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Essays on Income Distribution, Cycles and Economic Growth

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Introduction

This thesis consists of three chapters on mostly unrelated issues. The leitmotif linking them is the interplay between income distribution and real activity. The income distribution considered in each essay is either interpersonal, functional, or both.

Chapter 1 surveys the theoretical and empirical literature on the impact of interpersonal income distribution on economic growth. The first part analyzes the different transmission channels proposed in the theoretical literature. The second part examines the empirical literature, using statistical tools to identify the main factors influencing the reported results. Although the empirical evidence, partly reflecting its theoretical counterpart, is characterized by heterogeneous results, it is possible to identify the main elements driving the differences in estimates. Among these, a significant role is played by the cross-section/panel nature of the dataset, the type of estimator used, the country's level of development, and the length of the growth spells under analysis.

Chapter 2 proposes a Kaleckian theoretical model on the interaction between functional distribution, personal distribution and economic activity. The paper presents the endogeneity of the demand regime and the interaction between personal and functional income distribution as two intrinsically linked issues. By assuming that saving is a function of personal rather than functional income distribution, an increase in the labor share effectively boosts consumption and aggregate demand, not per se, but only as long as it reduces personal inequality. As the labor share increases, both the demand regime type – the *sign* of the slope of the demand schedule - and its strength- the *size* of the slope of the demand schedule - can endogenously change. Concerning the former, there can be a threshold value for the wage share beyond which there is a shift from wage-led to profit-led demand. Unlike most Kaleckian models, the analysis shows that profit inequality is as important as wage inequality in determining the demand regime type and its strength.

The last chapter focuses on the interaction between functional income distribution and the business cycle. The paper first provides a comprehensive literature review of the theories explaining the cyclical interaction between factor shares and economic activity. Secondly, it assesses if empirical evidence supports those theories, overcoming the strong criticalities present in the current empirical literature. To this end, a Bayesian VAR identified with sign restrictions is set up. The results suggest that cyclical fluctuations in the labor share are mainly driven by the pro-cyclicality of labor productivity - consistent with *overhead costs* and *risk distribution* theories - and by the Phillips Curve effect upheld by *Goodwin*. The model does not support Goodwin's expansive effect of a capital share rise. In contrast, there is partial evidence favoring the *biased technical change* theory.

1 Income distribution and growth in the economic literature

1.1 Introduction

The relationship between distribution and growth is one of the oldest and most debated issues in the history of economic thought. Consequently, economists' views on the topic have changed over the decades. The first approach - known as the 'classical approach' - arose from the combination of Say's law with the observation that individual propensity to save increases with income. While this approach saw income inequality as a possible growth driver because of the stimulus to capital accumulation, the subsequent advent and affirmation of the neoclassical paradigm led to a temporary sideline of the issue. In the marginalist view, the introduction of the representative agent removed individual differences in the propensity to save. A major change in the paradigm occurred in the past thirty years, with a gradual flourishing of theories that again see distribution as a factor that can undermine or promote economic growth. The purpose of Section 1.2 is indeed to expose the theoretical transmission channels proposed in the economic literature. It is clear from the many theories described - often with opposing effects - that it is difficult for a one-size-fits-all relationship between inequality and growth to exist. Instead, distribution is likely to act differently depending on the country's degree of development, financial system, soundness of its political institutions, or size and scope of its welfare system. The empirical literature reviewed in Section 1.3 reflects such complexity, remaining largely inconclusive regarding the impact of inequality on economic growth. Nevertheless, the main factors influencing the sign of the estimates emerge: the level of development, the panel/cross-section nature of the dataset, the estimator employed, and the length of the growth spells under analysis.

Finally, I want to clarify what this essay is and is not. First, this article only discusses the impact of interpersonal inequality on growth. The other side of the coin - the effect of growth on inequality - is out of the scope of this analysis. Although this is an equally important issue - if for no other reason than the simultaneous causality problem - it cannot be addressed on these lines for spatial reasons. Second, despite the many different types of inequality concepts, this paper deals only with income and wealth inequality, with a few exceptions related to inequality of opportunities in Section 1.2. Third, this survey will focus exclusively on the *interpersonal* distribution of income since the relationship between *functional* income distribution and real activity will be discussed in the second and third chapters. Fourth, although the empirical survey in Section 1.3.5 uses data on the estimates reported in the literature, it is not intended to be a meta-analysis. Its scope is only to support, with the help of data, some of the conclusions drawn. Fifth, this survey, especially in its theoretical part, is not intended to be comprehensive of every contribution published on the topic. Finally, although the article focuses on income distribution, I included some papers and transmission channels based on wealth distribution in the theoretical literature section. The stock of wealth is (in part) the result of accumulated income flows. Therefore, the two distributions are, to some extent, linked. We can reasonably expect the distribution of wealth to follow the income distribution with some lag. So, the choice to include also wealth-related transmission mechanisms is due to the will to give the reader a more comprehensive picture. It will be specified whenever we refer to wealth distribution instead of income distribution.

1.2 Theoretical transmission channels

The economic literature suggests different ways income distribution could affect economic growth. In this section, we are going to review these transmission channels.

1.2.1 Classical approach

This approach rests on the premise that the saving function is convex, i.e., the marginal propensity to save increases with income (Dynan et al. 2004 [48]; Carvalho and Rezai, 2016 [32]). If this is the case, and we assume that saving determines investment and not vice versa, then a redistribution toward those at the top of the distribution would raise the share of saving in national income and, consequently, the rate of capital accumulation. Bourgignon (1981) [28] provides a perfect example of this approach. The paper shows that if the saving function is convex, then a non-egalitarian equilibrium is Pareto superior to the egalitarian one. Individuals differ only in their wealth, which yields a given rate of return. Larger wealth (and income) inequality leads to greater per-capita output and consumption, making income and consumption higher for all individuals. Thus, a bottom-up redistribution produces a subsequent trickle-down effect. In Lewis (1954) [83] - since the engine of growth is the saving of capitalists - the way out from the under-development of a backward country necessarily entails an increase in the profit share with the consequent widening of inter-personal income inequality.

The two core assumptions of this approach are subject to two types of critiques. The first is the old Keynesian critique, according to which investment determines saving and not vice versa. If this is the case, an increase in inequality leading to a rise in the propensity to save would have a depressive rather than an expansionary effect on the economy. The second critique regards the impact of inequality on the aggregate saving rate. The observation that the propensity to save increases with income is well established in the economic literature (Dynan et al., 2004 [48]). However, this does not necessarily imply that higher inequality leads to a higher aggregate saving rate. This is only the case if we assume that following a change in the income distribution, the individual propensity to save along the whole income distribution remains unchanged. According to Levine et al. (2010) [82], it is, in fact, possible that following a bottom-up redistribution, those at the bottom of the distribution reduce their saving rate in an effort *to keep up with the Joneses.* Consequently, the saving share in national income falls instead of increasing as the classical approach expects. Several authors have tried to estimate the effect of changes in income inequality on the national saving rate

(Schmidt-Hebbel and Servén, 2000 [116]; Koo and Song, 2016 [74] and Smith, 2001 [121]), without reaching sharp conclusions.

1.2.2 Credit constraints approach

This channel emphasizes the interplay between credit market imperfections and inequality in determining the level of human and physical capital investments. When credit constraints are binding, wealth inequality reduces investments relative to their potential level. If lenders require a certain amount of wealth as collateral when granting a loan, or if the interest rate charged is a decreasing function of wealth, people who inherit too little end up being credit-constrained. Wealth redistribution allows more people to access credit to finance human or physical capital investments, leading to higher aggregate output. Furthermore, given that investments in human capital are characterized by diminishing returns to scale at the individual level (i.e., primary education has a higher return than secondary education, and so on), greater inequality implies that the most productive investments are not undertaken. This strand is also intrinsically linked to the concept of inequality of opportunities, as credit-constrained agents do not have the same financing options as wealthier ones.

Loury (1981) [86] was the first to highlight that wealth redistribution could relax credit constraints, leading to higher aggregate output. However, in his model, the redistribution effect is limited to the short run, as wealth distribution converges to the same ergotic distribution in the long run. Galor and Zeira (1993) [60] show that it is sufficient to assume a form of non-convexity in technology to generate multiple path-dependent long-run equilibria. In their model, it is the indivisibility of human capital investments to generate non-convexity in technology. This modification allows a one-time redistribution to have permanent effects, leading to different long-run equilibria. This happens because credit-constrained people cannot afford to invest in the fixed amount of capital that the indivisible investment requires, hence remaining stuck in a poverty trap. Therefore, initial incapacity tends to perpetuate itself in the long run.

Piketty (1997) [105] shows that the non-convexity of technology is not required to obtain multiple long-run equilibria. Instead, the same result can be achieved by endogenizing the interest rate. The interplay between wealth distribution and the interest rate generates path dependency. The higher the proportion of credit-constrained people, the higher will be the interest rate because of a lower net supply of capital. In turn, a high-interest rate reinforces the upward pressure on the number of credit-constrained people, making the high-interest rate equilibrium self-sustaining.

We find both elements in Banerjee and Newman (1993) [14]. Indivisibilities are present in physical rather than human capital investments. Secondly, the labor market plays the role played by the capital market in Piketty (1997) [105]. In other words, the endogenous variable is the wage level, while the interest rate is exogenous. The paper emphasizes the interconnection between wealth distribution and employment choices, which determine aggregate output. If a certain amount of capital is required to start an entrepreneurial activity, an individual who inherits lower wealth than this threshold is forced to borrow the remainder. Since imperfections in the credit market cause lenders to demand a certain amount of wealth as collateral, some end up being credit-constrained. Those people are forced to choose a lower-productivity occupation that does not require physical capital. Again, the initial distribution (and any redistribution of it) affects the development path of the economy towards different long-run equilibria. A different initial distribution may result in a future of prosperity rather than stagnation.

However, reducing inequality when credit constraints are binding could also negatively affect investment. In a model inspired by Banerjee and Newman (1993) [14], Ghatak and Jiang (2002) [61] show how a top-down one-time redistribution of wealth positively impacts long-run aggregate output only if it results in a larger number of individuals not being credit-constrained. A redistribution that brings affluent individuals below the minimum threshold necessary to borrow while not allowing the redistribution recipients to reach this minimum threshold would negatively affect aggregate investments.

In sharp contrast with the rest of this strand, Bhattacharya (1998) [22] suggests that the effect of a wealth redistribution policy could harm the per capita output level. This result follows from two assumptions. Firstly, the individual belonging to the entrepreneur class rather than the labor group is predetermined. Secondly, only entrepreneurs derive utility from leaving bequests to their offspring. Therefore, it is not possible for a worker, through saving, to bequeath his offspring enough wealth to start a capital-intensive higher value-added activity. In such a situation, a transfer reducing the ability of entrepreneurs to finance investment projects internally cannot be counterbalanced by an increased investment capacity of previously credit-constrained individuals (as in the rest of the literature). Therefore, wealth taxation with redistributive purposes negatively impacts the aggregate capital stock as *"bequests tend to mitigate credit market frictions and, in that sense, promote financial market efficiency, and capital accumulation"*.

Finally, Galor and Moav (2004) [58] combine the positive effect of inequality postulated by the classical approach of Section 2.1 with the negative impact of the credit-constraint strand of this section. The latter effect is implemented assuming that human capital, unlike physical capital, has diminishing returns to scale at the individual level. This implies that it is better to accumulate human capital by spreading it over more individuals than by concentrating it on fewer. In the early stages of development, when physical capital is scarce, the return on physical capital exceeds that on human capital. The growth process is driven exclusively by the accumulation of physical capital. At this stage, greater inequality is instrumental in promoting the growth process because of its stimulus to physical capital accumulation. In the advanced stages of the development process, due to the complementarity of physical and human capital, returns on the human capital rise to the point where it is worthwhile to invest in human capital. Credit constraints make the level of investment in human capital sub-optimal at this stage. This element, combined with the fact that rising wages tend to level out saving rates, means that a top-down redistribution become beneficial at this stage of development. Finally, when wages have grown so much that credit constraints are no longer binding, inequality no longer affects growth.

1.2.3 Equity-Efficiency trade-off

The trade-off posited here builds on the role differences in individual remuneration have in generating the right incentives for workers' efforts or investment choices. According to Mirrlees (1971) [90], the very fact that taxation - the primary redistributive tool - targets the level of individual output rather than its potential level means that any redistributive initiative involves a certain distortion of incentives and moral hazard. Since measuring individual skill levels (a proxy of the potential level of individual output) is often difficult, authorities resort to taxation on individual output. The latter potentially undermines worker effort and investment in human capital to the point that no one would be willing to do unpleasant work anymore in the case of a complete flattening of pay differentials. Similarly, Rebelo (1991) [111] shows how, in endogenous growth models, an increase in income taxation reduces the rate of return on private sector investment. This reduced incentive for accumulation, in turn, lowers capital and the economy's growth rate.

Beyond taxation, Lazear and Mosen (1979) [80] show how an unequal income distribution from paying some individuals well above their marginal product may be optimal. This can be the case when output is difficult or costly to monitor or when individuals are risk averse and the component of randomness in their income independent from individual effort is very high. In the first case, remuneration based on the position in the firm's hierarchy - ranking remuneration - and not on individual marginal productivity can compensate for the difficulty or cost of measuring the latter. For example, managers' compensation above their productivity could be justified based on the incentive that those salaries exercise not on the managers themselves, but on those who aspire to that position - typically those who are a step immediately below in the ranking. In the second case, ranking remuneration leads to lower income variance for risk-averse individuals whose wages have a high component of randomness out of their control.

However, as Okun (1975) [96] points out, the possible existence of a trade-off should not be understood as if anything that increases inequality is necessarily beneficial in terms of efficiency. For example, a technological innovation that increases unskilled workers' productivity can improve their living conditions and efficiency.

1.2.4 Fertility rates

This channel emphasizes the role of inequality in the interplay between fertility rates and educational choices. Indeed, distribution and human capital investment can be mediated not only by credit constraints, but also by the fertility rate. On the one hand, increased inequality may widen the fertility gap between rich and poor because of the opportunity cost people face in raising children. If raising children takes the same amount of time for both low-income and high-income parents, the opportunity cost of this time is different (Kremer and Chen, 2002 [75]; De la Croix and Doepke, 2003 [42]; Moav, 2005 [91]). In turn, people from the lower classes may invest less in the offspring's education if the return on investment in children's education depends on the parents' education (Morand, 1999 [92]; Moav, 2005 [91]). Well-educated parents can transmit soft skills to their offspring, offer direct teaching, or include them in specific social networks. For these reasons, for the same monetary investment in education, more educated parents have a higher return from investing in their children's education. The result is that high-income, well-educated parents tend to invest more in their children's education. Following an increase in inequality, from one generation to the next, the weight of the low-educated in the population increases, reducing per capita human capital (De la Croix and Doepke, 2003 [42]), physical capital (Moav, 2005 [91]), and thus growth.

However, a top-down redistribution policy could reduce the investment in the education of the rich without increasing that of the poor, who could use all the additional income to raise more children (Morand, 1999 [92]; De la Croix and Doepke, 2003 [42]). Instead, policies that aim to reduce the cost of education or increase the opportunity cost of fertility would be more effective

(Kremer and Chen, 2002 [75]; De la Croix and Doepke, 2003 [42]; Moav, 2005 [91]). Examples of these policies could be a compulsory and free public education system, laws that hinder child labor, reduction of subsidies linked to household size (Moav, 2005 [91]), and even the creation of a pension system. Indeed, one of the reasons people have children in developing countries is the income support they will provide to their parents when they are old (Voitchovsky, 2005 [128]; Morand, 1999 [92]). Given the multiplicity of equilibria characterizing these models, such policies could trigger a mechanism taking the economy out of the poverty trap, converging toward a long-term equilibrium characterized by lower inequality and higher growth (Kremer and Chen, 2002 [75]; Moav, 2005 [91]).

1.2.5 Crime

This strand focuses on the role of inequality in determining the extent and scale of people involved in illegal activities. Suppose people engage in criminal activities rather than a legal occupation based on the expected earnings differential between the two. Those in poverty are incentivized to engage in criminal activities, given the low prospects of earning from a legal one. Chiu and Madden (1998) [36] show how progressive income taxation can reduce the number of people involved in burglary by increasing low incomes and making legal alternatives more attractive. Within a search equilibrium framework, Burdett et al. (2003) [29] show how, in turn, a high crime rate reduces the performance of legal activities. Jonsten (2003) [69] in an OLG endogenous growth model suggests that increased crime induced by greater inequality - because of the opportunity costs outlined above - can reduce growth through two channels. First, the new people who engage in criminal activity will not invest in human capital, reducing the aggregate stock and income growth. Secondly, increased crime reduces the expected return from legal activities by making property rights less secure. The latter mechanism, in turn, disincentivizes investment in human capital by those who continue to engage in legal activities. Finally, Neanidis and Papadopoulou (2013) build a unified theoretical framework where the crime and fertility channels interact with each other and influence economic growth. Specifically, fertility enters through the trade-off between children's quantity and quality. The only difference is that the cost is not in terms of education but health. Child health is assumed to impact adult health, which is positively related to productivity. The key variable is the probability of escaping apprehension. As the latter increases, it generates a rise in both criminality and fertility and a reduction in expenditures on child health. However, the impact on growth is not predetermined. A change in the probability of escaping apprehension also impacts other channels, such as public health spending and saving. The net effect cannot be determined a priori.

1.2.6 Internal demand and the *size* effect

This channel emphasizes the importance of a local middle class large enough to generate the demand for manufactured goods necessary to support an industrialization process in a world with trade barriers. There are two main underlying assumptions. The first is some version of Engle's Law (hierarchical preferences), according to which the income share spent on food decreases as individual income increases. The middle class is the most important, as it spends its income mainly on industrial products. The upper class tends to spend more on hand-made or luxury imported products (both types do not involve the local industry). Finally, the income of the lower classes is absorbed almost entirely by food. It is then assumed - similarly to the indivisibilities in investments in the credit constraints channel - that for industrial production to be started, it is necessary to bear an initial fixed cost. Along these lines, Murphy et al. (1989) [93] show how, for an initial boom in agriculture or exports to kick-start a process of industrialization, it must be accompanied by a middle-class large enough to generate demand sufficient to cover the fixed costs required to undertake industrial production. However, similarly to the credit constraints channel, redistribution could also harm growth. Excessive equality in a poor society may imply that no one can cover even their basic needs, resulting in a lack of demand for industrial products. Mani (2001) emphasizes the importance of the medium-skilled intensive sector in a country's development process. If the initial distribution is highly unequal, by Engle's law there will be high demand for low-skilled intensive goods and low demand for medium-skilled goods. The distribution of income affects the distribution of returns as well. Medium-skilled workers do not receive a large income and cannot invest in their children's education. This implies that the initial distribution of income perpetuates over time. The demand for medium-skilled goods is critical to ensure that the children of those who are medium-skilled today will be high-skilled tomorrow. Initial high inequality prevents this process from taking place.

Zweimull (2000) [132] links distribution and market size to R&D vibrancy. A redistribution of wealth can expand the pool of potential customers for a new invention, making it profitable for a company to cover the fixed R&D costs required to start production. The increase in productivity, in turn, releases resources to be shifted to R&D, thereby increasing growth.

1.2.7 Innovation and the *price* effect

Foellmi and Zweimuller (2006) [53] introduce the *price effect* alongside the *size effect*. While the latter usually implies a negative effect of inequality on growth, the former entails a positive effect. The prize effect means that as inequality increases, some people are willing to pay a higher price for new inventions, making those products more valuable to producers and stimulating innovative activities. The additional R&D costs are, thus, financed with the resources freed up by the reduced consumption of the poor. Over time - despite the initial loss they suffered - lower classes could even increase their consumption thanks to the higher growth rate of the economy. We find both elements in Matsuyama (2002) [87]. On the one hand, when a new innovative product appears on the market, its price is high, and only the rich can afford it. As they begin to buy the product, the increase in market size induces an increase in productivity through learning by doing. This lowers the price, making it accessible to lower classes. In turn, the market size expansion further reduces the price. The distance between one class and another must not be excessive for this transmission mechanism to work. Indeed, excessive inequality can mean that the initial price reduction triggered by the rich's purchases is insufficient to make the product available to the lower classes. As before, also an overly egalitarian distribution can halt the trickle-down process. Excessive equality can mean that no one can initially afford the new innovation, preventing the cascade process from starting.

According to Foellmi and Zeimuller (2006) [53], the *price effect* is likely to dominate the *size effect*. Ten years later, Foellmi and Zeimuller (2017) [54] suggest an opposite conclusion. Assuming that wealthy consumers can reach a satiation point, their lower willingness to pay a high price for innovations could dampen the price effect. Given their distance from the satiation point, only an increase in inequality within the lower classes can result in a price effect larger than the size effect.

In addition, the price effect is more likely to exceed the size effect the larger the productivity gap between innovators and traditional producers.

1.2.8 Fiscal policy and the median voter mechanism

In a very famous contribution, Persson and Tabellini (1991) [104] argue that inequality harms growth because of the redistributive pressures it brings along. Their model combines endogenous growth and policy theories and hinges on two assumptions. Firstly, capital and knowledge accumulation incentives depend on individuals' ability to appropriate the fruits of their investments. Given this premise, tax distortions are harmful to economic growth. The second assumption is that the position of the median individual with respect to average income determines the level of redistribution. The lower the income of the median individual compared to the average income, the stronger the political pressure for redistribution, which ultimately reduces growth. Thus, it is not inequality per se detrimental to growth but the redistributive pressure it brings. Hence, the only redistributive policies effective in stimulating growth are those reducing pre-tax inequality. Similarly, Alesina and Rodrik (1994) [5] conclude that a low level of taxation maximizes growth.

This strand can be summarized in two key assumptions. First, the more unequal a society is, the higher the level of redistribution. Second, the higher the redistribution, the lower the private investment profitability and economic growth. Several authors have criticized this view. Regarding the first hypothesis, Saint-Paul and Vernier (1996) [115] point out that inequality is not necessarily associated with increased redistribution. Among the factors hindering this association is the possibility that inequality increases only among the poorest, leaving the mean and median unaffected. Political influence may also be unevenly distributed among social groups. In the USA, for example, there is low voter participation among the poorest. Moreover, the mean-to-median ratio is the determinant of taxation only in the case of a proportional tax rate and lump-sum transfers, but not necessarily in the case of progressive taxation. Also, the level of taxation preferred by the majority may fall as inequality increases if taxation is more distortionary towards groups at the tail end of the distribution. Lee and Roemer (1999) question the idea that an increase in inequality necessarily leads to greater redistribution. The tax base may shrink if inequality increases given the same tax rate. This would force the government to revise government spending downward, revitalizing private spending. Regarding the impact of taxation on private investment returns, Saint-Paul and Vernier (1996) [115] point out that the positive effects of redistribution can more than compensate for the negative effect through some of the other channels described above. Finally, certain types of public expenditure, such as education, can simultaneously reduce inequality and increase the stock of human capital.

1.2.9 Lobby, corruption and misallocation of resources

The interests of the wealthiest may not coincide with those of a country's growth and development. This can relate to several issues, such as the level of public spending on education, the security of property rights, efficiency in the allocation of public investment, and corruption and rent-seeking behavior of the political class. If this is the case, the higher inequality, the greater the power of the wealthy to diverge public policy from the interests of society.

The wealthy may seek to obstruct public investment in education, fearing a more educated population will oust them from power (Esterly, 2001 [49]). Galor et al. (2009) [59] focus on the role of land inequality in determining public education spending in a developing country. Because larger investments in education encourage a shift of labor from agriculture to the industrial sector, causing higher wages and lower returns in the former, landowners tend to oppose such policies. If land was more evenly distributed, everyone drew similar income from capital, labor and land. Consequently, political opposition to larger investments in education would be reduced, resulting in accelerated industrialization of the country. In Eicher et al. (2009) [51], the government faces a trade-off: subsidizing education increases GDP over time, along with the rents from corruption it extracts as a proportion of output, but reduces these rents in the short-run. The lower the initial inequality, the fewer poor people need to be subsidized, and the more a government is inclined to finance education. The initial wealth distribution affects the policy reforms undertaken by a country and its subsequent development path. High inequality can also make property rights more insecure. This can be the case of possible violent redistributive attempts from lower classes. It could also be associated with a highly corrupt court system, favoring acts of prevarication by large firms against small and medium-sized companies, reducing aggregate investments (Glaeser et al., 2002 [62]). Finally, greater inequality may increase the lobbying capabilities of the wealthy in channeling public investment to sectors of their interest, which do not necessarily represent the most efficient allocation of public resources (Esteban and Ray, 2006 [52]).

1.2.10 Trust and social capital

Social capital consists of the connections individuals build through social networks, norms, and trust in people outside their immediate circle. Higher inequality can reduce growth through this channel if, on the one hand, greater differences in income or wealth between individuals reduce social capital. On the other hand, the latter must negatively impact growth. We can expect inequality to affect trust and social capital because of the 'aversion to heterogeneity' argument (Uslaner, 2002 [126]; Alesina and La Ferrara, 2000 [6]). Individuals prefer to interact with people they perceive to be similar based on characteristics such as ethnicity or income. Greater distances within the income distribution tend to weaken the ties between different social groups and the feeling of sharing a common fate. It can foster the perception that society is a zero-sum game and that any gains by one social group can only come at someone else's expense (Rothstein and Uslaner, 2005 [113]). On the other hand, trust affects all those economic activities that rely on the actions of others to succeed. As Arrow (1972) [11] puts it: *"virtually every commercial transaction has within itself an element of trust, certainly any transaction conducted over a period of time. It can be plausibly argued that much of the economic backwardness in the world can be explained by the lack of mutual confidence"*. These trust-sensitive activities include all those transactions involving a future payment against a service provided now and business activities that need to delegate tasks to employees (Knack and Keefer, 1997 [72]). One of the conditions for an increase in the firms' size is sufficient interpersonal trust so that the hierarchical managerial structure can expand outside the narrow number of people in one's circle of friends and family (Cingano and Pinotti, 2016 [38]; Fukuyama, 1995 [57]). In terms of game theory, trust favors cooperative behaviors at the expense of defections (Algan and Cahuc, 2013 [7]). Trust can also affect human capital accumulation through greater incentive to provide credit to the poor, reducing the number of credit-constrained people (Knack and Keefer, 1997 [72]), and through greater effectiveness of public education (Coleman, 1988). Finally, a low level of trust is accompanied by a higher level of crime and insecurity, which diverts private and public resources to security services (Knack and Keefer, 1997 [72]).

1.2.11 Political instability, polarization and social conflict

Inequality could increase the propensity for political instability and social unrest by generating a more polarised society. The propensity to change executive power, whether within the democratic sphere or not, can increase policy uncertainty. This, in turn, could negatively affect investment decisions. For example, it may lead investors to postpone productive investments or - in the worst case - to relocate their assets abroad. However, the reverse relationship can also hold: an economic downturn can lead to greater political instability, resulting in an instability-stagnation vicious circle (Alesina et al., 1996 [3]). Moreover, inequality can have more radical consequences, such as increasing the probability of social unrest through coups, revolutions, or violence used as an instrument of political struggle. These events discourage private investment by undermining property rights' solidity (Alesina and Perrotti, 1996 [4]). Along the same lines, Keefer and Knack (2002) point out that polarization may increase the risk of sudden policy shifts that may jeopardize the certainty of property rights. Examples include substantial tax increases, expropriations, ceasing the protection of certain property rights, and banning specific contracts. To cope with these risks, firms may reduce their exposure in advance by switching to less efficient production techniques requiring less capital, reducing the scale of their activities, or even relocating abroad.

Cuckierman et al. (1989) [41] suggest that political instability and polarization may lead to greater reliance on seigniorage to finance public expenditure, increasing the social cost of inflation. Suppose the incumbent government thinks there is a good chance of being overthrown. In that case, high polarisation makes it a good strategy to maintain an inefficient tax system to avoid leaving a greater financing capacity in the hands of the successor. The incumbent government may find it convenient to draw funds to a greater extent by seigniorage rather than reforming the tax system. Along similar lines, Woo (2005) [130] shows how polarization and policy uncertainty can, on the one hand, induce the government to run an unmotivated budget deficit and, on the other hand, to respond pro-cyclically to fluctuations in government revenues, increasing macroeconomic volatility.

1.3 Empirical literature

Over the past three decades, the availability of datasets on income inequality allowed us to investigate the effect of inequality on growth empirically. Despite that, the debate did not reach a shared consensus, and the results are heterogeneous and largely dependent on the nature of the dataset and the estimation technique used. In the following sections, we will not analyze the empirical literature following the same categorization used for its theoretical counterpart. The reason is that most empirical studies focus on the overall relationship between inequality and growth rather than on individual transmission channels. The literature will therefore be divided mainly by the type of dataset and estimator used, two factors that primarily affect the results. Nevertheless, a few exceptions - mainly regarding the median voter channel - focus on individual transmission channels. These estimations will be mentioned within this framework.

