DEPARTMENT OF ECONOMICS WORKING PAPER SERIES

Changing dynamics and tail risks of aggregate demand and income distribution

Jose Barrales-Ruiz
Ivan Mendieta-Muñoz

Working Paper No: 2024-05

November 2024

University of Utah
Department of Economics
260 S. Central Campus Dr., GC. 4100
Tel: (801) 581-7481
Fax: (801) 585-5649
http://www.econ.utah.edu

Changing dynamics and tail risks of aggregate demand and income distribution

Jose Barrales-Ruiz* Ivan Mendieta-Muñoz†

November 20, 2024

Abstract

This paper examines the changes in the dynamic interactions between aggregate demand and income distribution in the USA. We focus on two periods that capture the relevant characteristics before and after contemporary neoliberal capitalism. We study the interactions between aggregate demand and income distribution in both periods using structural quantile vector autoregression models. This allows us to assess the informational content of the dynamic interactions at all parts of the relevant distributions, including the potential tail risks. The results show evidence of important reductions in the profit-led effect across the whole distribution of aggregate demand during neoliberalism; while profit squeeze dynamics have decreased at most parts of the distribution of income but have increased its downside risk, thus becoming more heterogeneous across the distribution of income. Notwithstanding the underlying transmission mechanisms have remained unaltered across the two periods, our results highlight that the interactions between aggregate demand and income distribution have become a more complex phenomenon to study since the mid-1980s.

Keywords: aggregate demand, income distribution, tail risks, quantile vector autoregression, neoliberalism.

JEL Classification: D33, E11, E12, E32.

*Researcher. Center of Economics for Sustainable Development (CEDES), Faculty of Economics and Government, Universidad San Sebastián and Universidad Católica de la Santísima Concepción. E-mail: jose.barrales@uss.cl

†Associate Professor. Department of Economics, University of Utah. Email: ivan.mendietamunoz@utah.edu

1 Introduction

Ever since the seminal contributions of Goodwin (1967) and Bhaduri and Marglin (1990), a large amount of literature has explored the relationship between aggregate demand (AD) and income distribution (ID) by highlighting the importance of distributional conflict for the study of the dynamic evolution of capitalism at the macroeconomic level. Nevertheless, there are three important topics that have remained relatively unexplored by this literature. First, have the interactions between AD and ID experienced an important breakdown due to the economic and public policies associated with contemporary neoliberal capitalism? Second, does AD and ID interact beyond the middle of the distributions such that there are relevant interactions between AD and ID at the tails of their distributions? Third, have the interactions at the tails of the distributions of AD and ID also experienced an important breakdown during neoliberal capitalism?

The current paper studies the three aforementioned questions for the US economy. We focus on two separate periods that capture the relevant dynamics before neoliberalism (BN) and after neoliberalism (AN): 1948:Q1-1984:Q4 and 1985:Q1-2020:Q1, respectively, thus considering that each subsample regime features its own specific ideologies, economic and public policies, and institutions. By emphasizing market-driven approaches to economic and social problems, such as deregulation and privatization practices, neoliberal policies have had consequences of utmost importance for income distribution and labor markets, which include but are not limited to the exacerbation of economic inequality, increased concentration of wealth at the top, increased labor market flexibility, weakened labor protections, lower wage growth, and a decline in union power (see, *e.g.*, Harvey 2005, Galbraith 2016 and Stansbury and Summers 2020, among others). Hence, *a priori*, it is possible that this paradigm shift in economic policy has had consequential changes in the relations between AD and ID and, importantly, that these relations have also experienced different outcomes at different parts of their respective probability distributions.[1]

Thus, in this paper we study the dynamic interactions between AD and ID *at all parts of the conditional probability distributions* for the periods BN and AN. To do so, we use structural

1. In section 2, we discuss that the probability distributions of AD and ID are considerably different for the periods BN and AN.

quantile vector autoregression (QVAR) models. This allows us to capture the complete distributional interactions of the variables, including the effects that take place in the left and right tails of the distributions of AD and ID, which we can connect with the concepts of tail risks and compare to the interactions that occur in the middle of the distributions. In order to study the dynamic interactions between AD and ID in each period, we proceed in two steps. First, we study the aggregative mechanisms by considering the effects of AD on ID and *vice versa*. Second, we dissect the relevant aggregative effects to understand the main transmission channels that explain the existence of these interactions, thus providing a granular analysis of the specific ways in which AD and ID interact at all parts of their distributions.

Our findings can be summarized as follows. Firstly, although we find evidence of profit-led dynamics at all parts of the conditional probability distribution of AD both BN and AN—summarized by a negative response of the growth rate of AD to a positive shock in the labor share of income, we find that there has been an important reduction of this effect AN across all parts of the distribution of AD. The reduction of the profit-led effect AN has been most important at the right tail and the middle of the distribution of AD.

Secondly, the dynamics of the profit-led effect both BN and AN can be explained exclusively by the effect of ID on investment dynamics, which implies that the main transmission mechanism of the profit-led dynamics has remained unaltered across the two periods.

Thirdly, although we find evidence of profit squeeze dynamics at most parts of the conditional probability distribution of ID—summarized by a positive response of the labor share of income to a positive shock in the growth rate of AD, we find that there have been important changes AN. While the profit squeeze effect has disappeared mainly at the middle of the distribution of ID, the left tail of the distribution of ID has experienced a relative increase in the profit squeeze effect AN. This means that the reduction of the profit squeeze effect is *not observed across at all parts* of the distribution of ID and that the profit squeeze effect AN is now mainly a skewed relation associated only with the downside risk for ID. This also implies that the dynamics of the profit squeeze effect have become more heterogeneous compared to the dynamics of the profit-led effect AN.

Fourthly, the dynamics of the profit squeeze effect both BN and AN can be explained by a stronger response of real wages to AD relative to the response of labor productivity to AD, which implies that the main transmission mechanisms of the profit squeeze dynamics have also remained unchanged between the two periods.

The present contribution is mainly related to two strands of literature.[2] First, a rapidly growing strand of literature has highlighted the changing patterns related to the interactions between AD and ID effects, mainly in the USA. Using a threshold vector autoregression (VAR) model, Carvalho and Rezai (2016) discuss that the rise after 1980 in income inequality has made the US economy more profit-led. Marques (2022) and Carrillo-Maldonado and Nikiforos (2024) used time-varying parameter VAR models, finding important evidence that the US economy has become progressively less profit-led over time. Mendieta-Muñoz et al. (2022), who considered a VAR model with a structural break to separate the periods before and after the mid-1980s, also found a weaker reaction of AD to changes in ID during the neoliberal period. Barrales-Ruiz, Von Arnim, and Mohammed (2023) considered a structural VAR model estimated in the frequency domain, finding that the mechanisms traditionally associated with the Goodwin pattern have considerably weakened since the mid-1980s; while Setterfield (2023) discussed that the Goodwin pattern seems to have broken down mainly since the 2000s because of the consolidation of neoliberal capitalism, in general, and the incomes policy based on fear implemented during the latter, in particular.[3]

These contributions have provided evidence of the changing interactions between AD and ID by considering only the interactions in the conditional mean of the probability distributions. In other words, only the *average effects* or *average interactions* between the distributions of AD and ID have been studied by the literature. By contrast, in the present contribution we provide a general characterization of the dynamic interactions between AD and ID since, besides the average effects, we assess the informational content of the dynamic interactions between AD and ID at all parts of the respective distributions. Importantly, the study of the interactions at the tails of the distributions of AD and ID is of particular relevance since this allows us to consider both the negative and positive risks associated with AD and ID effects, which can be summarized by the

2. The literature on the so-called wage-led or profit-led aggregate demand regimes and the distributive cycle is, indeed, voluminous. Our purpose in the current paper is not to review it in detail since comprehensive surveys on these topics have already been provided by Blecker (2016), Stockhammer (2017), Barrales-Ruiz et al. (2022) and Blecker, Cauvel, and Kim (2022), among others.

3. We return to these points in section 5.

interactions at the 10th and 90th percentiles of the distributions, respectively. In this sense, our contribution also presents a direct mapping from the potential changes in risk factors associated with AD and ID to different parts of their distributions before and after contemporary neoliberal capitalism.

Second, a separate and much less explored strand of literature has begun to explore the potential interactions between AD and ID that may exist beyond the mean of the distributions. Marques and Lima (2022) is a pioneering study. They tested for Granger causality in quantiles between AD and ID in twelve developed countries for the period 1960-2019, finding significant Granger causal effects from AD to ID in most countries that are heterogeneous across quantiles—namely, these are larger for more extreme quantiles—and some evidence of Granger causality from ID to AD for fewer countries in their sample.

Nevertheless, the approach followed by Marques and Lima (2022) considered only the concept of Granger causality in quantiles. Although informative, Granger causality is not sufficient to understand the structural interactions between the variables since it only tests whether one variable is useful for predicting (forecasting) the other one by using the reduced form representation of the VAR model. In our paper, we explicitly consider the structural interactions between AD and ID and dissect such interactions by using structural QVAR models, which allows us to construct the relevant impulse-response functions (IRFs) at all quantiles of the AD and ID distributions and, most importantly, to evaluate its changes before and after neoliberalism.

The rest of this paper comprises the following sections. Section 2 presents and discusses some stylized facts to underline the importance of considering BN and AN as two qualitatively and quantitatively distinct periods. The results that study the aggregative mechanisms are presented in section 3; while section 4 presents results that provide the granular analyses of the relevant aggregative effects. A discussion of the implications of our findings is presented in section 5. The final section 6 concludes the paper.

2 Stylized facts

In this paper, we measure AD and ID by the GDP growth rate (g_t) and the labor share of income (ψ_t), respectively.[4] Our measure of ψ_t corresponds to the percentage labor share of income for all employed persons of the nonfarm business sector obtained from the Bureau of Labor Statistics (BLS); while g_t corresponds to the percentage quarter-on-quarter growth rate of real GDP obtained from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis.

As mentioned in section 1, we studied the US economy for the period 1948:Q1-2020:Q1, emphasizing the differences between the periods BN (1948:Q1-1984:Q4) and AN (1985:Q1-2020:Q1).[5] To empirically motivate our decision to consider these two separate periods, we first show the trajectories of ψ_t (x-axis) and g_t (y-axis) in figure 1, highlighting the periods BN (blue) and AN (red).

[Insert figure 1 about here]

Overall, in both periods we observe the negatively inclined clockwise spirals discussed by previous literature (*e.g.*, Barbosa-Filho and Taylor 2006). However, we also observe that the fluctuations that have occurred AN are likely positively inclined, flatter, wider, and more scattered compared to the period BN. Moreover, BN the changes between ψ_t and g_t seem to have been relatively constant over time; while AN the changes between ψ_t and g_t seem to have been varying more frequently.

