Understanding inequality as a business cycle phenomenon Evidence from U.S. survey data

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Abstract

We study the effects of macroeconomic shocks on economic inequality. To identify the shocks, we impose sign restrictions on the impulse responses of the macroeconomic variables. We find that contractionary monetary policy shocks lead to increases in expenditures and consumption inequality, whereas income and earnings inequality is less affected. Contractionary aggregate supply and aggregate demand shocks, by contrast, lead to declines in expenditure and consumption inequality.

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

JEL codes: E00, E32, D63

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1 Introduction

Rising income inequality is an extensively discussed topic among policymakers and researchers. While the debate usually focuses on longer run trends and potential explanations involve structural aspects of the economy (e.g. labor market structures, globalization, education, and technological change), the effects of the business cycle, and in particular recessions, has received renewed attention in the aftermath of the Great Recession (e.g. Heathcote et al., 2010).[1]

In this paper, we study empirically how macroeconomic shocks that drive the business cycle, also influence inequality. We estimate vector autoregressive (VAR) models with quarterly U.S. macroeconomic data and inequality measures and impose combinations of zero and sign restrictions on the impulse responses of the macroeconomic variables to identify shocks.[2]

Our analysis is closely related to Coibion et al. (2017) and Mumtaz and Theophilopoulou (2017) who study the effects of monetary policy shocks on inequality. For the U.S., Coibion et al. (2017) show that contractionary monetary policy shocks increase inequality and account for a substantial fraction of the variation in inequality over time. Similar results are presented Mumtaz and Theophilopoulou (2017) using U.K. data. We follow Coibion et al. (2017) and calculate 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).[3] While we use a data set similar to Coibion et al. (2017), our analysis differs in terms of the estimation methodology as well as with respect to identification approach. Mumtaz and Theophilopoulou (2017) also apply a sign restriction restriction approach, but their focus is on monetary policy shocks, while we identify multiple shocks, including a monetary policy shock.

We find that contractionary monetary policy shocks lead to higher expenditure and consumption inequality, which is in line with Coibion et al. (2017) and also with the results presented in Mumtaz and Theophilopoulou (2017) for the UK. In contrast, income and consumption inequality generally falls in response to contractionary aggregate supply and demand shocks. Thus, business cycle dynamics affect expenditure and consumption inequality in both directions and whether inequality decreases or increases, crucially depends on the type of the shock hitting the economy. This heterogeneity in the effects of macroeconomic shocks on economic inequality suggests that different channels dominate in the propagation of the respective shock. The

[1] Barlevy and Tsiddon (2006) explore how recessions amplify secular trends in inequality.

[2] We impose standard restrictions that are frequently used in the literature (see e.g. Smets and Wouters, 2005; Peersman, 2005; Smets and Wouters, 2007; Fry and Pagan, 2011).

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

savings redistribution channel appears to be dominant in the propagation of monetary policy shocks. This channel states that an unexpected increase in interest rates or decrease in inflation will benefit savers and hurt borrowers, thereby generating an increase in consumption inequality (see e.g. Doepke and Schneider, 2006). By contrast, we observe that aggregate demand and aggregate supply shocks that lead to comparatively stronger and more persistent effects on the unemployment rate and economic activity, tend to decrease consumption and expenditures inequality. A plausible explanation for this positive relation of economic activity and consumption inequality is that high income households adjust consumption more strongly compared to low income households.

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 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 (CE). Each cross-section comprises of approximately 1500 to 2000 households. The CE is available quarterly since 1980 and the data is primarily used to revise the relative importance of goods and services in the market basket of the Consumer Price Index (CPI) in the U.S. However, the CE allows to construct a set of inequality measures (Gini, 9010th percentiles, cross-sectional standard deviations) for labor income, total income, consumption and total expenditures at high frequency. Household consumption is defined as the sum of non-durables (e.g. food and gasoline), services, and expenditures on durable goods (e.g. furniture, jewelry). We also consider a broader measure of household expenditures by adding mortgage and rent payments, health expenditures, education spending and other expenses to household consumption levels. In line with Coibion et al. (2017), we only use data until 2008q4 to avoid the kink in the Federal Funds rate that complicates the identification of monetary policy shocks.

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 that allow to identify aggregate demand, aggregate supply and monetary policy 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 which permits to calculate the change in inequality from t to $t+1$ 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, 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 the same directions. In other words, AS shocks present shifts of the Phillips curve. 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

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

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 to disentangle exogenous shocks in 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 an uninformative 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. (2017), 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 to obtain alternative decompositions $\Sigma_e = PQQ'P'$, and orthogonal shocks $u = (PQ)^{-1}e_t$. The matrix Q is constructed such that the zero restrictions are fulfilled. To obtain the distribution of permissible SVAR models we iterate the algorithm 1,000 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 1,000 draws of the matrix Q is reached (then we proceed without retaining any model). In most cases we find a permissible model for each 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).

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

3.1 Impulse response analysis

Figure 1 shows the distribution of the set-identified models in the impulse response function representation. The solid lines in the graphs represent the pointwise-median responses of the distribution of set-identified models, whereas the dashed lines represent the closest-to-median responses selected as proposed in Fry and Pagan (2011).[5] The bands indicate the 5th and the 16th percentiles as well as the 84th and the 95th percentiles of the distribution of set-identified models. Panel A shows the responses of the macroeconomic variables while Panel B shows the responses of the Gini coefficients. We consider first differences of Gini coefficients calculated from the survey answers on income, earnings, consumption and expenditures. Responses to AD shocks are shown in the first column, responses to AS shocks are in the second column and responses to an MP shock are in the third column.