The studies analyzed differ in a multitude of factors. The inequality index used is among the main differences in the literature. The most widely used is the Gini index, but income deciles or decile ratios are also used extensively. Other differences include the cross-sectional/panel nature of the datasets, the countries included in the sample, the estimator used, and the duration of growth spells analyzed. However, most share the following structure: GDP per capita growth rate is regressed on an inequality index, along with other covariates. Nonetheless, there are articles estimating a different structure, though in smaller numbers. Among these are studies estimating non-linear specifications or two-step structural models aiming to evaluate single transmission channels. As anticipated, the dataset type and estimator are the factors that most impact the sign of the relationship. Cross-section studies overwhelmingly report that inequality negatively affects growth. Panel studies find a positive sign regardless of the estimator used, except for System-GMM, where the relationship tends to be negative. Within each of these categories, a country's level of development appears to affect the magnitude of the effect: the higher the level of development, the less negative (or more positive) the impact of inequality on growth. Finally, an inspection of the estimates reported in the studies reveals the presence of magnitude publication bias in the papers' conclusions: authors tend to claim sharper results in the abstract or conclusion than their own estimates in the paper or appendices would suggest.

1.3.1 Cross-Section

The quality of inequality datasets available in the early 1990s was not high. The reason was that data were mainly assembled from different sources for each country, with differences in the income unit, income concept, and year of the observation. Moreover, the time coverage was generally not sufficient to conduct panel analyses. As a result, papers from those years are mainly based on cross-sectional datasets, OLS estimators, and average GDP growth rate over more than twenty-five years as the dependent variable. Studies based on those datasets typically find a *negative* and significant impact of income inequality on economic growth.

Persson and Tabellini (1991) [104] find, with a cross-sectional dataset, that an increase in the ratio of the share of income held by the wealthiest 20 percent of the population over the share of the bottom 40 percent has a negative and strongly significant impact on economic growth. When the estimation is replicated by partitioning the dataset between the democratic and non-democratic countries groups, the effect remains significant only for the democratic group. This result supports the median voter mechanism as the primary channel driving the impact of income inequality on economic growth. They repeat the estimation with a panel dataset. Once controlled for time and country fixed effects, they find a positive, although non-significant, impact of the share of income held by the top quintile of the population on economic growth. This result anticipates the trend characterizing the panel literature a few years later. Alesina and Rodrik (1994) [5] use two different cross-sectional datasets and - alternatively - the income share held by the different population quintiles and the income share held by the wealthiest five percent as measures of income inequality. They split both datasets between democratic and non-democratic countries. According to the results, both inequality measures negatively and significantly impact growth in democratic groups. In contrast, the effect disappears or is weaker in non-democratic regimes. As Perrson and Tabellini (1991) [104], they take this result as evidence supporting the median voter mechanism.

Perotti (1996) [103] finds that an increase in the share of income held by the middle class (third and fourth quintiles) positively impacts growth. However, unlike Alesina and Rodrik (1994) [5] and Persson and Tabellini (1991) [104], the paper does not find that controlling for the political regime influences the relationship between inequality and growth. A two-equation structural model is estimated to test the median voter theory better. The results show that inequality does not have a robust impact on the level of taxation; on the other hand, the latter does not have a robust effect on economic growth. Therefore, the paper remains skeptical that it is the median voter mechanism to determine the negative relationship between inequality and growth. In contrast, the estimation of similar structural models supports the theories of sociopolitical instability, fertility, and human capital investment. Clarke (1995) [39] tests the impact of four different inequality indices - Gini, Theil, coefficient of variation, and the ratio of the share of total income earned by the poorest forty percent of the population to the share of total income earned by the wealthiest twenty percent of the population - on subsequent growth. Regardless of the index used, the results indicate a negative impact of inequality on economic growth. An interaction term for democratic countries is then introduced to test the median voter channel. However, the associated coefficient is not significant, thus suggesting - as in Perotti (1996) [103] - that the political regime does not affect the link between inequality and growth.

1.3.2 Panel OLS, Fixed Effects and Differnce-GMM

In the late 1990s, the release of the higher quality Deininger and Squire's (1996) [43] dataset made it possible to move from a cross-sectional to a panel framework. The resulting new strand of literature usually finds a *positive* effect of initial inequality on subsequent economic growth. Beyond the panel feature and the superior quality of the income inequality data, another difference with the preceding strand is the duration of the growth spells under analysis. Whereas the cross-sectional literature typically takes average growth rates over periods of twenty-five or more years, the panel literature usually relies on five-years growth spells as reference periods.

Partridge (1997) [102] uses a panel dataset based on U.S. states. He finds the Gini positively and significantly affects subsequent economic growth. When the Gini is replaced by the share of income held by the middle quintile of the distribution, the associated coefficient is found to be positive and significant. However, if the Gini and median quintile are included together among the covariates, they both turn out to be positive and significant. This suggests that an overall more unequal income distribution positively impacts growth, but at the same time, a larger share of income held by the middle class positively affects growth. A subsequent 2SLS estimation tests the possible role played by the median voter theory. However, the results indicate - as in Clarke (1995) [39] and Perotti (1996) [103] - that the median quintile does not have much influence on government redistributive policies, and that the latter do not significantly impact growth: two necessary steps for the validation of the median voter theory. Li and Zou (1998) [84] extend Alesina and Rodrik's (1994) [5] specification to a panel framework using Deininger and Squire's (1996) [43] dataset, finding a positive relationship between inequality and growth. Next, they transform the panel dataset into a cross-sectional one by taking the average growth rate between 1960 and 1990 - as in Alesina and Rodrik (1994) [5] - to test whether it is indeed the cross-section/panel character that makes most of the difference. Interestingly, now the Gini index negatively and significantly impacts growth. Thus, the paper suggests how moving from a cross-sectional to a panel framework is sufficient to reverse the sign associated with the inequality index. Finally, the introduction of an interaction term for democratic countries reveals that the political regime is not relevant in determining the impact of inequality on economic growth, rejecting the median voter theory again. In a similar vein, Forbes (2000) [55] shows that Perotti's (1996) [103] result derives essentially from using a cross-sectional dataset, which does not allow to control for country-specific, time-invariant omitted variables. In fact, using again Deininger and Squire's (1996) [43] panel dataset, the paper does find a positive relationship between the Gini index and economic growth. Next, she checks that Perotti's (1996) [103] opposite results depend on the nature of the dataset. To this aim, the paper transforms Deininger and Squire's (1996) [43] dataset into the corresponding cross-sectional dataset as Li and Zou (1998) [84]. The results confirm that switching from a panel to a cross-sectional framework is sufficient to detect a negative effect of inequality on growth rather than a positive one. Barro (2000) [17], also relying on Deininger and Squire's (1996) [43] dataset, finds a different effect for advanced and developing countries. Indeed, by adding an interaction term between Gini and per capita GDP next to the Gini, he finds a positive impact of inequality on growth for high-income countries and a negative impact for low-income countries. This effect is confirmed by separate estimations for rich and developing countries. Similar results are found when the highest quintile of the distribution is used instead of Gini. When the lowest or median quintile is used, a positive and significant relationship with growth is found in low-GDP countries and negative in high-GDP countries.

Scholl and Klasen (2019) [117] dispute the positive effect of inequality on growth found in the Fixed Effect literature showing how this result is essentially driven by Eastern European countries transitioning to a market economy in the 1990s. After replicating the results of Forbes (2000) [55] with the SWIID dataset, they introduce an interaction term controlling for Eastern European countries. They show how this variable now absorbs all the positive effects of inequality on growth. From this, they conclude that the results of Forbes (2000) [55] - and implicitly of other similar papers like Partridge (1997) [102] and Li and Zou (1998) [84] - are essentially driven by countries transitioning from a planned to a market economy. However, once 'separate transition time dummies' are also introduced, they absorb the entire positive relationship between Gini and subsequent growth, suggesting that the rise in inequality and subsequent growth were unrelated events even in this group of countries. Indeed, the collapse of the USSR brought a sharp collapse in output associated with a substantial rise in inequality, producing a correlation between the increase in inequality in the early 1990s and subsequent economic recovery.

1.3.3 Panel System-GMM

The Panel literature finds a positive relationship between inequality and growth regardless of whether the estimator is Pooled OLS, Fixed Effects, Random Effects, or Difference-GMM. However, a negative relationship is obtained when the estimator is a System-GMM (Blundell and Bond, 1998 [25]).

Castelló-Climent (2010) [34], using data first from World Income Inequality Database and LIS, finds with a System GMM estimator (Blundell and Bond, 1998 [25]) that inequality harms economic growth. She emphasizes how this estimator yields opposite results compared to Forbes (2000)

[55]. When dividing countries by the level of GDP per capita, the paper finds a different effect in advanced and developing countries. In fact, similar to Barro (2000) [17], she finds that the coefficient associated with the Gini is positive for advanced countries while it is negative for middle and low-income countries.

Halter et al. (2014) [65] use data from both Deininger and Squire (1996) [43] and WIID. To test for a possible differential effect in the short and long run, they simultaneously include both the early and previous periods (lagged) Gini. The estimation - performed with a system-GMM (Blundell and Bond, 1998 [25]) - indicates that while the impact of an increase in inequality is positive on the short run (5 years) growth, the coefficient of the lagged Gini is negative, suggesting that the impact in the long run (10 years) is negative. As a possible explanation, they propose that growth-promoting effects arise from purely economic mechanisms (convex saving functions, credit constraints and incentives) that tend to set in relatively fast. In contrast, growth-reducing effects, mostly affecting the political spectrum (political instability, polarization, or social unrest) or affecting the education channel, tend to materialize only with a substantial lag.

Berg et al. (2018) [19] use Solt's (2009) [122] dataset based on a restricted selection of observations contained in the Standardized World Income Inequality Dataset. They use the post-tax Gini to measure inequality and include the difference between pre and post-tax Gini as a measure of redistribution. Using the System-GMM of Blundell and Bond (1998) [25], they find that higher inequality tends to lower growth, confirming - as in Castello-Climent (2010) [34] and Halter et al. (2014) [65] - that the use of this estimator tends to yield a negative relationship. Redistribution, in contrast, has a slightly positive - and insignificant - effect. A two-stage approach is then used to test different channels that could explain this negative relationship. They find evidence that higher inequality is associated with lower human capital, higher population growth and worse political institutions.

1.3.4 Non-linearities, separate effects and meta-analyses

Finally, some studies depart from the standard methods used in the categories above to analyze the impact of inequality on growth. Banerjee and Duflou (2003) [13] question the linearity of the relationship between inequality and growth. Using Deininger and Squire (1996) [43] dataset and the specifications of Perotti (1996) [103] and Barro (2000) [17], they show how by adding the squared variation in Gini among the regressors, the (linear) Gini coefficient is no longer significant. Moreover, Kernel regressions show how changes in either direction of the Gini index harm growth. Thus, any variation in inequality - regardless of the direction - lowers subsequent growth. There is an inverted-U shape relationship between changes in inequality and growth. They argue that this non-linearity can explain the mixed results found with linear models in the literature. Banerjee and Duflo hypothesize that this relationship arises from measurement errors in inequality. Larger errors in measuring inequality can be expected during periods of major distress (e.g., crises, wars). And since such periods are associated with sharp declines in GDP, this produces the statistical association between changes in inequality in any direction and negative economic growth. Sholl and Klasen (2019) [117] test Banerjee and Duflo's (2003) [13] hypothesis that both positive and negative changes in inequality negatively impact growth. To this end, they estimate piecewise regressions allowing different coefficients for the negative, positive, or zero changes in inequality to be estimated.

However, no significant relationship is found once controlled for time effects and Eastern European countries transitioning to a market economy.

Voitchosky (2005) [128] notes how, on a theoretical level, "*most of the positive mechanisms can be linked to inequality at the top end of the distribution* [e.g., effort incentives, saving, and investment] *while many of the detrimental effects can be traced to bottom end inequality or relative poverty* [e.g., poverty, crime, political unrest, credit constraints, and fertility channels]". She then estimates a model that allows for separate effects for the two opposite ends of the distribution. The paper relies on data from the Luxemburg Income Study on 90/75, 95/80, and 90/50 ratios to measure top-end inequality. The 50/10, 50/20, and 40/10 ratios measure bottom-end inequality. Evidence shows that inequality at the top end of the distribution positively affects growth, and inequality at the bottom has a negative impact. Therefore, she concludes that using a single income inequality statistic is insufficient to capture the true effect of inequality. Using only the Gini is likely to capture only the average of the various effects from different parts of the distribution. This would also explain the heterogeneity of results found in the literature.

Finally, Cunha Neves et al. (2016) [94] conducted the only meta-analysis on this topic in the literature. The paper collects only the estimates reported in each published paper indicated as the authors' preferred ones. These are the estimates on which the authors' conclusions are generally based. With these data on hand, the authors find a significant publication bias not in a particular direction but in magnitude. There is, hence, a tendency to publish papers that find a significant impact of inequality on growth. They also find that: cross-sectional estimates tend to find a stronger negative effect than panel estimates; the inclusion of regional dummies significantly reduces the effect found; the impact of inequality on growth is negative and more pronounced for developing countries than developed ones, suggesting that the transmission mechanisms are different in the two groups. The phenomenon studied by Aiyar and Ebeke (2020) [2] may contribute to the latter effect. They find evidence that inequality of opportunities (inter-generational mobility) mediates the impact of inequality on growth. In countries where inter-generational mobility is high, the effect of inequality appears to be less negative. If parents' conditions are not easily transmitted to their offspring, it is less likely that parents' income will affect their investment choices and human capital. Interestingly, Cunha Neves et al. (2016) [94] also find that the length of the growth spells under analysis affects the results. The longer the time unit, the more the results indicate that increasing inequality harms growth. This is consistent with what Halter et al. (2016) [65] suggested, namely, that increased inequality could affect growth positively in the short run and negatively in the long run.

1.3.5 A statistycal analysis

Part of the conclusions drawn in the previous sections from observing regularities in the literature can be supported by collecting data on the estimates reported in the reviewed papers. I collected the beta, t-statistic, standard error, inequality index, panel/cross-section nature of the dataset, and estimator for each reported estimate. A total of 348 observations were collected. Of these, only those based on the following structure were kept:

$$g_j = \alpha_j + \beta_i G_{i,j} + \sum_{k=1}^{K} \theta_{i,k} X_{i,j,k} + \epsilon_i \tag{1.1}$$

Where g is the GDP growth rate, β is the coefficient associated to the Gini index G, θ are the coefficients associated to other regressors X, ϵ is the error term, $i = 1, ..., N$ defines the i^{th} study, $j = 1, ..., J$ defines the j^{th} country and $k = 1, ..., K$ is the index related to other explanatory variables. All the estimates based on inequality indices other than the Gini were discarded since - each taken individually - not enough in number to conduct separate analyses. A total of 113 observations was thus eliminated, resulting in a final dataset consisting of 235 observations.

This analysis does not intend to be a meta-analysis but only aims to support - mainly through descriptive statistics - some of the conclusions drawn earlier. To compare otherwise heterogeneous studies, we calculate for each reported estimate the PCC index. This index can take values ranging from -1 (maximum negative correlation) to 1 (maximum positive correlation) and reads as follows:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}} \tag{1.2}$$

Where t_i and df_i are - respectively - the t-statistic associated with the i^{th} beta coefficient and the degrees of freedom in a regression structured as equation (1.1). When the t-statistic is not reported, but the standard error is, we derive it from the following relationship:

$$t_i = \frac{\beta_i}{SE(\beta_i)} \tag{1.3}$$

The first regularity is that cross-sectional estimates overwhelmingly find a negative coefficient associated with the Gini index. Figure (1.1) reports the PCC distribution for cross-sectional studies. It is evident how the estimated PCCs mainly lie in the interval $(-0.9, -0.4)$.

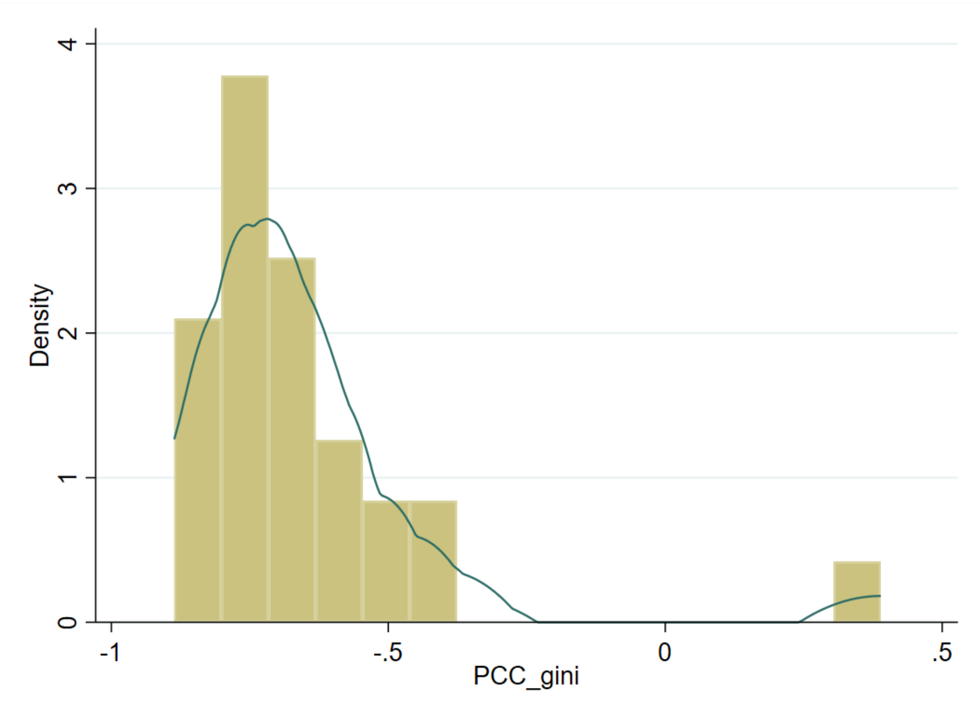

Figure 1.1: Cross-Sectional estimates

On the contrary, Panel estimates based on Fixed-Effects, 2SLS, and Arellano and Bond (1991) [10] GMM estimators find a positive impact of inequality on subsequent GDP growth. This is evident in Figure (1.2), which plots the distribution of PCC indices based on panel Pooled OLS, FE, 2SLS and Difference-GMM estimators.

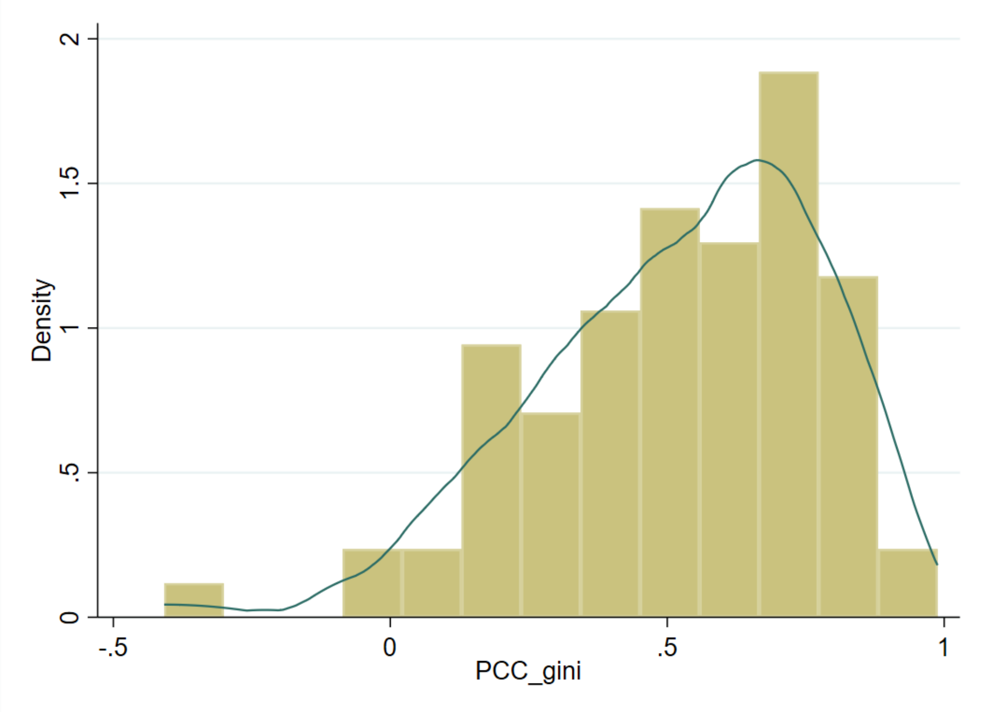

Figure 1.2: Pooled OLS, FE, 2SLS and Difference-GMM estimates

On the other hand, when in a panel setting, the estimator used is the System-GMM (Blundell and Bond, 1998 [25]), the relationship tends to be negative, although to a less clear-cut extent than in the other two groups (Figure 1.3).

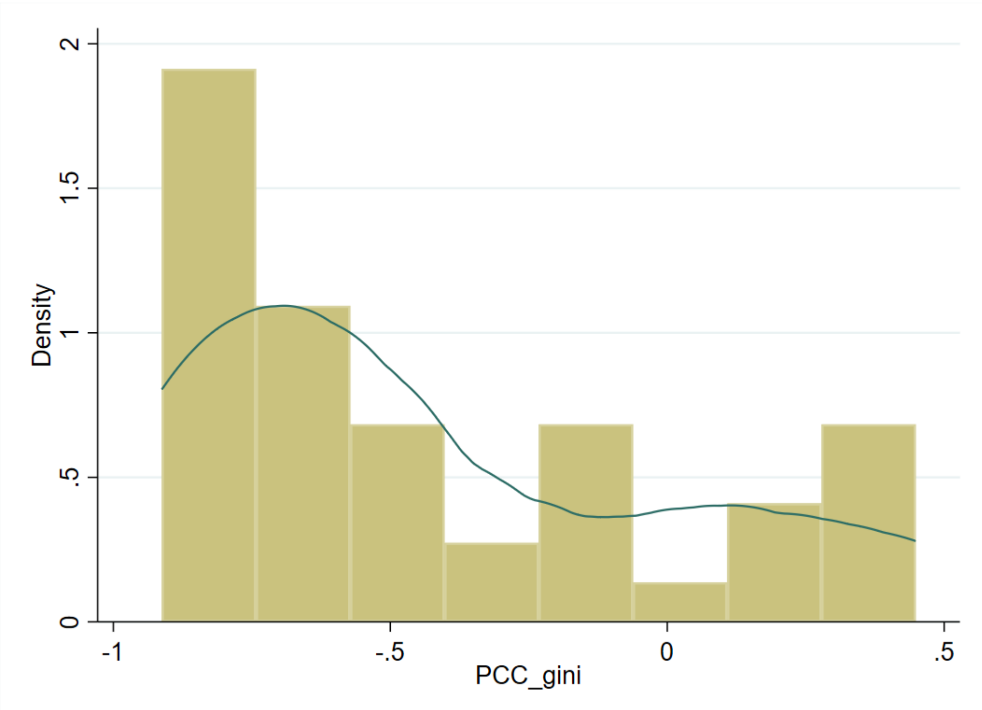

Figure 1.3: System-GMM in mixed samples only

The differences in results between the panel and cross-sectional literature are striking. In part, this could be explained by the argument made by Halter et al. (2016) [65] and Cunha Neves et al. (2016) [94]. Indeed, growth spells in cross-sectional datasets are much longer than in panel studies. It is usually around 20 to 25 years in the former, while it is between 5 and 10 years in the latter. The difference in results between the two types of datasets could reflect the different effects of inequality over short- and long-term time horizons, as Halter et al. (2016) [94] suggested. Accordingly, different channels would act in the two time horizons. In the short run, predominantly economic channels such as saving rate and credit constraints tend to operate. While in the long term, socio-political channels such as social unrest, political instability and polarization would prevail. This argument is reinforced by the fact that switching from a pooled OLS estimator to a fixed-effects estimator has little effect on the results. Thus, the difference cannot be attributed to unit-specific omitted variables not captured by the Pooled estimator.

Although proposed in a different context, Rada et al. (2022) [108] presented a similar argument. The paper attempts to capture this dual effect in a theoretical model. The distributive cycle à la Goodwin captures the short-run effect, and the biased technical change the long-run effect. In the short run, the wage increase raises the labor share (and reduces inequality) depressing investment and GDP growth. In the long run, however, it stimulates technological innovation in an attempt by firms to generate labor-saving innovation, raising labor productivity and growth.

As mentioned earlier, Cunha Neves et al. (2016) [94] detected the presence of magnitude publication bias in their meta-analysis. This bias refers to the tendency of authors or journals to publish only those studies that find significant estimates. Since authors with relatively small samples have more difficulty finding a significant relationship because of the larger standard errors, they are inclined to manipulate the estimates to obtain significant results. As the bias implies a positive relationship between the absolute value of the estimated coefficient and the associated standard error, it can be tested by estimating the following regression:

$$|t_i| = \gamma_0 + \gamma_1 \frac{1}{\omega_i} + e_i \tag{1.4}$$

Where t_i is the t-statistic associated with the i^{th} estimate and ω_i is the associated standard error. Table (1.1) shows the results obtained by Cunha Neves et al. (2016) [94].

Table 1.1: Magnitude bias: Cunha Neves et al. (2016)

Dependent variable	$\lvert t_i \rvert$
Constant	1.6918***
	(7.2824)
$1/\omega_j$	0.0061**
	(2.2168)
Obs	49

Notes: Coefficients are estimated by OLS.
t-Statistics reported in brackets, calculated from heteroscedasticity-autocorrelation consistent standard errors.
***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

However, a relevant difference exists between our dataset and Cunha Neves et al. (2016) [94]. Our dataset collects all the estimates reported within the papers reviewed earlier, including robustness tests and appendices. On the other hand, their dataset includes only those estimates indicated as preferred by their authors, or that match the paper's conclusions. Given this difference, we expect a lower or absent degree of publication bias in our dataset. Table (1.2) shows regression (1.4) estimation results with our dataset.

Table 1.2: Magnitude bias: own estimate

Dependent variable	$\lvert t_i \rvert$
Constant	1.96385***
	(16.47)
$1/\omega_i$	-0.0000174
	(-0.18)
Obs	235

Notes: Coefficients are estimated by OLS.
t-Statistics reported in brackets, calculated from heteroscedasticity-autocorrelation consistent standard errors.
***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

The coefficient related to the inverse of the standard error is not significant. Therefore, we can rule out magnitude publication bias in our dataset. This result suggests that the authors tend to report stronger conclusions than the estimates they have at hand would suggest.

1.4 Conclusion

The paper reviews the theoretical and empirical literature on the interpersonal distribution impact on economic growth. The theoretical literature proposes several possible transmission channels, embedding both negative and positive effects of inequality on growth. Most of these channels involve a negative impact of inequality on subsequent economic growth. It is the case of credit constraints, degree of democracy, fertility rates, crime, demand size, corruption, social capital, political instability, and polarization channels. Nevertheless, redistribution could exacerbate the phenomenon rather than mitigate it when per capita income is extremely low with credit constraints, internal demand, and fertility channels. For example, redistribution could reduce the investments of the wealthy without enabling the recipients to exceed the wealth threshold necessary to access the credit market. On the other hand, the channels embedding a positive effect of inequality on growth are the saving rate, effort incentives, and innovation channels.

The theory also suggests that these channels are likely to impact differently depending on the structural characteristics of a country, such as the level of development, the type and coverage of the pension, health and education systems, the solidity of institutions and the degree of financialization. In developing countries, for example, the proportion of credit-constrained people is higher than in advanced ones. Consequently, the effect of inequality on growth mediated by credit constraints will be more negative. The same applies to other channels. Indeed, the response of fertility, political instability, corruption and crime to increased inequality is likely stronger in emerging countries.

An increase in inequality often implies a correspondingly larger increase in poverty compared to advanced countries. In turn, poverty is strongly associated with increased crime, political instability, polarization and social conflict. In advanced countries, on the other hand, given the higher per capita income and a more robust welfare system, an increase in inequality will likely bring fewer people into poverty. Coupled with stronger institutions, this explains why these channels may play a less incisive role. On the other hand, the efficiency-enhancing effect of inequality is likely to manifest more in countries where a lower inequality of opportunity allows the exploitation of the income incentives that inequality brings. Moreover - as mentioned earlier - other channels, which usually involve a negative impact of inequality on growth, might even embed a positive effect in extremely low per capita income countries. These considerations suggest ruling out a one-size-fits-all conclusion favoring a deeper analysis of a country's structural characteristics.