4. The use of g_t to capture AD effects is not entirely standard in the literature since the baseline Kaleckian (or Structuralist) model uses capacity utilization as the preferred measure of economic activity, for example. Nevertheless, we believe that using g_t as a proxy for AD has several appeals. First, g_t is an *observed* variable that is also intuitive from a Keynesian approach, which emphasizes that (at least) year-to-year changes in economic activity are driven by AD effects. Second, capacity utilization is an *unobserved* variable and, therefore, a statistical construct that requires the use of a *latent* measure of potential output. The definition and construction of the latter using statistical models and methods is an extremely complex endeavor with several subtleties, as documented by recent research (Canova 2024; Li and Mendieta-Muñoz 2024).

5. We acknowledge that our division of the post-World War II period is somewhat subjective. For example, we might have considered the periods 1948:Q1-1973:Q4 and 1974:Q1-2020:Q1, where the former is often labeled as the "golden age," or, alternatively, we might have considered that the neoliberal period corresponds only to neoliberal boom (1990:Q1-2007:Q3, see Krämer, Proaño, and Setterfied 2023 and Setterfield 2023). However, instead of finding the optimal split in the post-World War II sample, our main interest in this paper is simply to capture a period that can be regarded as a meaningful representation of the neoliberal regime. The beginning of the latter can be associated with the second term of Ronald Reagan's presidency. Moreover, it is also worth mentioning that: (i) Mendieta-Muñoz et al. (2022) found evidence of a statistically significant structural break in their estimated model supporting the same split sample analysis; and (ii) the great majority of the results of Carrillo-Maldonado and Nikiforos (2024)—who used a fully flexible model by considering time-varying parameters—show that the most interesting time-varying distribution-led effects have occurred since 1985. Our sample ends in 2020:Q1 to avoid the potential effects of the COVID-19 recession.

Figure 2 illustrates the important differences across the two periods for the distributions of the individual time series by showing the constructed normal quantile-quantile plots for ψ_t and g_t.

[Insert figure 2 about here]

We observe that the probability distributions of ψ_t and g_t are not normally distributed for the period 1948:Q1-2020:Q1 since both distributions have more data located at the extremes and less data in the center compared to a normal distribution.[6] Nevertheless, the non-normality that both time series exhibit can be attributed almost exclusively to the period AN since only during this period the points follow a strong nonlinear pattern; while for the period BN the linearity of the respective points is clear.

These observations are also corroborated by the Shapiro-Wilk tests of normality (Royston 1995) for both ψ_t and g_t. The tests yield approximate p-values smaller than 0.01 for the period 1948:Q1-2020:Q1, larger than 0.05 for the period BN, and smaller than 0.01 for the period AN. This means that the null hypothesis that the samples of ψ_t and g_t come from normal distributions is rejected at the 5% level of significance for the period 1948:Q1-2020:Q1, not rejected for the period BN, and rejected again for the period AN.

To highlight further the implications of the differences across the two periods, in figure 3 we present again the trajectories over time of ψ_t and g_t by clearly separating both periods and including quantile regression analyses at three percentiles of interest: 10th, 50th (median), and 90th.[7] The respective coefficients associated with the different quantile regressions are summarized in table 1.

[Insert figure 3 about here]

[Insert table 1 about here]

For the period BN, the relationship between ψ_t and g_t seems to have been negative, although with varying degrees of strength across percentiles since the magnitude of impact that ψ_t had on g_t decreased as the latter moved from the 0.10 quantile to the 0.90 quantile. By contrast, for the period AN, the relationship between ψ_t and g_t seems to have been much more heterogeneous: the effect of ψ_t on g_t is statistically significant only for the 50th and 90th percentiles, and, most

6. In other words, we have heavy-tailed quantile-quantile plots for the distributions of ψ_t and g_t.

7. As mentioned in section 1, our in-depth analyses presented in sections 3 and 4 also focuses on these three percentiles.

interestingly, these effects have been positive. Considering only these partial effects, this would imply that BN there was strong evidence of profit-led effects; while AN there is strong evidence of wage-led dynamics.

The simple analyses presented in this section, which focus only on static frameworks, show that the changes over time of ψ_t and g_t as well as their relevant interactions have become a more complex phenomenon to study AN. Motivated by this preliminary evidence, the following sections use QVAR models to analyze these heterogeneous interactions. In brief, we aim at capturing the changes in the interactions between ψ_t and g_t by considering a dynamic modeling framework that allows us to assess the magnitude of such interactions at different parts of the conditional probability distributions, given the strong non-normal patterns present in both variables mainly AN.

3 Investigating the aggregate mechanisms

This section focuses on summarizing the dynamic effects of ψ_t on g_t, that is, the effect of ID on AD, and of g_t on ψ_t, that is, the effect of AD on ID. As mentioned in section 1, we estimated QVAR models following Chavleishvili and Manganelli (2024), which allow us to trace the dynamic interactions between the variables at any quantile of the respective distributions.[8]

We considered two bivariate QVAR models that included ψ_t and g_t: one estimated for the period BN and the other one estimated for the period AN. Each of the QVAR models incorporated two lags of the endogenous variables.[9] To solve the identification problem and construct the relevant IRFs, we followed a standard Cholesky decomposition, where we assumed that ψ_t is relatively more exogenous to g_t in the current period. This ordering of variables implies that ψ_t is ordered first in the system, followed by g_t (or, alternatively, that a shock to ψ_t affects g_t contemporaneously, but not *vice versa*). Although contentious, we are comfortable with this identification assumption because: (i) it is consistent with the classical theory of ID—which considers that ID is relatively more exogenous since it is mainly determined by institutions and social norms; and (ii) it has

8. A technical overview of the econometric method is presented in appendix A.

9. It is worth mentioning that standard VAR models that include ψ_t and g_t as endogenous variables and two lags present serial correlation problems. This problem is corrected if we increase the number of lags: to eleven BN and to five AN. However, the respective QVAR models estimated using these longer lag lengths yield fairly similar results to the ones estimated with only two lags; while the computational burden to estimate these models experienced a considerable increase. Because of this reason we are comfortable with reporting only the results obtained from QVAR models with a shorter lag length structure.

been widely implemented in studies that follow Kaleckian (or Structuralist) approaches (see, *e.g.*, Barrales-Ruiz et al. 2022 and Carrillo-Maldonado and Nikiforos 2024 for similar discussions).

Figure 4 presents the IRFs associated with the shock to ψ_t on ψ_t and g_t. The effect of ψ_t on g_t allows us to potentially identify whether AD exhibits mainly profit-led or wage-led characteristics. On the other hand, figure 5 shows the respective responses of ψ_t and g_t to shocks to g_t. The effect of g_t on ψ_t allows us to potentially identify whether ID exhibits mainly profit squeeze or forced saving characteristics. Importantly, each figure shows the responses at the three relevant percentiles—10th, 50th (median), and 90th. We determine the statistical significance of the response of each variable to the shock at each quantile by considering the (95%) confidence intervals: if the latter encloses the zero line, then we say that the response of that variable to the shock at the specific quantile is statistically non-significant.

[Insert figure 4 about here]

[Insert figure 5 about here]

The results in figure 4 indicate that profit-led dynamics are present both BN and AN—that is, the response of g_t to a shock in ψ_t tends to be negative and statistically significant in both periods at all quantiles. The profit-led effect seems to be relatively homogeneous across the three quantiles BN and AN, so the tails of the distribution of g_t do not seem to experience larger or different effects relative to the middle of its distribution. Nevertheless, compared to the period BN, there has been a considerable reduction of this effect across the three percentiles AN. Importantly, AN the negative response of g_t to a shock in ψ_t is only marginally statistically significant on impact and after one quarter across the three percentiles. This contrasts sharply with the effects BN, which are larger and statistically significant over longer horizons. The largest reductions in the profit-led effect have occurred at the 90th and 50th percentiles of the distribution of g_t, thus indicating that the right tail and the middle of the distribution of g_t are the ones that have experienced the largest decline in profit-led dynamics. Specifically, after one quarter, the effect of ψ_t on g_t was approximately 0.6 percentage points (pps) bigger BN than AN at the 90th percentile; 0.5 pps bigger BN than AN at the 50th percentile; and 0.2 pps bigger BN than AN at the 10th percentile.

Regarding the results in figure 5, there is evidence of profit squeeze dynamics—that is, the response of ψ_t to a shock in g_t tends to be positive and statistically significant. However, there are two heterogeneous effects that are highly important. First, profit squeeze dynamics BN were present only at the 10th and 50th percentiles of the distribution of ψ_t; while AN this effect is statistically significant only at the 10th percentile of the distribution. Second, profit squeeze dynamics AN at the 10th percentile distribution of ψ_t are larger and statistically significant over a longer horizon than profit squeeze dynamics BN. Specifically, at the 10th percentile of the distribution of ψ_t, BN the largest profit squeeze effect was approximately 0.15 pps and the response was statistically significant for approximately four quarters; whereas AN the largest profit squeeze effect is approximately 0.4 pps and the response is statistically significant for approximately fifteen quarters. These findings imply that there has been a reduction of the profit squeeze effect AN at the middle of the distribution of ψ_t; but the profit squeeze effect at the left tail of the distribution of ψ_t has increased.

4 Dissecting the aggregate mechanisms

The current section summarizes a set of results that offer a more granular analysis of the effects found in the previous section. Fewer contributions have tried to provide disaggregated analyses of the interactions between AD and ID in a dynamic context, perhaps because of the difficulties associated with finding meaningful results that are also consistent with the aggregative literature that includes only g_t (or another measure of AD) and ψ_t. For example, Mendieta-Muñoz et al. (2022) employed a non-recursive identification strategy in their disaggregated model as a first step in order to study the dynamics of ψ_t in a second step. Similarly, Cauvel (2023) found that if real wages and labor productivity (the two components of ψ_t) are considered instead of ψ_t, then the conclusions of the aggregative literature are not robust to different Cholesky orderings.[10]

To solve this conundrum, we proceeded as follows. Instead of incorporating additional variables into the reduced-form equations for g_t and ψ_t, which implies the estimation and identification of larger structural models, we considered separate models for each of the two possible dynamic structural interactions between the variables. This is evocative of the approach implemented by

10. Indeed, we found similar results to Cauvel (2023) when we estimated QVAR models between real wages, labor productivity and g_t. We also found inconsistent results with the aggregative literature if we consider QVAR models that decompose g_t into its relevant components (*i.e.*, investment growth rate and net exports growth rate). These results are available on request.

Barbosa-Filho and Taylor (2006), who also estimated separate reduced-form linear VAR models when trying to provide an in-depth analysis of the ID and AD effects.[11] To sum up, first, we focus on QVAR models that dissect the effect of ψ_t on g_t, which we present in section 4.1; and, second, we focus on QVAR models that dissect the effect of g_t on ψ_t, which are summarized in section 4.2.

4.1 Dissecting the profit-led effect

In section 3, we found evidence that the response of g_t to a shock in ψ_t tends to be negative, which can be associated with the existence of a profit-led mechanism. This effect is expected to be driven by the negative response of investment because a higher ψ_t implies a lower profit share of income, the negative response of net exports because a higher ψ_t implies decreased international competitiveness resulting from higher unit costs, or both effects. Hence, our main interest consists in understanding the effect of ψ_t on investment and net exports.

