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Size matters: measuring the effects of inequality and growth shocks

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Abstract: Understanding the relationship between income inequality and economic growth is of utmost importance to economists and social scientists. In this paper we use a Bayesian structural vector autoregression approach to estimate the relationship between inequality and growth via growth and inequality shocks for two large economies, China and the USA, for the years 1979–2018. We find that a growth shock is inequality-increasing, and an inequality shock is growth-reducing. We also find, however, that the sizes of the effects of these shocks are very small, accounting for under 2 per cent of the variance for both countries. Finally, we also find that the effects of the shocks dissipate within ten years, suggesting that the effects of these shocks are a short-term phenomenon.

Key words: inequality, growth, Bayesian structural vector autoregression, China, USA

JEL classification: C32, C33, D31, D63

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1 Introduction

One of the most important relationships examined in the economic literature is that between income inequality and economic growth over time. Economists and philosophers have long identified causal mechanisms between inequality and economic growth (Galor and Zeira 1993; Kuznets 1955; Piketty 2014). This relationship has recently gained particular attention due to increasing interest in the long-run impact of income, wealth, and health inequalities on a country's growth outcomes (Alvaredo et al. 2018; Anand and Segal 2008; Bourguignon and Morrisson 2002; Clarke et al. 2002; Durlauf et al. 2009; Gabaix et al. 2016; Ho and Heindi 2018; Kuhn et al. 2020; Milanovic 2018). The recent interest in the relationship between inequality and growth has also been aided by the greater availability of international inequality statistics, especially the Gini measure,[1] but also more recently with income percentile shares as an additional measure of inequality (available in the World Inequality Database 2019).

The empirical literature investigating this relationship has identified that the relationship between inequality and growth may be positive or negative, unstable, or even at best non-existent (see Bandyopadhyay 2018; Banerjee and Duflo 2003; Barro 2000; Berg et al. 2018; Brueckner and Lederman 2018; Castelló-Climent 2010; Erman and te Kaat 2019; Forbes 2000; Halter et al. 2014; Knowles 2005). However, there have been no investigations that explicitly estimate the size of the effect of these entities on each other. To fill this gap in the literature, in this paper we investigate the relationship between inequality and economic growth by estimating the size of the effects as shocks on each other, using a Bayesian vector autoregression (hereafter VAR) approach.

While a growing body of empirical literature has sought to identify causal mechanisms between inequality and economic growth (Galor and Zeira 1993; Kuznets 1955; Piketty 2014), there has been disagreement and considerable difficulty in pinning down this relationship empirically. Recent empirical literature has identified that the estimation of the relationship between inequality and growth is heavily dependent upon the nature of the estimation procedure involved (Berg et al. 2018; Herzer and Vollmer 2012; Juuti 2020). This literature has also suggested that the estimated relationship between economic growth and income inequality is an 'artefact' of the estimation procedure used. Another strand of literature has also recently identified that the relationship is highly sensitive to the inequality measure used, the time frame, and the country of study (Bandyopadhyay 2020). Mean-independent inequality measures reveal that there is no relationship between inequality and growth, while mean-dependent inequality measures reveal a negative relationship, albeit an unstable one.

Given that the relationship has proven to be difficult to empirically estimate, it is thus important for researchers to also estimate the size of the effects of inequality on growth and that of growth on inequality to ascertain the relative importance of their respective effects for policy-makers. Indeed, findings revealed by Dollar and Kraay (2002) and Voitchovsky (2005), for example, have already shown that our attention should be focused on identifying the relationship at specific parts of the income distribution and that 'growth is good for the poor' (Dollar and Kraay 2002). This literature asserts that our concern thus should be about the short-term effects of a growth shock rather than that of the entire distribution, summarized by the inequality measure.