Empirical studies are mainly based on linear models regressing per capita GDP growth rate on an inequality index alongside the traditional covariates from the growth literature. This model cannot disentangle the different transmission channels and only estimates an aggregation of their effects. Nevertheless, a small number of studies focus on individual transmission channels. However, their number is generally insufficient to draw robust conclusions, the only exception being the median voter channel. Regarding the latter, the evidence is weak, and most papers do not support the postulated effect.

The empirical literature estimating the aggregate relationship reflects the complexity highlighted by its theoretical counterpart, and the results are remarkably heterogeneous. Nevertheless, several regularities help to understand which factors influence the sign and magnitude of the relationship under analysis. First, studies based on a cross-sectional framework overwhelmingly find a negative impact of inequality on growth. Second, Panel analyses relying on Pooled OLS, Fixed-Effects, Random Effects, or Difference-GMM (Arellano and Bond, 1991 [10]) estimators find a positive relationship between income inequality and growth. In contrast, panel estimates based on the System-GMM (Blundell and Bond, 1998 [25]) estimator yield a negative coefficient associated with the Gini index, although to a less clear-cut extent than in the other two groups. This difference could indicate a different effect of inequality on different time horizons. The tendency of panel studies to find a positive impact of inequality on growth may stem from the short unit of time considered. In contrast, cross-sectional studies finding a negative relationship rely on longer growth spells. Therefore, the effect of inequality on growth could dipend on the time horizon. Third, studies controlling for the stage of development - either with an interaction term or by splitting the sample - find a smaller coefficient associated with inequality in developing countries compared to advanced countries. In other words, the effect tends to be more negative (or less positive) in low-income countries and more positive (or less negative) in high-income countries. This result supports the predictions of the theoretical literature, as most channels involving a negative effect will likely impact harder developing countries.

A statistical analysis of the dataset collecting the estimates reported in the reviewed papers confirms some of these conclusions. The factor most sharply affecting the sign of the relationship is the panel/cross-sectional nature of the dataset used. Studies employing cross-sectional datasets find that inequality negatively impacts subsequent growth. In contrast, studies based on panel datasets usually find that inequality positively impacts growth. The only exception is when, still in a panel framework, the System-GMM estimator is used. In this case, the estimates suggest a negative relationship. In contrast, factors such as the inequality index or the dataset quality do not seem relevant. Finally, a magnitude publication bias analysis reveals the authors' tendency to claim sharper results in the abstract or conclusion than their own estimates in the paper or appendices would suggest.

1.A Estimates reported in empirical studies

Legend

- Author(s): *authors and year of publication as indicated in the text.*
- PCC: *PCC index associated to the Gini coefficient computed as in Equation (1.2).*
- SE: *Standard Error associated to the PCC index*
- Countries: *denotes the group of countries included in the sample according to their level of development, political regime or geographical position.*
- Dataset: *indicates if the datasets used is panel (P) or cross-section (CS)*
- Estimator: *indicates the estimator employed.*

Table 1.A.1: Estimates reported in empirical studies

n°	Author(s)	SE	PCC	Countries	Dataset	Estimator
1	Partridge (1997)	0.32	0.63	Advanced	P	OLS
2	Partridge (1997)	0.21	0.54	Advanced	P	OLS
3	Partridge (1997)	0.19	0.60	Advanced	P	OLS
4	Partridge (1997)	0.23	0.39	Advanced	CS	OLS
5	Partridge (1997)	0.15	0.76	Advanced	P	OLS
6	Partridge (1997)	0.18	0.58	Advanced	P	OLS
7	Partridge (1997)	0.16	0.77	Advanced	P	2SLS
8	Deininger and Squire (1998)	0.30	0.85	Mixed		OLS
9	Deininger and Squire (1998)	0.38	0.36	Mixed		OLS
10	Deininger and Squire (1998)	0.42	0.56	Mixed		OLS
11	Deininger and Squire (1998)	0.36	0.31	Mixed		OLS
12	Deininger and Squire (1998)	0.48	0.29	Developing		OLS
13	Deininger and Squire (1998)	0.34	0.43	Developing		OLS
14	Deininger and Squire (1998)	0.46	0.40	Democracies		OLS

Continued on next page

Table 1.A.1 – *Continued from previous page*

n°	Author(s)	SE	PCC	Countries	Dataset	Estimator
15	Deininger and Squire (1998)	0.39	0.29	Democracies		OLS
16	Deininger and Squire (1998)	0.38	0.65	Non-Democracies		OLS
17	Deininger and Squire (1998)	0.31	0.55	Non-Democracies		OLS
18	Clarke (1995)	0.26	-0.68	Mixed	CS	OLS
19	Clarke (1995)	0.24	-0.73	Mixed	CS	OLS
20	Clarke (1995)	0.22	-0.77	Mixed	CS	WLS
21	Clarke (1995)	0.27	-0.66	Mixed	CS	2SLS
22	Clarke (1995)	0.22	-0.59	Mixed	CS	OLS
23	Clarke (1995)	0.22	-0.76	Mixed	CS	OLS
24	Li and Zou (1998)	0.33	0.81	Mixed	P	FE
25	Li and Zou (1998)	0.54	0.36	Mixed	P	RE
26	Li and Zou (1998)	0.26	0.69	Mixed	P	FE
27	Li and Zou (1998)	0.29	0.57	Mixed	P	RE
28	Li and Zou (1998)	0.32	0.77	Mixed	P	FE
29	Li and Zou (1998)	0.47	0.34	Mixed	P	RE
30	Li and Zou (1998)	0.25	0.67	Mixed	P	FE
31	Li and Zou (1998)	0.28	0.56	Mixed	P	RE
32	Li and Zou (1998)	0.32	0.83	Mixed	P	FE
33	Li and Zou (1998)	0.25	0.72	Mixed	P	FE
34	Li and Zou (1998)	0.31	0.79	Mixed	P	FE
35	Li and Zou (1998)	0.24	0.69	Mixed	P	FE
36	Li and Zou (1998)	0.27	-0.89	Mixed	CS	OLS
37	Li and Zou (1998)	0.31	-0.79	Mixed	CS	OLS
38	Li and Zou (1998)	0.24	-0.87	Mixed	CS	OLS
39	Li and Zou (1998)	0.27	-0.80	Mixed	CS	OLS
40	Li and Zou (1998)	0.36	-0.79	Mixed	CS	OLS
41	Li and Zou (1998)	0.37	-0.66	Mixed	CS	OLS
42	Li and Zou (1998)	0.26	-0.86	Mixed	CS	OLS
43	Li and Zou (1998)	0.27	-0.80	Mixed	CS	OLS
44	Li and Zou (1998)	0.30	0.41	Mixed	P	FE
45	Li and Zou (1998)	0.32	0.42	Mixed	P	FE
46	Li and Zou (1998)	0.34	0.46	Mixed	P	FE
47	Li and Zou (1998)	0.35	0.53	Mixed	P	FE
48	Li and Zou (1998)	0.29	0.51	Mixed	P	FE
49	Li and Zou (1998)	0.30	0.53	Mixed	P	FE
50	Li and Zou (1998)	0.30	0.60	Mixed	P	FE
51	Li and Zou (1998)	0.34	0.56	Mixed	P	FE
52	Li and Zou (1998)	0.30	0.80	Mixed	P	FE

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Table 1.A.1 – *Continued from previous page*

n°	Author(s)	SE	PCC	Countries	Dataset	Estimator
53	Li and Zou (1998)	0.34	0.74	Mixed	P	FE
54	Li and Zou (1998)	0.40	0.61	Mixed	P	FE
55	Li and Zou (1998)	0.32	0.77	Mixed	P	FE
56	Li and Zou (1998)	0.34	0.72	Mixed	P	FE
57	Li and Zou (1998)	0.31	0.79	Mixed	P	FE
58	Li and Zou (1998)	0.30	0.80	Mixed	P	FE
59	Li and Zou (1998)	0.34	0.73	Mixed	P	FE
60	Li and Zou (1998)	0.38	0.64	Mixed	P	FE
61	Li and Zou (1998)	0.31	0.79	Mixed	P	FE
62	Li and Zou (1998)	0.31	0.79	Mixed	P	FE
63	Li and Zou (1998)	0.31	0.79	Mixed	P	FE
64	Forbes (2000)	0.30	0.73	Mixed	P	FE
65	Forbes (2000)	0.32	0.70	Mixed	P	RE
66	Forbes (2000)	0.12	0.96	Mixed	P	Cham.
67	Forbes (2000)	0.32	0.70	Mixed	P	GMM-Diff
68	Forbes (2000)	0.40	0.47	Mixed	P	FE
69	Forbes (2000)	0.30	-0.75	Mixed	CS	OLS
70	Forbes (2000)	0.36	-0.60	Mixed	CS	OLS
71	Forbes (2000)	0.36	-0.60	Mixed	CS	OLS
72	Forbes (2000)	0.43	0.29	Mixed	P	OLS
73	Forbes (2000)	0.41	-0.41	Mixed	P	GMM-Diff
74	Forbes (2000)	0.29	0.76	Mixed	P	FE
75	Forbes (2000)	0.38	-0.51	Mixed	CS	OLS
76	Forbes (2000)	0.42	0.34	Mixed	P	OLS
77	Forbes (2000)	0.28	0.78	Mixed	P	FE
78	Forbes (2000)	0.42	-0.53	Mixed	CS	OLS
79	Forbes (2000)	0.34	0.73	Mixed	P	FE
80	Forbes (2000)	0.20	-0.83	Mixed	CS	OLS
81	Forbes (2000)	0.35	-0.04	Mixed	P	OLS
82	Forbes (2000)	0.27	0.65	Mixed	P	FE
83	Forbes (2000)	0.28	-0.66	Mixed	CS	OLS
84	Forbes (2000)	0.38	0.02	Mixed	P	OLS
85	Forbes (2000)	0.29	0.65	Mixed	P	FE
86	Forbes (2000)	0.38	-0.38	Mixed	CS	OLS
87	Forbes (2000)	0.39	0.33	Mixed	P	OLS
88	Forbes (2000)	0.27	0.75	Mixed	P	FE
89	Forbes (2000)	0.24	-0.73	Mixed	CS	OLS
90	Forbes (2000)	0.35	0.04	Mixed	P	OLS

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Table 1.A.1 – *Continued from previous page*

n°	Author(s)	SE	PCC	Countries	Dataset	Estimator
91	Forbes (2000)	0.29	0.57	Mixed	P	FE
92	Forbes (2000)	0.22	-0.72	Mixed	CS	OLS
93	Forbes (2000)	0.31	0.23	Mixed	P	OLS
94	Forbes (2000)	0.28	0.44	Mixed	P	FE
95	Forbes (2000)	0.24	-0.42	Mixed	CS	OLS
96	Forbes (2000)	0.22	0.58	Mixed	P	OLS
97	Forbes (2000)	0.23	0.48	Mixed	P	FE
98	Forbes (2000)	0.25	-0.66	Mixed	CS	OLS
99	Forbes (2000)	0.30	0.43	Mixed	P	OLS
100	Forbes (2000)	0.30	0.45	Mixed	P	FE
101	Forbes (2000)	0.25	-0.66	Mixed	CS	OLS
102	Forbes (2000)	0.30	0.41	Mixed	P	OLS
103	Forbes (2000)	0.29	0.48	Mixed	P	FE
104	Barro (2000)	0.26	-0.41	Developing	P	RE+3SLS
105	Barro (2000)	0.24	0.53	Advanced	P	RE+3SLS
106	Barro (2000)	0.25	-0.54	Mixed	P	RE+3SLS
107	Barro (2000)	0.23	-0.65	Developing	P	RE+3SLS
108	Barro (2000)	0.30	-0.03	Advanced	P	RE+3SLS
109	Barro (2000)	0.28	0.28	Mixed	P	RE+3SLS
110	Barro (2000)	0.26	-0.46	Developing	P	RE+3SLS
111	Barro (2000)	0.23	0.61	Advanced	P	RE+3SLS
112	Barro (2000)	0.28	-0.23	Mixed	P	RE+3SLS
113	Barro (2000)	0.27	0.38	Developing	P	RE+3SLS
114	Barro (2000)	0.25	-0.52	Advanced	P	RE+3SLS
115	Barro (2000)	0.28	-0.20	Mixed	P	RE+3SLS
116	Barro (2000)	0.22	-0.66	Developing	P	RE+3SLS
117	Barro (2000)	0.23	-0.59	Advanced	P	RE+3SLS
118	Banerjee and Duflo (2003)	0.44	0.10	Mixed	P	RE
119	Banerjee and Duflo (2003)	0.36	0.60	Mixed	P	FD
120	Banerjee and Duflo (2003)	0.34	0.64	Mixed	P	FE
121	Banerjee and Duflo (2003)	0.07	0.99	Mixed	P	GMM-Diff
122	Banerjee and Duflo (2003)	0.26	-0.18	Mixed	P	RE
123	Banerjee and Duflo (2003)	0.23	0.53	Mixed	P	FD
124	Banerjee and Duflo (2003)	0.22	0.55	Mixed	P	FE
125	Banerjee and Duflo (2003)	0.06	0.98	Mixed	P	GMM-Diff
126	Banerjee and Duflo (2003)	0.37	0.19	Mixed	P	RE
127	Banerjee and Duflo (2003)	0.37	0.24	Mixed	P	RE
128	Banerjee and Duflo (2003)	0.42	0.36	Mixed	P	RE

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Table 1.A.1 – *Continued from previous page*

n°	Author(s)	SE	PCC	Countries	Dataset	Estimator
129	Banerjee and Duflo (2003)	0.24	-0.23	Mixed	P	RE
130	Banerjee and Duflo (2003)	0.26	-0.24	Mixed	P	RE
131	Scholl and Klasen (2019)	0.24	0.42	Mixed	P	FE
132	Scholl and Klasen (2019)	0.26	0.15	Mixed	P	FE
133	Scholl and Klasen (2019)	0.26	0.07	Mixed	P	GMM-Diff
134	Scholl and Klasen (2019)	0.25	0.17	Mixed	P	FE
135	Scholl and Klasen (2019)	0.26	0.20	Mixed	P	FE
136	Scholl and Klasen (2019)	0.22	0.54	Mixed	P	FE
137	Scholl and Klasen (2019)	0.23	0.35	Mixed	P	FE
138	Scholl and Klasen (2019)	0.23	0.37	Mixed	P	FE
139	Scholl and Klasen (2019)	0.23	0.43	Mixed	P	FE
140	Scholl and Klasen (2019)	0.25	0.22	Mixed	P	GMM-Diff
141	Scholl and Klasen (2019)	0.25	0.36	Mixed	P	FE-2SLS
142	Scholl and Klasen (2019)	0.24	0.46	Mixed	P	FE-2SLS
143	Scholl and Klasen (2019)	0.26	0.08	Mixed	P	FE-2SLS
144	Castellò-Climent (2010)	0.26	-0.51	Mixed	P	GMM-Sys
145	Castellò-Climent (2010)	0.24	-0.58	Mixed	P	GMM-Sys
146	Castellò-Climent (2010)	0.30	-0.19	Low/Middle Income	P	GMM-Sys
147	Castellò-Climent (2010)	0.29	-0.24	High Income	P	GMM-Sys
148	Castellò-Climent (2010)	0.28	-0.24	High Income	P	GMM-Sys
149	Castellò-Climent (2010)	0.26	-0.52	OECD	P	GMM-Sys
150	Castellò-Climent (2010)	0.27	-0.33	OECD	P	GMM-Sys
151	Castellò-Climent (2010)	0.28	0.38	Advanced	P	GMM-Sys
152	Castellò-Climent (2010)	0.27	0.36	Advanced	P	GMM-Sys
153	Castellò-Climent (2010)	0.26	0.53	Europe	P	GMM-Sys
154	Castellò-Climent (2010)	0.25	0.52	Europe	P	GMM-Sys
155	Castellò-Climent (2010)	0.22	-0.65	Mixed	P	GMM-Sys
156	Castellò-Climent (2010)	0.23	-0.57	Mixed	P	GMM-Sys
157	Castellò-Climent (2010)	0.29	-0.15	Low/Middle Income	P	GMM-Sys
158	Castellò-Climent (2010)	0.28	0.01	Low/Middle Income	P	GMM-Sys
159	Castellò-Climent (2010)	0.27	-0.32	High Income	P	GMM-Sys
160	Castellò-Climent (2010)	0.26	-0.32	High Income	P	GMM-Sys
161	Castellò-Climent (2010)	0.27	-0.37	OECD	P	GMM-Sys
162	Castellò-Climent (2010)	0.27	-0.26	OECD	P	GMM-Sys
163	Castellò-Climent (2010)	0.28	0.22	Advanced	P	GMM-Sys
164	Castellò-Climent (2010)	0.27	0.21	Advanced	P	GMM-Sys
165	Castellò-Climent (2010)	0.26	0.44	Europe	P	GMM-Sys
166	Castellò-Climent (2010)	0.25	0.44	Europe	P	GMM-Sys

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Table 1.A.1 – *Continued from previous page*

n°	Author(s)	SE	PCC	Countries	Dataset	Estimator
167	Castellò-Climent (2010)	0.26	-0.21	Mixed	P	GMM-Sys
168	Castellò-Climent (2010)	0.30	-0.07	Mixed	P	GMM-Sys
169	Castellò-Climent (2010)	0.28	-0.38	Mixed	P	GMM-Sys
170	Castellò-Climent (2010)	0.23	0.50	Advanced	P	GMM-Sys
171	Castellò-Climent (2010)	0.30	0.12	Advanced	P	GMM-Sys
172	Castellò-Climent (2010)	0.25	0.57	Advanced	P	GMM-Sys
173	Castellò-Climent (2010)	0.25	0.34	European	P	GMM-Sys
174	Castellò-Climent (2010)	0.28	-0.33	European	P	GMM-Sys
175	Castellò-Climent (2010)	0.27	0.43	European	P	GMM-Sys
176	Castellò-Climent (2010)	0.27	-0.31	Mixed	P	GMM-Sys
177	Castellò-Climent (2010)	0.33	-0.21	Mixed	P	GMM-Sys
178	Hansen et al. (2014)	0.29	-0.01	Mixed	P	GMM-Sys
179	Hansen et al. (2014)	0.28	-0.19	Mixed	P	GMM-Sys
180	Hansen et al. (2014)	0.25	0.45	Mixed	P	GMM-Sys
181	Hansen et al. (2014)	0.26	0.32	Mixed	P	GMM-Sys
182	Hansen et al. (2014)	0.29	0.14	Mixed	P	GMM-Sys
183	Hansen et al. (2014)	0.29	-0.12	Mixed	P	GMM-Sys
184	Hansen et al. (2014)	0.26	0.37	Mixed	P	GMM-Sys
185	Hansen et al. (2014)	0.27	0.28	Mixed	P	GMM-Sys
186	Hansen et al. (2014)	0.28	0.35	Mixed	P	GMM-Sys
187	Hansen et al. (2014)	0.28	0.16	Mixed	P	GMM-Sys
188	Hansen et al. (2014)	0.27	0.34	Mixed	P	GMM-Sys
189	Hansen et al. (2014)	0.23	-0.75	Mixed	P	GMM-Sys
190	Hansen et al. (2014)	0.23	-0.77	Mixed	P	GMM-Sys
191	Hansen et al. (2014)	0.27	0.23	Mixed	P	GMM-Diff
192	Hansen et al. (2014)	0.27	0.18	Mixed	P	GMM-Diff
193	Hansen et al. (2014)	0.27	0.19	Mixed	P	GMM-Diff
194	Hansen et al. (2014)	0.27	0.27	Mixed	P	GMM-Diff
195	Hansen et al. (2014)	0.26	0.30	Mixed	P	GMM-Diff
196	Hansen et al. (2014)	0.26	0.33	Mixed	P	GMM-Diff
197	Ostry et al. (2018)	0.27	-0.88	Mixed	P	GMM-Sys
198	Ostry et al. (2018)	0.28	-0.77	Mixed	P	GMM-Sys
199	Ostry et al. (2018)	0.27	-0.75	Mixed	P	GMM-Sys
200	Ostry et al. (2018)	0.26	-0.56	Mixed	P	GMM-Sys
201	Ostry et al. (2018)	0.35	-0.80	Mixed	P	GMM-Sys
202	Ostry et al. (2018)	0.34	-0.66	Mixed	P	GMM-Sys
203	Ostry et al. (2018)	0.31	-0.64	Mixed	P	GMM-Sys
204	Ostry et al. (2018)	0.26	-0.55	Mixed	P	GMM-Sys

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Table 1.A.1 – *Continued from previous page*

n°	Author(s)	SE	PCC	Countries	Dataset	Estimator
205	Ostry et al. (2018)	0.28	-0.77	Mixed	P	GMM-Sys
206	Ostry et al. (2018)	0.28	-0.77	Mixed	P	GMM-Sys
207	Ostry et al. (2018)	0.28	-0.78	Mixed	P	GMM-Sys
208	Ostry et al. (2018)	0.30	-0.75	Mixed	P	GMM-Sys
209	Ostry et al. (2018)	0.27	-0.75	Mixed	P	GMM-Sys
210	Ostry et al. (2018)	0.29	-0.71	Mixed	P	GMM-Sys
211	Ostry et al. (2018)	0.28	-0.74	Mixed	P	GMM-Sys
212	Ostry et al. (2018)	0.31	-0.66	Mixed	P	GMM-Sys
213	Ostry et al. (2018)	0.24	-0.91	Mixed	P	GMM-Sys
214	Ostry et al. (2018)	0.46	-0.61	Mixed	P	GMM_level
215	Ostry et al. (2018)	0.24	-0.91	Mixed	P	GMM-Sys
216	Ostry et al. (2018)	0.46	-0.61	Mixed	P	GMM_level
217	Ostry et al. (2018)	0.24	-0.91	Mixed	P	GMM-Sys
218	Ostry et al. (2018)	0.35	-0.80	Mixed	P	GMM_level
219	Ostry et al. (2018)	0.39	-0.73	Mixed	P	GMM-Sys
220	Ostry et al. (2018)	0.35	-0.80	Mixed	P	GMM_level
221	Vpoitchosky (2005)	0.35	-0.03	Advanced	P	GMM-Sys
222	Vpoitchosky (2005)	0.26	-0.61	Advanced	P	GMM-Sys
223	Vpoitchosky (2005)	0.32	0.30	Advanced	P	GMM-Sys
224	Vpoitchosky (2005)	0.31	0.11	Advanced	P	GMM-Sys
225	Vpoitchosky (2005)	0.35	-0.11		P	GMM-Sys
226	Vpoitchosky (2005)	0.28	-0.52		P	GMM-Sys
227	Vpoitchosky (2005)	0.35	-0.09		P	GMM-Sys
228	Vpoitchosky (2005)	0.27	-0.57		P	GMM-Sys
229	Vpoitchosky (2005)	0.30	-0.52	Advanced	P	GMM-Sys
230	Vpoitchosky (2005)	0.33	0.07	Advanced	P	GMM-Sys
231	Vpoitchosky (2005)	0.32	0.40	Advanced	P	GMM-Sys
232	Vpoitchosky (2005)	0.33	0.01	Advanced	P	GMM-Sys
233	Vpoitchosky (2005)	0.35	0.19	Advanced	P	GMM-Sys
234	Vpoitchosky (2005)	0.33	-0.21	Advanced	P	GMM-Sys
235	Dabla-Norris et al. (2015)	0.28	-0.55	Mixed	P	GMM-Sys

2 Personal income distribution and the endogeneity of the demand regime

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2.1 Introduction

One of the key features of the Kaleckian model of growth, both in its original version (Rowtorn, 1981 [114]and Dutt, 1984[47]) and in its subsequent evolutions (Amadeo, 1987 [8]and Taylor, 1990[124]), is a saving function based on the functional distribution of income. Both in the former simplified versions where workers do not save at all and in the latter more advanced versions where a propensity to save out of wages is added, class-based distribution is fundamental in generating a wage-led demand regime. Other variants of the model, starting from the contribution of Bhaduri and Marglin (1990) [21] and Kurz (1990) [77], modify the other model's equation, the investment function, including the profit share to take into account the profitability impact on investment decisions. Blecker (1989) [24] introduces into the analysis the possible negative effects on the trade balance of an increase in the wage share in an open economy. With these evolutions, the positive effect on consumption of a lower profit share could be offset by the negative effect on investment and net exports. Depending on which of these opposite effects prevails, the demand will be wage-led or profit-led. However, in all these models, the consequence of adopting a saving function based on the functional distribution of income is that the demand will be either universally wage-led or profit-led. As already pointed out by Nikiforos (2016)[95], this conclusion is problematic, as an economy would reach its maximum capacity utilization rate either with a labor share tending towards one or zero, depending on whether it is wage-led or profit-led.

The introduction of an endogenous demand regime that bounds the "distribution-ledness" of an economy has been the object of different contributions. In all of them the non-linearity in the demand schedule comes, explicitly or not, from a changing propensity to invest and/or to save in the labor share level. In Palley (2013)[101] both mechanisms are at work, and a non-linear demand schedule is justified, on the one hand, with the presence of neoclassical capital stock adjustment costs and, on the other, with redistribution towards top-tier income households produced by a profit share increase. Only the saving channel is present in Palley (2015)[98], who introduces an endogenous wage bill split between workers and managers that in turn makes the demand regime endogenous: the increased economic activity following a pro-capital redistribution in a profit-led regime can trigger a redistribution of the wage bill towards workers if managers are a fixed normal cost. The redistribution generates a fall in the aggregate saving rate because workers' propensity to save is lower than that of managers. Both channels are present in Nikiforos (2016)[95], who explicitly assumes that the propensity to invest and the propensity to save change in response to the variations in the labor share. These two mechanisms, together with an unstable distribution of income influenced by class power, "distribution-ledness" of the economy and lagged effects, generate endogenous changes between wage-led and profit-led periods.

However, since a universally wage/profit-led demand is a direct consequence of a saving function based on functional income distribution, this paper proceeds by simply shifting from functional to personal distribution as the key distributional variable determining the saving rate. This perspective shift is not merely instrumental in generating a non-monotonic demand schedule. It seems more plausible that the individual propensity to save depends on the individual position in total income ranking, i.e., on personal income distribution[1], rather than on the type of income earned - wage or profit. Figure 2.1.1 - similar to the one reported in Carvalho and Rezai (2016)[32] - shows that the saving rate in the US economy is an increasing function of income quintiles[2].

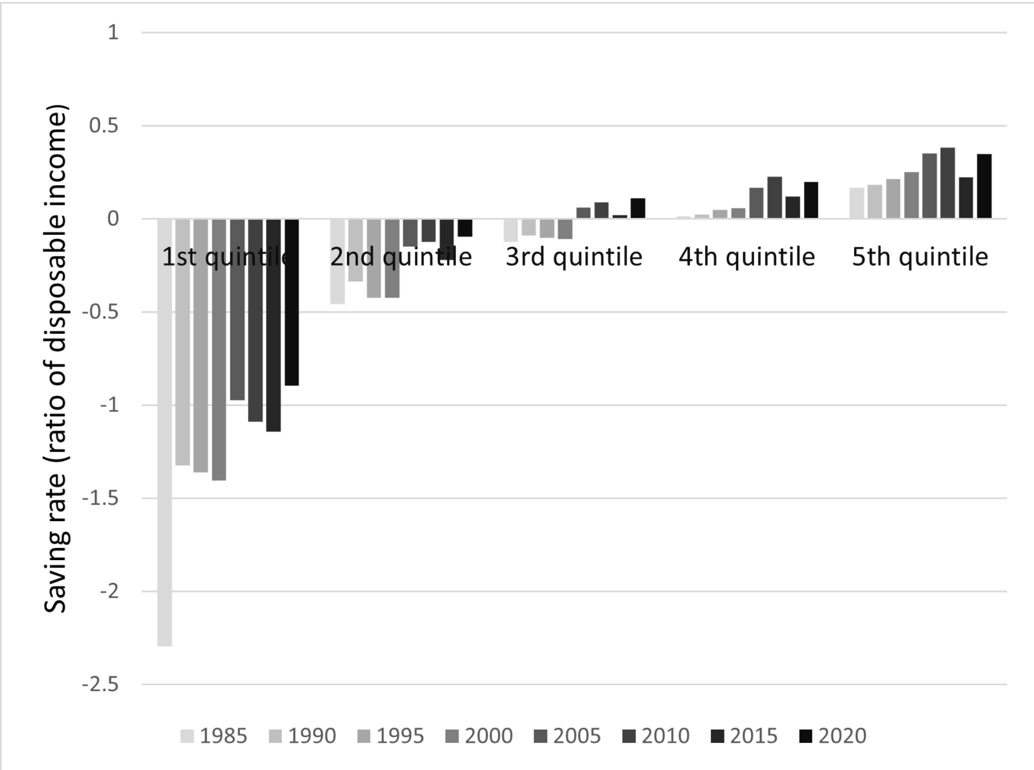

Figure 2.1.1: Saving rates across income quintiles in the US

As pointed out by Ranaldi (2022) [109] and Ranaldi and Milanovic (2021) [110], if the economy is populated by a majority of low-income workers who earn only labor income and a small number of high-income capitalists who earn only profit income, then functional income distribution can be a good proxy for personal income distribution. However, this simplification - which could be

[1]Dynan et al. (2004)[48]) provide empirical evidence of the positive relationship between saving rates and lifetime income - based on data from the Panel Study of Income Dynamics (PSID), the Survey of Consumer Finances (SCF) and the Consumer Expenditure Survey (CEX) - along with an extensive examination of empirical and theoretical debate on the issue. Evidence based on recent data from Consumer Expenditure Survey can also be found in Carvalho and Rezai (2016)[32].

