Inequality and the Business Cycle: Evidence from U.S. Survey Data

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Abstract

We study the effects of macroeconomic shocks on measures of economic inequality obtained from U.S. survey data. To identify aggregate supply, aggregate demand, and monetary policy shocks, we estimate vector autoregressions and impose sign and zero restrictions on impulse response functions. We find that the effects of the macroeconomic shocks on inequality depend on the type of shock as well as on the measure of inequality considered. Contractionary monetary policy shocks increase expenditure and consumption inequality, whereas income and earnings inequality are less affected. Adverse aggregate supply and demand shocks increase income and earnings inequality, but reduce expenditure and consumption inequality. Our results suggest that different channels dominate in the transmission of the shocks. The earnings heterogeneity channel is consistent with the inequality dynamics after monetary policy shocks, but it appears to be less crucial when the economy is hit by either aggregate supply or aggregate demand shocks. Using variance decompositions, we find that although the macroeconomic shocks account for large shares of the variation in the macroeconomic variables, their contributions to the dynamics of the inequality measures are limited.

Key words: Macroeconomic Shocks, Inequality, Structural Vector Autoregression, Zero and Sign Restrictions

JEL codes: E00, E32, D63

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1 Introduction

We study empirically how inequality responds to macroeconomic shocks that are generally considered to be the main driving forces behind the business cycle. While rising inequality is an extensively discussed topic, the potential role of business cycle dynamics has only received limited attention (Barlevy and Tsiddon 2006; Heathcote et al. 2010). Macroeconomic shocks can influence inequality through various channels. If the economy is hit by shocks, labor earnings are likely to fluctuate and according to the so-called earnings heterogeneity channel, earnings should be affected differently depending on where the household is located in the earnings distribution. Households at the bottom of the distribution are disproportionately affected by recessions and a general rise in unemployment (Hoynes et al. 2012; Guvenen et al. 2014). In addition, according to the income composition channel, different income categories may be exposed to changes in economic activity, and thus macroeconomic shocks, to different degrees. The savings redistribution channels suggests that fluctuations in the inflation rate give rise to changes in inequality since the real value of nominal assets and liabilities varies across groups of households (Doepke and Schneider 2006). In addition, inflation also influences the real interest rate which can have distributional effects through its effect on asset prices (Auclert 2015).

These channels give rise to potentially counteracting effects on inequality. Consider for instance the earnings heterogeneity channel. According to this channel, households at the bottom of the income distribution should be more strongly affected by an adverse shock, giving rise to higher inequality. The savings distribution channel, in contrast, predicts that the real losses in asset values should primarily affect high net-worth households. Thus, the overall effect is ambiguous and depends on the relative strengths of the individual channels.

We estimate vector autoregressive (VAR) models with quarterly U.S. macroeconomic data and inequality measures, and identify structural shocks by imposing combinations of zero and sign restrictions on the impulse responses of the macroeconomic variables.[1] Specifically, we focus on aggregate demand (AD), aggregate supply (AS), and monetary policy (MP) shocks, as it is well known that these shocks account for almost the entire variation of macroeconomic variables over the business cycle (Smets and Wouters 2007). We restrict prices and economic activity to move in opposite directions following an AS shock, whereas we restrict these two variables to move in the same direction in response to an AD shock. From a more structural point of view, AS and AD shocks represent broad categories of shocks. In standard DSGE models, the

[1] The necessary sign restrictions to identify these shocks are standard and frequently used in the literature (see e.g. Smets and Wouters 2005; Peersman 2005; Smets and Wouters 2007; Fry and Pagan 2011).

dynamics associated with an AD shock are consistent with e.g. consumer preference shocks and exogenous spending shocks, whereas AS shocks represent shocks to e.g. technology, price mark-ups, and wage mark-ups.

Our analysis is closely related to Coibion et al. (2017) and Mumtaz and Theophilopoulou (2017) who explore the effects of MP shocks on inequality. For the U.S., Coibion et al. (2017) show that contractionary MP shocks increase inequality. Similar results are presented in Mumtaz and Theophilopoulou (2017) using U.K. data. We follow Coibion et al. (2017) and use Gini coefficients for total income, labor earnings, consumption, as well as total expenditure based on household-level data from the Consumer and Expenditure Survey (CEX).[2] While we use the same data set as Coibion et al. (2017), our analysis differs in terms of the estimation methodology and with respect to the identification approach. Coibion et al. (2017) estimate the effects of narrative monetary policy shocks suggested by Romer and Romer (2004) using the local protection framework introduced by Jordà (2005). In contrast, we study the responses of inequality proxies in a VAR framework and impose zero and sign restrictions to identify the shocks. Although the local projection method provides a flexible way to estimate impulse responses functions, it requires regressors that can be interpreted as exogenous shocks. Therefore, this approach is not suitable for our purposes since proxies for AD and AS shocks are not readily available. Sign restrictions, in contrast, allow us to simultaneously identify different types of shocks in a unified framework. Mumtaz and Theophilopoulou (2017) also apply a sign restriction approach, but their focus is on MP shocks, while we identify multiple shocks, including a MP shock. Our paper is also related to Furceri et al. (2018), who construct an MP shock measure as the change in the short-term interest rate that is orthogonal to unexpected changes in real growth and inflation and show that contractionary MP shocks increase income inequality using a panel data set that includes developed and emerging economies. We contribute to this strand of the literature by studying the effects of macroeconomic shocks more broadly rather than focusing exclusively on the monetary policy shock.

Our findings indicate that contractionary monetary policy shocks result in higher expenditure as well as consumption inequality, while income and earnings inequality are less affected, which corroborates the results reported by Coibion et al. (2017), Mumtaz and Theophilopoulou (2017), and Furceri et al. (2018). At a more disaggregated level, we find that the responses to a monetary policy shocks are primarily driven by a widening gap between the 50th and the

[2] We also consider the cross-sectional standard deviation as well as the differences between the 90th and 10th percentiles as additional inequality measures.

10th percentile of the expenditure and consumption distributions. We also find that income and earnings inequality increase after adverse aggregate demand and aggregate supply shocks, whereas expenditure and consumption inequality tend to decline. While the responses of the Gini coefficients to AD shocks are mainly due to adjustments at the bottom of the expenditure and consumption distributions, it is primarily the top part of the distribution that matters in case of AS shocks.

According to a forecast error variance decomposition each of the shocks explains well below 10 percent of the unexpected variation of inequality regardless of the inequality measure and the forecast horizon, despite the fact that the shocks explain sizable shares of the variation of the macroeconomic variables. Thus, while our results confirm that these shocks can be considered driving forces behind the business cycle, their influence on the dynamics of inequality is limited.

Overall, we find that the effects that macroeconomic shocks exert on inequality depend on the type of shock as well as on the inequality measure considered. While our results suggest that although the earnings heterogeneity channel is consistent with the inequality dynamics in the aftermath of monetary policy shocks, it appears to be less crucial when the economy is hit by either AS or AD shocks.

The rest of the paper is structured as follows: Section 2 discusses the data set and the estimation methodology and Section 3 presents the results. Section 4 provides a discussion of the economic channels at play and Section 5 presents a series of robustness checks. Section 6 concludes the paper.

2 Data and Estimation

2.1 Measures of inequality

We rely on the inequality measures from Coibion et al. (2017) who exploit individual level information on expenditures, income, and demographic characteristics elicited through the Consumer Expenditure Surveys (CEX).[3] Each cross-section comprises approximately 1500 to 2000 households. The CEX is available quarterly since 1980 and although the data is primarily used to revise the relative importance of goods and services in the market basket of the Consumer Price Index (CPI), it can also be used for the construction of inequality measures (Gini coefficients, 90th-10th percentiles, cross-sectional standard deviations) at high frequency.

Following Coibion et al. (2017), we consider inequality in labor income, total income, consumption and, total expenditures. Total income includes labor earnings as well as financial

[3] The data is available through Lorenz Kueng's homepage (`lorenzkueng.droppages.com/`).

income, business income and transfers. Consumption is defined as the sum of non-durables (e.g. food and gasoline), services, plus some smaller durable goods (furniture, jewelry, household appliances, entertainment goods like televisions). This category does not include larger durable goods purchases such as houses and cars. Expenditures include the consumption category and larger durable consumption goods plus medical supplies and services, education expenses, mortgage payments, and the like. In line with Coibion et al. (2017), we only use data until 2008q4 to avoid the kink in the Federal Funds rate.