The responses of the macro variables to AD, AS and MP shocks in Figure 1 are fairly standard. Adverse shocks are associated with an increase in the unemployment rate. Interestingly, however, the responses of the unemployment rate across shocks display some heterogeneity. For a MP shock the response is somewhat short lived and fades out after two quarters while it is more persistent in case of an AD shock, and in particular for an AS shock, where the responses of the unemployment rate are located in the positive territory for more than two years. As the risk to become unemployed is higher for low-income households compared to high-income households cyclical unemployment affects households differently and thus suggests one channel through which the business cycle affects income and earnings inequality. Responses of the inflation rate differ in terms of the sign and persistency. While the inflation rate goes up in case of the AS shock, it goes down in case of AD and MP shocks. They are most persistent vis-à-vis AD shocks. This heterogeneity suggests channels through which business cycle shocks affect inequality differently. As nominal household debt and asset holdings are not equally distributed across households, shocks to the inflation rate propagate through the so called savings redistribution channel (see Doepke and Schneider (2006)), where net lenders vs. net borrowers loose or benefit depending on the direction the change in the inflation rate. The nominal interest rate responses also display some degree of heterogeneity across shocks. For an AD disturbance

[5]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.

it dips and goes through the trough after 4 quarters, while it remains positive compared to its pre-shock level for an AS and AD shock for two quarters. Interestingly, the change in the real interest rate is negative for an AD shock while it leads to an increase in case of a MP shock. This is relevant as e.g. Auclert (2015) relates changes in inequality to changes in the real interest rate that affects households differently depending on net assets, liabilities, and the maturity of those. Thus, in sum, the differences in the response of the macroeconomic variables across shocks opens the floor to a plethora of channels that relate the business cycle to income, earnings, expenditures and consumption inequality.

Panel B plots the impulse responses of Gini coefficients summarizing income, earnings, expenditures and consumption inequality, to AD, AS and MP shocks. Considering the cumulated responses of first differences of the inequality measures the following picture emerges from the analysis: Contractionary MP shocks precipitate revisions in the inequality measures that are, overall, less clear than what one would expect from the existing literature (Coibion et al., 2017; Mumtaz and Theophilopoulou, 2017). While inequality in expenditures and consumption tends to rise, which is in line with the existing literature, our results suggest a rather unsystematic effect of MP shocks onto income and earnings inequality. Quantitatively, our results suggest that for a one hundred basis point increase in the Federal Funds rate the expenditure Gini coefficient increases by approximately 0.01 after two to three years. This result is line with Coibion et al. (2017) who report a cumulative response of similar size and with Mumtaz and Theophilopoulou (2017) reporting an increase in a range of 0.009 - 0.03 for a one hundred basis points shock, for the UK, however. Albeit for consumption, income and earnings Gini coefficients, the results are less clear than expected from the existing literature.

Also for contractionary AS and AD shocks we find that income and earnings inequality does not react systematically to these shocks. A possible interpretation for the absence of a significant response is the existence of countervailing channels that may cancel out each other. Beyond, distributional effects of shocks may cancel out on the aggregate level although specific percentiles of households respond significantly as reported in Coibion et al. (2017) for the case of an MP shock.

Interestingly, in contrast to the responses of expenditure and consumption inequality to MP shocks, we observe that these measures tend to decrease vis-à-vis AD and AS shocks. Thus, business cycle dynamics affect expenditure and consumption inequality in both directions and whether inequality goes up or down depends on the nature of the shock. Specifically, for the AD shock we observe that the Gini coefficent of expenditures is predominantly negative from the second quarter onwards. Also for the Gini coefficients of consumption the responses are initially mostly negative. For the AS shock the expenditure Gini drops from quarter 2 onwards and we can report that the consumption Gini is predominately negative from the second to the sixth quarter. The Gini coefficients of expenditure drops persistenly after the second quarter.Overall our estimates support the findings in Coibion et al. (2017), suggesting that the responses of income and earnings inequality are weaker and less systematic than the responses of the Gini coefficients of consumption and expenditure inequality, also for the case of AD and AS shocks.

In addition to responses of the Gini coefficients, Figures 2, 3 and 4 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 income, earnings, consumption and expenditures.[6] To assess the effects of the macroeconomic shocks onto these measures, we replicate the estimations from above. The picture emerging from the responses of these alternative measures of inequality is very similar. 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.

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 set-identified models. Table 2 shows the median of contributions of the macroeconomic shocks at horizon h, together with the 16th and the 84th percentile of the distributions. We show the contributions of the macroeconomic shocks to the forecast errors of the expectation measures for horizons up to 8 quarters.

From Panel A of Table 2 we see that the structural shocks explain large shares of the forecast error variance of the macroeconomic variables. While the AD shock generally dominates the dynamics of the unemployment rate and the FFR, the AS shock captures the largest share of the forecast error variance of the inflation rate. The MP shock explains the forecast error variance of the macroeconomic data to a smaller extent. Overall, the shares of the forecast error variance accounted for by the shocks are of an order of magnitude similar to what other studies find (see e.g. Smets and Wouters, 2007; Ramey, 2016).

[6]The responses of the standard deviations and the P90-P10 differences are shown together with the respective responses of the macroeconomic variables in Figures A.1 and A.2 in the Appendix. As the responses of the macroeconomic variables are very similar across models, macroeconomic shocks appear to be well comparable.

In contrast to the macroeconomic variables, looking at Panel B of Table 2, the structural shocks generally explain smaller shares of the forecast error variance of the Gini coefficients ranging from negligible shares to slightly below 10 percent. Interestingly, even though the shares of the forecast error variance explained by the shocks we consider vary considerably in respect to the macroeconomic variables, we observe that the shocks are similarly important in shaping the dynamics of economic inequality. In particular it is striking that the MP shock is comparatively less important in shaping the dynamics of the FFR and and the unemployment rate, is equally important in explaining the forecast error variance of the inequality measures.

3.3 Additional analysis

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 5 shows the responses of the macroeconomic variables and the Gini coefficients corresponding to the model without the policy rate restriction in case of the AS shock. In addition, Figure 6 shows the responses of the Gini coefficients together with the responses of the standard deviation and the P90-P10 difference.[7]

It turns out that if we leave the response of the policy rate unrestricted, the policy rate tends to go down in the event of an AS shocks.This has some interesting implications for our analysis, as this effectively shuts down, or perhaps even reverses the interest rate channel of the propagation of the AS shock to inequality. Interestingly, even though interest rates now respond in a different direction, responses in inequality are largely unaffected and respond in comparable way than in the baseline. This suggest that in case of AS shocks, the interest rate distribution channel is not dominant and plays only a minor role in the propagation of these shocks to economic inequality.