[2]Data come from the Consumer Expenditure Survey and are available on the Bureau of Labor Statistics website.

reasonable for nineteenth-century early capitalism - does not necessarily hold in advanced economies. Indeed, the lower the compositional inequality - i.e., how the composition of income in capital and labor varies across the income distribution - the less changes in functional income distribution will be transmitted to inter-personal income inequality[3]. Two main factors differentiate an advanced economy from a 'classic capitalism' economy. Primarily, in modern economies, there is a sizable within-class inequality, from the part-time worker's low wage to the very high top manager pay, and from the small business profit income to the major shareholders of large retailer and tech companies. Secondly, the lower compositional inequality sometimes makes the class concept difficult to handle. Even though the majority of people earn most of their income either from labor or from capital, a certain number of people draw their income from both income sources. Although it typically represents a small part of their income, it is common for workers to draw income from interests and dividends paid on their savings. Another more prominent case is that of the self-employed, as their income is partly imputed to labor and partly to capital in official statistics. This paper, therefore, attempts to answer the following question. To what extent does a change in the functional income distribution affect the personal income distribution and aggregate demand?

The paper proceeds as follows. The saving function is microfounded following Carvalho and Rezai (2016)[32]: aggregating individual saving decisions, where individual consumption depends on the income deviation from the median individual, yields a positive relation between the aggregate saving rate and the Gini index. The Gini index is then decomposed, following Lerman and Yitzhaki (1985)[81], as a function of the Gini indices of wages and profits and of the functional distribution. From this decomposition, it derives that wage inequality and profit inequality play a symmetric, though opposite, role in determining the demand regime type - the *sign* of the slope of the demand schedule - and its strength - the *size* of the slope of the demand schedule. Moreover, since saving is a function of the personal income distribution rather than the functional one, raising the wage share is effective in reducing the aggregate saving rate, not per se, but only as long as it reduces personal inequality. As the labor share increases, depending on how it affects the personal distribution, the demand regime type and strength can endogenously change. In particular, there can be a threshold value of the wage share beyond which a further increase raises inequality rather than reducing it. This generates a shift from wage-led to profit-led demand. For this reason, when the saving rate is determined by personal distribution rather than functional distribution, a non-monotonic propensity to save in the labor share level can arise naturally, generating a non-monotonic demand schedule, without the need to make additional assumptions[4].

Another approach to introduce personal inequality within the Kaleckian model, adopted - among others[5] - by Lavoie (1996)[78], Palley (2014 and 2015)[97] and Tavani and Vasudevan (2014)[123], consists in introducing an unproductive managerial class, which shares wage income with workers. Inequality between these two classes of wage earners is a proxy for personal inequality. This approach has two major shortcomings. Firstly, it deals only with wage inequality, neglecting the other side of the coin: profit inequality. Secondly, it measures only the "between" inequality, as inequality within workers, managers and capitalists is not considered. These downsides may be applied to a similar

[3]See Milanovic (2018) for an empirical analysis of the strength of the association between functional and personal income distribution.

[4]Obviously, this does not mean that there are not other mechanisms that contribute to the endogeneity of the demand regime.

[5]For an extensive review of personal inequality in Kaleckian models see Hein (2018)[67].

approach, taken by Palley (2017a)[99] and (2017b)[100], which, however, realistically considers that both workers and capitalists earn both capital and labor income. Carvalho and Rezai (2016)[32] show that aggregating workers' individual saving functions where saving depends on the deviation between the individual's income and the median income yields a positive relationship between the aggregate saving rate and the Gini index. Although this approach considers within class inequality, personal income inequality is still limited to inequality within wage earners as the distribution of profit income is not taken into account.

The view of consumption upheld by this paper, where the main determinant of individual saving rate differences is the individual position in income ranking, is linked to the strand of literature, which draws primarily on Veblen's (1899)[127] "conspicuous consumption" and Duesenberry's (1949)[46] "relative income hypothesis"[6], that sees consumption demand mainly as a social phenomenon: individuals primarily consume to keep up with a certain social standard of well-being, reflected in a given consumption level and, thus, saving is mainly determined as a residual component once those needs have been attained. Within this setup, the determination of the consumption level targeted by individuals plays a critical role: depending on how this target is formulated, an *increasing* or *decreasing* relationship between the saving rate and personal inequality arises. The "expenditure cascades" hypothesis proposed by Frank et al. (2014)[82] predicts that, through a sort of trickle-down consumption mechanism, an increase in inequality within a group makes its saving rate decrease. According to this idea, individuals try to emulate the consumption behavior of those just above them in the income rank. Consequently, an increase in income and consumption of those at the top of income distribution, generates a reduction of saving rates along all the distribution in the attempt "to keep up with the Joneses". Along this line, the contributions of Setterfield and Kim (2016)[118], Kapeller and Schütz (2015)[71] and Kapeller et al. (2018)[70] show that, if a redistribution from labor to capital is coupled with an expenditure cascade effect, it can boost demand through a *consumption-driven profit-led regime.* On the contrary, the individual consumption function of Carvalho and Rezai (2016)[32] embeds a *positive* relationship between inequality and the aggregate saving rate. Each individual compares her consumption not with the income group immediately above in the income rank but with the median individual of the whole distribution. Instead of a continuum of consumption levels targeted by people, there is only one target for all, which should be seen as a threshold of social satisfaction rather than a target. This lack of consensus in the literature about the sign of the effect of personal inequality on the saving rate is pointed out by Prante (2018). The paper relies on Carvhalo and Rezai's (2016) saving function but remains agnostic about the sign of this effect. If we see the use of the functional income distribution in all the traditional Kaleckian and neo-Kaleckian models as a simple proxy for the personal distribution, it can be said that this literature falls under the Carvalho and Rezai category, as it predicts a drop in the aggregate saving rate following a redistribution from capital to wage. This paper can be led to this last approach, as its main goal is bounding the "distribution-ledness" of traditional neo-Kaleckian models, in which wage-led aggregate demand is, in principle, possible through the positive effect on consumption of a pro-labor redistribution. Nevertheless, as we will see later, relying on a saving function where the aggregate saving rate is a decreasing function of personal inequality does not significantly alter the main findings of this article.

[6]For an extensive review of this strand of literature see Trezzini (2005)[125].

The paper assumes - as done by Dutt (2016)[76] and others in the literature - that the saving rate is a function of personal rather than functional income distribution. The novelty lies in showing how this is sufficient to generate a set of relevant results. First, endogenous utilization regime changes may arise naturally without the need for further assumptions regarding the investment function. Second, even if such regime change does not occur, it shows that the utilization regime's degree of wage or profit-ledness - its “strength” - may not be constant. Koher (2018)[73] and Prante (2019)[107] already presented the possibility of endogenous distribution-ledness change. However, while in their models, the wage-led regime exhibits increasing marginal returns and the profit-led regime decreasing marginal returns, in this model, both regimes exhibit decreasing marginal returns under plausible parameter values. Third, it shows that in determining the regime *type* and its *strength* a symmetric, though opposite, role is played by wage and profit inequality, despite the role of the latter being neglected in the literature. Lastly, it offers a more general and comprehensive way of dealing with personal distribution, as any distribution can be virtually represented within the model.

The paper is organized as follows. Section 2.2 discusses the general model and its properties. As the model's features are strictly dependent on the particular distribution assumed for individual wages and profits, in Section 2.3, four particular distributions, among the infinite possibilities, are simulated better to understand the characteristics and implications of the model. This exercise is similar in spirit to the one conducted by Milanovic (2018)[89] but extended to the whole macroeconomic context. Section 2.4 analyzes what happens if the saving function embeds a decreasing relationship between personal inequality and the aggregate saving rate. Section 2.5 shows that model results are robust even if investment demand is a function of the profit share as in Badhuri and Marglin (1990)[21] and Kurz (1990)[77]. Section 3.5 concludes.

2.2 The Model

Investment is described by a simplified Keynesian accumulation function:

$$g^i = \gamma + \gamma_u(u - u_n) \tag{2.1}$$

where g^i is the investment to capital ratio, γ is the growth rate of autonomous investment, u is the rate of capacity utilization, u_n is the normal capacity utilization rate, and γ_u is the sensitivity of investment to the deviation of capacity utilization from its normal rate. The choice not to include any distributional variables in the investment function comes from focusing on consumption demand as the transmission channel from distribution to aggregate demand. Although the wage-led/profit-led distinction is traditionally linked to the sensitivity of the investment function to the functional distribution, in this model - as we will see - this change is not necessary to have a profit-led demand regime. The saving function is described in the following way:

$$g^s = s\frac{u}{v} \tag{2.2}$$

Where g^s is the saving to capital ratio, v is the capital to full capacity output ratio, and s, the average propensity to save, is microfounded as follows. Each individual income Y_i is equal to the sum of labor income and capital income:

$$Y_i = w_i \omega Y + p_i (1-\omega) Y \tag{2.3}$$

Where ω is the labor share, i.e., the relative share of output paid as compensation to employees. $1-\omega$ is the share paid to capital and w_i and p_i are, respectively, the portion of total wage mass and total profit mass earned by individual i. These individual shares are assumed to be constant over time[7]. Note that - as in the standard Kaleckian model - all profits are distributed to households, and there are no retained profits. This assumption will be relaxed in section 2.2.1.

Individuals take their saving decisions as follows:

$$S_i = a_0 Y_i + a_1 (Y_i - Y_m) \qquad a_0, a_1 \geq 0 \tag{2.4}$$

Saving S_i depends partly on individual income Y_i, through the coefficient a_0, and partly on its deviation from the median income Y_m, through the coefficient a_1, which is indeed a measure of how much saving decisions are affected by inter-personal distribution. The more affluent the individual is, the higher his saving rate. Aggregating the individual saving functions and assuming a Pareto distribution for income, Carvalho and Rezai (2016)[32] show that the aggregate saving rate can be written as:

$$s = a_0 + a_1 \left(1 - 4^{\frac{G_y}{1+G_y}} \frac{1-G_y}{1+G_y}\right) \tag{2.5}$$

Where G_y is the Gini index of total income. See Appendix 3.B for the derivation process. This equation - as shown in Appendix 2.B - states that a unique positive relationship links the saving rate and personal inequality: every decrease in personal inequality always reduces the saving rate, boosting aggregate demand. Note how, if there is no income inequality ($G_y = 0$), all individuals save the same portion of their income, and everyone has a saving rate equal to a_0. There is no difference between the individual and the aggregate saving rate. At the opposite end, if personal inequality is at its maximum ($G_y = 1$), then the aggregate saving rate equals the sum of a_0 and a_1.

The personal and functional income distribution are linked following the Lerman and Yitzhaki (1985)[81] Gini index decomposition[8] (equation 6). This decomposition is chosen because it is one of the few to link personal and functional income distribution and because, among those, it is the one that fits better within the model. Indeed, in Atkinson (2009)[12] personal inequality is expressed in terms of income variance rather than the Gini index. In Ranaldi (2022)[109] the Gini index is not a function of the Gini indices of wages and profits. The decomposition reads:

$$G_y = \rho_w G_w \omega + \rho_p G_p (1-\omega) \tag{2.6}$$

Where G_y is the Gini index for total income, G_w and G_p are the Gini indices for wages and

[7] This assumption implies that the flows of savings do not sum up to wealth over time; hence, the model must be intended in a short to medium-run perspective, as for a long-run analysis the assumption that p_i is constant must be released. In the long-run $\dot{p}_i = \frac{S_i}{K} - gp_i$, where K is the stock of wealth/capital. In other words, the wealth share is constant when the individual saves exactly the amount that corresponds to his share in the increase in total wealth; see Ederer and Rehm (2019)[50] and Palley (2017a)[99]. This issue is common to all contributions that, on the one hand, have wage earners with a positive saving rate and, on the other hand, do not consider wealth distribution.

[8] In general, for K income sources, the Gini index can be decomposed as $G = \sum_{k=1}^{K} \rho_k G_k S_k$, where s_k is the share of source k in total income.

profits, respectively. G_w measures the inequality in wage distribution across the whole population (and not only across wage earners). It is equal to zero when all people earn the same wage level and 1 when one individual earns all the wage mass. Analogously G_p measures the inequality in the profit distribution. ω is the labor share, and its complement $1-\omega$ is the profit share. Finally, ρ_w and ρ_p are the Gini correlation coefficients for wages and profits, respectively[9]. ρ_w measures the correlation between the individual's level of monetary wage and his or her position in the income ranking. It is defined as follows:

$$\rho_w = \frac{cov(W, f(Y))}{cov(W, f(W))} = \frac{\sum(W_j - \overline{W})(f(Y_j) - \overline{f}(Y))}{\sum(W_i - \overline{W})(f(W_i) - \overline{f}(W))} \tag{2.7}$$

Starting from the numerator, W_j and Y_j are the wage and total income of individual j, respectively. $\overline{W}$ is the average wage in the population. $f(Y_j)$ is the cumulative distribution of income at Y_j, i.e., individuals are sorted in ascending order by *income*, and $f(Y_j)$ thus represents the percentage of individuals with income less than or equal to Y_j. $\overline{f}(Y)$ is the mean value of $f(Y_j)$, equal to 0.5. Similarly, in the denominator, W_i is the wage of individual i. The only difference is that $f(W_i)$ is the cumulative distribution of *wages* at W_i, i.e., individuals are sorted in ascending order according to their wages and not income, and $f(W_i)$ thus represents the percentage of individuals with wages less than or equal to W_i. Again, $\overline{f}(W)$ is the mean value of $f(W_i)$.

ρ_w equals 1 (-1) when the wage level is an increasing (decreasing) function of income ranking. No individual at the same time has a lower wage than someone else but outranks him or her in the income ranking. Thus, the wage ranking and the income ranking overlap perfectly. In contrast, ρ_w is positive (negative), but smaller (greater) than 1 (-1), when it is only *on average* an increasing (decreasing) function of income ranking. In other words, there is at least one individual who at the same time has a lower salary than someone else but outranks him or her in the income ranking. The more this occurs, the lower the correlation coefficient is. However, negative values are unlikely in a real economy, as higher wage values are unlikely to be associated with lower income ranking positions on average. Lastly, ρ_w equals zero when there is no correlation between monetary wage and income ranking.

Likewise, ρ_p is a measure of the correlation between the individual profit income and the income ranking and a positive (negative) value indicates that capital income is *on average* an increasing (decreasing) function of the income ranking.

$$\rho_p = \frac{cov(P, f(Y))}{cov(P, f(P))} = \frac{\sum(P_j - \overline{P})(f_j(Y) - \overline{f}(Y))}{\sum(P_i - \overline{P})(f_i(P) - \overline{f}(P))} \tag{2.8}$$

Note that, while G_w and G_p are exogenous parameters (do not depend on ω), ρ_w and ρ_p are a function of ω. As ω increases, the income of all those who derive most of their income from labor grows. As these people surpass in the income ranking other individuals whose income is more capital intensive, the correlation between wage and income ranking (ρ_w) rises, and that between profit income and income ranking (ρ_p) decreases. Appendix C discusses the sign of the partial derivatives of the two correlation coefficients and shows that:

$$\frac{\partial \rho_w}{\partial \omega} \geq 0 \text{ and } \frac{\partial \rho_p}{\partial \omega} \leq 0 \; \forall \; \omega \tag{2.9}$$

[9]See Milanovic (2018) for empirical estimation of Gini correlation coefficients for several economies.

In particular, ρ_w increases every time an individual a surpasses in the income ranking an individual b whose individual share w_i of total labor income is smaller than a, otherwise it stays constant. Likewise, ρ_p decreases every time an individual a surpasses in the income ranking an individual b whose individual share p_i of total capital income is higher than a, otherwise it stays constant.

Therefore, equation (2.6) can be rewritten as:

$$G_y = \rho_w(\omega)G_w\omega + \rho_p(\omega)G_p(1-\omega) \tag{2.10}$$

According to equations (2.6) and (2.10), the functional distribution of income is not the only distributional variable that can affect personal distribution and demand. Indeed, provided ρ_w and ρ_p are greater than zero, every reduction in wage and/or profit inequality reduces personal inequality and, through equation (5), stimulates aggregate demand.

Equating equation (2.1) to equation (2.2) we get the equilibrium rate of capacity utilization:

$$u = \frac{(\gamma - \gamma_u u_n)v}{s(\omega, G_w, G_p) - \gamma_u v} \tag{2.11}$$

As in all Kaleckian models, to have a positive value for u, it must be assumed that $\gamma - \gamma_u u_n > 0$ and that the Keynesian stability condition holds, which in our case means that $s > \gamma_u v$. We can now turn to the core question of the paper: the impact of functional distribution on aggregate demand. Taking the partial derivative of equation 2.11 with respect to ω, we get:

$$\frac{\partial u}{\partial \omega} = -\frac{(\gamma - \gamma_u u_n)v}{[s(\omega, G_w, G_p) - \gamma_u v]^2}\frac{\partial s}{\partial \omega} \tag{2.12}$$

The sign of the partial derivative, and the demand regime, clearly depends only on the impact of ω on the saving rate ($\frac{\partial s}{\partial \omega}$). Accordingly, aggregate demand is wage-led (profit-led) if the saving rate decreases (increases) following a rise in the wage share. In turn - as shown in Appendix 2.B - the sign of the relationship between functional distribution and saving rate ($\frac{\partial s}{\partial w}$) depends only on the effect of changes in the wage share on personal inequality ($\frac{\partial G_y}{\partial \omega}$). If an increase in wage share leads to a reduction in personal inequality ($\frac{\partial G_y}{\partial \omega} < 0$), the saving rate falls, and the economy is wage-led ($\frac{\partial u}{\partial \omega} > 0$). Vice versa, if an increase in wage share leads to a rise in personal inequality ($\frac{\partial G_y}{\partial \omega} > 0$), the saving rate increases, and the economy is profit-led ($\frac{\partial u}{\partial \omega} < 0$).

Therefore, to analyze the demand regime type, it is sufficient to study the conditions under which an increase in the labor share leads to a higher or lower personal inequality. The following condition describes the reaction of personal distribution to changes in functional distribution:

$$\frac{\partial G_y}{\partial \omega} = G_w\left[\rho_w + \frac{\partial \rho_w}{\partial \omega}\omega\right] - G_p\left[\rho_p - \frac{\partial \rho_p}{\partial \omega}(1-\omega)\right] \tag{2.13}$$

What equation (2.13) tells us is that the *type* of demand regime - the *sign* of the slope of the demand schedule in the (u, ω) plane - and its *strength* - the *size* of the slope of the demand schedule - depend: on the level of the labor share (ω), on the initial value of parameters ρ_w and ρ_p, on their variation ($\frac{\partial \rho_w}{\partial \omega}$ and $\frac{\partial \rho_p}{\partial \omega}$) and on the inequality of wages (G_w) and profits (G_p) distributions. The impact of an increase in the wage share on personal inequality and aggregate demand depends on the action of three different forces. Firstly, it depends on the difference between ρ_w and ρ_p. Given that both coefficients are positive in a real economy, the greater the correlation between profit and income ranking compared to that between wages and income ranking, the more likely the net effect of an ω increase on G_y will tend to be negative. A ρ_p greater than ρ_w increases the probability that those who derive most of their income from wages (profits) are concentrated on average at the bottom (top) of the income distribution. In such a situation, increasing the wage share means redistributing from the top down, thus reducing personal inequality and stimulating aggregate demand. A second element is the difference between the Gini indices of wages and profits. The more unequal the distribution of profits relative to wages, the more the net effect of an increase in ω on G_y is likely to be negative. The reason is similar to the difference between the two correlation coefficients. A G_p greater than G_w increases the probability that those who derive most of their income from wages (profits) are concentrated at the bottom (top) of the income distribution. Indeed, provided that the ρ_p and ρ_w coefficients are positive, the higher the inequality index of a factor income, the more it tends to be concentrated in the hands of a few at the top of the distribution. Again, in such a situation, increasing the wage share means redistributing from top to bottom, thus reducing personal inequality and stimulating aggregate demand. Hence, an important finding derived in equation (2.13) is that profits inequality play a symmetric, though opposite, role as wage inequality in determining the regime type and its strength, despite being neglected in the literature. Finally, the last factor is the induced change in the correlation coefficients ($\frac{\partial \rho_w}{\partial \omega}$ and $\frac{\partial \rho_p}{\partial \omega}$). This effect always operates by reducing the effectiveness of functional income redistribution. Suppose that initially, the difference between the correlation coefficients and the Gini indices is such that the net effect of an increase in wage share on personal inequality is negative. The rise in ρ_w and the reduction in ρ_p operate by weakening the negative effect on inequality. The consequence is that the marginal impact on personal inequality and demand of an increase in the wage share is decreasing. The change in the two coefficients and the associated decreasing marginal effect on inequality may be such that the sign of the relationship between wage share and personal inequality (and demand) reverses, and a further increase in the wage share increases inequality rather than reducing it. The same considerations apply if, initially, the difference between the correlation coefficients and the Gini indices is such that the net effect of an increase in the profit share on personal inequality is negative.

To better grasp the intuition behind equation (2.13), suppose that initially, those who derive most of their income from wages are concentrated at the bottom of the income distribution, and those who derive most of their income from profit are, on average, concentrated at the top. In this situation, increasing the wage share means redistributing from the top down, thus reducing personal inequality and stimulating aggregate demand. However, the more the wage share increases - and the redistributive process continues - the less sharp will be the concentration at the bottom (top) end of the distribution of those whose income is more wage (profit) intensive. In other words, increasing the wage share has decreasing marginal effectiveness in reducing personal inequality and rising aggregate demand. This effect is reflected in equation (2.13) by the change in correlation coefficients ($\frac{\partial \rho_w}{\partial \omega}$ and $\frac{\partial \rho_p}{\partial \omega}$). As the labor share increases, it is in principle possible to reach a point where those who derive most of their income from wages will be, on average, concentrated at the top of the income distribution, and those who derive most of their income from profit will be on average concentrated at the bottom. From this point on, further increases in the wage share will raise inequality and reduce aggregate demand rather than increase it since we would be redistributing from the bottom up. In other words, there could be a wage share level that, once passed, would trigger an endogenous regime shift from wage-led to profit-led.

In the particular case in which, as ω increases, there is no change in income ranking, $\frac{\partial \rho_w}{\partial \omega}$ and $\frac{\partial \rho_p}{\partial \omega}$ are both equal to zero (see Appendix 2.A) and equation (2.13) reduces to:

$$\frac{\partial G_y}{\partial \omega} = G_w \rho_w - G_p \rho_p \tag{2.14}$$

Therefore, as long as the income ranking does not change, the first derivative is constant and no regime change can occur, be it initially wage or profit-led.

We can analyze the non-monotonicity of the relationship between wage share and aggregate demand - whose intuition we saw just above - analytically. Equating to zero equation (2.13) and solving for ω we obtain the critical value for ω, i.e., that value that once passed shifts the economy from a wage-led to a profit-led regime:

$$\omega^* = \frac{\rho_p G_p - \rho_w G_w - \frac{\partial \rho_p}{\partial \omega} G_p}{\frac{\partial \rho_w}{\partial \omega} G_w - \frac{\partial \rho_p}{\partial \omega} G_p} \tag{2.15}$$

Note that if the income ranking never changes, for instance because those who earn a higher wage have a higher profit income too, $\frac{\partial \rho_w}{\partial \omega}$ and $\frac{\partial \rho_p}{\partial \omega}$ are equal to zero and ω^* does not exist.

The economy is wage-led for wage share levels smaller than the critical value. On the contrary, the economy is profit-led for wage share levels higher than the critical value (see Appendix 2.C for the proof). In other terms:

$$\text{If } \omega < \omega^* \Rightarrow \frac{\partial u}{\partial \omega} > 0 \Rightarrow \text{ wage-led} \tag{2.16}$$

$$\text{If } \omega > \omega^* \Rightarrow \frac{\partial u}{\partial \omega} < 0 \Rightarrow \text{ profit-led} \tag{2.17}$$

Summing up, depending on the distribution of wages and profits, there can be an ω^* such that the regime is wage-led if $\omega < \omega^*$ and the regime is profit-led if $\omega > \omega^*$[10]. Provided the conditions for which $0 < \omega^* < 1$ hold and that ρ_w and ρ_p are positive, an increase (decrease) in G_w tends to lower (raise) ω^*, while an increase (decrease) in G_p tends to lower (raise) ω^*. In other words, the higher wage inequality and the lower profit inequality, the smaller the space for re-distributional policies toward wages with the aim of increasing the level of economic activity, as the boundary beyond which demand turns profit-led becomes more tightened. The intuition is similar to that of equation (2.13). As wage (profit) inequality increases, wages (profits) tend to concentrate higher in the income distribution, thus lowering the point beyond which an increase in wage (profit) share redistributes from the bottom up rather than the other way around.

Even if the change in the functional distribution of income is not such to make the *sign* of the slope of the demand schedule change, it does not mean that the *size* of the slope does not change at all. In other words, even if, as ω increases, a shift from a wage-led to a profit-led demand regime does not occur, it does not mean that the *wage-ledness* of the economy remains the same. However, analytically analyzing the linearity of the *distribution-ledness* of the two demand regimes -

[10] Note that, as we will see in Section 2.4, this result is reversed if the saving function embodies an 'expenditure cascade' mechanism. If the relationship between personal inequality and the saving rate is negative rather than positive as it is in equation (5), the demand regime is profit-led for $\omega < \omega^*$ and wage-led for $\omega > \omega^*$.

and hence the second derivative of equation (2.11) - is not straightforward. However, if there is a continuous change in income ranking and ω^* does exist, then there is a neighborhood of ω^* in which the second derivative is negative. To put it another way, if equation (2.11) is continuously derivable and has a point of maximum, then its second derivative must be negative in a neighborhood of this point. This implies that, as we get close to such ω^* from the wage-led area, the effectiveness of redistributional policies towards wages to stimulate aggregate demand is decreasing in ω, as we have seen when discussing equation (2.13). The same is true for a profit share increase in a profit-led regime: as we get close to ω^* from the profit-led area, the effectiveness of redistributional policies toward capital to stimulate aggregate demand is decreasing in $1-\omega$.

2.2.1 Introducing retained profits

Let d be the percentage of distributed profits so that $0 < d < 1$. Personal inequality is now computed not on the economy's total income but only on income that accrues to households, i.e., on the total income net of retained profits. Equation (2.6) becomes:

$$G_y = \rho_w G_w \overline{\omega} + \rho_p G_p (1 - \overline{\omega}) \tag{2.18}$$

where $\overline{\omega}$ and $1-\overline{\omega}$ are the wage and profit share of total disposable income. Rearranging the two shares in terms of the usual wage and profit shares, we obtain:

$$G_y = \rho_w G_w \frac{1}{1+\left(\frac{1-\omega}{\omega}\right) d} + \rho_w G_p \left[1 - \frac{1}{1+\left(\frac{1-\omega}{\omega}\right) d}\right] \tag{2.19}$$

Note that if $d = 1$ this condition is nothing but the Gini decomposition of Equation (2.6), that is, therefore, a special case when all profits are distributed to households.