2.2 Estimation

We estimate reduced-form VAR models of the type

$$x_t = c + \sum_{l=1}^{L} B_l x_{t-l} + e_t,$$

where x_t is a vector of endogenous variables, c is the constant, B_l is the matrix of reduced-form coefficients at lag l, and e_t is a vector of residuals with covariance matrix $\Sigma_e = E(e_t e_t')$. We estimate the VAR at $L = 4$ lags due to the quarterly frequency, however, we replicate the estimations with $L = 2$ as this is the optimal lag length suggested by the information criteria. The vector of endogenous variables contains the aggregated inequality measures along with macroeconomic data, which we use for the identification of AD, AS and MP shocks. As in Coibion et al. (2017), the inequality measures enter in first differences. Survey responses on consumption and total expenditures are available for more than one quarter. Therefore the first difference of inequality can be calcuted using respondents that are surveyed in both periods. This ensures that changes in inequality are not due to changes in the composition of respondents.

In the baseline estimation we include the seasonally adjusted civilian unemployment rate,[4] the inflation rate calculated as the annual growth rate of the seasonally adjusted CPI for urban consumers (i.e. inflation rate), and the Federal Funds rate (FFR) available through the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis.

2.3 Identification

We impose a combination of sign and zero restrictions on the impulse response functions to identify AD, AS, and MP shocks. Table 1 summarizes our identification scheme. In response to an adverse AD shock, economic activity and inflation decline. In the baseline specification,

[4] We also use the log of the real GDP as a proxy for economic activity in a robustness analysis.

we use the unemployment rate as a proxy for economic activity. Hence, we restrict the unemployment rate to increase and the inflation rate to decrease. According to a Taylor rule, the central bank responds to this shock by lowering the interest rate. Consequently, we restrict the policy rate to go down. Standard macroeconomic models predict that AS shocks, such as price mark-up shocks, wage mark-up shocks, or technology shocks (see e.g. Smets and Wouters 2007), move economic activity and inflation in opposite directions. Consistent with this, we restrict the unemployment rate and the inflation rate to go up. In addition, we restrict the response of the policy rate to increase. Here we essentially assume that the central bank puts relatively more weight on price stability in its objective function. Finally, to identify MP shocks we impose the restrictions that along with an increase in the interest rate, the unemployment rate rises and the inflation rate decreases. These restrictions are consistent with standard macroeconomic models (e.g. Smets and Wouters 2005, 2007) and are used widely in the empirical literature (Fry and Pagan 2011). All sign restrictions are imposed on impact plus the consecutive quarter.

In addition, we impose exclusion restrictions on the impulse response functions of the macroeconomic variables in case of the residual shocks. These restrictions allow us to disentangle exogenous shocks to inequality from endogenous responses of the inequality measures to the macroeconomic shocks. The intuition is that while inequality is permitted to respond to the macroeconomic shocks within the quarter, macroeconomic variables are assumed to be contemporaneously predetermined with respect to exogenous inequality shocks.

2.4 Algorithm

We estimate the reduced-form VAR using Bayesian methods with the Normal-Wishart distribution as a flat prior density for the reduced form coefficients. The posterior density of the reduced form coefficients is therefore Normal-Wishart with the location parameters $B = [B_1, \ldots, B_L]'$ and the covariance matrix Σ_e (Uhlig 1994). To identify structural shocks we apply a zero-and-sign-restrictions algorithm based on Rubio-Ramirez et al. (2010) and Arias et al. (2018), which works as follows: For each draw from the distribution of the reduced form parameters, we take the Choleski factor of $\Sigma_e = PP'$ and use random orthogonal matrices Q (where $Q'Q = I$) to obtain alternative decompositions $\Sigma_e = PQQ'P'$, and orthogonal shocks $u_t = (PQ)^{-1}e_t$. Employing the Gram-Schmidt algorithm, the matrix Q is constructed recursively such that the zero restrictions are fulfilled. We draw 500 candidate models from the posterior distribution of reduced from posterior and keep those for which we can find a permissible SVAR representation.[5]

Since the system is set-identified, the prior is only flat over the reduced form coefficients but not necessarily over the structural coefficients as the decomposition of the variance-covariance matrix Σ using random orthogonal matrices Q (where $Q'Q = I$) incorporates an implicit prior distribution (Baumeister and Hamilton 2015, 2017). However, as shown in Giacomini and Kitagawa (2015), inference is less sensitive to the distribution of Q if zero restrictions are imposed.

3 Results

In this section we present a discussion of impulses response functions and forecast error variance decompositions to investigate the effects of business cycle shocks on measures of economic inequality.

3.1 Impulse response analysis

Figure 1 shows the impulse response functions. The solid lines represent the pointwise-median responses, whereas the dashed lines represent the closest-to-median responses selected as proposed in Fry and Pagan (2011).[6] The bands indicate the 16th and the 84th percentiles of the identified models at each horizon. Panel A shows the responses of the macroeconomic variables and Panel B shows the cumulated responses of the Gini coefficients. Responses to MP shocks are shown in the first column, responses to AD shocks are in the second column and responses to an AS shock are in the third column.

We see from Panel A that the responses of the macroeconomic variables are fairly standard (Peersman 2005; Fry and Pagan 2011). Although we impose the sign restrictions only on impact plus one quarter, the majority of the responses are rather persistent, indicating that the restrictions are generally well supported by the data. The unemployment rate increases initially in response to a MP shock, but the effect fades out after two quarters. Following an AD shock,

[5] To obtain the permissible SVAR models we iterate the algorithm 500 times in the following steps. We draw one set of parameters from the posterior distribution of the reduced form VAR. For this set of parameters we check whether we can find a transformation that is admissible in terms of the sign restrictions. Specifically, we keep drawing Q matrices until either a permissible transformation is found (then we retain the candidate model and proceed with the next iteration of the algorithm) or a maximum number of 500 draws of the matrix Q is reached (then we proceed without retaining any model). In most cases we find a permissible model for the respective draw from the posterior distribution of the reduced form models, which is reassuring in terms of the empirical plausibility of the imposed sign restrictions (Giacomini and Kitagawa 2015). In the baseline estimation, we find 417 permissible SVAR models out of the 500 draws from the posterior of reduced form models.

[6] The closest-to-median responses are the responses from a single model which is selected such that the responses of this single model exhibit the minimum squared deviations from the pointwise-median responses among all permissible models.

the increase is more persistent and in response to an AS shock, the unemployment rate remains above its pre-shock level for more than two years. We observe the most protracted responses of the inflation rate and the interest rate in case of AD shocks.

Panel B displays the impulse response functions for the Gini coefficients. We see from the first column that although income and earnings inequality respond only unsystematically and largely insignificantly to the MP shocks,[7] expenditure inequality and also consumption inequality, albeit to a lesser extent and not significantly, increase. The effect on expenditure inequality is rather persistent. Overall, these findings confirm the results in Coibion et al. (2017) and Mumtaz and Theophilopoulou (2017).

Turning to the responses to an adverse AD shock reported in the second column, we see that income and earnings inequality initially increase, but decline below their pre-shock levels over the medium run. Expenditure and consumption inequality start to decline immediately in response to the shock. The response is more pronounced for expenditure inequality, but only short-lived and small for consumption inequality. The responses to the adverse AS shock are displayed in the last column. Here, we also observe that income and earnings inequality tend to increase, where the effect is somewhat less pronounced for income inequality. In contrast, the expenditure and consumption Gini coefficients decline. Thus, for AD and AS shocks, we observe a decoupling of the dynamics of consumption and expenditure inequality from income and earnings inequality.

Overall, we conclude that although all shocks give rise to recessionary effects in the sense of a higher unemployment rate, the effect on inequality depends on the type of shock and also the inequality measure under consideration. While declines in economic activity induced by an exogenous tightening of monetary policy gives rise to higher expenditure and consumption inequality, contractionary AD and AS shocks reduce expenditure and consumption inequality. As we will discuss in greater detail in Section 4, these findings suggest that different channels dominate the dynamics of the inequality measures depending on the type of shock.

3.2 Variance decompositions

To understand how important macroeconomic shocks are for the dynamics of economic inequality, we compute forecast error variance decompositions (FEVD) for the identified models. Table 2 shows the median of contributions of the macroeconomic shocks at selected horizons h, together with the 16th and 84th percentiles, for the macroeconomic variables (Panel A) and the

[7] For simplicity, we refer to an impulse response as being significant if the zero line lies outside the credibility bound.

inequality measures (Panel B).

We see from Panel A of Table 2 that the AD shock accounts for more than 70 percent of the variation in the unemployment rate and in the Federal Funds rate over shorter horizons. While the contributions to the dynamics of the inflation rate are lower, they still range from roughly 20 to 33 percent. The AS shock provides the largest contribution to the unexpected variation in the inflation rate, especially on impact. And the MP shock accounts for up to 37 percent of the forecast error of the Federal Funds rate. Thus, we conclude that the structural shocks explain the forecast error variance of the macroeconomic variables almost entirely. Overall, the shares of the forecast error variance accounted for by the shocks are of similar orders of magnitude as in other studies (see e.g. Smets and Wouters 2007; Ramey 2016).

