a maximum of 3, in levels (first column) or trend (second column). The second (third column) tests the null hypothesis that a series has a unit root against the alternative of stationarity. The third tests the null hypothesis that a series is stationary in levels (fourth column) or trend (fifth column) against the alternative of non-stationarity. The structural change test is a Chow test of the null hypothesis that a series does not have structural breaks around a constant (sixth column) or a trend (seventh column) and follows Zeileis, Leisch, Hornik, and Kleiber (2002). The p-values are obtained by obtaining the corresponding test statistics from 1000 simulated random time series with the length of the ones under analysis in which the null hypothesis is verified. These consist of a random walk in the case of the KPT and ADF tests, a white noise without and with a trend for, respectively, the constant and trend versions of the KPSS and SC Tests.

Legend: Δ - First difference operator such that $\Delta y_t = y_t - y_{t-1}$

Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

$$\mathbf{y}_{1,i,t} := [\Delta incGS_{i,t}, \Delta RGDP_{i,t}, \Delta open_{i,t}, \Delta pl_{i,t}, \Delta gov_{i,t}, \Delta enr_{i,t}], \quad (3.3)$$

$$\mathbf{y}_{2,i,t} := [\Delta incGS_{i,t}, \Delta inv_{i,t}, \Delta RGDP_{i,t}, \Delta open_{i,t}, \Delta pl_{i,t}, \Delta gov_{i,t}, \Delta redist_{i,t}, \Delta enr_{i,t}]. \quad (3.4)$$

In each one, the relevant variables are included in first differences to ensure that the stability condition is satisfied due to the conclusion from the previous analysis that all variables are $I(1)$. Then, as explained in Lütkepohl (2005, p. 25), the Wold Theorem permits the representation of $\mathbf{y}_t$ as a vector moving average (VMA) process as follows:

$$\mathbf{y}_t = \sum_{l=0}^{\infty} \Psi_l \mathbf{v}_{t-l}, \quad (3.5)$$

where we dropped $\boldsymbol{\eta}$ for simplicity. The terms Ψ_l are coefficients of an infinite polynomial on the Lag operator L , $\Psi(L) := \Psi_0 + \Psi_1 L + \Psi_2 L^2 + \dots$, with $L = \Delta$, which are obtained recursively from the equality $\Phi(L, p)\Psi(L) = \mathbf{I}_M$, with $\Psi_0 = \mathbf{I}_M$ and where $\Phi(L, p) := \mathbf{I} - \Phi_1 L - \dots - \Phi_p L^p$, is the characteristic polynomial of order p on the lag operator L . These represent the impulse responses that measure how a shock in $\mathbf{v}_t$ affects variables in $\mathbf{y}_t$. Specifically, by using (3.1) to define $\mathbf{y}_{t+1}$, $\mathbf{y}_{t+2}$ and so forth, it can be easily shown that $\Psi_{l,m,r} = \frac{\partial y_{m,t+l}}{\partial \epsilon_{r,t}}$, $r, m \in \{1, \dots, M\}$, $l \in \{1, \dots, \infty\}$, *i.e.*, each element of the matrix $\Psi_{l,m,r}$ represents the impact of a shock $\mathbf{v}_r$ at time t on some variable $\mathbf{y}_m$ on period $t + l$.

Since the non-diagonal elements of the covariance matrix $\boldsymbol{\Omega}$ are not necessarily equal to 0, these impulse responses are non-orthogonalized because they are based on correlated shocks. Bearing this in mind, we can consider instead a structural VAR model, where the shocks $\mathbf{v}_t$ are assumed to be a combination of a set of structural shocks $\boldsymbol{\epsilon}_t$ that are uncorrelated, economically identified, and have unit variance. This is accomplished by considering $\mathbf{v}_t = \mathbf{B}\boldsymbol{\epsilon}_t$, where $\mathbf{B}$ is the structural impact multiplier matrix,⁸ and analyze the impulse responses $\Psi_l \mathbf{B}$ instead. This requires identifying the structural shocks $\boldsymbol{\epsilon}_t$, which is discussed in more detail in the following section.

⁸Some authors such as Kilian and Lütkepohl (2017) define this matrix alternatively as $\mathbf{B}^{-1}$.

3.4.2 Identification

This subsection describes and justifies the relevant structural shocks that must be identified and the strategy to accomplish this.

To answer the first question concerning the relationship between inequality and growth, we need to identify a structural shock of inequality, $\epsilon_{N,t}$, and analyze the responses of real GDP per capita to such shock. For the second research question regarding the channels through which the former affects the latter, we also need to identify $\epsilon_{N,t}$ and analyze the responses of the intermediate variables of the transmission mechanisms analyzed in this paper, Fiscal Policy, Credit Market Imperfections, and Savings channels, to this shock.

To achieve this, we must consider an appropriate vector process. For the first research question, we consider that such a process must include an inequality measure, Real GDP per capita, and variables that simultaneously affect inequality and economic growth. To understand this, suppose that we consider a vector process with only the first two variables and identify the two structural shocks, $\epsilon_{1,t}$ and $\epsilon_{2,t}$, as structural shocks of inequality and Real GDP per capita, respectively, *i.e.*, $\epsilon_{N,t} \equiv \epsilon_{1,t}$ and $\epsilon_{G,t} \equiv \epsilon_{2,t}$. Since inequality is endogenous, the structural shock $\epsilon_{1,t}$ is, in fact, a conglomerate of shocks of variables outside the model that affect inequality in a particular manner that permits using them as an instrument for a shock of inequality (Kilian & Lütkepohl, 2017, p. 227). This implies that the validity of the identification of $\epsilon_{1,t}$ as an inequality shock $\epsilon_{N,t}$ requires assuming that there are no other variables outside of the model that simultaneously affect inequality and growth. Otherwise, Real GDP per capita responses to shocks of $\epsilon_{1,t}$ would result not only from the effects of inequality on growth but also from the simultaneous effects on both these variables of shocks of variables outside the model. This would invalidate the purpose of the analysis of the corresponding impulse responses since it would, for example, lead to the risk of findings a spurious relationship between inequality and growth.

A vector process with just inequality and growth would violate the assumption mentioned above because there are other variables that affect both. In this regard, and as explained in section 3.3, we consider inflation (Afonso & Lima, 2022), education (Huang et al., 2009; Lundberg & Squire, 2003), government expenditures and openness (Huang et al., 2009). Considering this, the first vector process is defined as in equation (3.3) and the set of structural shocks ϵ are each economically identified as a shock in each variable contained in $\mathbf{y}_{1,i}$, resulting in $\epsilon = [\epsilon_N, \epsilon_Y, \epsilon_O, \epsilon_P, \epsilon_G, \epsilon_E]$.

To answer the second research question, we need to include groups of variables that simultaneously affect inequality and each transmission variable for the same theoretical reasons above. The first is Real GDP per capita, due to the evidence that Real GDP per capita affects inequality (*e.g.*, Atems & Jones, 2015; Kuznets, 1955) and may exert a substantial influence on the decision-making process of economic agents (*e.g.*, Gobbin & Rayp, 2008),⁹ which can ultimately affect at least some of transmission variables. The second group, in the context of an analysis of a particular transmission channel of the ones under analysis, consists of other transmission variables. For example, education can affect inequality and investment decisions due to the complementary nature of physical and human capital (Galor & Moav, 2006). Another example is redistribution, which we consider can affect college enrollment rates by changing the economic obstacles faced by students interested in pursuing higher education. Moreover, the theoretical implications of each transmission channel can be easily extended to affect other transmission variables. For instance, the existence of credit market imperfections can cause inequality to have a negative impact not only on human capital accumulation but also on investment in physical capital. We also include the group of variables that jointly determines inequality and growth because it is reasonable to expect that they simultaneously affect other pairs of variables. Moreover, this permits analyzing the impacts of inequality on growth when controlling for the impacts of transmission channels.

Therefore, we consider a vector process that has all the variables in $\mathbf{y}_1$ but also all transmission variables, resulting in the second specification defined in equation (3.4). This straightforward approach allows us to analyze the extent to which transmission mechanisms are affected by each other. Moreover, it does not result in an unnecessary reduction of degrees of freedom due to the model reduction strategy we employ that, as described further ahead, results in the exclusion of irrelevant parameters. The set of structural shocks to be considered is defined in the same way about $\mathbf{y}_{2,i}$ and is $\boldsymbol{\epsilon} = [\boldsymbol{\epsilon}_N, \boldsymbol{\epsilon}_I, \boldsymbol{\epsilon}_Y, \boldsymbol{\epsilon}_O, \boldsymbol{\epsilon}_P, \boldsymbol{\epsilon}_G, \boldsymbol{\epsilon}_R, \boldsymbol{\epsilon}_E]$.

The identification strategy consists in imposing contemporaneous restrictions in the form of upper triangular zero restrictions to some parameters of matrix $\mathbf{B}$.¹⁰ We

⁹This is true even considering that Real GDP per capita is usually corrected by official national statistic institutions sometime after the corresponding year because it usually does not deviate substantially from official predictions, to which economic agents have access and, therefore, can use to inform their decisions.

¹⁰In this essay, we will use the terms “short run” and “contemporaneous” interchangeably and, bearing in mind that the frequency of the data is annual, these effects concern impacts within a year.

consider that this approach is the most adequate due to the persistent nature of most variables and the fact that, theoretically, most relations between variables do not materialize immediately in the short run.

If we define the general element of the structural impact matrix as $\gamma_{r,m}$ to represent the contemporaneous impact of ϵ_r on variable y_m , for the VAR models of y_1 and y_2 the specification of the corresponding structural matrices are as follows:

$$\mathbf{B}_1 = \begin{bmatrix} \gamma_{N,N} & 0 & 0 & 0 & 0 & 0 \\ \gamma_{Y,N} & \gamma_{Y,Y} & 0 & 0 & 0 & 0 \\ \gamma_{O,N} & \gamma_{O,Y} & \gamma_{O,O} & 0 & 0 & 0 \\ \gamma_{P,N} & \gamma_{P,Y} & \gamma_{P,O} & \gamma_{P,P} & 0 & 0 \\ \gamma_{G,N} & \gamma_{G,Y} & \gamma_{G,O} & \gamma_{G,P} & \gamma_{G,G} & 0 \\ \gamma_{E,N} & \gamma_{E,Y} & \gamma_{E,O} & \gamma_{E,P} & \gamma_{E,G} & \gamma_{E,E} \end{bmatrix}, \quad (3.6)$$

$$\mathbf{B}_2 = \begin{bmatrix} \gamma_{N,N} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{I,N} & \gamma_{I,I} & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{Y,N} & \gamma_{Y,I} & \gamma_{Y,Y} & 0 & 0 & 0 & 0 & 0 \\ \gamma_{O,N} & \gamma_{O,I} & \gamma_{O,Y} & \gamma_{O,O} & 0 & 0 & 0 & 0 \\ \gamma_{P,N} & \gamma_{P,I} & \gamma_{P,Y} & \gamma_{P,O} & \gamma_{P,P} & 0 & 0 & 0 \\ \gamma_{G,N} & \gamma_{G,I} & \gamma_{G,Y} & \gamma_{G,O} & \gamma_{G,P} & \gamma_{G,G} & 0 & 0 \\ \gamma_{R,N} & \gamma_{R,I} & \gamma_{R,Y} & \gamma_{R,O} & \gamma_{R,P} & \gamma_{R,G} & \gamma_{R,R} & 0 \\ \gamma_{E,N} & \gamma_{E,I} & \gamma_{E,Y} & \gamma_{E,O} & \gamma_{E,P} & \gamma_{E,G} & \gamma_{E,R} & \gamma_{E,E} \end{bmatrix}. \quad (3.7)$$

The zero restrictions of both matrices result from the following assumptions: (A1) Inequality is not contemporaneously affected by any of the variables we consider due to the persistent nature of this variable. Changes in inequality result from structural changes (*e.g.*, labor market institutions) that do not materialize in the short run; (A2) Investment and Real GDP per capita are more persistent than the variables measuring redistribution, government expenditures, openness and inflation. These are similarly affected by changes in structural factors (*e.g.*, human capital) or monetary policy that take some time impact the economy (Kilian & Lütkepohl, 2017, p. 222). Moreover, while investment decisions can be contemporaneously affected by many of the variables we include here, the proxy for investment that is used in this paper concerns the share of investment in GDP, which is the final outcome of investment decisions. These may take a substantial time to materialize due to adjustment and

installation costs (Kilian & Lütkepohl, 2017, p. 222); (A3) Policy variables (government expenditures and redistribution) can react contemporaneously to shocks of openness and inflation (*e.g.*, Giordano, Momigliano, Neri, & Perotti, 2007) but not the converse; (A4) Openness is not affected by contemporaneous shocks of policy variables or inflation because it changes slowly over time (Jin, 2006); (A5) Enrollment rates reflect instantaneous human capital investment decisions that, as a result, can be affected contemporaneously by any variable in the system; (A6) Shocks of government expenditures can contemporaneously affect redistribution but not the converse; (A7) Real GDP per capita can be contemporaneously affected by shocks in investment but not the converse. Changes in the investment share increase physical capital and, therefore, economic growth.

3.4.3 Model reduction strategy

The problems outlined in the literature review concerning the substantial number of parameters in a VAR model and the issues of other model reduction approaches lead us to develop an alternative to be applied in the context of VAR models of vector processes with more than two variables. It consists of obtaining information from pre-estimating bivariate VAR models for each pair of variables contained in the vector process under analysis to formulate, test and apply zero restrictions to the parameters of the corresponding VAR model. This information, in turn, consists of the lag structure of bivariate models and results of causality tests conducted in this context. We consider this approach adequate because bivariate models have the greatest number of degrees of freedom due to the reduced number of parameters. Therefore, we can obtain more precise information concerning the lag order and the parameters, which are estimated with more precision. This also leads to a more reliable identification of irrelevant parameters since they cannot be justified by the presence of other variables.

Specifically, considering a vector process $\mathbf{z}_t$, with $M > 2$, the model reduction strategy consists of the following steps:¹¹

1. For each pair of variables $\mathbf{z}_i$ and $\mathbf{z}_j$ contained in $\mathbf{z}$, determine the lag order of the corresponding VAR model, $p_{i,j}$, estimate it and conduct Granger and instantaneous causality tests in both directions of causality. Formally, both types are Wald tests of null hypotheses, which, in the case of a direction of

¹¹In the remainder of this section, we now drop the subscript t hereafter when referring to vector processes for simplicity of exposition.

causality from $\mathbf{z}_j$ to $\mathbf{z}_i$, are represented, respectively, by $H_{0,G,i,j}^{[\mathbf{z}_i, \mathbf{z}_j]} : \Phi_{l,i,j} = 0, \forall l \in \{1, \dots, p_{i,j}\}$ and $H_{0,I,i,j}^{[\mathbf{z}_i, \mathbf{z}_j]} : \Omega_{i,j} = 0$.

2. Estimate a VAR model of $\mathbf{z}$ with a lag p_{max} equal to the maximum lag of all bivariate VAR models, *i.e.*, $p_{max} := \max_{i,j} p_{i,j}$.
3. Check if there are potentially irrelevant variables to the system that are not theoretically relevant. These are variables for which all the results of individual causality tests conducted in step 1 suggest that they do not instantaneously or Granger cause any other variable in the system. More formally, a variable $\mathbf{z}_j$ is potentially irrelevant for the VAR model of $\mathbf{z}$ if in the context of each bivariate model of $[\mathbf{z}_i, \mathbf{z}_j], i \neq j, i \in \{1, \dots, M\}$, estimated in step 1 the null hypotheses $H_{0,G,i,j}^{[\mathbf{z}_i, \mathbf{z}_j]}$ and $H_{0,I,i,j}^{[\mathbf{z}_i, \mathbf{z}_j]}$ were not rejected at any significance level.
 - (a) If some variables $\mathbf{z}_j$ satisfy the previous condition, conduct Wald tests of the null hypotheses “ $\mathbf{z}_j$ does not Granger cause any other variable in the system” and “ $\mathbf{z}_j$ does not instantaneously cause any other variable in the system”, which formally are represented, respectively, as $H_{0,G,j}^{\mathbf{z}} : \Phi_{l,i,j} = 0, i \neq j, \forall l \in \{1, \dots, p_{max}\}$ and $H_{0,I,j}^{\mathbf{z}} : \Omega_{i,j} = 0, i \neq j$. If both are not rejected, remove the variables from the system.¹²
4. Repeat the previous step until there are no potential irrelevant variables, with the final vector process being $\mathbf{z}^*$.
5. Conduct a Wald test of a composite null hypotheses $H_0^{\mathbf{z}^*}$ of those that were not individually rejected in step 1 or are naturally imposed by the specification of the corresponding VAR models,¹³ which are described below, and do not contradict theoretical arguments:
 - (a) $H_{0,L,i,j}^{\mathbf{z}^*} : \Phi_{l,i,j} = \Phi_{l,j,i} = 0, \forall l \in \{p_{i,j}+1, \dots, p_{max}\}, i, j \in \{1, \dots, M\}, i \neq j$, if $\exists i : p_{i,j} < p_{max}$. The intuition is to consider the heterogeneous lag structure of the bivariate models and restrict to zero the coefficients of irrelevant lag terms.

¹²We consider that this is justifiable because in this case the proportion of the forecast mean squared error of all the remaining variables that is accounted by $\mathbf{z}_i$ is zero (Lütkepohl & Krätzig, 2004, p. 65), which we interpret as making it effectively irrelevant to the system.

¹³For example, a VAR model with a lag order of p , can be formulated as a VAR model of $p + j$, with $j \in \{1, \dots, \infty\}$ where the null hypothesis “all the coefficients concerning lags greater than p are zero” is imposed.

- (b) $H_{0,L,i,i}^{\mathbf{z}^*} : \Phi_{l,i,i} = 0, i \in \{1, \dots, M\}, \forall l \in \{p_{i,max} + 1, \dots, p_{max}\}$, if $\exists i : p_{i,max} < p_{max}$, where $p_{i,max} := \max_j p_{i,j}$, $j \in \{1, \dots, M\}$. The intuition is to restrict to zero the coefficients of lags of a variable $\mathbf{z}_i$ with respect to itself if they are effectively zero in all bivariate models of vector processes that contain $\mathbf{z}_i$.¹⁴
- (c) $H_{0,G,i,j}^{\mathbf{z}^*} : \Phi_{l,i,j} = 0, \forall l \in \{1, p_{i,j}\}, i \neq j$, if $H_{0,G,i,j}^{[\mathbf{z}_i, \mathbf{z}_j]}$ was not rejected in the context of VAR model of $[\mathbf{z}_i, \mathbf{z}_j]$. The purpose is to consider the null hypothesis $H_{0,G,i,j}^{\mathbf{z}^*}$ that a variable $\mathbf{z}_j$ does not Granger cause $\mathbf{z}_i$ in the context of the VAR model of $\mathbf{z}$ if this hypothesis was not rejected in the corresponding bivariate VAR model.

6. If the composite null hypothesis of the previous step is not rejected, impose the corresponding zero restrictions on the VAR model of $\mathbf{z}^*$. Otherwise, successively exclude particular sets of the null hypotheses described in step 3 until a composite null hypothesis is obtained that is not rejected.

Some notes are in order. The approach is flexible and not purely statistical because the researcher maintains a large degree of control over the variables excluded in step 3 and the specific zero restrictions imposed in step 5. This is not possible by resorting to, for instance, the LASSO approach. However, it is important because it permits considering of theoretical reasons not to exclude some variables or impose certain restrictions. For example, a variable could be kept in the model even if it does not Granger or instantaneously cause any other if the interest lies in analyzing how it is impacted by other variables. It is also possible to not impose that some variable $\mathbf{z}_i$ does not Granger cause $\mathbf{z}_j$ in the context of the VAR model of $\mathbf{z}^*$, even if the hypothesis of no Granger causality is not rejected in the context of the corresponding bivariate model. This could be justified by theoretical reasons, such as the existence of opposing effects of $\mathbf{z}_i$ on $\mathbf{z}_j$ that cancel each other out in the corresponding bivariate model but do not necessarily in the context of the model focused on $\mathbf{z}^*$.

Moreover, this approach also allows us to consider the increased complexity of dynamic relations in models focused on medium-sized vector processes in relation to

¹⁴As an example, consider a vector process with three variables, $\mathbf{z}_1$, $\mathbf{z}_2$ and $\mathbf{z}_3$, where the lag order of the VAR models of $[\mathbf{z}_2, \mathbf{z}_3]$, $[\mathbf{z}_1, \mathbf{z}_3]$ and $[\mathbf{z}_1, \mathbf{z}_2]$ are, respectively, 3, 2 and 2. This implies that $p_{max} = 3$ and $p_{1,max} = 2$ and, therefore, the null hypothesis $H_{0,L,1,1}^{\mathbf{z}^*} : \Phi_{3,1,1} = 0$ can be considered because this coefficient is effectively zero in all bivariate VAR models that contain $\mathbf{z}_1$. On the other hand, if the lag order of the VAR model of $[\mathbf{z}_1, \mathbf{z}_3]$ were 3 instead, then $p_{1,max} = p_{max} = 3$ and, as a result, this null hypothesis would no be considered because the coefficient $\Phi_{3,1,1}$ is not restricted to zero in one of the bivariate models.

bivariate models. The previous example can be used to illustrate this because if the researcher still tests for no Granger causality of $\mathbf{z}_i$ on $\mathbf{z}_j$ in the context of the model focused on the complete vector process, that null hypothesis can still be rejected. In this case, no zero restriction would be imposed, despite its relevance in the context of the bivariate model.

Finally, the fact that a variable $\mathbf{z}_i$ does not instantaneously cause another variable $\mathbf{z}_j$ does not lead *per se* to the imposition of any restriction on the coefficients of lag terms. This concerns the correlation of residuals obtained from the corresponding estimated equations, *i.e.*, the entries $\boldsymbol{\Omega}_{i,j}$ and $\boldsymbol{\Omega}_{j,i}$, which have a very complex relationship with $\boldsymbol{\Phi}_l$ and, therefore, make the possibility of imposing any restriction extremely difficult.

3.4.4 Bootstrap method

In the context of the analysis, we conduct statistical inference using the bootstrap method concerning not only impulse responses but also diagnostic tests of residuals and the causality tests used in the context of the model reduction strategy outlined above. This, in turn, is characterized by the following algorithm, which is adapted from Lütkepohl (2005, pp. 709-710) and Cavaliere, Rahbek, and Robert Taylor (2012):

1. Estimate a VAR model of $\mathbf{y}_t$ given by equation (3.1) and obtain estimates $\hat{\boldsymbol{\Phi}}_l$, with $l \in \{1, \dots, p\}$, $\hat{\boldsymbol{\eta}}$ and $(T - p)$ sets of residuals $\hat{\mathbf{v}}_t$, where p and T are the lag order of the model and the total number of observations, respectively.
2. Generate bootstrap residuals $\tilde{\mathbf{v}}_t$ from the original residuals $\hat{\mathbf{v}}_t$ by considering $\tilde{\mathbf{v}}_t := \hat{\mathbf{v}}_w$, where w is a variable that follows a discrete uniform distribution on $\{1, 2, \dots, T - p\}$.
3. Generate simulated observations $\tilde{\mathbf{y}}_t$ through equation (3.1), *i.e.*, $\tilde{\mathbf{y}}_t = \hat{\boldsymbol{\eta}} + \sum_{l=1}^p \hat{\boldsymbol{\Phi}}_l \tilde{\mathbf{y}}_{t-l} + \tilde{\mathbf{v}}_t$, where the p initial values are equal to the original p initial observations, *i.e.*, $\tilde{\mathbf{y}}_l = \mathbf{y}_l$, $l \in \{1, \dots, p\}$.
4. Generate the quantity of interest $\tilde{q}$, which can be an estimate of a parameter or a test statistic.
5. Repeat steps 2 to 4 a $\tilde{N}$ number of times.

When the algorithm is completed, an empirical cumulative bootstrap distribution of $\tilde{q}$, $\tilde{F}_{\tilde{q}}(x) \equiv P(\tilde{q} \leq x) := \frac{1}{\tilde{N}} \sum_{i=1}^{\tilde{N}} \mathbf{1}(q_i \leq x)$, is obtained, where $\mathbf{1}(s)$ is the indicator function, which is equal to 1 if the condition s is verified and zero otherwise.

When the quantity of interest $\tilde{q}$ is an estimate, we can obtain different types of confidence intervals, which are described in more detail in, for example, Kilian and Lütkepohl (2017, pp. 356–362). In this paper, for the impulse responses, we consider the Equal-tailed confidence interval, which, for a given significance level α , is defined as $CI_{ET} := [\hat{q} - \tilde{t}_{1-\alpha/2} \tilde{\sigma}(\hat{q}), \hat{q} - \tilde{t}_{\alpha/2} \tilde{\sigma}(\hat{q})]$. Here, $\hat{q}$ indicates the estimated quantity of interest in the original model, $\tilde{\sigma}(\hat{q})$ is a bootstrap estimate of the standard deviation of $\hat{q}$, defined as $\tilde{\sigma}(\hat{q}) = [(\tilde{N} - 1)^{-1} \sum_{i=1}^{\tilde{N}} (\tilde{q}_i - \bar{\tilde{q}})^2]^{0.5}$, where $\bar{\tilde{q}} = \tilde{N}^{-1} \sum_{i=1}^{\tilde{N}} \tilde{q}_i$, and $\tilde{t}_{1-\alpha/2}$ and $\tilde{t}_{\alpha/2}$ are, respectively, the $1-\alpha/2$ and $\alpha/2$ quantiles of the bootstrap t -statistic $\tilde{t} \equiv \tilde{\sigma}(\tilde{q})^{-1} (\tilde{q} - \hat{q})$. In turn, $\tilde{\sigma}(\tilde{q})$ is a nested bootstrap estimate of the standard deviation of $\tilde{q}$, defined as $\tilde{\sigma}(\tilde{q}) = [(\tilde{N} - 1)^{-1} \sum_{j=1}^{\tilde{N}} (\tilde{q}_{j,i} - \bar{\tilde{q}})^2]^{0.5}$, where $\bar{\tilde{q}}$ is a nested bootstrap estimate of $\tilde{q}$. The latter is obtained by following the bootstrap algorithm above but estimating, in step 1, a VAR model of $\tilde{\mathbf{y}}_t$ obtained from each bootstrap replication instead of $\mathbf{y}_t$ and repeating $\tilde{N}$ number of times steps 1 to 4. Although this approach is computationally intensive, as it implies a total of $\tilde{N} \times \tilde{N}$ number of bootstrap replications, this interval tends to be very accurate as it corrects for any bias and permits q to have an asymmetric distribution (Kilian & Lütkepohl, 2017, p. 361).

When the quantity of interest $\tilde{q}$ is a test statistic, the empirical distribution $\tilde{F}_{\tilde{q}}(x)$ is obtained under a null hypothesis H_0 . Therefore, we can use it to obtain p-values $\tilde{\alpha}$ which take different forms according to whether the values of $\tilde{q}$ are non-negative, non-positive or have no restrictions, which are, respectively, $\tilde{\alpha} = P(\tilde{q} > \hat{q}|H_0)$, $\tilde{\alpha} = P(\tilde{q} < \hat{q}|H_0)$, and $\tilde{\alpha} = 2\tilde{N}^{-1} \min \{P(\tilde{q} < \hat{q}|H_0), P(\tilde{q} > \hat{q}|H_0)\}$. To obtain $\tilde{F}_{\tilde{q}}(x)$ under H_0 , this null hypothesis must be imposed on the VAR model in step 3 used to generate the simulated observations $\tilde{\mathbf{y}}_t$. This is accomplished using three different approaches, depending on the nature of the test of interest.

In what concerns diagnostic tests of residuals for serial correlation, autoregressive conditional heteroskedasticity and structural breaks, the null hypothesis is naturally imposed by the transformation we used (resampling) to obtain bootstrap residuals since it eliminates any heteroskedasticity (unconditional and conditional) and serial dependence of the residuals. For Wald tests of coefficients, of which the Granger causality test is a particular case, the null hypothesis is imposed directly on the parameters that are estimated in step 1.

In the case of the instantaneous causality test, the relevant restrictions concern covariances between residuals. No restrictions can be directly imposed on these since they depend, in a complex manner, on the coefficients of the lag terms of the model. Bearing this in mind, we designed a strategy whereby the null hypothesis is imposed by

obtaining bootstrap residuals in step 2 not from the original residuals but rather from residuals corresponding to a transformed set of error terms $\mathbf{v}_t^*$, which have a variance-covariance matrix $\mathbf{\Omega}^*$ equal to the variance-covariance matrix of $\mathbf{v}_t$ but with zeros on the relevant entries. These new error terms are defined as $\mathbf{v}_t^* := \mathbf{B}_c^* \mathbf{B}_c^{-1} \mathbf{v}_t$, where $\mathbf{B}_c$ and $\mathbf{B}_c^*$ are, respectively, cholesky decompositions of $\mathbf{\Omega}$ and $\mathbf{\Omega}^*$.¹⁵ The latter is defined in the following manner:

$$\mathbf{\Omega}_{i,j}^* = \begin{cases} \mathbf{\Omega}_{i,j} & \text{if } i \notin w_1 \vee j \notin w_2, \\ 0 & \text{if } i \in w_1 \wedge j \in w_2, \end{cases} \quad (3.8)$$

where $w_1, w_2 \in \{1, \dots, M\}$ and $w_1 \neq w_2$ are the indexes of the error terms that are assumed not to be correlated. Bearing this in mind, we simply consider the residuals corresponding of these error terms, $\hat{\mathbf{v}}_t^* := \hat{\mathbf{S}}_c^* \hat{\mathbf{S}}_c^{-1} \hat{\mathbf{v}}_t$.

3.5 Results

3.5.1 Results of the bivariate models

We start by presenting the lag structure of the bivariate VAR models focused on variables of the United States and France in Table 3.3. The information used to choose the lag order of each bivariate model is described in detail in Tables 3.8 and 3.9 of appendix 3.A. We considered an interval of lags between 1 and 4 and estimated a VAR model for each one. Then, we obtained information criteria, performed a bootstrap serial correlation test and determined whether the stability condition was satisfied. This was assessed by calculating the maximum *modulus* of the eigenvalues of the companion matrix and determining whether it was smaller or equal to 1. Finally, we chose the lag for which most criteria pointed to be the optimal,¹⁶ conditional on the null hypothesis of no serial correlation not being rejected at a 5% significance level and the stability condition being satisfied. In both countries, the most appropriate lag order is 1, but some models are of order 2, especially in the United States.

¹⁵It can be easily be shown that $\mathbb{E}(\mathbf{v}_t^* (\mathbf{v}_t^*)') = \mathbf{\Omega}^*$. Considering the definition of the error term as in the text, we have that $\mathbb{E}(\mathbf{v}_t^* (\mathbf{v}_t^*)') = \mathbf{B}_c^* \mathbf{B}_c^{-1} \mathbb{E}(\mathbf{v}_t \mathbf{v}_t') (\mathbf{B}_c^* \mathbf{B}_c^{-1})' = \mathbf{B}_c^* \mathbf{B}_c^{-1} \mathbf{\Omega} (\mathbf{B}_c^* \mathbf{B}_c^{-1})'$. Further noting that $\mathbf{\Omega} = \mathbf{B}_c \mathbf{B}_c'$ and that $\mathbf{\Omega} = \mathbf{B}_c^* (\mathbf{B}_c^*)'$, we have that $\mathbb{E}(\mathbf{v}_t^* (\mathbf{v}_t^*)') = \mathbf{B}_c^* \mathbf{B}_c^{-1} \mathbf{B}_c \mathbf{B}_c' (\mathbf{B}_c^{-1})' (\mathbf{B}_c^*)' = \mathbf{B}_c^* \mathbf{B}_c^{-1} \mathbf{B}_c \mathbf{B}_c' (\mathbf{B}')^{-1} (\mathbf{B}_c^*)' = \mathbf{B}_c^* (\mathbf{B}_c^*)' = \mathbf{\Omega}^*$.

¹⁶In the case of a tie between information criteria, we opted for the lowest lag for which there was no evidence of serial correlation.

Table 3.3: Lag order of VAR models focused on different pairs of variables

(a) United States

	$\Delta incGS_{US}$	Δinv_{US}	$\Delta RGDP_{US}$	Δpl_{US}	$\Delta open_{US}$	Δgov_{US}	$\Delta redist_{US}$
Δinv_{US}	1						
$\Delta RGDP_{US}$	2	2					
Δpl_{US}	1	1	1				
$\Delta open_{US}$	2	1	2	1			
Δgov_{US}	1	1	1	1	1		
$\Delta redist_{US}$	1	1	1	1	1	1	
Δenr_{US}	1	1	2	1	1	1	1

(b) France

	$\Delta incGS_{FR}$	Δinv_{FR}	$\Delta RGDP_{FR}$	Δpl_{FR}	$\Delta open_{FR}$	Δgov_{FR}	$\Delta redist_{FR}$
Δinv_{FR}	1						
$\Delta RGDP_{FR}$	1	1					
Δpl_{FR}	1	1	1				
$\Delta open_{FR}$	2	1	1	1			
Δgov_{FR}	1	1	1	1	1		
$\Delta redist_{FR}$	1	1	1	1	1	1	
Δenr_{FR}	1	1	1	1	1	1	1

Source: Authors' own computations.

Note: Each element of this Table represents the lag order chosen for the VAR model in first differences of a vector process that contains that variables in the corresponding column and row.

We then estimated each model with the chosen lag and conducted bootstrap Granger and instantaneous causality tests. The results are in Table 3.4, of which we highlight some of the most important. Concerning the relationship between inequality and growth, the Granger causality tests reveal that it is not possible to reject the null hypothesis of no Granger causality in both directions. Nonetheless, the instantaneous causality test leads to a rejection of the null hypothesis of no instantaneous causality between both variables at the 5% level. This could result from a contemporaneous relationship or simultaneous effects of other variables. We also highlight that the null hypothesis of no instantaneous causality is rejected at 1% level for several pairs of variables. These include $\Delta incGS_{US}$ and $\Delta redist_{US}$ and also many pairs of variables containing Δinv_{US} and $\Delta RGDP_{US}$. The results also suggest that the latter Granger causes other variables in the system, including $\Delta incGS_{US}$. This reinforces the notion that changes in $\Delta RGDP_{US}$ have important effects that must be considered when performing growth regressions.

Table 3.4: Bootstrap causality tests in bivariate models focused on the US

(a) Bootstrap Granger causality test

	$\Delta incGS_{US}$	Δinv_{US}	$\Delta RGDP_{US}$	Δpl_{US}	$\Delta open_{US}$	Δgov_{US}	$\Delta redist_{US}$	Δenr_{US}
$\Delta incGS_{US}$		0.438	6.779**	1.538	10.947***	0.000	2.835*	5.403**
Δinv_{US}	0.296		20.432***	0.598	3.228*	0.149	0.013	1.800
$\Delta RGDP_{US}$	0.357	9.301**		1.527	5.135*	0.481	0.013	1.738
Δpl_{US}	1.897	0.668	4.565**		0.051	7.054**	0.171	0.001
$\Delta open_{US}$	0.410	1.401	5.749*	0.006		1.951	0.700	0.005
Δgov_{US}	1.892	0.207	0.312	0.162	0.561		0.028	0.350
$\Delta redist_{US}$	0.148	4.471**	3.260*	0.881	3.795*	0.668		2.912
Δenr_{US}	0.051	0.195	14.377***	0.159	1.419	1.140	0.006	

(b) Bootstrap instantaneous causality test

	$\Delta incGS_{US}$	Δinv_{US}	$\Delta RGDP_{US}$	Δpl_{US}	$\Delta open_{US}$	Δgov_{US}	$\Delta redist_{US}$
Δinv_{US}	1.736						
$\Delta RGDP_{US}$	5.430**	20.361***					
Δpl_{US}	1.092	2.520	0.011				
$\Delta open_{US}$	0.002	16.283***	9.679***	1.325			
Δgov_{US}	1.706	11.721***	13.460***	0.337	0.908		
$\Delta redist_{US}$	11.091***	7.252*	2.981	3.847*	4.380	3.227	
Δenr_{US}	0.053	14.523***	6.453**	0.672	9.570***	8.105**	5.581**

Source: Authors' own computations.

Note: The test statistic in row i and column j is a Wald test statistic of the Null Hypothesis “variable j does not Granger cause variable i ”, in the case of Granger causality tests, and “variable j does not instantaneously cause variable i ”, in the case of instantaneous causality tests. Both are tested in the context of a bivariate model of a vector process comprised of variables j and i . In the case of the instantaneous causality test, the aforementioned null hypothesis implies that the covariance of the residuals in Ω of equations of variables j and i is zero. Since this matrix is symmetric, it is equivalent to the null hypothesis “variable i does not instantaneously cause variable j ”. The p-values of the tests are based on a bootstrap distribution of 2000 bootstrap values of the corresponding test statistics. For more details, see section 3.4.4.

Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

In the case of France, the results concerning both Granger and instantaneous causality tests are quite different and indicate a much less evident relationship between all the variables in general. The Granger causality tests indicate that a single null hypothesis of no Granger causality is rejected at the 5% level which is “ $incGS_{FR}$ does not Granger cause $RGDP_{FR}$ ”. The results of the bootstrap instantaneous causality suggest contemporaneous relationships between pairs of variables which were also found to have a relationship in this time-frame in the United States. However, the number of pairs for which the null hypothesis of no instantaneous causality is not rejected is much higher. Bearing in mind the results of the Granger causality tests, the results suggest that some variables only have a contemporaneous relationship.

Table 3.5: Bootstrap causality tests in bivariate models focused on France

(a) Bootstrap Granger causality test

	$\Delta incGS_{FR}$	Δinv_{FR}	$\Delta RGDP_{FR}$	Δpl_{FR}	$\Delta open_{FR}$	Δgov_{FR}	$\Delta redist_{FR}$	Δenr_{FR}
$\Delta incGS_{FR}$		0.297	0.002	1.493	4.862*	0.055	0.461	0.445
Δinv_{FR}	0.244		0.288	2.618	2.419	7.792**	0.074	0.085
$\Delta RGDP_{FR}$	4.595**	0.550		0.548	3.683*	0.867	0.864	0.240
Δpl_{FR}	1.748	0.098	0.044		0.356	1.344	1.040	0.000
$\Delta open_{FR}$	7.129**	0.000	1.243	3.416*		0.187	0.757	4.352**
Δgov_{FR}	2.443	0.000	2.455	0.027	1.513		0.000	6.861**
$\Delta redist_{FR}$	0.171	0.049	0.691	1.064	0.079	0.008		0.001
Δenr_{FR}	0.022	3.737*	2.913	0.111	2.629	0.435	2.158	

(b) Bootstrap instantaneous causality test

	$\Delta incGS_{FR}$	Δinv_{FR}	$\Delta RGDP_{FR}$	Δpl_{FR}	$\Delta open_{FR}$	Δgov_{FR}	$\Delta redist_{FR}$
Δinv_{FR}	0.054						
$\Delta RGDP_{FR}$	0.242	12.328***					
Δpl_{FR}	0.374	1.745	0.022				
$\Delta open_{FR}$	0.519	16.914***	2.929*	1.822			
Δgov_{FR}	0.038	6.240**	5.981***	0.092	0.546		
$\Delta redist_{FR}$	16.789***	0.019	0.005	0.221	0.449	0.100	
Δenr_{FR}	2.673	0.112	0.560	0.175	0.303	0.055	1.805

Source: Authors' own computations.

Note: For the See Table 3.4.

Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

3.5.2 Model reduction

Considering the results of the previous section, we now apply the remaining steps of the model reduction strategy outlined in section 3.4.3. We start by estimating a VAR model focused on the vector processes $\mathbf{y}_{1,i}$ and $\mathbf{y}_{2,i}$, for $i \in \{US, FR\}$, with a lag order of 2 for both countries, which is the maximum lag of the bivariate models, as shown by the lag structure previously presented.

We assess the existence of variables in the corresponding vector processes that are potentially irrelevant to the analysis, following steps 3 and 4. This results in the identification of Δpl in the vector processes concerning both countries since it does not instantaneously or Granger cause any other variable. Therefore, we conduct tests of the null hypotheses that this variable does not Granger cause or instantaneously cause any other variable contained in each of the four vector processes we consider in the context of the VAR model estimated for each one. The results are in Table 3.6. Both null hypothesis are not rejected at any significance level in all vector processes except in the case of $\mathbf{y}_{2,US}$, where the null hypothesis of no instantaneous causality is rejected at a 5% significance level.

Table 3.6: Bootstrap causality and instantaneous causality tests to determine the relevance of including Δpl in the vector processes

(a) $\mathbf{y}_{1,US}$	
Null Hypothesis	statistic
Δpl_{US} does not Granger cause $\Delta incGS_{US}$, $\Delta RGDP_{US}$, $\Delta open_{US}$, Δgov_{US} , and Δenr_{US} .	17.878
Δpl_{US} does not instantaneously cause $\Delta incGS_{US}$, $\Delta RGDP_{US}$, $\Delta open_{US}$, Δgov_{US} , and Δenr_{US} .	2.915
(b) $\mathbf{y}_{2,US}$	
Null Hypothesis	statistic
Δpl_{US} does not Granger cause $\Delta incGS_{US}$, Δinv_{US} , $\Delta RGDP_{US}$, $\Delta open_{US}$, Δgov_{US} , $\Delta redist_{US}$, and Δenr_{US} .	9.813
Δpl_{US} does not instantaneously cause $\Delta incGS_{US}$, Δinv_{US} , $\Delta RGDP_{US}$, $\Delta open_{US}$, Δgov_{US} , $\Delta redist_{US}$, and Δenr_{US} .	17.552**
(c) $\mathbf{y}_{1,FR}$	
Null Hypothesis	statistic
Δpl_{FR} does not Granger cause $\Delta incGS_{FR}$, $\Delta RGDP_{FR}$, $\Delta open_{FR}$, Δgov_{FR} , and Δenr_{FR} .	7.146
Δpl_{FR} does not instantaneously cause $\Delta incGS_{FR}$, $\Delta RGDP_{FR}$, $\Delta open_{FR}$, Δgov_{FR} , and Δenr_{FR} .	3.948
(d) $\mathbf{y}_{2,FR}$	
Null Hypothesis	statistic
Δpl_{FR} does not Granger cause $\Delta incGS_{FR}$, Δinv_{FR} , $\Delta RGDP_{FR}$, $\Delta open_{FR}$, Δgov_{FR} , $\Delta redist_{FR}$, and Δenr_{FR} .	9.469
Δpl_{FR} does not instantaneously cause $\Delta incGS_{FR}$, Δinv_{FR} , $\Delta RGDP_{FR}$, $\Delta open_{FR}$, Δgov_{FR} , $\Delta redist_{FR}$, and Δenr_{FR} .	3.934

Source: Authors' own computations.