The equilibrium rate of capacity utilization depends now also on d, since, as stated in equation (5), s is a positive function of G_y, which in turn is a function of d, ω, G_w and G_p (equation 2.19). Equation (2.11) becomes:

$$u = \frac{(\gamma - \gamma_u u_n)v}{s(d, \omega, G_w, G_p) - \gamma_u v} \tag{2.20}$$

We can now focus on the impact of distributed profits on aggregate demand:

$$\frac{\partial u}{\partial d} = \frac{-(\gamma - \gamma_u u_n)v}{(s - \gamma_u v)^2} \frac{\partial s}{\partial d} \tag{2.21}$$

The partial derivative depends only on the response of the saving rate to changes in d.

$$\frac{\partial s}{\partial d} = \frac{\partial s}{\partial G_y} \frac{\partial G_y}{\partial d} \tag{2.22}$$

Which in turn depends exclusively on $\frac{\partial G_y}{\partial d}$, since $\frac{\partial s}{\partial G_y}$ is always positive, as already pointed out in the discussion regarding equation (5). The main point of interest is, thus, how the percentage of distributed profits affects personal inequality.

$$\frac{\partial G_y}{\partial d} = \frac{(\omega - 1)\omega(\rho_w G_w - \rho_p G_p)}{[d(1-\omega) + \omega]^2} \tag{2.23}$$

The sign of the partial derivative clearly depends on $\rho_w G_w - \rho_p G_p$. A reasoning similar to that made for equation (2.13) applies here. If profits concentrate mainly in the upper (lower) part of the distribution, then a rise in d increases (decreases) total inequality (G_y). Indeed, the higher (lower) is $\rho_p G_p$ relative to $\rho_w G_w$, the more profits tend to concentrate in the upper (lower) tail of the distribution, and an increase in distributed profits would mean further increasing (reducing) their income, raising (lowering) inequality.

$$\text{If } \rho_w G_w < \rho_p G_p \Rightarrow \frac{\partial G_y}{\partial d} > 0 \Rightarrow \frac{\partial u}{\partial d} < 0 \tag{2.24}$$

$$\text{If } \rho_w G_w > \rho_p G_p \Rightarrow \frac{\partial G_y}{\partial d} < 0 \Rightarrow \frac{\partial u}{\partial d} > 0 \tag{2.25}$$

In other words, the percentage of distributed profits amplifies the impact of profits distribution on inequality and aggregate demand.

2.3 Some distributional examples

To better understand the properties of the model, I simulate in this section four particular distributions among the infinite possibilities[11]. For simplicity, the following simulations are based on the standard model without distinguishing between distributed and not distributed profits. This exercise is similar in spirit to the one conducted by Milanovic (2018)[89], but the distributional part is integrated within the macroeconomic context. Firstly, I simulate a 'classical' income distribution, as it might have been in nineteenth-century capitalism. The population is divided into two groups: 70 % of people earn only labor income and the remaining 30 % draw their income only from capital. There is perfect equality in wages and profit earned within those two groups. Thus, this distribution is characterized - to employ the terminology of Ranaldi (2022)[109] - by a very high compositional inequality. In statistical terms, there can be 'between' inequality in this distribution, but there is always 'within' equality. This does not imply that G_w and G_p are equal to 0 because the Gini indices are computed on the whole population, not on subgroups. Starting from the bottom-left panel of Figure (2.3.1), it can be noted that ω^* exists and is equal to 0.7. For wage share values smaller than 0.7, rising the wage share to stimulate aggregate demand is an effective policy, as it increases capacity utilization. This is no more true for values beyond 0.7, for which, on the contrary, an effective policy would be increasing the profit share. Note that the reaction of aggregate demand to changes in the functional distribution (bottom-left panel) strictly follows the pattern of the response of personal inequality to changes in functional distribution (upper-left panel): the economy is wage-led (profit-led) only as long as an increase in the labor share reduces (increases) personal inequality. In the two right panels, it can be noted that to the left of ω^*, ρ_w and ρ_p are equal to -1 and 1, respectively, and constant. The two values reflect the fact that, up to ω^*, wage (profit) income is a decreasing (increasing) function of the income rank, as all wage (profit) earners lie in the bottom (upper) part of the distribution. The situation reverses beyond ω^*, when ρ_w and ρ_p become equal to 1 and -1, respectively. The two parameters are constant up to ω^* and beyond it because as ω increases, there is no change in the income ranking. The only exception is when ω is

[11] All the following simulations are based on an economy populated by 1000 individuals and the following parameters calibration: $u_n = 0.7$, $\gamma = 0.12$, $\gamma_u = 0.05$, $v = 2$, $a_0 = 0.3$ and $a_1 = 0.2$.

equal to 0.7, the point at which all the wage earners simultaneously surpass in the income rank all the profit earners.

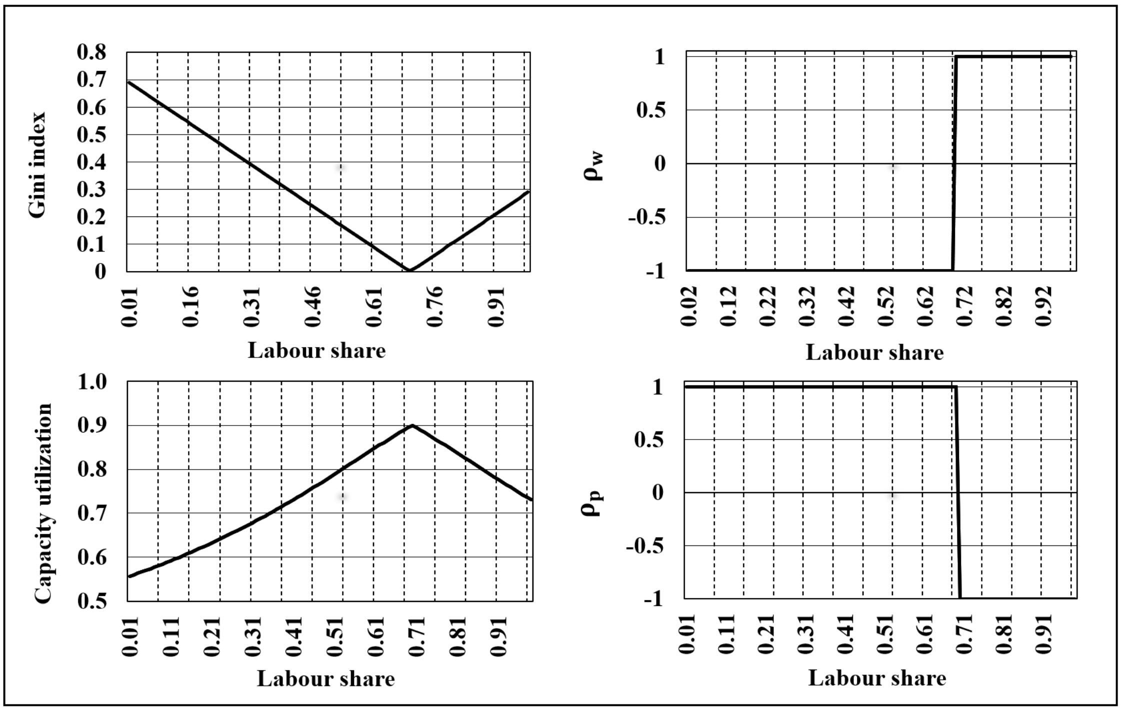

Figure 2.3.1: Distribution 1

In the second distribution (Figure 2.3.2), wage and profit levels are correlated, as it could be in a population only made of self-employed autonomous workers, where their stock of wealth is proportional to their wage, assuming a uniform rate of return on capital. All people earn both labor and capital income. Thus, there are no more subgroups here, but the more an individual earns a high wage, the higher his or her capital income. The parameters ρ_w and ρ_p equal 1 for every ω (right panels) since both the wage and the profit level are an increasing function of the income ranking. In this case the demand regime *type* and its *strength* depend only on which between G_w and G_p is greater. Indeed equation (2.13) reduces to:

$$\frac{\partial G_y}{\partial \omega} = G_w - G_p \tag{2.26}$$

In this example, the economy is always profit-led since it is assumed that $G_w > G_p$. Moreover, ω^* in this case does not exist, since $\frac{\partial \rho_w}{\partial \omega}$ and $\frac{\partial \rho_p}{\partial \omega}$ are always zero and the denominator of equation (2.15) is consequently null. These characteristics can be noted looking at the two left panels: an increase in the wage share always raises personal inequality (upper-left panel), leading to a lower capacity utilization (bottom-left panel). A redistribution policy from wage to capital is always effective in stimulating aggregate demand. Summing up, the economy is always wage-led (profit-led) if $G_w < G_p$ ($G_w > G_p$), and a threshold value for ω beyond which there is a regime change does not exist.

The third distribution (Figure 2.3.3) is characterized by profit equality[12] and wage inequality:

[12]Actually, profits are not strictly equal for all but are generated by a distribution with a very low dispersion which yields negligible individual differences. This modification is necessary since a profit income strictly equal for everyone

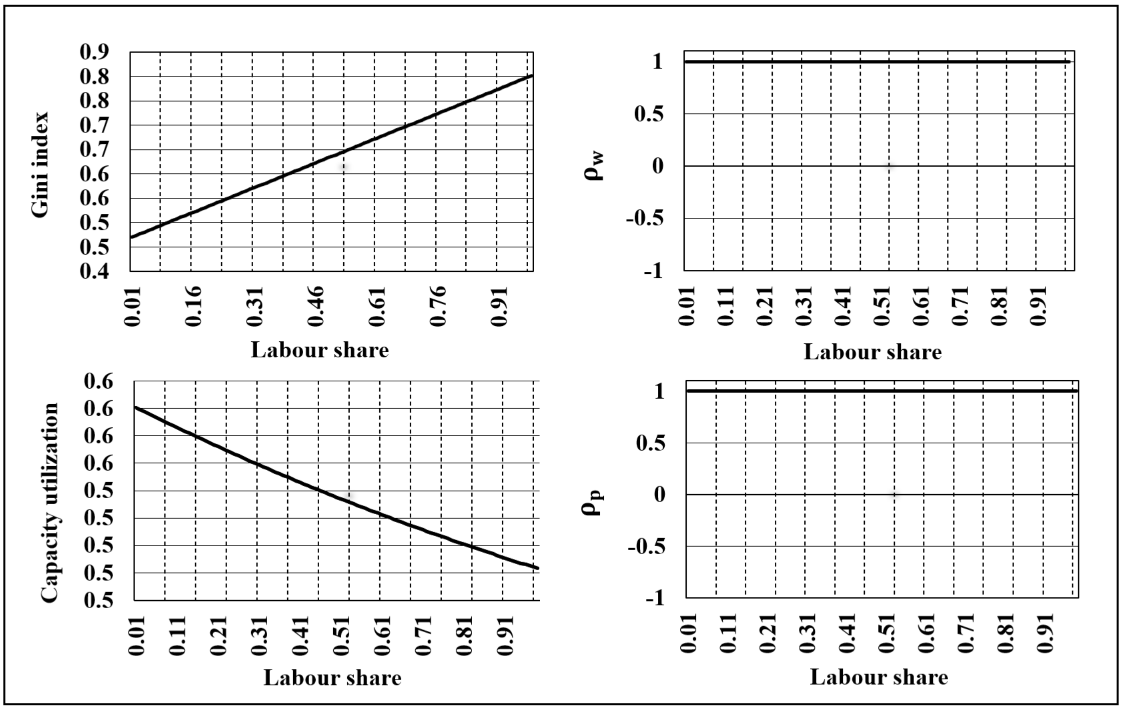

Figure 2.3.2: Distribution 2

again, all people have both labor and capital income, and everyone earns the same profits, but they earn different wages. It is a sort of economy of cooperatives where everyone owns the same stock of capital, but skills and wages are different. G_p and ρ_p are equal to 0 (bottom-right panel), as profit income is equally distributed and uncorrelated with income ranking. Instead, ρ_w is always equal to 1 (upper-right panel), being wages an increasing function of income ranking. Equation (2.13) reduces to:

$$\frac{\partial G_y}{\partial \omega} = G_w \tag{2.27}$$

Since profits are the income source equally distributed across the population, an increase in labor share in total income increases total inequality by an amount equal to the Gini index for wages. As in the previous example, ω^* does not exist since the denominator of equation (2.15) is null. These characteristics can be noted looking at the two left panels: an increase in the wage share always raises personal inequality - equal to G_y - (upper-left panel), which in turn leads to a lower capacity utilization (bottom-left panel). A redistribution policy from wage to capital is effective in stimulating aggregate demand. The opposite occurs with wages equally distributed across the population and profits unequally distributed.

We have so far investigated particular income distributions; they are helpful to understand model properties but are far from providing a realistic representation of the economy. The fourth and last distribution example (Figure 2.3.4) tries to reproduce some traits of income distribution in a real economy. Two Pareto distributions randomly generate individual quotas of wage and profit shares. There is, thus, a continuum of individuals who always differ in income composition and

would have made ρ_p - as well as G_y and u - impossible to compute, as the denominator of Equation (2.8) would have been null.

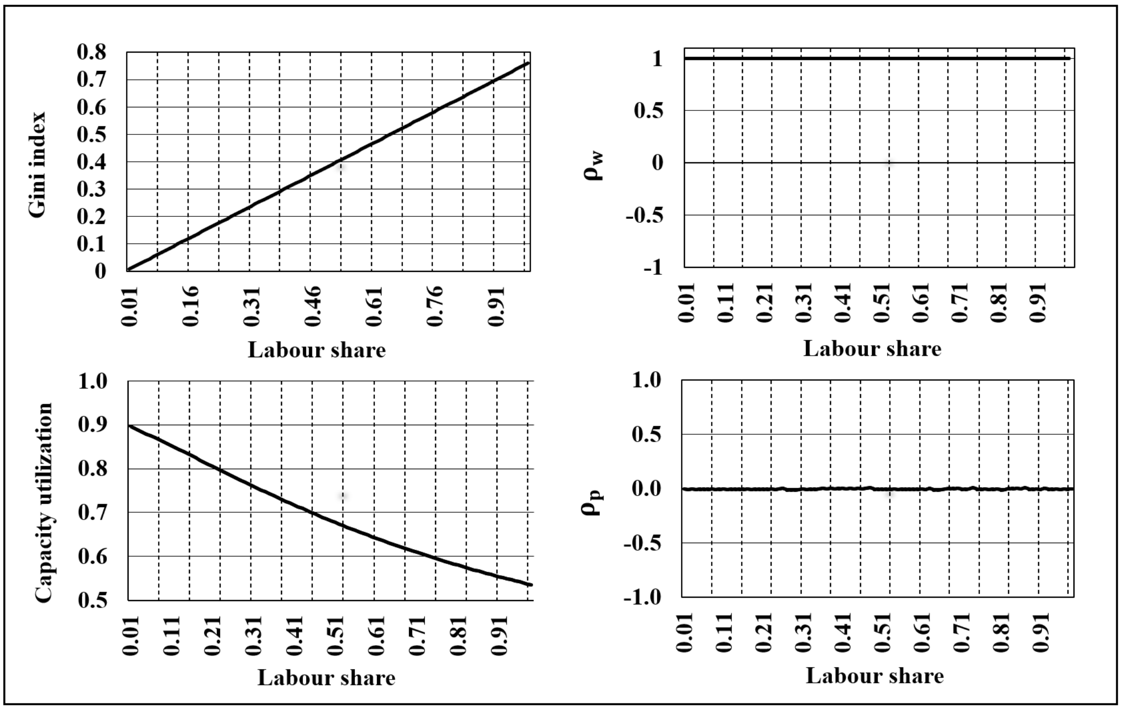

Figure 2.3.3: Distribution 3

income levels. Differently from previous distributions, as ω changes, there is a continuous change in the income ranking, and the parameters ρ_w and ρ_p are never constant (right panels). These two parameters are never negative despite changing as the labor share increases. This reflects that both wage and profit are always *on average* an increasing function of the income rank. From the two left panels, it is evident that ω^* exists and is equal to 0.67. Therefore, a redistributive policy from capital towards wage is effective to stimulate aggregate demand up to a wage share level equal to 0.67; further increases in the wage share beyond this value reduce capacity utilization. Moreover, it is worth noting that the second derivative of the curve in the bottom-left panel is always negative. This implies that, to the left of ω^*, the effectiveness of re-distributional policies towards wage is decreasing in ω and, to the right of ω^*, the effectiveness of re-distributional policies toward capital is decreasing in $1 - \omega$. Summing up, redistributing from capital to wage reduces personal inequality (upper-left panel) up to ω equal to 0.67; beyond this value, the redistribution increases inequality rather than reducing it. This pattern, through the positive relationship between personal inequality and the aggregate saving rate of equation (5), is transmitted to the demand schedule (bottom-left panel). Initially positively sloped in the (ω, u) plane, the demand schedule continuously rotates downward, eventually becoming negatively sloped once outpassed ω^*.

Functional income distribution is not the only distributional variable that can affect aggregate demand in this model, and the last distributional example can be used to analyze also the impact of changes in inequality among wages and profits. As already pointed out when discussing equation (2.15), provided ρ_w and ρ_p are positive, as it is likely to be in a real economy, a reduction in wage inequality shifts ω^* to the right, increasing the span of ω over which the economy is wage-led (Figure 2.3.5). On the contrary, a reduction of profit inequality shifts ω^* to the left, reducing the span of ω over which the economy is wage-led (Figure 2.3.6).

Moreover, from equation (2.6), it is clear that provided ρ_w and ρ_p are positive, a decrease in

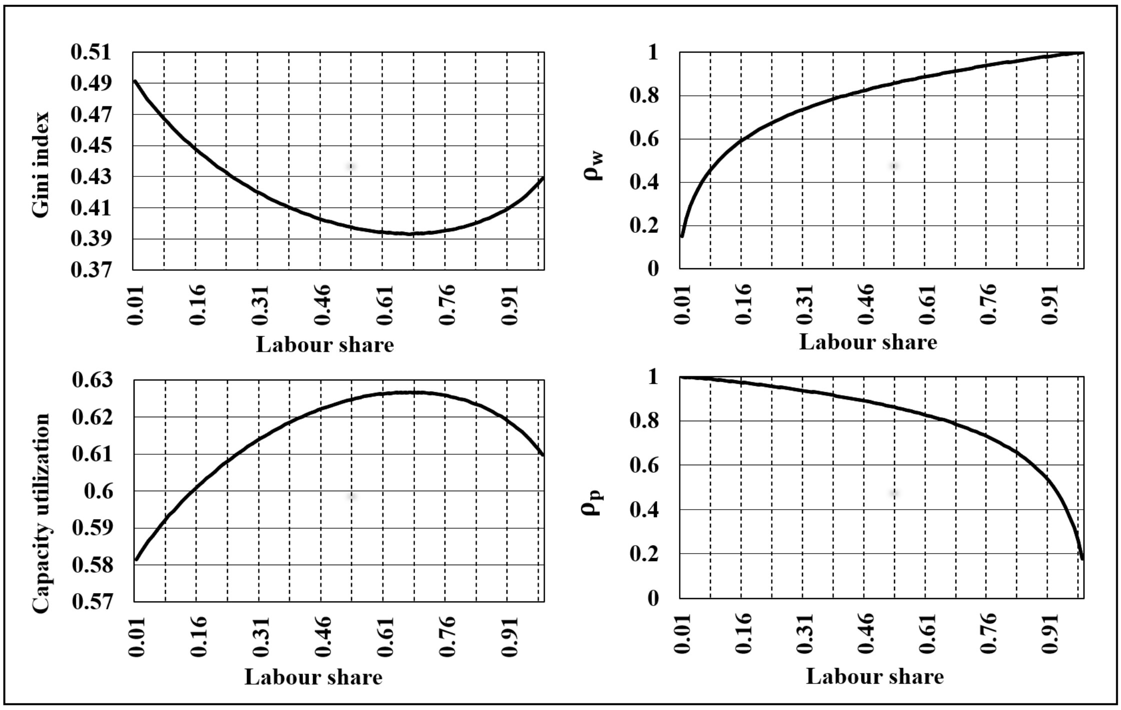

Figure 2.3.4: Distribution 4

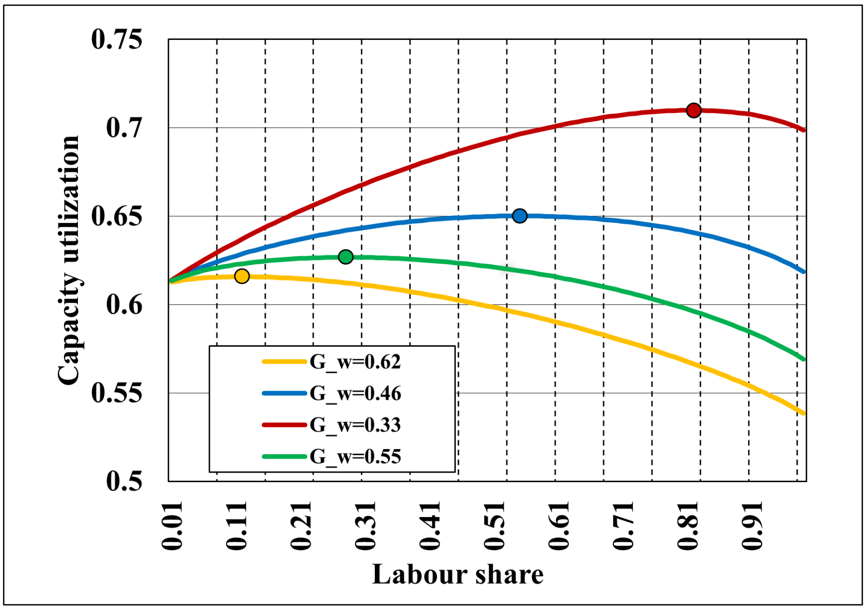

Figure 2.3.5: G_w

wage and/or profit inequality always reduces overall inequality, which in turn stimulates aggregate demand. This is evident in Figures (2.3.5) and (2.3.6), where, following a reduction in G_w or G_p, the new curve always lies above the old one. Thus, as opposed to policies that aim to change the functional distribution, reducing inequality within wages and profits always stimulates aggregate demand under plausible parameter values.

Lastly, it is left to the reader to imagine how the curves behave in the case where the economy is characterized by perfect income composition equality. In this case - as mentioned in the introduction - a change in the functional distribution has no impact on personal inequality and, therefore, on

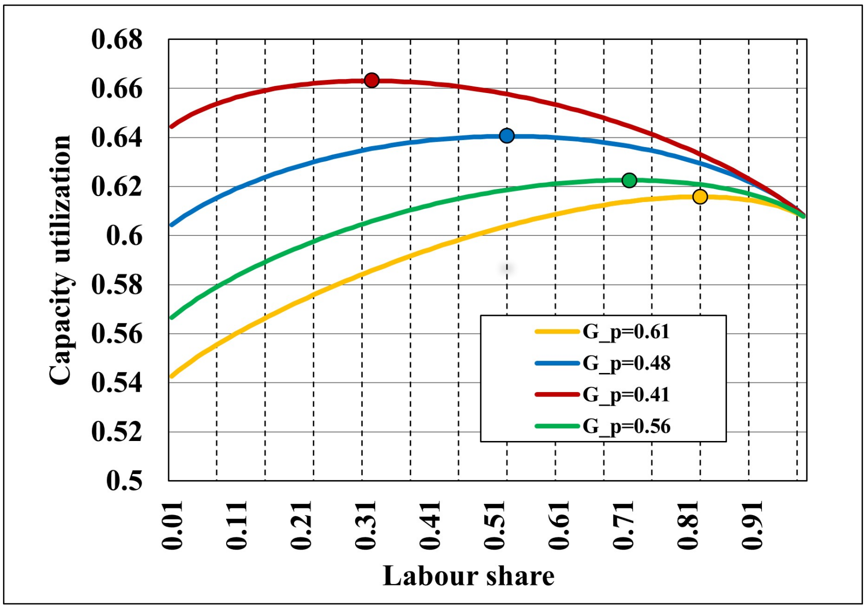

Figure 2.3.6: G_p

aggregate demand. It follows, for example, that a society with a low level of compositional inequality is better shielded from structural changes leading to greater automation of the production process.

2.4 The ‘expenditure cascades’ case

What we have seen so far was based on a positive relationship between inequality and the aggregate saving rate. Since, as pointed out by Prante (2018)[106], this is a sensitive assumption, the purpose of this section is to show that the main findings of this paper hold even if an inverse relationship links the aggregate saving rate and inequality. To this aim, suppose that, in place of equation (5), we have[13]:

$$s = a_0 - a_1 G_y \tag{5b}$$

Inserting (5b) in (2.2) we get the new saving function. The rest of the model is the same and it would be redundant to repeat it here. There are only two other differences. The first regards equation (2.38) in Appendix 2.B, which now becomes:

$$\frac{\partial s}{\partial G_y} = -a_1 < 0 \tag{2.28}$$

This condition implies that, differently from the model of sections 2.2 and 2.3, a reduction (increase) in inequality increases (reduces) the aggregate saving rate. The second difference, stemming from equation (2.28), is that now the economy is wage-led (profit-led) if an increase in the labor share raises (lowers) inequality rather than reducing it. Therefore, as in Section 2.2, it is sufficient to study the conditions under which an increase of the labor share leads to a higher or lower personal inequality: these conditions are the same stated in equation (2.13) to (2.15). In other words, the

[13] This equation, differently from equation (5), is not microfounded. This is because aggregating individual consumption functions where each individual targets a different consumption level as in Frank et al. (2014), is not so straightforward.

determinants of ω^* are the same; the only difference is that now the economy is profit-led to the left of ω^* and wage-led to the right. This happens because a reduction in inequality - which as before occurs to the *left* of ω^* - now increases the saving rate. Likewise, an increase in inequality - which as before occurs to the *right* of ω^* - now decreases the saving rate. The only difference with the model of Section 2.2 concerns the span of ω over which the demand schedule is wage-led or profit-led, which results reversed. However, all the results of Section 2.2 - the possibility of an endogenous change in the regime *type* and its *strength* and the role of profit and wage inequality in determining them - are preserved.

The differences with the model of Sections 2.2 and 2.3 can be better understood by simulating the distribution 4 of Section 2.3 again (Figure 2.4.1).

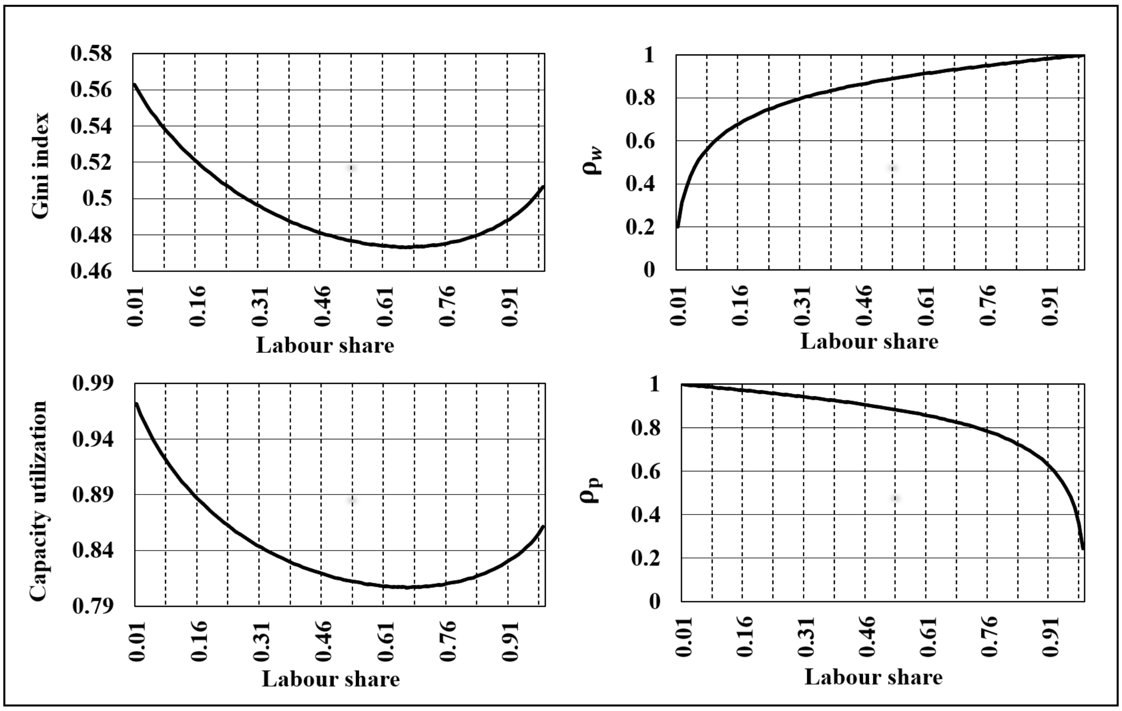

Figure 2.4.1: The 'expenditure cascade' case

The only difference with Figure 2.3.4 concerns the demand schedule in the $(u,\,\omega)$ plane, which now results reversed.