Panel B of Table 2 presents the variance decomposition of the inequality measures. Across shocks, the contributions to the respective inequality measures are of comparable orders of magnitude. In contrast to the macroeconomic variables, the structural shocks generally explain only small shares of the forecast error variance of the Gini coefficients. Specifically, the contributions of the shocks range from negligible shares for shorter horizons to up to roughly 8.50 percent for longer horizons in some cases. Thus, although the identified shocks explain substantial shares of the variation of the macroeconomic variables, their contributions to the forecast error variance of the inequality measures remain limited.

3.3 Disaggregated Data

To obtain a more detailed picture of how inequality measures are influenced by the macroeconomic shocks, we re-estimate our baseline VAR and report the percent change of the 90th, 50th, and 10th percentile of the income, earnings, expenditure, and consumption distribution.

Figures 2, 3, and 4 summarize the responses to MP, AD, and AS shocks. As expected, adverse macroeconomic shocks tend to affect income, earnings, expenditure, and consumption negatively. However, we observe several differences across shocks and across measures.[8]

According to the subfigures in the first row of Figures 2, income developments are barely affected by the monetary policy shock regardless of the position in the income distribution.

[8]It has to be noted that income and earnings are not elicited in consecutive quarters. Therefore, the changes of different percentiles of the earnings and income distribution may also reflect compositional changes. Consumption and expenditures, in contrast, are elicited from households each quarter, which allows us to take account of potential changes in composition and households through the composition of the sample across periods when measuring the changes in consumption and expenditures by percentile each quarter. Specifically, following Coibion et al. (2017) households are ranked according to either their consumption or expenditures. Then, households near the 90th, 50th, and 10th percentiles are isolated, and the percent changes in their consumption and expenditures is considered. Applying this procedure each quarter yields a time series of changes for each percentile controlling for composition effects.

While this is also true for earnings dynamics in 50th and the 10th percentile of the earnings distribution, as shown in the second row, we also observe a strong and significant decline in the 10th percentile, which is consistent with the earnings heterogeneity channel. These developments are mirrored in increases in expenditures in the 50th and 90th percentile and the decline in the 10th percentile. To some extent we also observe a similar pattern for consumption, albeit the responses are largely insignificant in the 10th and the 90th percentile. Thus, we conclude that the increase in the expenditure and consumption Gini coefficients in response to contractionary MP shocks reported above is primarily driven by a widening of the gap between the 50th and the 10th percentile.

Following an AD shock, we see from Figure 3 that income and earnings decline in each percentile, with stronger reactions in the 10th percentile, especially for earnings. Thus, we again find evidence in favor of the earnings heterogeneity channel. Nevertheless, expenditure and consumption evolve somewhat differently here. While we observe generally insignificant responses in the 50th and 90th percentiles, with the exception of consumption in the 50th percentile, expenditure and consumption even tend to increase over the medium run in the 10th percentile, although only marginally significantly. Hence, the responses of spending Gini coefficients to AD shocks are driven by adjustments in the bottom and top percentiles.

Finally, turning to the responses to the AS shock shown in Figure 4, we see that income and earnings decline significantly. The response of earnings in the 10th percentile is an exception here, but the response is also rather imprecisely estimated. Hence, the earnings heterogeneity channel appears to play only a limited role in the aftermath of AS shocks. Expenditure and consumption are rather unresponsive in the 50th percentile and decline significantly in the 90th percentile and, to a lesser extent, also in the 10th percentile. In other words, the lower spending inequality in response to adverse AS shocks occurs primarily through reduced spending in the top part of the distribution consistent with the savings redistribution channel.

4 Discussion

In the previous section we have shown that although contractionary MP shocks lead to higher expenditure and consumption inequality, contractionary AS and AD shocks give rise to declines in these inequality measures. Although a structural analysis of the channels that are at work is beyond the scope of the paper, we now provide a discussion of how potential channels, which have been emphasized in the literature, may contribute to the reported responses of inequality to shocks.

According to the earnings heterogeneity channel households located at the bottom of the earnings distribution are the ones most at risk of falling behind even further during economic downturns. Our results reported in Section 3.4 suggest that labor earnings decline disproportionately in response to contractionary monetary policy and aggregate demand shocks, but not in the aftermath of aggregate supply shocks. In addition, earnings losses associated with adverse aggregate supply and demand shocks do not appear to feed through to consumption and expenditure in the bottom percentiles. Thus, while our results are consistent with an active earnings heterogeneity channel for the transmission of monetary policy shocks to inequality, in line with the interpretation in Coibion et al. (2017), this channel appears to be less important for the transmission of aggregate demand and aggregate supply shocks.

The savings redistribution channel and the real interest rate exposure channel emphasize wealth effects. According to the savings redistribution channel, a front-loaded unanticipated increase in inflation gives rise to a wealth transfer from high net-worth households to low net-worth households. And the real interest rate exposure channel (see e. g. Auclert 2015) holds that changes in the real interest rate affect households differently depending on net assets, liabilities, and the maturity of those, which, in turn, influences inequality.

Since the percentiles of the distribution of households are only to a certain degree informative about a household's asset holdings and net-worth and since the CEX survey does not offer reliable information to infer respondents' wealth directly, we follow Coibion et al. (2017) and classify households according to their demographics as a proxy for their net-worth.[9] For each group of households, we calculate average income, labor earnings, expenditure, and consumption (in log-levels) and take the difference between the group averages.

Figure 5 shows the responses of the differences between high and low net-worth households are largely unsystematic following a monetary policy shock. Thus, neither the lower inflation rate nor any induced changes in the real interest rate give rise to wealth effects that are pronounced enough to lead to significant changes the differences between high net-worth and low net-worth households.

The figure also shows that following an adverse AD shock, inflation declines. While high net-worth households should benefit from the lower inflation rate according the savings redistri-

[9]Low net-worth households are 30 to 40 years old, white, with a male head in the household, have no financial income, and positive mortgage payments. By contrast, high net-worth households are 55 to 65 years old, white households with a male head in the household, have positive financial income, and have no mortgage payments. See also Doepke and Schneider (2006), who argue that high net-worth households are older ones and own their homes and receive financial income, while lower net-worth households are younger, have fixed rate mortgages, and receive no financial income. Kumhof et al. (2015) documents a large increase in debt leverage of low-income and middle-income households from 1983 onward, which in turn, increases the importance of this effect.

bution channel, the rather pronounced decline in the interest rate suggests that the real interest rate also declines, which should benefit low net-worth households according to the real interest rate exposure channel. We see that with the excepton of earnings, the differences between high net-worth and low net-worth households decline significantly, which is consistent with the real interest rate exposure channel.

Finally, turning to the responses to the AS shock displayed in the last column, we see that differences between high net-worth and low net-worth households tend to increase. Although these responses suggest that low net-worth households are adversely affected to a larger degree than high net-worth households, which is at odds the savings redistribution channel and the real interest rate exposure channel, the responses are generally weak.

In short, the differences between high and low income households are largely unresponsive following MP and AS shocks, which suggests that wealth effects play only a minor role in the aftermath of these shocks. Nevertheless, the dynamics induced by AD shocks are consistent with the interpretation that low net-worth households benefit from lower real interest rates.

5 Robustness Analysis

In this section we present a number of robustness checks to support our results.

5.1 Other measures for inequality

In addition to responses of the Gini coefficients, Figures 6, 7, and 8 summarize the responses of the other measures we consider to proxy cross-sectional inequality. I.e., the standard deviation, and the difference between the 90th and the 10th percentile of the distribution of income, earnings, consumption and expenditures. To assess the effects of the macroeconomic shocks onto these measures, we replicate the estimations from above but use either standard deviations or the difference between the 90th and the 10th percentile instead of Gini coefficients. The picture emerging from the responses of these alternative measures of inequality is overall similar to the responses of the Gini coefficients. That is, we observe less systematic responses of income and earnings inequality compared to expenditure and consumption inequality. In addition, expenditure and consumption inequality tends to go up in case of the MP shock while it goes down in case of AD and AS shocks.

5.2 Alternative identification of AS shocks

To disentangle AS from AD and MP shocks using sign restrictions, it is not necessary, per se, to impose a restriction on the response of the policy rate in case of the AS shock. Figure 9 shows the responses of the macroeconomic variables and the Gini coefficients corresponding to an identification scheme without the restriction on the policy rate in case of the AS shock.

Considering the third column showing the responses to AS shocks, it turns out that if we leave the response of the policy rate unrestricted, the policy rate tends to decline following an AS shock. This has some interesting implications for our analysis, as this effectively shuts down, or even reverses the response of nominal interest rates in the propagation of the AS shock to inequality.