The lack of precise growth–inequality estimates stands in contrast to the standard of estimating growth–poverty elasticities. There is a large literature that measures growth–poverty elasticities, identifying policy mechanisms that can be particularly useful for developing economies (Bourguignon 2003; see Arndt et al. 2017 for a detailed survey of the literature). The estimations in this paper are a step forward in filling this void in the literature.

[1] The principal and most widely used source of inequality data is the World Income Inequality Database (WIID; United Nations University 2019) and the World Bank Indicators.

In this paper, we use a Bayesian VAR approach to estimate the size of the effects of an inequality shock on growth, and that of a growth shock on inequality, using two large countries, China and the USA, in the period 1979–2018. Even though these countries have highly comparable gross domestic product (GDP), especially in the last 20 years, their policy approaches over the period of study are very different. In particular, Chinese economic policy has had a heavy emphasis on poverty alleviation over the period of the study, thus classifying it more as a developing country in comparison to the USA.

The macroeconomic literature has devoted a multitude of methodologies to the estimation of the effects of shocks to the economy.[2] For our analysis, we undertake our estimation using recent methods proposed by Baumeister and Hamilton (2018). These authors develop a procedure in which a researcher can tailor the identifying assumptions using Bayesian prior information about the signs and also the magnitudes of the parameter values of interest. In this approach we allow our inference to be guided not just by prior information about signs, but also about magnitudes. The innovation offered by this method thus results in more accurate estimates of the structural VAR and the impulse responses that are generated. To specify our model, we include terms of trade as an additional variable that underpins the relationship, following from the empirical literature that emphasizes the role of international trade in determining this relationship (Banerjee and Duflo 2003; Barro 2000). Inclusion of the terms of trade also allows us to observe its relative importance in determining both growth and inequality.

There are three main findings that result from our analysis. First, we find that a growth shock is inequality-increasing. We also find that an inequality shock is growth-reducing. These results are the same for the USA and China, and accord with a lot of the earlier literature (see Bandyopadhyay 2018; Banerjee and Duflo 2003; Barro 2000; Berg et al. 2018; Brueckner and Lederman 2018; Castelló-Climent 2010; Erman and te Kaat 2019; Forbes 2000; Halter et al. 2014; Knowles 2005). Second, estimates of the variance decompositions reveal that the sizes of these effects are very small. This is the most salient finding of the paper. A growth shock to inequality accounts for only 2 per cent of the variation of inequality. Similarly, an inequality shock to growth also accounts for under 2 per cent of the variation in economic growth. In comparison, a terms of trade shock accounts for a larger amount of variation of both inequality and growth. Third, we find that the effects of these shocks are dissipated within 10–15 years at the most, and quite often within 10 years. This result also accords with recent literature addressing different countries (Bandyopadhyay 2020).[3]

For the estimation of our model we use several percentile share ratios as our preferred measure of inequality instead of using the popular Gini. There are several reasons for this. Percentile share ratios are increasingly shown in the recent literature to be better representatives of inequality over time, and indeed are being used for studies gauging long-term inequality. (Gabaix et al. 2016; Smith et al. 2019). For example,the World Inequality Database (2019), with this approach, also focuses entirely on the estimation of percentile share income ratios as a relevant measure of inequality. Bandyopadhyay (2020) also reveals percentile share ratios to have favourable dynamic econometric properties as inequality measures. In addition, Cobham et al. (2013) and Cobham and Sumner (2015) recommend percentile share ratio measures, in particular the Palma measure,[4] as most suitable for arriving at policy advice (Alvaredo et al. 2018; Gabaix et al. 2016; Kuhn et al. 2020; Milanovic 2018; Smith et al. 2019).[5]

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[2] For a brief introduction to the different modern approaches see Barsky and Sims (2011), Mountford and Uhlig (2009), Ramey (2011), and Zeev and Pappa (2017).

[3] Bandyopadhyay (2020) uses all developed country cases, namely, Denmark, Switzerland, and the UK. The effects of the shocks are estimated using a standard traditional VAR approach.