2.5 The case of a 'profit share-augmented' investment function

So far, we have seen that a profit-led regime is possible even without assuming that investment demand is a function of the profit share. Nevertheless, what would happen if the investment function is à la Badhuri and Marglin? In such a case, in place of equation (2.1), we would have:

$$g^i = \gamma + \gamma_u(u - u_n) + \gamma_p(1 - \omega) \tag{2.1b}$$

Where $\gamma_p \geq 0$. Equating this investment function to the saving equation (2.2) yields the following equilibrium capacity utilization rate:

$$u = \frac{[\gamma + \gamma_p(1-\omega) - \gamma_u u_n]\, v}{s(\omega, G_w, G_p) - \gamma_u v} \tag{2.29}$$

The difference with equation (2.11) is that now the profit share has an impact not only on the denominator via the aggregate saving rate but also on the numerator through the parameter γ_p. The next natural step would be to compute ω^*. However, since this is not as straightforward as with the original investment function, I will only simulate here what happens to ω^* when γ_p varies to avoid overburdening the paper. To do this, I use an income distribution similar to the one in figure (2.3.4) and analyze how the demand schedule changes in the (u, ω) plane as the sensitivity of the investment to the profit share (γ_p) increases. In other words, we can see how the bottom-left panel of figure (2.3.4) changes. Since the variations in this parameter do not affect the other three panels of figure (2.3.4) we can leave them out and focus only on the corresponding bottom-left panel (Figure 2.5.1).

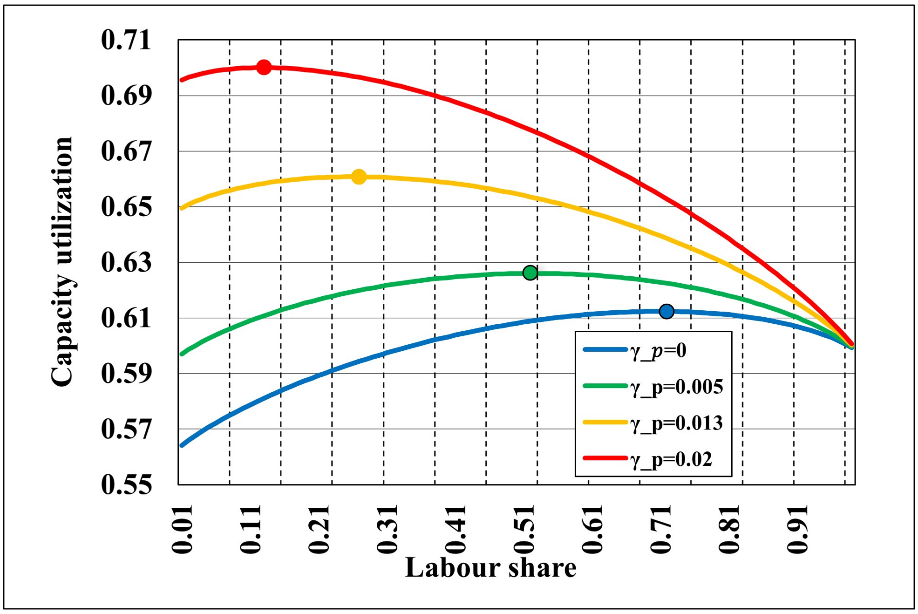

Figure 2.5.1: The case of a 'profit share-augmented' investment function

As the sensitivity of investment to the profit share increases, on the one hand, this stimulates the aggregate demand, as the new curve always lies above the old one. On the other hand, ω^* shifts leftwards, meaning that the span of the wage share over which the economy is wage-led reduces. Note that when $\gamma_p = 0$, we are back to the baseline model of section (2.2). The effect of an increase in the γ_p parameter on both the *aggregate demand* level and the *distribution-ledness* of the economy is similar to the effect of a reduction in profit inequality (Figure 2.3.6). However, the transmission mechanism is entirely different. Indeed, a change in profit inequality affects aggregate demand through the saving rate (consumption demand channel), while a change in sensitivity of investment to the profit share affects investment demand.

2.6 Conclusion and considerations

The paper assumes - as done by others in the literature - that the saving rate is a function of personal, rather than functional income distribution. This means that individuals make their consumption decisions based on their position in the income rank and not on their income type. The paper shows how a series of significant results stems from this assumption: (i) wage and profit inequality play a symmetric, though opposite, role in determining the utilization regime *type* and its *strength* - the degree of wage or profit-ledness of the demand regime; (ii) as the labor share increases, depending on the distribution of wages and profits, there may be an endogenous regime change, i.e. there can be a threshold value of the wage share where the economy shifts from a wage-led to a profit-led utilization regime. (iii) Even without passing such a threshold, as the labor (profit) share increases, the effectiveness of redistributional policies - i.e. the degree of wage or profit-ledness of the utilization regime - is decreasing in the wage (profit) share level under plausible parameter values. (iv) The percentage of distributed profits amplifies the impact of profits distribution on inequality and aggregate demand.

These results hold even if the saving function is of the "expenditure cascade" type rather than a la Carvalho and Rezai (2016)[32], i.e., the relationship between personal inequality and the saving rate is negative rather than positive. The only difference concerns the span of the wage share over which the demand schedule is wage-led or profit-led, which results reversed. Also, the results are robust even considering the investment demand as a function of the profit share. There are other points affecting our results that are worth discussing. Obviously, different results would be possible if the *distribution schedule* was not simply assumed flat as we did in the paper. Indeed, Barrales and Von Armin (2017) [15] find a bidirectional relationship between labor share and output. A point to consider for future research would be to extend the model by including the impact of demand on distribution through another equation. This framework would allow analyzing different possible multiple equilibria solutions. Another point concerns the assumption that individual shares of total wealth are constant. As the savings flows do not sum up to the individual stock of wealth over time, this confines the model to a short to medium-run perspective. In a long-run framework, as highlighted by Ederer and Rehm (2019)[50] and Palley (2017)[99], individual shares of total wealth must be endogenized or, put it differently, wealth distribution must be taken into account. Further research along this line is required to extend the model to a long-run perspective.

2.A The aggregate saving function

The aggregate saving function can be derived similarly to Carvalho and Rezai (2016). Assuming that income distribution follows a Pareto type I distribution, the mean μ and the median z of a Pareto distribution are defined as:

$$\mu = \frac{x\alpha}{\alpha - 1} \text{ and } z = 2^{\frac{1}{\alpha}} \tag{2.30}$$

Where x is the Pareto index.

Individual saving decisions are described by Equation (2.4) here repeated for convenience:

$$S_i = a_0 Y_i + a_1(Y_i - Y_m) \tag{4}$$

The aggregate saving is equal to the sum of all individual savings:

$$S = \int [a_0 Y_i + a_1(Y_i - Y_m)] f(Y) dY = a_0\mu + a_1(\mu - z) = \left[a_0 + a_1\left(1 - \frac{z}{\mu}\right)\right]\mu \tag{2.31}$$

With a constant coefficients production function it is true that $\mu L = \frac{uK}{v}$, or normalizing L to one ($L \equiv 1$):

$$\mu = \frac{uK}{v} \tag{2.32}$$

From equation (2.30) $x = \mu\frac{\alpha-1}{\alpha}$ or, substituting equation (2.32), $x = \frac{\alpha-1}{\alpha}\frac{uK}{v}$. Therefore, equation (2.32) can be rewritten as:

$$\mu = \frac{\alpha - 1}{\alpha}\frac{uK}{v}\frac{\alpha}{\alpha - 1} \tag{2.33}$$

Substituting equation (2.33) in equation (2.31):

$$S = \left[a_0 + a_1\left(1 - \frac{2^{\frac{1}{\alpha}}(\alpha - 1)}{\alpha}\right)\right]\frac{uK}{v} \tag{2.34}$$

Dividing by $Y = \frac{uK}{v}$ we obtain the saving function in terms of the saving rate:

$$s = \left[a_0 + a_1\left(1 - \frac{2^{\frac{1}{\alpha}}(\alpha - 1)}{\alpha}\right)\right] \tag{2.35}$$

Bearing in mind that the Gini index of a Pareto distribution is defined as $G_y = \frac{1}{2\alpha-1}$, equation (2.35) can be rearranged as:

$$s = a_0 + a_1 \left(1 - 4^{\frac{G_y}{1+G_y}} \frac{1 - G_y}{1 + G_y}\right) \tag{5}$$

2.B Study of the derivative of u with respect to ω

The partial derivative of equation (2.11) with respect to ω is:

$$\frac{\partial u}{\partial \omega} = \frac{-(\gamma - \gamma_u u_n)v}{[s - \gamma_u v]^2} \frac{\partial s}{\partial \omega} \tag{2.36}$$

Where:

$$\frac{\partial s}{\partial \omega} = \frac{\partial s}{\partial G_y} \frac{\partial G_y}{\partial \omega} \tag{2.37}$$

The first term is always positive, indeed:

$$\frac{\partial s}{\partial G_y} = a_1 4^{G_y/(1-G_y)} \left[\frac{2(1+G_y) - (1-G_y)\ln 4}{(1+G_y)^3} \right] > 0 \tag{2.38}$$

Therefore, the sign of $\frac{\partial u}{\partial \omega}$ depends only on $\frac{\partial G_y}{\partial \omega}$.

2.C Properties of the Gini correlation index

Let's define:

$$\rho_w = \frac{cov(W, f(Y))}{cov(W, f(W))} = \frac{\sum(W_j - \overline{W})(f_j(Y) - \overline{f}(Y))}{\sum(W_i - \overline{W})(f_i(W) - \overline{f}(W))} = \frac{A}{B} \tag{2.39}$$

The first partial derivative of ρ_w with respect to ω is:

$$\frac{\partial \rho_w}{\partial \omega} = \frac{\frac{\partial A}{\partial \omega} B - \frac{\partial B}{\partial \omega} A}{B^2} \tag{2.40}$$

Where B is always greater than zero, $\frac{\partial B}{\partial \omega}$ is always positive and constant, A can be either positive or negative, and $\frac{\partial A}{\partial \omega}$ is smaller than zero if A is negative, and greater than zero if A is positive. The sign of equation (2.40) depends on the sign of the numerator, which will always be greater or equal to zero, as can be noted in figure (2.C.1) and (2.C.2). In those two figures, random values[14] of w_i and p_i are generated from a Pareto distribution with different combinations of the parameter α[15]. For each of them, the responses of ρ_w and ρ_p to changes in ω are plotted on the vertical axis.

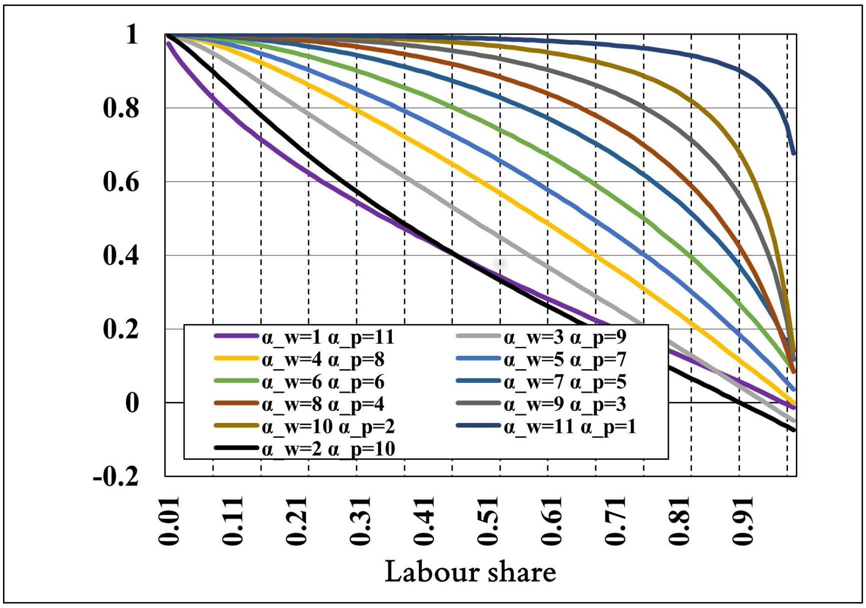

Figure 2.C.1: ρ_w

In particular, as ω increases, if at least one individual surpasses in the income ranking someone else with a lower individual share w_i of total wage mass, then:

$$\frac{\frac{\partial A}{\partial \omega}}{\frac{\partial B}{\partial \omega}} > \frac{A}{B} \Rightarrow \frac{\partial \rho_w}{\partial \omega} > 0 \tag{2.41}$$

If, instead, the increase in labor remuneration is not sufficient to make at least one individual better off than someone else with a lower individual share w_i of total wage mass, then:

$$\frac{\frac{\partial A}{\partial \omega}}{\frac{\partial B}{\partial \omega}} = \frac{A}{B} \Rightarrow \frac{\partial \rho_w}{\partial \omega} = 0 \tag{2.42}$$

[14]1000 values are generated, which corresponds to an economy populated by 1000 individuals.

[15]When income follows a Pareto distribution the Gini index has a closed-form solution. In this case: $G_w = \frac{1}{2\alpha_w - 1}$ and $G_p = \frac{1}{2\alpha_p - 1}$.

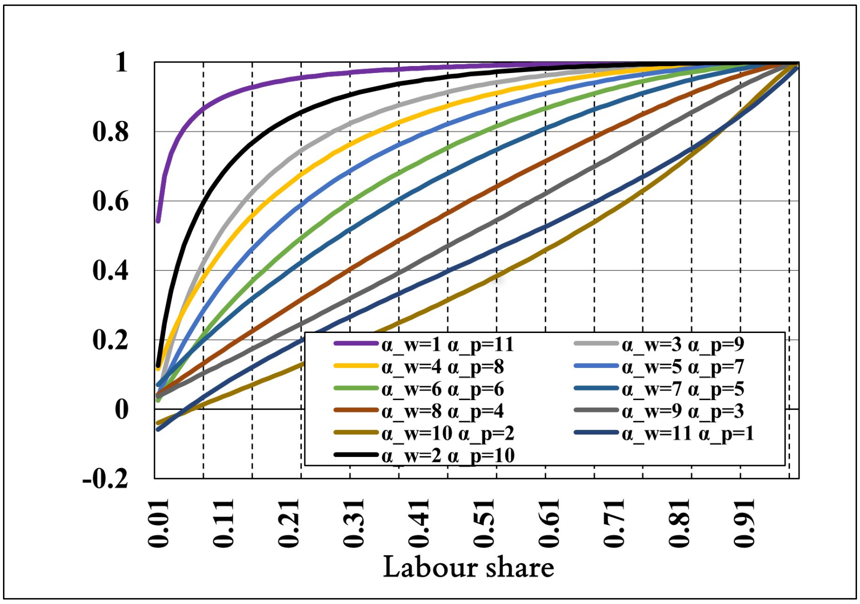

Figure 2.C.2: ρ_p

Analogous reasoning applies to ρ_p. By expressing ρ_p in the same form as equation (2.39), as ω increases, if at least one individual surpasses in the income ranking someone else with a higher individual share p_i of total profit mass, then:

$$\frac{\frac{\partial A}{\partial \omega}}{\frac{\partial B}{\partial \omega}} < \frac{A}{B} \Rightarrow \frac{\partial \rho_p}{\partial \omega} < 0 \tag{2.43}$$

While, if the increase in labor remuneration is not sufficient to make at least one individual better-off than someone else with a higher individual share p_i of total profit mass, then:

$$\frac{\frac{\partial A}{\partial \omega}}{\frac{\partial B}{\partial \omega}} = \frac{A}{B} \Rightarrow \frac{\partial \rho_p}{\partial \omega} = 0 \tag{2.44}$$

This behavior of parameters ρ_w and ρ_p can be better understood in the following example, where the change in income ranking is not continuous given the small number of individuals.

2.C.1 Example with a three persons economy

Suppose three individuals populate the economy. This makes it easier to understand what happens to ρ_w and ρ_p when ω varies. Each of the three earns the following shares w_i of the total wage mass ωY:

- $w_1 = 0.3$
- $w_2 = 0.7$
- $w_3 = 0$

And the following shares p_i of the total profit mass $(1-\omega)Y$:

- $p_1 = 0.1$

- $p_2 = 0.3$
- $p_3 = 0.6$

Thus, individuals sorted by w_i in ascending order are $i = (3, 1, 2)$, while individuals sorted by p_i in ascending order are $i = (1, 2, 3)$. In figure (2.C.3) the level of individual monetary incomes, ρ_w and ρ_p are plotted. As we have stated in equations 2.42 and (2.44), as ω increases, ρ_w and ρ_p remain constant unless there is a change in the income ranking. This happens at $\omega = 0.29$ where individual 2 surpasses individual 3 in the income ranking and at $\omega = 0.62$ where individual 1 surpasses individual 3. In those two points $\frac{\partial \rho_w}{\partial \omega} > 0$ and $\frac{\partial \rho_p}{\partial \omega} < 0$ as stated in equations (2.41) and (2.41).

In brief, as ω increases, ρ_w increases every time an individual a surpasses in the income ranking an individual b whose individual share w_i of total labor income is smaller than a, otherwise it stays constant. Likewise, ρ_p reduces every time an individual a surpasses in the income ranking an individual b whose individual share p_i of total capital income is higher than a. Otherwise, it stays constant.

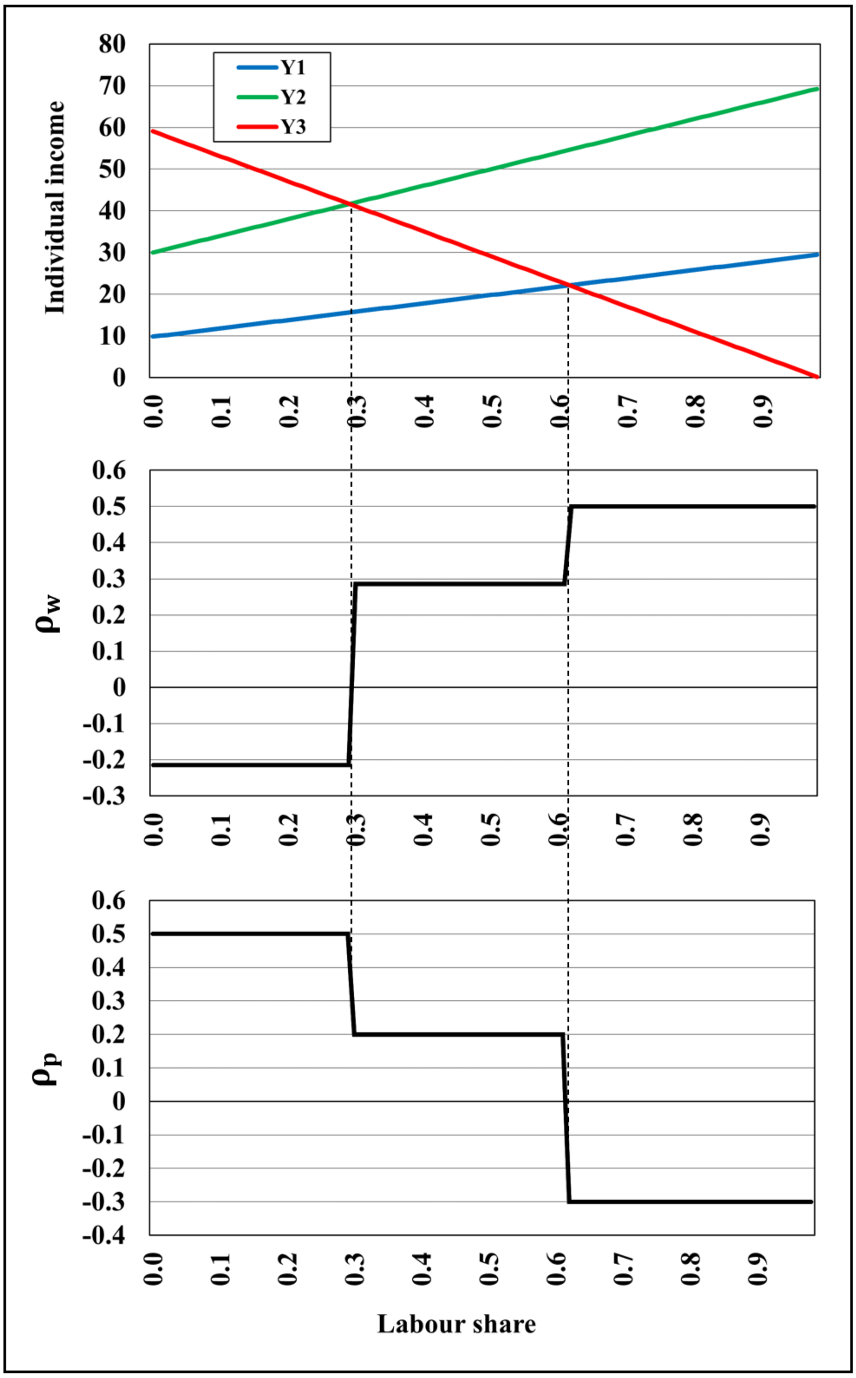

Figure 2.C.3: ρ_w and ρ_p in a three persons economy

2.D Demand regimes and the threshold value of the labor share

Substituting $\omega = \omega^* - \varepsilon$ in equation (2.13), where ω^* is defined as in equation (2.15), $\varepsilon > 0$, and $\frac{\partial \rho_p}{\partial \omega} \leq 0$ and $\frac{\partial \rho_w}{\partial \omega} \geq 0$, we obtain:

$$\frac{\partial G_y}{\partial \omega} = G_p \frac{\partial \rho_p}{\partial \omega} \varepsilon - G_w \frac{\partial \rho_w}{\partial \omega} \varepsilon \leq 0 \tag{2.45}$$

Which along with equations (2.36), (2.37) and (2.38) proves equation (2.16).

Likewise, substituting $\omega = \omega^* + \varepsilon$ in equation (2.13), we obtain:

$$\frac{\partial G_y}{\partial \omega} = G_w \frac{\partial \rho_w}{\partial \omega} \varepsilon - G_p \frac{\partial \rho_p}{\partial \omega} \varepsilon \geq 0 \tag{2.46}$$

Which along with equations (2.36), (2.37) and (2.38) proves equation (2.17).

3 Business cycle and factor income shares: a VAR sign restrictions approach

3.1 Introduction

The persistent cyclicality of factor shares of income is becoming increasingly recognized as a business cycle stylized fact (see, among others, Young, 2004 [131]; Rius- Rull and Llopis, 2010 [112]; Shaio and Silos, 2014 [119]; Boldrin, 2019 [27]; Barrales-Ruiz et al., 2022 [16]). This observed recurrent pattern takes the following form. The labor share falls during the early expansionary phase of the business cycle. However, the fall in labor share reaches its peak earlier than the output increase. Thus, in the late output expansionary phase, the labor share reverses its trend and starts rising along with output. Empirically, the diverging movement of the labor share and output during the early output expansion phase results in a *simultaneous* negative correlation. In contrast, the subsequent increase of the labor share in the late output expansion phase produces a *lagged* positive correlation. Figure (3.1.1) plots the leads and lags correlations between the quarterly US labor share and the real GDP from 1951 to 2019. The series are from the Bureau of Labor Statistics. After taking the natural logarithm, the data were processed with the Hodrick-Prescott filter to obtain the cyclical component. The negative contemporaneous correlation (-0.32) confirms that the labor share is slightly counter-cyclical. As expected, the maximum correlation (about 0.47) is reached after four lags and is higher than the contemporaneous one. This pattern indicates that the labor share lags output, i.e., an increase in GDP is correlated with a rise in the labor share some quarters later.

Several theories have been proposed to explain this phenomenon. According to Goodwin (1967)[64], a fall of the labor share increases output by stimulating private investment, generating the simultaneous negative correlation. Then, as production and employment grow, increasing pressure on wages pushes up the labor share, causing the lagged positive correlation. According to Ambler and Cardia (1998)[9] and Hornstein (1993)[68], it is the presence of the so-called *overhead costs* to produce the simultaneous negative correlation. By acting as fixed costs, overhead costs cause unit costs to fall as output increases, resulting in higher profits per unit of output and a fall in the labor share. Gomme and Greenwood (1995)[63] and Boldrin and Horvath (1995)[26] see the *distribution of risk* between workers and entrepreneurs during the business cycle as the cause of the simultaneous negative correlation. Since workers want to insure themselves against wage fluctuations, they enter into contracts with entrepreneurs that prevent wages from matching movements of labor productivity. Consequently, the increase in labor productivity during an upturn results in a simultaneous GDP rise and labor share fall. Finally, there is the theory of *biased*

Figure 3.1.1: Correlation of Labor‘s share (t+i) and Real GDP (t)

technical change (Young, 2004[131]; Boldrin et al., 2019[27]). Rising labor costs and labor share induce firms to direct R&D toward technologies that allow substituting labor for capital. The resulting increase in labor productivity leads to a parallel rise in output and fall in labor share, generating the simultaneous negative correlation.

The soundness of these theories is difficult to assess because of the shortcomings characterizing the VAR literature on this topic. Authors mostly rely on a bivariate GDP-labor share model identified with a recursive Cholesky's scheme. The variables' ordering is justified based on the single theory they want to test. However, this method a priori discards the role that the other theories might play, forcing the results in a specific direction. Another critical issue is that the usually employed bivariate structure does not allow the different channels theorized in the literature to be properly disentangled and tested. This paper set up a Bayesian VAR identified with sign restrictions to overcome these criticalities. The variables entering the model are real GDP, hours worked, nominal hourly wage, Consumer Price Index and the number of workers who left their job voluntarily. To the best of my knowledge, this is the first paper to use the sign restrictions approach on this topic and to test the different theories in a single framework.

The results suggest that pro-cyclical labor productivity mainly drives the counter-cyclicality of the labor share. This phenomenon is consistent with the theories of *overhead costs* and *risk distribution*. In contrast, the evidence supporting the expansive effect of a capital share rise upheld by Goodwin is weak. Nevertheless, the results support the other pillar of Goodwin's model - *the Philips curve mechanism* - which explains the observed lagging behavior of the labor share to output. Finally, the results partially support the *biased technical change theory*.

The remainder of the paper is organized as follows. Section 3.2 reviews the theoretical channels the literature proposes to explain the cyclicality of factor shares of income. Section 3.3 summarizes and discusses the empirical literature, highlighting its main shortcomings. Section 3.4 builds a Bayesian VAR model identified with sign restrictions to test the theories reviewed in Section 3.2

and overcome the critical issues outlined in Section 3.3. Section 3.5 concludes.

3.2 Theoretical literature

The first theory on the cyclical interaction between functional income distribution and output can be attributed to Goodwin (1967) [64]. The model traces the predator-prey models used in biology (Lotka, 1925 [85]; Volterra, 1936 [129]), where labor and capital conflict with each other but exist symbiotically. Workers consume all of their income, while entrepreneurs save it all. Say's law ensures that all entrepreneurs' savings are invested, causing an increase in the profit share to have an expansionary effect on output and producing the looked-for simultaneous negative correlation between labor share and GDP. A Phillips curve ensures that following the tightening of the labor market caused by the output expansion, wages begin to rise with some lags. The lagged wage increase reduces the profit share and output until the subsequent wage fall restarts the cycle. Phases of contraction follow production and profit share expansion phases in a clockwise cycle in the profit share-activity plan. Note that real wage growth rate changes drive all labor share movements, as labor productivity growth is constant.

The second strain of theoretical literature focuses on factor substitution generated by 'biased technical change' as the driver of functional distribution fluctuations across the business cycle. Biased technical change (Blanchard et al., 1997 [23]; Caballero and Hammour, 1998 [30] and Acemoglu, 2002 [1]) refers to any introduction of new technologies, change in production methods, or change in the organization of work that increase labor productivity allowing to substitute labor with capital in response to an increase in labor costs. The rise of labor productivity and GDP reduces the original increase in the labor share, generating the looked-for negative correlation between labor share and GDP. Young (2004) [131] was the first to propose this mechanism as a possible source of the labor share counter-cyclicality. This argument is used to justify stochastic factors' elasticities in the Cobb-Douglas production function. Since in a Cobb-Douglas production function, the output elasticity of a factor represents its income share, changes in the latter automatically cause variations in factor productivity, as predicted by the theory of biased technical change. The cyclicality of factor shares is not self-sustaining as in Goodwin (1967) but stems from exogenous stochastic shocks as in all RBC models. A more structured model is that of Boldrin et al. (2019) [27], which splits the business cycle into two phases. During the *growth phase*, output growth is driven by the adoption of labor-saving technologies, i.e., by replacing a less advanced type of capital with a new vintage incorporating more advanced technology. In this phase, the profit share increases because labor productivity rises more than real wages due to the capital replacement process. During the *build-up phase* - i.e., when all the capital of the old vintage has been entirely replaced by the new one - firms keep widening the new capital, the employment increases, and so does the real wage. In this phase, lower output growth, a declining capital price, and a rising wage reduce the profit share. When, during the build-up phase, the price of capital has declined enough, it becomes profitable to start replacing the old capital with a more advanced vintage, and a new growth phase begins. In this paper, the fluctuations of the labor share during the business cycle are not occasional events arising as a response to exogenous shocks but are *"systematic and recurrent features of the economy"*. In other words, there is no balanced growth path; instead, the economy endogenously alternates between upturns accompanied by a rising profit share and downturns accompanied by a falling profit share. Furthermore, cyclical variations in factor prices are the engine of technological progress and long-run economic growth. This model and Goodwin (1967) [64] are the only ones generating a self-sustaining cycle in the factor shares of income. All other models described in the rest of this section only reproduce the observed correlations between variables following exogenous stochastic shocks. They do not generate endogenous cycles in the labor share-activity plane.