Interestingly, even though the policy rate tends to respond in a different direction, responses in inequality are largely unaffected similar to those obtained with our baseline specification. A plausible explanation for this similarity is that, as in the baseline, the real interest rate tends to go down. In fact, it does so to an even larger extent without the sign restriction on the FFR. This somewhat suggests that ultimately the real interest rate rather than nominal interest rates matter for the effects of AS shocks on inequality.

5.3 Further robustness checks

While we estimate the reduced form VAR using four lags in the baseline specification to impose only weak restrictions on the dynamics, the optimal lag length suggested by information criteria tends to be two. Thus, we replicate the baseline estimation using two lags. Figure 10 shows the responses to MP, AD, and AS shocks. The results obtained from the different lag specification are closely comparable to the baseline results which supports the robustness of our results.

Finally, we use an alternative output measure, namely the logarithm of the real gross domestic product (GDP). Figure 11 shows the responses to MP, AD, and AS shocks. Even though the responses of the Gini coefficients summarizing expenditure and consumption inequality to AD shocks are slightly more dispersed, overall, a very similar picture emerges from this analysis which corroborates the robustness of the baseline results.

6 Summary

We use vector autoregressive models to study the responses of different measures of inequality to macroeconomic shocks. Our results suggest that although inequality in expenditures and consumption tends to rise following a contractionary MP shock, the effect on income and earnings inequality is rather unsystematic. Also following AS and AD shocks, income and earnings inequality do not react very systematically. However, we find that expenditures and consumption inequality tends to decline in response to adverse AD and AS shocks. Thus, the shocks give rise to different dynamics in economic inequality and the overall effect depends on the type of the shock hitting the economy.

Finally, while AD, AS and MP shocks are the main drivers of the business cycle, in the sense that they account for almost the entire variation in the macroeconomic variables, they account only for a limited amount of the variation in inequality. We thus conclude that inequality is not primarily a business cycle phenomenon.

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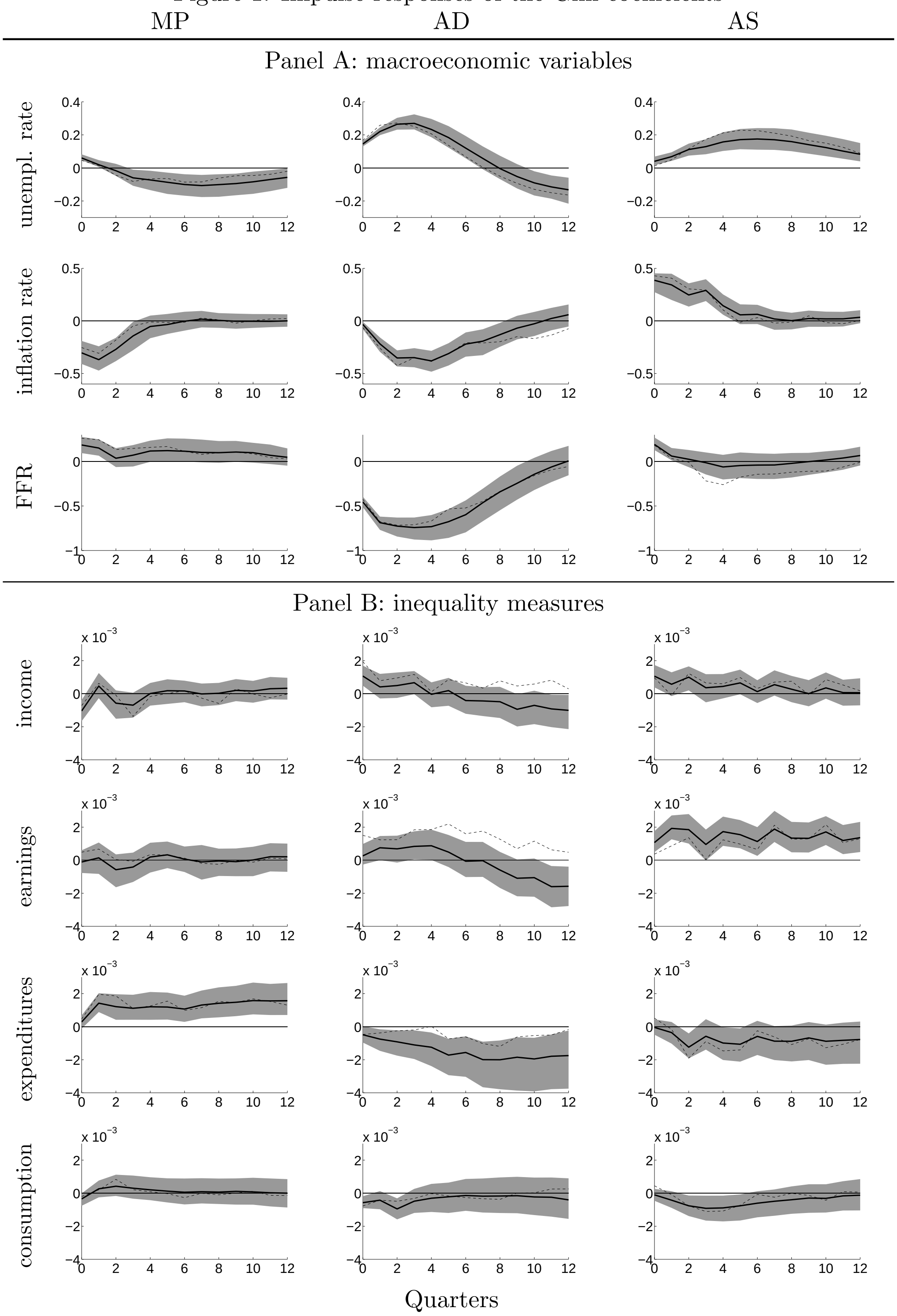
Table 1: Sign restrictions on the impulse responses

	AD	AS	MP	Residual 1	Residual 2	Residual 3
unemployment rate	↑	↑	↑	0	0	0
inflation rate	↓	↑	↓	0	0	0
FFR	↓	↑	↑	0	0	0
income inequality						
earnings inequality						
expenditure inequality						
consumption inequality						

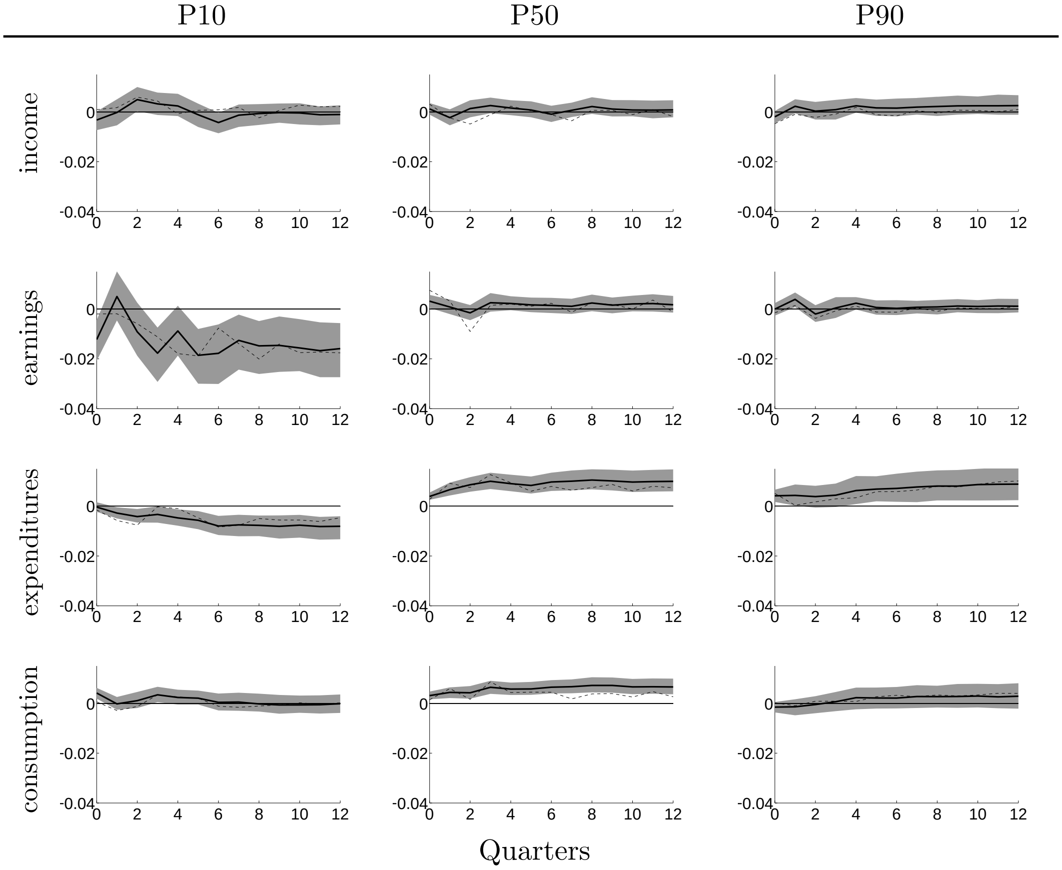
Notes: Sign restrictions on the macroeconomic variables are imposed on impact plus one quarter.