Note: The p-values of the tests are based on a bootstrap distribution of 2000 bootstrap values of the corresponding test statistics. For more details, see section 3.4.4.

Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Based on these results we decide to remove Δpl from all vector processes, with the exception of $\mathbf{y}_{2,US}$, resulting in the following final vector processes:

$$\mathbf{y}_{1,i}^* := [\Delta incGS_i, \Delta RGDP_i, \Delta open_i, \Delta gov_i, \Delta enr_i], i \in \{US, FR\}, \quad (3.9)$$

$$\begin{aligned} \mathbf{y}_{2,i}^* := & [\Delta incGS_i, \Delta inv_i, \Delta RGDP_i, \Delta pl_i, \Delta open_i, \Delta gov_i, \\ & \Delta redist_i, \Delta enr_i], i = US, \end{aligned} \quad (3.10)$$

$$\begin{aligned} \mathbf{y}_{2,i}^* := & [\Delta incGS_i, \Delta inv_i, \Delta RGDP_i, \Delta open_i, \Delta gov_i, \\ & \Delta redist_i, \Delta enr_i], i = FR. \end{aligned} \quad (3.11)$$

The structural impact matrices considered in the context of the SVAR model of each vector process are now, respectively, $\mathbf{B}_1^*$, $\mathbf{B}_2$ and $\mathbf{B}_2^*$, where $\mathbf{B}_1^*$ and $\mathbf{B}_2^*$ are, respectively, submatrices of $\mathbf{B}_1$ are $\mathbf{B}_2$ without the rows and columns concerning Δpl . Therefore, all the assumptions previously concerning the identification of structural shocks remain exactly the same.

Finally, we conduct bootstrap Wald tests of null hypotheses consistent with the lag structure and the results of the bivariate Granger causality tests, as explained in steps 5 and 6 of the model reduction strategy outlined in section 3.4.3. We do not impose zero restrictions on the coefficients of the lag terms of $incGS$ in the equation of $RGDP$, because we prefer to leave these parameters unrestricted since they are related to the effects that are the main focus of the analysis in this paper.

The results are in Table 3.7 and indicate that we cannot reject any of the null hypotheses relevant to each vector process at any significance level. Therefore, we can estimate a VAR model for each vector process with the corresponding zero restrictions.

Table 3.7: Bootstrap Wald test of the null hypothesis consistent with the lag structure and Granger causality tests of bivariate models.

Null Hypothesis	χ^2	F	No. rest.
$H_0^{y_{1,US}^*}$	37.489	1.172	32
$H_0^{y_{2,US}^*}$	131.528	1.289	102
$H_0^{y_{1,FR}^*}$	48.816	1.319	37
$H_0^{y_{2,FR}^*}$	84.427	1.030	82

Source: Authors' own computations.

Note: The null hypothesis are identified by the vector process that is modeled. They consist of zero restrictions on coefficients that follow the model reduction strategy of section 3.4.3 and theoretical considerations described in the main text of this section. The p-values of the tests are based on a bootstrap distribution of 2000 bootstrap values of the corresponding test statistics. For more details, see section 3.4.4.

Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

3.5.3 Impulse response analysis

We now conduct an impulse response analysis of the VAR models focused on the four vector processes under analysis.

The results concerning the United States are in Figure 3.2. In panel (a), they indicate that a shock of inequality in the US has a statistically significant negative on GDP per capita contemporaneously, with no effects on other time horizons. It also shows a negative effect of growth on inequality that is statistically significant in the medium run. In panel (b), it is apparent that inequality shocks increase redistribution but the latter does not appear to affect economic performance directly or indirectly through its determinants such as investment. Moreover, inequality shocks also do not appear to affect enrollment rates or investment rates, although in the case of the latter most of the values of the confidence intervals are negative. We find a statistically significant negative effect of inequality shocks on economic growth, even when controlling for transmission variables, that occurs contemporaneously. These results suggest that increases in inequality may depress economic performance through transmission channels other than those under analysis.

Figure 3.3 depicts the results concerning France. In panel (a), we can observe a negative effect of inequality shocks in France on growth that is statistically significant in the short and medium run with no effects of growth on inequality. In panel (b), we also found that inequality increases redistribution. However, similarly to the

American economy, the latter does not have a statistically significant on economic performance. Inequality also does not appear to affect investment or enrollment rates. Moreover, a negative effect of an inequality shock on growth is still present, despite the presence of the relevant theoretical variables through which such an effect should operate. Therefore, these results suggest that in France, as in the case of the United States, inequality might affect economic performance through other mechanisms.

3.5.4 Robustness checks

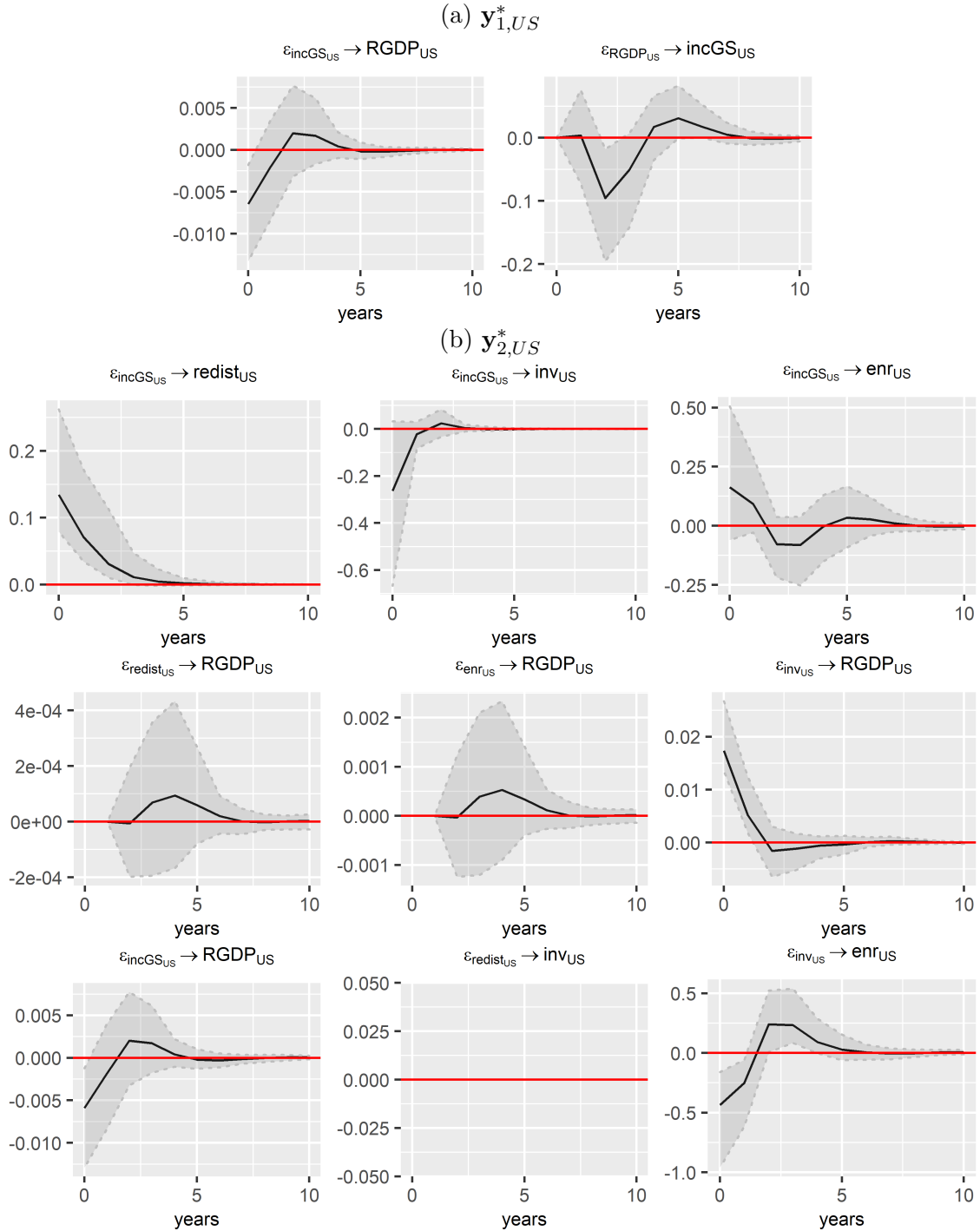
We conduct robustness checks of the estimated VAR models, with the results in appendix 3.B. In Table 3.10, we present the results of diagnostic tests of the residuals of all the estimated VAR models. They indicate for all models that the null hypothesis that the residuals are not serial correlated and do not have autoregressive conditional heteroskedasticity cannot be rejected at any significance level. We consider this as evidence that the models are well-specified. Moreover, the stability condition is satisfied for all models, which is an expected result considering that all the corresponding bivariate models are also stable.

We also analyze the possible existence of structural breaks. This is necessary to assess the stability of the results in the context of VAR models focused on relatively long periods, as in our case. Moreover, in the particular case of this paper, this analysis is motivated additionally by the evidence found in the context of the analysis of individual time series that suggest the existence of structural breaks in many.

This analysis is accomplished with the sample split Chow test, which is implemented following Lütkepohl and Krätzig (2004, p. 135). It implies selecting a particular year where a structural break is suspected of having occurred, estimating VAR models by subperiods defined according to the location of the potential structural break and determining if the estimated variance-covariance matrix has suffered structural changes. This matrix can change not only due to changes in parameters but also in the correlation of the residuals due to the effects of variables outside the model that occur specifically in one of the periods. This is relevant because the analysis period encompasses crisis periods, such as the global financial crisis of 2007-2008. These events simultaneously affected inequality and growth, but their effects are not necessarily captured by the variables we consider.

We conduct this test individually for a range of years, determine if there is evidence of structural breaks in any and, if there is, choose the location of the structural break as

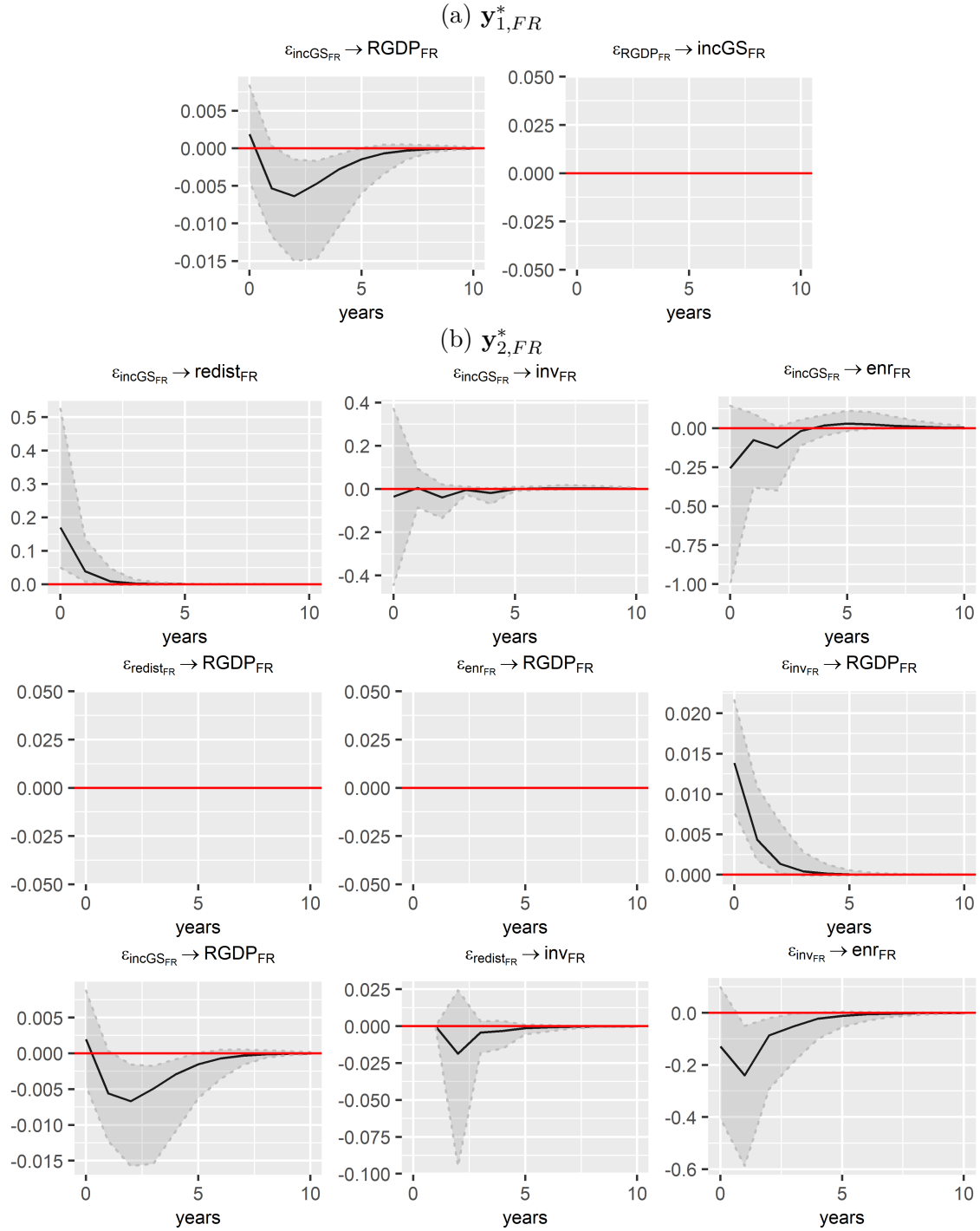
Figure 3.2: Selected orthogonal impulse response functions with 95% bootstrap Equal-tailed confidence intervals for the VAR models of $\mathbf{y}_{1,US}^*$ and $\mathbf{y}_{2,US}^*$



Source: Authors' own computations.

Note: The estimates and confidence intervals of the impulse responses are represented, respectively, by solid black lines and gray bandwidths. In the case of the latter, the relevant bootstrap quantities were obtained from stable VAR models that, in turn, were generated by 2000 bootstrap replications and 500 nested bootstrap replications, as described in detail in section 3.4.4.

Figure 3.3: Selected orthogonal impulse response functions with 95% bootstrap Equal-tailed confidence intervals for the VAR models of $\mathbf{y}_{1,FR}^*$ and $\mathbf{y}_{2,FR}^*$



Source: Authors' own computations.

Note: See Figure 3.2.

the year associated with the lowest p-value. We consider that this approach is the most adequate because it is exhaustive since it considers all plausible possibilities and permits considering theoretical or empirical reasons for selecting the years to which apply this test. Additionally, it avoids subjective considerations in the selection of the location of the structural break, in case of evidence supporting its existence, by considering an objective criterion.

We choose to analyze breaks in the years between 1982 and 1995. This permits considering subsamples periods sufficiently long to estimate adequate VAR models and is a plausible range considering the results of the individual structural change tests and the plots in Figure 3.1, which suggest the existence of breaks in this period.¹⁷ The results are in Table 3.11. In the case of the VAR models of $\mathbf{y}_{1,FR}^*$ and $\mathbf{y}_{2,FR}^*$, the null hypothesis of no structural breaks is not rejected for any of the considered years for any significance level. By contrast, in the case of the VAR models of $\mathbf{y}_{1,US}^*$ and $\mathbf{y}_{2,US}^*$, the null hypothesis of no structural breaks is rejected at 5% level for years in the range, respectively, 1989-1990 and 1988-1992. Moreover, the largest test statistic is associated with 1989 in both. Therefore, we conclude that there are no structural breaks in the models concerning France but only in the United States. Moreover, in the latter case, the structural break most likely occurred in 1989.

In the case of France, these results are surprising considering the presence of structural breaks in individuals series. We interpret this as evidence that the structural shifts found in individual series do not represent structural changes in the relation between variables. On the other hand, in the case of the United States, we interpret the results as evidence that the structural factors underlying, for example, the structural shift in inequality in the 1980s (*e.g.*, Bound and Johnson 1992; Piketty and Saez 2003) lead to significantly shifts in the relationship between inequality, growth and the transmission variables between them that only materialized completely in 1989.

Considering this, we now perform the previous impulse response analysis in the subperiods 1962-1989 and 1990-2018 for the United States, with the corresponding results in Figures 3.4 and 3.5 of appendix 3.B. We find some results that are qualitatively the same across both periods, namely the positive and statistically significant effect of inequality on redistribution and the non-statistically significant impact of shocks of the

¹⁷We also determined that the stability condition was verified in the estimated VAR models by subperiods resulting from the division implied by each year we consider. Otherwise, we would have excluded years that resulted in the estimation of unstable VAR models in at least one subperiod.

latter on economic growth and investment. However, the first is substantially weaker in relation to the effect found in the analysis of the entire period. We also obtain other results that are different in both periods. In particular, we obtain a non-statistically significant effect of inequality on growth in the first period that becomes negative and statistically significant in the second, with and without controlling for transmission variables. Moreover, we find contemporaneous effects of inequality on enrollment rates in each subperiod that are negative in the first and positive in the second. These contrary effects can explain the non-statistically significant results found in the context of the entire analysis period.

Comparing these results to those obtained for the whole sample, we obtain more non-statistically significant or weaker results. This is an expected outcome because an analysis by subperiods implies a substantial loss in degrees of freedom and, consequently, much wider confidence intervals for the impulse response estimates. Nonetheless, we obtained qualitatively similar results to those obtained for the entire analysis period, with the differences suggesting that the negative effects of inequality on growth are mostly present after 1989.

Finally, we also conduct a robustness check of the identification approach, by considering the opposite assumption of (A7). This is also plausible because changes in Real GDP per capita can influence investment decisions and, in turn, the investment share. Bearing this in mind, we consider the corresponding alternative specification to $\mathbf{B}_2$, and $\mathbf{B}_2^*$, where instead of the baseline specification where $\gamma_{I,G} = 0$ and $\gamma_{G,I}$ is unrestricted, $\gamma_{G,I} = 0$ and $\gamma_{I,G}$ is unrestricted. The results concerning $\mathbf{y}_{2,US}^*$ and $\mathbf{y}_{2,FR}^*$ are, respectively, in Figures 3.6 and 3.7 and it is apparent that the main effects of interest remain qualitatively the same.

3.6 Concluding Remarks

In this paper, we offer a new perspective to the inequality-growth literature with a Structural Vector autoregressive (SVAR) analysis of this relationship and the corresponding channels in the United States and France in 1962-2018, which constitutes an important contribution for two reasons. The first is the focus of the analysis, which is on two individual economies, because it considers the country-specific nature of this relationship, which so far has been neglected by most of the literature (Neves & Silva, 2014). The second is the methodological approach

adopted to conduct this analysis. We have conducted a time series analysis, which, in relation to the panel data models usually employed in the literature, presents several advantages. These include more information through impulse response analyses that take into account not only lagged dynamics but also contemporaneous relationships and more precise results to the explicit modeling of lagged dynamics of all endogenous variables. We also considered the importance of taking into account variables that simultaneously affect both inequality and growth and employed techniques to achieve more accurate results. These were model reduction techniques that impose zero restrictions on irrelevant parameters to reduce the parameter space and the extension of bootstrap methods to causality and diagnostic tests of residuals. Moreover, we have also developed new techniques. The first is a model reduction technique that not only provides more information with a pre-analysis of bivariate models and flexible by providing control over what restrictions are applied. The second is a new bootstrap method that produces a numeric approximation of the distribution of the instantaneous causality test statistic.

Our results indicate that an increase in inequality has a statistically significant negative effect on growth in the medium run in France and in the very short run in the United States. In the analysis of transmission channels, we found, in both countries, a statistically significant positive effect of inequality on redistribution, no effects of the latter on economic performance, and no effects of inequality on enrollment rates. Moreover, we also find a negative and statistically significant effect of inequality on growth, even when controlling for transmission variables. These results are not expected theoretically by the mechanisms we consider in this paper and, therefore, suggest the existence of alternative or more complex versions of the existing mechanisms that were not yet established in the literature. We found evidence of structural change only in the SVAR model focused on the United States. An analysis by subperiods shows that the main results still hold with changes indicating that the negative effects of inequality on growth found in the initial analysis mainly occurred in 1990-2018. Moreover, we also found statistically significant effects of inequality on enrollment rates in the analysis by subperiods, which were positive in 1962-1989 and negative in 1990-2018. The results of the methodological approach also justify its relevance by leading to the exclusion of many irrelevant parameters and providing important information regarding the bivariate relationships between all pairs of variables, which is useful on its own.

The different results found between the two economies are important for several

reasons. They reinforce the notion suggested by authors such as Neves and Silva (2014) that this relationship is indeed country-specific. By showing that inequality increases redistribution and the latter does not affect output in any manner, they also contrast with the conclusions of Berg et al. (2018) and Gründler and Scheuermeyer (2018), who point to the importance of the negative impacts of inequality on economic growth through the fiscal policy channel. The analysis focused on theoretical channels produced results that suggest that the inequality-growth relationship might materialize through mechanisms other than those considered. Additionally, the negative impact of inequality on growth found in both countries also contrasts with the conclusions of papers that predict a positive or non-statistically significant on growth in advanced economies (*e.g.*, Caraballo, Dabús, & Delbianco, 2017; Gründler & Scheuermeyer, 2018). In this regard, they are more in line with the conclusions of authors such as Atems and Jones (2015) and Brueckner and Lederman (2018).

Our methodological approach is not without limitations. First, multiple variables can simultaneously affect inequality and growth, namely those concerning the labor market, which cannot be quantified or for which there is no data. Second, despite the substantial parameter reduction achieved by the model reduction strategy, the confidence intervals for many impulse responses still include zero. This suggests that it is not possible to remove all the irrelevant variables from the system to be analyzed. Third, some results ceased to be statistically significant in the analysis by subperiods in the US. Fourth, in general, the results of the SVAR approach with short-run restrictions may vary according to the assumptions made concerning the contemporaneous impacts of the various shocks.

Nonetheless, these limitations do not jeopardize the validity and robustness of the conclusions we have achieved and are adequately addressed. In the case of the first, we include the largest possible number of these variables bearing in mind their relevance and data availability. In the case of the second, it is a natural consequence of the size of the sample, which is still longer than the work with the most similar focus as ours, Gobbin and Rayp (2008), and they would be even wider if this methodological approach were not adopted. Regarding the third, this result is expected considering analysis by subperiods imply using much fewer degrees of freedom and, therefore, less precision. Finally, in what concerns the fourth, our results are reliable because they are based on plausible assumptions, and we have shown that they do not change substantially with alternative and equally plausible specifications.

Our paper has important implications for future research. The first is that more

attention should be placed in the analysis of the determinants of inequality. This is important to determine if more variables need to be considered in this type of analysis and to identify adequate policies to reduce inequality by directly reducing market inequality at its source and not only through redistribution policies. The second is that future papers should employ even more sophisticated econometric techniques for the analysis. For example, considering the existence of structural breaks in many of the time series under analysis and, therefore, of the underlying VAR model, future researchers should consider estimating a Markov-switching VAR model (Kilian & Lütkepohl, 2017) to determine if the inequality-growth relationship is characterized by different regimes. Another approach is cointegration analysis, which is relevant considering not only the fact that all variables are integrated of order 1, but also the theoretical long-run relationships that can exist and are not accounted for by this analysis. The third is the exploration of the impacts of using different inequality measures on the results of the inequality-growth relationship. This paper used Gini coefficients retrieved from one of the most used databases in the inequality-growth literature, SWIID, which facilitates the comparison of the results of our paper with others with the same focus. Nonetheless, considering the recent developments in inequality databases, such as the World Inequality Database (Alvaredo et al., 2016), it would be interesting to determine the extent to which the results are affected by using different inequality measures and why. A fourth possibility is exploring and developing additional theoretical channels between inequality and growth, considering that the existing ones cannot adequately explain some of the results we obtained. Finally, a fifth possibility is considering more sophisticated approaches to identify structural shocks. These could be using theoretical models of inequality to directly estimate an inequality shock or an identification approach based on imposing sign restrictions to the impulse responses of the various variables of interest.

Finally, the results also lead to the recommendation of policies to be implemented in the context of both economies. Policymakers interested in reducing inequality without jeopardizing economic performance can continue to do so by enacting redistribution policies since they do not appear to negatively affect economic performance. Nonetheless, considering the negative effect of inequality even when considering other variables, they can also reduce market inequality directly in the first place, by addressing its root institutional causes, such as those related to the labor market institutions.

3.A Lag selection of Bivariate models

Table 3.8: Information criteria, bootstrap serial correlation tests and stability condition for different lag orders of VAR models of bivariate vector processes containing variables that concern the United States

(a) $\mathbf{y} = [\Delta incGS_{US}, \Delta inv_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-1.940	-1.854*	-1.715*	0.144	1.518	0.446
2	-1.989*	-1.846	-1.614	0.137*	0.976	0.603
3	-1.907	-1.706	-1.382	0.149	0.537	0.621
4	-1.830	-1.571	-1.154	0.162	0.186	0.802
(b) $\mathbf{y} = [\Delta incGS_{US}, \Delta RGDP_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-1.061	-0.975	-0.836*	0.346	1.705	0.364
2	-1.156*	-1.012*	-0.781	0.315*	0.637	0.614
3	-1.068	-0.866	-0.542	0.345	0.459	0.651
4	-0.926	-0.667	-0.250	0.399	0.597	0.657
(c) $\mathbf{y} = [\Delta incGS_{US}, \Delta pl_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-1.805*	-1.719*	-1.580*	0.164*	0.911	0.754
2	-1.684	-1.541	-1.309	0.186	1.449	0.760
3	-1.641	-1.439	-1.115	0.194	1.383	0.804
4	-1.678	-1.420	-1.003	0.188	1.110	0.799
(d) $\mathbf{y} = [\Delta incGS_{US}, \Delta open_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-3.033	-2.946	-2.807*	0.048	2.340**	0.461
2	-3.134*	-2.990*	-2.759	0.044*	1.308	0.597
3	-3.111	-2.909	-2.585	0.045	0.952	0.668
4	-3.073	-2.814	-2.397	0.047	0.342	0.809

Source: Authors' own computations.

Note: The usual information criteria are the Akaike information criterion (AIC) (Akaike, 1974), the Hannan-Quinn information criterion (HQIC) (Hannan & Quinn, 1979), the Bayesian or Schwarz information criterion (BIC) (Schwarz, 1978) and the Final prediction error (FPE) criterion (Akaike, 1969). The bootstrap serial correlation test is the Breusch-Godfrey Lagrange Multiplier test (Breusch, 1978; Godfrey, 1978), implemented following the description in Lütkepohl and Krätzig (2004, pp. 128-129), which is the most appropriate approach when a low order serial correlation of the residuals is expected (Lütkepohl & Krätzig, 2004, p. 129), as is the case considering the annual frequency of the data. Moreover, we set a order of 2 for the auxiliary regressions, as defined in the aforementioned reference. For each lag, the bootstrap p-values are obtained as described in section 3.4.4. The stability condition, described in Definition 1, is verified if $\max |\lambda| \leq 1$, *i.e.*, if the maximum *modulus* of the eigenvalues λ of the companion matrix of the VAR model defined in (3.2) is less or equal to 1, because this implies that all eigenvalues are necessarily inside the complex unit circle and the model is stable. The superscript * is used to indicated the optimal lag for each information criterion, and the significance levels, for serial correlation test, as follows: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 3.8: (cont.)

(e) $\mathbf{y} = [\Delta incGS_{US}, \Delta gov_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-13.271*	-13.185*	-13.046*	0.000*	1.710*	0.481
2	-13.201	-13.057	-12.826	0.000	2.547***	0.419
3	-13.188	-12.986	-12.662	0.000	1.534	0.715
4	-13.188	-12.929	-12.512	0.000	0.709	0.790

(f) $\mathbf{y} = [\Delta incGS_{US}, \Delta redist_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-5.494*	-5.407*	-5.268*	0.004*	1.299	0.436
2	-5.478	-5.335	-5.103	0.004	0.755	0.610
3	-5.409	-5.208	-4.884	0.004	0.339	0.686
4	-5.313	-5.054	-4.638	0.005	0.484	0.772

(g) $\mathbf{y} = [\Delta incGS_{US}, \Delta enr_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.595*	-2.509*	-2.370*	0.075*	1.012	0.467
2	-2.544	-2.400	-2.168	0.079	0.790	0.591
3	-2.443	-2.242	-1.918	0.087	0.501	0.652
4	-2.309	-2.050	-1.634	0.100	0.635	0.703

(h) $\mathbf{y} = [\Delta inv_{US}, \Delta RGDP_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	0.886	0.972	1.111	2.426	2.616**	0.270
2	0.628*	0.772*	1.003*	1.876*	0.568	0.617
3	0.751	0.952	1.276	2.125	1.120	0.678
4	0.813	1.072	1.488	2.270	0.324	0.796

(i) $\mathbf{y} = [\Delta inv_{US}, \Delta pl_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	1.179*	1.265*	1.404*	3.252*	1.023	0.802
2	1.244	1.388	1.620	3.475	0.800	0.795
3	1.307	1.509	1.832	3.708	0.973	0.885
4	1.301	1.560	1.977	3.700	0.491	0.925

(j) $\mathbf{y} = [\Delta inv_{US}, \Delta open_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-0.704*	-0.617*	-0.479*	0.495*	0.687	0.249
2	-0.619	-0.475	-0.244	0.539	1.316	0.434
3	-0.505	-0.304	0.020	0.605	1.538	0.629
4	-0.582	-0.323	0.093	0.563	0.551	0.781

(k) $\mathbf{y} = [\Delta inv_{US}, \Delta gov_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-10.582*	-10.496*	-10.357*	0.000*	0.796	0.160
2	-10.475	-10.331	-10.100	0.000	0.935	0.341
3	-10.373	-10.172	-9.848	0.000	2.087**	0.642
4	-10.451	-10.192	-9.776	0.000	1.167	0.801

Table 3.8: (cont.)

(l) $\mathbf{y} = [\Delta inv_{US}, \Delta redist_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.423*	-2.336*	-2.197*	0.089*	0.877	0.398
2	-2.390	-2.246	-2.014	0.092	1.175	0.620
3	-2.287	-2.085	-1.761	0.102	0.708	0.718
4	-2.326	-2.067	-1.650	0.098	0.641	0.851
(m) $\mathbf{y} = [\Delta inv_{US}, \Delta enr_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-0.061*	0.025*	0.164*	0.941*	0.830	0.483
2	0.015	0.158	0.390	1.016	0.695	0.362
3	0.086	0.287	0.611	1.093	0.707	0.661
4	0.174	0.433	0.849	1.198	0.850	0.793
(n) $\mathbf{y} = [\Delta RGDP_{US}, \Delta pl_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	2.075*	2.161*	2.300*	7.964*	1.363	0.790
2	2.100	2.244	2.475	8.175	1.079	0.834
3	2.163	2.364	2.688	8.725	0.664	0.914
4	2.268	2.527	2.944	9.731	0.678	0.940
(o) $\mathbf{y} = [\Delta RGDP_{US}, \Delta open_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	0.511	0.597	0.736*	1.668	1.606	0.284
2	0.429*	0.573*	0.804	1.537*	0.355	0.640
3	0.576	0.778	1.102	1.785	0.864	0.642
4	0.606	0.865	1.281	1.845	0.303	0.787
(p) $\mathbf{y} = [\Delta RGDP_{US}, \Delta gov_{US}]$						
Lag	AIC	HICQ	BIC	FPE	BG	Max $ \lambda $
1	-9.782*	-9.696*	-9.557*	0.000*	1.323	0.287
2	-9.731	-9.587	-9.356	0.000	1.006	0.477
3	-9.618	-9.416	-9.092	0.000	0.725	0.619
4	-9.591	-9.332	-8.916	0.000	0.931	0.739
(q) $\mathbf{y} = [\Delta RGDP_{US}, \Delta redist_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-1.381*	-1.294*	-1.155*	0.251*	0.918	0.455
2	-1.377	-1.233	-1.001	0.253	0.750	0.548
3	-1.263	-1.062	-0.738	0.284	0.617	0.645
4	-1.205	-0.946	-0.530	0.302	0.628	0.762
(r) $\mathbf{y} = [\Delta RGDP_{US}, \Delta enr_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	1.208	1.294	1.433	3.348	2.437**	0.499
2	1.024*	1.168*	1.399*	2.788*	0.523	0.630
3	1.079	1.280	1.604	2.951	0.719	0.751
4	1.165	1.424	1.841	3.230	0.173	0.811

Table 3.8: (cont.)

(s) $\mathbf{y} = [\Delta pl_{US}, \Delta open_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	0.099*	0.185*	0.324*	1.104*	0.920	0.815
2	0.177	0.321	0.552	1.195	0.722	0.799
3	0.251	0.453	0.777	1.290	0.788	0.897
4	0.240	0.499	0.915	1.280	0.370	0.927
(t) $\mathbf{y} = [\Delta pl_{US}, \Delta gov_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-10.202*	-10.116*	-9.977*	0.000*	0.973	0.818
2	-10.144	-10.000	-9.768	0.000	0.793	0.808
3	-10.066	-9.865	-9.541	0.000	0.535	0.849
4	-10.072	-9.813	-9.396	0.000	0.802	0.929
(u) $\mathbf{y} = [\Delta pl_{US}, \Delta redist_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.095	-2.009*	-1.870*	0.123	1.455	0.795
2	-2.100*	-1.956	-1.725	0.123*	0.646	0.834
3	-2.034	-1.832	-1.508	0.131	0.784	0.875
4	-2.007	-1.748	-1.331	0.135	0.693	0.908
(v) $\mathbf{y} = [\Delta pl_{US}, \Delta enr_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	0.656*	0.743*	0.882*	1.928*	0.800	0.813
2	0.768	0.912	1.144	2.159	0.787	0.777
3	0.841	1.042	1.366	2.325	0.811	0.876
4	0.953	1.212	1.629	2.613	1.058	0.916
(w) $\mathbf{y} = [\Delta open_{US}, \Delta gov_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-11.442*	-11.356*	-11.217*	0.000*	0.772	0.261
2	-11.332	-11.188	-10.956	0.000	0.775	0.404
3	-11.231	-11.030	-10.706	0.000	2.943**	0.644
4	-11.379	-11.120	-10.703	0.000	0.994	0.792
(x) $\mathbf{y} = [\Delta open_{US}, \Delta redist_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-3.479*	-3.392*	-3.254*	0.031*	0.792	0.410
2	-3.449	-3.305	-3.074	0.032	1.111	0.594
3	-3.323	-3.122	-2.798	0.036	1.450	0.703
4	-3.430	-3.171	-2.754	0.033	0.459	0.880
(y) $\mathbf{y} = [\Delta open_{US}, \Delta enr_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-0.892*	-0.806*	-0.667*	0.410*	1.065	0.446
2	-0.771	-0.627	-0.396	0.463	1.404	0.366
3	-0.738	-0.537	-0.213	0.480	2.081*	0.661
4	-0.798	-0.540	-0.123	0.453	1.073	0.797

Table 3.8: (cont.)

(z) $\mathbf{y} = [\Delta gov_{US}, \Delta redist_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-13.553*	-13.467*	-13.328*	0.000*	1.570	0.473
2	-13.517	-13.373	-13.142	0.000	0.848	0.565
3	-13.415	-13.213	-12.889	0.000	1.302	0.714
4	-13.411	-13.152	-12.735	0.000	1.305	0.785
(aa) $\mathbf{y} = [\Delta gov_{US}, \Delta enr_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-11.067*	-10.981*	-10.842*	0.000*	1.218	0.527
2	-10.958	-10.814	-10.582	0.000	1.853*	0.452
3	-10.835	-10.633	-10.309	0.000	3.249***	0.628
4	-11.026	-10.767	-10.350	0.000	1.556	0.786
(ab) $\mathbf{y} = [\Delta redist_{US}, \Delta enr_{US}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.933*	-2.847*	-2.708*	0.053*	1.475	0.482
2	-2.926	-2.782	-2.551	0.054	1.082	0.605
3	-2.881	-2.680	-2.356	0.056	0.868	0.760
4	-2.800	-2.541	-2.124	0.061	1.440	0.807

Table 3.9: Information criteria, bootstrap serial correlation tests and stability condition for different lag orders of VAR models of bivariate vector processes containing variables that concern France

(a) $\mathbf{y} = [\Delta incGS_{FR}, \Delta inv_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.409*	-2.323*	-2.184*	0.090*	0.867	0.672
2	-2.340	-2.196	-1.965	0.096	0.765	0.556
3	-2.319	-2.118	-1.794	0.099	0.390	0.769
4	-2.205	-1.946	-1.530	0.111	0.816	0.818
(b) $\mathbf{y} = [\Delta incGS_{FR}, \Delta RGDP_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-1.357*	-1.270*	-1.132*	0.258*	0.965	0.675
2	-1.302	-1.158	-0.927	0.272	0.425	0.622
3	-1.221	-1.019	-0.696	0.296	0.254	0.786
4	-1.074	-0.816	-0.399	0.344	0.529	0.795
(c) $\mathbf{y} = [\Delta incGS_{FR}, \Delta pl_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	1.369*	1.455*	1.594*	3.931*	1.221	0.638
2	1.476	1.620	1.851	4.380	1.531	0.523
3	1.458	1.659	1.983	4.311	0.503	0.663
4	1.452	1.711	2.128	4.303	0.898	0.867
(d) $\mathbf{y} = [\Delta incGS_{FR}, \Delta open_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-3.389	-3.303	-3.164*	0.034	1.643	0.695
2	-3.456*	-3.312*	-3.081	0.032*	0.557	0.680
3	-3.383	-3.182	-2.858	0.034	0.144	0.773
4	-3.252	-2.993	-2.577	0.039	0.304	0.816
(e) $\mathbf{y} = [\Delta incGS_{FR}, \Delta gov_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-13.362*	-13.276*	-13.137*	0.000*	1.001	0.678
2	-13.298	-13.154	-12.923	0.000	0.872	0.468
3	-13.248	-13.047	-12.723	0.000	0.667	0.768
4	-13.169	-12.910	-12.494	0.000	0.501	0.805
(f) $\mathbf{y} = [\Delta incGS_{FR}, \Delta redist_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-6.668*	-6.582*	-6.443*	0.001*	1.382	0.727
2	-6.590	-6.446	-6.215	0.001	1.652	0.590
3	-6.607	-6.406	-6.082	0.001	0.967	0.777
4	-6.592	-6.333	-5.917	0.001	2.132*	0.805

Source: Authors' own computations.

Note: See Table 3.8.

Table 3.9: (cont.)

(g) $\mathbf{y} = [\Delta incGS_{FR}, \Delta enr_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.862*	-2.776*	-2.637*	0.057*	1.712	0.650
2	-2.785	-2.641	-2.409	0.062	1.707	0.651
3	-2.820	-2.618	-2.294	0.060	0.433	0.768
4	-2.715	-2.456	-2.039	0.067	1.325	0.833
(h) $\mathbf{y} = [\Delta inv_{FR}, \Delta RGDP_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	2.391*	2.477*	2.616*	10.925*	0.320	0.422
2	2.498	2.642	2.873	12.172	0.533	0.633
3	2.605	2.807	3.131	13.581	0.496	0.730
4	2.671	2.930	3.347	14.562	0.772	0.772
(i) $\mathbf{y} = [\Delta inv_{FR}, \Delta pl_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	5.348*	5.435*	5.574*	210.328*	0.138	0.271
2	5.488	5.632	5.864	242.133	0.099	0.309
3	5.629	5.831	6.155	279.398	0.422	0.435
4	5.770	6.029	6.446	322.828	0.871	0.547
(j) $\mathbf{y} = [\Delta inv_{FR}, \Delta open_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	0.066*	0.152*	0.291*	1.068*	0.350	0.074
2	0.170	0.314	0.546	1.187	0.501	0.449
3	0.278	0.479	0.803	1.325	0.526	0.566
4	0.345	0.604	1.021	1.422	0.442	0.746
(k) $\mathbf{y} = [\Delta inv_{FR}, \Delta gov_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-9.601*	-9.515*	-9.376*	0.000*	0.459	0.208
2	-9.523	-9.379	-9.148	0.000	0.396	0.494
3	-9.391	-9.190	-8.866	0.000	0.592	0.469
4	-9.334	-9.075	-8.659	0.000	0.818	0.736
(l) $\mathbf{y} = [\Delta inv_{FR}, \Delta redist_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.070*	-1.983*	-1.844*	0.126*	0.317	0.231
2	-1.958	-1.814	-1.582	0.141	0.449	0.396
3	-1.851	-1.650	-1.326	0.158	0.606	0.593
4	-1.798	-1.539	-1.122	0.167	0.201	0.751
(m) $\mathbf{y} = [\Delta inv_{FR}, \Delta enr_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	1.113*	1.199*	1.338*	3.044*	1.037	0.437
2	1.145	1.289	1.520	3.146	0.961	0.646
3	1.172	1.374	1.698	3.241	0.573	0.743
4	1.200	1.459	1.875	3.343	0.325	0.763

Table 3.9: (cont.)

(n) $\mathbf{y} = [\Delta RGD P_{FR}, \Delta pl_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	6.557*	6.643*	6.782*	704.387*	0.160	0.375
2	6.684	6.828	7.059	800.635	0.155	0.529
3	6.833	7.034	7.358	930.707	0.164	0.441
4	6.972	7.231	7.648	1074.084	1.558	0.562
(o) $\mathbf{y} = [\Delta RGD P_{FR}, \Delta open_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	1.678*	1.764*	1.903*	5.357*	0.690	0.325
2	1.748	1.892	2.123	5.751	0.677	0.493
3	1.801	2.002	2.326	6.073	0.906	0.727
4	1.905	2.164	2.581	6.768	1.426	0.680
(p) $\mathbf{y} = [\Delta RGD P_{FR}, \Delta gov_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-8.378*	-8.291*	-8.152*	0.000*	0.612	0.273
2	-8.320	-8.176	-7.945	0.000	0.466	0.600
3	-8.177	-7.976	-7.652	0.000	0.425	0.569
4	-8.099	-7.840	-7.423	0.000	0.347	0.758
(q) $\mathbf{y} = [\Delta RGD P_{FR}, \Delta redist_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-0.969*	-0.882*	-0.744*	0.380*	0.170	0.421
2	-0.839	-0.695	-0.464	0.433	0.298	0.408
3	-0.696	-0.495	-0.171	0.500	0.602	0.487
4	-0.638	-0.379	0.037	0.532	0.269	0.763
(r) $\mathbf{y} = [\Delta RGD P_{FR}, \Delta enr_{FR}]$						
Lag	AIC	HQ	SC	FPE	BG	Max $ \lambda $
1	2.258*	2.345*	2.483*	9.568*	0.768	0.394
2	2.287	2.431	2.662	9.856	0.331	0.623
3	2.436	2.637	2.961	11.463	1.660	0.605
4	2.503	2.762	3.179	12.310	1.474	0.741
(s) $\mathbf{y} = [\Delta pl_{FR}, \Delta open_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	4.422*	4.508*	4.647*	83.256*	0.299	0.250
2	4.524	4.668	4.899	92.320	0.059	0.489
3	4.671	4.872	5.196	107.128	0.072	0.482
4	4.813	5.072	5.489	124.010	0.667	0.569
(t) $\mathbf{y} = [\Delta pl_{FR}, \Delta gov_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-5.514*	-5.428*	-5.289*	0.004*	0.302	0.304
2	-5.415	-5.271	-5.039	0.004	0.384	0.438
3	-5.266	-5.065	-4.741	0.005	0.574	0.507
4	-5.179	-4.920	-4.503	0.006	1.137	0.736

Table 3.9: (cont.)