[4] The Palma ratio is the ratio of the top 10 per cent of the population's share of gross national income (GNI), divided by the poorest 40 per cent of the population's share of GNI. It provides a policy-relevant indicator of the extent of inequality in each country and is also considered to be particularly relevant for poverty-reduction policy.

[5] However, for robustness, undertaking the estimations in this paper using available Gini measures (and other mean-dependent measures) for comparative purposes is highly recommended and discussed later in the paper.

The paper is organized as follows. In Section 2 we discuss the current literature on the inequality and growth relationship and the problems that characterize the estimation process identified in the literature. Section 3 presents the model that we estimate and the results estimated from that model. Section 4 discusses the results obtained in light of the current literature. Section 5 summarizes the findings in the paper and concludes.

2 What does the inequality and growth literature say?

There is a large and well-documented literature on the estimated relationship between economic growth and inequality. The literature is inconclusive on the exact nature of the relationship. It reports negative, positive, and no significant relationships between inequality and economic growth (see Bandyopadhyay 2018; Banerjee and Duflo 2003; Barro 2000; Berg et al. 2018; Brueckner and Lederman 2018; Castelló-Climent 2010; Erman and te Kaat 2019; Forbes 2000; Halter et al. 2014; Herzer and Vollmer 2012; Juuti 2020; Knowles 2005; Niño-Zarazúa et al. 2017). The literature has typically shown that the relationship is highly sensitive to the sample studied, the estimation methodology, and the time frame in use. In addition, given the lack of a long time series of data, the time spans of the studies are generally short, often with a small number of years but a relatively large number of cross-sectional units. Recent literature also suggests that the varied results and conclusions about the estimated relationship could well be an outcome of the econometric methodology in use (Berg et al. 2018; Herzer and Vollmer 2012; Juuti 2020).

The recent empirical literature that has examined and estimated the relationship between economic growth and inequality is quite large. Using recent time-dependent methods (such as panel regression or cointegration methods) and with the availability of high-quality data, the literature has now rejected the inverted-U relationship that derived from the seminal work of Kuznets (1955) and has uncovered several other relationships (see Juuti 2020 for an excellent survey of the literature). Following the publication of the Deninger and Squire (1996) dataset and eventually the WIID (United Nations University 2019) datasets, which have high-quality data for Ginis and quintile shares of income, the majority of further studies have used two principal approaches to estimating the relationship: cross-section or panel regression approaches, which accounts for the vast majority, and time series approaches (Bandyopadhyay 2020; Herzer and Vollmer 2012). This literature typically identifies a significant positive or negative relationship between inequality and growth. Halter et al. (2014), in particular, reveal that studies using time-dependent methods generate a positive relationship, while studies exploiting the cross-section variation only generate a negative relationship. Halter et al. (2014) also find that mechanisms generating a negative relationship work over the longer term and are reflected in level-based estimators. Bandyopadhyay (2020), however, uses over 100 years of data and does not obtain the same negative relationship as reported by Halter et al. (2014). Studies using non-parametric approaches (Bandyopadhyay 2020; Banerjee and Duflo 2003), on the other hand, deduce that there is no significant relationship between these entities.

There is a large theoretical and empirical literature that has proposed several mechanisms underpin the positive and negative relationships between inequality and growth. Some of the literature also concludes that the relationship is particularly dependent on the time frame (see Halter et al. 2014 for details). Inequality is growth-reducing via: its influence on the intergenerational transmission of inequalities in wealth (Banerjee and Duflo 2003; Galor and Zeira 1993), the median voter's decisions on the post-tax income distribution (Perotti 1996), the political economy outcomes of inefficient state bureaucracies (Acemoglu et al. 2011), weak legal structures (Glaeser et al. 2003), and political instability (Bénabou 1996). Due to their influence via education, evolution of wealth distribution, and political economy routes, thus, the effects are slow to come into effect and pan out over the medium to long run. Inequality is growth-enhancing, however, by its effect on aggregate savings (Kaldor 1955; Kuznets 1955) and the effects on investments in research and developments (Foellmi and Zweimüller 2006). These effects rely upon standard economic mechanisms (such as market imperfections and convex saving functions), and thus are short term in their impact.