Figure 1: Impulse responses of the Gini coefficients



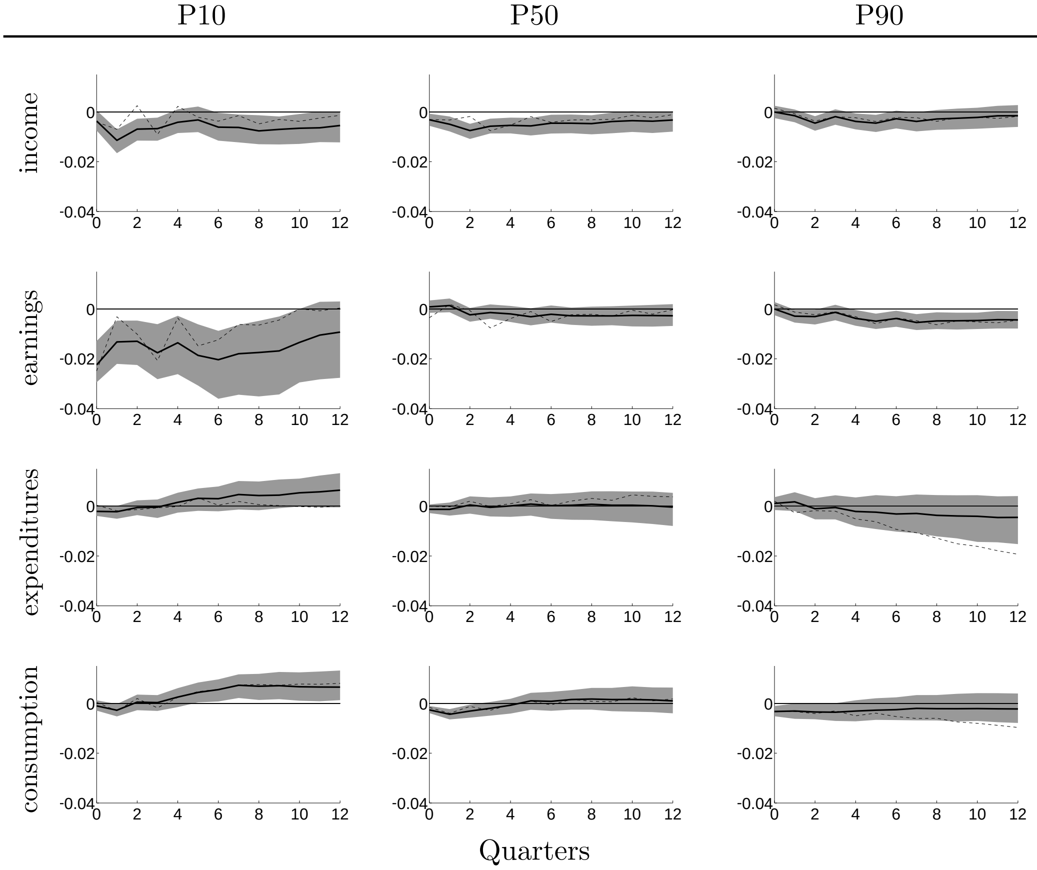
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles. A rise in the Gini index indicates higher inequality.

Figure 2: Impulse responses of percentiles to MP shocks



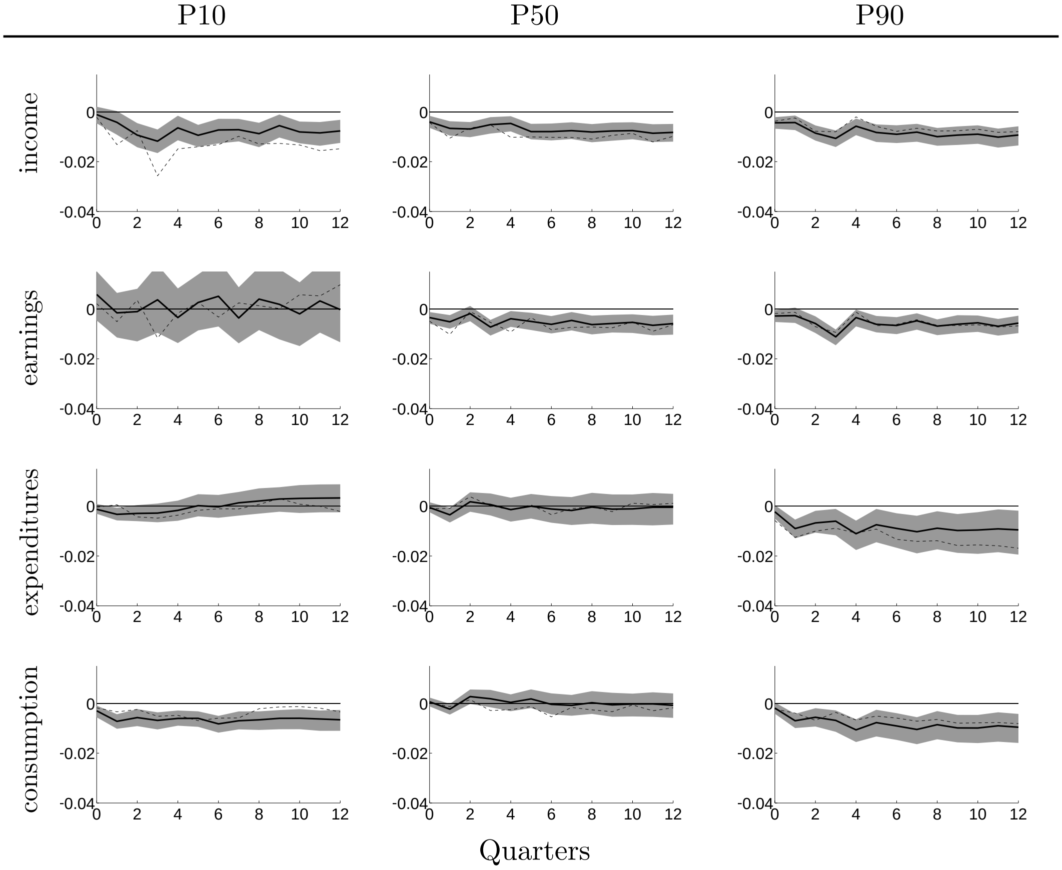
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles.

Figure 3: Impulse responses of percentiles to AD shocks



Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles.

Figure 4: Impulse responses of percentiles to AS shocks



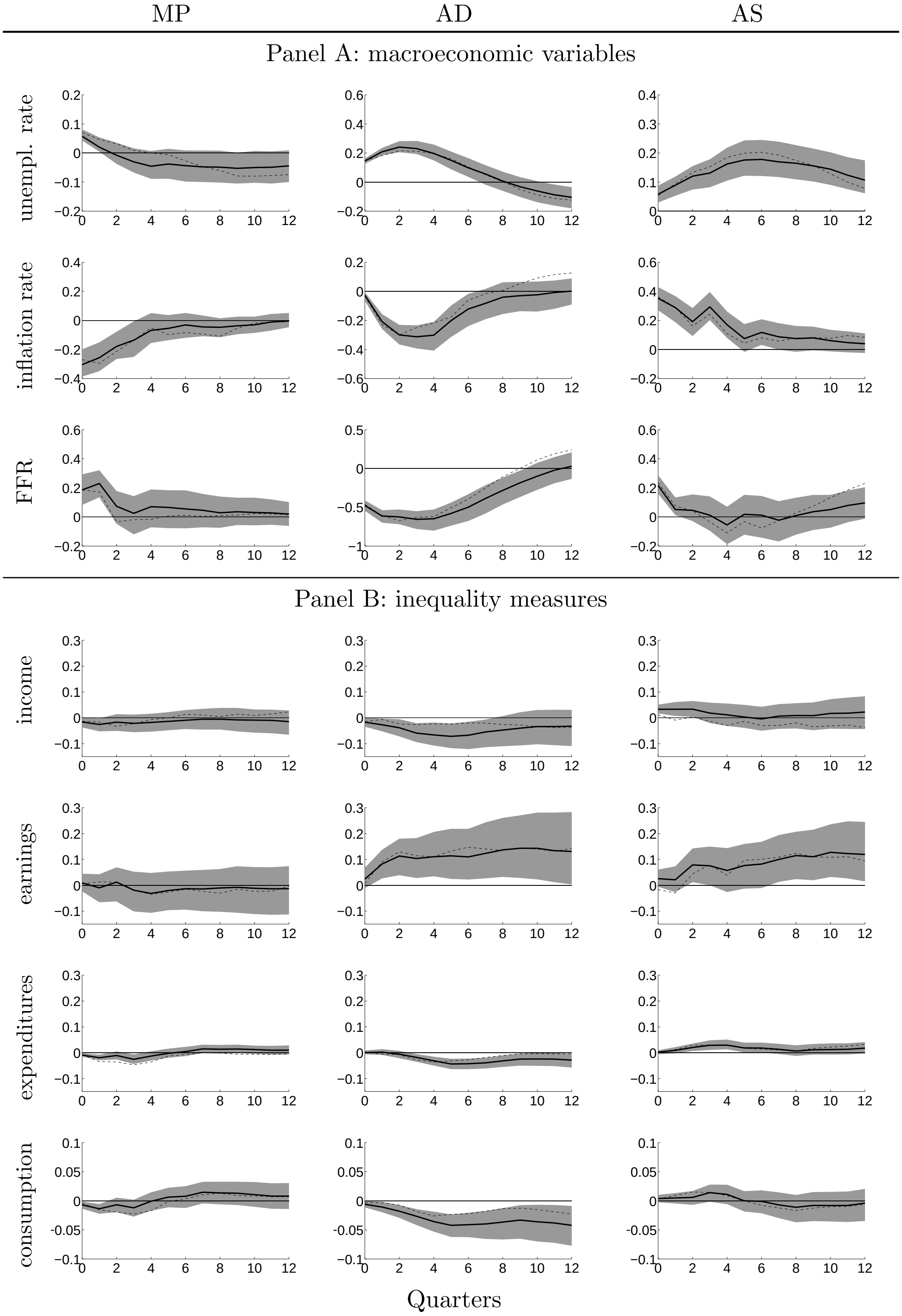
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles.