4 Summary

We use autoregressive models to study the responses of different measures of inequality to macroeconomic shocks, which we identify using sign restrictions. Our results show that the effects of contractionary monetary policy shocks are in line with the results reported in the existing literature (Coibion et al., 2017; Mumtaz and Theophilopoulou, 2017). While inequality in expenditures and consumption tends to rise, we find a rather unsystematic effect of MP shocks on income and earnings inequality. Also for contractionary aggregate supply and aggregate

[7]We show the corresponding responses of the macroeconomic variables in Figures A.3 and A.4 in the Appendix.

demand shocks we find that income and earnings inequality does not react particularly systematically to these shocks. Interestingly, however, in contrast to the responses of expenditure and consumption inequality to MP shocks, we observe that these measures tend to decrease vis-à-vis aggregate demand and aggregate supply shocks. Thus, business cycle dynamics affect expenditure and consumption inequality in both directions and whether inequality decreases or increases, crucially depends on the type of the shock hitting the economy.

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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						
consumption inequality						
expenditure inequality						

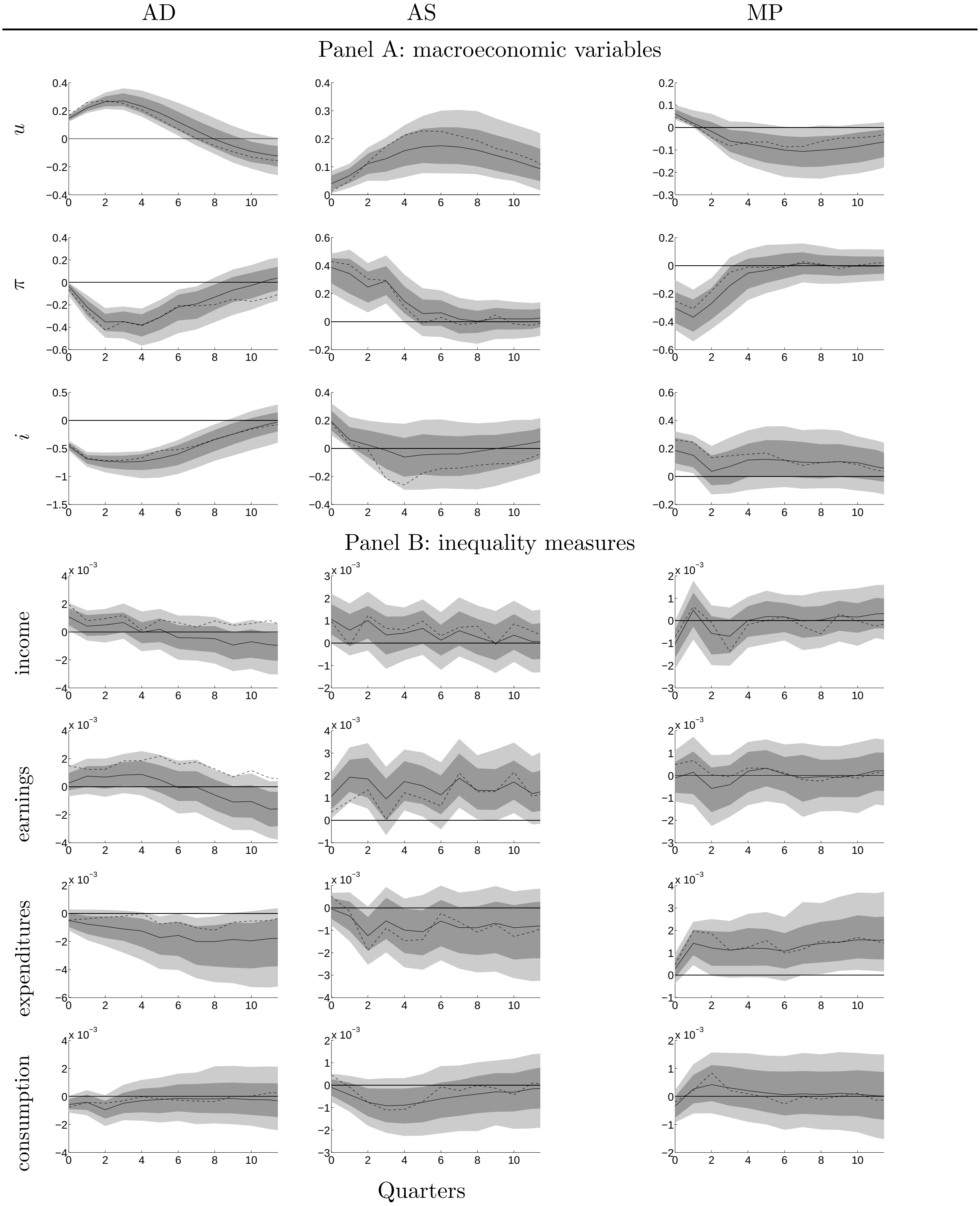
Notes: Sign restrictions on the macroeconomic variables are imposed on impact plus one quarter.