The third strain of literature focuses on the role played by increasing return to scale. The pro-cyclicality of profit share is caused by the presence of 'overhead costs', which generate increasing returns to scale. Overhead costs are all those expenses associated with running a business that cannot be directly linked to producing a product or service (e.g., rent, facilities, management pay, insurance, accounting, or legal expenses). They act as fixed costs, generating a fall in unit labor costs and labor share as output increases. Ambler and Cardia (1998) [9] build an RBC model in which the production function differs from the conventional Cobb-Douglas in two aspects. Firstly, it shows decreasing average costs due to the overhead costs. Secondly, a return to scale parameter determines if the decreasing average costs are coupled with constant or decreasing marginal costs, amplifying the factor shares oscillations. On the other hand, the effect of overhead costs is counterbalanced by the possibility of firms entering (exiting) the market when the economy is in an upturn (downturn) phase. In the limiting case where the entry/exit is instantaneous, the distributive cycle disappears since the increase (decrease) in output is entirely borne by new firms' entry (exit) into the market. In this case, output per firm is constant, and so are the aggregate average costs. This is what happens in Devereux et al. (1996) [44], which therefore represents a limiting case of Ambler and Cardia (1998) [9] when the entry/exit of new firms into the market is instantaneous. On the other extreme, in Hornstein (1993) [68], as there is no possibility of entry/exit from the market, the fluctuation of factor shares is at its maximum.

The work by Hansen and Prescott (2005) [66] shares with this strand the hypothesis of non-constant return to scale, although the returns are decreasing and generated by a different mechanism. They use a decreasing return to scale assumption at the plant level to guarantee that operating many small identical plants is optimal rather than one large one. In this economy, not all plants are permanently used in the production process, but there can be some idle capacity. When capacity constraints do not bind, plant capital is not a scarce factor and, consequently, does not earn income. Hence, in this case, the labor share is larger. When during periods of expansion, all capacity is used, the return on capital increases, generating a pro-cyclical profit share.

The fourth strand of literature focuses on the distribution of the risk between workers and entrepreneurs over the business cycle and, more generally, on the role played by a non-competitive wage setting. The main idea is that workers enter into contracts with capitalists that prevent wages from falling during a recession (as if they were determined only by marginal labor productivity) and vice versa during an expansion. In other words, workers' will to insure themselves against business cycle fluctuations makes real wages acyclical, which, combined with pro-cyclical labor productivity, generates the looked-for counter-cyclicality of the labor share. Gomme and Greenwood (1995) [63] assume that *"built into labour income is an insurance component designed to provide workers with some degree of protection against business cycle fluctuations. This insurance component inserts a wedge between marginal product of labour and measured wages"*. Boldrin and Horvath (1995) take a similar approach [26] which, differently from Gomme and Greenwood (1995), assumes that the desire of workers to hedge against the risk of fluctuations in the economic cycle stems from a double assumption. Firstly, since workers are not endowed with wealth, they cannot access (imperfect) financial markets like their employers to achieve intertemporal consumption smoothing. Secondly, employers are less risk-averse than workers and thus more willing to take on the business cycle risks by agreeing on partially fixed wages for a certain period before output is realized.

Closely to this strand of literature, Rios-rull and Choi (2009) [37] depart from the baseline RBC model by adding frictions in the labor market and a non-competitive wage setting. These two changes generate a countercyclical labor share. This occurs because as output increases, on the one hand, search and matching frictions cause employment to have a lagging behavior. On the other hand, Nash bargaining creates a wedge that prevents the real wage from adjusting immediately to productivity changes. However, the model fails in replicating the looked-for hump-shaped response of the labor share to an output shock found in Rios-Rull and Llopis (2010) [112]. Indeed - as we will see later - in a distribution-activity VAR identified with Cholesky where the activity variable is ordered first, the Impulse Response Function of the labor share to an output shock is negative on impact but overshoots after five quarters. Nash Bargaining is sufficient to replicate the counter-cyclicality but not the overshoot. Shao and Silos (2014) [119] introduce barriers to market entry to capture this effect. A productivity shock reduces the effective capital needed for a start-up to enter the market, reducing the demand for capital per entrant. The countercyclical interest rate dampens the initial fall in labor share, reducing the contemporaneous negative correlation with output and bringing it closer to that observed in the data. In addition, the costly entry delays the rise in wages and employment by producing the looked-for hump-shaped IRF of the labor share to a productivity shock. With the same aim of reproducing the observed overshooting, Colciago and Rossi (2015) [40] introduce a countercyclical mark up generated by the entry of new firms into the market after an expansive shock. The stronger competition resulting from a larger number of firms pushes down the mark up, resulting in an overshoot and a labor share higher than the initial one.

Finally, the fifth strain of literature relies on a standard Cobb-Douglas production function making the share parameter stochastic. Since in a Cobb-Douglas production function the factors' output elasticities represent factor shares, shocks to the latter result in changes in output. The aforementioned Young (2004) [131] relies on an RBC model with stochastic factors' elasticities in the Cobb-Douglas production function. Casteneda et al. (1998) [33] also propose a model along these lines, although their aim is not to analyze the relationship between functional income distribution and real activity. Rios-Rull and Llopis (2009) [112] firstly estimate a bivariate activity-labor share VAR identified with Cholesky with the activity variable ordered first. Then, the estimated relationship is plugged into the Cobb-Douglas production function of an RBC model. As the TFP increases, the labor share falls on impact because of their estimated negative relationship.

3.3 Empirical literature

The VAR literature on this topic can be divided into two strands. Both are based on bivariate[1] distribution-activity models identified via Cholesky. The first strand (Carvalho and Rezai, 2016 [32]; Basu and Gautham, 2020 [18]; Barrales-Ruiz et al., 2022 [16]) orders the labor share before the real activity variable, thus assuming that distribution can have a contemporaneous impact on

[1] Sometimes a third variable is added, but the results remain essentially the same.

output but not vice versa. This assumption is justified based on Goodwin's (1967) [64] model. Accordingly, labor productivity growth is constant, and real wage growth rate changes entirely drive movements in the labor share. Given the labor productivity stickiness, it is reasonable to expect that the labor share does not respond immediately to changes in output. The results stemming from this identification scheme are that following a positive shock to the labor share, the GDP fall is instantaneous and long-lasting. After a positive shock to GDP, the profit share decreases gradually from the second quarter onwards. These results, firmly in line with the predictions of Goodwin's model, are therefore brought to support this theory. Moreover, the support for this strand is not limited to Goodwin's model but more generally by the classical distribution theory, employed also by the Kaleckian model.

Conversely, the second strand of literature orders the activity variable before the labor share, implicitly assuming that the former can impact the latter simultaneously but not vice versa. Following the empirical literature of Goodwinian inspiration, we will refer to the ordering of the variables of the first strand as 'standard ordering' and to that suggested by the second strand as 'reverse ordering'. Rius-Rull and Llopis (2010) [112], taking an RBC as their theoretical reference model, order productivity (and alternatively GNP) before labor share. Colciago and Rossi (2015) [40] and Shao and Silos (2014) [119] replicate this result. These papers find that an increase in real activity triggers an instantaneous fall in the labor share, which after about five quarters overshoots and remains at a higher level than it was at the beginning. The output response to a positive labor share shock is non-significant or positive. Cauvel (2019) [35] attempts to demonstrate the inconsistency of the standard ordering, which would ignore the strong procyclicality of labor productivity due to overhead costs. Firstly, he demonstrates that the results are profoundly different by reversing the variables ordering. Then, he shows that once the procyclicality of labor share is taken into account by cleaning up the labor share of its cyclical component, even applying the standard ordering, the expansionary effect of an increase of the capital share disappears.

Finally, one of the few approaches that use a different identification scheme is worth mentioning. Mendieta-Munoz et al. (2022) [88] employ a four-variable VAR that, although based on zero restrictions, allows productivity to depend on output (and indirectly on labor share) and the latter to depend on productivity. The paper finds results in line with those of the 'standard ordering' strand, at least for 1948-1984.

3.3.1 A critique

The results obtained with the standard ordering have two shortcomings. First, imposing that economic activity cannot have any contemporaneous impact on the distribution a priori rules out the hypothesis that procyclical movements in labor productivity drive cyclical fluctuations in the labor share, as suggested by Cauvel (2019) [35] and Lavoie (2017) [79]. Therefore, the associated results could be spurious associations from forcing the model in that direction. A similar criticism can be made against reverse ordering in limiting the theories of Goodwin and biased technical change. Indeed, in these theories, the direction of causality runs from distribution to real activity, which is limited in the reverse ordering by a zero restriction on the contemporaneous reaction of output to changes in functional distribution. However, there is a fundamental difference concerning the implicit assumptions in the two identification schemes. A reaction of labor productivity following an output shock could be automatic and instantaneous, as in the case of overhead costs or risk distribution theories. On the other hand, any direction of causality from distribution to economic activity requires a reaction on the part of economic agents, which can take more time to show significant effects. This is the case of a rise of firms' investment following an increase in the profit share predicted by the Goodwin model or the biased technical change triggered by the rise in labor cost. The slower response of agents makes the assumption embodied in the reverse ordering - no response of economic activity to changes in labor share for a quarter - less restrictive. The higher the frequency of the time series, the less restrictive is the reverse ordering.

We now come to the second criticism that can be made of the standard ordering. According to the models that apply this identification scheme, the expansionary effect caused by an increase in the profit share explains the negative correlation between labor share and economic activity. However, a shock to the labor share as such does not exist. Different shocks that give rise to an increase in the labor share can have an opposite effect on GDP. For example, the profit share could increase both following a decrease in wages and an increase in the mark up. However, in the first case, there would be a fall in prices and the real exchange rate and vice versa in the second, with potentially opposite effects on GDP.

This paper aims to overcome the critical issues associated with both Cholesky's orderings through a more sound identification scheme based on the sign restrictions approach. Through this new framework, this paper aims to determine the main theoretical mechanisms that drive the distributional cycle by examining whether there is empirical evidence supporting the theories outlined in Section 3.2.

3.4 Empirical strategy

3.4.1 Data

The data used in the following models refer to the U.S. economy from 2001q1 to 2019q4 and come from the Bureau of Labor Statistics. The reason for choosing this short period is the unavailability of earlier data regarding the number of workers who left their job voluntarily ($QUITS$) collected by the *Job Openings and Labor Turnover Survey* of the BLS. The particular sample used could affect the results. Section 3.4.2 compares the estimates with this sample for the bivariate model with the literature above as a preliminary robustness check. The results align with those in the literature for more extended periods. Nevertheless, as suggested by Nikiforos (2017) [95] and Carrillo-Maldonado and Nikiforos (2023) [31], the cyclical behavior of labor share may have changed over the decades. Future extensions of this model should consider a longer sample and time-varying features to capture such changes.

Actually, the variable *quits* is not fundamental for our analysis. The only reason it has been included in the model is that it is essential for correctly identifying the model, as we will see later. In addition to *quits*, the other variables used in this paper are the total number of hours worked in the economy ($HOURS$), real GDP (GDP)[2], nominal hourly wages ($WAGES$), the Consumer Price Index (CPI) and the labor share ($LABOR\ SHARE$). The natural logarithm of these variables is

[2]The real GDP series is obtained by dividing the corresponding nominal series by the Consumer Price Index provided by the BLS.

plotted in Appendix 3.A. Note that by combining the series of nominal wages, CPI, hours worked, and real GDP, it is possible to reconstruct the labor share series provided by the Bureau of Labor Statistics. This is why - unlike the bivariate models of section 3.4.2 based on labor share and GDP - in section 3.4.3, the labor share does not enter directly into the model. All variables are in natural logarithms and enter the model in levels; the Bayesian specification of the model is, in fact, compatible with non-stationary variables (Sims, 1990 [120]).

3.4.2 The bivariate model

The purpose of this section is twofold. First, to show how the widely used Cholesky ordering, besides not being theoretically sound - as discussed in Section 3.3.1 - is not robust to variable inversion. Second, the results of the bivariate model are intended to show that even with this short sample period, the findings are in line with those found in the literature using longer samples. This allows us to compare the results from the bivariate model identified via Cholesky with a sign-restricted model in the next section. The coincidence of results does not rule out the possibility that the sample may affect the model identified with sign restrictions. However, on the contrary, the non-coincidence would indicate the peculiarity of this dataset. In this case, it would be better to avoid comparing the conclusion of the sign-restricted model with the rest of the literature.

The reduced form of the estimated model reads:

$$Y_t = C + \sum_{i=1}^{n} A_i Y_{t-i} + u_t \tag{3.1}$$

Where Y_t is the vector of endogenous variables: $Y_t = [GDP_t; \text{labor share }_t]$, C is a vector of reduced-form constants, A_i is a matrix of reduced form parameters and u_t is a vector of reduced-form errors. The model is estimated with a Bayesian approach based on an Independent Normal-Wishart prior[3]. Hyperparameters are selected in such a way as to maximize the marginal likelihood through a grid search procedure. In section 3.4.3 a *dummy initial observation strategy* restricts the prior toward unit roots or cointegration to prevent draws obtained from the posterior from being characterized by explosive unit roots (Dieppe et al., 2018 [45]).

As is well known, to perform structural analysis in a VAR framework, it is necessary to map the reduced-form errors to the structural ones by imposing restrictions on the variance-covariance matrix through the B matrix.

$$u_t = B\epsilon_t \tag{3.2}$$

The simplest method is to obtain B from a Cholesky decomposition of the variance-covariance matrix. This way, the variable ordered first in the vector Y will be exogenous on impact to the second, but not vice versa.

We first run the model with the labor share ordered first and GDP as the second variable (*standard ordering*). Figure (3.4.1) shows the resulting Impulse Response Functions.

[3]Since there is no closed-form solution for the posterior distribution, it is necessary to use the Gibbs sampler. This MCMC algorithm approximates the true distribution. The algorithm requires a certain number of iterations to approximate the posterior with sufficient accuracy; 100,000 draws are then performed, of which the first 80,000 are discarded. Hence, parameter estimates are based only on the last 20,000 draws.

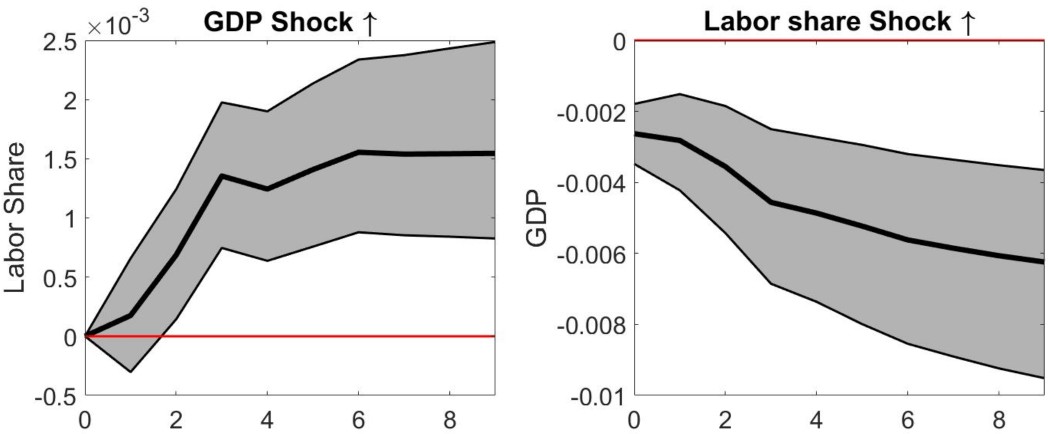

Figure 3.4.1: IRF with the standard ordering

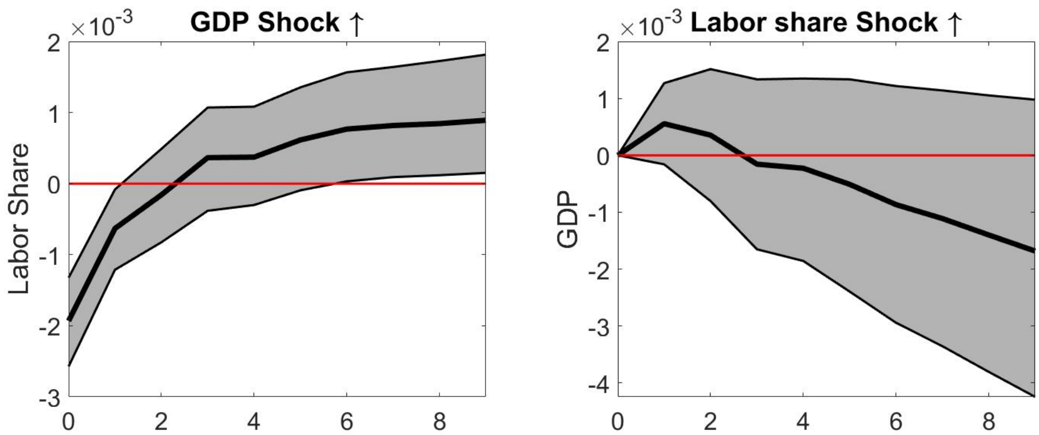

Figure 3.4.2: IRF with the reverse ordering

As can be seen, GDP reacts negatively to an increase in the labor share, while the latter responds positively from the third quarter onward to an increase in GDP. These results perfectly align with the literature that adopts this Cholesky ordering (Carvalho and Rezai, 2016 [32]; Basu and Gautham, 2020 [18]; Barrales-Ruiz et al., 2022 [16]).

Figure (3.4.2) shows the results from the same model with the variables ordering reversed, i.e., with the *GDP* exogenous on impact to the *labor share*, but not vice versa (*reverse ordering*).

The response of the labor share to an increase in GDP is very different from the previous one. It is negative on impact and overshoots after seven quarters, becoming positive. These results are in line with those found by Rios-Rull and Llopis (2009) [112] and Cauvel (2019) [35] in bivariate models identified with the reverse ordering. Notice that the response of GDP to an increase in the labor share is non-significant, which is firmly at odds with the results obtained with the previous ordering.

Given the theoretical criticalities of both Cholesky orderings and the non-robustness of the results to their inversion, we rely on sign restrictions as an alternative identification scheme. Through this method, we can test the predictions of the theories exposed in Section 3.2 and check if the results of one of the two (if at all) strands of empirical literature are supported.

3.4.3 A sign restrictions approach

In this section, to overcome the theoretical and empirical criticalities exposed above, we estimate a five variables model identified with the sign restrictions approach. This approach fixes the fundamental structural identification problem - each VAR in reduced form corresponds to infinite VARs in structural form - retaining all possible structural models associated with a single reduced form that satisfies the imposed sign restrictions. The consequence is that there is no longer a mapping between shocks and variables, as in Cholesky. The median is generally taken of all the IRFs generated in this way, and credibility intervals are constructed based on their distribution.

The benefit of this new framework is twofold. On the one hand, it allows us to avoid imposing hardly justifiable zero restrictions and, on the other, to decompose what in the bivariate model were the shocks to GDP and labor share into the shocks that theoretically drive these two variables. The applied identification scheme is reported in Table (3.4.1) and Table (3.4.2).

	Demand ↑	Workers Bargaining Power ↑	Firm Bargaining Power ↓	Automation ↑
Hours	+	/	/	-
Wages	/	/	/	/
CPI	+	/	-	-
GDP	+	/	/	+
Quits	+	/	/	-

Table 3.4.1: Sign Restrictions on periods 1 and 2

	Demand ↑	Workers Bargaining Power ↑	Firm Bargaining Power ↓	Automation ↑
Hours	+	/	/	-
Wages	+	+*	+	-
CPI	+	+*	-	-
GDP	+	/	/	+
Quits	+	-	/	-

* it is further assumed that nominal wages increase more than prices

Table 3.4.2: Sign Restrictions on period 3

The five variables that enter the model are: hours worked, nominal hourly wage, consumer price index (CPI), real GDP and the number of voluntary quits from the labor market. Note that it is possible to reconstruct the same labor share of the bivariate model from these variables. The structural shocks are: aggregate demand, automation, labor bargaining power, and firm bargaining power. Given the small sample, the model is estimated with two lags to preserve degrees of freedom[4]

All the restrictions are applied on the first three quarters except for the nominal hourly wage, which is restricted just on the third quarter. The rationale of this choice is not to force wages to

[4]Nevertheless, Section 3.4.5 estimates different lag specifications as a robustness check.

istantly vary if they were sticky. As we will see, only for the shock to workers' bargaining power, restrictions on prices and quits are imposed just on the third quarter after the shock. Finally, it is worth mentioning that I took inspiration from Bergholt et al. (2019) [20] and Foroni et al. (2018) [56] for the specific restrictions employed. In particular, I draw from the latter for the demand and automation shock and from both for disentangling workers' and firms' bargaining power shocks.

In detail, a positive *aggregate demand* shock is the shock that generates an increase in hours worked, GDP, price level, and the number of workers voluntarily quitting their jobs for the first three quarters. The nominal wage is restricted to rise only in the third quarter, allowing for wage stickiness. The rationale behind the job quit restriction comes from the observation that this variable generally increases in periods of expansion in line with the number of new people hired (Appendix 3.B). This phenomenon is probably due to the labor market's greater job opportunities and dynamism when aggregate demand increases. The probability of quickly getting a new job is higher in periods of expansion, making it less risky to quit your current job voluntarily. This variable is necessary to disentangle the demand shock from the workers' bargaining power shock. If we did not assume that an increase in demand has an opposite impact on quits than an increase in workers' bargaining power, the two shocks would be identical (Table 3.4.2). Both shocks would increase wages and prices, and they would not be identified.

Since we restricted all variables in this shock, we are not interested in the response of the variables entering the model but rather in the response of labor share, labor productivity and real wages. These variables can easily be derived by combining the responses of the nominal wage, prices, hours worked, and GDP. The Impulse Response Functions of the labor share, labor productivity and real wages are computed as follows:

$$ln(LS_t) = ln(Hours_t) + ln(NominalWage_t) - ln(GDP_t) - ln(CPI_t) \tag{3.3}$$

$$ln(PROD_t) = ln(GDP_t) - ln(Hours_t) \tag{3.4}$$

$$ln(RealWage_t) = ln(NominalWage_t) - ln(CPI_t) \tag{3.5}$$

For each of the thousands of retained draws, the IRFs of labor share, labor productivity, and real wage are constructed from the IRFs of the model variables as indicated by the equations above. From the distribution of IRFs derived in this manner, we take the median and the 16th and 84th percentiles to construct the credibility intervals. This is the method employed in Figures (3.4.4) and (3.4.5).

The response of these three variables to the demand shock allows us to evaluate the predictions of the theories discussed in Section 3.2. Any fall in the labor share on impact caused by increased labor productivity would support the *overhead costs* theory. It would also be compatible with the *risk distribution* theory if coupled with a real wage that does not immediately respond to the shock. On the contrary, a labor share that does not respond significantly to the shock, coupled with a lagged real wage and labor share increase, would confirm the predictions of the *Goodwin cycle.* This pattern would also support the soundness of the *standard ordering* identification scheme.

A positive shock to the *bargaining power of workers* is assumed to increase the real hourly wage and the price level (because firms face higher production costs) after two quarters and a fall in the number of workers quitting their jobs. This last assumption is fundamental to disentangle this shock from the demand and automation shocks. It is motivated by the fact that fewer workers may decide to leave their job as the working conditions improve. Alternatively, vice versa, more workers choose to leave their jobs when working conditions deteriorate. Furthermore, only the posterior draws producing a rise in nominal wages larger than prices are retained to ensure that this shock increases real wages. The variables *hour* and *GDP* are left unrestricted. A gradual increase in labor productivity that generates a parallel rise in output such that an initial increase in labor share dies out would support the *biased technical change* theory. A GDP fall would support both *Goodwin's model* and the soundness of the *standard ordering*.

A positive shock to *firms' bargaining power* is identified as an increase in the mark up. Hence, it is specified imposing the price level to rise for the first three quarters and the nominal wage to fall only in the third quarter. The other variables are left unrestricted. If the bivariate model - which does not distinguish between sources of variation in labor share - is robust, we would expect the GDP to respond in the same direction after both an increase in workers' bargaining power and a fall in firms' bargaining power. Conversely, an output response of the opposite sign would indicate that the results of a shock to the labor share are misleading.

Finally, an *automation shock* is identified imposing an increase in GDP and a fall in hours worked, nominal wages, prices and quits. The latter is motivated in a similar way to the demand shock. The labor demand lowers following a positive automation shock, resulting in fewer workers leaving their jobs because of concerns about finding another position.

Figure (3.4.3) shows the theoretical differences compared with the bivariate model. In the latter, there are only two types of shocks, one distributive (labor share) and one to GDP (last line of Figure 3.4.3). In the sign restrictions model, the labor share shock is decomposed into two sub-shocks (bargaining power of firms and workers), allowing for a possible different response of the GDP (second line, Figure 3.4.3). What was the GDP shock in the bivariate model has also been partitioned into two sub-shocks: an aggregate demand shock and an automation shock. Finally, the first row of Figure 3.4.3 divides these shocks into demand shocks (aggregate demand shock) and supply shocks (automation, firms, and labor bargaining power shocks).

<table>
<tr><th>Demand Shocks</th><th colspan="3">Supply shocks</th></tr>
<tr><td>Demand</td><td>Automation</td><td>Workers bargaining power</td><td>Firms bargaining power</td></tr>
<tr><td colspan="2">GDP</td><td colspan="2">Distribution</td></tr>
</table>

Figure 3.4.3: Structural shocks

3.4.4 Results

Figure (3.4.4) shows model variables' structural Impulse Response Functions. These are constructed taking the median, the 16th, and 84th percentile of the thousands of retained draws. Figure (3.4.5) combines each of these retained draws as stated in Eq. (3.3), (3.4) and (3.5) taking again the median, and the 16th and 84th percentile as credibility intervals.

After a positive *demand shock*, the response of the labor share (Figure 3.4.5) is negative on impact to become non-significant from the third quarter onwards, eventually overshooting the initial level, although not significantly. At the same time, the impact response of labor productivity is positive, to become non-significant from the second quarter. In contrast, the response of real wages is non-significant on impact and then becomes increasingly positive (and statistically significant) from the fifth quarter onward.

We can conclude that fluctuations in demand produce a countercyclical labor share driven by procyclical movements in labor productivity. This result supports the theory of *overhead costs*. It also aligns with the *risk distribution* theory. Real wages do not react immediately to changes in labor productivity but begin to increase significantly only after five quarters. This lagged increase in real wages contributes to the overshooting of the labor share even though it is not statistically significant. This behavior of real wages is also in line with the Phillips Curve mechanism in *Goodwin*'s model. Overall, this shock suggests that cyclical fluctuations in the labor share are driven by procyclical labor productivity - as theorized by *overhead cost* and *risk distribution* theories - coupled with a real wage that lags outputs - as in the *Goodwin cycle*. While the former effect generates the observed countercyclicality, the induced lagged increase in real wages causes the labor share to return to its initial level.

We can now compare these results with the existing empirical literature. Firstly, the labor share instantaneous reaction to the demand shock is close to that of the labor share to a GDP shock in the bivariate model identified with the *reverse ordering*. In both cases, there is an initial decline in the labor share. However, whereas in the bivariate model the initial decline is followed by a clear-cut overshooting, the overshooting part is absent in our model. Secondly, the instantaneous drop in labor share observed in our model is completely missing in the *standard ordering* results, in which the change in labor share is never negative.

A positive *labor bargaining power* shock raises hours worked given the same nominal wage and output (Figure 3.4.4). This results in a gradual but steady increase in labor productivity, such that it more than offsets the rise in real wages. Consequently, the labor share declines rather than increase as expected (Figure 3.4.5).

This outcome is partly consistent with the *biased technical change* theory. Indeed, the increase in productivity can be interpreted as the result of firms' efforts to replace the labor factor, which has become more expensive. A missing piece is an initial increase in the labor share associated with the wage increase. In addition, GDP increases with a much longer lag than expected (roughly 30 quarters). A possible interpretation is that the initial increase in productivity comes at the expense of hours worked, which fall in the attempt to replace the labor factor. Gradually the hours worked return to the initial level and, after about 30 quarters, the higher productivity is passed on from lower hours to a higher GDP.