(u) $\mathbf{y} = [\Delta pl_{FR}, \Delta redist_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	1.721*	1.807*	1.946*	5.591*	0.603	0.290
2	1.825	1.969	2.200	6.211	0.984	0.497
3	1.923	2.125	2.449	6.867	1.072	0.590
4	1.946	2.205	2.622	7.051	1.427	0.786
(v) $\mathbf{y} = [\Delta pl_{FR}, \Delta enr_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	5.020*	5.107*	5.246*	151.506*	0.888	0.432
2	5.061	5.205	5.436	157.972	1.330	0.568
3	5.184	5.385	5.709	178.969	0.570	0.596
4	5.319	5.578	5.994	205.578	0.639	0.655
(w) $\mathbf{y} = [\Delta open_{FR}, \Delta gov_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-10.268*	-10.182*	-10.043*	0.000*	0.566	0.054
2	-10.220	-10.076	-9.845	0.000	0.484	0.484
3	-10.078	-9.877	-9.553	0.000	0.579	0.516
4	-10.010	-9.751	-9.335	0.000	0.444	0.731
(x) $\mathbf{y} = [\Delta open_{FR}, \Delta redist_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.998*	-2.912*	-2.773*	0.050*	0.736	0.243
2	-2.966	-2.822	-2.591	0.052	0.759	0.466
3	-2.826	-2.624	-2.300	0.059	0.921	0.522
4	-2.810	-2.551	-2.135	0.061	0.374	0.775
(y) $\mathbf{y} = [\Delta open_{FR}, \Delta enr_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	0.143	0.229*	0.368*	1.154	1.532	0.497
2	0.101*	0.245	0.476	1.107*	0.807	0.592
3	0.126	0.327	0.651	1.138	0.699	0.709
4	0.182	0.441	0.858	1.208	0.356	0.752
(z) $\mathbf{y} = [\Delta gov_{FR}, \Delta redist_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-12.989*	-12.903*	-12.764*	0.000*	0.496	0.229
2	-12.929	-12.786	-12.554	0.000	0.581	0.395
3	-12.797	-12.595	-12.271	0.000	0.988	0.392
4	-12.749	-12.490	-12.073	0.000	0.637	0.760
(aa) $\mathbf{y} = [\Delta gov_{FR}, \Delta enr_{FR}]$						
Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-9.862*	-9.775*	-9.637*	0.000*	0.864	0.340
2	-9.815	-9.671	-9.439	0.000	1.093	0.647
3	-9.682	-9.481	-9.157	0.000	1.584	0.548
4	-9.638	-9.379	-8.962	0.000	0.636	0.732

Table 3.9: (cont.)

(ab) $\mathbf{y} = [\Delta redist_{FR}, \Delta enr_{FR}]$

Lag	AIC	HQIC	BIC	FPE	BG	Max $ \lambda $
1	-2.555*	-2.469*	-2.330*	0.078*	0.517	0.452
2	-2.430	-2.286	-2.055	0.088	0.504	0.591
3	-2.350	-2.149	-1.825	0.096	0.258	0.609
4	-2.217	-1.958	-1.542	0.110	0.560	0.657

3.B Robustness checks

Table 3.10: Bootstrap diagnostic tests of serial correlation and autoregressive conditional heteroskedasticity of residuals and stability condition of the estimated VAR models

y	BG	ARCH	Max $ \lambda $
$y_{1,US}^*$	0.968	735.000	0.629
$y_{2,US}^*$	0.546	1764.000	0.815
$y_{1,FR}^*$	0.370	735.000	0.485
$y_{2,FR}^*$	0.208	1372.000	0.485

Source: Authors' own computations.

Note: The diagnostic tests consist on the Breusch-Godfrey (BG) (Breusch, 1978; Godfrey, 1978), and the autoregressive conditional heteroskedasticity (ARCH) Lagrange Multiplier tests (Engle, 1982) of, respectively, serial correlation and conditionally heteroskedasticity. We set a order of 1 for the auxiliary regressions of the BG procedure to have enough degrees of freedom to obtain the test statistic in the context of models estimated for larger vector processes. For more details concerning this serial correlation test and max $|\lambda|$, see Table 3.8.

Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

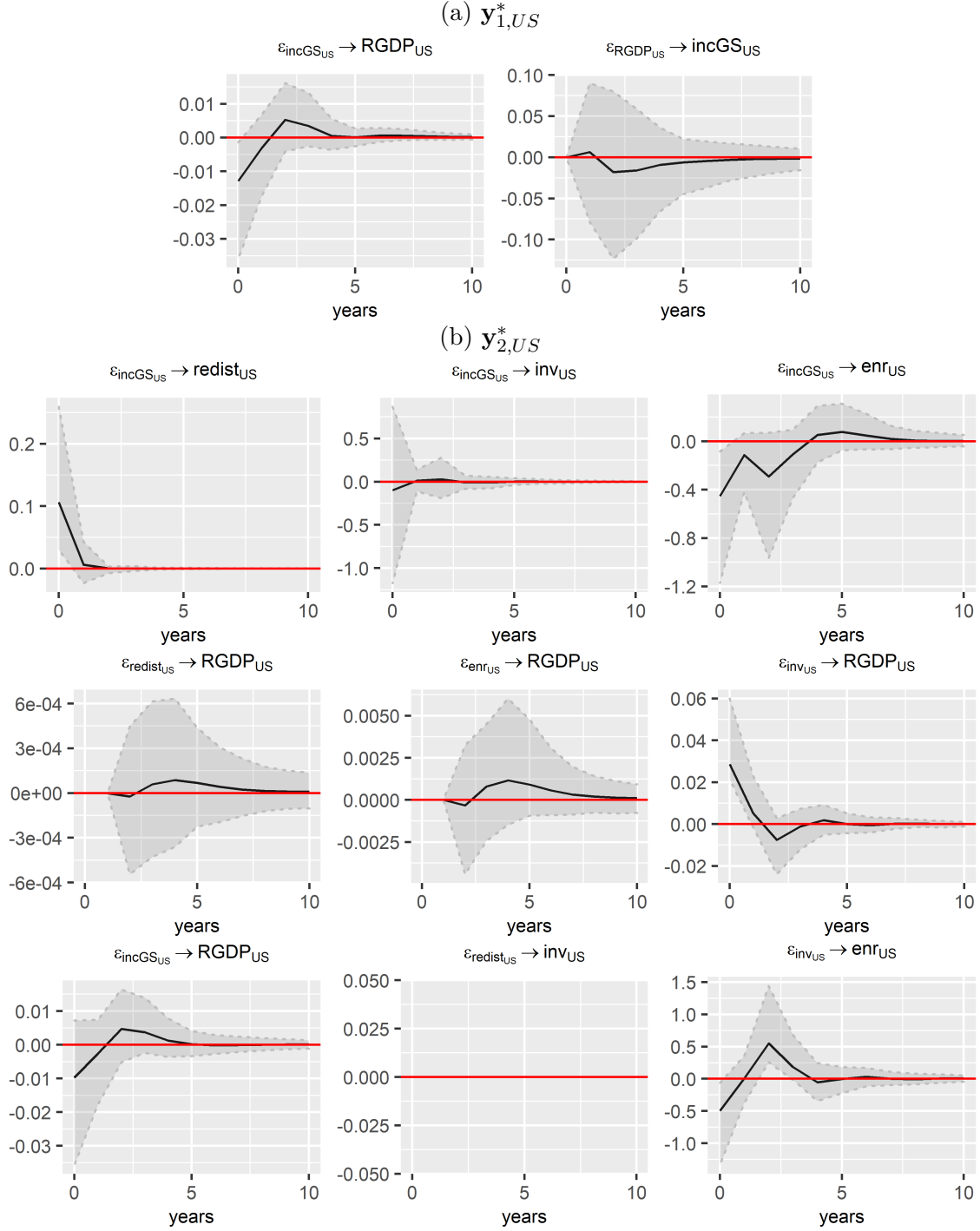
Table 3.11: Bootstrap sample split Chow test for structural change of the estimated VAR models

(a) $y_{1,US}^*$			(b) $y_{2,US}^*$			(c) $y_{1,FR}^*$			(d) $y_{2,FR}^*$		
SBY	Statistic	p-value	SBY	Statistic	p-value	SBY	Statistic	p-value	SBY	Statistic	p-value
1982	30.258	0.320	1982	30.346	0.457	1982	28.847	0.158	1982	16.982	0.559
1983	29.206	0.348	1983	30.226	0.457	1983	31.001	0.098	1983	16.613	0.574
1984	31.296	0.278	1984	32.190	0.389	1984	30.107	0.118	1984	11.330	0.790
1985	34.298	0.192	1985	31.854	0.404	1985	29.037	0.154	1985	11.614	0.784
1986	34.037	0.193	1986	35.843	0.289	1986	24.969	0.294	1986	8.609	0.871
1987	36.531	0.144	1987	41.750	0.171	1987	24.582	0.312	1987	9.276	0.848
1988	47.443	0.028	1988	59.572	0.018	1988	26.769	0.226	1988	12.040	0.764
1989	48.580	0.023	1989	62.448	0.013	1989	29.891	0.127	1989	17.234	0.551
1990	42.758	0.063	1990	60.072	0.022	1990	24.057	0.334	1990	10.779	0.804
1991	39.411	0.095	1991	59.505	0.021	1991	26.520	0.230	1991	15.759	0.616
1992	40.988	0.080	1992	59.493	0.021	1992	20.316	0.533	1992	28.061	0.173
1993	26.352	0.468	1993	34.087	0.342	1993	21.232	0.489	1993	26.066	0.230
1994	28.137	0.394	1994	37.546	0.244	1994	20.358	0.519	1994	25.910	0.241
1995	29.915	0.320	1995	36.414	0.279	1995	22.975	0.393	1995	29.498	0.151

Source: Authors' own computations.

Note: This procedure tests the null hypothesis of no structural changes against the alternative of structural change in a particular year (Lütkepohl & Krätzig, 2004, p. 135). The p-values of the tests are based on a bootstrap distribution of 2000 bootstrap values of the corresponding test statistics. For more details, see section 3.4.4.

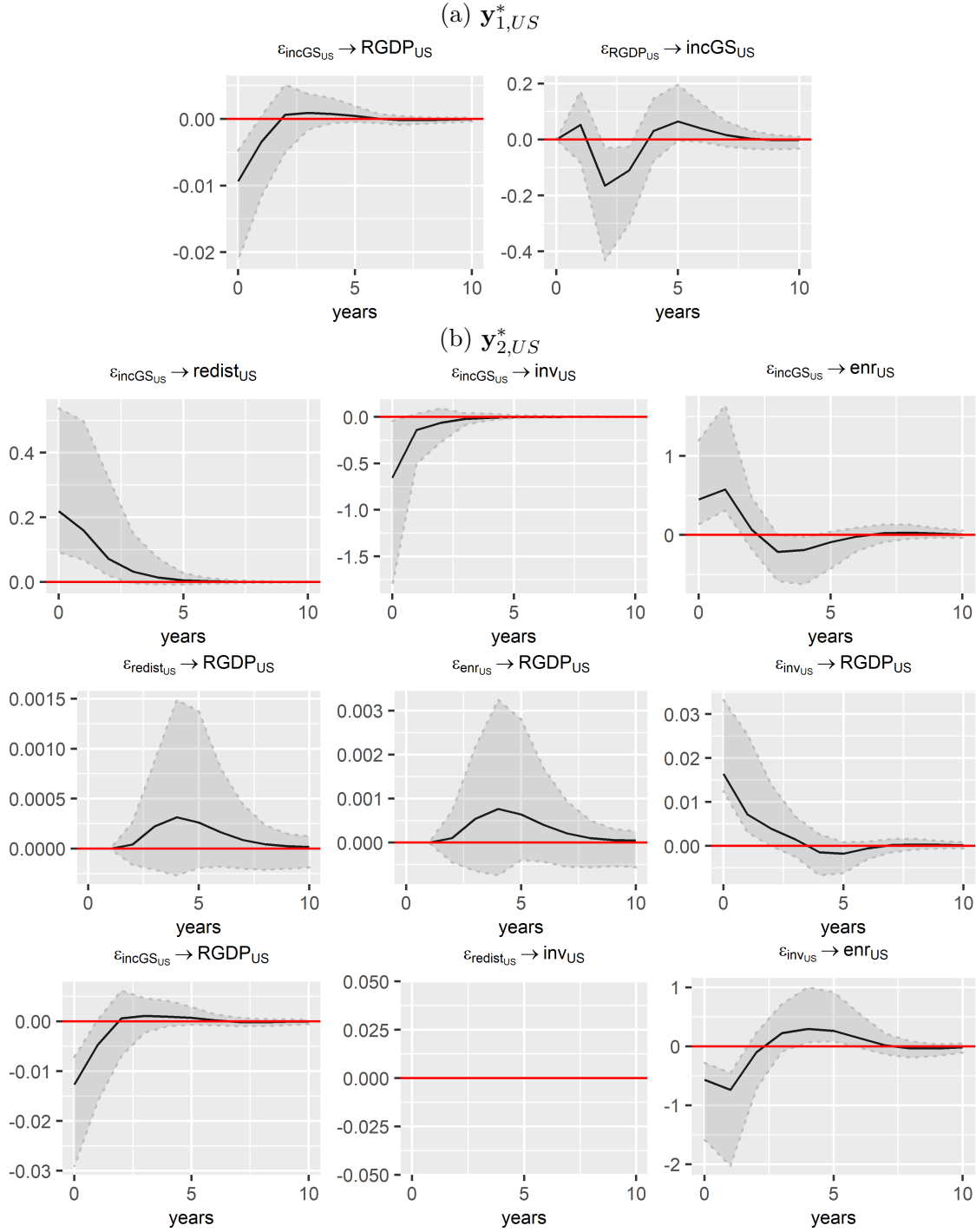
Figure 3.4: Selected orthogonal impulse response functions with 95% bootstrap Equal-tailed confidence intervals for the VAR models of $\mathbf{y}_{1,US}^*$ and $\mathbf{y}_{2,US}^*$ concerning the period 1962-1989



Source: Authors' own computations.

Note: See Figure 3.2.

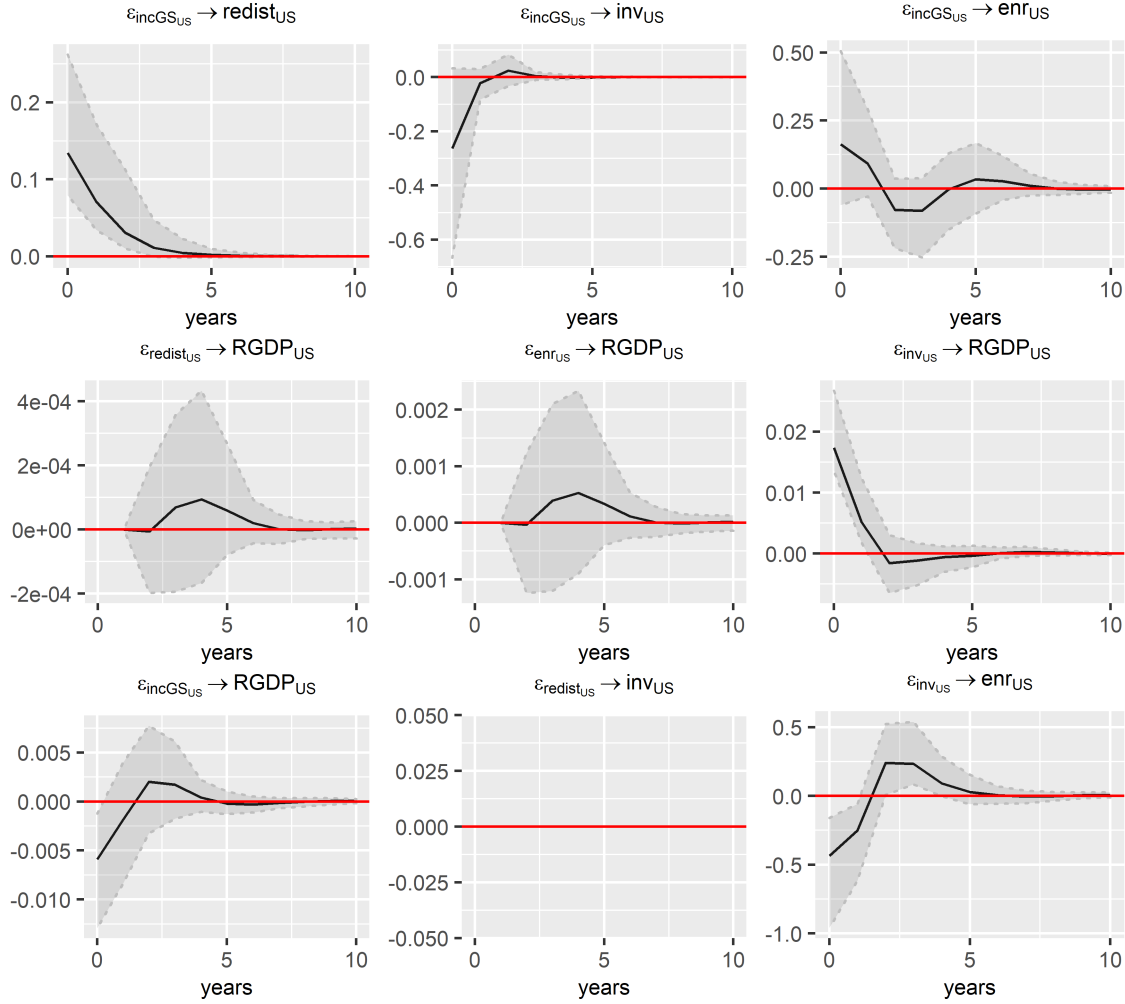
Figure 3.5: Selected orthogonal impulse response functions with 95% bootstrap Equal-tailed confidence intervals for the VAR models of $\mathbf{y}_{1,US}^*$ and $\mathbf{y}_{2,US}^*$ concerning the period 1990-2018



Source: Authors' own computations.

Note: See Figure 3.2.

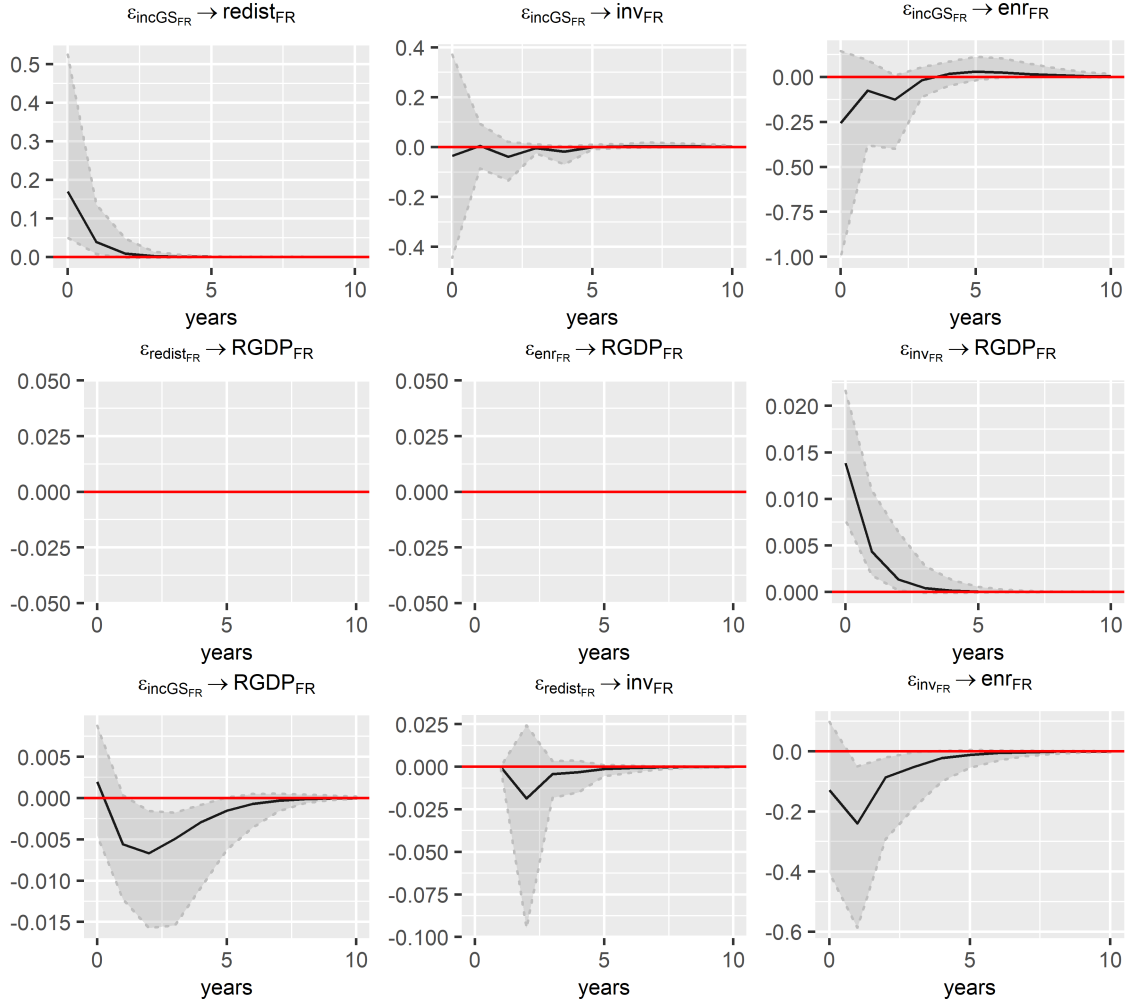
Figure 3.6: Impulse response functions with 95% bootstrap Equal-tailed confidence intervals for a VAR model of $\mathbf{y}_{2,US}^*$ with an alternative specification to the Structural Impact Matrix



Source: Authors' own computations.

Note: See Figure 3.2.

Figure 3.7: Impulse response functions with 95% bootstrap Equal-tailed confidence intervals for a VAR model of $\mathbf{y}_{2,FR}^*$ with an alternative specification to the Structural Impact Matrix



Source: Authors' own computations.

Note: See Figure 3.2.

Chapter 4

How does inequality affect growth
in the European Union? A
structural panel vector
autoregressive analysis

4.1 Introduction

The interest in analyzing the economic consequences of inequality has grown over the years due to the increasing disparity trends in various economies and the lack of a clear empirical consensus regarding how this phenomenon can affect growth.

A meta-analysis data of Neves et al. (2016) on the inequality-growth literature dedicated to analyzing the empirical relationship between these variables reveals that the average impact of inequality on growth is non-statistically significant, reflecting substantially heterogeneous results. The methodological approach employed in this literature, despite being heterogeneous in some aspects, can, in general, be characterized by a focus on panels with a substantial number of different countries and the estimation of single equation dynamic models. The dependent variable is usually economic growth or GDP per capita, calculated as the average of n number of years (n -year average), and the regressors include a measure of inequality, control variables and possibly other variables, such as intermediate variables of transmission channels (*e.g.*, Barro, 2000; Bengoa & Sanchez Robles, 2005; Berg et al., 2018; Gründler & Scheuermeyer, 2018; Halter et al., 2014; D. J. Lee & Son, 2016; Voitchovsky, 2005). We consider that this approach has significant limitations that could explain the heterogeneity in the results and, therefore, should be addressed using appropriate alternatives.

First, many variables of interest are endogenous due to their persistence, the existence of bi-directional relationships, and the fact that many are simultaneously determined (Huang et al., 2009; Lundberg & Squire, 2003). The endogeneity issue is addressed by estimating such models using the system GMM (*e.g.*, Gründler & Scheuermeyer, 2018) or Three-Stage Least Squares (Barro, 2000) estimators. However, in this context, a panel vector autoregressive (VAR) approach is more appropriate because it combines the dynamic single equation modeling approach with VAR models, resulting in the simultaneous estimation of equations where the dynamics of all endogenous variables are explicit. Therefore, when many of the variables of interest are endogenous and have bi-directional relationships, such as in the case of the inequality-growth relationship and its transmission channels, this approach leads to more precise results than those obtained in conventional panel data models (Atems & Jones, 2015). Additionally, in panel VAR models, one can obtain information not only concerning the lagged dynamics of the variables but also of contemporaneous relationships, which is captured by the variance-covariance matrix of the residuals, and analyze both in impulse response functions. This aspect is not explicitly

considered by conventional panel data models, but authors such as Lundberg and Squire (2003) and Huang et al. (2009) have shown, using other approaches, that doing so can have a significant impact on the results that are obtained.

Second, the systematic use of n -year averages of Real GDP per capita or economic growth can entail several problems. These include loss of information and distortions caused by not considering the variability over time and space of business cycles, the preclusion of analyses focused on short-run dynamics and the possibility of canceling out effects that act with different lags in opposite directions (Attanasio, Picci, & Scorcu, 2000). Second, considering large panels of countries can lead to measurement errors due to the lack of quality of certain data, especially from developing countries, and issues of comparability due to the different methodological approaches used to calculate many variables (Atems & Jones, 2015). Moreover, we also question the extent to which the conclusions based on such studies are useful to the design of appropriate policies due to the substantial institutional, cultural, and other differences between the analyzed economies.

Bearing this in mind, we propose to analyze the inequality-growth relationship in the context of a structural panel VAR analysis of countries from the European Union. We will analyze not only the inequality-growth relationship but also the way and the extent to which this relationship is materialized through some of the transmission mechanisms most theoretically relevant considering the level of development of the analyzed countries. Moreover, we also consider variables that simultaneously affect the relationship between inequality and growth because their absence can lead to misleading conclusions.

The focus on these countries is motivated by different reasons. The first is the absence of studies on the inequality-growth relationship focused on these economies, despite the relevance of this analysis. Fredriksen (2012) analyzes the evolution of inequality in twenty EU countries and concludes that intra-country inequality has risen substantially while inter-country inequality has decreased. Since these trends remain relevant, analyzing their potential effects on economic growth is important, especially considering that sustainable economic performance is one of the fundamental objectives of the European Union.¹ The second is the common

¹Specifically, article 3 of the Lisbon Treaty states that one of the fundamental objectives of the European Union is to “achieve “sustainable development based on balanced economic growth and price stability and a highly competitive market economy with full employment and social progress”. Retrieved on the 20th of September 2022 from “https://european-union.europa.eu/principles-countries-history/principles-and-values/aims-and-values_en”.

institutional background of these countries because it allows the resulting analysis to produce useful results for designing policies appropriate for the specific realities these economies represent. The third is the possibility of obtaining quality annual data for each member state with harmonized definitions, which reduces the likelihood of measurement errors.

Our work is closely related to Herzer and Vollmer (2012), who analyzed the inequality-growth relationship in the context of a panel cointegration approach, Atems and Jones (2015), due to the adoption of the Panel VAR approach to analyze the inequality-growth relationship, and the recent contribution of Soava, Mehedintu, and Sterpu (2020), which analyzed this relationship in the context of the European Union. However, our approach differs in important aspects. We innovate in relation to the first two with the explicit analysis of transmission channels and by considering multiple variables that affect the inequality-growth relation. We also innovate specifically in relation to Herzer and Vollmer (2012) by analyzing the dynamics at all time horizons and not just the long run. Moreover, the most homogeneous division of countries considered by the authors was developed and developing countries, among which there are still many important differences that can cause some of the problems already described. Our contribution is also specifically different from Soava et al. (2020) due to the adoption of the structural panel VAR approach.

We found that inequality has no statistically significant impacts on economic growth. However, an analysis of transmission channels shows that it has statistically significant effects on redistribution and investment, which are, respectively, positive and negative and, in the case of the latter, only occur contemporaneously. In an analysis of subsamples of countries with higher and lower than average GDP per capita, we found that such effects are more prevalent in the latter. The results are overall robust to the addition of control variables that can potentially affect inequality and growth, the inclusion of dummies to take into account the effects of the global financial and European Sovereign debt crises, different specifications concerning the maximum number of instruments and lag order, and also alternative assumptions for identifying the structural shocks of interest. Nonetheless, other results, namely a positive impact of inequality in investment in the medium run, were not robust to the inclusion of these variables. This suggests that some are actually caused by the simultaneous impact of shocks of these variables on the models.

The remainder of this essay is structured as follows: Section 4.2 describes the data analyzed in this essay and includes a panel unit root analysis; Section 4.3 describes

the panel VAR model and details concerning the impulse response analysis we conduct, with a particular focus on the identification of structural shocks; Section 4.4 contains the main results; Section 4.5 concludes.

4.2 Data

4.2.1 Description

Our data consists of a balanced panel of 513 annual observations that concern all the 27 country members (as of 2021) of the European Union in the period 2001-2019 of nine variables. They are characterized in detail in Table 4.1 and plotted in Figure 4.1.

In general terms, these include proxies for (a) income inequality, (b) economic growth, (c) intermediate variables of the main transmission channels we intend to analyze in this paper, described in detail below, (d) control variables that can simultaneously affect inequality and growth. We resort to four sources: the Standardized World Income Inequality Database, Version 9.3, June 2022 (Solt, 2020), hereafter SWIID, is used to retrieve the Gini coefficient of market incomes; the Barro and Lee dataset (Barro & Lee, 2013; J.-W. Lee & Lee, 2016), hereafter BL, is used to retrieve five-year values of education years that are used to construct the human capital index; the Eurostat database (Lahti, Huovari, Kainu, & Biecek, 2017), hereafter ES, is used to retrieve values for private sector debt; the Penn World Table 10.0 (Feenstra et al., 2015), hereafter PWT, is used to retrieve all the remaining variables. We resorted to most of these sources because they are well-established and many are used by related papers in the literature (Berg et al., 2018; Gründler & Scheuermeyer, 2018).

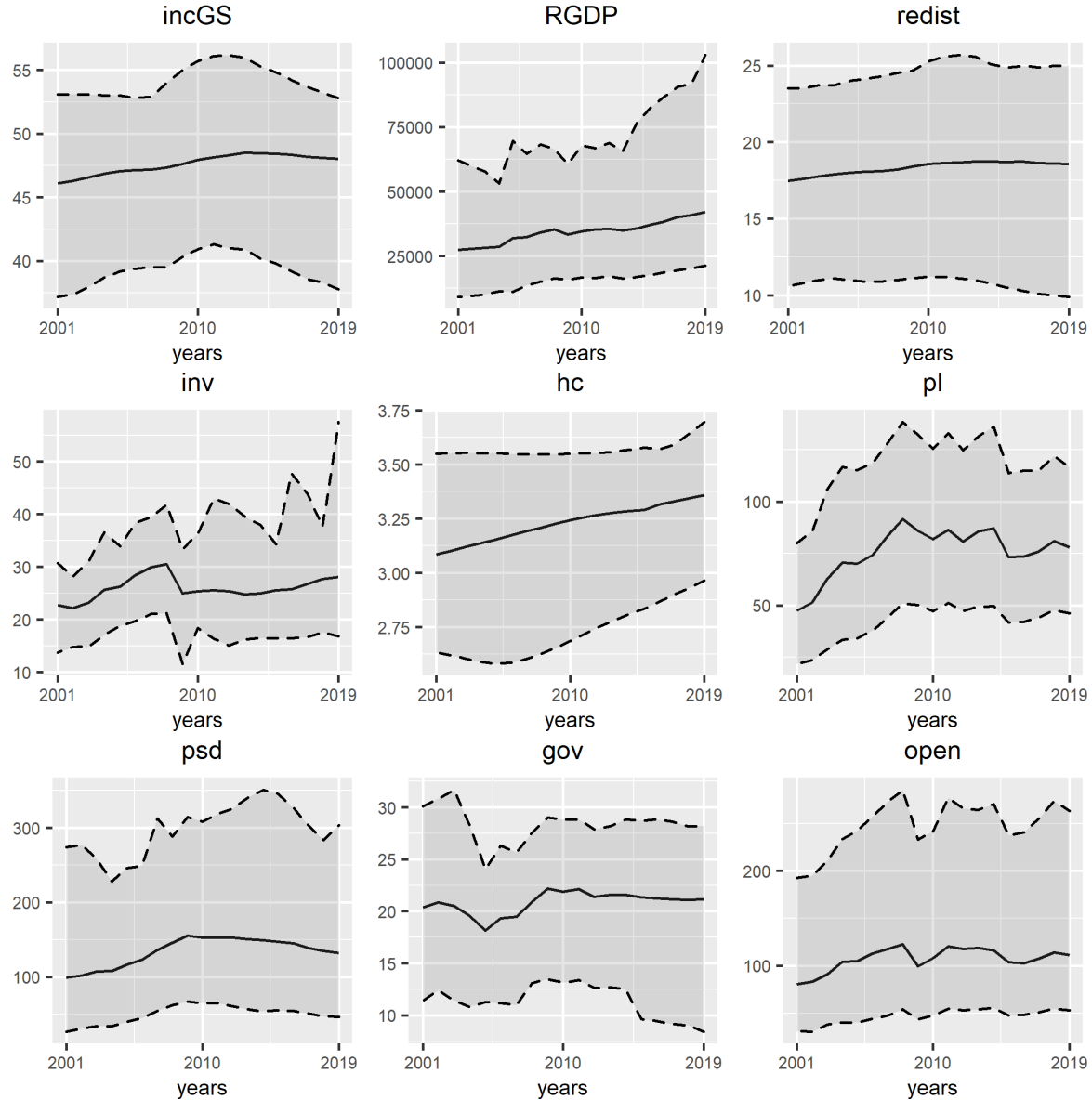
Table 4.1: Description of the data

Variable	Description	Source
$incGS^{(a)}$	Gini of the pre-tax national income of the entire distribution of income.	SWIID
$rgdp^{(b)}$	Logarithm of GDP per capita at current PPP (in millions of 2017 international dollars).	PWT
$redist^{(c)}$	Difference between the estimate of the Gini index of inequality in equivalized household market (post-tax) and disposable (pre-tax) incomes.	SWIID
$hc^{(c)(d)}$	Logarithm of human capital index based on a Mincerian log-linear relationship with (i) years of education, which are spline interpolated from the five-year values of the Barro and Lee Dataset (Barro & Lee, 2013; J.-W. Lee & Lee, 2016); (ii) a rate of return to schooling, which is assumed to be constant and equal to 10% (J.-W. Lee & Lee, 2016).	BL
$inv^{(c)}$	Share of investment in Real GDP at current PPP (in millions of 2017 international dollars).	PWT
$pl^{(d)}$	Logarithm of price level of household consumption, with the benchmark being the price level in the US in 2017.	PWT
$psd^{(d)}$	The ratio to GDP per capita of the consolidated stock of liabilities (Debt Securities and Loans) held by non-financial corporations, households and non-profit institutions serving households.	ES
$gov^{(d)}$	Share of government consumption in Real GDP at current PPP (in millions of 2017 international dollars).	PWT
$open^{(d)}$	Sum of the absolute values of shares of merchandise exports and imports in Real GDP at current PPP (in millions of 2017 international dollars).	PWT

Note: Spline interpolation is an interpolation method whereby new points within a boundary of existing ones are determined by a spline function, which contains multiple piecewise cubic polynomials. In this case, we use the spline of Forsythe (1977) where end conditions are determined by fitting an exact cubic through the last four points of each end of the data. (a) Proxy for aggregate inequality; (b) Proxy for economic productivity; (c) Proxies for the intermediate variables of transmission channels; (d) Proxies for variables that can simultaneously affect inequality and growth.

Legend: BL - Barro and Lee Dataset (Barro & Lee, 2013; J.-W. Lee & Lee, 2016); ES - Eurostat database (Lahti et al., 2017); PWT - Penn World Table 10.0 (Feenstra et al., 2015); SWIID - Standardized World Income inequality Database, Version 9.3, June 2022 (Solt, 2020); PPP - purchasing-power-parity.

Figure 4.1: Plot of the cross-sectional mean and range of the variables of interest of 27 EU members during 2001-2019



Source: See Table 4.1.

Note: For a variable r and each $t \in \{2001, \dots, 2019\}$, $\mathbf{y}_{t,r}$, the cross-sectional mean, represented by a solid black line, is defined as $\bar{\mathbf{y}}_{t,r} := N^{-1} \sum_{i=1}^N \mathbf{y}_{i,t,r}$, where N is the number of countries. The range is represented by a gray bandwidth and corresponds to the interval $[\min(\mathbf{y}_{i,t,r}), \max(\mathbf{y}_{i,t,r})]$.

Some additional notes to the information provided in Table 4.1 are in order. In what concerns group (c), we focus our analysis on some of the most relevant transmission channels considered in the literature and for which adequate proxies of the corresponding transmission variables are available. Bearing in mind the survey of

Neves and Silva (2014) and more recent papers that have analyzed transmission channels (*e.g.*, Gründler & Scheuermeyer, 2018), we focus on the Credit Market Imperfections, Fiscal Policy, and Savings channels, which are described in detail in Table 4.2. The intermediate variables of these channels are, respectively, redistribution intensity, human capital, and the aggregate savings rate, which we proxy, respectively, by *redist*, *hc* and *inv* in line with papers with a similar focus as ours (*e.g.*, Barro, 2000; Gründler & Scheuermeyer, 2018).

Table 4.2: Description of the main transmission channels analyzed in the paper

Transmission channel	Description and authors	Intermediate variable (proxy)
Fiscal Policy channel	Inequality increases societal pressures on policymakers for increased redistribution. This, in turn, creates distortions that reduce investment incentives and, hence growth (Alesina & Perotti, 1996; Alesina & Rodrik, 1994; Persson & Tabellini, 1994).	redistribution (<i>redist</i>)
Credit market imperfections channel	In the presence of imperfections in the credit market, an increase in inequality increases the proportion of the population that is unable to conduct investments in human capital. This decreases the average human capital and, therefore, growth (Galor & Moav, 2004; Galor & Zeira, 1993).	human capital (<i>hc</i>)
Savings channel	An increase in inequality leads to a higher aggregate saving rate by leading to a higher concentration of income in rich individuals, who are assumed to save more than those with lower incomes. This, in turn, leads to higher investment rates, which promotes economic growth (Kaldor, 1955).	savings rate (<i>inv</i>)

Group (d) contains variables that can simultaneously affect inequality and growth. As explained in detail in section 4.3.2, this is important to avoid reaching erroneous conclusions (Lundberg & Squire, 2003). Considering the relevance and data

availability of various possibilities, we include government expenditures, openness, education, inflation, and financial development. The first two are considered by some authors, such as Huang et al. (2009), as potentially affecting inequality and growth, and are also commonly used in growth regressions in general (*e.g.*, Acheampong, 2018) and the inequality-growth literature in particular (*e.g.*, Gründler & Scheuermeyer, 2018).

Inflation can decrease investment incentives, which penalize growth, and such negative effects affect some sectors of the economy more than others, leading to increased disparities (Afonso & Lima, 2022). The empirical relevance of considering inflation is also shown, for instance, in the paper of Huang et al. (2009), in which, in the context of a simultaneous equation model, inflation had a statistically significant effect on both inequality and growth. Education was also found to be empirically relevant for determining both variables in some papers (Huang et al., 2009; Lundberg & Squire, 2003). Moreover, it is also theoretically relevant since it is also considered a growth determinant in the context of endogenous growth models and contributes to less inequality by decreasing the share of uneducated workers earning low wages and the overall variance of earnings after a certain threshold is crossed (Knight & Sabot, 1983).

The importance of financial development in determining inequality and growth can be interpreted as an immediate consequence of the Credit market imperfections channel. It leads to a more equal allocation of income and increased possibilities of investment in human capital by those at the bottom of the income distribution, which benefits growth. This conclusion has also been supported empirically by numerous studies that find that an increase in financial development leads to a decrease in the Gini coefficient (Clarke et al., 2006; Huang et al., 2009) and an increase in economic performance (Hassan, Sanchez, & Yu, 2011; Huang et al., 2009).

We use the usual proxies for these variables. The only exception concerns the proxy for financial development, which in the literature is usually the ratio of domestic credit to the GDP (*e.g.*, Hassan et al., 2011; Huang et al., 2009). However, we found missing observations for this variable in some years for some countries included in our analysis. Therefore, we opted instead for the ratio of consolidated Private Sector Debt to GDP, retrieved from the ES database. There is a high correlation between both variables, as attested by the correlation of 0.78 concerning common observations of both in the period of analysis, and a higher value is usually indicative of higher access of firms and households to credit, thus reflecting increases in financial development (Bauer,

Granziera, et al., 2017).

In the subsequent analyses of this paper, we demeaned (subtracted the mean) and standardized all the variables of interest by country.

4.2.2 Panel unit root tests

We now apply panel unit root tests to the variables of interest. This analysis is important because the panel VAR model we describe further ahead is usually applied to stationary variables (*e.g.*, Atems and Jones 2015), which have constant and finite mean, variance and covariance structure. However, many variables in economics are not stationary in levels but rather in first differences (Atems & Jones, 2015). In this case, they are integrated of order one due to the presence of a unit root.

Following the usual approach in the literature (*e.g.*, Atems and Jones 2015), we consider two types of tests. The first type, represented by the Im-Pesaran-Shin (IPS) (Im, Pesaran, & Shin, 2003) and the Maddala-Wu (MW) (Maddala & Wu, 1999) tests, is based on augmented Dickey-Fuller regressions estimated for individual time series. These procedures test the null hypothesis that all the series are integrated of order one against the alternative that they are stationary, either around a constant or a constant and trend. The second type of test, represented by the Hadri (HAD) test (Hadri, 2000; Hadri & Larsson, 2005), is based on the results of individual KPSS tests applied to individual series. These procedures test the null hypothesis that all time series are stationary against the alternative that at least one has a unit root. Both approaches are used to complement each other.

The results are in Table 4.3. In what concerns the variables in levels, in general, the results of all tests lead to a rejection of the corresponding null hypotheses. These results are expected and can be interpreted as an indication that some series are integrated while others are already stationary in levels. However, the null hypotheses are also rejected in tests applied to first differences. Considering the previous interpretation, this is an unexpected result since it implies that some series are stationary in first differences and integrated of order one while others are integrated of order one in first differences, and, therefore, integrated of order two in levels. Nonetheless, we consider plausible to proceed by considering that all series are integrated of order one because we find no theoretical reasons to expect a higher level of integration for these variables. Moreover, as we show further ahead, we obtain stable estimates of panel VAR models focused on variables in first differences, a result which would not be plausible if some

series that were integrated of order two.