Table 2: Forecast error variance decomposition

	h	AD shock	AS shock	MP shock
		Panel A: macroeconomic variables		
unempl. rate	0	76.94 (64.44, 87.58)	5.49 (0.97, 17.73)	12.84 (7.43, 24.38)
	2	79.89 (71.95, 87.37)	11.08 (4.63, 18.82)	3.28 (1.78, 5.91)
	4	69.26 (59.68, 79.54)	16.21 (7.92, 26.06)	4.49 (2.16, 9.47)
	8	47.41 (35.01, 60.35)	24.43 (13.65, 40.24)	8.35 (3.10, 17.81)
	20	44.04 (29.75, 55.49)	23.88 (12.74, 36.73)	9.10 (3.26, 20.85)
inflation rate	0	0.44 (0.03, 2.50)	60.77 (29.75, 84.34)	37.74 (14.38, 68.33)
	2	19.46 (12.43, 28.61)	37.58 (16.94, 57.80)	33.34 (14.94, 57.75)
	4	29.52 (20.22, 40.16)	29.35 (14.50, 47.50)	23.31 (9.96, 40.54)
	8	33.41 (22.44, 45.40)	22.71 (11.39, 40.24)	17.99 (8.30, 31.44)
	20	33.22 (22.98, 45.06)	22.21 (11.48, 37.93)	16.43 (7.70, 30.31)
FFR	0	71.44 (57.38, 82.87)	12.98 (5.50, 25.04)	11.61 (3.02, 26.62)
	2	85.58 (78.48, 90.66)	3.38 (1.47, 7.25)	4.47 (1.70, 11.34)
	4	83.29 (76.33, 89.22)	3.04 (1.42, 6.00)	3.73 (1.36, 8.77)
	8	77.23 (65.43, 85.80)	3.07 (1.41, 6.68)	3.98 (1.49, 10.05)
	20	67.71 (54.15, 78.90)	6.77 (3.46, 12.79)	5.61 (2.73, 11.74)
		Panel B: Gini coefficients		
income	0	2.64 (0.58, 6.49)	2.82 (0.40, 7.07)	2.66 (0.45, 6.26)
	2	3.63 (1.16, 7.31)	3.75 (1.38, 8.18)	8.28 (3.12, 14.57)
	4	4.76 (2.03, 8.17)	4.92 (2.40, 9.59)	8.30 (3.80, 14.60)
	8	5.35 (2.63, 8.67)	6.34 (3.19, 10.83)	8.37 (4.25, 14.15)
	20	5.78 (3.11, 9.58)	7.00 (3.70, 11.81)	8.32 (4.26, 13.96)
earnings	0	0.48 (0.03, 2.22)	2.48 (0.57, 6.41)	0.47 (0.05, 1.94)
	2	1.92 (0.75, 4.02)	4.78 (2.39, 7.93)	2.81 (0.82, 6.36)
	4	2.48 (1.23, 4.67)	6.89 (3.73, 10.61)	3.92 (1.72, 7.77)
	8	3.79 (2.16, 6.21)	8.32 (4.59, 12.74)	4.75 (2.52, 8.40)
	20	4.70 (2.90, 7.33)	8.73 (5.12, 13.55)	5.02 (2.77, 8.75)
expenditures	0	1.18 (0.11, 4.07)	0.48 (0.04, 1.87)	0.52 (0.05, 2.16)
	2	3.07 (1.12, 6.10)	4.48 (1.95, 8.59)	6.55 (3.07, 11.43)
	4	3.87 (1.64, 6.97)	7.07 (3.76, 11.69)	6.99 (3.71, 11.36)
	8	5.59 (3.18, 8.62)	7.65 (4.31, 12.57)	7.18 (4.20, 11.27)
	20	6.30 (3.64, 9.35)	8.12 (4.80, 13.29)	7.30 (4.41, 11.32)
consumption	0	2.46 (0.36, 5.79)	0.46 (0.03, 2.06)	0.96 (0.12, 4.00)
	2	5.10 (2.24, 9.16)	3.11 (1.27, 6.48)	5.11 (2.15, 9.26)
	4	6.75 (3.92, 10.74)	4.07 (1.87, 7.03)	5.57 (2.88, 9.54)
	8	7.31 (4.48, 11.24)	5.18 (2.66, 8.20)	6.11 (3.35, 9.79)
	20	8.26 (4.92, 12.73)	5.78 (3.16, 9.04)	6.35 (3.62, 9.90)

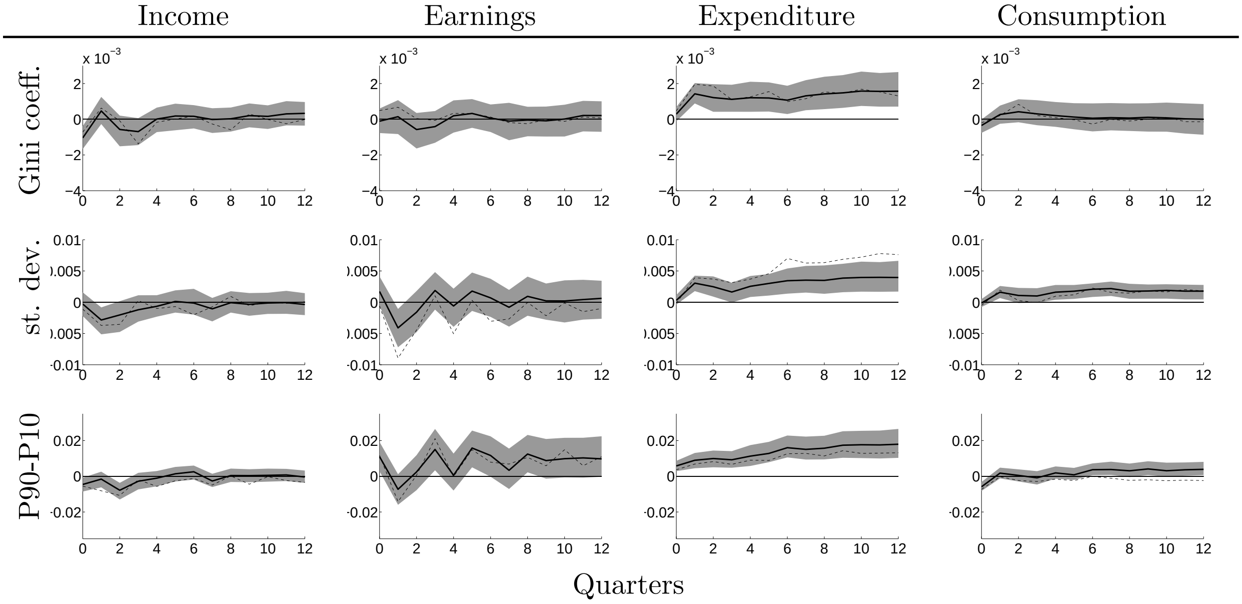
Notes: We indicate the median of the contributions in the FEVDs computed for each model for the respective horizon h in quarters, together with the 16th and 84th percentiles.