Another strand of literature has also identified a different set of relationships between inequality and economic growth using different types of inequality measures. This literature has focused on the different performances of absolute, intermediate, and relative inequality measures in measuring global- or national-level inequalities (Bandyopadhyay 2018, 2020; Niño-Zarazúa et al. 2017). Bandyopadhyay (2018) identifies, using standard GMM regression methods, a stable relationship between inequality and economic growth for mean-independent measures of inequality (i.e. the absolute Gini). However, mean-dependent measures of inequality (the relative Gini measure) reveals an unstable negative relationship. This finding is also revealed by Bandyopadhyay (2020), where a long-run approach is undertaken (using data for over 100 years) and the relationship between economic growth and inequality is found to be non-existent for mean-independent measures. This work also finds that mean-independent measures respond to a growth shock in a different manner, compared with mean-dependent measures, owing to the different dynamic properties of the inequality measures. The relationship between inequality and economic growth is thus revealed to be highly dependent upon the measure of inequality in use.

Thus, the estimation of the inequality and growth relationship will depend upon:

1. the inequality measure that is in use—whether it is mean-dependent or mean-independent;
2. the nature of the estimation method that is being used—namely regression analyses (for example, different panel regression methods) and panel cointegration analyses; and
3. the sample in use.

Thus, the literature tells a difficult story: while different inequality measures and different econometric techniques may result in different relationships between inequality and growth, these same relationships are also not robust over the long run due to the dynamic properties of the inequality measures being in flux.[6] From the policy-makers' point of view, though, the picture at hand is not as gloomy. Typically, policy-makers of national governments work with short-run effects, especially in a democratic set up, where the term in office is determined by the election cycle. Hence, our current interest in this paper, in investigating the effect of a shock, is also limited to the short run as well, though the model is set up to observe the effect for up to 20 years.

Another aspect of the estimations in these studies, especially of those using GMM panel regression analyses, is that it is evident that the sizes of the regression coefficients are quite small. This result suggests that the growth or inequality effects are quite small, something that comes through in the non-relationship obtained with the non-parametric estimates of Banerjee and Duflo (2003) and Bandyopadhyay (2020).

To our knowledge, there is currently no study that explicitly sets out to estimate the exact size of the effect of a growth shock on inequality (or an inequality shock on growth). It is important for researchers to ascertain the size of the effects of these shocks. This is because the highly sensitive and unstable nature of the inequality and growth relationship derived in earlier empirical studies could be due to the small effect each has on the other. In addition, from a policy-makers' point of view, it would be useful to measure the size of the effect of a shock for GDP growth on inequality and vice versa. If the effect of a positive growth shock on inequality is estimated to be quite large, this would be of major policy significance. Also, if we find that the effect of a positive growth shock has a medium-term effect, in that the impact lasts for over ten years, then this is also of great policy significance.

[6] This is due to changes in the properties of the income distribution over time, from which the inequality measures are estimated (see Bandyopadhyay 2020 for more details.

Thus, in this paper, to estimate the size of the effect of a shock, we undertake an estimation procedure popularized in the macro-econometric literature using a structural VAR approach. We adopt the new approaches recently popularized by Baumeister and Hamilton (2015, 2018), which employ a Bayesian approach. The Bayesian approach is particularly useful for empiricists to provide more informed estimates of the effects of the shocks. In their proposed method, they use the system of variables in the model (i.e. in our case inequality and growth, among others) to generate prior 'beliefs' (i.e. prior distributions) about the underlying economic structure, which are then used to place some plausible restrictions on the values of the parameters estimated. The method then generates the relevant posterior distributions using the prior information. These posterior distributions are then used to estimate the effects of a growth shock on inequality (or an inequality shock on growth). The procedure thus allows us to also estimate the exact size of the effect of a shock: we are able to estimate the proportion of the variation in our variable of interest—for example, economic growth, due to the effect of a inequality shock by estimating variance decompositions. Our estimated model will also estimate the proportion of variation in inequality that is due to the effect of a GDP growth shock. We describe the method and sampling algorithm in greater detail in Section 3.