Table 4.3: Panel Unit root tests of the variables of interest

	IPS		MW		HAD	
	Con	Con and Tr	Con	Con and Tr	Con	Con and Tr
<i>incGS</i>	-4.251***	-7.620***	210.880***	323.736***	49.856***	30.700***
$\Delta incGS$	-5.689***	-6.161***	163.290***	263.421***	13.983***	14.379***
<i>RGDP</i>	2.759	-4.959***	41.059	184.121***	49.394***	20.491***
$\Delta RGDP$	-14.519***	-9.474***	438.779***	297.161***	-1.413	1.279
<i>redist</i>	-5.211***	-3.365***	197.284***	150.538***	40.728***	35.174***
$\Delta redist$	-6.040***	-9.052***	188.620***	356.755***	15.366***	10.109***
<i>inv</i>	-4.827***	-9.114***	179.155***	344.619***	20.895***	16.056***
Δinv	-14.117***	-11.529***	414.725***	364.564***	-1.771	1.476*
<i>hc</i>	0.986	-10.838***	205.118***	549.523***	56.243***	36.485***
Δhc	-10.121***	-8.209***	281.704***	300.185***	18.765***	15.757***
<i>pl</i>	-7.859***	-1.912**	177.621***	78.666**	23.587***	41.686***
Δpl	-12.000***	-13.484***	298.700***	384.466***	7.880***	-1.082
<i>psd</i>	-6.235***	1.431	188.264***	142.610***	34.389***	41.019***
Δpsd	-5.624***	-8.269***	180.982***	240.634***	17.710***	8.336***
<i>govc</i>	-4.039***	-9.157***	153.805***	527.100***	26.261***	17.845***
$\Delta govc$	-16.126***	-14.030***	535.639***	621.837***	-2.258	-0.169
<i>Open</i>	-2.699***	-4.841***	89.326***	163.214***	21.205***	19.679***
$\Delta Open$	-16.117***	-13.717***	488.711***	422.563***	-0.913	1.131

Source: Authors' own computations.

Note: The panel unit root tests are the Im-Pesaran-Shin (IPS) (Im et al., 2003), the Maddala-Wu (MW) (Maddala & Wu, 1999) and the Hadri test (HAD) (Hadri, 2000; Hadri & Larsson, 2005) tests. The IPS and MW tests are based on the estimation of augmented Dickey-Fuller regressions for each time series. Both test the null hypothesis that all series have a unit root against the alternative that all are stationary. The difference between both is that the former is a standardized t-bar test based on the average of the ADF statistics across different cross-sectional units, while the latter is an inverse chi-square test based on the combination of p-values of individual ADF tests. The HAD test is based on the results of individual KPSS tests applied to individual series and tests the null hypothesis that all time series are stationary against the alternative that at least one has a unit root. We apply an extension proposed by Hadri and Larsson (2005) to the original test introduced in Hadri (2000), which makes an adjustment factor to the original test statistic that considers the specific finite time dimension of the sample. For each test, we consider a version of stationarity around a constant (Con) or a constant and a trend (Con and Tr), which, in the case of the IPS and MW tests, distinguish two alternative hypotheses of stationarity while in the case of HAD these concern the null hypotheses that are being tested.

Legend: Δ - First difference operator such that $\Delta \mathbf{y}_{i,t} = \mathbf{y}_{i,t} - \mathbf{y}_{i,t-1}$.

Significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

4.3 Methodology

4.3.1 Panel Vector autoregressive model

In this paper we analyze a balanced panel of N cross-sectional units and T observations with a Panel Vector autoregressive (VAR) model of order p , extended to include strictly exogenous variables as described in detail in Sigmund and Ferstl (2021):

$$\mathbf{y}_{i,t} = \boldsymbol{\eta} + \boldsymbol{\mu}_i + \sum_{l=1}^p \boldsymbol{\Phi}_l \mathbf{y}_{i,t-l} + \boldsymbol{\Phi}_x \mathbf{x}_{i,t} + \mathbf{v}_{i,t}, \quad (4.1)$$

where $\mathbf{y}_{i,t}$ is a vector process of M endogenous variables, $\boldsymbol{\eta}$ is a vector of M constant terms, $\boldsymbol{\mu}_i$ is a vector of M unobserved fixed effects, $\boldsymbol{\Phi}_l$ is the coefficient of the lag term l , $\mathbf{x}_{i,t}$ is a vector of n strictly exogenous variables, $\boldsymbol{\Phi}_x$ is the corresponding coefficient, and $\mathbf{v}_{i,t}$ is a vector of M error terms that are i.i.d. distributed and of which the following assumptions are made: $\mathbb{E}(\mathbf{v}_{i,t}) = \mathbf{0}_{M \times 1}$, $\mathbb{E}(\mathbf{v}_{i,t} \mathbf{v}_{i,t}') = \boldsymbol{\Omega}$, $\mathbb{E}(\mathbf{v}_{i,t} \mathbf{v}_{i,j}') = \mathbf{0}_{M \times M}$, $j \neq t$, where $\mathbf{0}$ is a zero matrix and $\boldsymbol{\Omega}$ is a $M \times M$ positive definite matrix.²

In the case of this essay, the cross-sectional units consist of 27 EU member countries (as of 2021) and for each we have 18 observations of variables in first differences between 2002 and 2019. This implies that $N = 27$, $T_i = T = 18, \forall i$ and a total number of observations equal to $N \times T = 486$. We consider the following four alternative specifications for the vector process $\mathbf{y}_{i,t}$:

$$\mathbf{y}_{1,i,t} := [\Delta incGS_{i,t}, \Delta RGDP_{i,t}], \quad (4.2)$$

$$\mathbf{y}_{2,i,t} := [\Delta incGS_{i,t}, \Delta inv_{i,t}, \Delta hc_{i,t}, \Delta RGDP_{i,t}, \Delta redist_{i,t}], \quad (4.3)$$

$$\mathbf{y}_{3,i,t} := [\Delta incGS_{i,t}, \Delta hc_{i,t}, \Delta RGDP_{i,t}, \Delta open_{i,t}, \Delta pl_{i,t}, \Delta gov_{i,t}, \Delta psd_{i,t}], \quad (4.4)$$

$$\mathbf{y}_{4,i,t} := [\Delta incGS_{i,t}, \Delta inv_{i,t}, \Delta hc_{i,t}, \Delta RGDP_{i,t}, \Delta open_{i,t}, \Delta pl_{i,t}, \Delta gov_{i,t}, \Delta redist_{i,t}, \Delta psd_{i,t}], \quad (4.5)$$

where Δ is the first difference operator, whereby $\Delta \mathbf{y}_{i,t} = \mathbf{y}_{i,t} - \mathbf{y}_{i,t-1}$. As explained

²Sigmund and Ferstl (2021) also include a vector of pre-determined variables that are sequentially exogenous, *i.e.*, they are assumed to be uncorrelated with future and current disturbances but can potentially be correlated with past disturbances. For this specification to be relevant, it would be necessary to assume that some variables that are considered endogenous are contemporaneously exogenous, *i.e.*, uncorrelated with current disturbances, which we do not consider necessary for any variable of the system.

further ahead, $\mathbf{y}_1$ and $\mathbf{y}_2$ are considered, respectively, to analyze the effects of inequality shocks on growth and on the transmission variables of the three transmission channels analyzed in this essay, Fiscal Policy, Credit Market Imperfections and Savings channels. The processes $\mathbf{y}_3$ and $\mathbf{y}_4$ serve the same purpose as $\mathbf{y}_1$ and $\mathbf{y}_2$, respectively, but contain additional control variables, for reasons described in more detail in the following section. These variables are all included in first differences due to the results of the panel unit root tests pointing to all being integrated of order 1 and to ensure that the stability condition, described further ahead, is verified. In the case of $\mathbf{x}$, in the baseline specification, we do not consider strictly exogenous variables. However, as described further ahead, we will add dummy variables to conduct a robustness check.

The estimation of the model requires the elimination of the fixed effect, which is accomplished by applying an appropriate transformation Δ^* to the original variables that results in the following specification:

$$\Delta^* \mathbf{y}_{i,t} = \sum_{l=1}^p \Phi_l \Delta^* \mathbf{y}_{i,t-l} + \Phi_x \Delta^* \mathbf{x}_{i,t} + \Delta^* \mathbf{v}_{i,t}. \quad (4.6)$$

We define Δ^* as the first difference transformation Δ .³ We estimate the parameters $\Phi = [\eta, \Phi_1, \dots, \Phi_p, \Phi_x]'$ using the two-step System Generalized Method of moments (GMM) with collapsed moment conditions. The complete details concerning the estimation procedure are in appendix 4.B. We choose this estimator because it is more appropriate than the alternative, the Difference GMM estimator. The latter only uses lagged variables in levels as instruments for first difference variables, and this approach is not appropriate when variables are highly persistent (Neves & Silva, 2014), as is the case of inequality and other variables we consider. On the other hand, the System GMM estimator uses not only these instruments but complements them with lagged first difference variables as instruments for variables in levels.

One of the conditions required for the assumptions underlying the System GMM estimator to be valid is that $\Delta^* \mathbf{y}_t$ is not systematically related to the fixed effect μ_i , which, as explained in Sigmund and Ferstl (2021), holds if the panel VAR model satisfies the stability condition below (Lütkepohl, 2005, p. 15):

³Alternatively, the fixed effect could be removed by defining Δ^* as the forward orthogonal transformation operator $\Delta^\perp$, whereby $\Delta^\perp \mathbf{y}_{i,t} := \sqrt{\frac{T_i-t}{T_i-t+1}} \left(\mathbf{y}_{i,t} - \frac{1}{T_i-t} \sum_{j=1}^{T_i} \mathbf{y}_{i,t+j} \right)$. This renders $\Delta^\perp \mathbf{y}_{i,t}$ orthogonal to the original variables (Arellano & Bover, 1995).

Definition 2 (Stability Condition). A panel VAR model is stable if the *moduli* of the eigenvalues λ of the companion matrix below of the VAR model, which is obtained by representing (4.6) in a panel VAR model of order 1, are all less or equal to 1:

$$\Phi_{comp} := \begin{bmatrix} \Phi_{p-1}^O & \Phi_p \\ \mathbf{I}_{M(p-1)} & \mathbf{0} \end{bmatrix}, \quad \Phi_{p-1}^O := [\Phi_1, \dots, \Phi_{p-1}]. \quad (4.7)$$

4.3.2 Impulse response analysis

After estimating the panel VAR model, one can conduct an impulse response analysis, which consists in determining the impact of shocks on the endogenous variables of the system at various periods afterward. For this purpose, we first need to obtain the Vector Moving Average (VMA) representation of (4.1). If we drop the terms not related to the endogenous variables for simplicity, as they do not affect the impulse responses, this is the following:

$$\mathbf{y}_{i,t} = \sum_{j=0}^{\infty} \Psi_j \mathbf{v}_{i,t-j}, \quad (4.8)$$

where Ψ_j are terms of an infinite polynomial on the Lag operator L , $\Psi(L) := \Psi_0 + \Psi_1 L + \Psi_2 L^2 + \dots$, with $L = \Delta$. These are obtained recursively from the equality $\Phi(L, p) \Psi(L) = \mathbf{I}_M$, with $\Psi_0 = \mathbf{I}_M$ and where $\Phi(L, p) := \mathbf{I} - \Phi_1 L - \dots - \Phi_p L^p$, is the characteristic polynomial of order p on the lag operator L . From here, we can obtain the impulse response function, which measures the impact of a shock r within the set of shocks $\mathbf{v}_{i,t}$, $v_{i,t,r}$, on the endogenous variable m after k periods, $\mathbf{y}_{i,t+k,m}$, which is as follows:

$$IRF(m, k, r) := \frac{\partial \mathbf{y}_{i,t+k,m}}{\partial \mathbf{v}_{i,t,r}} = \Psi_{k,m,r}, k \in \{0, 1, \dots, \infty\}, \quad (4.9)$$

where $\Psi_{k,m,r}$ is the element of row m and column r of the matrix Ψ_k . The shocks represented by the error terms $\mathbf{v}_{i,t}$, which will be designed henceforth reduced error terms, are not economically identified and are not independent of each other because the non-diagonal elements of the variance-covariance matrix Ω are not necessarily equal to zero. The alternative is the Orthogonal Impulse Response Function (OIRF), which quantifies the impact of an alternative set of structural errors $\epsilon_{i,t}$ that are orthogonal and have unit variance, *i.e.*, $\mathbb{E}(\epsilon_{i,t} \epsilon_{i,t}') = \mathbf{I}$, and are economically identified. This is obtained by considering the following relationship between reduced and structural error terms

$\mathbf{v}_{i,t} = \mathbf{B}\boldsymbol{\epsilon}_{i,t}$, where $\mathbf{B}$ is the structural impact matrix,⁴ and implies that $\boldsymbol{\Omega} = \mathbf{B}\mathbf{B}'$. The OIRF is as follows:

$$OIRF(m, k, r) := \frac{\partial y_{i,t+k,m}}{\partial \epsilon_{i,t,r}} = \boldsymbol{\Psi}_{k,m,r} \mathbf{B}_{m,r}, k \in \{0, 1, \dots, \infty\}, \quad (4.10)$$

where $\mathbf{B}_{m,r}$ is the element of row m and column r of the matrix $\mathbf{B}$. This specification shows that the OIRF analysis implies specifying the set of structural shocks of interest $\boldsymbol{\epsilon}_{i,t}$ and the structural impact matrix $\mathbf{B}$.

The specification of $\boldsymbol{\epsilon}_{i,t}$ depends on the analyses to conduct. One is the quantification of the impact of inequality shocks on economic growth, and, therefore, one of the shocks must be necessarily economically identified as a shock of inequality, $\boldsymbol{\epsilon}_{i,t,incGS}$. Since inequality is an endogenous variable, this shock must be instrumented by a collection of exogenous shocks of all the variables outside the model that affect it (Kilian & Lütkepohl, 2017, p. 227). Therefore, the validity of instrumenting this collection of shocks as an inequality shock rests on the assumption that any shock that contemporaneously affects inequality does not simultaneously affect economic growth. To achieve this, $\boldsymbol{\epsilon}_{i,t,incGS}$ must be orthogonal to all shocks that can potentially affect both variables. Considering section 4.2, this implies that the set of structural shocks must contain shocks of inflation, education, financial development, government expenditures, and openness.

Another analysis is the determination of the transmission channels through which the effects of inequality on growth are materialized. This implies quantifying the impulse responses of each transmission variable of the main mechanisms we consider, Fiscal Policy, Credit Market Imperfections, and Savings channels, to an inequality shock. For this purpose, we should similarly consider shocks that can simultaneously affect inequality and each transmission variable, which requires considering different sets of variables.

The first is Real GDP per capita, as this variable is quite relevant in the decision-making process of economic agents (Gobbin & Rayp, 2008). Moreover, it also concatenates the effects of many variables that can also have important simultaneous effects in the variables we consider. The second is the transmission variables of other channels, given their theoretical interdependence. For example, education can affect inequality and investment decisions, considering the complementary nature of physical and human capital (Galor & Moav, 2006). Redistribution intensity can affect

⁴Some authors such as Kilian and Lütkepohl (2017) define this matrix alternatively as $\mathbf{B}^{-1}$.

investment incentives and human capital by affecting college enrollment rates due to changes in the economic obstacles faced by students interested in pursuing higher education. Moreover, the theoretical implications of each transmission channel on the corresponding variables can be easily extended to others. This is exemplified by the fact that credit market imperfections can lead inequality to have a negative impact not only on human capital accumulation but also on investment in physical capital. Therefore, when analyzing transmission channels, we need to consider shocks of all the transmission variables, redistribution, human capital and investment, and real GDP per capita. Finally, we also need to consider shocks of control variables affecting inequality and growth because it is reasonable to expect that they simultaneously affect other pairs of variables. Moreover, this permits analyzing the impacts of inequality on growth when controlling for the impacts of transmission channels.

These shocks are identified by considering the alternative specifications of the vector processes defined in (4.2) to (4.5). Specifically, (4.4) and (4.5) are used, respectively, to analyze the impacts of inequality on growth and the different transmission variables. We also analyze these vector processes without control variables, as defined in (4.2) and (4.3), to determine the extent to which the results are affected by the latter.

In turn, the specification of $\mathbf{B}$ must result from considering plausible economic restrictions. In the case of this essay, we opt for imposing short-run or contemporaneous restrictions⁵ due to the persistent nature of many of the variables of interest and the fact that, in many cases, the relevant relationships can only theoretically exist in the medium or long run. This implies applying direct restrictions to $\mathbf{B}$.⁶ Since we analyze various vector processes, several structural impact matrices must be specified. In this regard, we will specify the structural impact matrix $\tilde{\mathbf{B}}$ associated with the largest vector process we consider. The structural impact matrices corresponding to smaller vector processes can easily be obtained by removing irrelevant rows and columns from this one since they share common variables. The specification is such that the following relationship between reduced and structural error terms holds:

⁵Considering the annual frequency of the data, these refer to restrictions of impacts within a year.

⁶Alternatively, it is also possible to accomplish this by considering long-run restrictions. These consist in the application of restrictions to a long-run matrix $\mathbf{F}$ that is related to $\mathbf{B}$ through the following relationship $\mathbf{B} = \Psi(L)\mathbf{F}$. We do not consider this alternative due to the reasons described in the main text.

$$\begin{bmatrix} \mathbf{v}_{i,t,incGS} \\ \mathbf{v}_{i,t,inv} \\ \mathbf{v}_{i,t,hc} \\ \mathbf{v}_{i,t,RGDP} \\ \mathbf{v}_{i,t,open} \\ \mathbf{v}_{i,t,pl} \\ \mathbf{v}_{i,t,gov} \\ \mathbf{v}_{i,t,redist} \\ \mathbf{v}_{i,t,psd} \end{bmatrix} = \underbrace{\begin{bmatrix} \tilde{\mathbf{B}}_{1,1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \tilde{\mathbf{B}}_{2,1} & \tilde{\mathbf{B}}_{2,2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \tilde{\mathbf{B}}_{3,1} & \tilde{\mathbf{B}}_{3,2} & \tilde{\mathbf{B}}_{3,3} & 0 & 0 & 0 & 0 & 0 & 0 \\ \tilde{\mathbf{B}}_{4,1} & \tilde{\mathbf{B}}_{4,2} & \tilde{\mathbf{B}}_{4,3} & \tilde{\mathbf{B}}_{4,4} & 0 & 0 & 0 & 0 & 0 \\ \tilde{\mathbf{B}}_{5,1} & \tilde{\mathbf{B}}_{5,2} & \tilde{\mathbf{B}}_{5,3} & \tilde{\mathbf{B}}_{5,4} & \tilde{\mathbf{B}}_{5,5} & 0 & 0 & 0 & 0 \\ \tilde{\mathbf{B}}_{6,1} & \tilde{\mathbf{B}}_{6,2} & \tilde{\mathbf{B}}_{6,3} & \tilde{\mathbf{B}}_{6,4} & \tilde{\mathbf{B}}_{6,5} & \tilde{\mathbf{B}}_{6,6} & 0 & 0 & 0 \\ \tilde{\mathbf{B}}_{7,1} & \tilde{\mathbf{B}}_{7,2} & \tilde{\mathbf{B}}_{7,3} & \tilde{\mathbf{B}}_{7,4} & \tilde{\mathbf{B}}_{7,5} & \tilde{\mathbf{B}}_{7,6} & \tilde{\mathbf{B}}_{7,7} & 0 & 0 \\ \tilde{\mathbf{B}}_{8,1} & \tilde{\mathbf{B}}_{8,2} & \tilde{\mathbf{B}}_{8,3} & \tilde{\mathbf{B}}_{8,4} & \tilde{\mathbf{B}}_{8,5} & \tilde{\mathbf{B}}_{8,6} & \tilde{\mathbf{B}}_{8,7} & \tilde{\mathbf{B}}_{8,8} & 0 \\ \tilde{\mathbf{B}}_{9,1} & \tilde{\mathbf{B}}_{9,2} & \tilde{\mathbf{B}}_{9,3} & \tilde{\mathbf{B}}_{9,4} & \tilde{\mathbf{B}}_{9,5} & \tilde{\mathbf{B}}_{9,6} & \tilde{\mathbf{B}}_{9,7} & \tilde{\mathbf{B}}_{9,8} & \tilde{\mathbf{B}}_{9,9} \end{bmatrix}}_{\tilde{\mathbf{B}}} \begin{bmatrix} \boldsymbol{\epsilon}_{i,t,incGS} \\ \boldsymbol{\epsilon}_{i,t,inv} \\ \boldsymbol{\epsilon}_{i,t,hc} \\ \boldsymbol{\epsilon}_{i,t,RGDP} \\ \boldsymbol{\epsilon}_{i,t,open} \\ \boldsymbol{\epsilon}_{i,t,pl} \\ \boldsymbol{\epsilon}_{i,t,gov} \\ \boldsymbol{\epsilon}_{i,t,redist} \\ \boldsymbol{\epsilon}_{i,t,psd} \end{bmatrix}. \quad (4.11)$$

This matrix is lower-triangular, which implies that the structural shocks are economically identified recursively: the inequality error term $\mathbf{v}_{i,t,incGS}$ is affected by a single structural shock, $\boldsymbol{\epsilon}_{i,t,incGS}$, which implies that this shock is a structural shock of inequality. The investment error term $\mathbf{v}_{i,t,inv}$ is affected by only this shock and $\boldsymbol{\epsilon}_{i,t,inv}$, which implies that the latter must necessarily be the structural shock of investment. The human capital error term $\mathbf{v}_{i,t,hc}$ is affected by these shocks and $\boldsymbol{\epsilon}_{i,t,hc}$, which implies that the latter is a structural shock of human capital, and so forth.

The specification above results from several assumptions described below by decreasing order of importance.

Assumption 1. *Inequality is more persistent than any other variable in the system.*

Assumption 2. *Investment, human capital and Real GDP per capita are more persistent than the variables measuring financial development, redistribution, government expenditures, openness and inflation.*

Assumption 3. *Policy variables (government expenditures and redistribution) can react contemporaneously to shocks of openness and inflation but not the converse.*

Assumption 4. *Openness is not contemporaneously affected by shocks of policy variables or inflation.*

Assumption 5. *A shock of inflation can contemporaneously affect private sector debt.*

Assumption 6. *Shocks of the variable measuring financial development do not affect any other variable contemporaneously.*

Assumption 7. *Shocks of government expenditures can affect redistribution contemporaneously but not the converse.*

Assumption 8. *Real GDP per capita can be contemporaneously affected by investment and human capital shocks but not the converse.*

Assumption 9. *Human capital can be contemporaneously affected by a shock of investment but not the converse.*

Assumption 1 implies that inequality is not contemporaneously affected by any other shock. This is justified by the fact that most factors that contribute to changes in the inequality of market incomes are institutional factors that take time to have any effects and are not related to any of the remaining variables considered here. Assumption 2 is justified by the fact that, although investment decisions can change rapidly following some shock, these take time to materialize in changes in effective investment. One major factor is the time required for new investment projects to be completed due to adjustment and installation costs. Consequently, since physical capital is an essential factor of production, GDP per capita adjusts slowly (Kilian & Lütkepohl, 2017, p. 222). Using a similar rationale, we do not expect human capital to change rapidly following some shock of other variables. Even if they lead to contemporaneous changes in enrollment rates at higher levels of education, it takes time for these effects to be reflected in changes in the average schooling years of the population. On the other hand, we consider that there are no reasons to justify such a similar level of persistence in the case of the remaining variables.⁷

Assumption 3 is justified by the usual practice in the literature of considering that policy variables can be informed by prices, openness, and other variables (*e.g.*, Giordano et al. 2007), while 4 is due to the notion that openness changes slowly over

⁷We must highlight that these assumptions concern the proxies being used for the variables under analysis. This distinction is important because, for instance, while financial development is expected to evolve slowly, the proxy used to measure it, private sector debt, can change rapidly in the short run.

time (Jin, 2006). Assumption 5 results from the fact that an increase in inflation can effectively increase the cost of borrowing (Bauer et al., 2017). Assumption 6 is made due to the absence of theoretical arguments that justify a contemporaneous impact of this variable on the remaining ones. Finally, the remaining assumptions concern the relations between pairs of variables and are made to identify the corresponding matrix parameters.

4.4 Results

We start by determining the appropriate lag order for each model by considering the model selection procedure proposed by Andrews and Lu (2001). This implies estimating a panel VAR model for multiple lag orders, calculating several moment selection criteria analogous to the information criteria BIC and HQIC and selecting the model that minimizes most.⁸ These criteria are based on the statistic of the Sargan-Hansen J-test of overidentification (Hansen, 1982; Sargan, 1958), hereafter Hansen test, which tests the null hypothesis that the overidentifying restrictions of a model estimated by GMM are valid. It is also used as a general misspecification test (Yamagata, 2008). Moreover, we also determined the lags for which the stability condition was verified to exclude those that resulted in the estimation of unstable models. The assessment of the stability condition, in turn, is verified by calculating the largest *modulus* of the eigenvalues of the companion matrix of the corresponding estimated VAR model, defined in (4.7), and is verified if it is smaller or equal to 1, since this implies that all eigenvalues are inside the complex unit circle.

We chose a range of lag orders between 1 and 4, with the latter chosen bearing in similar panel VAR models (*e.g.*, Atems & Jones, 2015). We considered a maximum lag of the instruments for the dependent variable $p_{y,max}$ equal to 6 for all models. This permits comparing the models and avoids using an excessive number of instruments as this is the lowest number of instruments necessary to estimate the panel VAR model with the highest lag order (4).⁹ The results concerning the baseline specifications are in Table 4.4 of appendix 4.A. We concluded that the appropriate lag order for all models

⁸Andrews and Lu (2001) also introduced another criterion, AIC, but they do not recommend its application for lag selection due to not being consistent and leading to a positive probability of not selecting sufficient over-identifying restrictions, even asymptotically. Therefore, we do not consider it here.

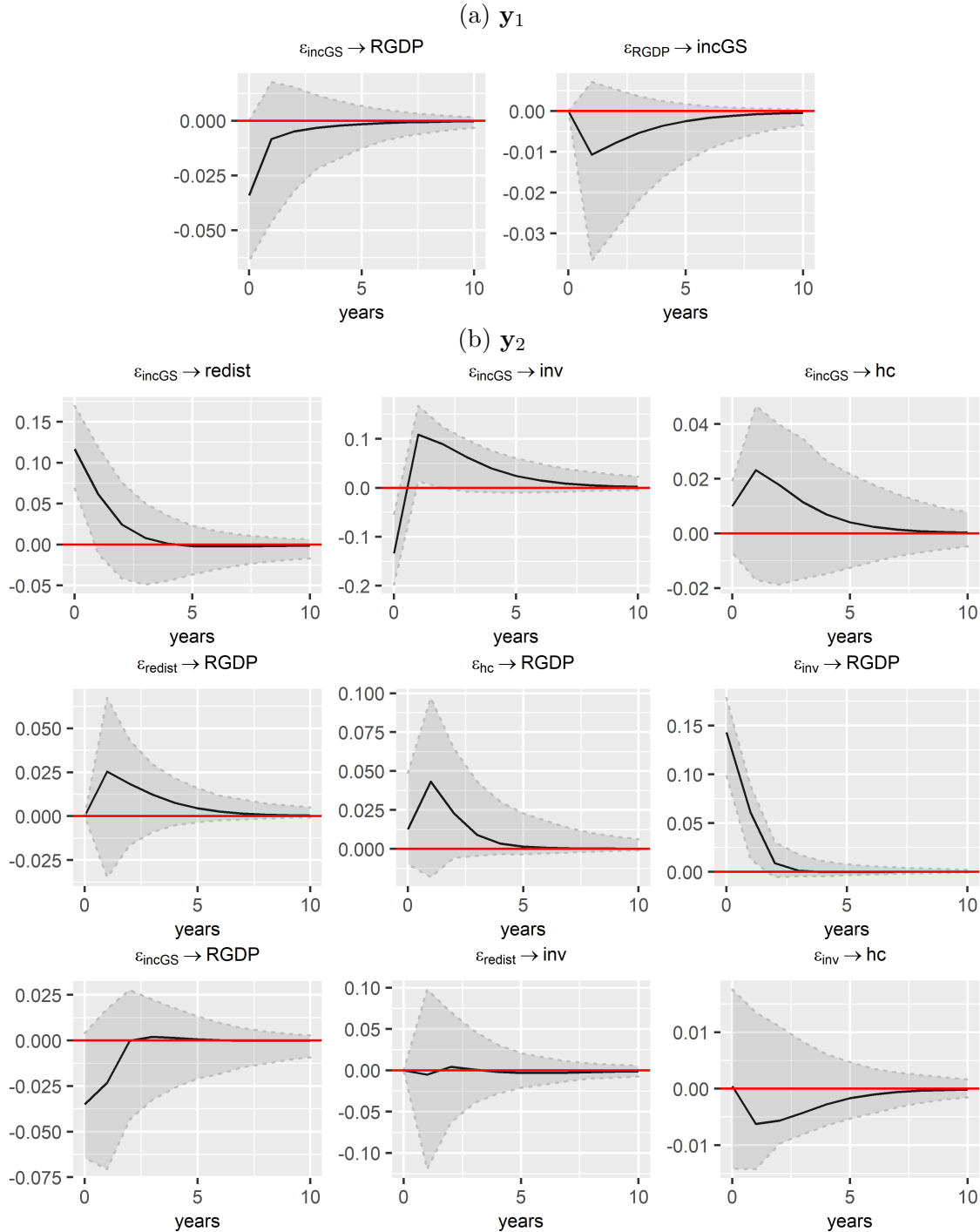
⁹In this paper, we always consider the minimum lag of the instruments for the dependent variable $p_{y,min}$ as 2.

is 1 since it is the optimal lag according to most criteria, the corresponding panel VAR models are stable, and the Hansen overidentification test does not reject the null hypothesis that the over-identifying restrictions are valid, indicating no specification problems such as serial correlation.

The OIRF of the panel VAR models focused on $\mathbf{y}_1$ and $\mathbf{y}_2$ are in Figure 4.2. In panel (a), we see that, although the OIRF estimates are negative, inequality and growth do not appear to have statistically significant effects on each other. In panel (b), we can see that a shock of inequality has a statistically significant positive impact on redistribution. Considering that redistribution is measured as the difference between the Gini coefficient of market and net incomes, we consider that one possible explanation for this result is that an inequality shock concerning market incomes does not lead to an immediate increase of inequality in net incomes due to the absorption of its effects, to a certain extent, by a prevailing tax system that is progressive in nature. Interestingly, it also has statistically significant effects on investment that are negative in the very short run and positive afterward. Moreover, it does not appear to have a statistically significant effect on human capital in any time frame. These findings suggest that the non-statistically significant relation between inequality and growth results from opposing effects of inequality on investment. Finally, a shock of redistribution does not have any statistically significant effects on growth determinants, investment and human capital, or on growth directly.

In Figure 4.3, we depict the OIRF focused on $\mathbf{y}_3$ and $\mathbf{y}_4$, which add control variables to the previous two vector processes. There are some changes, such as the positive effect of inequality on investment in the short run becoming non-statistically significant. Nonetheless, confidence intervals for impulse responses in this time horizon still contain mostly positive values. Moreover, the direct impacts of inequality on growth become even weaker, with the confidence intervals concerning contemporaneous effects containing more positive values than before. Otherwise, the results are qualitatively similar to those obtained without control variables. Therefore, we conclude that a small portion of the positive effects of inequality on investment is explained by the simultaneous impact of some control variables on inequality and investment.

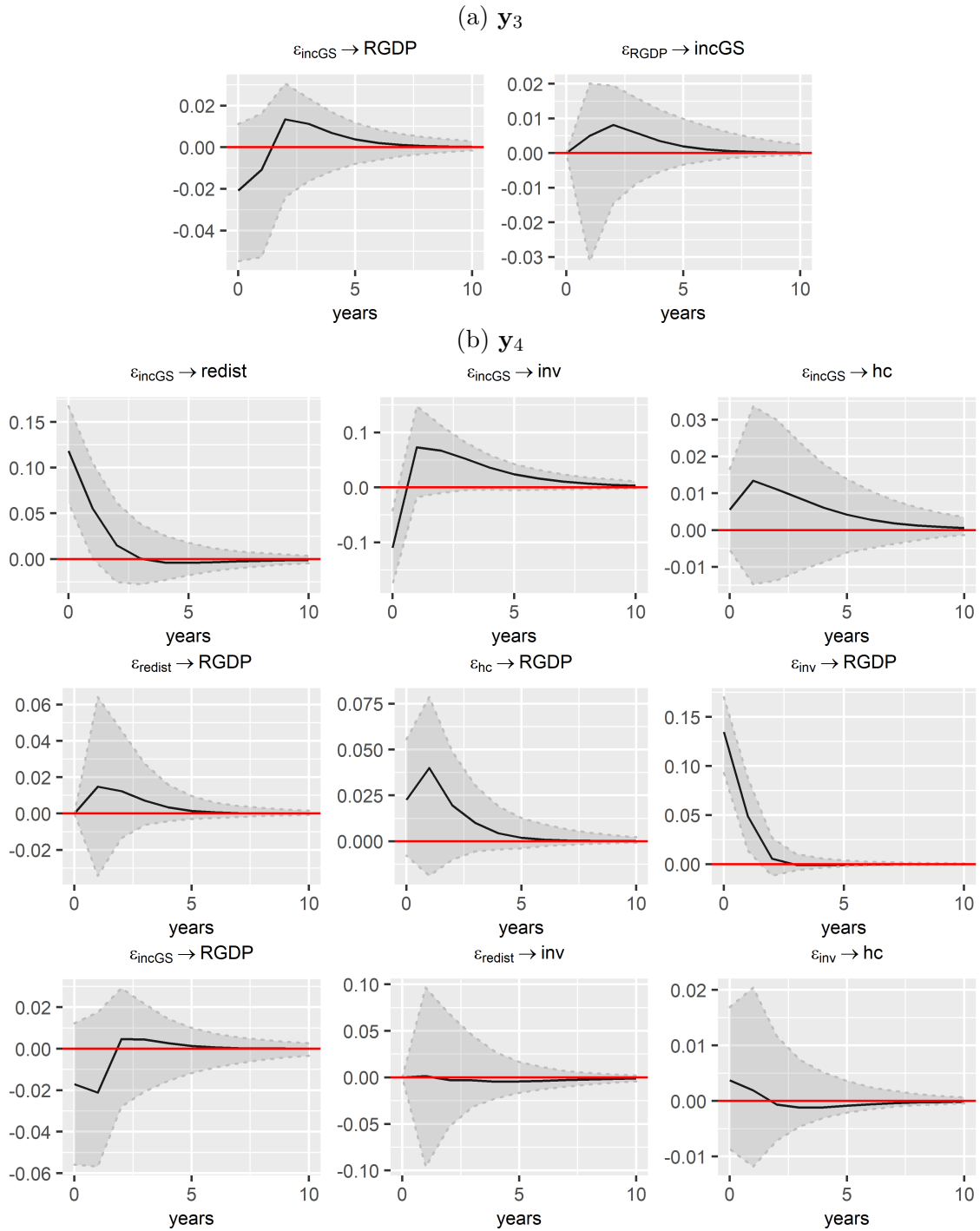
Figure 4.2: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_1$ and $\mathbf{y}_2$



Source: Authors' own computations.

Note: The estimates and confidence intervals of the impulse responses are represented, respectively, by solid black lines and gray bandwidths. The latter is defined as the interval between the $\alpha/2$ and $1 - \alpha/2$ quantiles of the empirical distribution of 1000 bootstrap estimates of $\Psi_{k,m,r}$ (Kilian & Lütkepohl, 2017, p. 357). Each is obtained from estimating stable panel VAR models for cross-sectional resamples of the original dataset (Kilian & Lütkepohl, 2017; Sigmund & Ferstl, 2021).

Figure 4.3: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_3$ and $\mathbf{y}_4$



Source: Authors' own computations.

Note: See Figure 4.2.

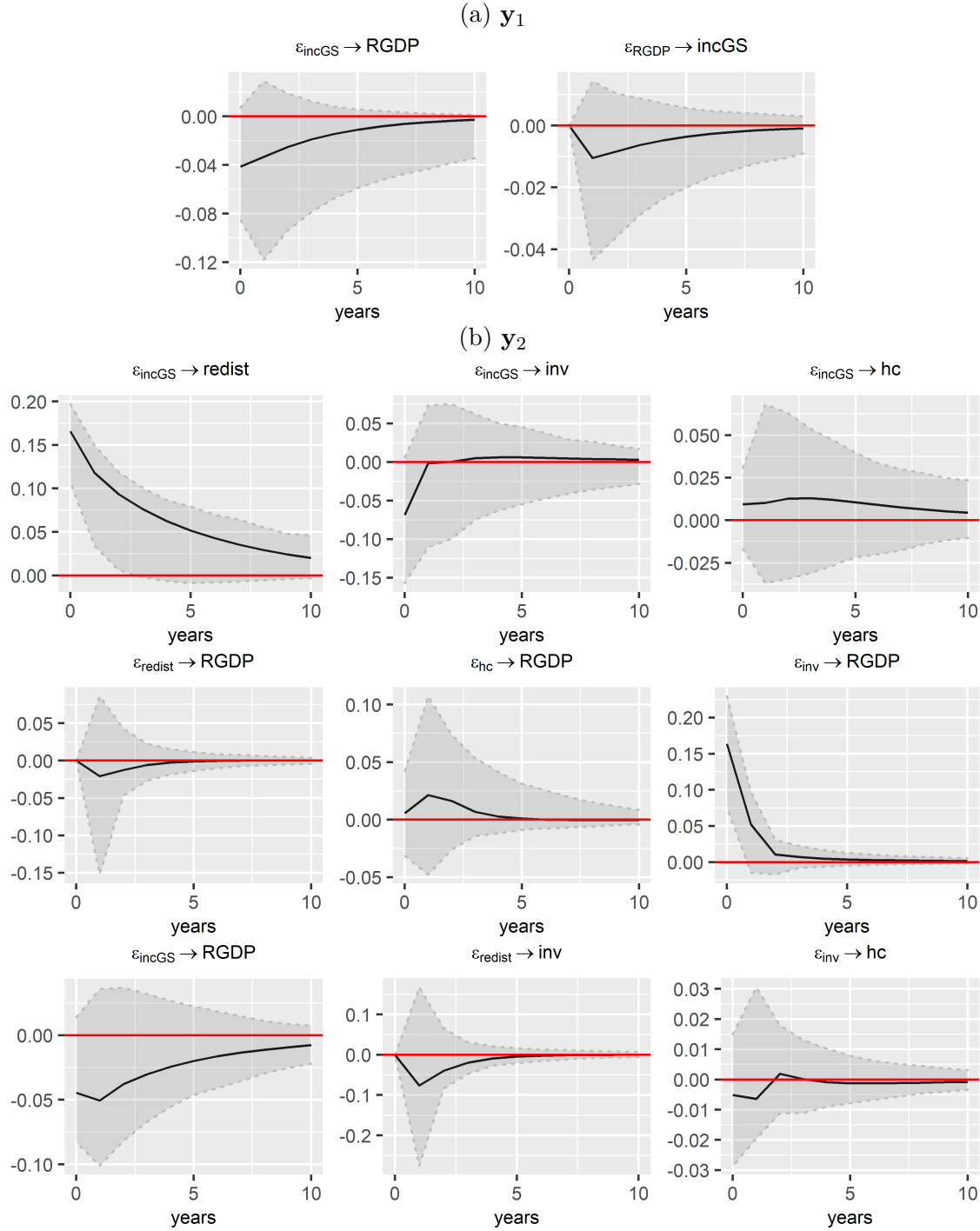
In the literature, there is some evidence that the inequality-growth relationship is non-linear, namely concerning GDP per capita (*e.g.*, Bengoa and Sanchez Robles 2005; Henderson et al. 2015) and of transmission channels potentially being different according to the levels of development (Neves & Silva, 2014). We analyze this possibility in the context of our analysis by following a similar approach to Soava et al. (2020) and conducting the previous analysis within two additional panels comprised of high-GDP and low-GDP countries. These are countries with a GDP time average above and below the pooled GDP average *i.e.*, the average of GDP across time and countries, of the original panel. The list of countries of each group is in the Table of appendix 4.C.¹⁰

We estimate the corresponding panel VAR models with the same lag as before, which we chose based on the same criteria as for the baseline specification, shown in Tables 4.5 and 4.6 of appendix 4.A, respectively. The corresponding OIRF are depicted in Figures 4.4 to 4.7 of appendix 4.C. Overall, the results obtained for both subgroups are qualitatively similar to those concerning the original sample, namely the non-statistically significant impact of inequality and growth on each other and of redistribution on investment and economic growth. However, in high-GDP EU members, a shock of inequality does not have any statistically significant effect on investment, with or without control variables. Nonetheless, in both cases, the confidence interval for contemporaneous responses continues to contain mostly negative values. Moreover, the responses of GDP per capita to redistribution shocks are non-statistically significant in both subgroups, with or without control variables. Nonetheless, in low-GDP EU countries, the confidence intervals of all responses contains mostly positive values.

Therefore, we can draw two conclusions from this analysis. The first is that the negative effects of inequality on investment found in the entire dataset are explained mainly by negative economic impacts of increased disparities in low-GDP EU countries. The second is that these results also suggest the existence of potentially different transmission channels within countries at different stages of development, as suggested in the literature (*e.g.*, Neves & Silva, 2014).

¹⁰We also indicate the accession year of each country to the EU in the same Table. It is apparent that countries belonging to the low-GDP group coincide almost entirely with those that acceded to the European Union during the analysis period. The only exceptions are Portugal and Greece.