Table 2: Forecast error variance decomposition: SPF

	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)
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)
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)
		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)
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)
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)
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)

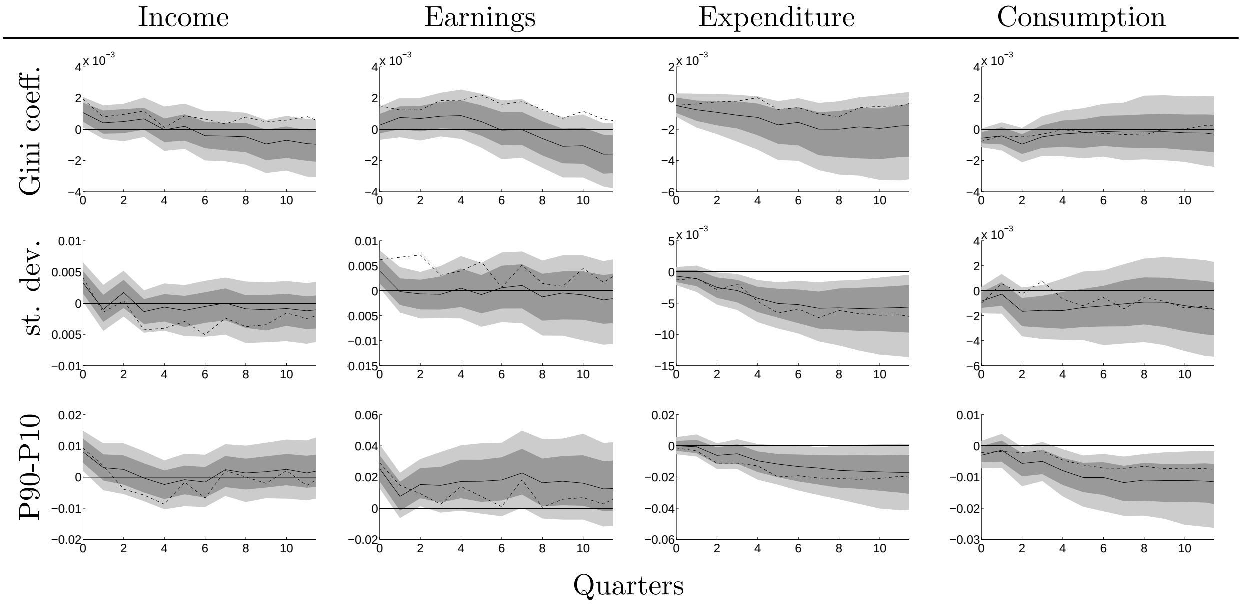
Notes: We indicate the median of the contributions in the FEVDs computed for each set-identified model for the respective horizon h in quarters, together with the 16th and the 84th percentile of the contributions in the FEVDs.

Figure 1: Impulse responses of the Gini coefficients



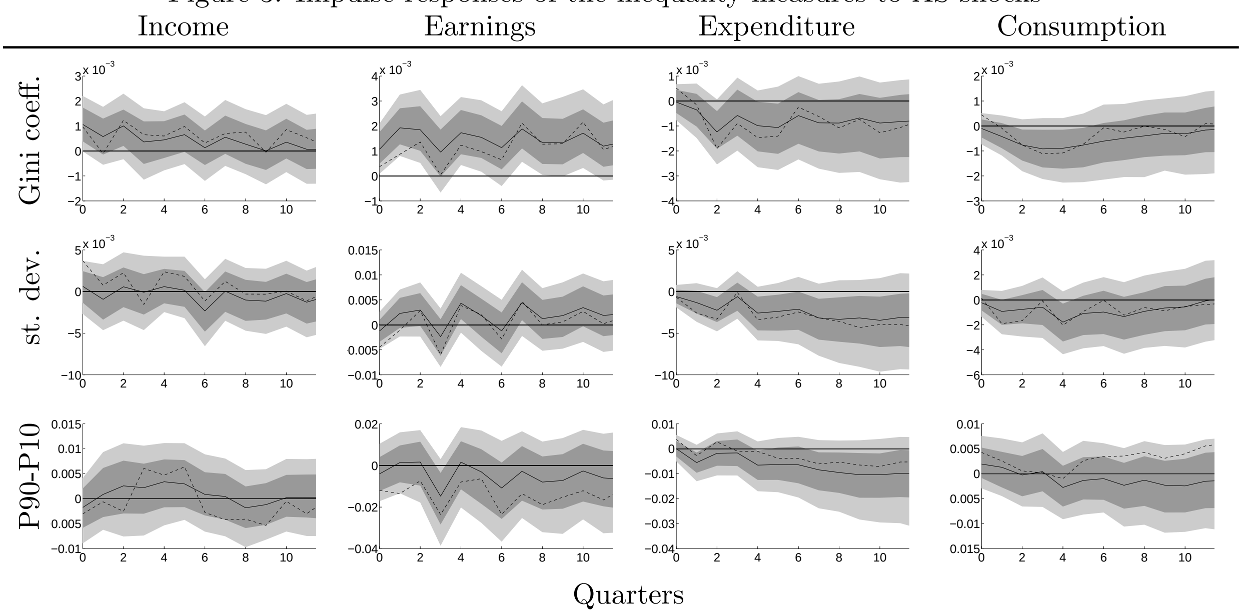
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