We estimated four different QVAR models with two lags each. Two QVAR models incorporated ψ_t, g_t and the real investment growth rate (i_t) for the periods BN and AN; while the other two incorporated ψ_t, g_t and the growth rate of real next exports (x_t) also for the periods BN and AN.[12] In order to identify the models, we deployed Cholesky decompositions that are consistent with the one used to generate the aggregative results in section 3. Hence, the QVAR models deployed to study the effects on i_t used the following Cholesky ordering: $\psi_t \rightarrow g_t \rightarrow i_t$; while the ones deployed to study the effects on x_t considered $\psi_t \rightarrow g_t \rightarrow x_t$. The relevant IRFs are presented in figures 6 and 7, respectively.

[Insert figure 6 about here]

[Insert figure 7 about here]

Main results can be summarized as follows. First, i_t is the only variable that exhibits negative and

11. Importantly, however, Barbosa-Filho and Taylor (2006) did not estimate any of the structural interactions between the variables and, hence, they did not construct the relevant IRFs.

12. Both i_t and x_t were constructed using data obtained from the National Income and Product Accounts (NIPA) of the Bureau of Economic Analysis (BEA). We used “Table 1.1.5. Gross Domestic Product,” which shows nominal values of the components of GDP; and “Table 1.1.9. Implicit Price Deflators for Gross Domestic Product,” which shows the respective implicit price deflators. The i_t series corresponds to the percentage quarter-on-quarter growth rate of real gross private domestic investment, constructed as nominal gross private domestic investment divided by its implicit price deflator. The x_t series corresponds to the percentage quarter-on-quarter growth rate of real net exports, constructed as nominal net exports of goods and services divided by its implicit price deflator.

statistically significant changes to shocks in ψ_t both BN and AN (figure 6); while the response of x_t to shocks to ψ_t (figure 7) tends to be statistically non-significant. Second, there has been an important reduction in the magnitude of the response of i_t to a shock in ψ_t AN that has occurred mainly at the 90th and 50th percentiles of the distribution of i_t.

Therefore, complementing the aggregative results found in section 3, this subsection shows the following. First, the existence of the profit-led effect is essentially explained by the dynamics of i_t. Second, the reduction in the profit-led effect AN that is most prominent at the right tail (90th percentile) and the middle (50th percentile) of the distribution of g_t is directly associated with the weaker response of i_t to shocks to ψ_t precisely at these parts of its distribution.

4.2 Dissecting the profit squeeze effect

Section 3 showed that the response of ψ_t to a shock to g_t tends to be positive, which can be associated with the existence of a profit squeeze mechanism. The two main components of ψ_t are real wages and labor productivity, *i.e.*, the numerator and denominator of ψ_t, respectively. This implies that the profit squeeze effect is expected to be driven by the positive response of real wages to a shock to g_t because, as AD rises, real wages are expected to rise since the relative bargaining power of workers increases. However, the response of labor productivity to a shock in g_t is also expected to be positive because of the well-known Kaldor-Verdoorn mechanism. This implies that, for the profit squeeze mechanism to exist, the positive response of real wages to g_t must be larger than that of labor productivity.

Therefore, our main interest consists in understanding the effect of g_t on real wages and labor productivity. We estimated four new QVAR models with two lags each. Two QVAR models incorporated ψ_t, g_t and the growth rate of real wages (w_t) for the periods BN and AN; while the other two incorporated ψ_t, g_t and the labor productivity growth rate (p_t) also for the periods BN and AN.[13] To identify the models, we again deployed Cholesky decompositions consistent with the one used in section 3. For the QVAR models that studied the effects on w_t, we used the Cholesky ordering $\psi_t \rightarrow g_t \rightarrow w_t$. For the QVAR models that studied the effects on p_t, we considered

13. Both w_t and p_t were constructed using data obtained from the BLS for the nonfarm business sector. The w_t series corresponds to the percentage quarter-on-quarter growth rate of real hourly compensation, constructed as hourly compensation deflated by the consumer price deflator; while the p_t series corresponds to the percentage quarter-on-quarter growth rate of labor productivity, defined as output per hour.

$\psi_t \rightarrow g_t \rightarrow p_t$. The IRFs for each QVAR model are presented in figures 8 and 9.

[Insert figure 8 about here]

[Insert figure 9 about here]

Figure 8 shows that, compared to the period BN, AN the positive response of w_t to g_t has decreased as the effects tend to be smaller and statistically significant over fewer quarters ahead after the shock. However, the response of w_t to a shock in g_t at the 10th percentile of its distribution AN is larger compared to the period BN and it is also statistically significant over a slightly longer horizon. Figure 9 shows that the response of p_t to shocks to g_t tends to be positive, and that it has also been relatively weaker AN than BN across the different percentiles of its distribution. Importantly, the responses of w_t to g_t tend to be larger than the responses of p_t to g_t at most horizons after the initial shock, which implies that a shock g_t tends to increase ψ_t, thus explaining the existence of the profit squeeze effect.

To summarize, the results in this subsection complement the ones found in section 3 and are instrumental in understanding the following. First, as expected, the existence of the profit squeeze effect is explained by the combination of a stronger positive response of w_t to shocks to g_t compared to the positive response of p_t to g_t. Second, the reduction in the profit squeeze effect AN is mainly observed at the middle and right tails of the distributions of w_t and p_t. Third, the increase in the profit squeeze effect AN observed only at the left tail (10th percentile) of the distribution of ψ_t is directly associated with the combination of a relatively stronger response of w_t and a weaker response of p_t to shocks to g_t precisely at the left tails of their respective distributions.

5 Discussion

Perhaps the three most interesting findings presented in sections 3 and 4 are the following. First, the profit-led effect has decreased across the whole distribution of aggregate demand during contemporary neoliberal capitalism. Second, during the neoliberal period, the profit squeeze effect has decreased mainly at the middle of the distribution of income; while the left tail of the distribution of income has experienced a relative increase in profit squeeze dynamics. Third, both before and after neoliberalism, the existence of the profit-led effect can be explained by the dynamics of investment; while the existence of the profit squeeze effect can be explained by the combination of the effects associated with real wages and productivity. This section provides a discussion of the reasons that help to understand these changes, as well as the potential implications related to our findings.

We believe that the reduction of the profit-led effect during neoliberal capitalism across the whole distribution of aggregate demand—that is, across the left tail, right tail, and the middle of the distribution of g_t—is closely related to the reduction in the labor share of income and the potential non-linear effects associated with the latter. As discussed by Krämer, Proaño, and Setterfied (2023), capitalism can be deemed as a highly dynamic growth process embedded in a historically contingent social context that is relatively enduring but ultimately transmutable. In table 2 we present a summary of descriptive statistics that, in the context of the present article, show the relevant economic outcomes derived from the particular set of institutions that determined the relations between capital and labor BN and AN—and, therefore, manifest the particular nature of distributional conflict in both periods.

[Insert table 2 about here]

Compared to the period 1948:Q1-1984:Q4, the period 1985:Q1-2020:Q1 is characterized by important reductions in the means (medians) of ψ_t, g_t and i_t.[14] The mean (median) of ψ_t has experienced a reduction of approximately 3.5 (2.7) pps during the neoliberal period. This means that the initial point of departure of any shock in ψ_t is considerably lower AN than BN. In other words, since ψ_t is lower AN, the pressure that shocks in ID (measured by ψ_t) can have on AD (measured by g_t) is also lower during this period. Since the profit-led effect is driven by the response of i_t to ψ_t, then this also implies that firms' investment has experienced lower pressure associated with shocks to ψ_t AN.

All in all, the changes BN and AN highlight the existence of important non-linearities regarding the

14. Table 2 also shows that the neoliberal period is characterized by a higher volatility (standard deviation) of ψ_t, and a lower standard deviation of both g_t and i_t. In this sense, the so-called Great Moderation, which highlights the relative stability of the economy and the lower volatility of g_t, has coincided with a higher volatility of ψ_t, which is likely caused by the measures undertaken to increase labor market flexibility that have increased the volatility of w_t. The third and fourth moments of the distributions of ψ_t, g_t and i_t have also increased considerably AN, which can be seen by the respective increases in skewness and kurtosis. Taken together, these statistics corroborate the discussion in section 2, which shows that the data is clearly non-normally distributed AN.

effects of ID on AD, such that, as ψ_t decreased AN, the economy seems to have become relatively less profit-led. This effect resonates with Taylor (1990), who discussed that an economy can be wage-led at low level of wages but profit-led at high levels, mainly because investment tends to become more sensitive to real wages as the latter rises.[15]

Similarly, the more heterogeneous changes of the profit squeeze effect during neoliberal capitalism across the distribution of income—that is, a reduction of this effect at the middle of the distribution of income but an increase of the effect at the left tail of the distribution of income—reflect the importance of the change in incomes policies AN and the asymmetric and non-linear effects derived from the latter.

As also discussed by Cornwall (1990) and Setterfield (2022, 2023), incomes policies are both formal and informal institutions that determine the wage-setting and price-setting behavior, which moderate the inflation rate, increase incomes, and mediate and reconcile the conflicting claims on aggregate income. In contrast to the period BN, neoliberalism successfully institutionalized an incomes policy based on fear, that is, a model of domination where conflict is ameliorated by means of coercion and the imposition of capitalists' preferred distributional settlement on workers. This was a consequence of the systematic process explicitly designed to weaken the bargaining power of workers implemented by corporations and the state, which, overall, succeeded in increasing worker insecurity. This process was clear, for example, via the introduction of new labor law reforms designed to make unionization harder and de-unionization easier; the increase in short-term, part-time, temporary and gig employment instead of promoting long-term, full-time, permanent employment; downsizing practices that threaten unemployment regardless of the phase of the business cycle; and the threat of unemployment derived from (domestic or international) plants relocation. This means that, as the bargaining power of workers has been lower AN compared to BN, any positive shock in g_t AN no longer increases w_t or ψ_t as much as during the period BN. In other words, compared to the period BN, workers can

15. Of course, there are other contributions that can also be used to motivate the existence of non-linear dynamics of AD and investment. First, Bhaduri and Marglin (1990) and, most importantly, Palley (2013) also discussed alternative theoretical combinations that allow for the existence of a non-linear response of the AD schedule; but several of these possibilities seem to be less relevant given the empirical findings across the two periods. Second, strong non-linear patterns have been found for investment dynamics (see, *e.g.*, Mendieta-Muñoz and Sündal (2022), Mendieta-Muñoz (2024) and references therein); but these contributions do not connect the non-linearity of AD with ψ_t.

no longer benefit from increases in g_t during the neoliberal period because their relative bargaining power is now lower.

The effect described above can explain the reduction of the profit squeeze mechanism in the middle of the distribution of income. Nevertheless, our results also indicate an increase in the profit squeeze effect at the left tail of the distribution of income. This effect can be interpreted as a relative increase in the left-hand-side or negative tail risk associated with the profit squeeze effect, such that the lower end of the distribution of ψ_t is the one that is affected by shocks in g_t AN. This suggests that extreme negative outcomes in ψ_t are more sensitive to changes in g_t or, alternatively, that shocks in g_t are more likely to influence the extreme negative outcomes of ψ_t AN (rather than the average or positive outcomes). Therefore, the profit squeeze effect AN is now only associated with downside risk or adverse scenarios for ψ_t: the profit squeeze effect AN is now a skewed relationship such that lower shocks in g_t can have an impact on ψ_t only when ψ_t is lower.