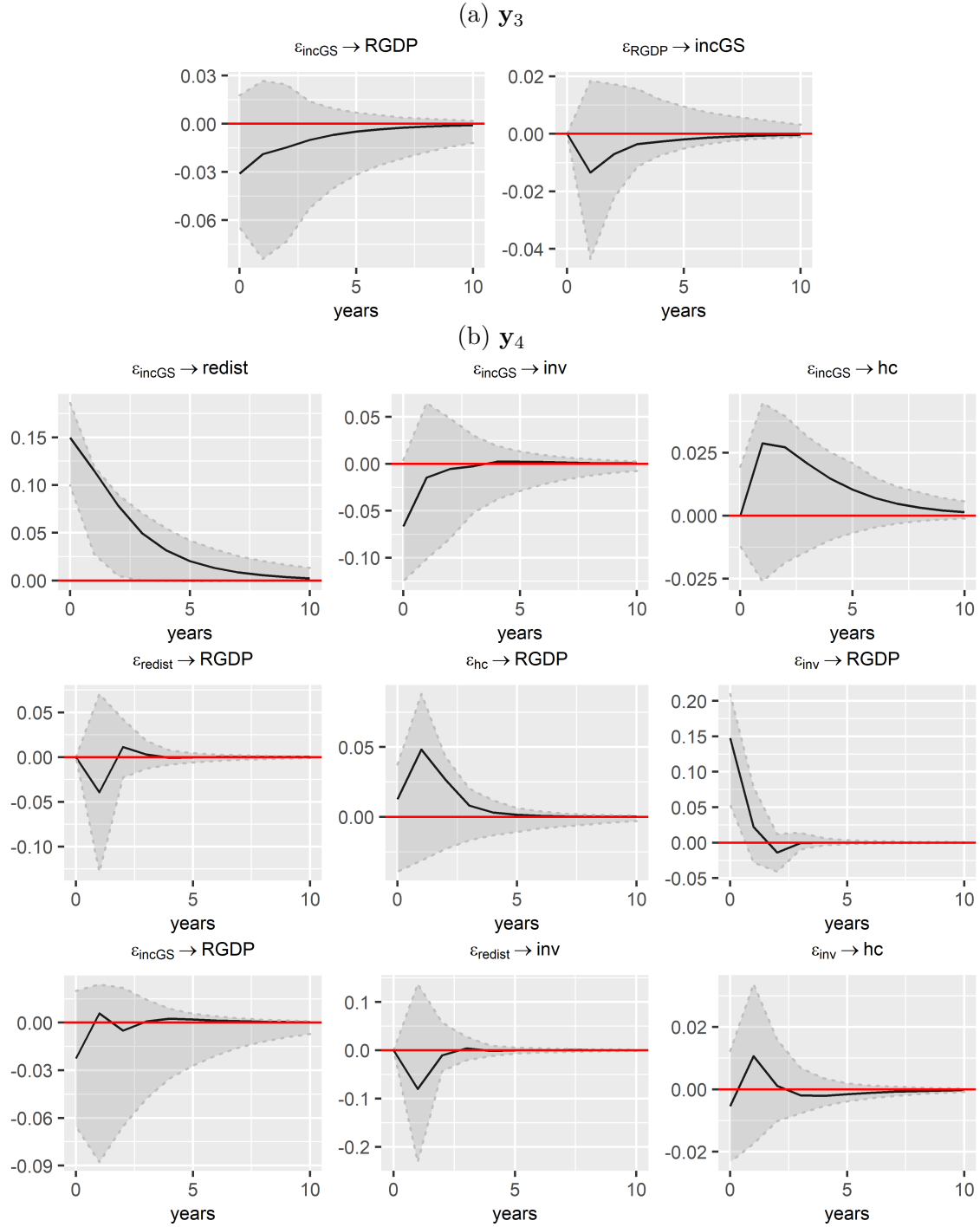
Figure 4.4: Selected orthogonal impulse response functions and 95% standard standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_1$ and $\mathbf{y}_2$ estimated for a panel of EU countries with a GDP time average above the pooled average



Source: Authors' own computations.

Note: See Figure 4.2 and Table 4.9 in appendix 4.C.

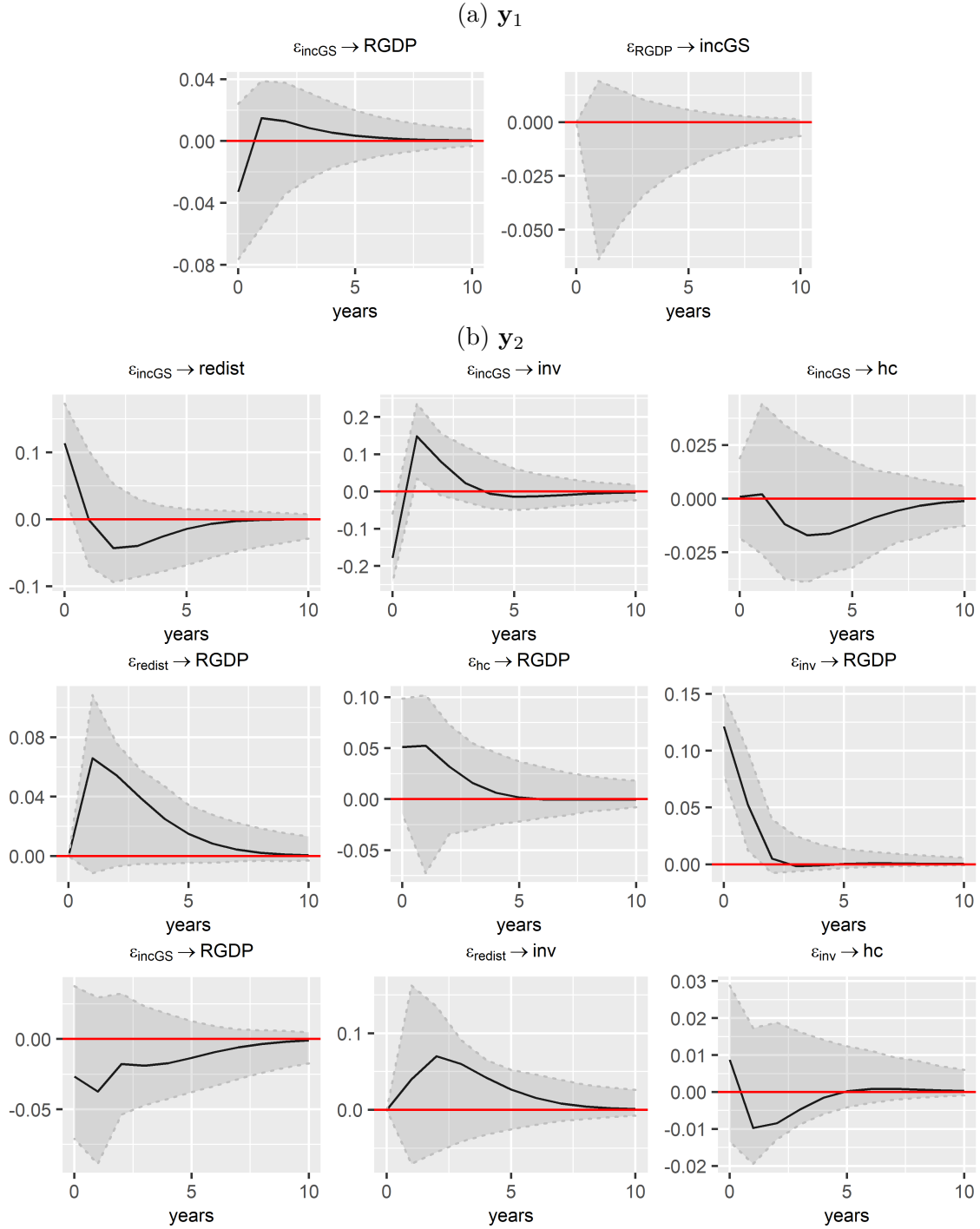
Figure 4.5: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_3$ and $\mathbf{y}_4$ estimated for a panel of EU countries with a GDP time average above the pooled average



Source: Authors' own computations.

Note: See Figure 4.2 and Table 4.9 in appendix 4.C.

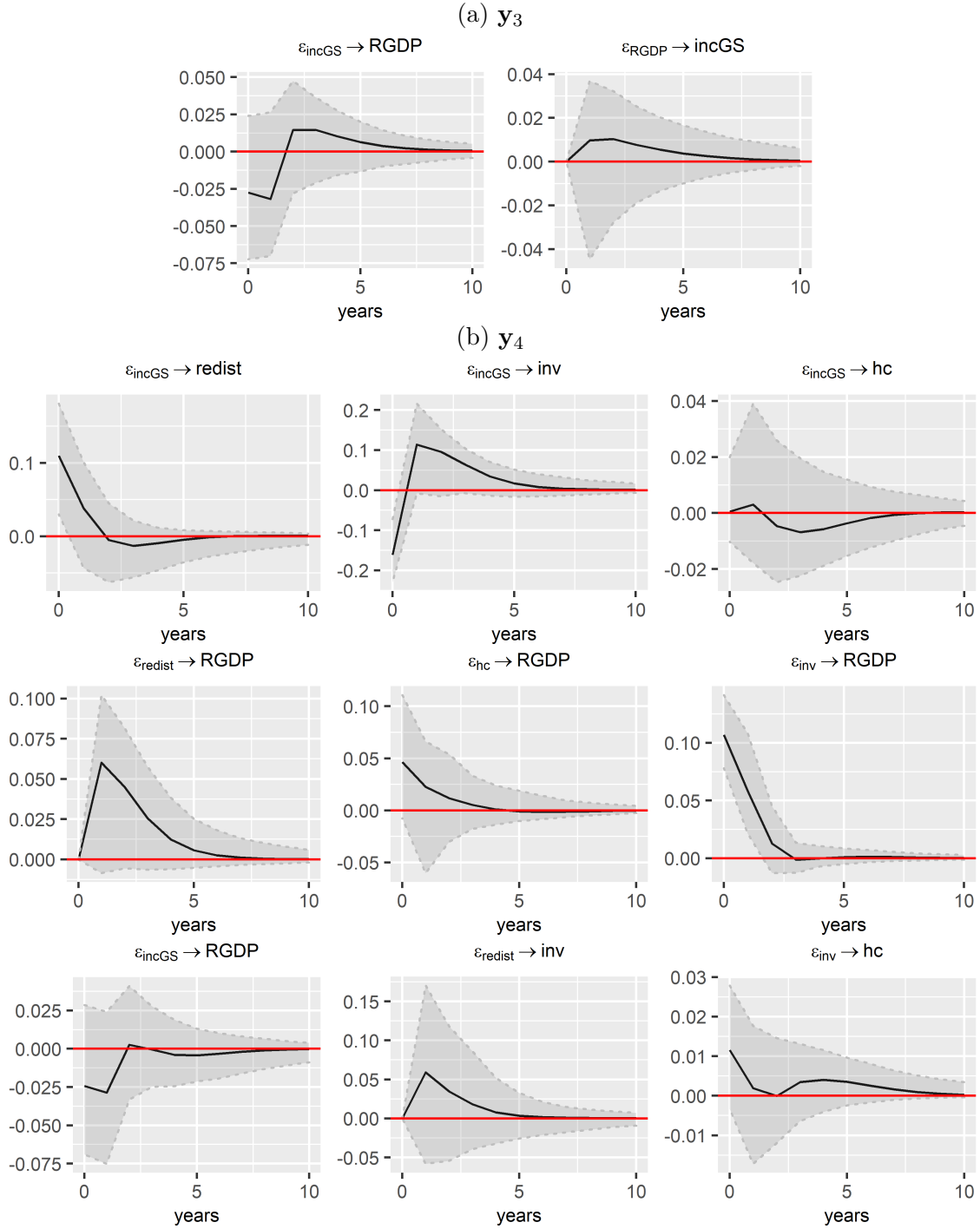
Figure 4.6: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_1$ and $\mathbf{y}_2$ estimated for a panel of EU countries with a GDP time average below the pooled average



Source: Authors' own computations.

Note: See Figure 4.2 and Table 4.9 in appendix 4.C.

Figure 4.7: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_3$ and $\mathbf{y}_4$ estimated for a panel of EU countries with a GDP time average below the pooled average



Source: Authors' own computations.

Note: See Figure 4.2 and Table 4.9 in appendix 4.C.

The period of analysis comprises the global financial crisis of 2007-2008 and the European Sovereign Debt crisis of 2010-2012. They need to be considered to correctly identify the structural shock of inequality since both have contributed to increased inequalities and decreased economic performance during this period. Some variables besides inequality and growth included in the model reflect the specific impact of these events, such as the investment share, which, as shown in Figure 4.1, suffered, on average, a substantial drop following the global crisis. However, it is quite unrealistic to assume that most of the effects of both crises are captured by all variables, especially considering that both crises affected European countries asymmetrically (Lane, 2012).

Bearing this in mind, we define $\mathbf{x}_{i,t} := [D_{CC,i,j}, D_{CA,i,j}]$, where:

$$D_{CC,i,j} := \begin{cases} 1 & \text{if } t = j, j \in t_c, \\ 0 & \text{otherwise,} \end{cases} \quad (4.12)$$

$$D_{CA,i,j} := \begin{cases} 1 & \text{if } t = j, j \in t_c \wedge i \in i_c, \\ 0 & \text{otherwise,} \end{cases} \quad (4.13)$$

where t_c are the crisis years and i_c are the set of economies that were assymmetrically affected by both crisis, which are defined following the literature (*e.g.*, De Marco 2019; Lane 2012). Specifically, we define the former as $t_c = \{2007, 2008, 2009, 2010, 2011, 2012\}$, where we also include a dummy for 2009 for simplicity and because the effects of the global financial crisis were still felt in Europe in this period (Lane, 2012). The latter is defined as $i_c = \{\text{Portugal, Ireland, Italy, Greece and Spain}\}$. These belong to the group of peripheral nations that were disproportionately affected by both crises due to several reasons, namely the severe macroeconomic imbalances at the onset of the financial crisis and the subsequent loss in the ability to repay the financial debt, which led to the necessity of foreign assistance in most.¹¹

We estimate the panel VAR models with these dummy variables with the corresponding OIRF in Figures 4.8 and 4.9 of appendix 4.C. The results are qualitatively similar to those obtained in the baseline specification. However, the positive impact of inequality on investment that was statistically significant without control variables in the baseline specification is now non-statistically significant. Nonetheless, the corresponding confidence intervals for the OIRF after the immediate

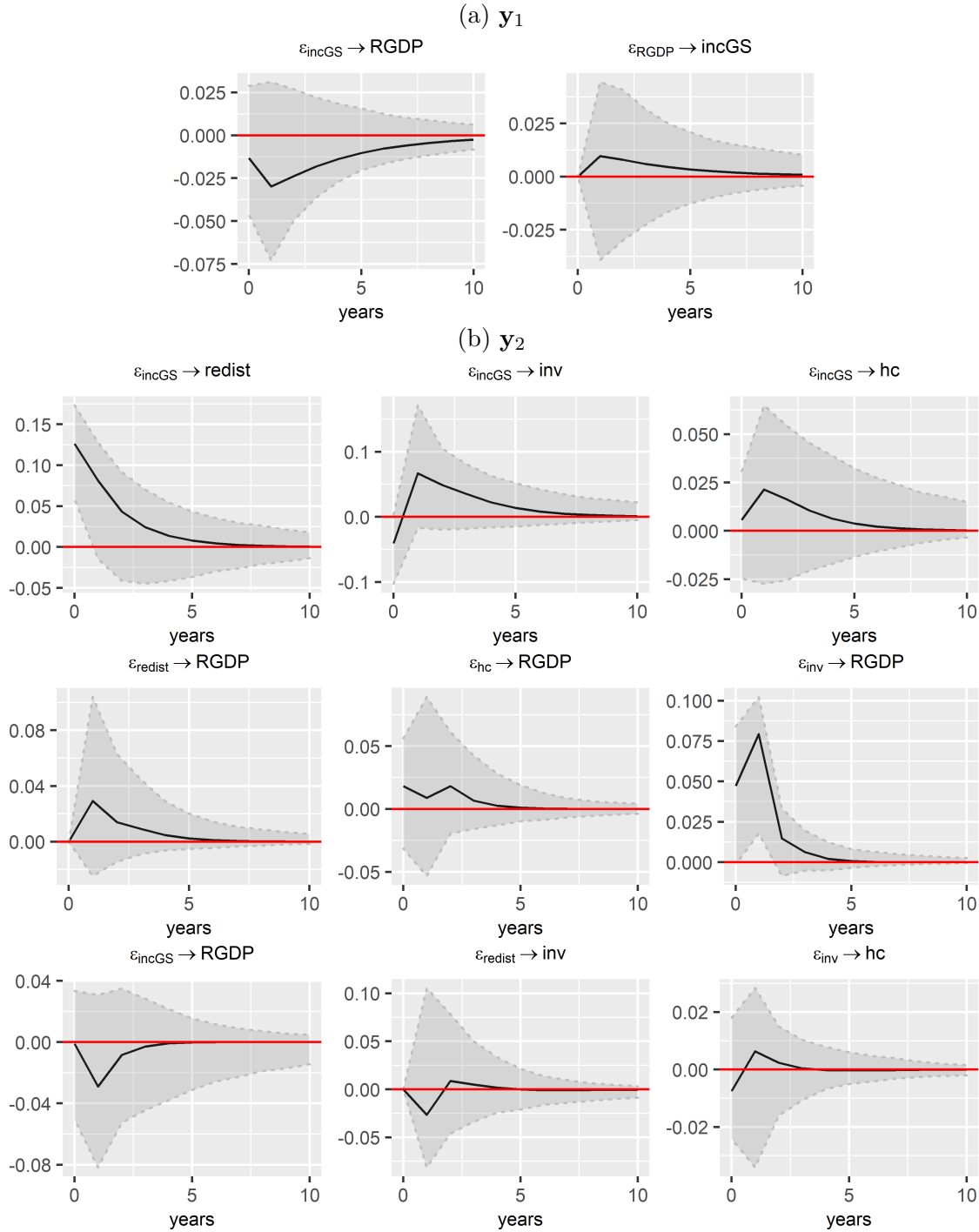
¹¹For more details, see Lane (2012).

short run still contain mostly positive values. This result is expected considering the potential simultaneous impact on inequality and investment of financial crises. However, even when control variables are added, inequality continues to have a statistically significant negative impact on investment.

We further test the robustness of the results to changes in particular estimation and model specifications. In Figures 4.10 and 4.11 of appendix 4.C, we reduce the number of instruments by changing the maximum lag of the instruments of the dependent variables from 6 to 3. Overall the results are similar, with the most important difference being the positive impacts of inequality on investment shortly after the short run becoming non-statistically significant with or without control variables. In Figures 4.12 and 4.13, we conduct the opposite exercise and estimate the model with a maximum lag for the instruments of the dependent variables of 9 instead of 6, which increases the number of instruments. In this case, the results are quite similar to those obtained in the baseline specification. In Figures 4.14 and 4.15, we also estimate the model with a lag order of 2 instead of 1. Despite some changes in the sign of some impulse responses, the overall results are also qualitatively similar to those obtained for the baseline specification. The most significant change is the positive impact of inequality on investment after the immediate short run ceasing to be statistically significant, although the corresponding confidence intervals in this time frame continue to contain mostly positive values.

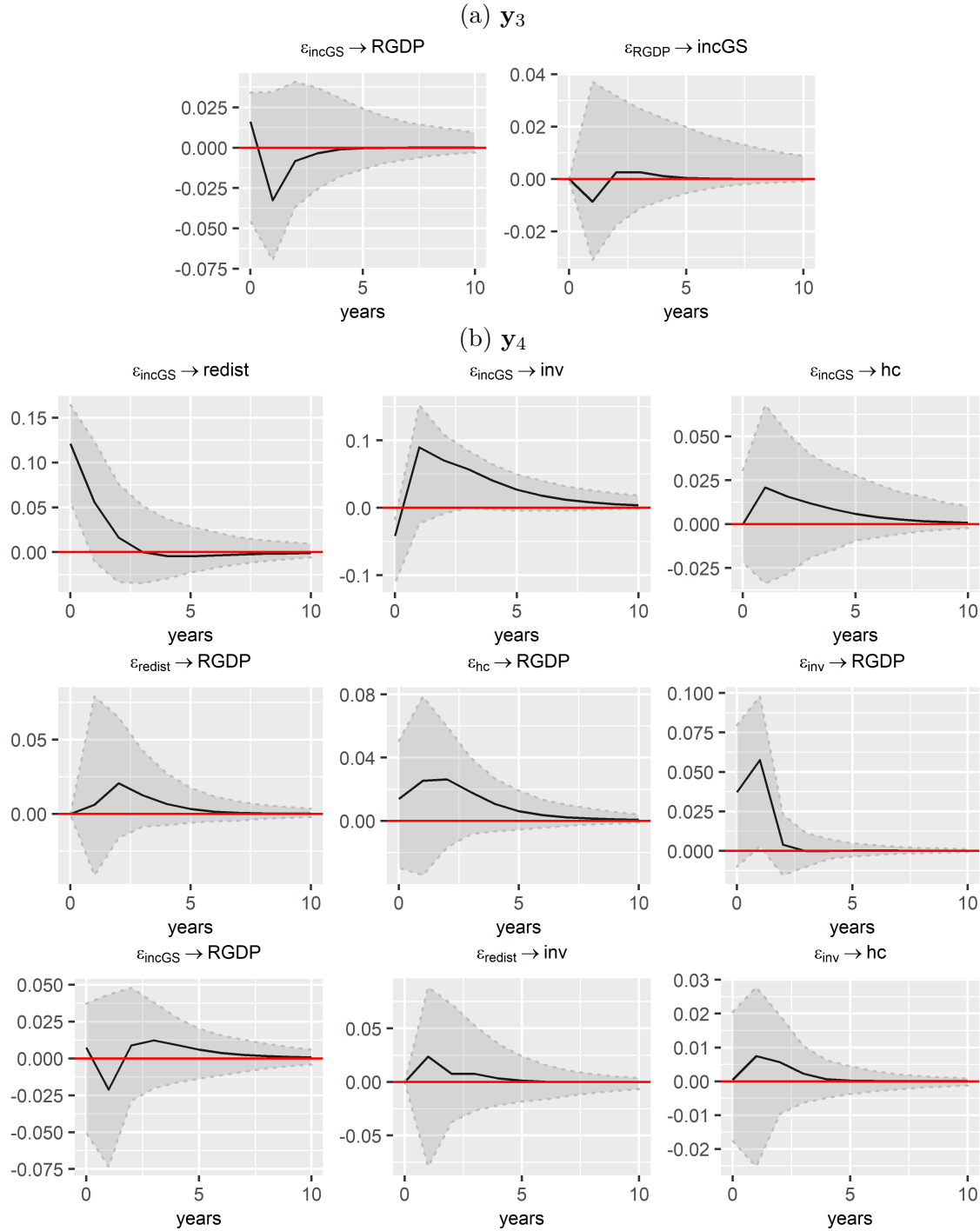
We also test the robustness of the model's results focused on $\mathbf{y}_4$ to changes in assumptions 8 and 9. The first alternative assumption is that human capital can contemporaneously affect investment but not the converse, which is the direct opposite of assumption 9. The latter implied that $\tilde{\mathbf{B}}_{3,2}$ was freely estimated while $\tilde{\mathbf{B}}_{2,3}$ was restricted to zero, while the alternative implies the converse, *i.e.*, $\tilde{\mathbf{B}}_{3,2}$ is restricted to zero, while $\tilde{\mathbf{B}}_{2,3}$ is left unrestricted. The second assumption is that Real GDP per capita can contemporaneously affect human capital and investment but not the converse, which, similarly, is the opposite of assumption 8. Since the latter implied that $\tilde{\mathbf{B}}_{4,2}$ and $\tilde{\mathbf{B}}_{4,3}$ were unrestricted and that $\tilde{\mathbf{B}}_{2,4}$ and $\tilde{\mathbf{B}}_{3,4}$ were restricted to 0, the alternative implies letting $\tilde{\mathbf{B}}_{4,2}$ and $\tilde{\mathbf{B}}_{4,3}$ be freely estimated, and restricting $\tilde{\mathbf{B}}_{2,4}$ and $\tilde{\mathbf{B}}_{2,3}$ to 0 to achieve identification. The results are in Figures 4.16 and 4.17 of appendix 4.C, respectively, and in both there is no noticeable difference concerning the main results obtained with the original assumptions.

Figure 4.8: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR models of $\mathbf{y}_1$ and $\mathbf{y}_2$ with dummies to account for common and specific effects on European peripheral nations of the global financial crisis of 2007-2008 and the European Sovereign Debt Crisis of 2010-2011



Source: Authors' own computations.
Note: See Figure 4.2.

Figure 4.9: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR models of $\mathbf{y}_3$ and $\mathbf{y}_4$ with dummies to account for common and specific effects on European peripheral nations of the global financial crisis of 2007-2008 and the European Sovereign Debt Crisis of 2010-2011



4.5 Concluding Remarks

In this paper, we analyze the inequality-growth relationship and its transmission channels in the European Union countries during 2001-2019 in the context of a structural Panel VAR model. In doing so, we provide a valuable contribution to the empirical literature for two reasons: First, the use of a panel VAR model instead of the usual panel Data models allows us to obtain more information concerning the relationships between the variables of interest by also considering contemporaneous effects. Moreover, it also permits obtaining more precise results by explicitly modeling the lagged dynamics of all endogenous variables. Second, our focus avoids some of the pitfalls of choosing panels with heterogeneous countries, namely data harmonization problems and difficulties in reaching useful conclusions for the design of policies that are adequate to suit the very different institutional backgrounds of such economies. Moreover, we also innovate in relation to similar works by accounting for variables that can potentially affect both inequality and growth, which is essential for an appropriate identification of structural disturbances of the former. Finally, we focus on countries of the European Union, which have been seldom analyzed in what concerns this issue despite its importance considering the positive developments in within-country inequality trends that have characterized these economies in more recent years.

Our results indicate that inequality has a non-statistically significant impact on economic growth. However, the inclusion of transmission variables shows a statistically significant negative contemporaneous effect on investment, a positive impact on redistribution, and no statistically significant impact on human capital accumulation. Moreover, only investment was found to have a statistically significant positive effect on growth, with the remaining transmission variables, redistribution and human capital, not having any effect. Finally, redistribution also does not affect investment or human capital. In an analysis divided by subgroups of EU countries with higher and lower than average GDP per capita, we find that these effects are more prevalent in the latter. Overall, these results are robust to the addition of control variables that can potentially affect inequality and growth, to the inclusion of dummy variables to account for the effect of the global financial and European Sovereign Debt crises, to different specifications of the model concerning the number of instruments for the dependent variables and the lag order, and also to alternative identification assumptions of structural shocks. Nonetheless, we also obtained other

results that were not robust to the inclusion of these variables, namely a positive impact of inequality in investment in the medium run. This implies that some effects found without control variables are caused by the simultaneous impact of shocks of these variables on the models, which highlights the importance of considering them in these analyses.

These findings stand in contrast with those obtained by some existing works, which posit negative effects of inequality in the long run and positive in the short run (*e.g.*, Halter et al., 2014), and also the existing theoretical channels, which only predict impacts mainly in the long run. We conclude that inequality has complex effects on economic growth that the existing theoretical frameworks cannot adequately explain. Moreover, empirically, many relevant effects appear to occur contemporaneously, highlighting the importance of our approach, which explicitly considers relationships in such time horizon, to detect such effects.

Our work has limitations. These include the lack of alternative measures of the variables of interest and the potential impact on the results of some model and estimation specifications set by the researcher. Nonetheless, these do not jeopardize the validity of our results. In what concerns the first aspect, the measures we consider are commonly used by empirical works focused on the inequality-growth relationship (*e.g.*, Gründler & Scheuermeyer, 2018), which facilitates the comparison of the results. Regarding the second aspect, we have shown that we still arrive at the main results using a different lag order, number of instruments or alternative identification assumptions.

Finally, our paper has important implications for European policymakers, who could further enact more robust redistribution policies to decrease the adverse effects of inequality without risking negative repercussions on the economic performance of European economies. Moreover, in this regard, they could strive to directly bend market inequality through adequate economic reforms of each country's labor market, especially in laggard economies. There are also important new venues to explore through future research. First, more updated studies on the inequality-growth relationship using a similar structural panel VAR approach should be conducted in other groups of countries that are also relatively homogeneous, such as Latin America or Asia. Second, future research should explore the impact of considering not only different measures of inequality but also different sources, which is possible thanks to the emergence of other databases, such as the World Inequality Database (Alvaredo et al., 2016). Third, future time series studies could explore more sophisticated

approaches to identify the shock of inequality in a manner that addresses the issue of simultaneity. This could be accomplished, for example, by developing theoretical models that establish the determinants of inequality, estimating such models, using them to produce an instrument for a shock of inequality orthogonal to such variables, and analyzing its impacts on economic growth. Another possibility is identifying the parameters of the structural impact matrix using a sign restriction approach, where sign restrictions are imposed on some coefficients.

4.A Lag selection and stability condition

Table 4.4: Andrews and Lu (2001) Moment and Model selection criteria (MMSC) and stability condition of panel VAR models estimated with the baseline specification for several lag orders

(a) y_1							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-98.671*	-53.033*	6	0.677	22.697	20	0.304
2	-74.567	-38.730	6	0.497	21.495	16	0.160
3	-54.095	-27.754	6	0.611	17.123	12	0.145
4	-28.542	-11.362	6	0.732	18.345	8	0.019

(b) y_2							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-757.764*	-472.524*	6	0.625	0.790	125	1.000
2	-599.863	-375.880	6	0.851	0.526	100	1.000
3	-444.732	-280.098	6	0.705	0.385	75	1.000
4	-292.901	-185.532	6	0.977	0.138	50	1.000

(c) y_3							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-1485.827*	-926.757*	6	0.630	0.938	245	1.000
2	-1175.918	-736.911	6	0.874	0.844	196	1.000
3	-871.235	-548.554	6	0.838	1.194	147	1.000
4	-573.967	-363.523	6	0.855	0.390	98	1.000

(d) y_4							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-2456.779*	-1532.603*	6	0.651	0.933	405	1.000
2	-1944.443	-1218.737	6	0.798	0.817	324	1.000
3	-1441.598	-908.186	6	0.881	0.582	243	1.000
4	-949.083	-601.206	6	0.933	0.364	162	1.000

Source: Authors' own computations.

Note: The vector processes are defined in (4.2) to (4.5). The Sargan-Hansen J-test of overidentification (Hansen, 1982; Sargan, 1958), hereafter Hansen test, evaluates the null hypothesis that the overidentifying restrictions are valid and the corresponding statistic, number of degrees of freedom, and p-value are in the last three columns. The Model and Moment selection criteria introduced by Andrews and Lu (2001) are analogous to the homonymous information criteria used to choose the lag order of VAR models. They penalize model specifications that result in lower values of the Hansen's J-test statistic of over-identifying restriction and benefit those that use more over-identifying restrictions. The parameter $p_{y,max}$ is the maximum lag of the instruments of the dependent variables for each specification. The stability condition, described in Definition 2, is verified if $\max |\lambda| \leq 1$, *i.e.*, if the maximum *modulus* of the eigenvalues λ of the companion matrix of the panel VAR model defined in (4.7) is smaller or equal to 1. The superscript * indicates the optimal lag according to each criterion conditional on the stability condition being satisfied.

Table 4.5: Andrews and Lu (2001) Moment and Model selection criteria (MMSC) and stability condition of the panel VAR models estimated for a panel of EU countries with a GDP time average above the pooled average

(a) $\mathbf{y}_1$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-104.386*	-68.942*	6	0.854	0.764	20	1.000
2	-82.480	-54.742	6	0.684	0.608	16	1.000
3	-60.937	-40.624	6	0.651	0.551	12	1.000
4	-40.217	-27.023	6	0.799	0.182	8	1.000
(b) $\mathbf{y}_2$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-656.472*	-434.944*	6	0.746	0.715	125	1.000
2	-518.806	-345.444	6	0.893	0.490	100	1.000
3	-383.955	-257.002	6	0.958	0.342	75	1.000
4	-252.440	-169.980	6	0.952	0.053	50	1.000
(c) $\mathbf{y}_3$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-1287.170*	-852.976*	6	0.796	0.917	245	1.000
2	-1017.025	-677.235	6	0.644	0.795	196	1.000
3	-752.727	-503.898	6	1.112	0.496	147	1.000
4	-494.647	-333.025	6	1.009	0.239	98	1.000
(d) $\mathbf{y}_4$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-2128.355*	-1410.606*	6	0.716	0.930	405	1.000
2	-1681.803	-1120.110	6	0.610	0.715	324	1.000
3	-1244.688	-833.358	6	0.979	0.436	243	1.000
4	-817.709	-550.539	6	0.927	0.367	162	1.000

Source: Authors' own computations.

Note: See Table 4.4.

Table 4.6: Andrews and Lu (2001) Moment and Model selection criteria (MMSC) and stability condition of the panel VAR models estimated for a panel of EU countries with a GDP time average below the pooled average

(a) $\mathbf{y}_1$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-108.954*	-70.793*	6	0.592	0.658	20	1.000
2	-85.925	-56.030	6	0.405	0.733	16	1.000
3	-64.029	-42.113	6	0.752	0.136	12	1.000
4	-42.144	-27.891	6	0.793	0.040	8	1.000
(b) $\mathbf{y}_2$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-684.376*	-445.867*	6	0.719	0.703	125	1.000
2	-541.050	-354.209	6	0.706	0.560	100	1.000
3	-400.613	-263.637	6	0.922	0.420	75	1.000
4	-263.531	-174.454	6	0.970	0.119	50	1.000
(c) $\mathbf{y}_3$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-1341.846*	-874.368*	6	0.676	0.910	245	1.000
2	-1060.778	-694.569	6	0.853	0.778	196	1.000
3	-784.738	-516.266	6	0.731	1.287	147	1.000
4	-516.516	-341.925	6	0.898	0.238	98	1.000
(d) $\mathbf{y}_4$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-2218.744*	-1445.974*	6	0.692	0.915	405	1.000
2	-1754.022	-1148.657	6	0.835	0.795	324	1.000
3	-1298.873	-855.072	6	1.045	0.474	243	1.000
4	-853.866	-565.257	6	0.871	0.360	162	1.000

Source: Authors' own computations.

Note: See Table 4.4.

Table 4.7: Andrews and Lu (2001) Moment and Model selection criteria (MMSC) and stability condition of the panel VAR models estimated for a panel of EU countries with a GDP time average below the pooled average

(a) $\mathbf{y}_1$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-266.731*	-166.326*	6	0.728	0.280	44	1.000
2	-239.809	-150.216	6	0.518	0.346	40	1.000
3	-213.383	-134.359	6	0.614	0.273	36	1.000
4	-187.503	-118.787	6	0.792	0.042	32	1.000
(b) $\mathbf{y}_2$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-1122.223*	-700.068*	6	0.646	0.436	185	1.000
2	-959.311	-600.938	6	0.481	1.311	160	1.000
3	-801.050	-504.710	6	0.735	0.160	135	1.000
4	-644.637	-408.425	6	0.858	0.049	110	1.000
(c) $\mathbf{y}_3$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-1995.761*	-1245.010*	6	0.650	0.751	329	1.000
2	-1680.546	-1053.393	6	0.771	0.542	280	1.000
3	-1370.403	-863.333	6	0.862	0.557	231	1.000
4	-1065.271	-674.446	6	0.838	1.392	182	1.000
(d) $\mathbf{y}_4$							
Lag	MMSC		$p_{y,max}$	Max $ \lambda $	Hansen's J-test		
	BIC	HQIC			stat	df	p-value
1	-3112.356*	-1941.733*	6	0.523	0.746	513	1.000
2	-2589.049	-1621.442	6	0.611	4.630	432	1.000
3	-2081.694	-1311.210	6	0.788	1.454	351	1.000
4	-1582.130	-1002.334	6	0.846	0.283	270	1.000

Source: Authors' own computations.

Note: See Table 4.4.

4.B Panel VAR estimation details

The Method of moments implies considering the following set of L moment conditions:

$$\mathbb{E}[\mathbf{g}_i(\Phi)] = \mathbf{0}_{L \times 1}, \quad (4.14)$$

where $\mathbb{E}$ is the expected value operator. The objective is to find an estimate of Φ that results in the corresponding sample moments $\mathbf{g} = \frac{1}{N} \sum_{i=1}^N \mathbf{g}_i$, with $\mathbf{g}_i$ defined further ahead, being as close to zero as possible. The Generalized method of moments allows L to be greater than the number of parameters to estimate and the corresponding procedure implies minimizing the following value function:

$$\Pi(\Phi) := \mathbf{g}(\Phi) \Lambda^{-1} \mathbf{g}'(\Phi), \quad (4.15)$$

where Λ is the inverse of the weighting matrix, which will also be defined further ahead. In the case of the estimation of a panel VAR model, $\mathbf{g}_i(\Phi)$ takes the following form:

$$\mathbf{g}_i(\Phi) := (\mathbf{I}_M \otimes \mathbf{Q}_i^+) \text{vec}(\tilde{\mathbf{U}}_i), \quad (4.16)$$

$$\tilde{\mathbf{U}}_i := [(\Delta^* \mathbf{U}_i)', \mathbf{U}_i']', \quad (4.17)$$

where $\otimes$ is the Kronecker product, $\mathbf{Q}_i^+$ is a matrix of instruments, vec is the column stacking operator and $\mathbf{U}_i := [\boldsymbol{\mu}_i + \mathbf{v}_{i,p+1}, \dots, \boldsymbol{\mu}_i + \mathbf{v}_{i,T}]'$ is obtained by considering the following stacked representation of (4.1) over t ,

$$\mathbf{Y}_{i,0} = \mathbf{W}_i \Phi + \mathbf{U}_i, \quad (4.18)$$

$$\mathbf{Y}_{i,l} := [\mathbf{y}_{i,p+1-l}, \dots, \mathbf{y}_{i,T-l}]', \quad (4.19)$$

$$\mathbf{W}_i := [\mathbf{1}, \mathbf{Y}_{i,1}, \dots, \mathbf{Y}_{i,p}, \mathbf{X}_i], \quad (4.20)$$

$$\mathbf{X}_i := [\mathbf{x}_{i,p+1}, \dots, \mathbf{x}_{i,T}]', \quad (4.21)$$

where $\mathbf{1}$ is a vector of ones. Similarly, $\Delta^* \mathbf{U}_i := [\dots, \Delta^* \mathbf{v}_{i,t \in \mathbb{T}(\Delta^* \mathbf{v})}, \dots]'$ is obtained by considering the analogous stacked representation over t of (4.6), where $\mathbb{T}(\Delta^* \mathbf{v}) = \{p+2, \dots, T\}$ is the set of periods for which $\Delta^* \mathbf{v}_{i,t}$ is defined, considering that $\Delta^* = \Delta$.

The Panel VAR System GMM estimator is then as follows:

$$\text{vec}(\hat{\Phi}_{SGMM}) = [(\mathbf{I}_M \otimes \mathbf{S}'_{QW}) \Lambda^{-1} (\mathbf{I}_M \otimes \mathbf{S}_{QW})]^{-1} (\mathbf{I}_M \otimes \mathbf{S}'_{QW}) \Lambda^{-1} \text{vec}(\mathbf{S}_{Qy}), \quad (4.22)$$

where

$$\mathbf{S}_{QW} := N^{-1} \sum_{i=1}^N \mathbf{Q}_i^+ \tilde{\mathbf{W}}_i, \quad (4.23)$$

$$\mathbf{S}_{Qy} := N^{-1} \sum_{i=1}^N \mathbf{Q}_i^+ \tilde{\mathbf{Y}}_i, \quad (4.24)$$

with $\tilde{\mathbf{W}}_i := [(\Delta^* \mathbf{W}_i)', \mathbf{W}_i']'$ and $\tilde{\mathbf{Y}}_i := [(\Delta^* \mathbf{Y}_i)', \mathbf{Y}_i']'$. The one-step estimator $\hat{\Phi}_{SGMM,1S}$ considers the weighting matrix $\mathbf{\Lambda} = \mathbf{\Lambda}_{1S}$, where:

$$\mathbf{\Lambda}_{1S} := \mathbf{I}_M \otimes (N^{-1} \sum_{i=1}^N \mathbf{Q}_i^+ \mathbf{D}^+ (\mathbf{D}^+)' (\mathbf{Q}_i^+)', \quad (4.25)$$

$$\mathbf{D}^+ := [\mathbf{D}'_{(T-p-1) \times (T-p)}, \mathbf{I}_{T-p}]', \quad (4.26)$$

$$\mathbf{D}_{(T-p-1) \times (T-p)} := \begin{bmatrix} -1 & 1 & 0 & 0 & \dots & 0 \\ 0 & -1 & 1 & 0 & \dots & 0 \\ 0 & 0 & \ddots & \vdots & \dots & 0 \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \dots & \dots & -1 & 1 \end{bmatrix}. \quad (4.27)$$

The two-step estimator, which is asymptotically more efficient than the one-step estimator (Sigmund & Ferstl, 2021), considers alternatively $\mathbf{\Lambda} = \mathbf{\Lambda}_{2S}$, where $\mathbf{\Lambda}_{2S}$ is the variance-covariance matrix of the sample moments conditions, *i.e.*:

$$\mathbf{\Lambda}_{2S} := N^{-1} \sum_{i=1}^N \hat{\mathbf{g}}_i \hat{\mathbf{g}}_i' = N^{-1} \hat{\mathbf{G}} \hat{\mathbf{G}}', \quad (4.28)$$

where $\hat{\mathbf{G}} := [\hat{\mathbf{g}}_1, \dots, \hat{\mathbf{g}}_N]$, and $\hat{\mathbf{g}}_i = \mathbf{g}_i(\hat{\Phi}_{SGMM,1S})$. The System GMM moment conditions (Blundell & Bond, 1998) consists of two sets corresponding to the moment conditions necessary to estimate the system of equations (4.1) and (4.6). The set corresponding to equation (4.6) is the set of Difference moment conditions defined in the following manner:

$$\mathbb{E}[\Delta^* \mathbf{v}_{i,t} \mathbf{y}'_{i,t-j}] = \mathbf{0}, j \in \{p_{y,min}, \dots, \max(t-1, p_{y,max})\}, t \in \mathbb{T}(\Delta^* \mathbf{v}), \quad (4.29)$$

$$\mathbb{E}[\Delta^* \mathbf{v}_{i,t} (\Delta^* \mathbf{x}_{i,t})'] = \mathbf{0}, t \in \mathbb{T}(\Delta^* \mathbf{v}), \quad (4.30)$$

where $p_{y,min}$ and $p_{y,max}$ are, respectively, the minimum and maximum lag of the first difference instruments for the dependent variable such that $p_{y,max} \geq p_{y,min} \geq 2$.

The second set corresponding to equation (4.1), is defined as follows:

$$\mathbb{E}[(\mathbf{v}_{i,t} + \boldsymbol{\mu}_i)(\Delta^* \mathbf{y}_{t-1})'] = \mathbf{0}, t \in \{\max(3, p+1), \dots, T\}, \quad (4.31)$$

$$\mathbb{E}[(\mathbf{v}_{i,t} + \boldsymbol{\mu}_i) \mathbf{x}_t'] = \mathbf{0}, t \in \{p+1, \dots, T\}, \quad (4.32)$$

$$\mathbb{E}[\mathbf{v}_{i,t} + \boldsymbol{\mu}_i] = \mathbf{0}, t \in \{p+1, \dots, T\}. \quad (4.33)$$

Each moment condition consists of an orthogonality condition that defines an instrument and, therefore, the greater the number of moment conditions, the greater the number of instruments. This can lead to certain problems, as described in detail in Roodman (2009), such as overfitting and loss of precision. To address this issue, we consider the approach proposed by the latter to reduce the number of instruments, which consists of defining the moment conditions concerning a cross-sectional unit i based on the expected value over all time periods for which there are observations.