Figure 2: Impulse responses of the inequality measures to AD shocks



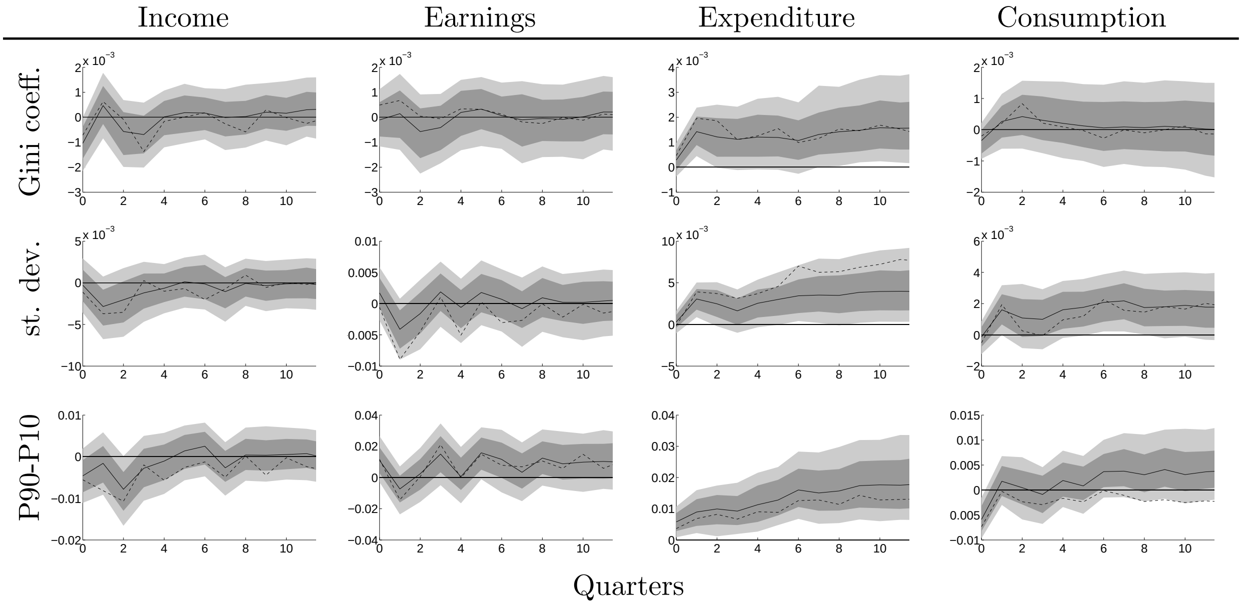
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

Figure 3: Impulse responses of the inequality measures to AS shocks



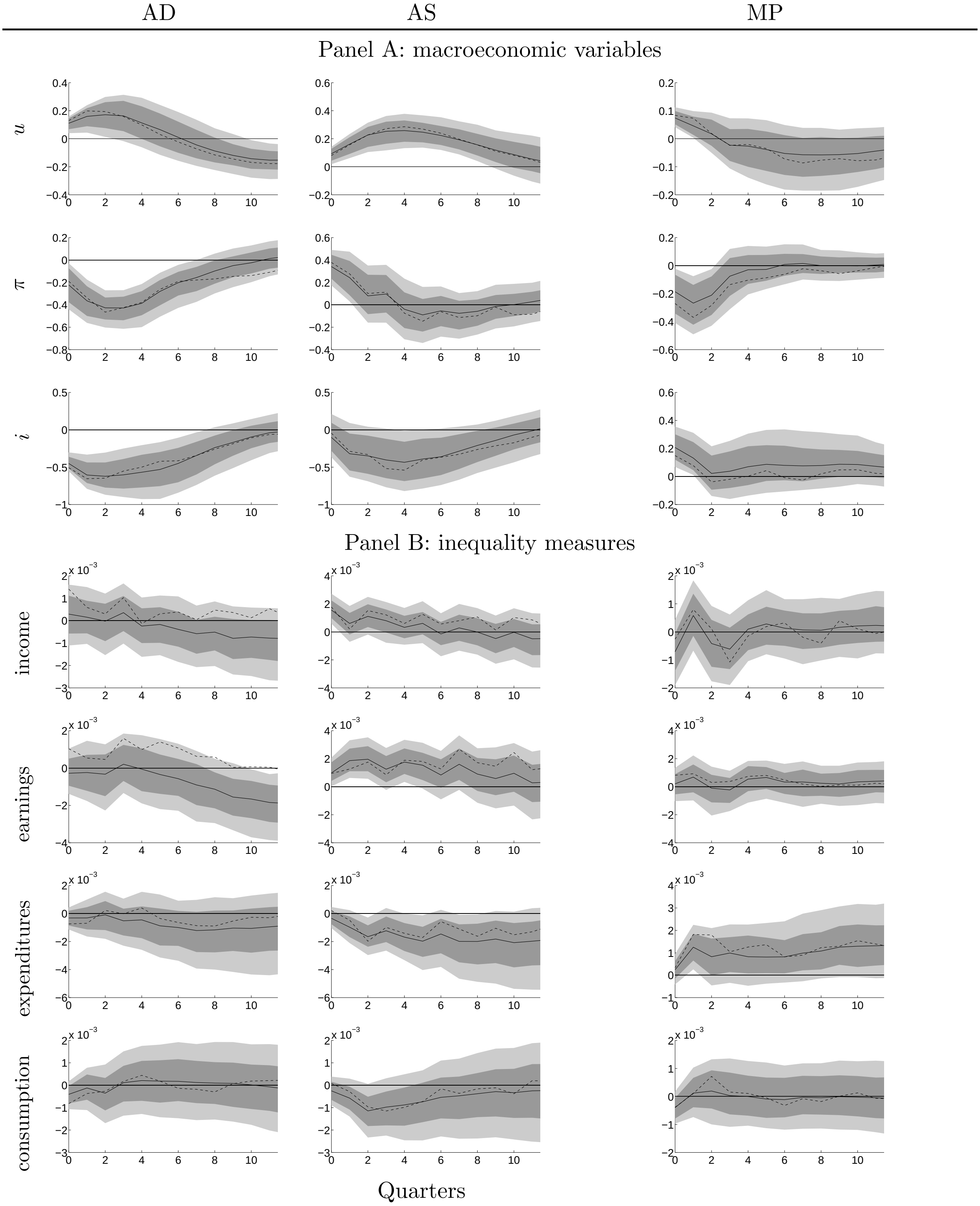
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