In addition to the economic growth and inequality measures as our principal entities of interest, following the empirical and theoretical literature we model the mechanism underpinning the inequality and growth relationship via one of the heavily studied macroeconomic routes: international trade. We thus include the terms of trade as a third variable in our three-equation model. The empirical literature has given significant importance to the role of trade in underpinning this relationship (for example, see Banerjee and Duflo 2003; Barro 2000).

3 The effect of growth shocks and inequality shocks

We now introduce the data used for our analysis. The period of study spans from 1959 to 2018. We use a three-equation model for our estimations using three variables: economic growth, measured as the annual growth rate of GDP, expressed as a percentage; the terms of trade; and several measures of income inequality. We use up to five inequality measures, as percentile share ratios: percentile ratios of the 30th to 80th percentiles (perc(30:80)) for China only), 10th to 90th percentile ratios (perc(10:90)), 0th to 50th percentile ratios (perc(0:50)), 50th to 90th percentile ratios (perc(50:90)), and 99th to 100th percentile ratios (perc(99:100)). All of these measures have been obtained from the World Inequality Database (2019), with the exception of those for China for the period 1959–69 for perc(30:80). We estimate the percentile share ratio for perc(30:80) using the China database CHARLS.[7]

Our third variable is the terms of trade, to represent the role of trade in determining the relationship between inequality and growth. For the USA the GDP growth and terms of trade variables have been obtained from the World Bank's World Development Indicators database. For China these variables have been obtained from the China Stock Market & Accounting Research (CSMAR) database. We have chosen to use these two variables from the CSMAR database (and not from the World Bank database) due to the former making available continuous data for the full time period. For the periods over which there is an overlap in years for both data sources, there is a strong association between the variables from the two data sources.

[7] For China we have complete data from the WID (2019) for 1970–2018. To allow for a longer time period prior to 1979, we make use of the China Health and Retirement Survey (CHARLS) dataset to generate the inequality measures for 1959–69.The CHARLS database consists of a representative sample drawn from around 10,000 households and 17,500 individuals in 150 counties/districts and 450 villages/resident committees. Individuals are followed up every two years and all data are made public one year after the end of data collection.

There are several reasons why we have chosen to use the percentile share ratios as our preferred measure of inequality. There is an established literature that has identified econometric problems with the use of popularly used measures (such as the Gini) (Bandyopadhyay 2018, 2020; Niño-Zarazúa et al. 2017). Our analysis thus follows a growing body of work that uses top percentile shares and percentile ratio measures (including the Palma measure (Cobham and Sumner 2013; Cobham et al. 2015)[8] for dynamic analyses, especially for arriving at policy advice (Alvaredo et al. 2018; Gabaix et al. 2016; Kuhn et al. 2020; Milanovic 2018; Smith et al. 2019). For the sake of comparability, however, we also undertake the estimations using Gini measures that are available in the United Nations University (2019) database. For our purposes we require a time series of inequality measures to undertake the estimations.

We present our results for two countries: China and the USA. We have chosen China and the USA to represent a large developing country and a large developed country, respectively, which have highly comparable economies. China's successful growth experience in the last 30 years places it as a highly comparable country to the USA (van der Wiede and Narayan 2019; Zilibotti 2017). In particular, the period 2000–18, in particular, can be considered to be a phase over which the growth and inequality experience in China and the USA is highly comparable. The institutional reforms introduced in the 1980s in China led to the rapid and stellar rise of GDP in purchasing power parity (PPP) terms, bringing it to comparable levels with those of OECD countries. The convergence was particularly pronounced during the first decade of the twenty-first century, when China grew at unprecedented annual rates close to 10 per cent. In addition, the USA and China have experienced comparable levels of relative intergenerational mobility for individuals born in the 1980s, particularly for income and education.