In the case of the Difference moment conditions, the corresponding collapsed versions are as follows:

$$\mathbb{E}[\sum_{t \in \mathbb{T}(\Delta^* \mathbf{v})} \Delta^* \mathbf{v}_{i,t} \mathbf{y}_{i,t-j}'] = \mathbf{0}, j \in \{p_{y,min}, \dots, \max(t-1, p_{y,max})\}, \quad (4.34)$$

$$\mathbb{E}[\sum_{t \in \mathbb{T}(\Delta^* \mathbf{v})} \Delta^* \mathbf{v}_{i,t} (\Delta^* \mathbf{x}_{i,t})'] = \mathbf{0}, \quad (4.35)$$

The collapsed version of the second set of moment conditions is the following:

$$\mathbb{E}[\sum_{t=\max(3,p+1)}^T (\mathbf{v}_{i,t} + \boldsymbol{\mu}_i)(\Delta^* \mathbf{y}_{t-1})'] = \mathbf{0}, \quad (4.36)$$

$$\mathbb{E}[\sum_{t=p+1}^T (\mathbf{v}_{i,t} + \boldsymbol{\mu}_i) \mathbf{x}_t'] = \mathbf{0}, \quad (4.37)$$

$$\mathbb{E}[\sum_{t=p+1}^T (\mathbf{v}_{i,t} + \boldsymbol{\mu}_i)] = \mathbf{0}. \quad (4.38)$$

From here, the matrix $\mathbf{Q}_i^+$ can be defined in the following manner:

$$\mathbf{Q}_i^+ := \begin{bmatrix} \mathbf{Q}_{FD,i}^{col} & \mathbf{0} \\ \mathbf{0} & \mathbf{Q}_{S,i}^{col} \end{bmatrix}, \quad (4.39)$$

$$\mathbf{Q}_{FD,i}^{col} := \begin{bmatrix} \mathbf{Q}_{FD,i,y,p+2}^{col} & \mathbf{Q}_{FD,i,y,p+3}^{col} & \cdots & \mathbf{Q}_{FD,i,y,T}^{col} \\ \Delta^* \mathbf{x}_{i,p+2} & \Delta^* \mathbf{x}_{i,p+3} & \cdots & \Delta^* \mathbf{x}_{i,T} \end{bmatrix}, \quad (4.40)$$

$$\mathbf{Q}_{FD,i,y,t}^{col} := \begin{cases} \mathbf{0} & \text{if } p_{y,min} > t - 1, \\ \mathbf{q}_{FD,i,y,t} & \text{if } p_{y,min} \leq t - 1 \wedge p_{y,max} \geq t - 1, \\ [\mathbf{q}'_{FD,i,y,t}, \mathbf{0}]' & \text{if } p_{y,min} \leq t - 1 \wedge p_{y,max} < t - 1, \end{cases} \quad (4.41)$$

$$\mathbf{q}_{FD,i,y,t} := [\mathbf{y}'_{i,t-p_{y,min}}, \dots, \mathbf{y}'_{i,\max(1,t-p_{y,max})}]', \quad (4.42)$$

$$\mathbf{Q}_{S,i}^{col} := \begin{bmatrix} \mathbf{Q}_{S,i,y,p+1}^{col} & \mathbf{Q}_{S,i,y,p+2}^{col} & \cdots & \mathbf{Q}_{S,i,y,T}^{col} \\ \mathbf{x}_{i,p+1} & \mathbf{x}_{i,p+2} & \cdots & \mathbf{x}_{i,T} \\ 1 & 1 & \cdots & 1 \end{bmatrix}, \quad (4.43)$$

$$\mathbf{Q}_{S,i,y,t}^{col} := \begin{cases} \mathbf{0} & \text{if } t = p + 1 \wedge p = 1, \\ \Delta^* \mathbf{y}_{i,t-1} & \text{if } t > p + 1 \vee p > 1. \end{cases} \quad (4.44)$$

The dimensions of $\mathbf{G}$ are $L \times N$ and, therefore, the dimensions and rank of the covariance matrix $\mathbf{\Lambda}_{2S}$ are, respectively, $L \times L$ and $\min(L, N)$. It is expected that the total number of moment conditions L is greater than the number of units N , implying that $\mathbf{\Lambda}_{2S}$ is singular since its rank is $N < L$. This issue is usually addressed by applying the Moore-Penrose generalized inverse but Xiao (2020) highlights that such a procedure can introduce significant biases and instability in the resulting estimates. He suggests an alternative for obtaining the inverse that consists of introducing randomly generated noises to make the weighting matrix invertible. In this paper, we design an approach based on the one proposed by the author for inverting the two-step weighting matrix, where additional moment conditions are simulated until the weighting matrix is non-singular. Specifically, it consists in the following recursive algorithm at each iteration $a \geq 1$, with $\mathbf{G}_0 = \mathbf{G}$ and $\mathbf{\Lambda}_a^\dagger = \mathbf{\Lambda}_{2S}^\dagger$:

1. Define a matrix $\mathbf{H}_a$ whose elements are i.i.d. disturbances from the standard normal distribution with dimensions $L \times (L - N)$;
2. Define $\mathbf{G}_a = [\mathbf{G}_{a-1}, \mathbf{H}_a]$, and calculate $\mathbf{\Lambda}_a^\dagger = N_a^{-1} \mathbf{G}_a \mathbf{G}_a'$, where $N_a = N + a \cdot (L - N)$;

3. If $\mathbf{\Lambda}_a^\dagger$ is of full rank, replace $\mathbf{\Lambda}_{2S}^\dagger$ with $\mathbf{\Lambda}_a^\dagger$. Otherwise, repeat the algorithm.

To illustrate the relevance of this methodological approach to the analysis we perform, we conducted 20000 Monte Carlo simulations of panel data with $M = 2$ and the same dimensions as our baseline dataset, *i.e.*, $N = 27$ and $T = 18$, generated by stable panel VAR models of order 1. We estimated each model using the two different approaches to invert the weighting matrix, random noise procedure (RN) and the generalized inverse (GI). We then determined the precision of each of these estimates by obtaining the mean (MSE), minimum and maximum of its squared error, which is the squared difference between them and the real coefficients used to simulate the data. We determined the relative efficiency of each one by calculating the percentage of simulations where the corresponding procedure resulted in coefficient estimates with a smaller MSE than the alternative. We also obtained the mean, minimum and maximum of the standard deviation of the coefficient estimates across the simulations.

The results are in Table 4.8 and clearly show that the RN procedure leads to more precise estimates, on average, than the GI. Approximately 57% of the simulations using the former resulted in a smaller MSE and, on average, the mean, minimum and maximum squared error of the estimates across the simulations are all smaller using the RN procedure. We also obtain, on average, coefficient estimates with a lower standard deviation, as shown by its lower mean and minimum in relation to the one obtained with GI, although the maximum value is slightly higher using the latter.

Table 4.8: Results of 20000 Monte Carlo simulations of stable panel VAR models

		RN	GI
SE	mean	0.3341	0.3398
	min	0.0005	0.0014
	max	1.6278	1.6506
	Rel. ef.	57.12 %	42.88 %
Std. dev.	mean	1.4814	1.5121
	min	0.0254	0.1189
	max	2.7647	2.7618

Source: Authors's own calculations.

Note: In each Monte Carlo simulation, we generated a dataset with two endogenous variables and the same number of units and periods as the one we analyze in this essay. To do so, we considered a Data Generating Process (DGP) consisting of a panel VAR model as defined in equation (4.1) with a lag order of 1. The relevant elements were obtained in the following way: (i) the vector of constants $\tilde{\boldsymbol{\eta}}$ was obtained from the standardized normal distribution; (ii) the coefficients of the lag terms $\tilde{\boldsymbol{\Phi}}_1$ were obtained from the first M rows of a simulated companion matrix $\tilde{\boldsymbol{\Phi}}_{comp}$, which, in turn, was simulated using $M \times p$ eigenvalues from a uniform distribution between 0.2 and 0.5. This interval was defined to satisfy the stability condition described in Definition 2; (iii) each vector of residuals $\tilde{\mathbf{v}}_{i,t}$ was obtained from the standardized normal distribution (iv) no fixed effects were considered for simplification. Then in each simulation, we obtained two estimates $\hat{\boldsymbol{\Phi}} = [\hat{\boldsymbol{\eta}}, \hat{\boldsymbol{\Phi}}_1]$ of the coefficients of the panel VAR model in a manner that differed only in the method used to obtain the weighting matrix, which consisted in using the Moore-Penrose generalized inverse in one case and the random noise procedure described in the text in the other. If the stability condition did not hold for one, we excluded all estimates and repeated the previous simulation and estimation procedure until both estimated panel VAR models were stable. Then finally, for each one, we calculated the squared error (SE), defined as $SE = (\hat{\boldsymbol{\Phi}} - \tilde{\boldsymbol{\Phi}})^2$, where $\tilde{\boldsymbol{\Phi}} = [\tilde{\boldsymbol{\eta}}, \tilde{\boldsymbol{\Phi}}_1]$, and obtained its mean (MSE), minimum and maximum. The column “Rel. ef.” represents the share of simulations in which the corresponding procedure resulted in coefficient estimates with a smaller MSE than the alternative. We also calculated the standard deviation of the coefficient estimates obtained with each procedure, and, similarly, obtained its mean, minimum and maximum across the simulations.

4.C Robustness checks Tables and Figures

Table 4.9: List of 27 member countries of the European Union (as of 2021) with a time average Real GDP per capita below and above the pooled average and the corresponding accession year

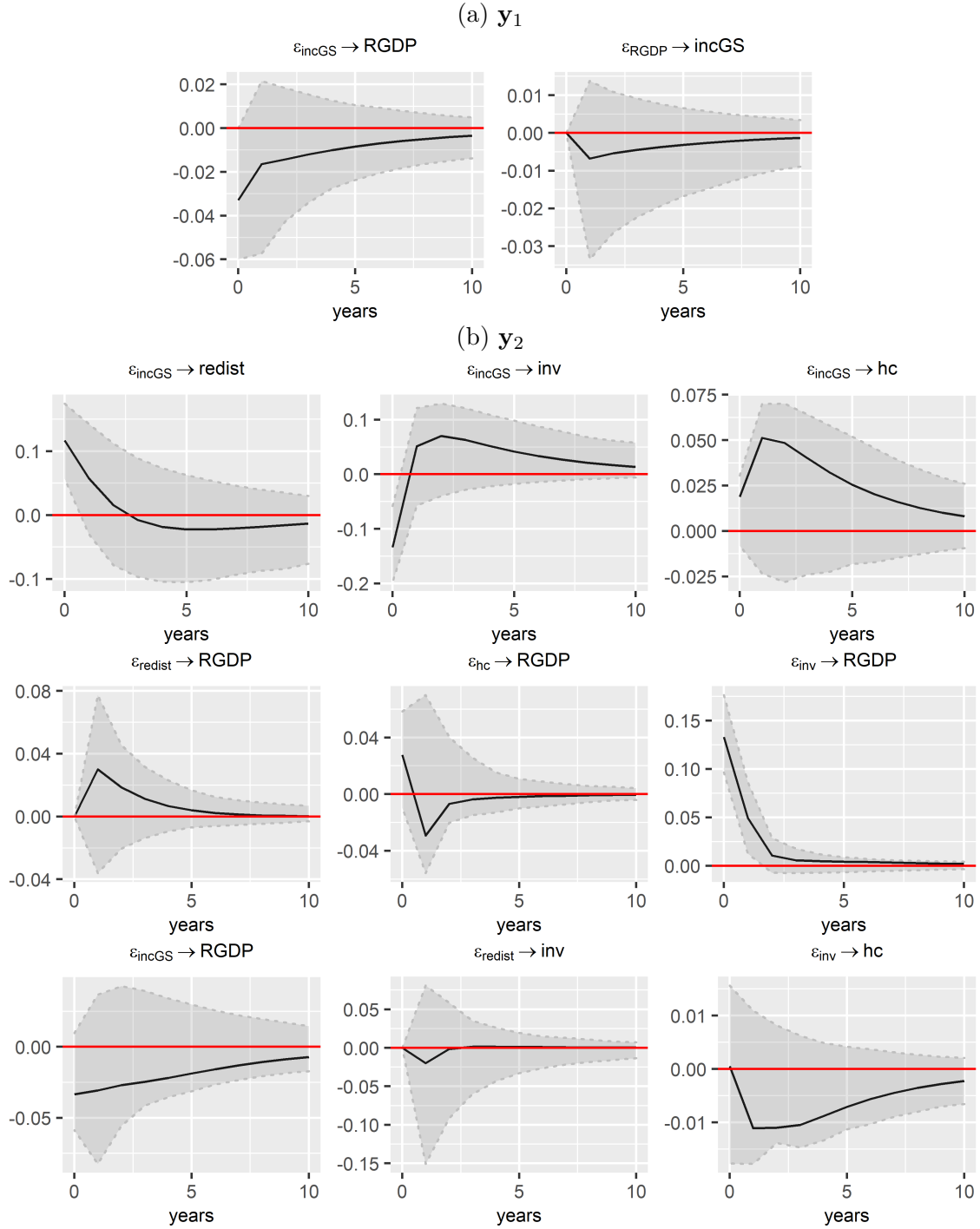
(a) High-GDP countries			(b) Low-GDP countries		
Country	Time average of Real GDP per capita	Accession year to the European Union	Country	Time average of Real GDP per capita	Accession year to the European Union
Austria	43151	1995	Bulgaria	14188	2007
Belgium	38987	1958	Croatia	18768	2013
Denmark	43338	1973	Cyprus	28302	2004
Finland	39372	1995	Czech Republic	28284	2004
France	37527	1958	Estonia	21529	2004
Germany	42816	1958	Greece	26858	1981
Ireland	55037	1973	Hungary	21212	2004
Italy	36838	1958	Latvia	18274	2004
Luxembourg	67009	1958	Lithuania	19606	2004
Spain	32157	1986	Malta	26550	2004
Sweden	43791	1995	Poland	20483	2004
The Netherlands	47220	1958	Portugal	26280	1986
			Romania	15574	2007
			Slovak Republic	22247	2004
			Slovenia	27549	2004

Source: See Table 4.1. For the accession years, we consulted the following website, which is the part of the official website of the European Parliament:

“https://www.europarl.europa.eu/external/html/euenlargement/default_en.htm”.

Note: Real GDP per capita is measured in millions of 2017 international dollars. The pooled average of the Real per capita is 34410. Considering T^* the number of observations for the variables in levels, this is calculated as $\overline{RGDP} = \frac{1}{NT^*} \sum_{t=1}^{T^*} \sum_{i=1}^N RGDP_{i,t}$.

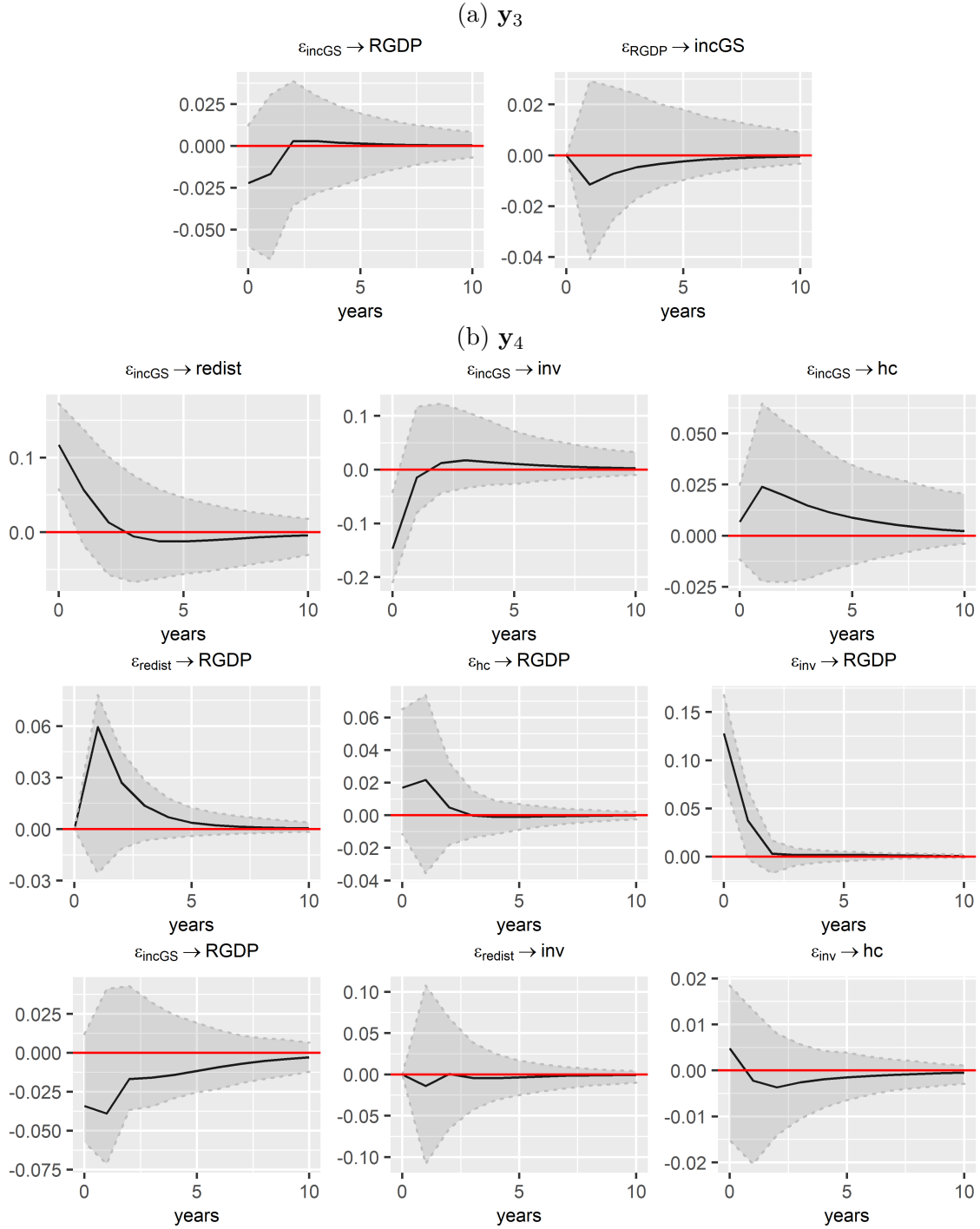
Figure 4.10: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of y_1 and y_2 with a maximum lag of the instruments for the dependent variables of 3



Source: Authors' own computations.

Note: See Figure 4.2.

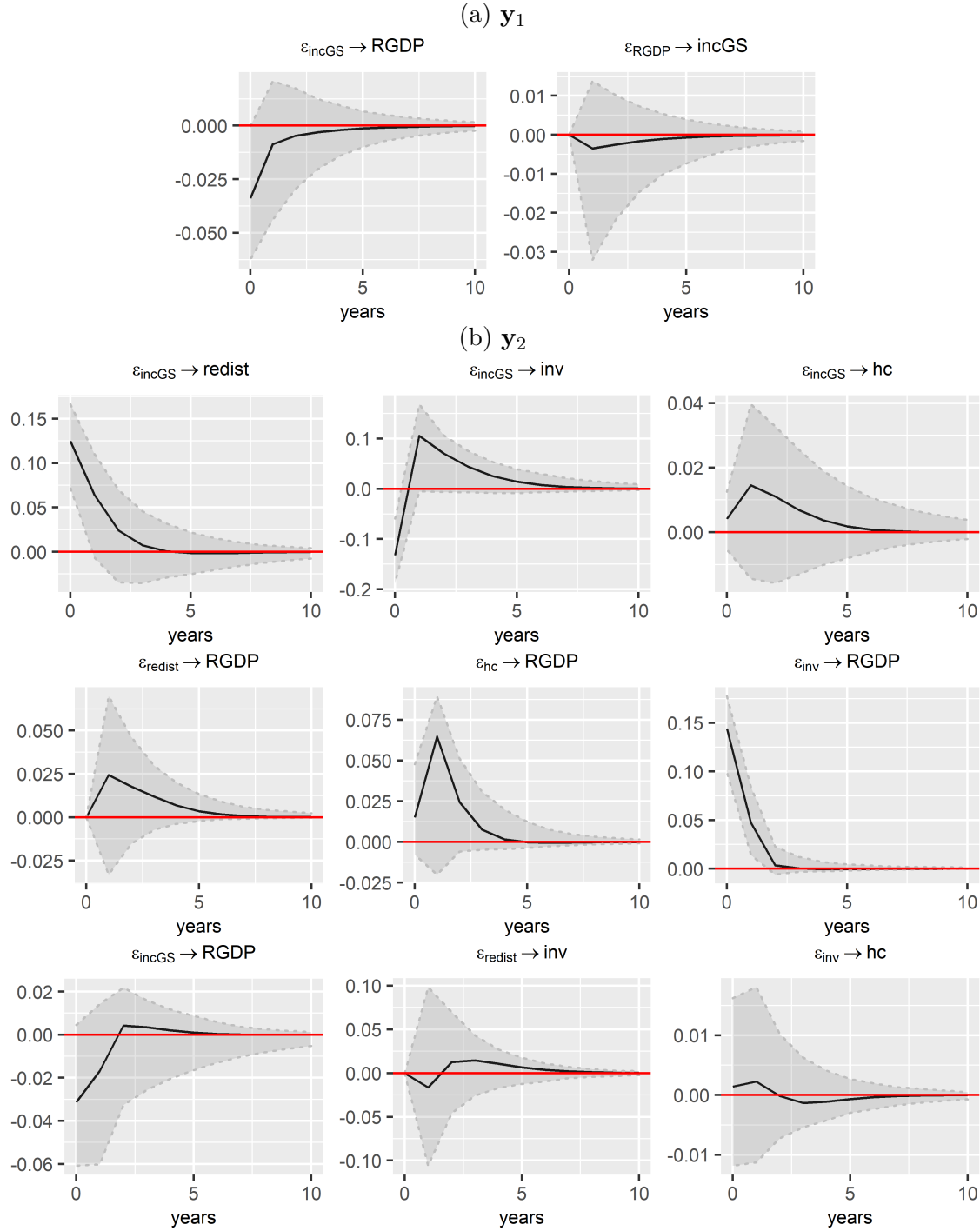
Figure 4.11: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_3$ and $\mathbf{y}_4$ with a maximum lag of the instruments for the dependent variables of 3



Source: Authors' own computations.

Note: See Figure 4.2.

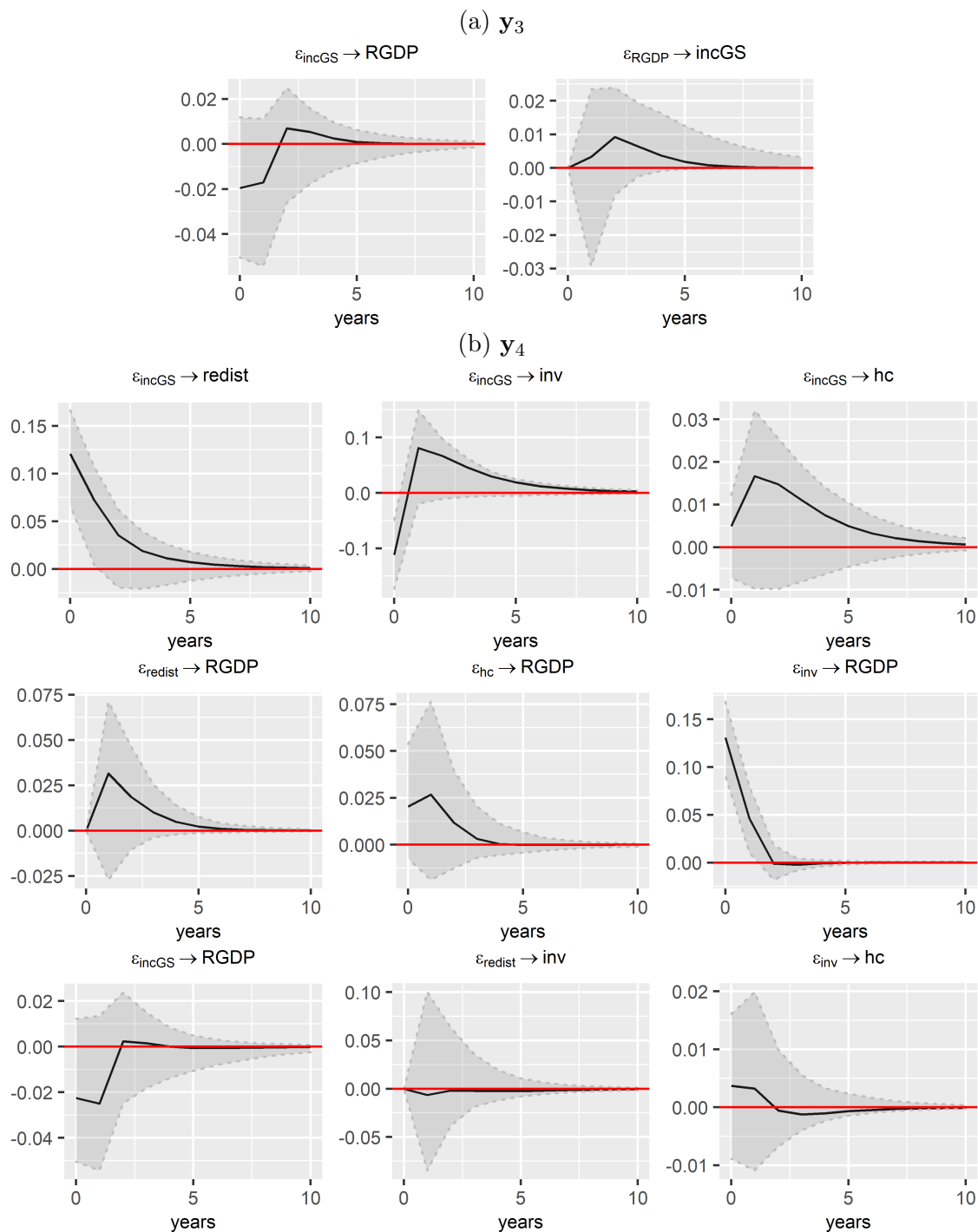
Figure 4.12: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of y_1 and y_2 with a maximum lag of the instruments for the dependent variables of 9



Source: Authors' own computations.

Note: See Figure 4.2.

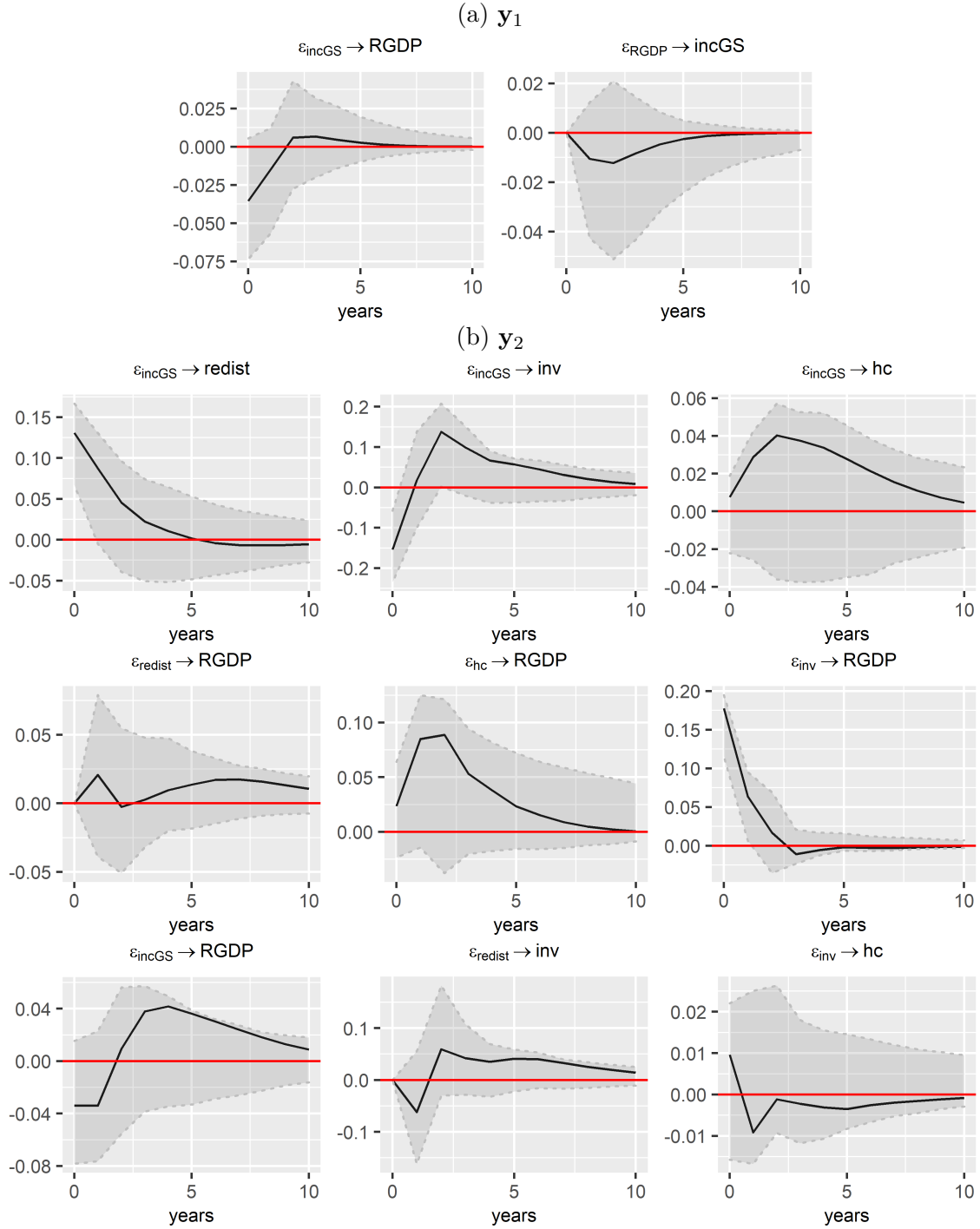
Figure 4.13: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_3$ and $\mathbf{y}_4$ with a maximum lag of the instruments for the dependent variables of 9



Source: Authors' own computations.

Note: See Figure 4.2.

Figure 4.14: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_1$ and $\mathbf{y}_2$ with a lag order of 2



Source: Authors' own computations.

Note: See Figure 4.2.

Figure 4.15: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of y_3 and y_4 with a lag order of 2

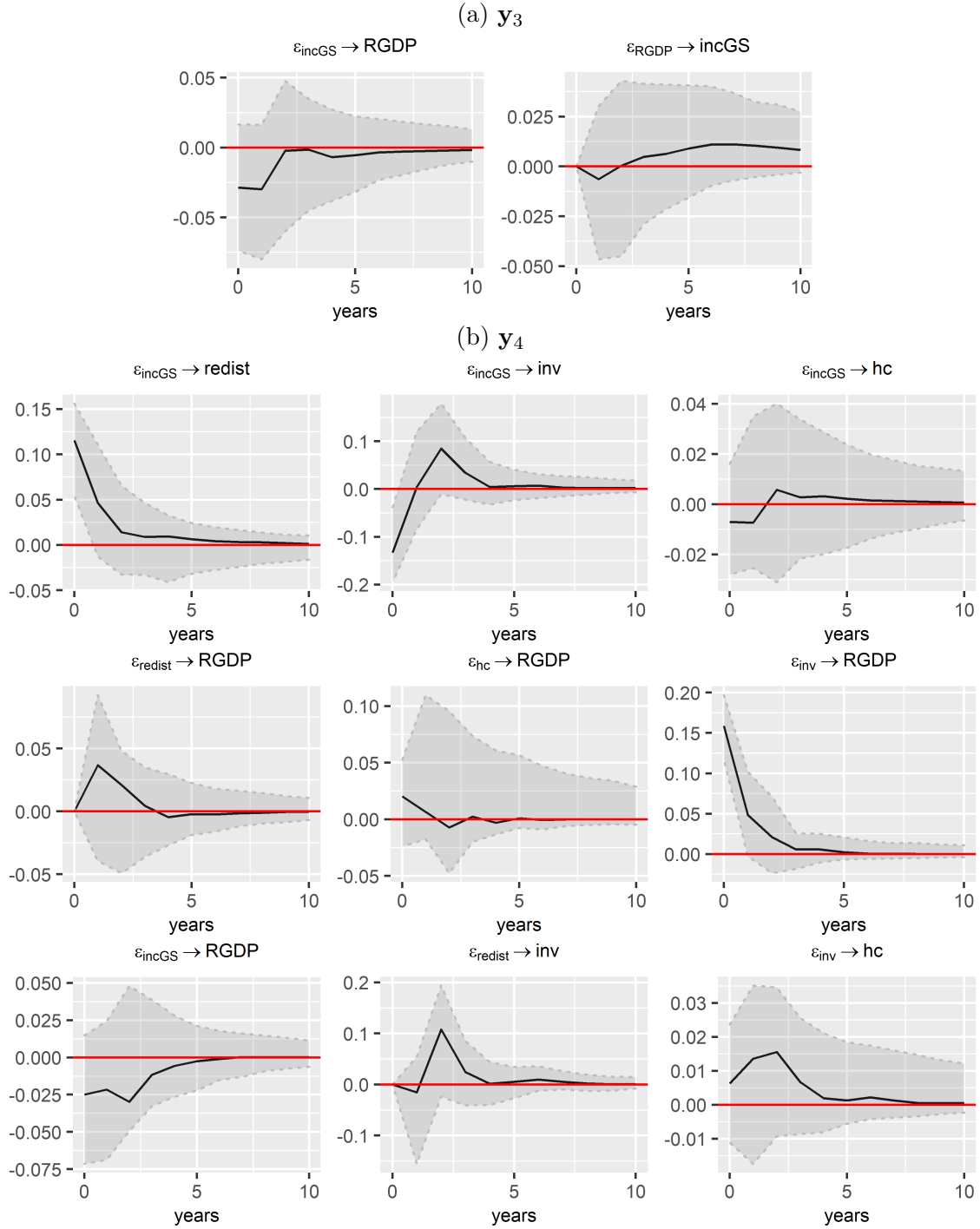
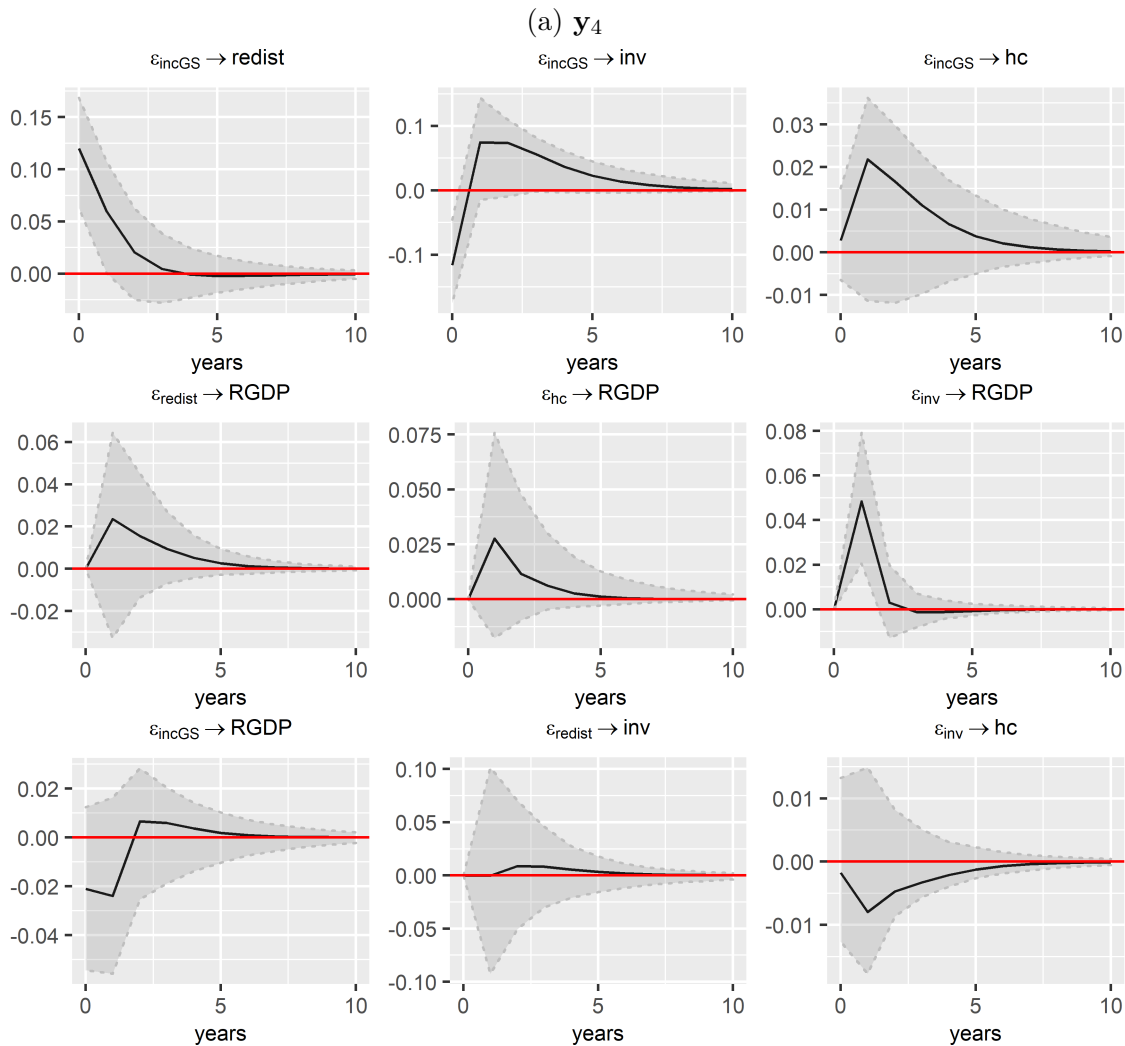
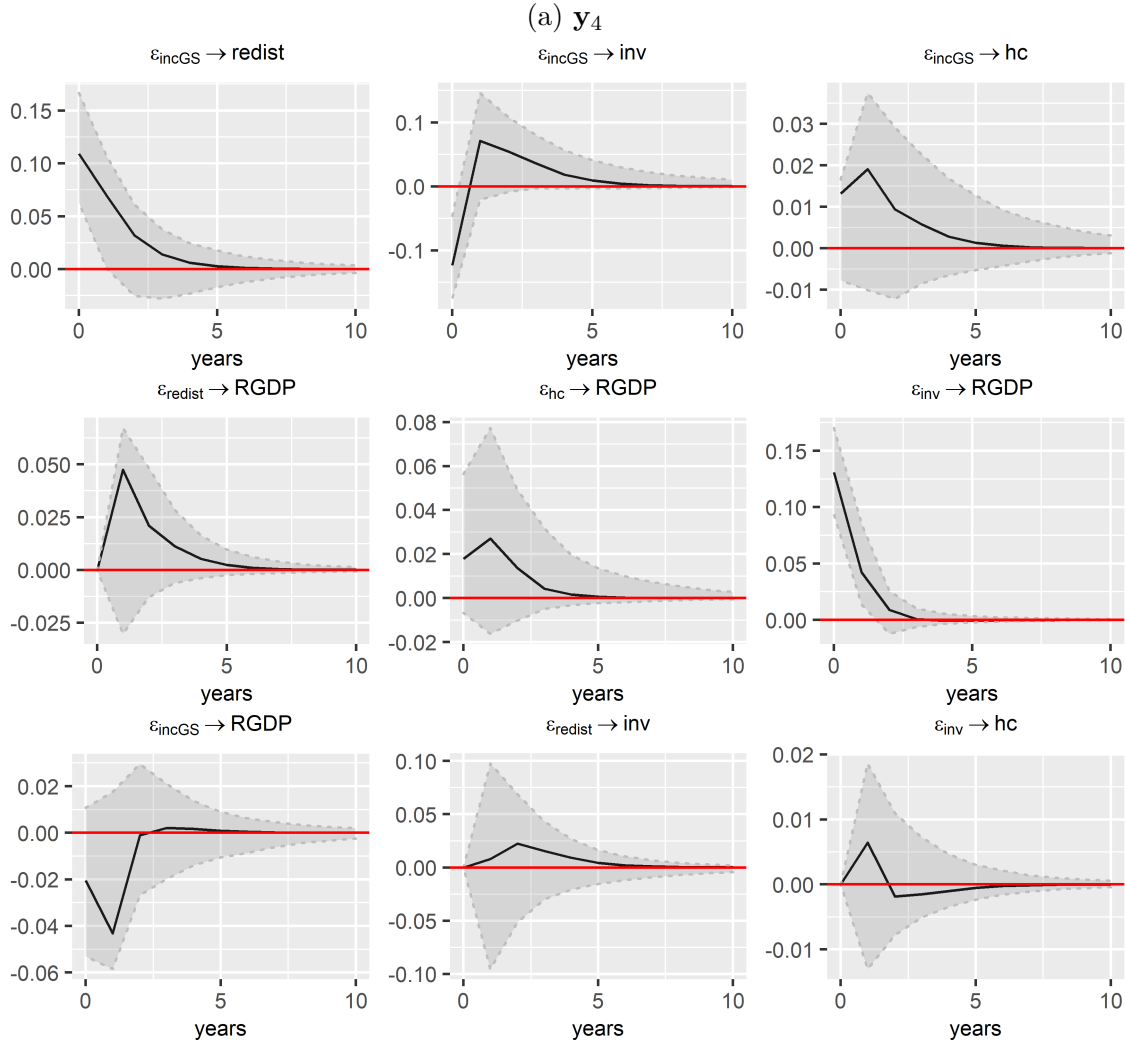


Figure 4.16: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_4$ where instead of assumption 8 it is assumed that Real GDP per capita can contemporaneously affect investment and human capital



Source: Authors' own computations.
Note: See Figure 4.2.

Figure 4.17: Selected orthogonal impulse response functions and 95% standard bootstrap confidence intervals for a panel VAR model of $\mathbf{y}_4$ where instead of assumption 9 it is assumed that human capital can contemporaneously affect investment



Source: Authors' own computations.

Note: See Figure 4.2.