Figure 5: Impulse responses of differences between high and low net-worth households



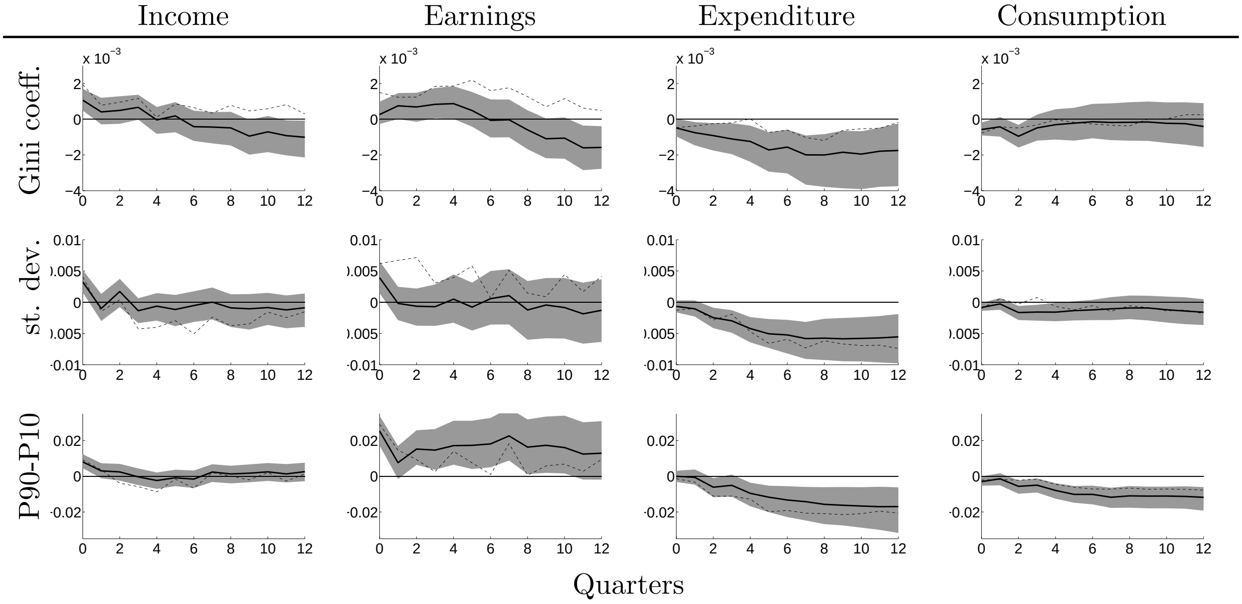
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles. Differences between high and low net-worth households are calculated from group means of income, labor earnings, expenditures and consumption (in log-levels)

Figure 6: Impulse responses of the inequality measures to MP shocks



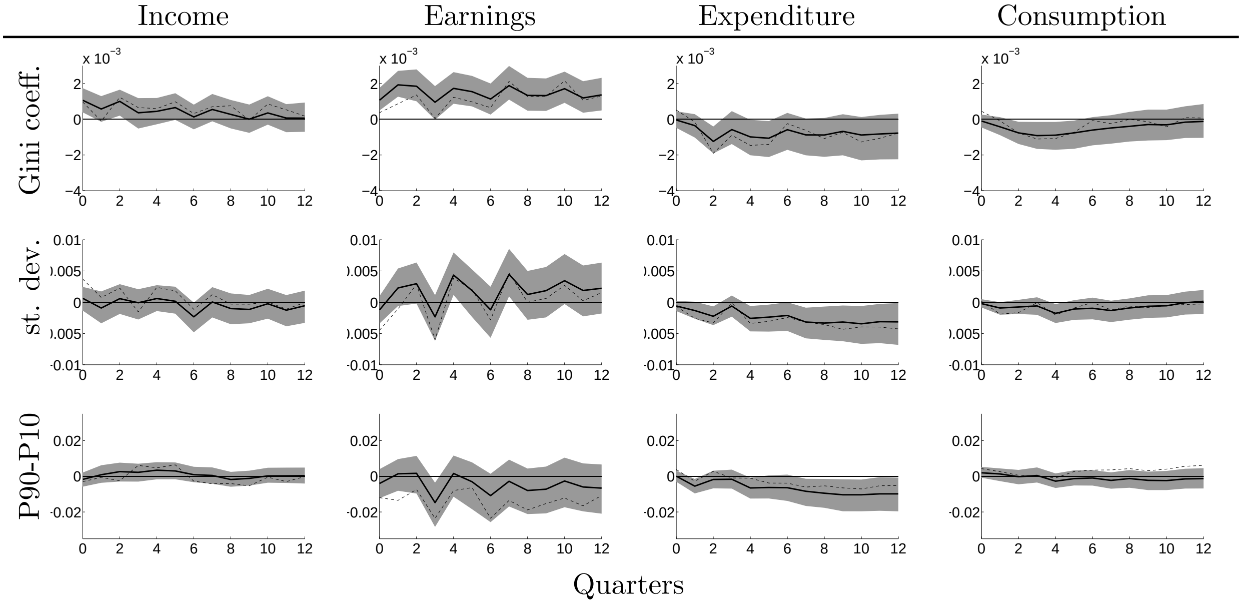
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles.

Figure 7: Impulse responses of the inequality measures to AD shocks



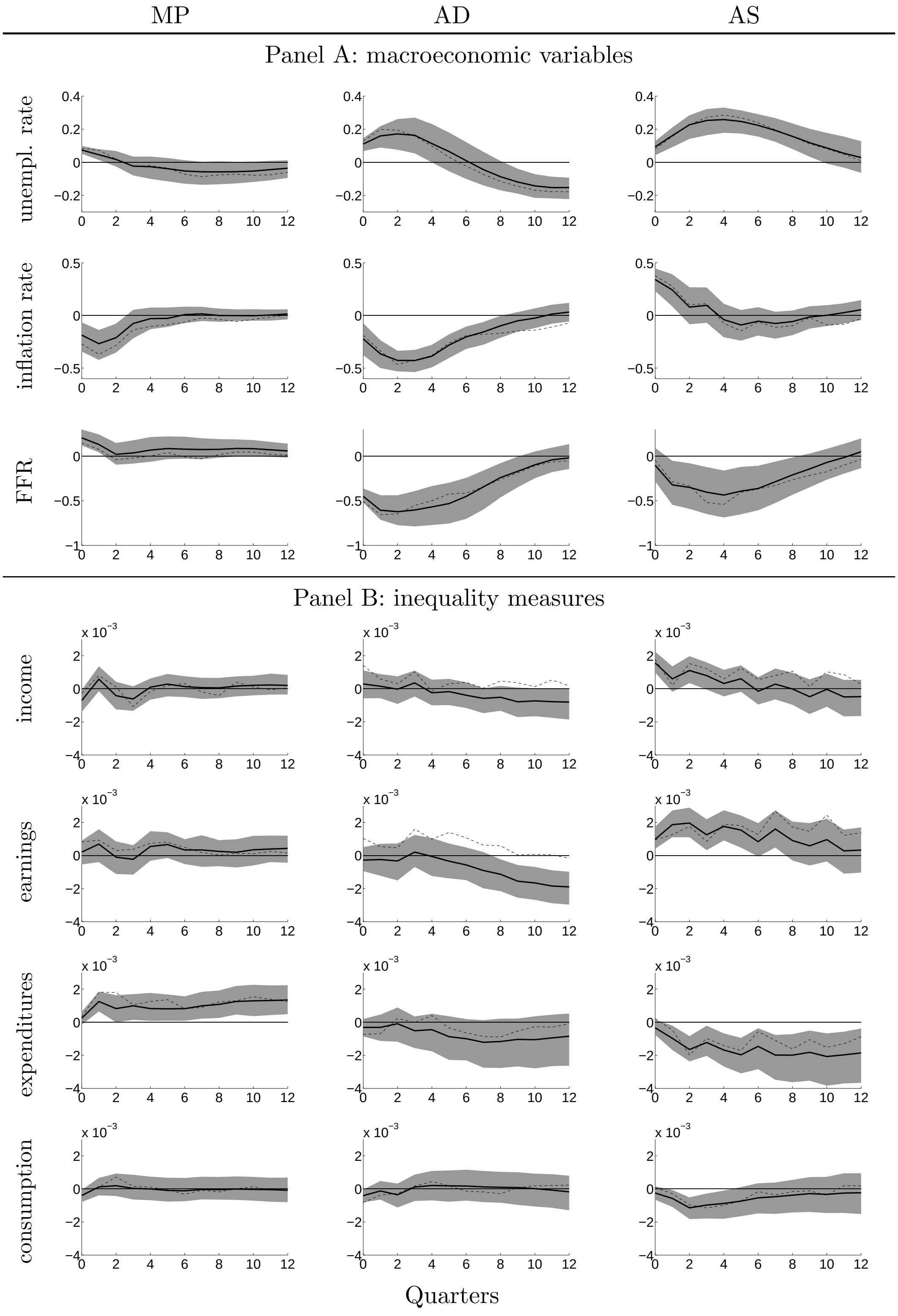
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles.