Figure 4: Impulse responses of the inequality measures to MP shocks



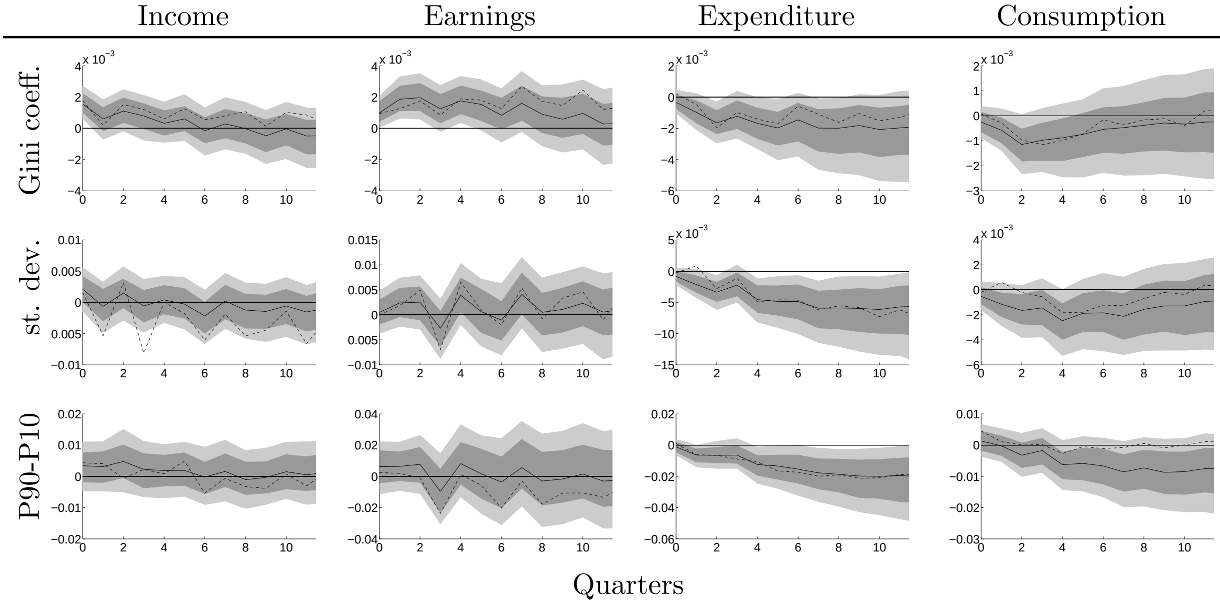
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

Figure 5: 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 error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

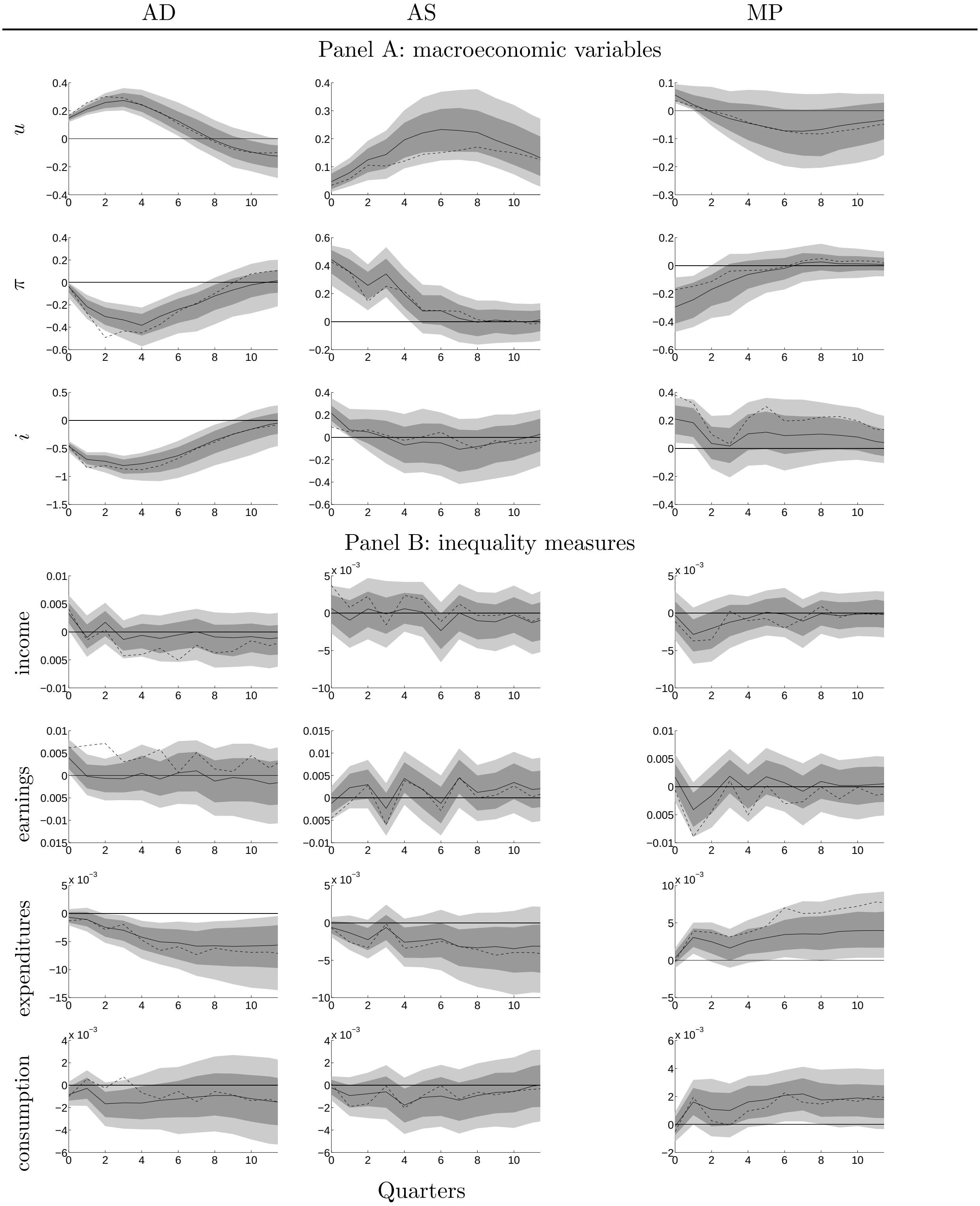
Figure 6: Impulse responses of the inequality measures to AS shocks



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 error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