Chapter 5

Effects of Monetary Policy on the Skill Premium and the Growth rate in a Directed Technical Change model with heterogeneous Cash-in-Advance constraints

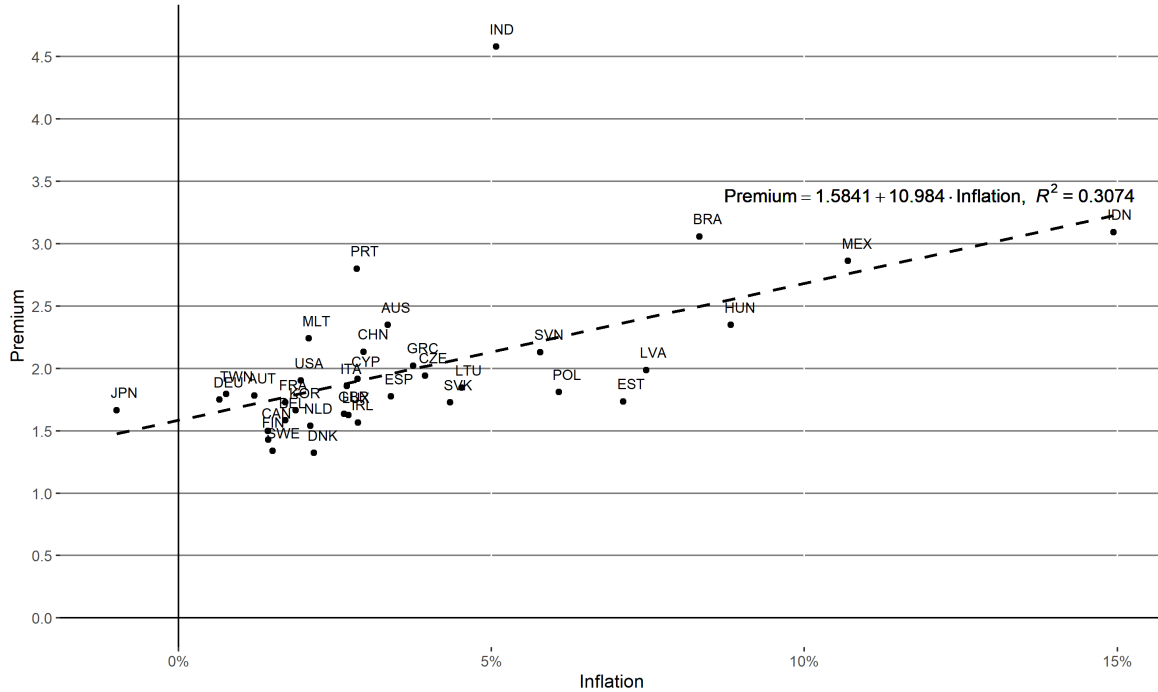
This chapter was accepted for publication in 2022 in the *International Journal of Finance and Economics*.

5.1 Introduction

The relationship between inflation and economic growth has long been debated among monetary economists (Benhabib & Spiegel, 2009; Cameron, Hum, & Simpson, 1996; Gil & Iglésias, 2020; Valdovinos & Fernández, 2003), but the same cannot be said of the relationship between inflation and skill premium. Some papers in the literature have discussed and analyzed some channels through which inflation can affect different parts of the income distribution in different manners. On the one hand, an increase in expected inflation can have a higher cost for households at the bottom of the distribution for several reasons, such as the fact that they use more cash to conduct their daily transactions (Albanesi, 2007; Erosa & Ventura, 2002), they consume more basic goods and services, which are usually more affected by inflation than other types of goods and their income sources consist mostly in transfer and wage incomes, which are less indexed to inflation than non-wage income earned by higher-income earners (O’Farrell, Rory, Rawdanowicz, & Inaba, 2016). On the other hand, unexpected increases in inflation can result in transfers of wealth from rich and old households to young middle-class households that have fixed-rate mortgage debt (Doepke & Schneider, 2006). Since skilled workers tend to be at the top of the income distribution, these channels suggests a connection between inflation and the skill premium, which is, indeed, confirmed by empirical evidence. As shown in Figure 5.1, we obtain a positive and statistically significant relationship between inflation and the skill premium with real data collected from the Socio Economics Accounts (February 2012 release) of the World Input-Output Database (Timmer et al., 2015) in the period 1995-2009. However, to the best of our knowledge, with the exception of Afonso and Sequeira (2022), no paper so far has sought to explicitly analyze this relationship theoretically.

We fill this gap with an expansion of the Directed Technical Change (DTC) model with horizontal innovation by Acemoglu (2002) without scale effects. This expansion consists in considering the existence of Cash-in-Advance (CIA) constraints in the R&D and manufacturing sectors of the economy that are possibly different between high- (or skilled) and low-skilled (or unskilled) sectors. We opted for this approach because the DTC literature has provided the main framework for explaining the emergence of the skill premium in developed and developing countries since the 1980s (*e.g.*, Acemoglu, 2002). Moreover, the basis from the DTC literature are endogenous growth models, which, in turn, have been extended by several authors to accommodate the introduction of Cash-in-Advance (CIA) restrictions in the R&D and intermediate-good sectors of the

Figure 5.1: Relation between the average skill premium (vertical axis; y-axis) and average inflation rate in percentage points (horizontal axis; x-axis) for countries included in the Socio Economics Accounts (February 2012 release) of the World Input-Output Database (Timmer et al., 2015) and the time period 1995-2009.



Source: Socio Economics Accounts (February 2012 release) of the World Input-Output Database (Timmer et al., 2015).

Note: (1) The average skill premium is the time average of the ratio of wages of skilled to unskilled workers. These, in turn, are calculated by taking the ratio of earnings of employees to billed hours. Since in the data we have three skill levels (low, medium and high-skilled workers) in which only the latter has some form of tertiary education – see Section 5.3 – and the literature with two skill levels considers the latter as high-skilled (or skilled) as well (*e.g.*, Afonso & Magalhães, 2020), we follow the same approach and treat medium-skilled workers as low-skilled (or unskilled). (2) The average inflation rate is the time average of the annual variation of the CPI of the value added in each country. (3) The countries covered by Socio Economics Accounts (February 2012 release) of the World Input-Output Database include all members of the EU at 1 January 2007 and 13 other major economies that were chosen with the intention of covering most the world GDP in 2008 (85% at 2008 prices) and due to considerations related to data availability. From these group we only excluded Bulgaria, Turkey, Romania and Russia due to these showing much higher average inflation rates than the remaining countries. Including these countries in the analysis would still imply a positive relation between inflation and the skill premium, but less evident.

Legend: AUS - Australia; AUT - Austria; BEL - Belgium; BRA - Brazil; CAN - Canada; CHN - China; CYP - Cyprus; CZE - Czech Republic; DNK - Denmark; EST - Estonia; FIN - Finland; FRA - France; DEU - Germany; GRC - Greece; HUN - Hungary; IND - India; IDN -Indonesia; IRL - Ireland; ITA - Italy; JPN - Japan; KOR - South Korea; LVA - Latvia; LTU - Lithuania; LUX - Luxembourg; MLT - Malta; MEX - Mexico; NLD - The Netherlands; POL - Poland; PRT - Portugal; SVK - Slovak Republic; SVN - Slovenia; ESP - Spain; SWE - Sweden; TWN - Taiwan; GBR - The United Kingdom; USA - The United States.

economy to explain the inflation-growth relationship (Chu & Cozzi, 2014; Chu, Cozzi, Lai, & Liao, 2015; Chu, Ning, & Zhu, 2019; Gil & Iglésias, 2020).

CIA constraints consist in necessities by producers/entrepreneurs of liquidity in order to make payments and are included in R&D-driven growth models (Stockman, 1981; Wang & Yip, 1992) in order to introduce money demand and analyze the relation between inflation and growth. In this latter case, it is usually considered a CIA constraint on R&D investment (Chu & Cozzi, 2014; Gil & Iglésias, 2020), which is justified by strong liquidity requirements from R&D investment (Brown, Fazzari, & Petersen, 2009; Brown, Martinsson, & Petersen, 2012; Brown & Petersen, 2009, 2011, 2015; Cozzi, Pataracchia, Ratto, & Pfeiffer, 2017; Falato & Sim, 2014; Lyandres & Palazzo, 2016) and by the nature of assets held by R&D firms, which are mainly intangible and subject to asymmetric information (Alam & Walton, 1995; Zantout, 1997). CIA constraints are also considered in the manufacturing sector (*e.g.*, Liu, Tsou, & Wang, 2008), which is consistent with the ample evidence of the production being cash intensive (Bates, Kahle, & Stulz, 2009; Brown & Petersen, 2011; McLean, 2011; Mikkelsen & Partch, 2003; Opler, Pinkowitz, Stulz, & Williamson, 1999). However, they are usually considered to be less stringent than in the R&D Sector (*e.g.*, Chu & Cozzi, 2014; Gil & Iglésias, 2020).

In this literature, CIA constraints are not considered to be different between unskilled and skilled firms. This possibility, however, should be explored since firms operating in the “low-tech” sectors are usually smaller than those operating in “high-tech” (Hirsch Kreinsen, 2008), which, in turn, face more financial constraints than larger firms due to the lack of history and information (*e.g.*, Beck & Demirguc Kunt, 2006; Cao & Leung, 2016; Czarnitzki & Hottenrott, 2011; Ferrando & Ruggieri, 2018). Moreover, there is some evidence that suggests that exporting firms usually employ relatively more skilled labor due to the expertise required by international trade (Matsuyama, 2007) and face less financial constraints than non-exporting firms (Chaney, 2016). Considering such findings from the literature, it becomes perceptible to extend the setup of the DTC literature to include different CIAs in the R&D and manufacturing sectors of the economy that are allowed to be different between skilled and unskilled firms.¹

¹To give more economic intuition, consider two firms 1 and 2. Firm 1 invests in finding a new farming machinery or fertilizer, *i.e.*, it is a firm from a sector that employs unskilled labor. Firm 2 tries to invent a new gasoline refinery method, *i.e.*, it is a firm in the chemical sector, employing skilled labor in the form of engineers. We expect that, on average, firm 1 would have in general more difficulties in obtaining external finance both at the invention (R&D) and production stage due to being smaller than

Therefore in this model, we introduce channels through which inflation affects the skill premium in different ways:

- directly due to the CIA constraints associated with labor in the production of final goods.
- indirectly, due to the complementarity between labor and machines in the production of final goods, through some channels; owing to the CIA constraints associated with
 - machines/intermediate goods in the production of final goods;
 - machines/intermediate goods production itself;
 - R&D activities devoted to discover new machines/intermediate goods.

The results of this paper indicate that considering differences in CIA constraints across sectors results in a negative effect on inequality, by increasing the skill premium, and an increased pernicious effect on economic performance than when such differences are ignored. Therefore, they are of especial interest to developing countries with high inflation environments that are unable to conduct credible monetary policies but are, nonetheless, interested in reducing inequalities, by leading to the suggestion of two alternative policies: (i) monitor and alleviate liquidity constraints faced by various sectors of the economy, with a especial focus on unskilled sectors, (ii) conduct structural reforms to increase the relative importance of the skilled sector of the economy.

The remainder of this study proceeds as follows. The theoretical model is spelled out in section 5.2, bearing in mind technology and prices, directed technical change and preferences and monetary authority. Section 5.3 is directed at presenting and justifying the calibration carried out in the numerical analysis. In section 5.4 we present, analyze and interpret the main numerical results and in section 5.5 we conduct a sensitivity analysis of the model to changes in some parameters. Finally, section 5.6 concludes.

5.2 Theoretical model

In the baseline model, rational infinitely-lived dynastic households inelastically supply labor, skilled and unskilled, maximize utility obtained with the consumption of the

firm 2, because this is what is suggested by the literature. In this paper we abstract from analyzing the relation between firm characteristics, such as sector of activity and size, and liquidity constraints and take them as given.

homogeneous final good of all its own members, pay taxes and earn income from labor and from investments in financial assets and money balances. From the production side, the aggregate final good is composed by final goods from two sectors, unskilled (L -sector) and skilled (H -sector), which, in turn, use specific labor and a continuum of specific non-durable machines/intermediate goods. Each intermediate good is produced in monopolistic competition using as inputs a design that grants a perpetual protected patent and units of aggregate final good. This design is sold by the R&D sector, where there is perfect competition and, therefore, free entry and every potential entrant dedicates aggregate final good to produce or invent successful horizontal designs. Therefore there is technological knowledge bias in this model favoring the H -sector if the number of varieties of intermediate goods produced in this sector is higher relative to the L -sector, which, in turn, causes each skilled worker to produce relatively more output and a wage differential between sectors – the skill premium.

In this model, following Chu and Cozzi (2014) and Gil and Iglésias (2020), we introduce CIA constraints in the R&D and in the manufacturing sectors, the latter affecting the costs of hiring labor, using intermediate goods and producing them.² Each constraint implies that producers are required to borrow a share of the aforementioned costs each moment in time from households. This amount is then repaid with interest, determined by the prevailing nominal interest rate, which is entirely determined the monetary authority (the only form of government in the model). In each sector CIA constraints are allowed to affect H - and the L -sectors in a different way. As we show in both the theoretical and numerical results we obtain, this implies that a change in the nominal interest rate affects relative costs and incentives to invest in each sector in a manner that ultimately affects the skill premium.

²We abstract from the more conventional CIA constraint on consumption, or, more generically, from money-in-utility or a liquidity/pecuniary-transaction-costs specification in the households' optimization problem (*e.g.*, Feenstra, 1986), as we wish to focus on the worldwide production and technology sectors of the model and their interaction with the monetary sector.

5.2.1 Technology and prices

The final good,³ which is unique, is produced competitively using skilled and unskilled inputs, respectively, Y_H and Y_L , in the following Constant Elasticity of Substitution (CES) production function:⁴

$$Y = \left[\gamma_H Y_H^{\frac{\varepsilon-1}{\varepsilon}} + \gamma_L Y_L^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \gamma_L + \gamma_H = 1 \quad (5.1)$$

where: (i) Y_L and Y_H are the outputs produced in the L - and H -sectors, respectively; (ii) γ_L and γ_H are distribution parameters that determine the relative importance of the L - and H -sector in the economy,⁵ respectively and (iii) $\varepsilon \in (0, +\infty)$ is the elasticity of substitution between outputs from the two sectors: if $\varepsilon > (<) 1$ then the outputs of the L - and the H -sector are gross substitutes (complements). The maximization problem of real profits is given by $\max_{Y_H, Y_L} \pi_Y$, where $\pi_Y = Y - p_H Y_H - p_L Y_L$, and $p_j = \frac{P_j}{P_Y}$, $j \in \{L, H\}$ is the real price of the output of each sector.⁶ After some calculations, the relative price of the H -sector is the following:

$$\frac{p_H}{p_L} = \frac{\gamma_H}{\gamma_L} \left(\frac{Y_H}{Y_L} \right)^{-\frac{1}{\varepsilon}}. \quad (5.2)$$

Moreover, if we normalize P_Y to 1, we also have that $[p_H^{1-\varepsilon} + p_L^{1-\varepsilon}]^{\frac{1}{1-\varepsilon}} = 1$. The output in each sector is produced with labor, H or L , and a continuum of complementary intermediate goods/machines, x_H or x_L , in the $[0, A_H]$ or $[0, A_L]$ interval, respectively. The production function for the j -sector, $j \in \{L, H\}$, is:

$$Y_j = \frac{j^\alpha}{1-\alpha} \int_0^{A_j} x_j(i)^{1-\alpha} di \quad (5.3)$$

where: (i) A_j captures the state of the j -sector complementary technological knowledge (ii) α is the income share of labor. The producer must pay costs associated with the

³In this paper when we mention “output” we are more precisely referring to the “value added” of the economy. Since output is produced with labor and capital and, in our case, as it will be made clear further ahead, the factors are labor and intermediate goods, we can interpret intermediate goods in the context of our model as replacing the role of capital in the production function.

⁴For simplicity, we suppress the time argument from all the variables, only using it when strictly necessary to avoid unnecessary confusion.

⁵From the maximization problem described further ahead, it can easily be shown that $\gamma_j = p_j^{\frac{\varepsilon-1}{\varepsilon}} \left(\frac{P_j Y_j}{Y} \right)^{\frac{1}{\varepsilon}}$, $j \in \{L, H\}$.

⁶By real we mean that is the ratio of the price of the output in each sector to the price of final output. All prices and costs in this paper are to be regarded in this way.

factors used in the production of output, workers and complementary machines, whose relative real prices are w_j and q_j , respectively.

In line with the literature that considers cash-in-advance constraints, we consider that the producer must borrow a fraction of the cost of each factor from the households that is potentially different between sectors – $\Psi_j \in [0, 1]$ for labor and $\Upsilon_j \in [0, 1]$ for complementary machines. In turn, s/he reimburses this amount with interest in the following period. Therefore, each moment in time the costs for using labor and machines are given, respectively, by $(1 - \Psi_j) \cdot w_j \cdot j + (1 + \iota) \cdot \Psi_j \cdot w_j \cdot j = (1 + \Psi_j \cdot \iota) \cdot w_j \cdot j$ and $\int_0^{A_j} [(1 - \Upsilon_j) \cdot q_j(i) \cdot x_j(i) + (1 + \iota) \cdot \Upsilon_j \cdot q_j(i) \cdot x_j(i)] di = \int_0^{A_j} (1 + \Upsilon_j \cdot \iota) \cdot q_j(i) \cdot x_j(i) di$, where ι is the nominal interest rate, determined by the monetary authority, which, as shown latter on, is positively related with inflation. Therefore, this implies that the maximization problem in the j -sector of real profits is $\max_{j, x_j} \pi_{Y_j}$, where $\pi_{Y_j} = p_j \cdot Y_j - (1 + \Psi_j \cdot \iota) w_j \cdot j - \int_0^{A_j} (1 + \Upsilon_j \cdot \iota) \cdot q_j(i) \cdot x_j(i) di$. From the First Order Conditions (F.O.C.), $\frac{\partial \pi_j}{\partial j} = 0$ and $\frac{\partial \pi_j}{\partial x_j(i)} = 0$, it results the following:

$$w_j = \alpha \frac{p_j \cdot Y_j}{(1 + \Psi_j \cdot \iota) j} \quad (5.4)$$

$$x_j(i) = \left[\frac{p_j}{q_j(i) (1 + \Upsilon_j \cdot \iota)} \right]^{\frac{1}{\alpha}} \cdot j \quad (5.5)$$

Intermediate goods are produced in monopoly using a design supplied by the R&D sector that grants Intellectual Property Rights (IPRs) protection and a χ units of aggregate output. In similarity to the producer of output in the j -sector, the producer of intermediate goods must borrow a fraction $\Omega_j \in [0, 1]$ of the cost of producing an intermediate good from households. Considering that Y is a numeraire, this implies a marginal cost of $(1 + \Omega_j \cdot \iota) \cdot \chi$ and the following maximization problem for the producer of intermediate good i in sector j : $\max_{q_j} \pi_j(i)$, where $\pi_j(i) = x_j(i) \cdot [q_j(i) - (1 + \Omega_j \cdot \iota) \cdot \chi]$ is the profit of intermediate-good i in the j -sector. From the F.O.C., $\frac{\partial \pi_j(i)}{\partial q_j(i)} = 0$, it results that $q_j(i) = \frac{(1 + \Omega_j \cdot \iota) \cdot \chi}{1 - \alpha}$ which, bearing in mind (5.3), (5.4) and (5.5), allows to obtain the following:

$$Y_j = \left[\frac{p_j}{\chi \cdot (1 + \Omega_j \cdot \iota) \cdot (1 + \Upsilon_j \cdot \iota)} \right]^{\frac{1 - \alpha}{\alpha}} j \cdot A_j \cdot (1 - \alpha)^{\frac{1 - 2\alpha}{\alpha}}, \quad (5.6)$$

$$w_j = \alpha \frac{(1 - \alpha)^{\frac{1-2\alpha}{\alpha}} \cdot [\chi \cdot (1 + \Omega_j \cdot \iota) \cdot (1 + \Upsilon_j \cdot \iota)]^{\frac{\alpha-1}{\alpha}}}{(1 + \Psi_j \cdot \iota) \cdot j} p_j^{\frac{1}{\alpha}} \cdot A_j \cdot j, \quad (5.7)$$

$$\pi_j(i) = \alpha \left[\frac{(1 + \Omega_j \cdot \iota) \chi}{1 - \alpha} \right]^{\frac{\alpha-1}{\alpha}} \left(\frac{p_j}{1 + \Upsilon_j \cdot \iota} \right)^{\frac{1}{\alpha}} j \quad (5.8)$$

By substituting (5.6) into (5.2), we obtain the relative price and output of the H -sector:

$$\frac{p_H}{p_L} = \left(\frac{\gamma_H}{\gamma_L} \right)^{\frac{\epsilon \cdot \alpha}{\sigma}} \left[\frac{(1 + \Omega_H \cdot \iota) (1 + \Upsilon_H \cdot \iota)}{(1 + \Omega_L \cdot \iota) (1 + \Upsilon_L \cdot \iota)} \right]^{\frac{1-\alpha}{\sigma}} \left(\frac{A_H \cdot H}{A_L \cdot L} \right)^{-\frac{\alpha}{\sigma}} \quad (5.9)$$

$$\frac{Y_H}{Y_L} = \left[\frac{\gamma_H (1 + \Omega_L \iota) (1 + \Upsilon_L \iota)}{\gamma_L (1 + \Omega_H \iota) (1 + \Upsilon_H \iota)} \right]^{\frac{\epsilon(1-\alpha)}{\sigma}} \left(\frac{A_H H}{A_L L} \right)^{\frac{\alpha \epsilon}{\sigma}} \quad (5.10)$$

where $\sigma = 1 + \alpha(\epsilon - 1)$ is the elasticity of substitution between units of labor from different sectors. Combining equations (5.7) and (5.9), we obtain the relative return of the skilled labor:

$$\frac{w_H}{w_L} = \frac{1 + \Psi_L \cdot \iota}{1 + \Psi_H \cdot \iota} \left[\frac{(1 + \Omega_L \cdot \iota) (1 + \Upsilon_L \cdot \iota)}{(1 + \Omega_H \cdot \iota) (1 + \Upsilon_H \cdot \iota)} \right]^{\frac{(\epsilon-1)(1-\alpha)}{\sigma}} \left(\frac{\gamma_H}{\gamma_L} \right)^{\frac{\epsilon}{\sigma}} \left(\frac{H}{L} \right)^{-\frac{1}{\sigma}} \left(\frac{A_H}{A_L} \right)^{\frac{\sigma-1}{\sigma}}. \quad (5.11)$$

In turn, we obtain the relative profitability of innovators in the H -sector from (5.8) and (5.9):

$$\frac{\pi_H(i)}{\pi_L(i)} = \left(\frac{1 + \Omega_H \cdot \iota}{1 + \Omega_L \cdot \iota} \right)^{\frac{\sigma-\epsilon}{\sigma}} \left[\frac{\gamma_H \cdot (1 + \Upsilon_L \cdot \iota)}{\gamma_L \cdot (1 + \Upsilon_H \cdot \iota)} \right]^{\frac{\epsilon}{\sigma}} \left(\frac{A_H}{A_L} \right)^{-\frac{1}{\sigma}} \left(\frac{H}{L} \right)^{\frac{\sigma-1}{\sigma}}. \quad (5.12)$$

5.2.2 Directed technical change

Now, we analyze how the results of the model are affected by considering that the rate and the direction of the technological knowledge are both endogenous. In the perfectly competitive R&D sector there is free entry and each potential entrant devotes a quantity of aggregate final good to produce a successful design, which is protected by a system of patents, and allows the introduction of a new machine/intermediate-good that is complementary to skilled or unskilled, *i.e.*, a new firm $i \in [0, A_j]$ belonging to sector $j \in \{L, H\}$. According to Acemoglu (2002), technologies that complement the

skilled and unskilled sectors change over the time according to the following motion equation:

$$\dot{A}_j = \frac{\lambda \cdot Z_j}{j} \quad (5.13)$$

where: λ and Z_j are, respectively, a productivity parameter and the R&D expenditures directed at discovering a new j -sector intermediate good, $j \in \{L, H\}$, and thus $Z = Z_H + Z_L$ are the total R&D expenditures. This variable is determined by the free-entry condition, which is given by the following expression:

$$\dot{A}_j \cdot V_j(i) = Z_j \cdot (1 + \Phi_j \cdot \iota). \quad (5.14)$$

This implies that the present value of all the profit flows that a single innovator will receive for the discovery of a new intermediate good during the time s/he enjoys the projection of a patent, $V_j(i)$, times the number of new discoveries (each corresponds to a firm), $\dot{A}_j$, must be equal to the effective aggregate R&D expenditures in that sector, $Z_j (1 + \Phi_j \cdot \iota)$. Hence, the latter is assumed to have a operational component Z_j and a financial component $\Phi_j \cdot \iota \cdot Z_j$ that requires a share $\Phi_j \in [0, 1]$ of money from households. Moreover, the value function of a technology of a monopolist that discovers one of the intermediate goods must satisfy the following Hamilton-Jacobi-Bellman condition $r \cdot V_j(i) - \dot{V}_j(i) = \pi_j(i)$, $j \in \{L, H\}$, where, remember, $\pi_j(i)$ is the instantaneous profit for sectors $j \in \{L, H\}$ already specified in (5.8) and r is the real market interest rate.

Taking into account the free-entry condition and equation (5.13) we have that $\dot{V}_j(i) = 0$. Replacing this in the Hamilton-Jacobi-Bellman condition we obtain an expression for the real interest rate

$$r = \frac{\pi_j(i) \cdot \lambda_j}{j \cdot (1 + \Phi_j \cdot \iota)}. \quad (5.15)$$

Equalizing across sectors leads to $\frac{V_H(i)}{V_L(i)} = \frac{\pi_H(i)}{\pi_L(i)}$. Moreover, solving for $V_j(i)$ in the free-entry condition, dividing across sectors and replacing with the previous expression we obtain the following:

$$\frac{\pi_H(i)}{\pi_L(i)} = \frac{1 + \Phi_H \cdot \iota}{1 + \Phi_L \cdot \iota}. \quad (5.16)$$

This result has an intuitive explanation: In equilibrium, the relative profitability of the

H -sector (LHS), $\frac{\pi_H(i)}{\pi_L(i)}$, must be equal to the relative cost of investing R&D Resources in this sector (RHS), $\frac{1+\Phi_H \cdot \iota}{1+\Phi_L \cdot \iota}$. Replacing $\pi_j(i)$ with (5.8) we can obtain the following expression for the technological-knowledge bias:

$$\frac{A_H}{A_L} = \left(\frac{1 + \Omega_H \cdot \iota}{1 + \Omega_L \cdot \iota} \right)^{\sigma - \epsilon} \left[\frac{\gamma_H \cdot (1 + \Upsilon_L \cdot \iota)}{\gamma_L \cdot (1 + \Upsilon_H \cdot \iota)} \right]^\epsilon \left[\frac{1 + \Phi_L \cdot \iota}{1 + \Phi_H \cdot \iota} \right]^\sigma \frac{L}{H} \quad (5.17)$$

Expression (5.17) represents the relative productivity of skilled and unskilled technologies and is the key result of the Directed Technical Change (DTC) literature. Moreover, bearing in mind (5.17), we are able to analyze the implications of endogenous technological-knowledge bias on the relative wage, since, by complementarity between factors in (5.1), changes in wage inequality are tightly connected to the technological-knowledge bias – see equation (5.11). Substituting (5.17) into (5.11), we obtain the skill premium (*i.e.*, the relative return on skilled labor):

$$W = \frac{1 + \Psi_L \cdot \iota}{1 + \Psi_H \cdot \iota} \left(\frac{1 + \Omega_L \cdot \iota}{1 + \Omega_H \cdot \iota} \right)^{\epsilon - \sigma} \left(\frac{1 + \Upsilon_L \cdot \iota}{1 + \Upsilon_H \cdot \iota} \right)^{\epsilon - 1} \left[\frac{1 + \Phi_L \cdot \iota}{1 + \Phi_H \cdot \iota} \right]^{\sigma - 1} \left(\frac{\gamma_H}{\gamma_L} \right)^\epsilon \frac{L}{H}, \quad (5.18)$$

emerging the following proposition:

Proposition 1. If CIA constraints affect skilled and unskilled sectors differently in at least in one sector of activity, inflation affects the skill premium though the positive relation between inflation and the nominal interest implied by the Fischer equation, shown below.

Proof. Directly from equations (5.17) □

5.2.3 Preferences and monetary authority

As preferences are identical for both types of workers, $j = L, H$, there is a representative household, which maximizes the discounted intertemporal lifetime utility subject to the flow budget constraint, having perfect foresight concerning the technological-knowledge progress overtime. The utility function is $U = \int_0^\infty \left(\frac{C(t)^{1-\theta}-1}{1-\theta} \right) e^{-\rho t} dt$, where $\rho > 0$ is the subjective discount rate and $\theta > 0$ is the inverse of the inter-temporal elasticity of substitution. The economy is populated by a fixed number of infinitely-lived households who consume and collect income from

investments in financial assets and in money balances (*e.g.*, Chu & Cozzi, 2014), and from labor supply. Individuals are unskilled if their ability level is inferior to some threshold level $\tilde{a}$ and skilled otherwise. Since individuals supply labor, if we denote $z(a)$ as the number of hours supplied by individuals of ability level a , we have that the total number of hours supplied by unskilled and skilled individuals are given, respectively, by the following expressions: $L = \int_0^{\tilde{a}} z(a) \cdot da$ and $H = \int_{\tilde{a}}^1 z(a) \cdot da$. In this specification, both L and H are inelastic and, therefore, exogenous.

The flow budget constraint is $\dot{K} + \dot{m} = r \cdot K + \sum_{j=L,H} w_j \cdot j - C + \tau - I \cdot m + \iota \cdot b$, where: $K = \sum_{j=L,H} K_j$ is the household's real financial assets/wealth holdings; r is the real interest rate; w_j is the wage paid in the j -sector, and households inelastically supply labor, L or H ; m is the households' real money balances; τ denotes a lump-sum transfer/tax from the monetary authority; I is the inflation rate, which determines the cost of holding money; b is the amount of money borrowed from households by producers of output, intermediate goods and firms in the R&D sector to finance costs that were already described such that $b < m$. From standard dynamic optimization, we derive a no-arbitrage condition between real money balances and real financial assets (this amounts to the well-known Fisher equation) and the optimal path of consumption (the households' Euler equation):

$$\iota = r + I, \quad (5.19)$$

$$\dot{C} = \frac{1}{\theta} \cdot (r - \rho) \cdot C, \quad (5.20)$$

whereas the transversality conditions are $\lim_{t \rightarrow +\infty} e^{-\rho t} \cdot C(t)^{-\theta} \cdot a(t) = 0$ and $\lim_{t \rightarrow +\infty} e^{-\rho t} \cdot C(t)^{-\theta} \cdot m(t) = 0$.

We consider that the monetary authority adopts an inflation-targeting framework and its monetary policy instrument is the nominal interest rate, ι , through which affects the macroeconomic variables by operating through the CIA constraints (*e.g.*, Bernanke & Mishkin, 1997; Chu & Cozzi, 2014). Hence, with a change in the nominal interest rate, the CIA constraints generate forces that transmit different inflation costs, which distort the incentives and the use of economic resources in the different sectors. We follow the literature and assume that the nominal interest rate is exogenously chosen by the monetary authority, so that $\iota = \bar{\iota}$.⁷ Thus, the inflation rate, I , which corresponds

⁷The monetary policy rule that is assumed in this paper is compatible with the monetary policy feedback rule, which is adopted – implicitly or explicitly – by most monetary authorities in developed

to the growth rate of the nominal price of the final good, $I \equiv \frac{\dot{P}}{P}$, is endogenously determined according to the Fisher equation (5.19), for each r : $I = \iota - r$. Hence, in line with the empirical observation, which indicates that the inflation rate is endogenous and is indirectly controlled through the monetary policy instrument that is the nominal interest rate (*e.g.*, Bernanke & Mishkin, 1997), the Fisher equation reveals that the inflation rate is endogenous in the sense that relies on the real economic macroeconomic conditions reflected in the endogenous real interest rate, although it is regulated by the exogenous choice of the nominal interest rate by the monetary authority.⁸

Denoting the nominal money supply by M , the real money supply/balances is $m = \frac{M}{P}$ and, in terms of growth rates, it results, respectively, that $\mu \equiv \frac{\dot{M}}{M}$ and $\frac{\dot{m}}{m} = \mu - I$. Hence, knowing the value of I from the Fisher equation, the growth rate of the nominal money supply will be endogenously determined: $\mu = \frac{\dot{m}}{m} + I = \frac{\dot{m}}{m} + \iota - r$. That is, the monetary authority will endogenously adjust the money growth rate to whatever

countries (*e.g.*, Ahmad, 2016; Carare & Tchaidez, 2005; Clarida, Gali, & Gertler, 2000; Mehra & Minton, 2007; Sauer & Sturm, 2007), but also emerging economies (*e.g.*, Caporale, Helmi, Çatık, Ali, & Akdeniz, 2018). According to this general rule, which nests the well-known Taylor Rule (Taylor, 1993) as a special case (Clarida et al., 2000), monetary authorities adjust the interest rate in response to changes in the actual or expected values of inflation and output in relation to their target levels. Therefore, in its simplest version, the interest rate can be expressed by the following equation: $i_t = \bar{i} + \xi_\pi (I_t - I) + \xi_Y \left(\frac{Y_t - Y}{Y} \right)$, where $I_t - I$ and $\frac{Y_t - Y}{Y}$ are the inflation and output gaps, respectively, ξ_π and ξ_Y are parameters measuring the sensitivity of the interest rate in relation do such gaps and $\bar{i}$ is the long run interest rate set exogenously by the central bank. In this paper, we assume that the economy is in the long run equilibrium and, therefore, there are no inflation nor output gaps, which implies that the monetary policy that is assumed in this paper is a particular case of this rule. This is justified by the focus of this paper on the medium and long run impacts of monetary policy in line with other papers with the same focus (*e.g.*, (Anzoategui, Comin, Gertler, & Martinez, 2019; Benigno & Fornaro, 2018; Chu & Cozzi, 2014; Chu, Cozzi, Furukawa, & Liao, 2017; Chu & Ji, 2016; Chu et al., 2019). Moreover, this also justifies why we do not opt for a monetary policy where the nominal interest rate is endogenously determined by minimizing a monetary authority loss function. Such approach is usually applied when the monetary authority is faced with a trade-off in the short run between price stability and an efficient level of output (Galí, 2008; Prescott, 1977, pp. 96-97), which is not an issue relevant to this paper due to the long run focus of our analysis.

⁸Therefore, we assume inflation targeting, whereby the central bank determines the target for the inflation rate and uses the nominal interest rate as an instrument to achieve this goal. This is justified both by the conduct and the objectives of most central banks, which place price stability as one of its core objectives and announce a numerical target for this variable (Hammond, 2012), and by the fact that it allows the model to establish in a simple and meaningful manner a relationship between monetary policy and the skill premium through inflation, which is the main objective of this paper. Nonetheless, we do not necessitate this assumption for producing the main results of the model. Alternatively, we can consider that the inflation rate is exogenously determined outside the model and the nominal interest rate is endogenously determined by the Fisher equation. This yields exactly the same results, which is important because it shows that the conclusions of our model can be extended to countries where monetary authorities do not control directly or indirectly inflation due to not being able to conduct a price stability policy with enough credibility or at all, such as in the case of, for instance, developing countries with high inflation environments.

level is needed for the interest rate ι to prevail. As usual in the literature, we consider that, to balance its budget, the monetary authority returns the seigniorage revenues to households as a lump-sum transfer, *i.e.*, $\tau = \dot{M}/P = \frac{(\dot{m} \cdot P)}{P} = \frac{\dot{m} \cdot P + \dot{P} \cdot m}{P} = \dot{m} + I \cdot m$.

5.2.4 Macroeconomic Aggregation

From the monetary authority we arrive at following equation for the money supply: $m = \frac{\tau - \dot{m}}{I}$. Considering that the money market is in equilibrium, *i.e.*, that the supply of money, determined by the previous equation, is equal to money demand, as determined by households, we substitute the previous m in the households budget constraint for the previous expression to arrive at $\dot{K} = r \cdot K + \sum_{j=L,H} w_j \cdot j - C + \iota \cdot b$. We now consider the following expressions: (i) $b \equiv \sum_{j=L,H} (A_j \cdot \Omega_j \cdot \chi \cdot x_j(i) + A_j \cdot q_j(i) \cdot \Upsilon_j \cdot x_j(i) + \Psi_j \cdot \iota \cdot w_j \cdot j + Z_j \cdot \Phi_j)$, which results from considering that a equilibrium in the loan market implies that the supply of loans by households (LHS) is equal to the total demand (RHS); (ii) $r \cdot K = \sum_{j=L,H} \pi_j \equiv \sum_{j=L,H} A_j \cdot \pi_j(i)$ and $\dot{K} = \sum_{j=L,H} Z_j \cdot (1 + \Phi_j \cdot \iota)$, which results from considering the definition of assets as $K \equiv \sum_{j=L,H} \int_0^{A_j} V_j(i) \cdot di = \sum_{j=L,H} A_j V_j(i)$, the Hamilton-Jacobi-Bellman and free-entry conditions; (iii) equations (5.4), (5.5) and $q_j \cdot (1 + \Upsilon_j \cdot \iota) \cdot x_j = (1 - \alpha) \cdot p_j \cdot Y_j$, from the F.O.C. of the profit-maximization problem of the producer of output in sector j ; (iv) $Y = \sum_{j=L,H} p_j \cdot Y_j$, from the maximization problem of the producer of the aggregate final good considering the fact that the production function is CES; (v) $\pi_j(i) \equiv [q_j - (1 + \Omega_j \cdot \iota) \cdot \chi] \cdot x_j(i)$, from the definition of profits of the producer intermediate good j . Replacing the expressions (i)-(v) in the households budget constraint and rearranging we obtain the aggregate resource constraint of the economy:

$$Y = C + \chi \cdot X + Z \quad (5.21)$$

5.2.5 Balanced Growth Path (BGP)

The next proposition summarizes the dynamics of the economy both outside and in the BGP.

Proposition 2. There is a unique and stable BGP given by equation (5.17) along which all the variables including output, consumption, intermediate goods, R&D expenditures

and the number of varieties in each sector grow at the following growth rate obtained from the Euler Equation (5.20):

$$g = \frac{1}{\theta} \left\{ \lambda \alpha \left(\frac{1-\alpha}{\chi} \right)^{\frac{1-\alpha}{\alpha}} \times \left[\gamma_H^\epsilon \left[(1 + \Omega_H \cdot \iota)^{\frac{1-\alpha}{\alpha}} (1 + \Upsilon_H \cdot \iota)^{\frac{1}{\alpha}} (1 + \Phi_H \cdot \iota) \right]^{1-\sigma} + \left[\gamma_L^\epsilon \left[(1 + \Omega_L \cdot \iota)^{\frac{1-\alpha}{\alpha}} (1 + \Upsilon_L \cdot \iota)^{\frac{1}{\alpha}} (1 + \Phi_L \cdot \iota) \right]^{1-\sigma} \right]^{\frac{1}{\sigma-1}} - \rho \right\} \quad (5.22)$$

Proof. We start by proving that the number of varieties in each sector grows at the same rate, *i.e.*, $\left(\frac{\dot{A}_H}{A_H} \right) = \left(\frac{\dot{A}_L}{A_L} \right)$. Let's suppose that $\left(\frac{\dot{A}_H}{A_H} \right) < \left(\frac{\dot{A}_L}{A_L} \right)$. This implies $\left(\frac{A_H}{A_L} \right) < \left(\frac{A_H}{A_L} \right)_{BGP}$ where $\left(\frac{A_H}{A_L} \right)_{BGP}$ is defined by equation (5.17). By equation (5.12) and (5.16) we have that $\left(\frac{\pi_H}{\pi_L} \right) > \left(\frac{\pi_H}{\pi_L} \right)_{BGP} = \frac{1+\Phi_H \cdot \iota}{1+\Phi_L \cdot \iota}$, which implies that the relative profitability of H -sector is larger than its relative cost. This would drive entrants to increase relative R&D expenditures in the H -sector, *i.e.*, $\frac{Z_H}{Z_L} > \left(\frac{Z_H}{Z_L} \right)_{BGP}$, where $\left(\frac{Z_H}{Z_L} \right)_{BGP} = \frac{H}{L} \left(\frac{A_H}{A_L} \right)_{BGP}$ is obtained using the R&D production and $\left(\frac{A_H}{A_L} \right)_{BGP} = 0$. This, in turn, would lead to an increase in the growth rate of the number of varieties in the H -sector, *i.e.*, $\left(\frac{\dot{A}_H}{A_H} \right) > \left(\frac{\dot{A}_L}{A_L} \right)$, which would cause $\left(\frac{A_H}{A_L} \right)$ to increase, leading to the opposite effects described above until the no-arbitrage condition of investing in both sectors was met again, *i.e.*, when $\frac{A_H}{A_L} = \left(\frac{A_H}{A_L} \right)_{BGP}$ and $\left(\frac{\dot{A}_H}{A_H} \right) = \left(\frac{\dot{A}_L}{A_L} \right)$. If $\left(\frac{\dot{A}_H}{A_H} \right) > \left(\frac{\dot{A}_L}{A_L} \right)$ the exact opposite dynamics would take place $\frac{A_H}{A_L}$ would decrease monotonically until it reached the BGP again.

From the expression (5.6), we can see that output in each sector is proportional to the corresponding number of varieties. Therefore, since aggregate output is proportional to the output of each sector using the fact that, since Y is produced by a CES Production function, $Y = \sum_{j=L,H} p_j Y_j$, we can conclude that the growth rate of output is equal to the growth rate of the number of varieties and a similar rationale can be applied to aggregate intermediate inputs and R&D expenditures. Finally, the aggregate resource constraint implies that Consumption also grows at this rate. $\square$

Finally, the following proposition summarizes the impacts of the CIA constraints on the growth rate:

Proposition 3. From (5.22), under substitutability between outputs (*i.e.*, $\epsilon > 1$), which is achieved if factors are substitutable (*i.e.*, $\sigma > 1$). the existence of CIA constraints causes inflation to have a negative effect on the growth rate of the

economy though the positive relation between inflation and the nominal interest implied by the Fischer equation and the negative relation between CIA constraints in each sector and the economic growth rate, *ceteris paribus*. This negative effect is only affected by symmetric differences in CIA parameters within each sector if $\gamma_L \neq \gamma_H$. In particular, if $\gamma_L > \gamma_H$ this negative effect is amplified if CIA constraints are relatively more stringent in the L -sector and more reduced otherwise.

Proof. Directly from equation (5.22) and the Fisher equation (5.19). $\square$

5.3 Calibration

In this section we present and justify the baseline calibration we used in the model to obtain numerical results, which is summarized in Table 5.1.

In what concerns the baseline CIA constraints, in the absence of empirical evidence supporting specific values of each individual constraint, we consider the following calibration: $\Phi_H = \Phi_L = 0.75$ and $\Psi_H = \Psi_L = \Upsilon_H = \Upsilon_L = \Omega_H = \Omega_L = 0.25$. This approach is in line with the literature that suggests the existence of CIA constraints in the manufacturing and R&D sectors, but more preeminent in the later (*e.g.*, Chu & Cozzi, 2014; Gil & Iglésias, 2020). Moreover, as it will be explained with more details in the following section, this calibration allows to explore differences between CIA constraints affecting the skilled and unskilled sectors in an adequate manner.