Figure 8: Impulse responses of the inequality measures to AS shocks



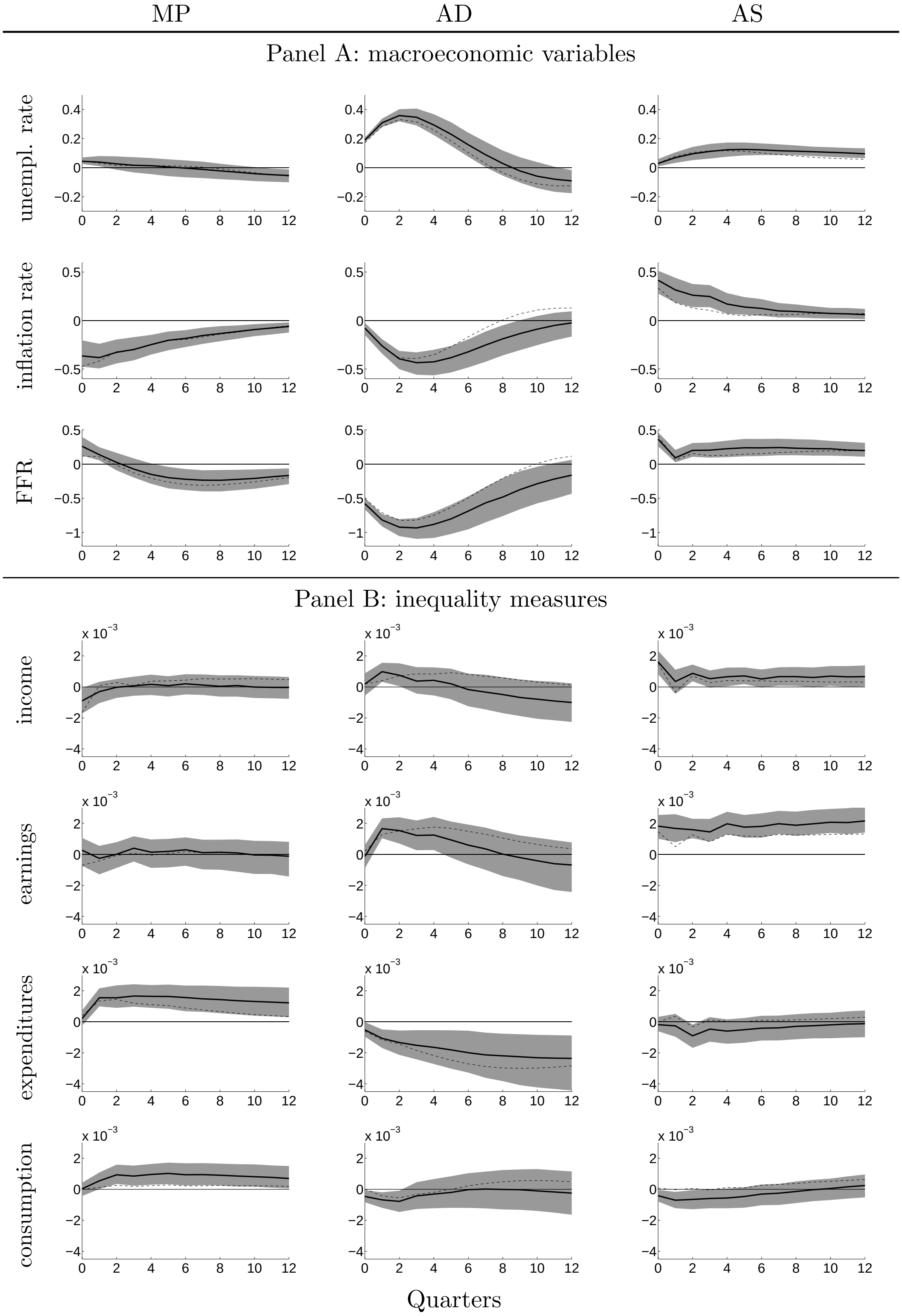
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles.

Figure 9: Impulse responses of the Gini coefficients (alternative AS shock identification)



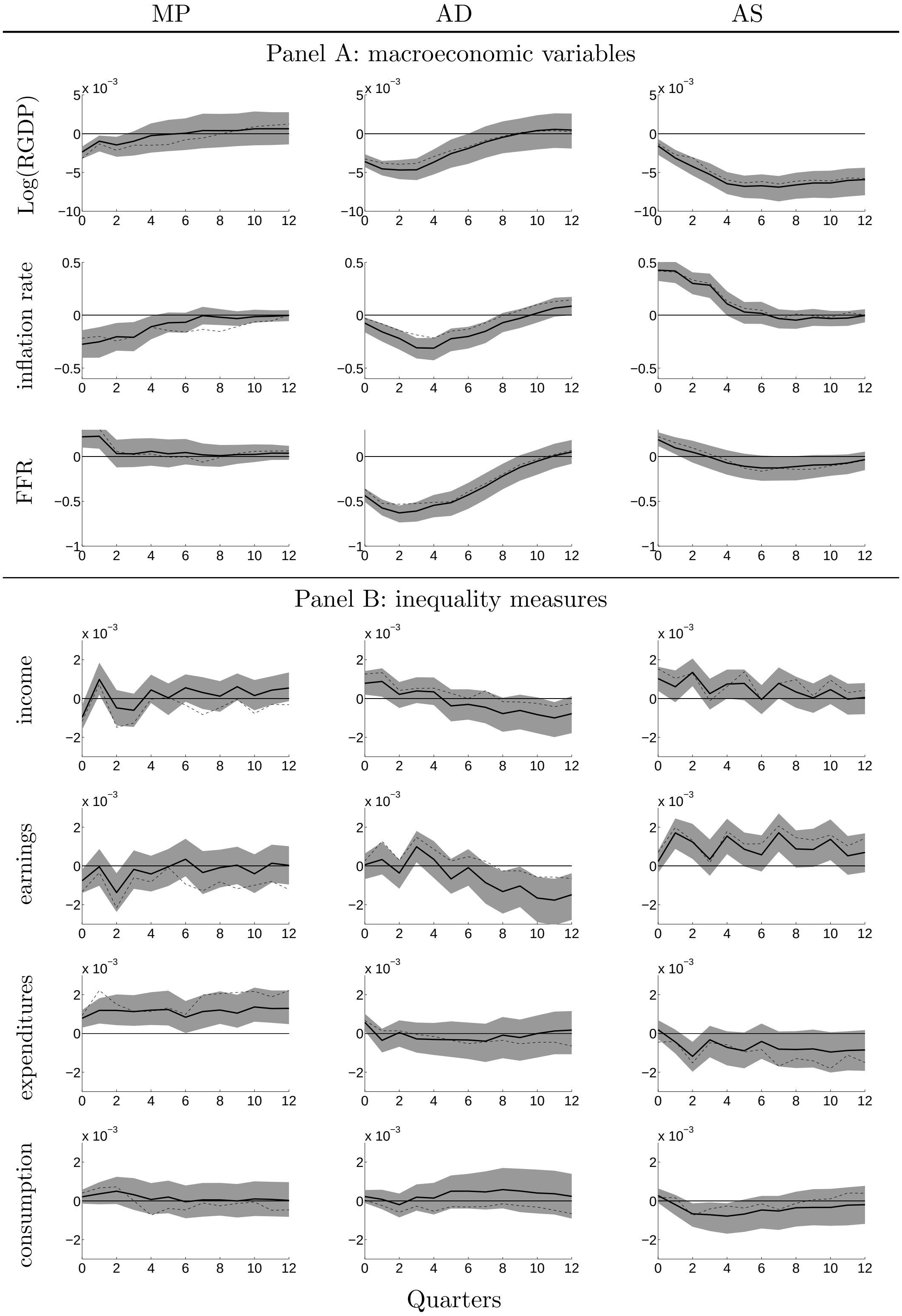
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles. A rise in the Gini index indicates higher inequality.

Figure 10: Impulse responses of the Gini coefficients (estimation with two lags)



Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles. A rise in the Gini index indicates higher inequality.

Figure 11: Impulse responses of the Gini coefficients (estimation with real GDP)



Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The bands indicate the 16th percentiles as well as the 86th percentiles. A rise in the Gini index indicates higher inequality.