The lack of an initial increase in the labor share makes it difficult to judge the supposed

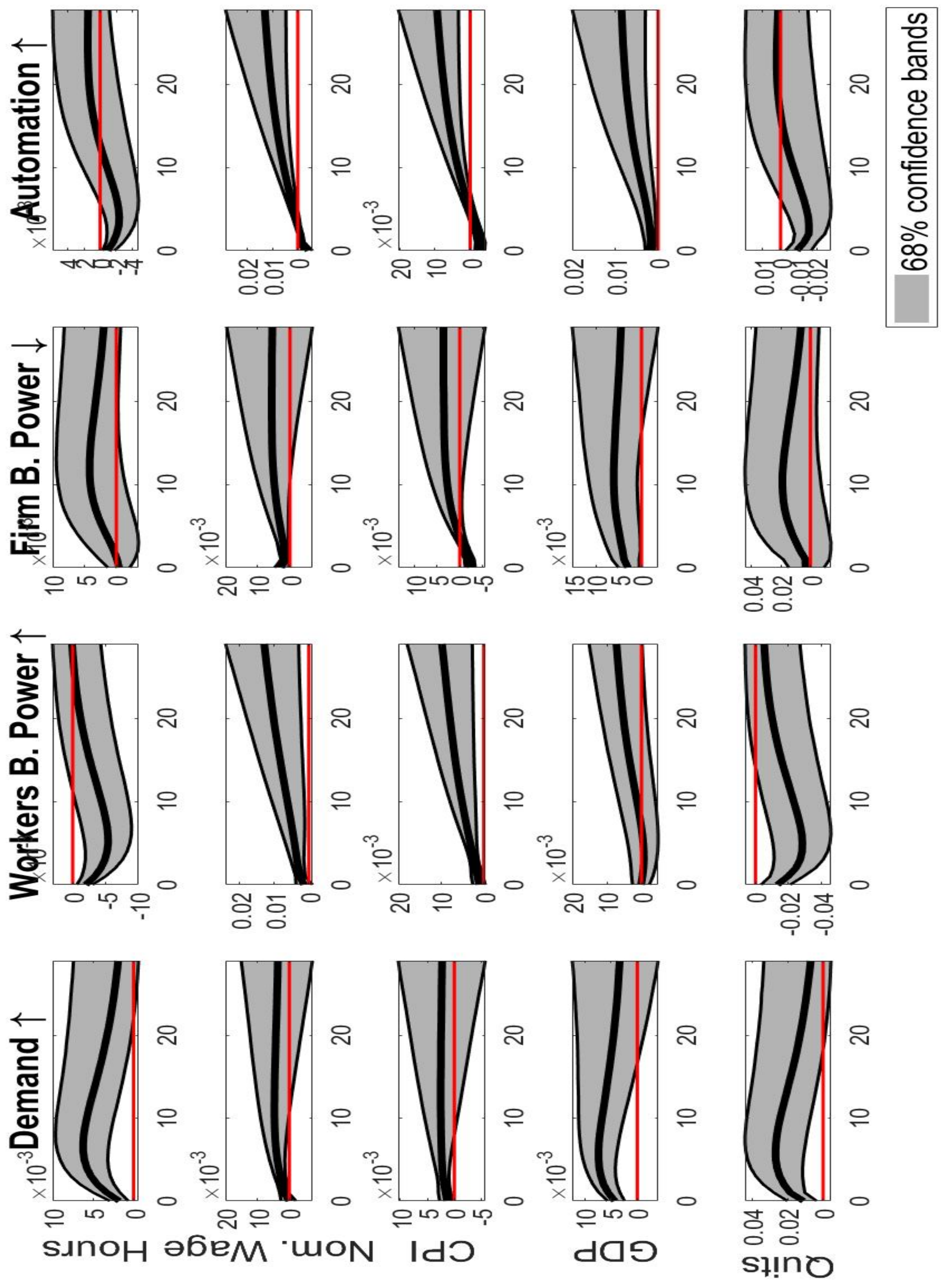

Figure 3.4.4: IRFs to structural changes

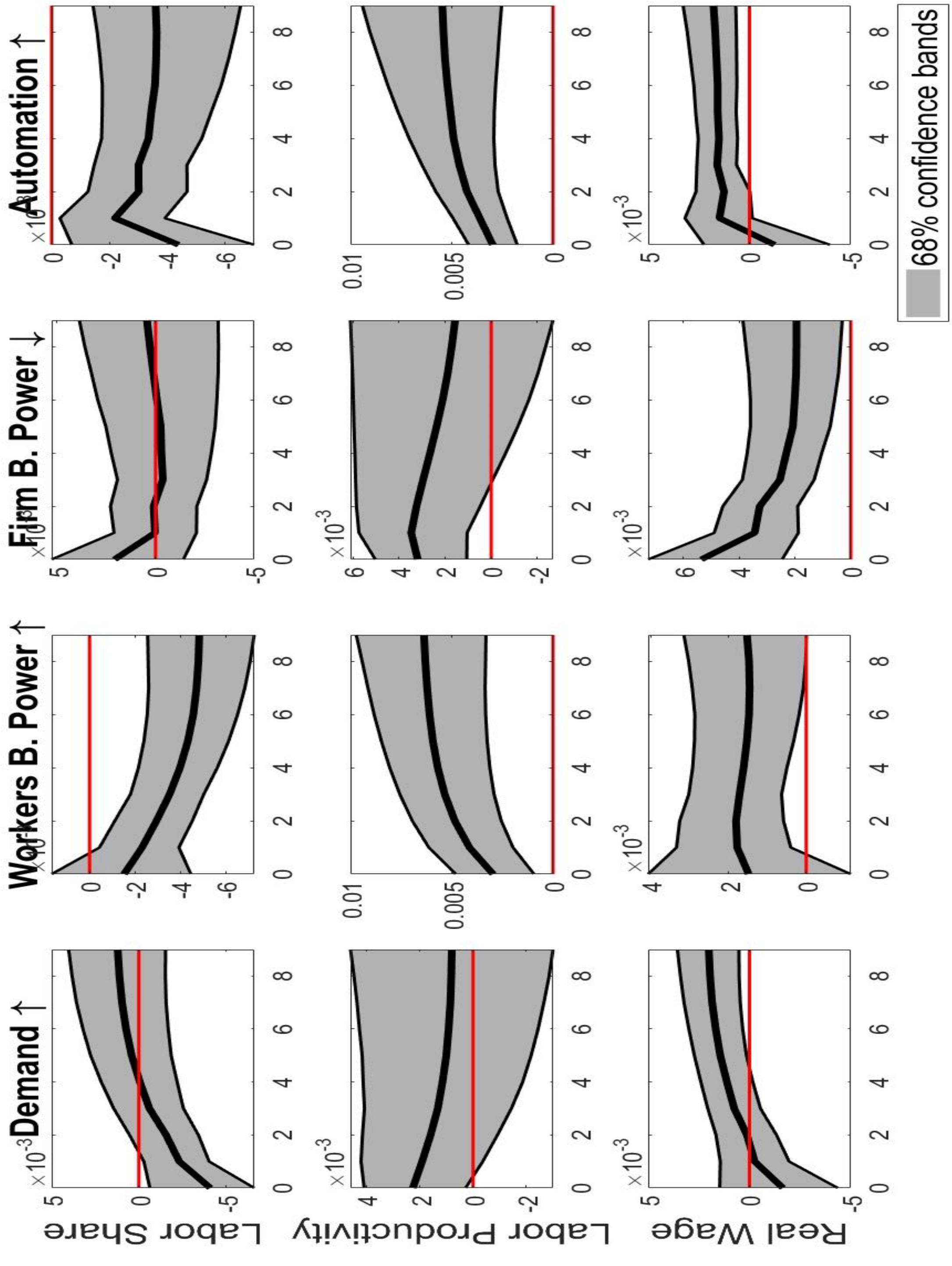

Figure 3.4.5: Implied IRFs to structural changes

contractionary effect of a labor share increase predicted by *Goodwin*'s model. Nevertheless, this shock produces a positive association between profit share and output, as in Goodwin (1967)[64]. However, the increase in wages and workers' bargaining power triggers an increase in profit share and output paradoxically. Therefore, the mechanism must be different from the one intended in Goodwin's model.

A reduction in *Firms bargaining power* increases GDP (Figure 3.4.4), labor productivity, and real wages (Figure 3.4.5). This aligns with standard economic theory following a reduction of the degree of monopoly, indicating that the shock is well captured. However, although the median labor share reaction is positive on impact as expected, it is not significant. This happens because the simultaneous increase in labor productivity offsets a large part of the increase in the real wage.

Overall, we can observe that the two distributional shocks (workers' and firms' bargaining power) do not generate reactions in labor share and GDP comparable to those generated with the standard ordering identification. This weakens the clear-cut expansionary effect of a labor share fall found by the standard ordering literature.

Finally, the *Automation shock* produces - inevitably because of the imposed identification - a fall in the labor share and an increase in labor productivity on impact (Figure 3.4.5). Unlike the demand shock, the labor share does not return to the original level after the initial decline but remains at a lower point.

3.4.5 Sensitivity Analysis

As a first robustness check, we estimate the same model with three and four lags to check whether the number of lags used could affect the results. The results - not reported for convenience - are almost identical to those shown in Figures (3.4.4) and (3.4.5).

In Section 3.4.3, in the *workers' bargaining power* shock, only the posterior draws producing a rise in nominal wages greater than prices were retained to ensure that the shock generated a rise in real wages. To check that this method does not affect our results, we replace it with the direct restriction that the real wage increases, which enters as the sixth variable in the model. The new identification scheme is shown in Table 3.4.3. This check aims only to confirm the direction of the IRFs, while undue weight should not be given to their significance. The reason is that the available degrees of freedom are largely exceeded with an additional variable, and the confidence intervals are no longer reliable.

	Demand ↑	Workers Bargaining Power ↑	Firm Bargaining Power ↓	Automation ↑
Hours	+	/	/	-
Nom. Wage	+	+	+	-
Prices	+	+	-	-
GDP	+	/	/	+
Quits	+	-	/	-
Real Wage	/	+	/	-

Table 3.4.3: Sign Restrictions on period 3

There is only one difference to the previous model. It is further imposed that the real wage increases in the third quarter following both a positive shock to workers' bargaining power and a negative shock to firms' bargaining power. In addition, the real wage is restricted to decrease in response to a positive automation shock. The resulting structural IRFs are shown in Figure (3.4.6). Figure (3.4.7) shows the implied IRFs of labor share, labor productivity, and real wage. The real wage IRF no longer comes from the combination of nominal wages and prices but directly from the new real wage variable entering the model. The latter is also used to calculate the labor share as follows:

$$LS_t = Hours_t + RealWage_t - GDP_t \tag{3.6}$$

Labor productivity is calculated as in Eq. (3.4).

The results obtained are in line with those found in the previous section. The main differences concern the response of labor productivity and real wages to the demand shock. The IRFs of these two variables maintain the same sign. However, the lower bound is on the zero line for labor productivity, and the real wage response is non-significant. Nevertheless, their combined effect does not alter the negative impact response of labor share. In any case, given the large number of degrees of freedom consumed by adding the sixth variable, the results obtained from the previous section's model remain more reliable.

Finally, it is also worth mentioning some possible limitations of the sign restrictions approach. This method is less restrictive than Cholesky's but requires the theoretical priors underlying the restrictions to be plausible. For example, we can imagine a demand shock passed on prices more than on hours worked. Alternatively, workers could react weakly to changes in working conditions, resulting in quits not moving much in response to the model's shocks. Not all of these variations can be tested in the model. For example, we need a variable (*quits* in our case) that moves in the opposite direction in response to the demand and workers' bargaining power shocks for the model to be correctly identified. A variable with such characteristics should then be identified to replace *quits*. Future research should consider this point.

3.5 Conclusion

The first part of the paper provided a comprehensive review of the theoretical and empirical literature explaining the observed cyclicality of factor shares of income. The empirical literature on this topic relies on VAR models identified with Cholesky schemes, whose restrictions skew results in favor of specific theories while ruling out others. Moreover, the associated results are not robust to the inversion of the variables' ordering.

In the second part of the paper, a Bayesian VAR model identified with sign restrictions was set up to overcome these criticalities. The results suggest that the pro-cyclicality of labor productivity mainly drives counter-cyclical fluctuations in the labor share, consistent with *overhead costs* and *risk distribution* theories. Indeed, the instantaneous fall of the labor share following a demand shock is compatible with the increasing returns to scale generated by overhead costs. Regarding risk distribution theory, the instantaneous rise in productivity coupled with sticky real wages is consistent with the workers' will to set acyclical wages to hedge against business cycle risk. Also,

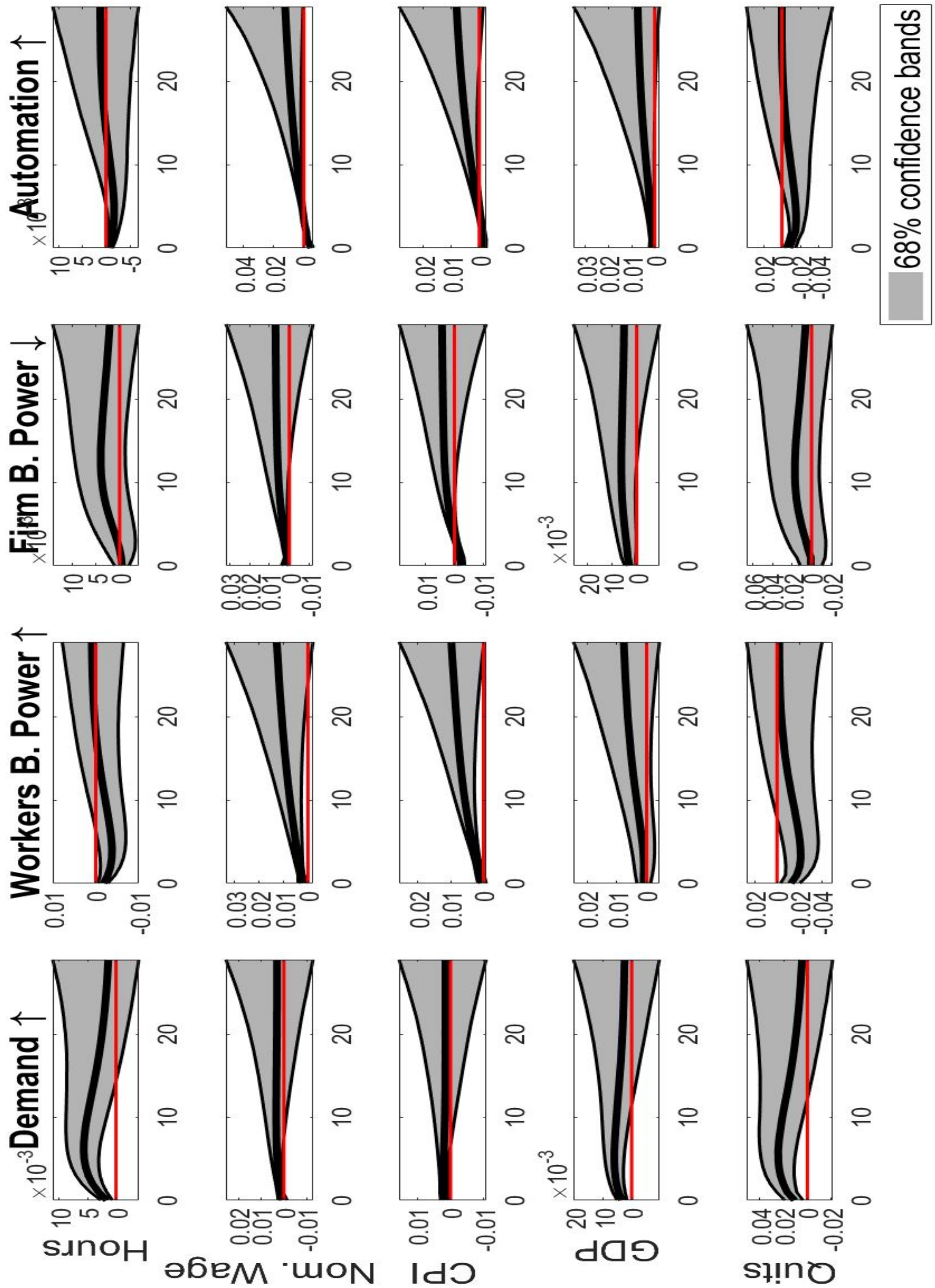

Figure 3.4.6: Structural IRFs

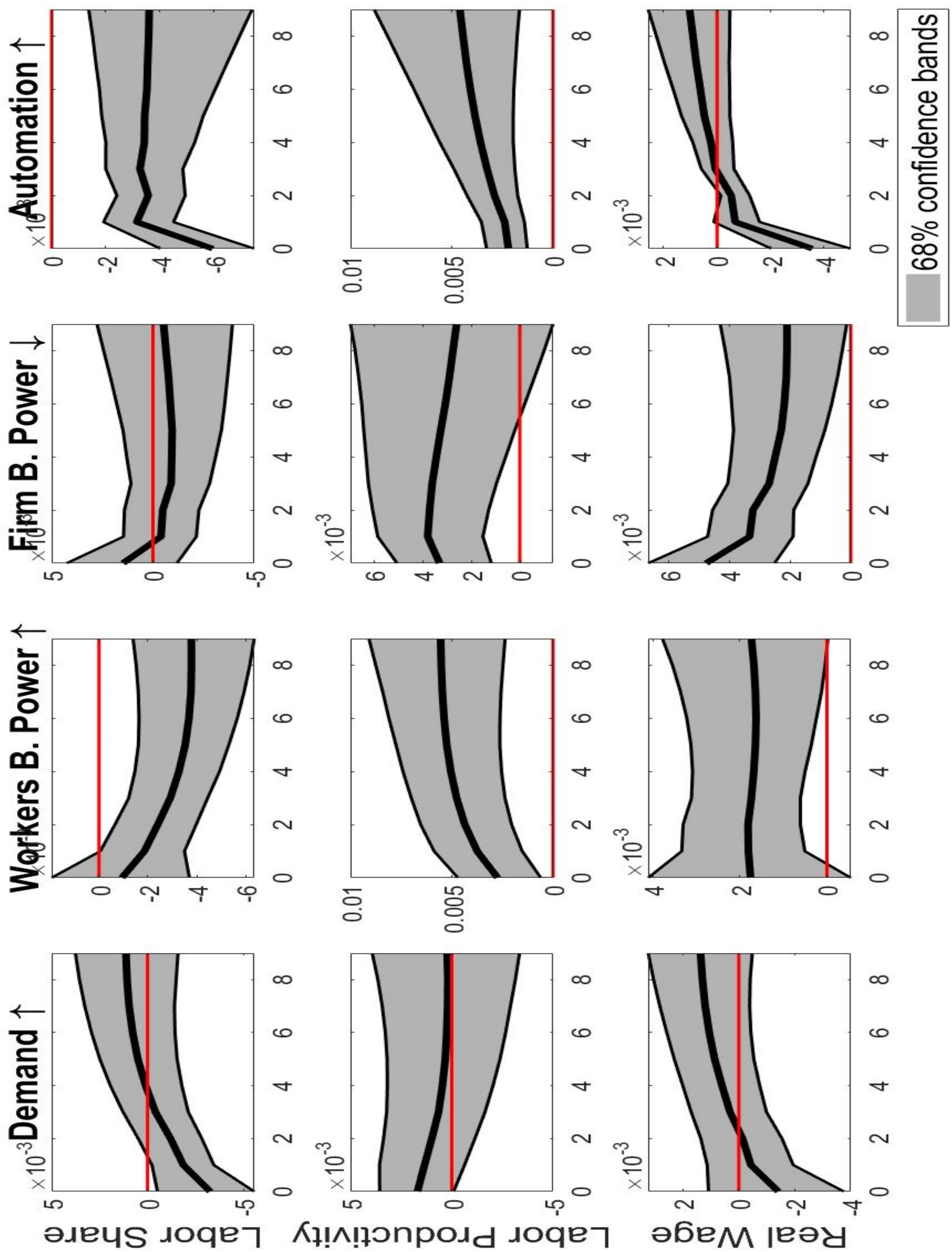

Figure 3.4.7: Implied structural IRFs

the lagged response of the real wage to the demand shocks contributes to the retraction of the fall in the labor share to the initial level, supporting the Phillips curve mechanism proposed by *Goodwin*. In contrast, it is difficult to judge the other prediction of Goodwin's model - the contractionary effect of an increase in the labor share. Indeed, following a rise in workers' bargaining power, the growth of real wages is more than offset by an increase in labor productivity, yielding - paradoxically - a fall in the labor share. Nevertheless, as in Goodwin's model, this shock produces a negative association between labor share and output, although the underlying mechanism generating it is necessarily different. The rise in labor productivity following an increase in workers' bargaining power can be interpreted as the result of firms' efforts to replace the labor factor, which has become more expensive, consistently with the *biased technical change theory*. However, a similar observation as for Goodwin's model applies here. Namely, the comovement between labor productivity and real wages does not correspond to a positive correlation between labor productivity and labor share as expected by the theory. Indeed, the labor share falls because labor productivity grows more than real wages.

The results are at odds with those found by the literature relying on bivariate activity-distribution models identified with Cholesky, where the distribution variable is ordered first. This identification scheme a priori rules out the theories of overhead costs and risk distribution and the hypothesis that pro-cyclical movements in labor productivity drive counter-cyclical fluctuations in the labor share. My model supports this hypothesis instead. In contrast, the results are compatible with those found by the strand of literature ordering the activity variable before the labor share in a Cholesky scheme.

Finally, among the possible weaknesses of the model is the brevity of the sample. In this regard, future research should consider a longer sample and time-varying features to capture the historical evolution of the cyclical interaction between labor share and output.

3.A Variables

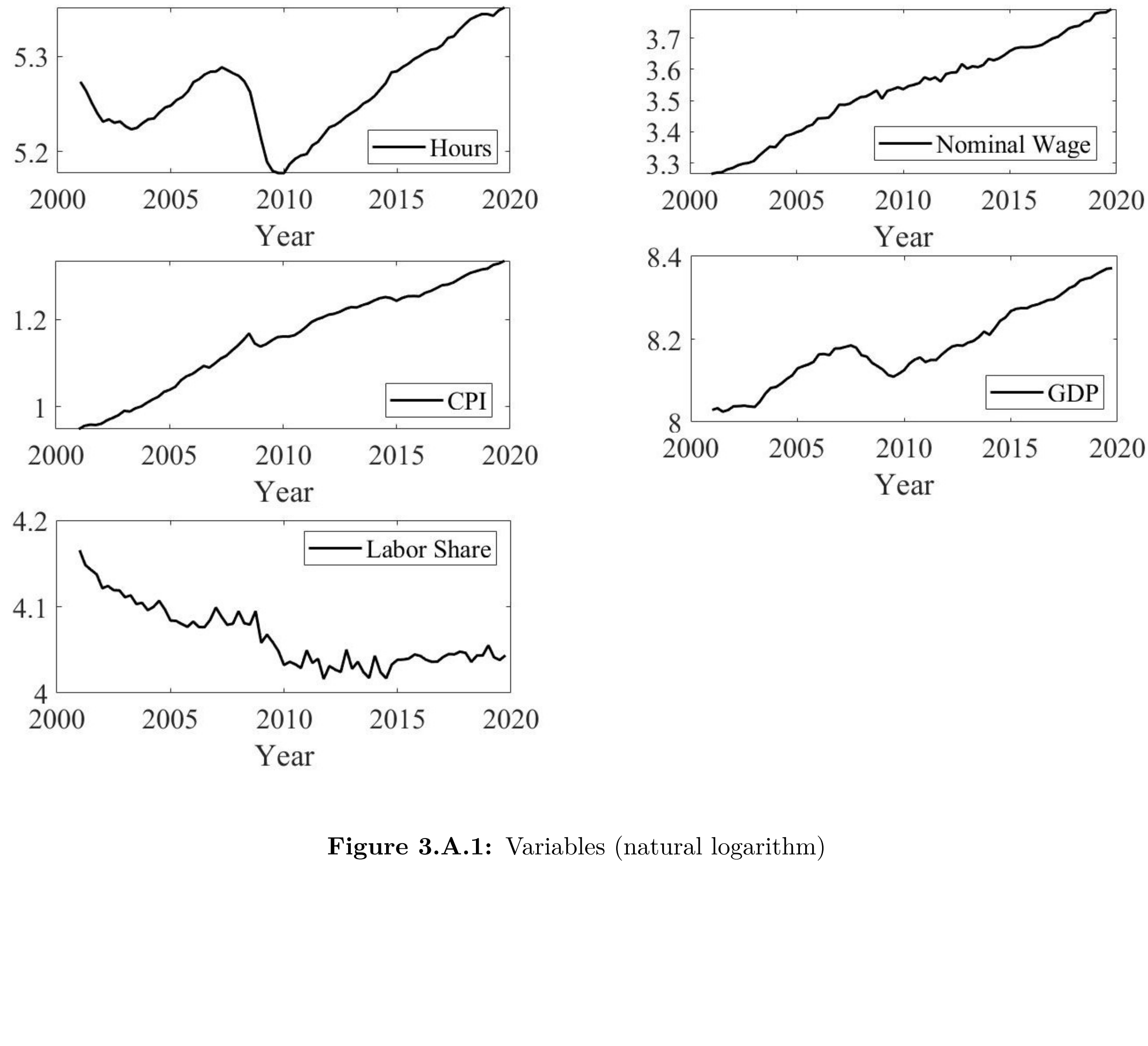

Figure 3.A.1: Variables (natural logarithm)

3.B Labor turnover over the business cycle

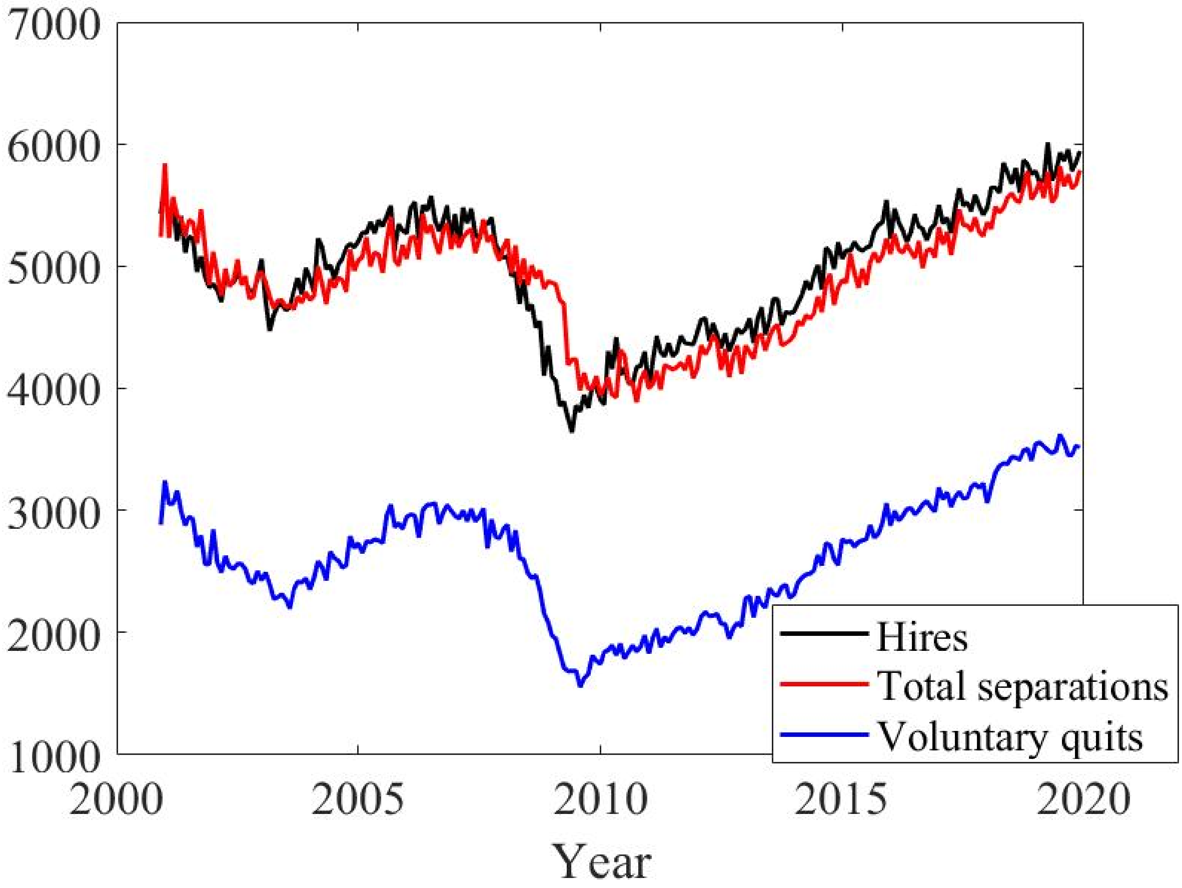

Figure 3.B.1: Labor turnover over the business cycle

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