Turning to the potential nature of the inequality and growth relationship one could expect, the case for the USA is clearly one in which growth is associated with rising inequalities. One could, however, expect the situation to be the reverse for China due to its strong equalizing policies. But the evidence seems to suggest rising inequalities for China, too. Theories that describe a positive relationship between inequality and growth may work best to describe both countries' inequality-and-growth stories.

To be able to measure the effects of a shock to these two entities, we estimate using a commonly studied three-variable annual model with a system that describes the movements of economic growth (Equation 1), inequality (Equation 2), and terms of trade using the structural VAR approach. We follow the approach used by Baumeister and Hamilton (2018), with some innovations in terms of the methodology for the selection of the prior and posterior distributions, described below.

The VAR specification adopted in this paper can be presented as the following:

$$Cx_t = Fz_{t-1} + \varepsilon_t \tag{1}$$

where x_t is a 3×1 vector of inequality, GDP growth, and terms of trade, and z_{t-1} is a 12×1 vector containing the four lags of x_t and a constant, ε_t is an 3×1 vector of structural innovations following the distribution given by:

$$\varepsilon_t \sim N(0, D) \tag{2}$$

We assume matrix C can be inverted, then Equation 1 can be transformed into:

$$x_t = C^{-1}Fz_{t-1} + C^{-1}\varepsilon_t \tag{3}$$

$$E(C^{-1}\varepsilon_t\varepsilon_t^{'}C^{'-1}) = C^{-1}D(C^{'})^{-1} = A \tag{4}$$

[8] The Palma ratio is the ratio of the top 10 per cent of the population's share of GNI divided by the poorest 40 per cent of the population's share of GNI. It provides a policy-relevant indicator of the extent of inequality in each country and is also considered to be particularly relevant for poverty-reduction policy-making.

where $\hat{C^{-1}D}$, and $\hat{A}$ can be obtained by OLS (ordinary least squares) regression of x_t on z_{t-1}. In addition, the residuals of Equation 3 can be written as:

$$\hat{C^{-1}}\varepsilon_t = x_t - \hat{C^{-1}}Dz_{t-1} \tag{5}$$

Under usual circumstances, without any specific information about elements of A, the model would be unidentified and there would be no basis for drawing conclusions from the data about the effects of a shock to the system. The conventional approach is to place strong restrictions on the elements of A (assumed to be a 'dogmatic' prior). Baumeister and Hamilton (2015, 2018) propose that prior beliefs about the underlying economic structure are used to place some plausible restrictions on the values of the parameters. For this, we use the Bayesian approach following Baumeister and Hamilton (2018): we want to ascertain how the observations of the series of x_t revise the prior beliefs of matrices C, F, D. To simplify our analysis, we assume that D is a diagonal matrix. The prior of C is given by $p(C)$. Then, following Baumeister and Hamilton (2018), we assume the conditional distribution of D and F are $p(D|C)$ and $p(F|C,D)$, respectively.

For example, the prior distribution of D is:

$$p(d_{ii}|C) = f(d_{ii}, u_i, \sigma_i) \text{ for } d_{ii} > 0, \text{ and } 0 o.w \tag{6}$$

where u_i and σ_i are parameters corresponding to the prior of C, $p(C)$. For F, we assume that each row of F follows a normal distribution, $N(a_i, d_{ii}m_i)$, as a prior:

$$p(F|D,C) = \prod_{i=1}^{12} p(f_i|D,C) \tag{7}$$

Then, the aggregate prior is given by:

$$p(C,F,D) = p(C)\prod_{i=1}^{12} p(d_{ii}|C)p(f_i|C,D) \tag{8}$$

where $i = 1$ to 12 represents the 12 diagonals in F.[9] With this prior distribution, we can express the log-likelihood function of the observations as follows:

$$p(x_0, \ldots x_{60}|C,D,F) = \prod_{t=1}^{60} f(\varepsilon_t|C,F,D)) \tag{9}$$

where ε_t is the error term in Equation 1, following $N(0,D)$, and $t = 1 \ldots 60$ is the number of years. To implement, we first collect the unknown elements in C in a vector c, and define the distribution of c as:

$$c \sim N(0, u, \sigma) \tag{10}$$

We consider this distribution to be the prior for C, $p(C)$. Maximizing the likelihood function will generate the first posterior of $p(C,F,D|x_0, \ldots x_{60})$.

We hereafter employ the Metropolis–Hastings algorithm to draw the parameters $\hat{C}, \hat{F}, \hat{D}$ from the posterior distribution to generate 20,000 impulse response functions (IRFs) and their confidence intervals (CIs). In the figures of the structural IRFs (and the variance decompositions) in Section 3.1 we plot the mean and 75 per cent CIs based on the 20,000 draws:

$$\begin{aligned}\frac{dx_{t+s}}{d\varepsilon_t'} &= \frac{\Delta x_{t+s}}{d\varepsilon_t'} + \frac{\Delta x_{t+s-1}}{d\varepsilon_t'} + \ldots + \frac{\Delta x_t}{d\varepsilon_t'} \\ &= (I_3 - C^{-1}F_1 - C^{-1}F_2 - \ldots - C^{-1}F_4)^{-1}C^{-1}\end{aligned} \tag{11}$$

[9] The 12 diagonals correspond to the three variables and four lags.

where F_j corresponds to the coefficients of lag j terms of x_t.

To generate the draws from the posterior distribution $p(C,F,D|x_0,x_1,\ldots,x_{60})$, we undertake the following method. Let $C_1 = C_*$, where C_* is derived by maximizing the log-likelihood function. We generate $C_n = C_n + f(\hat{P}^{-1})v_{n+1}$, where v_{n+1} is a 3×1 vector of independent normal distributions with mean 0 and variance 1. Let $L(C)$ be the log-likelihood function when $C = C, \hat{P}\hat{P}' = \frac{d^2L(C)}{dCdC'}_{C=C_*}$ and $f(a) = (X'(a)X(a) - (X'(a)Z)(Z'Z)^{-1}(Z'X(a))$ for any a. If the log-likelihood on C_{n+1} is greater than the log-likelihood on C_n, then $C_{n+1} = C_{n+1}.o.w\ C_{n+1} = C_n$. We repeat this procedure for $n = 20,000$, which thus gives us C. Thereafter we repeat the same procedure to generate draws for F and D.