Hence, our results also underline the importance of previous contributions that have discussed the possibility of asymmetric and non-linear effects of AD on ID. Specifically, considering the changes BN and AN regarding the effects of g_t on ψ_t at the middle of the distribution, we believe that our findings support the view of Nikiforos and Foley (2012) and Palley (2013), who propose a distributive schedule that decreases at low utilization (or AD) levels. Nevertheless, our results for the period AN align more closely with Tavani, Flaschel, and Taylor (2011) and Assous and Dutt (2013), who suggest an inverted S-shape for the distributive schedule. Our analysis reveals a non-linear relationship where positive shocks in g_t tend to increase ψ_t by raising w_t more than p_t; however, during the period AN this effect is limited to scenarios where both g_t and ψ_t are relatively low.

We conclude this section by pointing out three important implications associated with our analyses that we believe are crucial. First, we found evidence of a relative decline in profit-led dynamics across the whole distribution of aggregate demand and a relative decline in profit squeeze dynamics in the middle of the distribution of income since the mid-1980s. However, the former effect remains statistically significant; while the latter effect has increased at the left tail of the distribution of income. The implication of these findings is that distributional conflict is, indeed, an enduring feature of capitalist dynamics that has not disappeared during neoliberal capitalism (see also Krämer, Proaño, and Setterfied 2023 and Setterfield 2023). Second, overall, we suggest that future theoretical and empirical studies consider mainly the period of neoliberal capitalism as the period that is more relevant and representative of the recent dynamic interactions between AD and ID.[16] Third, our paper has only provided evidence regarding the changes in the short-run dynamic relations between AD and ID. This implies that the study of the potential changes in the long-run dynamic interactions between AD and ID before and after neoliberalism is an important research project that still remains to be done.[17]

6 Final remarks

This paper studies the changes in the dynamic interactions between aggregate demand and income distribution in the USA during the post-World War II period. We focus on two periods aimed at capturing the relevant characteristics of the US economy before and after contemporary neoliberal capitalism, thus considering that each period is defined by specific ideologies, economic and public policies, and institutions that shape the dynamics of distributional conflict.

For each period, we examine the dynamic effects of aggregate demand on income distribution and *vice versa* at all parts of the probability distributions using structural quantile vector autoregression models. This allows us to provide a general characterization of the relevant dynamic interactions since, besides the more well-known interactions in the middle of the distributions, we also study the potential interactions at the tails of the distributions that can be associated with the concepts of tail risks. Finally, we conduct dissected analyses aimed at providing more granular inquiries in order to understand the main transmission channels that explain the aggregative results.

Although we find evidence of profit-led and profit squeeze dynamics in both periods, we find important evidence that highlights a substantial change in both effects since the mid-1980s. The importance of the profit-led effect has decreased across all parts of the distribution of aggregate demand. On the other hand, the importance of the profit squeeze effect has also decreased—

16. Alternatively, highly flexible models that explicitly capture the relevant time-varying effects throughout the post-World War II period, such as Marques (2022) and Carrillo-Maldonado and Nikiforos (2024), are also especially relevant.

17. For instance, Blecker (2016), Kiefer et al. (2020), Rada et al. (2023), among others, discuss that capitalist economies exhibit wage-led characteristics in the long-run. In our context, the combination of a lower ψ_t and g_t during the neoliberal period shown in table 2 also offers evidence in favor of this possibility.

mainly at the middle of the distribution of income; but the diminished profit squeeze effect is not observed across all parts of the distribution of income: the left tail of the distribution of income has experienced an increase in the profit squeeze effect. We show that, both before and after the mid-1980s, the existence of the profit-led effect can be explained exclusively by the effects of the labor share of income on investment; while the existence of the profit squeeze effect can be explained by the stronger response of real wages to aggregate demand relative to that of labor productivity.

These findings imply that, while the reduction of the profit-led effect during the last decades is homogeneous across the distribution of aggregate demand, profit squeeze dynamics have become relatively more heterogeneous across the distribution of income. Specifically, the profit squeeze effect is now mainly a skewed effect associated only with the downside risk of income distribution. Although the underlying transmission mechanisms of both effects have remained unchanged, our results emphasize that the dynamic interactions between aggregate demand and income distribution have become a more complex phenomenon to study since the mid-1980s.

References

Assous, Michael, and Amitava K. Dutt. 2013. "Growth and income distribution with the dynamics of power in labour and goods markets." *Cambridge Journal of Economics* 37 (6): 1407–1430.

Barbosa-Filho, Nelson H., and Lance Taylor. 2006. "Distributive and demand cycles in the US economy—A structuralist Goodwin model." *Metroeconomica* 57 (3): 122–137.

Barrales-Ruiz, Jose, Ivan Mendieta-Muñoz, Codrina Rada, Daniele Tavani, and Rudiger von Arnim. 2022. "The distributive cycle: Evidence and current debates." *Journal of Economic Surveys* 36 (2): 468–503.

Barrales-Ruiz, Jose, Rudiger Von Arnim, and Mikidadu Mohammed. 2023. "Income distribution and economic activity: A frequency domain causal exploration." *Metroeconomica* 74 (2): 306–327.

Bhaduri, Amit, and Stephen A. Marglin. 1990. "Unemployment and the real wage: the economic basis for contesting political ideologies." *Cambridge Journal of Economics* 14 (4): 375–393.

Blecker, Robert A. 2016. "Wage-led versus profit-led demand regimes: the long and the short of it." *Review of Keynesian Economics* 4 (4): 373—390.

Blecker, Robert A., Michael Cauvel, and Y. K. Kim. 2022. "Systems estimation of a structural model of distribution and demand in the US economy." *Cambridge Journal of Economics* 46 (2): 391–420.

Bose, Arup, and Snigdhansu Chatterjee. 2003. "Generalized bootstrap for estimators of minimizers of convex functions." *Journal of Statistical Planning and Inference* 117 (2): 225–239.

Canova, Fabio. 2024. "FAQ: How do I estimate the output gap?" *The Economic Journal* forthcoming.

Carrillo-Maldonado, Paul, and Michalis Nikiforos. 2024. "Estimating a time-varying distribution-led regime." *Structural Change and Economic Dynamics* 68 (March): 163–176.

Carvalho, Laura, and Armon Rezai. 2016. "Personal income inequality and aggregate demand." *Cambridge Journal of Economics* 40 (2): 491—505.

Cauvel, Michael. 2023. "The neo-Goodwinian model reconsidered." *European Journal of Economics and Economic Policies: Intervention* 20 (2): 183—246.

Chavleishvili, Sulkhan, and Simone Manganelli. 2024. "Forecasting and stress testing with quantile vector autoregression." *Journal of Applied Econometrics* 39 (1): 66–85.

Cornwall, John. 1990. *The Theory of Economic Breakdown: An Institutional-Analytical Approach.* Cambridge: Basil Blackwell.

Galbraith, James K. 2016. *Inequality: What Everyone Needs to Know.* New York City: Oxford University Press.

Goodwin, Richard M. 1967. "A growth cycle." In *Socialism, Capitalism and Growth: Essays Presented to Maurice Dobb,* edited by Charles H. Feinstein, 54–58. Cambridge: Cambridge University Press.

Harvey, David. 2005. *A Brief History of Neoliberalism.* New York City: Oxford University Press.

Kiefer, David, Ivan Mendieta-Muñoz, Codrina Rada, and Rudiger Von Arnim. 2020. "Secular stagnation and income distribution dynamics." *Review of Radical Political Economics* 52 (2): 189–207.

Koenker, Roger, and Zhijie Xiao. 2006. "Quantile autoregression." *Journal of the American Statistical Association* 101 (475): 980–990.

Krämer, Hagen M., Christian Proaño, and Mark Setterfied. 2023. "The Marx-Keynes-Schumpeter system, part I: Long waves and short cycles in the capitalist growth record." In *Capitalism, Inclusive Growth, and Social Protection: Inherent Contradiction or Achievable Vision?,* edited by Hagen M. Krämer, Christian Proaño, and Mark Setterfied, 21–46. Northampton: Edward Elgar.

Li, Mengheng, and Ivan Mendieta-Muñoz. 2024. "Dynamic hysteresis effects." *Journal of Economic Dynamics and Control* 163 (June): 104870.

Marques, André M. 2022. "Reviewing demand regimes in open economies with Penn World Table data." *Manchester School* 90 (6): 730–751.

Marques, André M., and Gilberto Tadeu Lima. 2022. "Testing for Granger causality in quantiles between the wage share in income and productive capacity utilization." *Structural Change and Economic Dynamics* 62 (September): 290–312.

Mendieta-Muñoz, Ivan. 2024. "Time-varying investment dynamics in the USA." *Economics* 18 (1): 20220091.

Mendieta-Muñoz, Ivan, Codrina Rada, Márcio Santetti, and Rudiger von Arnim. 2022. "The US labor share of income: what shocks matter?" *Review of Social Economy* 80 (4): 514–549.

Mendieta-Muñoz, Ivan, and Doğuhan Sündal. 2022. "Business cycles, financial conditions, and nonlinearities." *Metroeconomica* 73 (2): 343–383.

Nikiforos, Michalis, and Duncan K. Foley. 2012. "Distribution and capacity utilization: conceptual issues and empirical evidence." *Metroeconomica* 63 (1): 200–229.

Palley, Thomas I. 2013. *Enriching the neo-Kaleckian growth model: Nonlinearities, political economy, and financial factors.* Technical report 335. University of Massachussets Amherst, Political Economy Research Institute (PERI), Working Paper Series.

Rada, Codrina, Daniele Tavani, Rudiger von Arnim, and Luca Zamparelli. 2023. "Classical and Keynesian models of inequality and stagnation." *Journal of Economic Behavior and Organization* 211 (July): 442–461.

Royston, Patrick. 1995. "A remark on Algorithm AS 181: The W-test for normality." *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 44 (4): 547–551.

Setterfield, Mark. 2022. "Neoliberalism: An entrenched but exhausted growth regime." *Ensayos Económicos* 79 (May): 1–18.

Setterfield, Mark. 2023. "Whatever happened to the 'Goodwin pattern'? Profit squeeze dynamics in the modern American labour market." *Review of Political Economy* 35 (1): 263–286.

Stansbury, Anna, and Lawrence H. Summers. 2020. "The declining worker power hypothesis: An explanation for the recent evolution of the American economy." *Brookings Papers on Economic Activity* 51 (Spring): 1–77.

Stockhammer, Engelbert. 2017. "Determinants of the wage share: A panel analysis of advanced and developing economies." *British Journal of Industrial Relations* 55 (1): 3–33.

Tavani, Daniele, Peter Flaschel, and Lance Taylor. 2011. "Estimated non-linearities and multiple equilibria in a model of distributive-demand cycles." *International Review of Applied Economics* 25 (5): 519–538.

Taylor, Lance. 1990. "Real and money wages, output and inflation in the semi-industrialized world." *Economica* 57 (227): 329–353.