The remaining parameters are calibrated using values commonly used in the literature:⁹ $\alpha = 0.625$, $\rho = 0.02$ and $\theta = 1.5$ (*e.g.*, Barro & Sala-i Martin, 2004; Jones & Williams, 2000). We also set $\chi = 1 - \alpha = 0.375$ in accordance with the Acemoglu (2002). Finally, there is a widespread agreement established long ago in the literature that $\sigma > 1$; however, in spite of the difficulty of obtaining point estimates for this parameter, it is considered likely that it varies between 1.4 and 2 (*e.g.*, Acemoglu, 2002; Angrist, 1995; Freeman, 1986). Therefore, we opt for $\sigma = 1.7$, which is the intermediate value for the possible range of this parameter.

⁹We follow this approach instead of direct estimation because there is a widespread consensus in the literature of the values of many parameters and our approach allows to compare directly our results with the relevant literature that also pursues a similar calibration. Moreover, some parameters, such as the elasticity of substitution, are notoriously difficult to be estimated precisely (*i.e.*, Acemoglu, 2002) and therefore such approach would imply not only a complex econometric approach but the risk of obtaining unreliable and inconsistent results with the literature due to, for instance, the specificities of the sample under analysis.

Table 5.1: Calibration used in the model

Parameter	Value	Description	Justification
ρ	0.02	Subjective discount rate	Values commonly used in the literature (<i>e.g.</i> , Barro & Sala-i Martin, 2004; Jones & Williams, 2000)
θ	1.5	Inter-temporal elasticity of substitution	
α	0.625	Exogenous labor share	
γ_L	0.5406	Relative importance of the L -sector	Ensures that the model produces the estimates of the steady-values of the growth rate, $g^* = 0.0279$, and skill premium, $W^* = 1.878$, obtained from the Data.
γ_H	0.4594	Relative importance of the H -sector	
λ	0.3284	R&D Productivity parameter	
σ	1.7	Elasticity of substitution between factors	An average of the range of possible point estimates for this parameter, [1.4,2] (<i>e.g.</i> , Acemoglu, 2002; Angrist, 1995; Freeman, 1986)
ι	0.0794	Nominal interest rate	Fisher and Euler equations
I	0.0175	Inflation	Values calculated from the Data
$\frac{H}{L}$	0.3771	Relative skilled-labor supply	
χ	0.375	Units of output required for each unit of intermediate input	Value set in line with Acemoglu (2002)
Υ_j	0.25	Share of the price of intermediate inputs borrowed from households in sector j	(1) Evidence of the existence of CIA constraints in the manufacturing and R&D sectors (<i>e.g.</i> , Chu & Cozzi, 2014; Gil & Iglésias, 2020). (2) Ensures that CIA constraints are always more stringent in the R&D sector in relation to manufacturing, in line with the literature (<i>e.g.</i> , Chu & Cozzi, 2014; Gil & Iglésias, 2020), even when considering symmetric differences around these values between skilled and unskilled sectors
Ψ_j	0.25	Share of the cost of labor inputs borrowed from households in sector j	
Ω_j	0.25	Share of the marginal cost of Intermediate goods borrowed from households in sector j	
Φ_j	0.75	Share of R&D cost borrowed from households in sector j	

Additionally, we obtain values for labor endowments, H and L , the skill premium, W , and the economic growth rate¹⁰ from data retrieved from the Socio Economics Accounts (February 2012 release) of the World Input-Output Database (Timmer et al., 2015) for 36 countries and covering a time period of 1995-2009.¹¹ The three labor skill

¹⁰In this particular case, since output in our model is defined as gross value added, we defined the economic growth rate accordingly as the growth rate of the gross value added at constant prices.

¹¹The country sample that is analyzed in the paper corresponds to all members of the EU at 1 January 2007 and 13 other major economies, which were chosen due to considerations related to data availability and with the intention of covering most the world GDP in 2008 (85% at 2008 prices), in order to obtain results that are representative of most economies in the world. From these group we only excluded Bulgaria, Turkey, Romania and Russia due to these showing much higher average inflation rates than the remaining countries. In what concerns the time span of the analysis, our

types considered in the database are classifications based in the International Standard Classification of Education (ISCED): low-skilled (ISCED categories 1 and 2), medium-skilled (ISCED 3 and 4), and high-skilled (ISCED 5 and 6). Since most literature that include only two skill levels (unskilled and skilled) considers skilled workers as those with some degree of tertiary education (*e.g.*, Afonso & Magalhães, 2020), which corresponds to ISCED 5 and 6, we also follow this approach and consider all medium-skilled workers as unskilled workers.

Considering a variable X for sector s in country c at time t as $X_{s,c,t}$, we start by calculating the sectoral averages of the variables of interest for each country and year, *i.e.*, we obtain $X_{c,t} = \sum_s^{N_s} \nu_{s,c,t} X_{s,c,t}$ where $\nu_{s,c,t}$ is the weight attributed to sector s in country c at time t , and $N_s = 35$ is the number of sectors of activity.¹² Then, we calculate the time averages for each country, *i.e.*, we obtain $X_c = \frac{1}{T} \sum_t^T X_{c,t}$, where $T = 15$ is the number of time periods. Finally, we obtain the average of these values weighted by the average relative importance of each economy, *i.e.*, we obtain, $X = \sum_c^{N_c} \psi_c X_c$, where $\psi_c = \frac{VA_c}{\sum_z^{N_c} VA_z}$, with $N_c = 36$ as the number of countries considered in our data set and VA_c as the time average of the gross value added of country c at constant prices converted to Dollars using exchange rates from Penn World Table 9.1 (Feenstra et al., 2015), *i.e.*, $VA_c = \frac{1}{T} \sum_t^T VA_{c,t}$. This resulted in $\frac{H}{L} = 0.3771$, $W = 1.878$, $g = 0.0279$ and $I = 0.0175$. From here, we obtain the real interest rate using the Euler Equation $r = \theta g + \rho = 0.0619$ and then the Fischer equation (5.19) to obtain the nominal interest rate $\iota = r + I = 0.0794$.

Finally, we calibrate γ_L and λ to ensure that the model produces the aforementioned values of the steady-state growth rate and skill premium, considering the baseline calibration of the model already described and the estimates we have obtained for the relative supply of skilled labor. In particular, bearing in mind (5.18),

choice of the period 1995-2009 is justified by several reasons: (i) availability of the data in the Social Economics Account Database, which is constrained to this period; (ii) lack of adequate data for the purposes of this paper for years after 2009 and before 1995 from other sources; (iii) the fact that, in more recent years, the monetary policy followed by many central banks included unconventional measures in response to the global financial crisis of 2007-2008 (*i.e.*, Bhar & Malliaris, 2021).

¹²In the case of the skill premium, it is calculated as the ratio of the average wage per hour of skilled to unskilled workers, *i.e.*, $W_{c,t} = \frac{w_{H,c,t}}{w_{L,c,t}}$. In turn, the average wage per type of worker of type $j \in \{L, H\}$ of country c at time t , $w_{j,c,t}$, is obtained by summing the corresponding earnings and hours and then dividing the former by the latter, *i.e.*, $w_{j,c,t} = \frac{\sum_s^{N_s} EARNINGS_{s,j,c,t}}{\sum_s^{N_s} HOURS_{s,j,c,t}}$. This is the same as an average of the wage of each sector weighted by the relative number of hours of workers of type j , *i.e.*, $w_{c,t,j} = \sum_s^{N_s} \nu_{s,c,t,j} w_{s,c,t,j}$, where $\nu_{s,c,t,j} = \frac{j_{s,c,t}}{L_{s,c,t} + H_{s,c,t}}$. The remaining variables are also summed and divided across sectors which imply they are simple averages of each sector.

using the baseline calibration and considering a steady state value for $\frac{H}{L}$, we can set γ_L and $\gamma_H = 1 - \gamma_L$ so that the model produces the desired value for W . Then, bearing in mind these parameters and equation (5.22) we can then define λ to obtain the desired steady state value for g . Considering that $\frac{H}{L} = 0.3771$, $W = 1.878$, and $g = 0.279$, this resulted $\gamma_L = 0.5406$, $\gamma_H = 1 - \gamma_L = 0.4594$ and $\lambda = 0.3284$.

5.4 Results

In this section we analyze the impacts of differences between CIA constraints in the skilled and unskilled sectors on monetary policy. We do so by calculating the elasticities of the skill premium and the growth rate with respect to the nominal interest rate evaluated at the corresponding steady-state values - represented henceforth by the superscript $*$ - which are obtained from the corresponding equations, resulting in the following formulas for each one:

$$E_{\iota}^{g*} \equiv \frac{\partial g}{\partial \iota} \frac{\iota^*}{g^*} = -\frac{r^*}{g^* \theta} \frac{\gamma_H^{\epsilon} [f_H^g(\iota^*)]^{1-\sigma} E_{\iota}^{f_H^g} + \gamma_L^{\epsilon} [f_L^g(\iota^*)]^{1-\sigma} E_{\iota}^{f_L^g}}{\gamma_H^{\epsilon} [f_H^g(\iota^*)]^{1-\sigma} + \gamma_L^{\epsilon} [f_L^g(\iota^*)]^{1-\sigma}} \quad (5.23)$$

$$E_{\iota}^{W*} \equiv \frac{\partial W}{\partial \iota} \frac{\iota^*}{W^*} = E_{\iota}^{f_L^W(\iota^*)} - E_{\iota}^{f_H^W(\iota^*)} \quad (5.24)$$

where

$$f_j^g(\iota^*) = (1 + \Omega_j \iota^*)^{\frac{1-\alpha}{\alpha}} (1 + \Upsilon_j \iota^*)^{\frac{1}{\alpha}} (1 + \Phi_j \iota^*) \quad (5.25)$$

$$E_{\iota}^{f_j^g(\iota^*)} \equiv \frac{\partial f_j^g(\iota)}{\partial \iota} \frac{\iota^*}{f_j^g(\iota^*)} = \frac{1-\alpha}{\alpha} \frac{\Omega_j \cdot \iota^*}{1 + \Omega_j \cdot \iota^*} + \frac{1}{\alpha} \frac{\Upsilon_j \cdot \iota^*}{1 + \Upsilon_j \cdot \iota^*} + \frac{\Phi_j \cdot \iota^*}{1 + \Phi_j \cdot \iota^*} \quad (5.26)$$

$$f_j^W(\iota^*) = (1 + \Psi_j \cdot \iota^*) (1 + \Omega_j \cdot \iota^*)^{\epsilon-\sigma} (1 + \Upsilon_j \cdot \iota^*)^{\epsilon-1} (1 + \Phi_j \cdot \iota^*)^{\sigma-1} \quad (5.27)$$

$$E_{\iota}^{f_j^W(\iota^*)} \equiv \frac{\partial f_j^W(\iota)}{\partial \iota} \frac{\iota^*}{f_j^W(\iota^*)} = \left\{ \begin{array}{l} \frac{\Psi_j \cdot \iota^*}{1 + \Psi_j \cdot \iota^*} + (\epsilon - \sigma) \frac{\Omega_j \cdot \iota^*}{1 + \Omega_j \cdot \iota^*} + \\ + (\epsilon - 1) \frac{\Upsilon_j \cdot \iota^*}{1 + \Upsilon_j \cdot \iota^*} + (\sigma - 1) \frac{\Phi_j \cdot \iota^*}{1 + \Phi_j \cdot \iota^*} \end{array} \right\} \quad (5.28)$$

Then, we calculate these elasticities for different combinations of CIA parameters¹³ in different sectors whose arithmetic average is equal to the corresponding aggregate value set in the baseline calibration. For instance, in the case of CIA constraints

¹³Since the model was calibrated to produce the steady-state values of the growth rate and premium as described in the previous section, by varying the CIA parameters we also vary these steady-state values.

affecting the R&D sector, we calculate the steady state elasticities of the growth rate and skill premium for all possible combinations of possible CIA parameters (between 0 and 1) that on average are equal to the aggregate value of $\Phi = 0.75$, *i.e.*, $\frac{\Phi_H + \Phi_L}{2} = \Phi = 0.75$. Therefore, we only consider combinations of CIA parameters that are symmetric around the corresponding aggregate values,¹⁴ because it is the simplest approach and does not distort the results. Moreover, the differences in CIA parameters we explore are associated with parameters that are consistent with CIA constraints in the R&D sector being more stringent than in other sectors of activity.¹⁵ Finally, it also allows to explore differences in an adequate range that is equal to 1 ($0.5 - (-0.5)$) for every scenario.

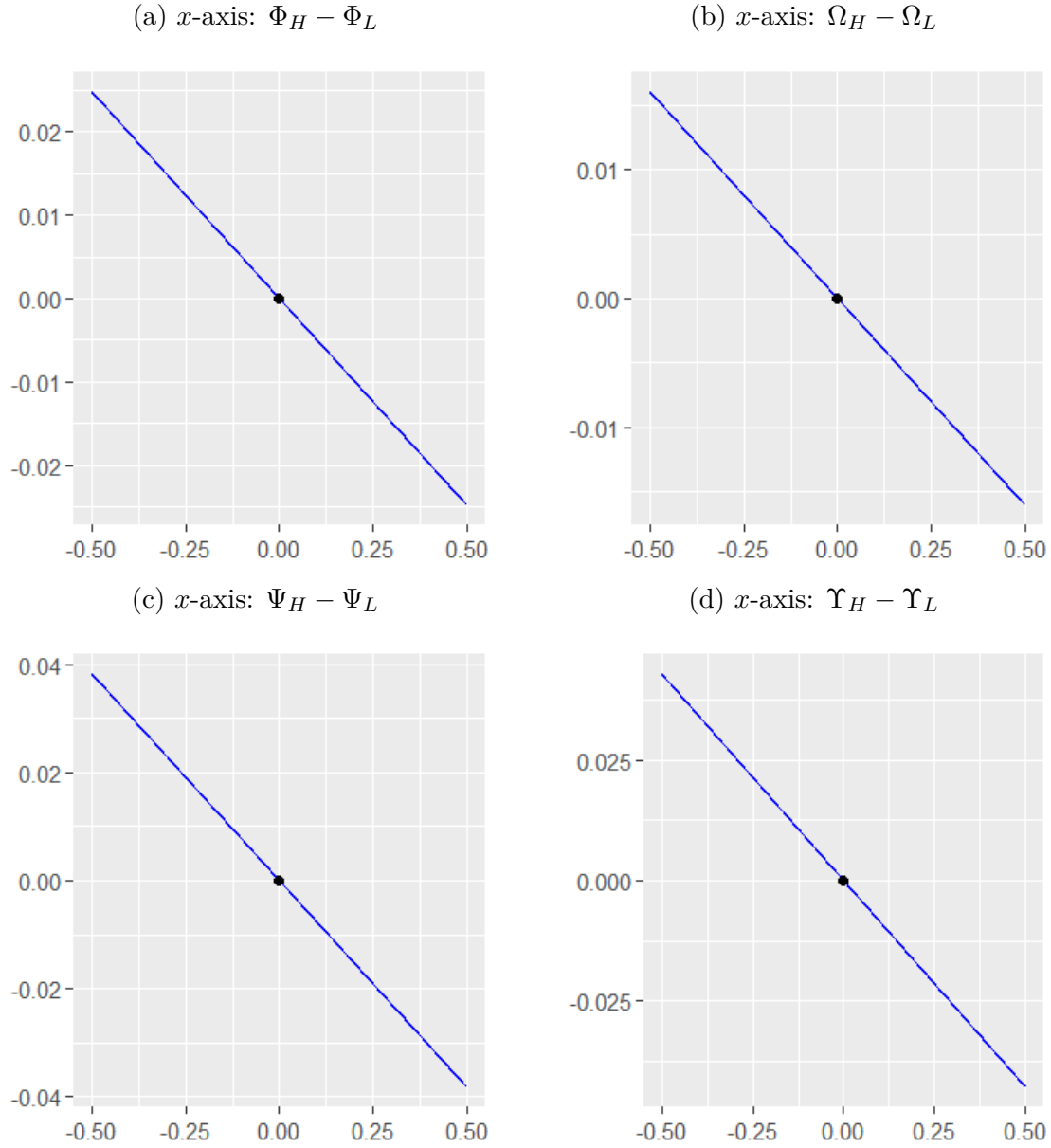
In Figure 5.2 we apply the described analysis to the elasticity of the skill premium with respect to the nominal interest rate. In line with proposition 1, we can see that if CIA constraints are equal across sectors, monetary policy has no effect on the skill premium. However, the higher the differences between sectors the more impact monetary policy has on the skill premium. In particular, the more stringent CIA constraints are in the L -sector, the more positive is the impact of an increase in inflation on the skill premium and vice-versa. This effect is especially stronger for differences in CIA constraints affecting the costs of units of labor.

In Figure 5.3, we focus on the impacts of differences between CIA parameters on the elasticity of the growth rate with respect to the nominal interest rate. In line with proposition 3, we can see that when CIA constraints are equal to each other and to the baseline values in every sector, $E_t^g < 0$, which is consistent with the results from other authors of the literature such as Gil and Iglésias (2020). However, when we consider differences between CIA constraints that are also consistent with the aggregate values of the baseline scenario, E_t^g varies, except for differences in CIA constraints affecting demand for labor, *i.e.*, $\Psi_H - \Psi_L$. In particular, more stringent CIA constraints in the L -sector increase the negative impact of monetary policy on the growth rate of output.

¹⁴Considering the previous example, this implies that we consider considering the following pairs of parameters (Φ_H, Φ_L) : $(\Phi_H = 0.7; \Phi_L = 0.8)$; $(\Phi_H = 0.65; \Phi_L = 0.75)$, and so forth., *i.e.*, values of Φ_H and Φ_L that are symmetric around $\Phi = 0.75$.

¹⁵Specifically, it can easily be shown that by calibrating the baseline CIA parameters in accordance with the previous section and considering them an arithmetic average of two sectors, we have that $\Phi_j \in [0.5, 1]$; $\Omega_j, \Psi_j, \Upsilon_j \in [0, 0.5], j = L, H$.

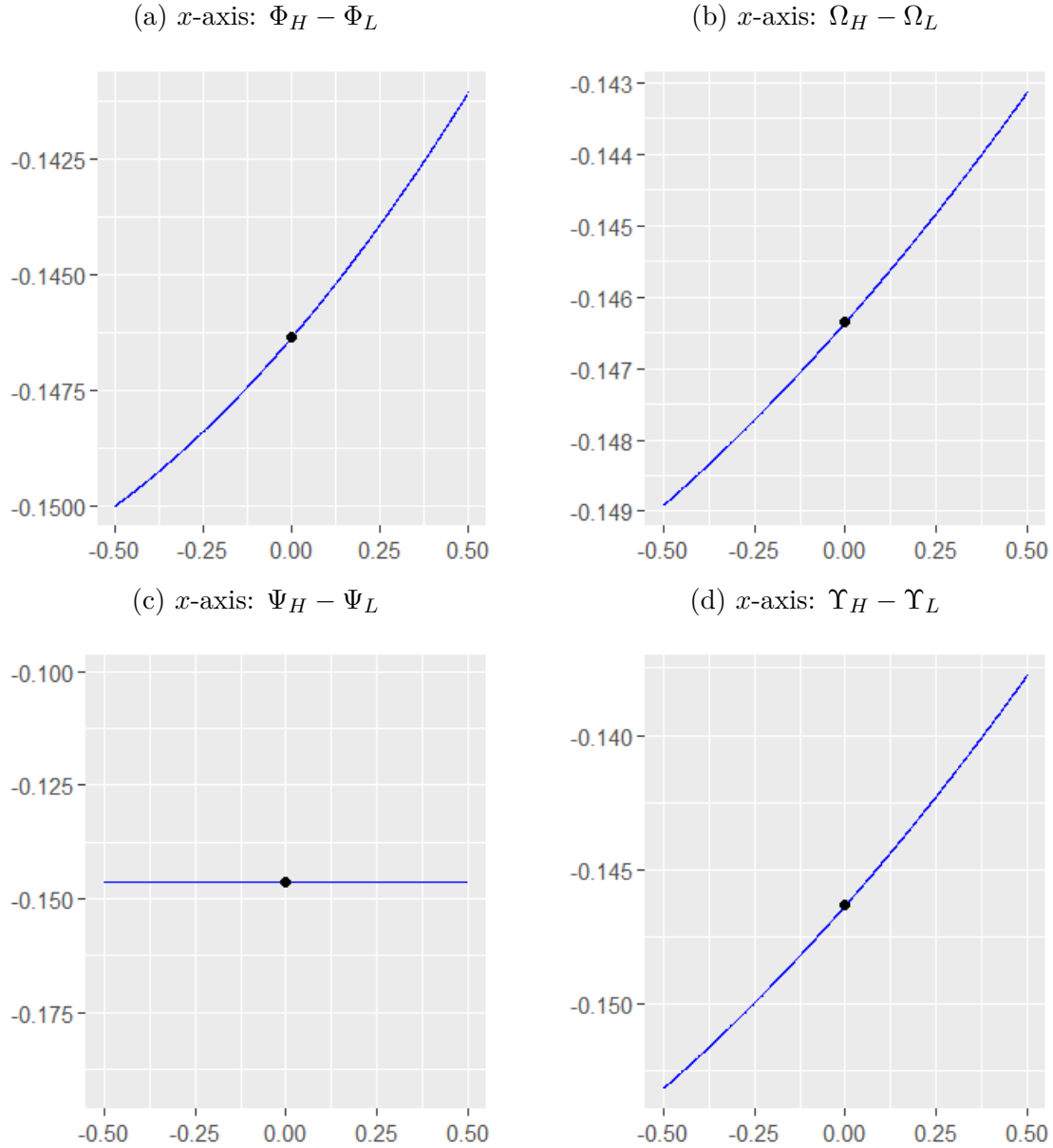
Figure 5.2: Elasticity of the skill premium with respect to the nominal interest rate (vertical axis; y-axis) for differentials of CIA parameters between the H - and the L - sectors (horizontal axis; x-axis) affecting the R&D sector (panel a), the supply of intermediate goods (panel b), demand for labor (panel c) and demand for intermediate goods (d)



Source: Authors' own computations.

Note: The differentials result from considering all combinations of CIA parameters in both sectors that are between 0 and 1 and equal to a simple arithmetic average equal to the values set in the baseline scenario.

Figure 5.3: Elasticity of the growth rate with respect to the nominal interest rate (vertical axis; y-axis) for differentials of CIA parameters between the H - and the L - sectors (horizontal axis; x-axis) affecting the R&D sector (panel a), the supply of intermediate goods (panel b), demand for labor (panel c) and demand for intermediate goods (d)



Source: Authors' own computations.

Note: The differentials result from considering all combinations of CIA parameters in both sectors that are between 0 and 1 and equal to a simple arithmetic average equal to the values set in the baseline scenario.

We now explain the channels through each differential in each sector of activity affects monetary policy. If $\Phi_L > \Phi_H$, CIA constraints affect more R&D producers in the L -sector than in the H -sector. Therefore, an increase in inflation, and thus the nominal interest rate through the Fisher equation, leads to an increase of costs for producers which is relatively higher in the former.¹⁶ Following this, the relative investment in R&D in the L -sector decreases, which contributes to a lower relative growth rate of new varieties of intermediate goods in this sector.¹⁷ This leads to an increase of the technological-knowledge bias,¹⁸ which, by implying relative less new varieties produced in the L -sector, leads to a drop in the relative output of this sector,¹⁹ and thus an increase of the skill premium.²⁰ Moreover, by implying larger absolute costs on both sectors but that affect relatively more the L -sector, this also leads to a drop of the growth rate of the outputs produced in both sectors that is higher for the L -sector and lower for the H -sector in relation to the baseline scenario.²¹ Since $\gamma_L > \gamma_H$, this implies that the growth rate of output is affected more negatively than in the case of homogeneous CIA constraints.²²

If $\Omega_L > \Omega_H$, the same increase in inflation increases the relative marginal cost of producing intermediate goods in the L -sector, driving producers to increase prices,²³ which decreases the relative demand by producers of output in this sector.²⁴ This leads to a reduction of relative output²⁵ and of relative profits of producers of intermediate goods in the L -sector,²⁶ which leads to the same effects described in the previous paragraph that result in an increase of the skill premium and a decrease of the growth rate of the economy.

If $\Upsilon_L > \Upsilon_H$, the policy under analysis leads to an increase in the cost of using intermediate goods in the L -sector relative to the H -sector, which decreases its relative demand,²⁷ resulting in a decrease in relative output and profitability in the L -sector

¹⁶See equation (5.16).

¹⁷See equation (5.13) and divide across sectors.

¹⁸See equation (5.17).

¹⁹See equation (5.10).

²⁰See equation (5.18) or equation (5.4) and, in this case, divide across sectors.

²¹See equation (5.6).

²²See equation (5.22).

²³Remember the optimal price defined by the producer of intermediate good i in sector j , $q_j(i) = \frac{1-\alpha}{(1+\Omega_j \cdot \iota) \cdot \chi}$.

²⁴See equation (5.5) and divide across sectors.

²⁵See equation (5.10).

²⁶See equation (5.12).

²⁷See (5.5) and divide across sectors.

through the same mechanism described in the previous paragraph and with similar consequences.

Finally, if $\Psi_L > \Psi_H$, an increase in inflation increases the relative cost of unskilled labor and, as result, has a positive direct effect on the skill premium²⁸ without affecting the technological-knowledge bias nor the growth rates of new varieties. Therefore, the growth rate of output in each sector and, consequently, the growth rate of the economy is unaffected.

5.5 Sensitivity Analysis

In this section, we follow a similar approach as some authors in the literature such as Gil and Iglésias (2020) and analyse the sensitivity of the results by calculating the elasticities of the skill premium and growth rate for different parameters and comparing them with the results obtained using the baseline calibration. We do so both for the baseline and representative scenarios of differences concerning CIA parameters between the H - and L -sectors that favor the former, considering the evidence from the literature that suggests this to be the case in reality.

The first sensitivity analysis is conducted with respect to the labor share parameter, which we define as $\alpha = 0.55$, to take into account the substantial discussion in the literature regarding the decrease of the labor share of income (*e.g.*, Afonso & Lima, 2020; Bental & Demougin, 2010; Elsy, Hobijn, & Şahin, 2013; Karabarbounis & Neiman, 2014). In the second and third ones we set $\lambda = 0.4$ and $I = 0.1$ in order to analyze how the relation between heterogeneous CIA constraints and monetary policy changes with a higher technological capability²⁹ and inflation, respectively, which is especially important to determine its effectiveness in countries at different levels of development since they usually differ in these parameters. Finally, in the fourth one we consider $\gamma_L = 0.4$, which is justified for several reasons: (i) proposition 3 establishes that the results regarding the impacts of monetary policy on the growth rate in the presence

²⁸See (5.18).

²⁹Alternatively, we could have determined how the results change in an environment characterized by low R&D expenditures. Since the model is characterized by R&D driven growth, where the growth rate of the economy is driven by the increase in the number of intermediate goods/machines, we can analyse this case by determining the R&D productivity parameter that results in a zero steady-state growth rate. Bearing in mind (22), this condition implies that $\lambda_{(g^*=0)} = \rho \left[\alpha \left(\frac{1-\alpha}{\chi} \right)^{\frac{1-\alpha}{\alpha}} \left[\gamma_H^\epsilon [f_H^g(\iota)]^{1-\sigma} + \gamma_L^\epsilon [f_L^g(\iota)]^{1-\sigma} \right]^{\frac{1}{\sigma-1}} \right]^{-1}$, where $f_j^g(\iota)$ is defined by equation (5.25), which, bearing in mind the baseline calibration model, implies $\lambda_{(g^*=0)} = 0.1061$.

of heterogeneous CIA constraints depend on this parameter, (ii) the service sector, which is skill-intensive, is growing rapidly not only in the US (Buera & Kaboski, 2012) but also in developing economies such as India (Mukherjee, 2013), which highlights the importance of analyzing a scenario where the relative importance of the unskilled sector in the economy is lower than the skilled sector, (iii) considering alternative values of γ_L , in conjunction with the sensitivity analysis on λ , allows to determine the impacts of considering alternative values for certain variables such as the skill premium and the relative supply of skilled labor.

Table 5.2: The elasticity of the skill premium and growth rate with respect to the nominal interest rate, E_t^{W*} and E_t^{g*} , respectively, for representative scenarios of CIA constraints in the various sectors in relation to the baseline specification and different values of α , λ , I and γ_L .

Calibration	baseline	$\alpha = 0.55$	$\lambda = 0.4$	$I = 0.1$	$\gamma_L = 0.4$
E_t^{W*}					
baseline	0.0000	0.0000	0.0000	0.0000	0.0000
$\Phi_H = 0.5; \Phi_L = 1$	0.0248	0.0248	0.0248	0.0451	0.0248
$\Omega_H = 0.5; \Omega_L = 1$	0.0149	0.0149	0.0149	0.0271	0.0149
$\Psi_H = 0.5; \Psi_L = 1$	0.0354	0.0354	0.0354	0.0644	0.0354
$\Upsilon_H = 0.5; \Upsilon_L = 1$	0.0396	0.0396	0.0396	0.0722	0.0396
E_t^{g*}					
baseline	-0.1464	-0.1589	-0.1464	-0.2864	-0.1464
$\Phi_H = 0.5; \Phi_L = 1$	-0.1500	-0.1626	-0.1500	-0.2916	-0.1427
$\Omega_H = 0.5; \Omega_L = 1$	-0.1813	-0.2066	-0.1813	-0.3517	-0.1769
$\Psi_H = 0.5; \Psi_L = 1$	-0.1464	-0.1589	-0.1464	-0.2864	-0.1464
$\Upsilon_H = 0.5; \Upsilon_L = 1$	-0.2396	-0.2649	-0.2396	-0.4607	-0.2279

Source: Authors' own computations.

Note: Each column/row represents combinations of changes in relation to the baseline calibration of the model concerning parameters that determine CIA constraints (first column) and other parameters of the model (first row).

The results are in Table 5.2. While the effectiveness of monetary policy on the skill premium is not affected by changes in the labor share, this is not the case in the case of the growth, where a decrease of this parameter exacerbates the already negative effect of an increase of the nominal interest rate on the growth rate of the economy,

across all scenarios. Moreover, this negative effect is magnified when CIA constraints are heterogeneous in relation to the baseline scenario.

Differences in R&D Productivity do not appear to affect the impacts of the monetary policy on either the skill premium and the growth rate.³⁰ Higher inflation, through the relation to the nominal interest rate implied by the Euler equation, in general expands the magnitude of the effects of monetary policy on both the skill premium and the growth rate, especially in the presence of heterogeneous CIA constraints. A lower relative importance of the unskilled sector in the economy, represented by $\gamma_L = 0.4$, does affect the elasticity of the skill premium in any scenario. However, it results in a less negative elasticity of the growth rate when differences in CIA constraints across sectors are considered, except when they only concern the demand for labor.

Finally, by combining the results of the sensitivity analysis on λ and γ_L , we can determine the impact of considering alternative steady state values for some variables since they impact the model by changing the calibration of these parameters. This task is simplified considering that the results are invariant with respect to λ . On the one hand, since alternative values for g^* can only be achieved by considering different values for λ , this implies that the results would be the same if we had considered alternative values for the steady state growth rate. On the other hand, from (5.18) we can see that if we had considered a higher steady state value of the skill premium or of the relative supply of skilled labor and the remaining parameters as defined by the baseline calibration, this would have implied a lower calibrated parameter γ_L . Therefore, we can extend the previous conclusions from the analysis of $\gamma_L = 0.4$ to the case of a higher skill premium or a higher relative supply of skilled labor.³¹

³⁰Therefore, our results are also valid for industries with low R&D expenditures, characterized by a low R&D productivity parameter that yields a zero steady state growth rate.

³¹We do not evaluate the impact of specific alternative values for these variables because we expect neither to reach any meaningful different conclusions than those obtained from the sensitivity analysis on γ_L nor to obtain meaningful differences for the estimates of these variables in relation to the literature, which can be concluded after comparing some values with those obtained by other authors. For instance, Mallick and Sousa (2017) resorted to the NBER-CES Manufacturing Industry Database and obtained, for the United States in the period 1980-2009, averages for the ratio of total labor compensation and relative supply of skilled labor equal to 0.7242 and 0.4438, respectively, while we obtain corresponding values to these variables of 0.844 and 0.442, respectively, which are quite similar despite the different time period and methodology employed by the aforementioned authors.

5.6 Concluding remarks

In this paper we expanded the baseline Directed Technical Change model of Acemoglu (2002) without scale effects by including CIA constraints in the R&D and in the manufacturing parts of the economy that are allowed to affect skilled and unskilled firms differently.

The results indicate that monetary policy affects the skill premium in the presence of heterogeneous CIA constraints between the skilled and unskilled sectors, even if such differences are ignored and represented by an average value for the whole economy. Analyzing the individual impacts of each CIA constraint, in the case these being more pernicious to the L -sector, an increase in the nominal interest increases the skill premium through several channels. It increases the relative costs of innovating in this sector (in the case of the R&D sector), decreases the relative profitability of such efforts (in the case of demand and supply of intermediate goods), and increases the relative costs of using unskilled labor (in the case of differences in CIA constraints directly affecting this variable).

Regarding the impacts on the growth rate, the baseline results are consistent with the literature, with a negative impact of inflation on the growth rate. However, considering the same baseline scenario of more stringent CIA constraints in the L -sector, the same channels described before also magnify the negative impact of an increase in the nominal interest rate on the growth rate of the economy. This occurs due to the higher relative importance of the L -sector on the economy.

Finally, by analyzing the impacts of changes in key parameters, we find that a lower labor share and a higher inflation magnify the impacts of monetary policy on the growth rate and, in the case of the latter, also on the skill premium, especially in the presence of heterogeneous CIA constraints. However a higher R&D productivity does not change the effectiveness of any of these policies. A lower relative importance of the unskilled sector in the economy does not affect the skill premium, but, in general, reduces the negative impacts of an increase in inflation on the growth rate in the presence of heterogeneous CIA constraints. These conclusions are also valid if we had considered higher steady state values for the skill premium and relative supply of skilled labor, with alternative values of the growth rate not having any effect on the results.

The results of this paper are important for several reasons. Firstly, they provide a new channel through which price instability can contribute to increased inequality, which is important considering that this fact is empirically supported by our own findings

and other authors in the literature (*i.e.*, Albanesi, 2007). Secondly, they highlight the importance of avoiding averaging certain variables for the whole economy when determining the long run economic effects of inflation in the context of endogenous growth models by showing that, in the specific case of CIA constraints, this results not only in underestimating the negative impact of inflation on growth but also ignoring its effects on inequality.

Thirdly, they have important policy implications, especially for countries with high levels of inflation that are not able to conduct credible monetary policies to achieve price stability. Specifically, they show that such countries may follow two policies to mitigate the negative impacts of inflation:

- The first is to determine and reduce differences in liquidity constraints faced by the various sectors of the economy, with a special focus on unskilled sectors, considering the evidence from the literature, which would not only reduce the negative impacts of price instability on inequality but also on growth, due to the still high importance of the unskilled sectors in such economies.
- The second policy consists on the promotion of structural reforms to increase the relative importance of the skilled sector in the economy, which, despite not affecting inequality, would contribute to dampen the negative effect of inflation on growth.

In this paper, we analyzed a range of reasonable possibilities of differences in liquidity constraints in the absence of empirical evidence suggesting specific values. Therefore, we consider that future research should be dedicated to quantify the differences in liquidity constraints faced by each sector. Moreover, it would be relevant to conduct more in-depth empirical and theoretical analysis of what additional characteristics of firms operating in this sector other than size are connected to such different liquidity constraints.

Chapter 6

Conclusion

This Thesis provides four essays with different and innovative contributions to the inequality-growth literature.

In the first essay, we develop and employ an innovative methodological approach to systematize the literature on economic inequality since the 1950s and identify seven different clusters, that include a cluster dedicated to analyzing the relationship between inequality and growth. We found that the latter is one of the most important clusters in the inequality literature in general, as shown by a substantial number of average citations of works within this area. Moreover, the emergence of theoretical and empirical works in this area was prompted, respectively, by the development of endogenous growth theory growth models and the increased availability of data in the 1990s. Therefore, this essay provides a valuable contribution to the inequality literature, in general, and the inequality-growth literature, in particular, since it contextualizes this cluster's emergence and shows its importance over the years. Moreover, it also revealed extensive literature that showed the complexity of the relationship of inequality with other variables, being caused, impacted or simultaneously determined with many, such as growth. As explained further ahead, the latter proved to be a highly relevant aspect for the remaining essays of this Thesis.

The second and third essays consist of empirical analyses of the inequality-growth relationship and the main transmission channels through which such relationship materializes that address important issues found in the literature. In particular, the inequality-growth literature mainly consists of empirical analyses using panel data models focused on heterogeneous countries. As we explain in both essays, this approach poses limitations. This is not the most efficient manner to address the specific sources of endogeneity of the variables of interest. Moreover, the resulting conclusions are not necessarily informative considering the heterogeneous background of the countries under study. Bearing this in mind, we conducted two empirical analyses focusing on homogeneous countries that have been consistently experiencing significant increases in within-country inequality and are important economies in the global economy. These are two individual countries, the United States and France, in the case of the second and the European Union in the case of the third. In both, we conducted an orthogonal impulse response function (OIRF) analysis based on the estimation of structural vector autoregressive (VAR) models. This approach has been seldom considered in the inequality-growth literature, despite its relevance as it permits obtaining more information and more precise results by explicitly considering contemporaneous relationships and modeling the lagged dynamics of all endogenous

variables.

The OIRF analysis we conduct in both essays is focused on determining how economic growth reacts to inequality shocks. One of the fundamental aspects is the identification of a structural shock of inequality. This requires making assumptions based on economic theory and considering variables that can potentially affect both. This is necessary because, since all variables are endogenous, including inequality, the shock identified as a shock of inequality is an instrument comprised of a conglomerate of exogenous shocks to the model that affect inequality. Therefore, ignoring variables that can potentially simultaneously affect inequality and growth can result in such shock not being an adequate instrument. It would contain not only shocks that only affect inequality specifically but also inequality and growth simultaneously, leading to the risk of finding spurious relationships between both variables. Bearing in mind the findings in the literature, especially those from the first essay, it is crucial to consider this aspect because many variables can affect both inequality and growth and the few works in the literature that have considered them have shown that doing so can substantially affect the results (Huang et al., 2009; Lundberg & Squire, 2003).

Since any approach has advantages and limitations, we chose explicitly two approaches where the former compensated for the latter. The second essay has the advantage of analyzing a relatively long period and explicitly considering the country-specific nature of the inequality-growth relationship. However, this narrow focus comes at the cost of observations. On the other hand, the third essay includes many more observations but EU members, despite having a common set of institutions, have a certain level of heterogeneity. Moreover, the analysis period is much shorter than the second, and the approach involves using the System GMM estimator, whose validity depends on the quality of the available instruments. In contrast, this is not an issue in the case of the second essay since the VAR equations are estimated by Ordinary Least Squares (OLS), which does not require instruments.

The results of both essays are interesting and novel for several reasons. First, including variables that simultaneously affect inequality and growth proved relevant in both essays in different ways. In the second essay, the causality tests showed that almost all the variables that can theoretically affect inequality and growth simultaneously had a statistically significant impact in some of the variables of interest. In the third essay, we found some results that did not hold when these variables were considered, which allowed us to focus on those that were robust to their inclusion.

Second, both essays permitted reaching common conclusions. Inequality

- increases redistribution intensity, but the latter does not affect economic growth.
- does not affect human capital accumulation.

We consider the different focus, methodology, and analysis periods of both essays as proof of their robustness.

Third, they reinforce the notion that the inequality-growth relationship is country-specific and that caution must be exerted when attempting to draw generalized conclusions from the obtained results. This is illustrated by the different results obtained in the case of the United States and France, where, for instance, inequality appears to affect growth in different time horizons, and a structural change seems to occur in the former, with the impacts appearing to be more negative after 1989. This is also seen by comparing some results obtained in both essays. In the second essay, we found that it decreases growth in individual countries such as the United States and France. However, in the third essay, it does not affect growth in EU members on average, although it affects investment negatively. Moreover, we also find evidence of more negative effects of inequality on growth in laggard economies than in more advanced ones.

Fourth, these results are consistent with more recent findings from the literature, which point to a negative impact of inequality on growth, but simultaneously contradict notions that have been established for some time. The first is the idea that the impact of inequality on growth in developed countries is non-statistically significant and positive. This idea is disputed by the results of the second essay, which is focused on two of the most advanced economies in the world, the United States and France, and revealed negative effects of inequality on growth in both countries. The second is that inequality decreases growth by increasing redistribution and decreasing human capital, which is directly contradicted by the results of both essays. The third is the notion that the relationship between inequality and growth only operates in the long run, which can be questioned by the contemporaneous effects of inequality on either growth or investment found in both essays. This demonstrates the complexity of the inequality-growth relationship. Furthermore, it reinforces the importance of considering different methodological approaches in empirical analyses to reach more robust conclusions. In this regard, it demonstrates the relevance of considering a VAR modeling approach with variables that jointly determine inequality and growth.

These conclusions have important implications. For policymakers, they lead to the recommendation of policies aimed at decreasing net inequality by increasing the intensity of redistribution policies, which do not hamper economic growth, but also by directly identifying and addressing institutional factors responsible for the substantial levels of market inequality. For researchers, our empirical work opens venues for future studies to explore. First, more empirical studies should be conducted with a time series approach, such as the ones we conduct focused on different economies, both individually and in homogeneous groups. Second, more in-depth theoretic analyses should be conducted to explain the contemporaneous relationships found in both empirical essays that reevaluate the existing transmission channels or design new ones. Third, more sophisticated approaches could be considered in the identification of inequality shocks, such as through the estimation of theoretical models that establish the determinants of inequality and growth and alternative approaches to identify the structural shocks of interest (for example, sign restrictions).

In the fourth essay, we analyze the impacts of inflation on the Skill Premium and growth rate in the context of a canonical Directed Technical Change (DTC) model with unskilled and skilled sectors, which we extend by considering cash-in-advance (CIA) constraints affecting each one in a potentially different manner. In the presence of CIA constraints more stringent to the unskilled sector, in line with the empirical evidence, an increase in inflation leads to a higher skill premium and a lower growth rate. The Skill Premium can be considered a measure of income inequality since it is the ratio of the wages of workers with a college degree to those without one. Therefore, the results of this essay provide a theoretical contribution to consider inflation as a variable that can simultaneously affect inequality and growth. This aspect proved to be highly relevant in the empirical essays of this Thesis.

They also have significant implications. For researchers, they underline the importance of avoiding aggregating all variables of interest in similar analyses when there are plausible differences because that could result in missing relevant effects. Moreover, they also open interesting venues to explore in the future, such as the quantification of liquidity constraints faced by each sector and more sophisticated models that include transitional dynamics. For policymakers, they provide suggestions for those interested in reducing the adverse effects of inflation on inequality (Skill Premium) and economic growth, namely through the reduction of liquidity constraints faced by the various economic sectors. This issue is currently of crucial importance not only for developing economies but also for advanced ones.

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