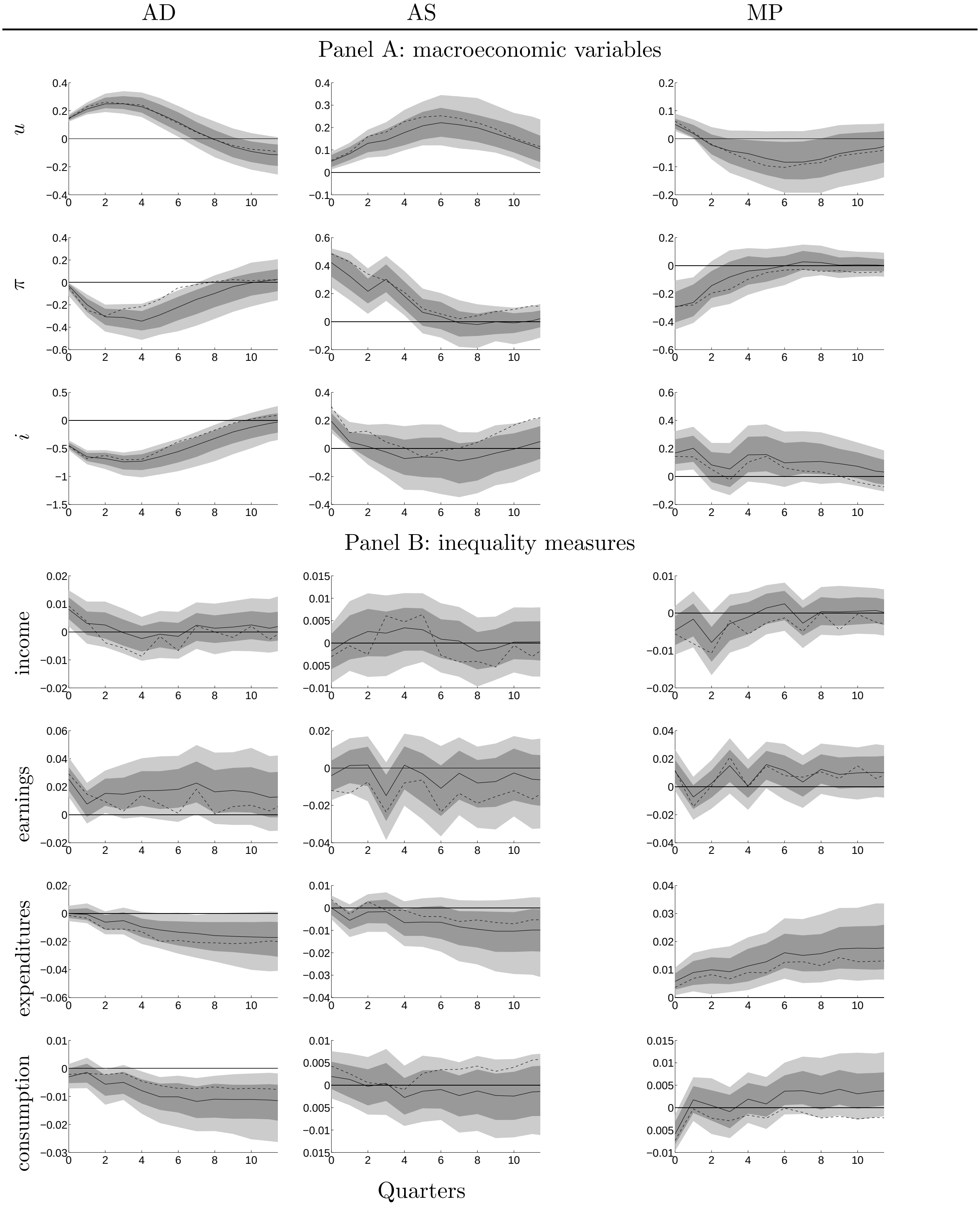
Appendix

Figure A.1: Impulse responses of the cross-sectional standard deviation



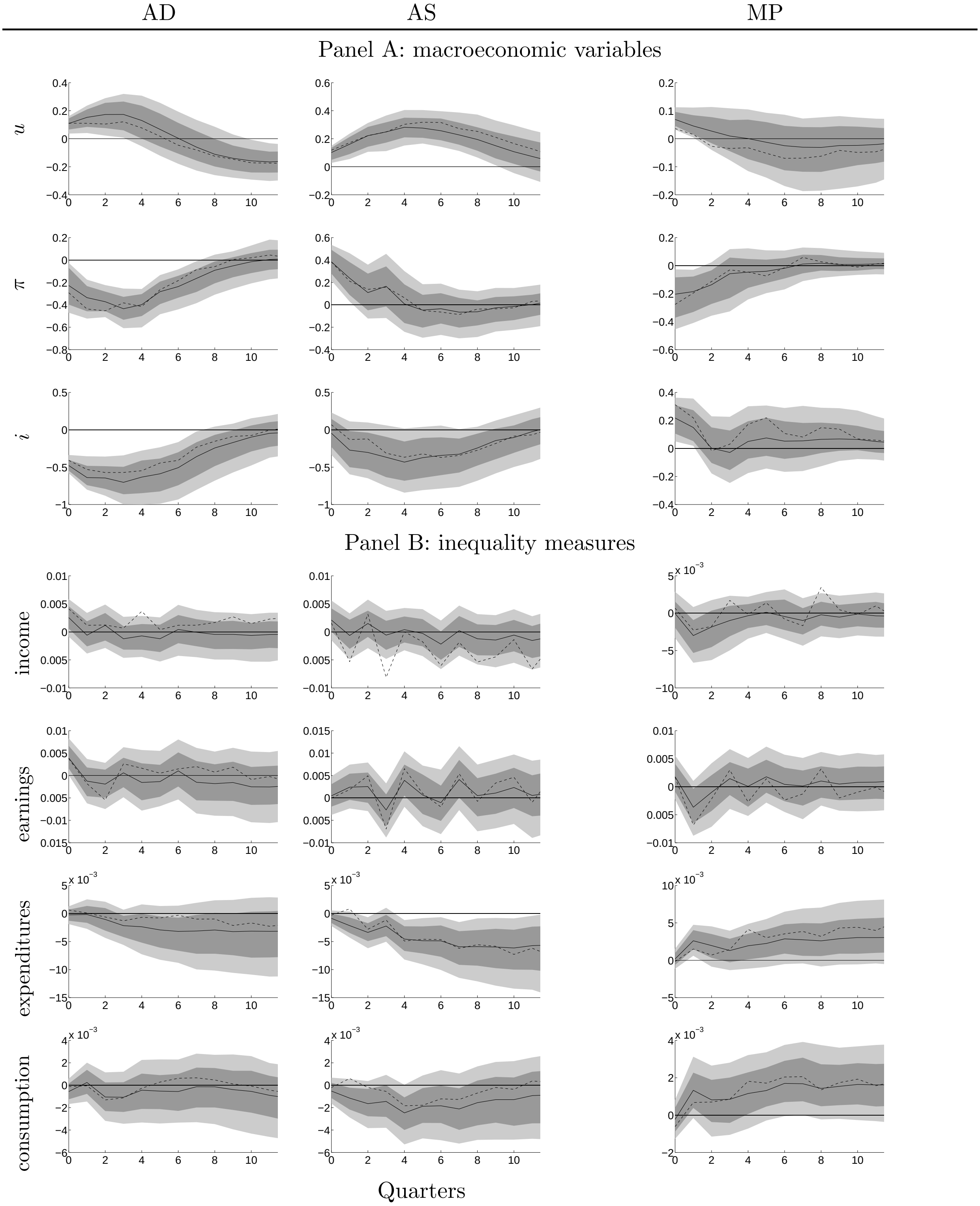
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