Wei, Ying. 2008. "An approach to multivariate covariate-dependent quantile contours with applications to bivariate conditional growth charts." *Journal of the American Statistical Association* 103 (481): 397—409.

A Structural quantile vector autoregression models

As discussed by Chavleishvili and Manganelli (2024), QVAR models can be regarded as a generalization of the univariate quantile autoregression models proposed by Koenker and Xiao (2006) combined with the triangular structure proposed by Wei (2008) to address the issue of multivariate quantile. This appendix provides an overview of this approach.

We assume the following:

1. $\{Y_t\}$ is a time series vector such that $\{Y_t\} \equiv \{[Y_{1t}, Y_{2t}, ..., Y_{nt}]'\}$, where n and t denote the variables considered and the time series observations, respectively.

2. $\Omega_{1t} \equiv \{Y_{1t}, Y_{2t}, ...\}$ and $\Omega_{it} \equiv \{Y_{i-1,t}, \Omega_{i-1,t}\}$, $i = 2, ..., n$, represent the recursive information set.

3. $\{U_t\}$ is a sequence of n vectors such that $\{U_t\} \equiv [U_{1t}, U_{2t}, ..., U_{nt}]'$ and each $U_{it}, i = 1, ..., n$, is an independent and identically distributed (i.i.d.) standard uniform random variable.

4. A covariance stationary recursive QVAR model of order 1, that is, a QVAR(1) model.[18]

Following Wei (2008), we can formally say that, since each realization of U_{it} has support over $(0, 1)$, then to each realization of U_{it} corresponds a specific i-quantile of the QVAR(1) model. Thus, the reduced form of the latter can be expressed as follows:

$$Y_t = \nu(U_t) + B(U_t)Y_{t-1}, \tag{A.1}$$

where $\nu(U_t) \equiv [I_n - A_0(U_t)]^{-1} \omega(U_t)$; $B(U_t) \equiv [I_n - A_0(U_t)]^{-1} A_1(U_t)$; I_n is the n-dimensional identity matrix; $A_0(U_t)$ is an nXn lower triangular coefficient matrix with zeros along the main diagonal; $\omega(U_t)$ is an $nX1$ vector of intercepts; and $A_1(U_t)$ is an nXn coefficient matrix.

Following equation A.1, we specify a random coefficient QVAR(1) model:

$$Y_t = \nu + B(U_t)Y_{t-1} + \varepsilon(U_t), \tag{A.2}$$

18. The generalization to a QVAR(q) model, where q denotes the lag order, is straightforward using the companion form. We omit this extension since it solely involves a more elaborate mathematical notation.

where $\varepsilon(U_t) \equiv \nu(U_t) - \nu$ denote the structural shocks.[19]

Let us now assume that the structural shocks in $\varepsilon(U_t)$ are orthogonal with variance normalized to one, and that C is a matrix of unknown structural parameters. We can define $\varepsilon(U_t)$ as:

$$C\varepsilon(U_t) \equiv \epsilon(U_t), \qquad \varepsilon(U_t) \sim (0, I_n). \tag{A.3}$$

We then consider the following individual shock, $\varepsilon_i^*(U_t)$:

$$\varepsilon_i^*(U_t) = \varepsilon(U_t) + \delta\iota, \tag{A.4}$$

where $\delta > 0$ is a scalar and ι is a vector of zeros with 1 in the i^{th} position.

Equation A.4 implies that $\varepsilon_i^*(U_t)$ effects the whole distribution of Y_{it} and not the value of Y_{it}. Hence, the impulse-response at time t is defined as:

$$\Delta_t^i(U_t) \equiv Y_t^* - Y_t = C\delta\iota, \tag{A.5}$$

where Y_t^* is the shocked variable.

For the periods ahead ($i.e.$, $h > 1$), the quantile impulse-response is now quantile-path dependent:

$$\Delta_{t+h}^i(U_{t+h} \mid U_t, U_{t+1}, ..., U_{t+h-1}) = B(U_{t+h})...B(U_{t+1})C\delta\iota. \tag{A.6}$$

Clearly, identification of the QVAR model requires knowledge of the structural matrix C in equation A.3. The identification problem can be summarized by using the covariance matrix Σ_ϵ. The latter can be defined via the structural representation in equation A.3:

$$\Sigma_\epsilon = E\left[\epsilon(U_t)\epsilon(U_t)'\right] = CC'. \tag{A.7}$$

Since a QVAR model can also be represented as a VAR model (equation A.2), standard

19. We highlight two important details. First, the vector $\nu \equiv E[\nu(U_t)]$ can be estimated by simulation—by generating random draws of U_t and estimating the corresponding recursive QVAR model. Second, if $B(U_t) = B$ for all $U_t \in (0,1)^n$, then the QVAR model in equation A.2 corresponds to a standard VAR model.

identification strategies of the VAR literature can also be applied to QVAR models. As discussed in the main text, we deploy recursive identification strategies, which imply lower-triangular Cholesky decompositions of Σ_ϵ such that $\Sigma_\epsilon = PP'$, where P are the relevant lower triangular matrices. Since these decompositions are unique, then $P = C$, and the estimated QVAR models are identified such that quantile impulse-response functions can be constructed.

Figures

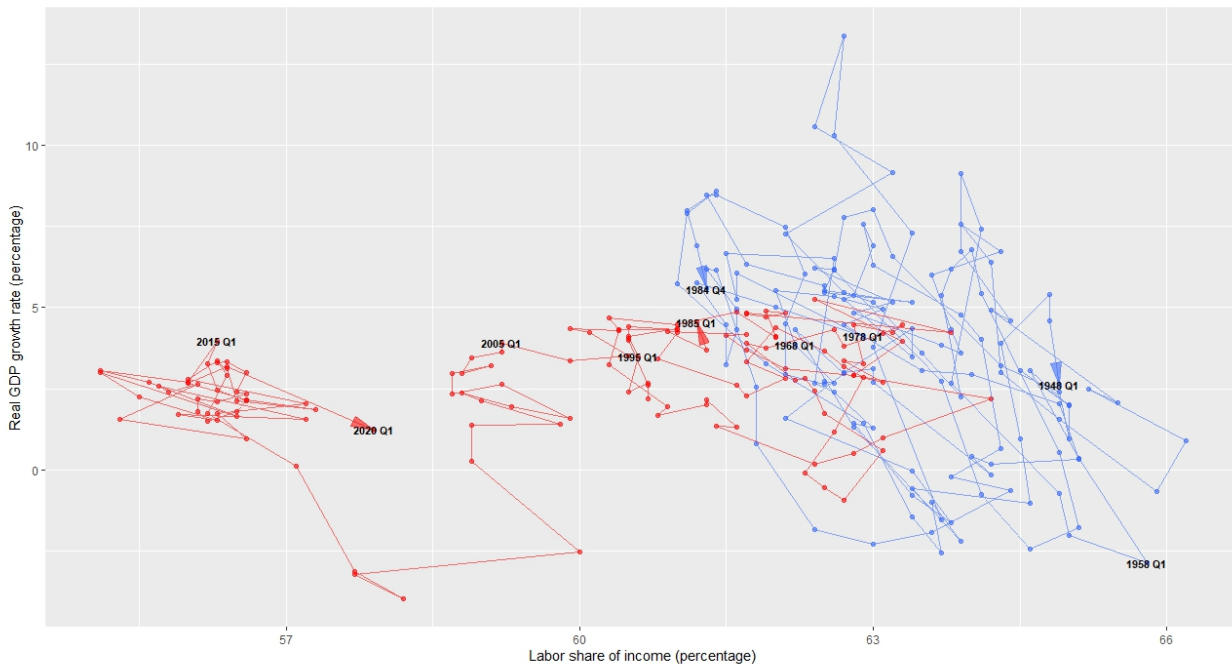


Figure 1: USA, 1948:Q1-2020:Q1. Changes of the labor share of income and real GDP growth rate. We show the combination of observations for the labor share of income and real GDP growth rate connected over time for the period BN (1948:Q1-1984:Q4) in blue and AN (1985:Q1-2020:Q1) in red. The rightmost (leftmost) blue arrow indicates 1948:Q1 (1984:Q4). The rightmost (leftmost) red arrow indicates 1985:Q1 (2020:Q1).

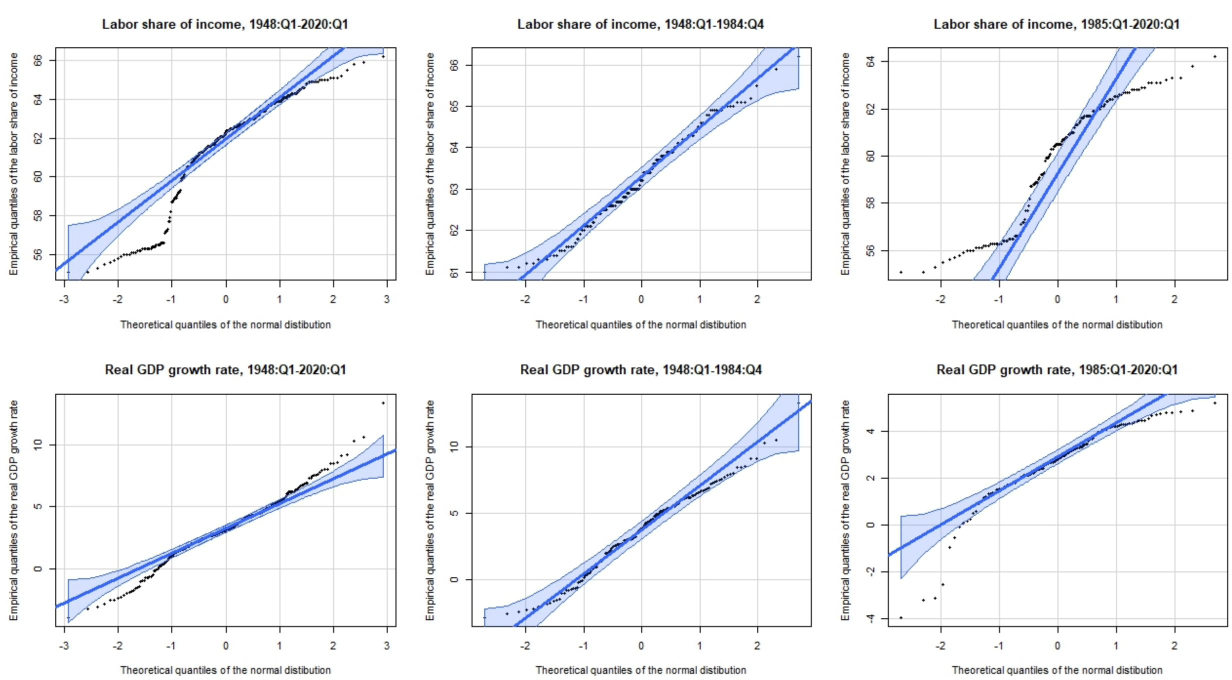


Figure 2: Normal quantile-quantile plots for the labor share of income and the real GDP growth rate in the USA. Shaded areas show the respective 95% pointwise confidence intervals.

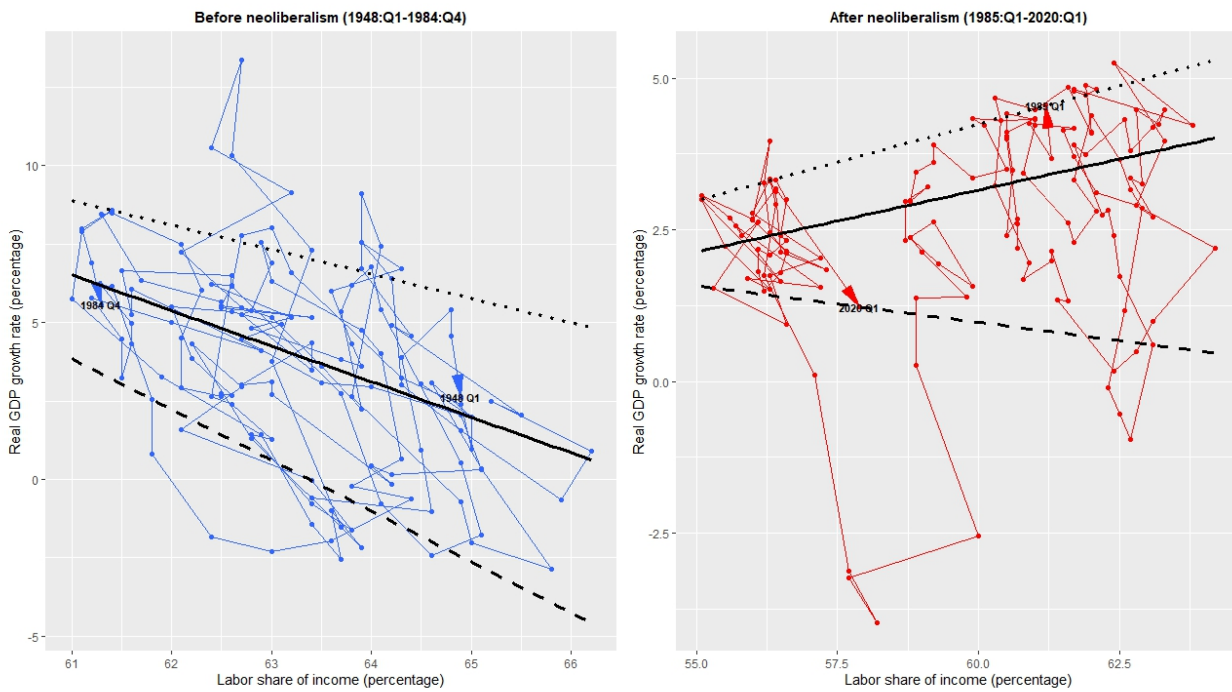
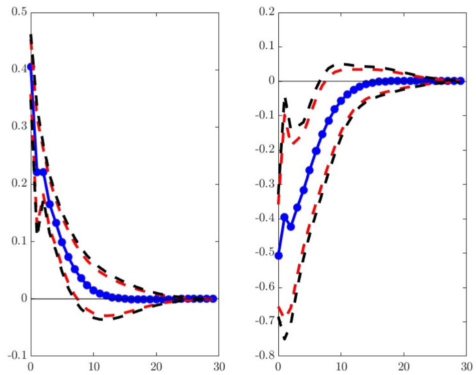
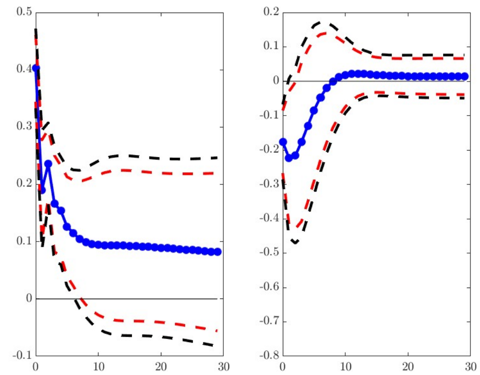


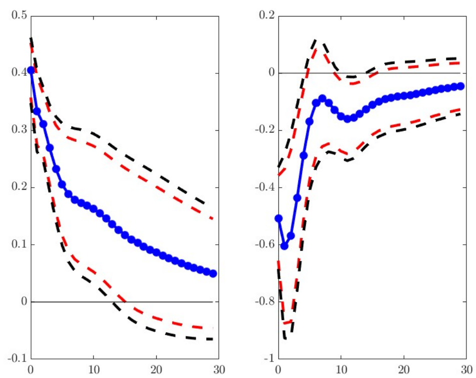
Figure 3: USA, 1948:Q1-2020:Q1. Changes of the labor share of income and real GDP growth rate together with quantile regression lines at three different percentiles. We show the combination of observations for the labor share of income and real GDP growth rate connected over time for the period BN (1948:Q1-1984:Q4) in blue and AN (1985:Q1-2020:Q1) in red. The rightmost (leftmost) blue arrow indicates 1948:Q1 (1984:Q4). The rightmost (leftmost) red arrow indicates 1985:Q1 (2020:Q1). The black dashed lines show quantile regression lines at the 10th percentile. The black straight lines show quantile regression lines at the 50th percentile (median). The black dotted lines show quantile regression lines at the 90th percentile.



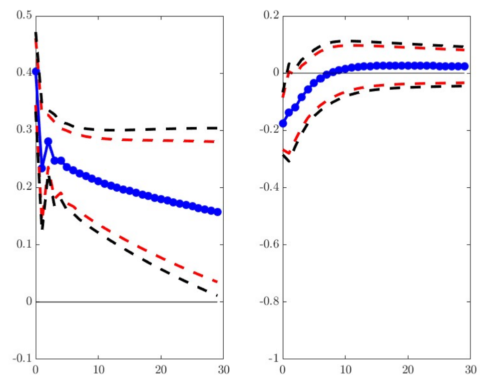
(a) Responses at the 10th percentile before neoliberalism (1948:Q1-1984:Q4)



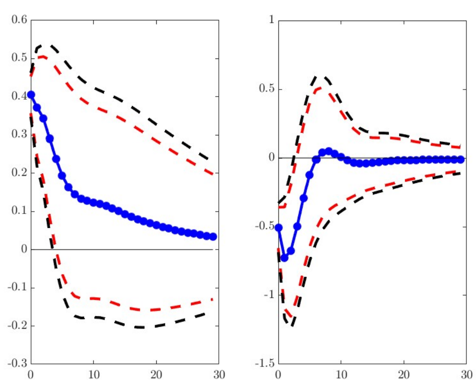
(b) Responses at the 10th percentile after neoliberalism (1985:Q1-2020:Q1)



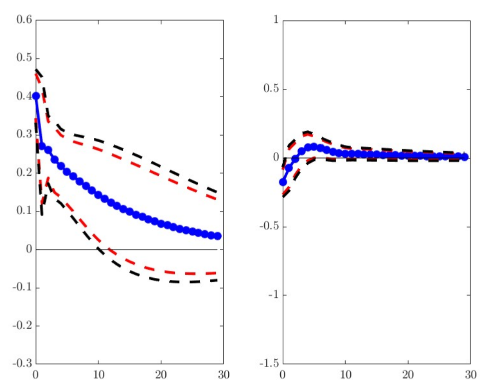
(c) Responses at the 50th percentile before neoliberalism (1948:Q1-1984:Q4)



(d) Responses at the 50th percentile after neoliberalism (1985:Q1-2020:Q1)

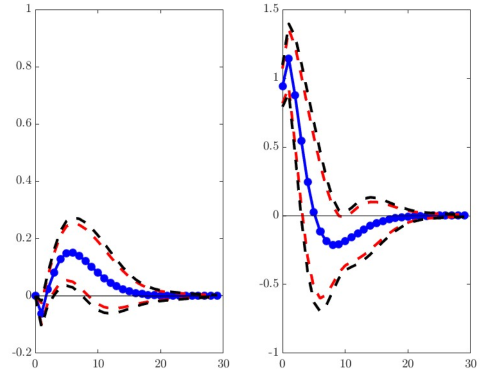


(e) Responses at the 90th percentile before neoliberalism (1948:Q1-1984:Q4)

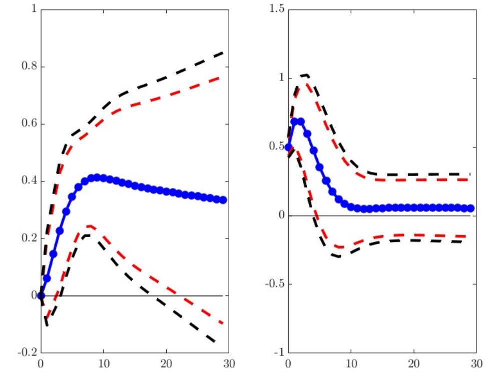


(f) Responses at the 90th percentile after neoliberalism (1985:Q1-2020:Q1)

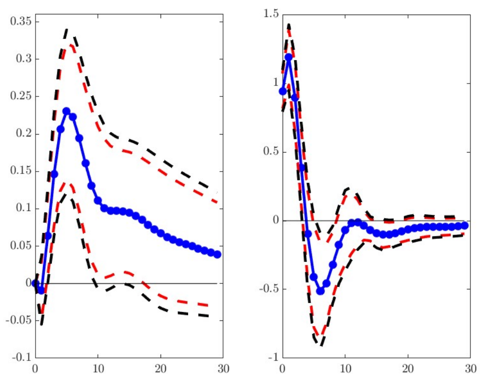
Figure 4: Responses at different percentiles of the labor share of income (leftmost figures) and the GDP growth rate (rightmost figures) to a shock to the labor share of income obtained from QVAR models BN (1948:Q1-1984:Q4) and AN (1985:Q1-2020:Q1). Red and black dashed lines correspond to the 90% and 95% confidence intervals, respectively. The horizontal axes show the number of quarters ahead.