Figure A.2: Impulse responses of the 90th-10th difference



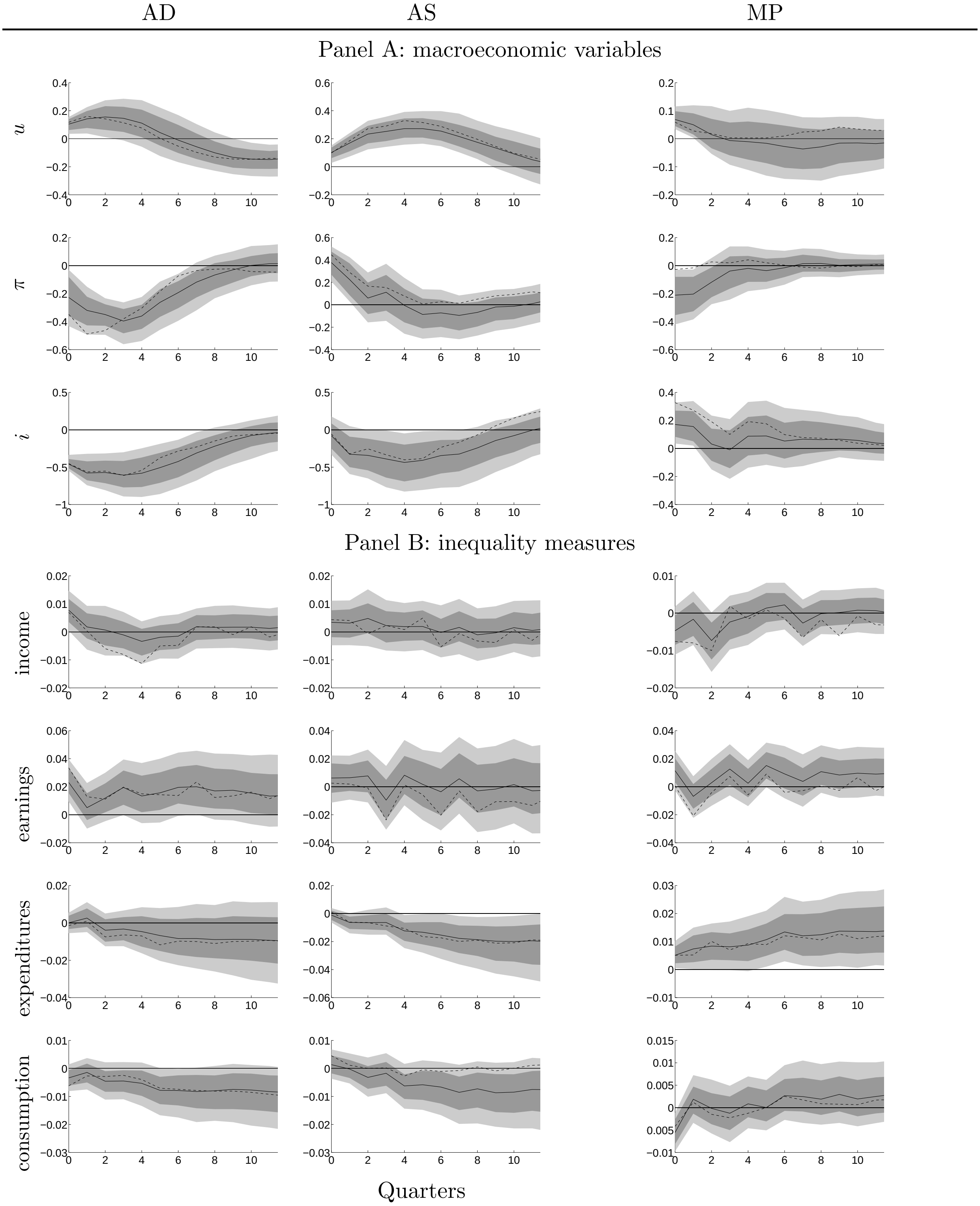
Notes: The solid lines represent the pointwise median responses, whereas the dashed lines represent the closest to median response selected as proposed in Fry and Pagan (2011). The error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

Figure A.3: Impulse responses of the cross-sectional standard deviation



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 error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.

Figure A.4: Impulse responses of the 90th-10th difference



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 error bands represent the distribution of the set identified models (we indicate the 5th and 16th percentiles as well as the 86th and 95th percentiles). A rise in the Gini index indicates higher inequality.