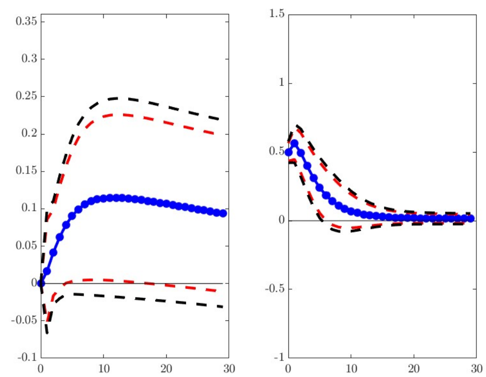
(a) Responses at the 10th percentile before neoliberalism (1948:Q1-1984:Q4)



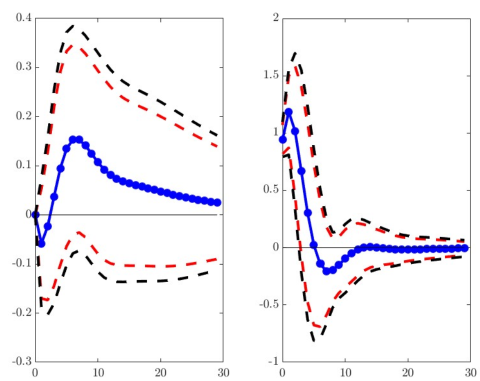
(b) Responses at the 10th percentile after neoliberalism (1985:Q1-2020:Q1)



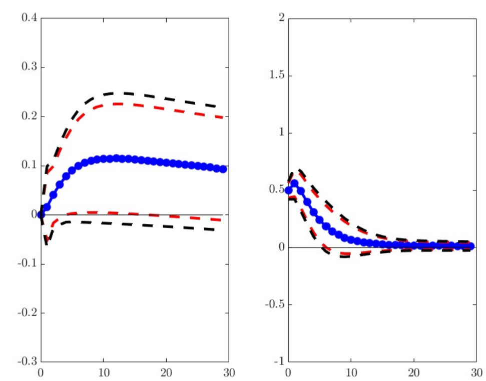
(c) Responses at the 50th percentile before neoliberalism (1948:Q1-1984:Q4)



(d) Responses at the 50th percentile after neoliberalism (1985:Q1-2020:Q1)

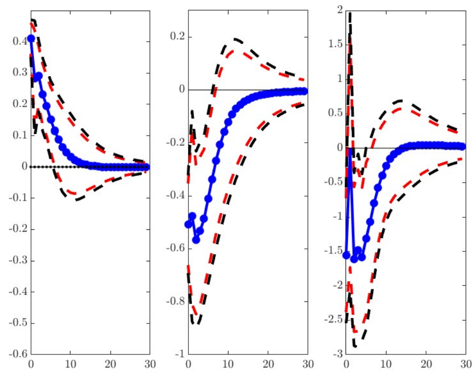


(e) Responses at the 90th percentile before neoliberalism (1948:Q1-1984:Q4)

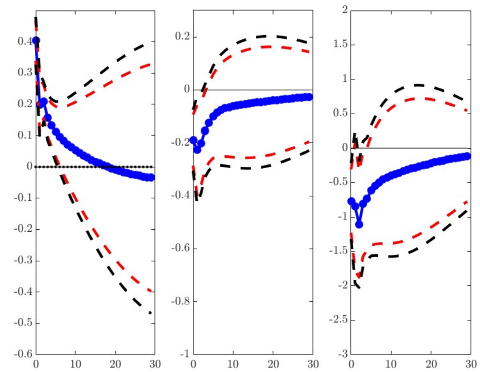


(f) Responses at the 90th percentile after neoliberalism (1985:Q1-2020:Q1)

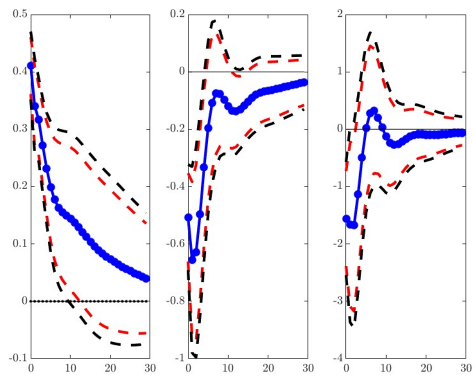
Figure 5: Responses at different percentiles of the labor share of income (leftmost figures) and the GDP growth rate (rightmost figures) to a shock to the GDP growth rate obtained from QVAR models BN (1948:Q1-1984:Q4) and AN (1948:Q1-1984:Q4). Red and black dashed lines correspond to the 90% and 95% confidence intervals, respectively. The horizontal axes show the number of quarters ahead.



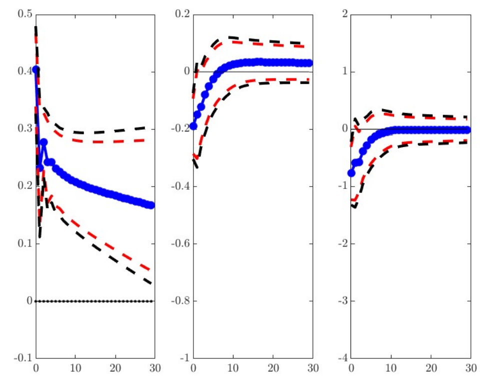
(a) Responses at the 10th percentile before neoliberalism (1948:Q1-1984:Q4)



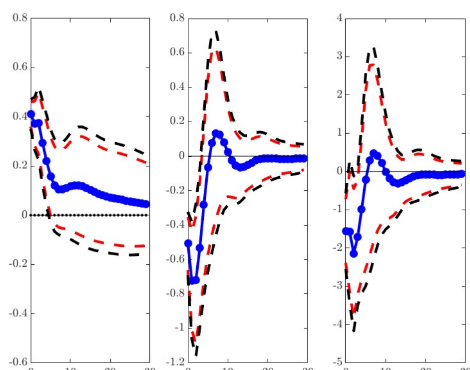
(b) Responses at the 10th percentile after neoliberalism (1985:Q1-2020:Q1)



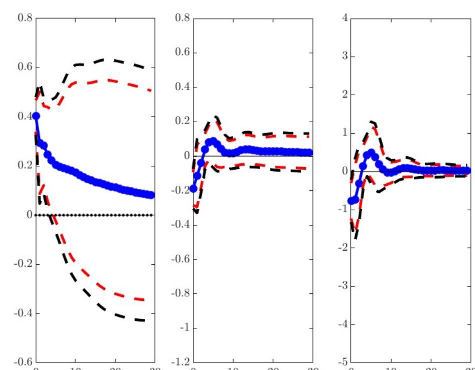
(c) Responses at the 50th percentile before neoliberalism (1948:Q1-1984:Q4)



(d) Responses at the 50th percentile after neoliberalism (1985:Q1-2020:Q1)

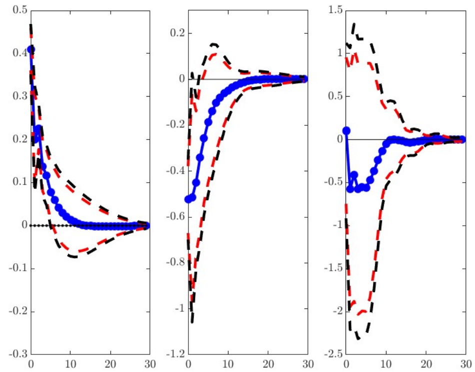


(e) Responses at the 90th percentile before neoliberalism (1948:Q1-1984:Q4)

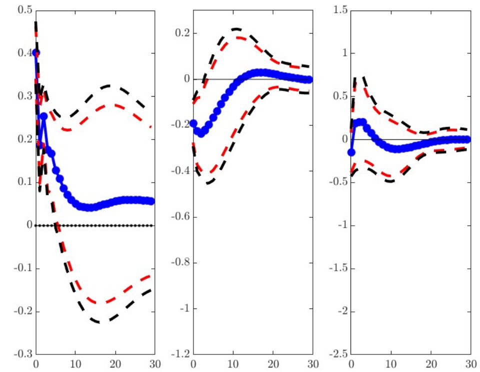


(f) Responses at the 90th percentile after neoliberalism (1985:Q1-2020:Q1)

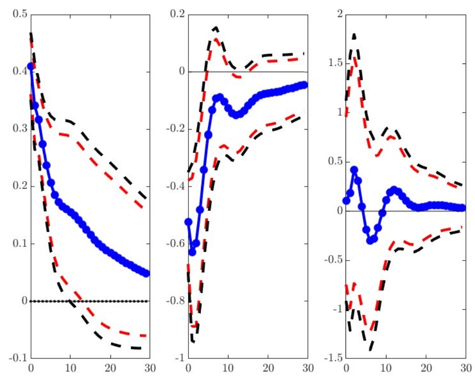
Figure 6: Responses at different percentiles of the labor share of income (leftmost figures), GDP growth rate (middle figures), and investment growth rate (rightmost figures) to a shock to the labor share of income obtained from QVAR models BN (1948:Q1-1984:Q4) and AN (1948:Q1-1984:Q4). Red and black dashed lines correspond to the 90% and 95% confidence intervals, respectively. The horizontal axes show the number of quarters ahead.



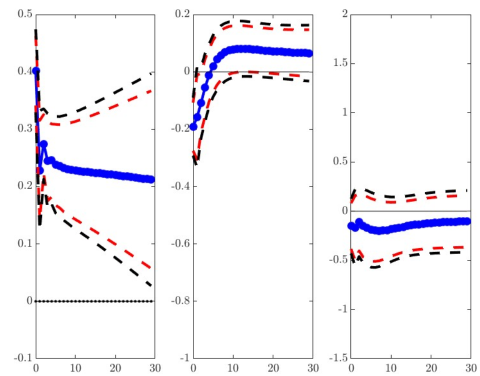
(a) Responses at the 10th percentile before neoliberalism (1948:Q1-1984:Q4)



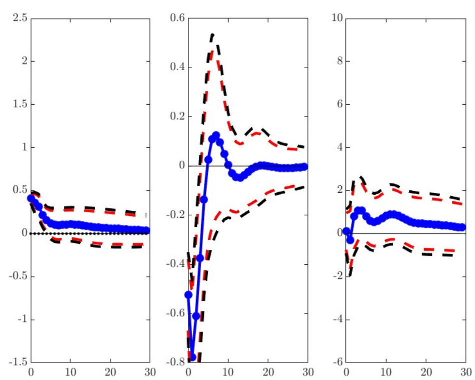
(b) Responses at the 10th percentile after neoliberalism (1985:Q1-2020:Q1)



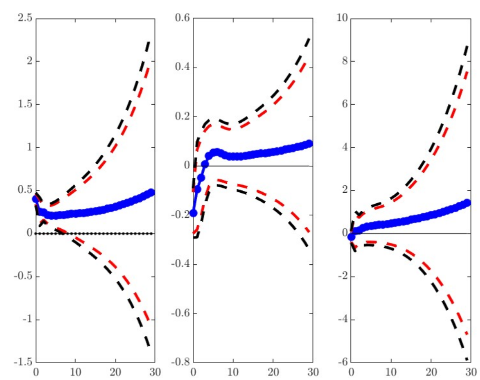
(c) Responses at the 50th percentile before neoliberalism (1948:Q1-1984:Q4)



(d) Responses at the 50th percentile after neoliberalism (1985:Q1-2020:Q1)

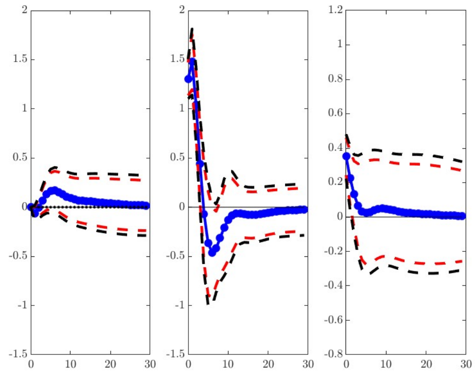


(e) Responses at the 90th percentile before neoliberalism (1948:Q1-1984:Q4)

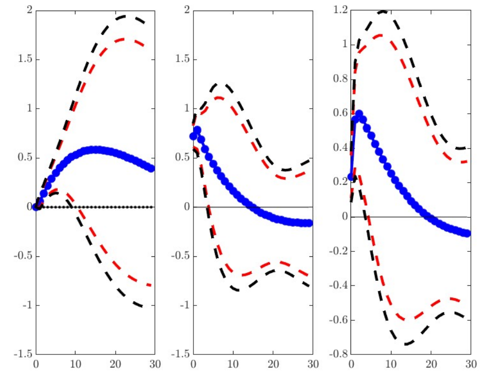


(f) Responses at the 90th percentile after neoliberalism (1985:Q1-2020:Q1)

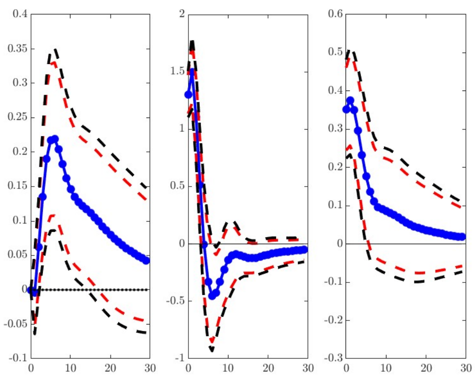
Figure 7: Responses at different percentiles of the labor share of income (leftmost figures), GDP growth rate (middle figures), and net exports growth rate (rightmost figures) to a shock to the labor share of income obtained from QVAR models BN (1948:Q1-1984:Q4) and AN (1948:Q1-1984:Q4). Red and black dashed lines correspond to the 90% and 95% confidence intervals, respectively. The horizontal axes show the number of quarters ahead.



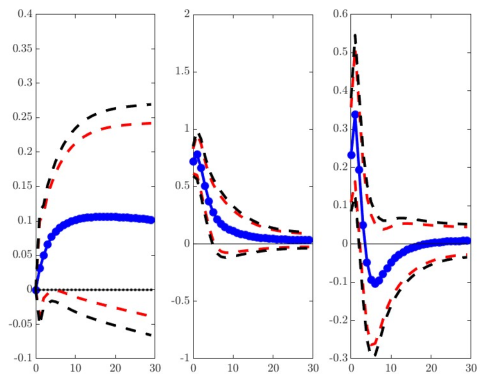
(a) Responses at the 10th percentile before neoliberalism (1948:Q1-1984:Q4)



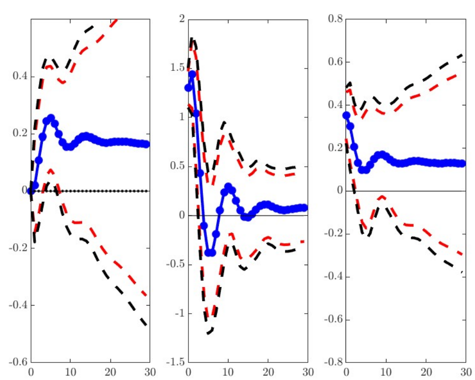
(b) Responses at the 10th percentile after neoliberalism (1985:Q1-2020:Q1)



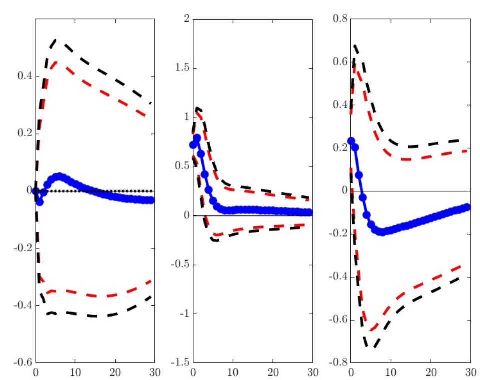
(c) Responses at the 50th percentile before neoliberalism (1948:Q1-1984:Q4)



(d) Responses at the 50th percentile after neoliberalism (1985:Q1-2020:Q1)

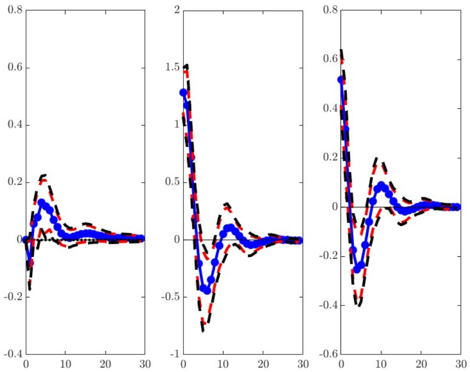


(e) Responses at the 90th percentile before neoliberalism (1948:Q1-1984:Q4)

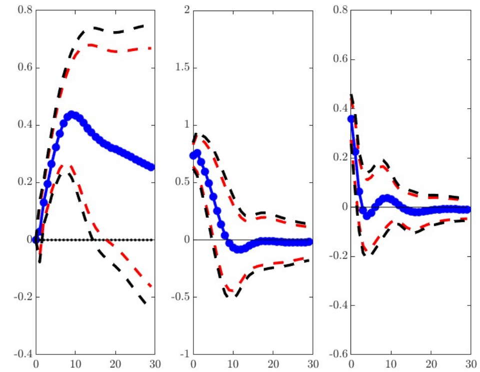


(f) Responses at the 90th percentile after neoliberalism (1985:Q1-2020:Q1)

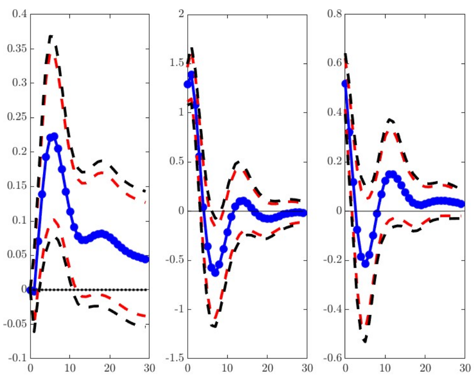
Figure 8: Responses at different percentiles of the labor share of income (leftmost figures), GDP growth rate (middle figures), and real wage growth rate (rightmost figures) to a shock to the GDP growth rate obtained from QVAR models BN (1948:Q1-1984:Q4) and AN (1948:Q1-1984:Q4). Red and black dashed lines correspond to the 90% and 95% confidence intervals, respectively. The horizontal axes show the number of quarters ahead.



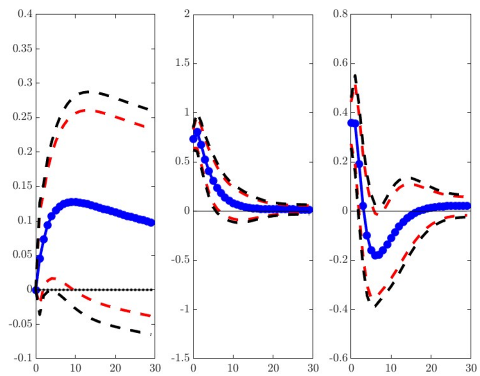
(a) Responses at the 10th percentile before neoliberalism (1948:Q1-1984:Q4)



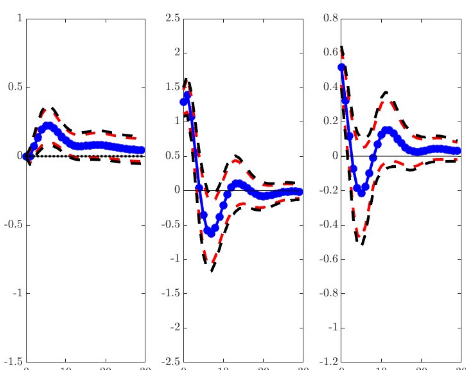
(b) Responses at the 10th percentile after neoliberalism (1985:Q1-2020:Q1)



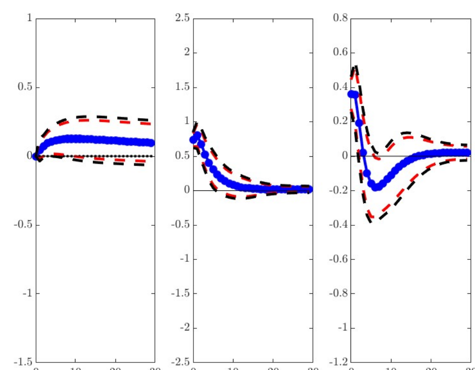
(c) Responses at the 50th percentile before neoliberalism (1948:Q1-1984:Q4)



(d) Responses at the 50th percentile after neoliberalism (1985:Q1-2020:Q1)



(e) Responses at the 90th percentile before neoliberalism (1948:Q1-1984:Q4)



(f) Responses at the 90th percentile after neoliberalism (1985:Q1-2020:Q1)

Figure 9: Responses at different percentiles of the labor share of income (leftmost figures), GDP growth rate (middle figures), and labor productivity growth rate (rightmost figures) to a shock to the GDP growth rate obtained from QVAR models BN (1948:Q1-1984:Q4) and AN (1948:Q1-1984:Q4). Red and black dashed lines correspond to the 90% and 95% confidence intervals, respectively. The horizontal axes show the number of quarters ahead.

Tables

Table 1: GDP growth rate equation, $g_t = \beta_0 + \beta_1 \psi_t + e_t$, estimated via quantile regressions at three different percentiles

Period	Intercept: β_0			Coefficient on labor share of income: β_1		
	10th^	50th^	90th^	10th^	50th^	90th^
1948:Q1-1984:Q4	102.668**	75.625**	56.376**	-1.620**	-1.133**	-0.779*
	(25.394)	(12.156)	(21.266)	(0.401)	(0.193)	(0.336)
1985:Q1-2020:Q1	8.209	-9.089*	-10.874**	-0.121	0.204**	0.252**
	(7.525)	(3.529)	(1.592)	(0.125)	(0.061)	(0.027)

Notes: Standard errors computed via the xy-pair method (Bose and Chatterjee 2003) with 5,000 replications are shown in parenthesis. ^ indicates the different percentiles; while * and ** denote significance at the 5% and 1% level, respectively.

Table 2: Descriptive statistics for the main variables before and after neoliberal capitalism

Period	Mean	Median	Standard deviation	Skewness	Kurtosis
Labor share of income: ψ_t					
1948:Q1-1984:Q4	63.26	63.20	1.18	0.08	-0.73
1985:Q1-2020:Q1	59.76	60.50	2.59	-3.16	-1.36
Real GDP growth rate: g_t					
1948:Q1-1984:Q4	3.69	3.87	3.14	-0.05	-0.31
1985:Q1-2020:Q1	2.68	2.82	1.60	-1.47	3.48
Real investment growth rate: i_t					
1948:Q1-1984:Q4	4.56	6.74	13.95	0.60	-0.02
1985:Q1-2020:Q1	3.26	4.58	7.58	5.17	-1.69
Real wage growth rate: w_t					
1948:Q1-1984:Q4	1.94	1.98	1.51	-0.28	-0.02
1985:Q1-2020:Q1	1.07	1.07	1.67	-0.51	0.14
Labor productivity growth rate: p_t					
1948:Q1-1984:Q4	2.31	2.30	1.99	-0.33	-0.06
1985:Q1-2020:Q1	1.92	1.71	1.38	0.27	0.70

Notes: All variables were measured in percentages.