3.1 Empirical results

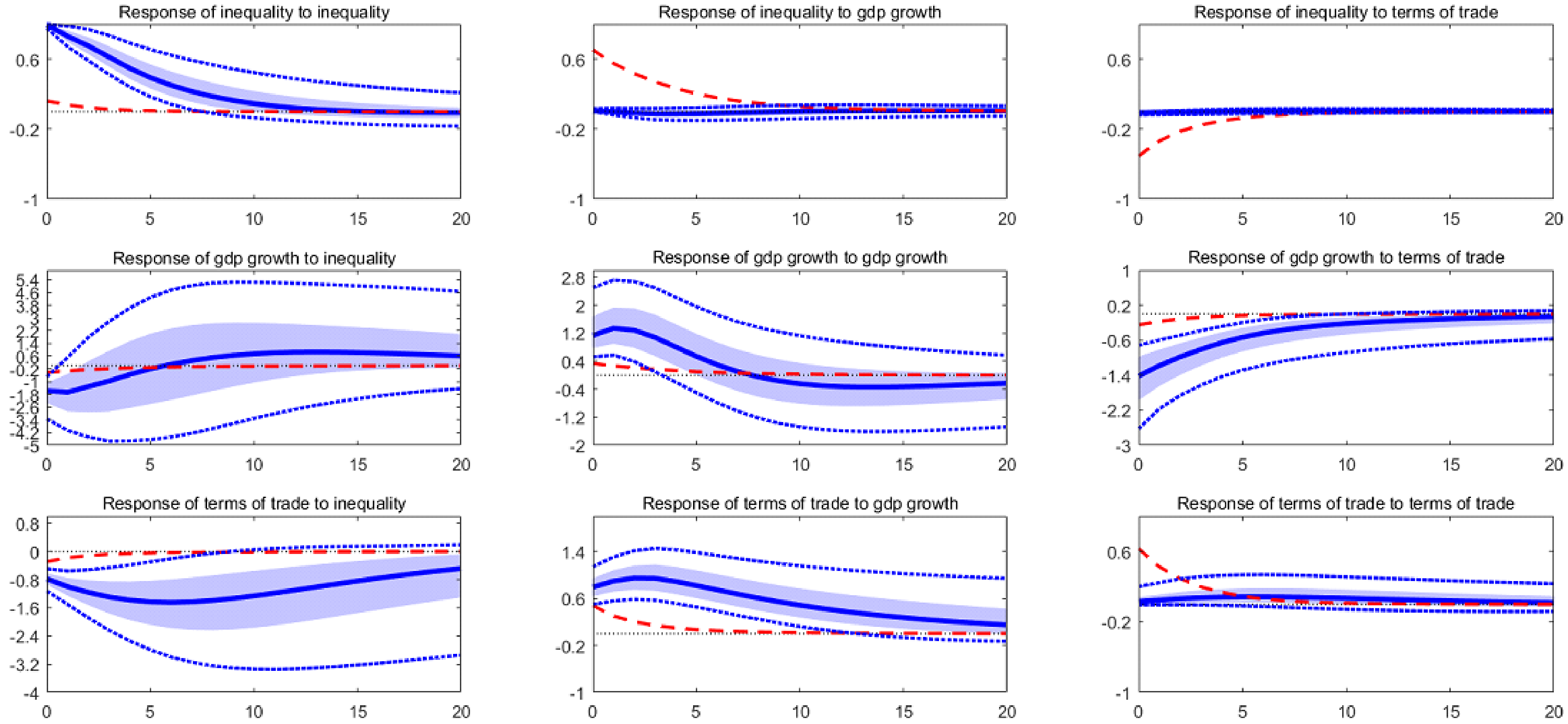
We present our estimations below for China and the USA using annual data from 1959 to 2018. For China, we use distributional data from the CHARLS dataset to generate our inequality measures from 1959 to 1969 due to unavailability of these years in the World Inequality Dataset (2019). Due to the nature of the sample used in CHARLS, the trends in the inequality measures estimated from CHARLS are not a perfect match with the data from the World Inequality Dataset (2019) in terms of the trend. However, these years are not directly used in the estimations because the data 20 years prior to 1979 are used for the sampling procedure described earlier. The estimations below are thus presented on the basis of data from 1979 to 2018.

The posterior IRFs are plotted in Figures 1 and 2 and are calculated with respect to a one standard deviation change in the variable of interest. The red dashed lines in Figures 1 and 2 plot the median of the estimated prior distributions for 20 time periods. Although the medians of our prior distribution for structural IRFs die out fairly quickly, the uncertainty we associate with this prior information grows significantly as the horizon increases. The solid blue lines in the structural IRFs are the median of the posterior distribution. The shaded blue region in the impulse response panels represent the 75 per cent posterior credibility regions and the dashed lines indicate 95 per cent regions.

In Figure 1 we present the IRFs for the Chinese case, using the perc(30:80) inequality measure. The effect of an inequality shock on the three variables (inequality, GDP growth, and terms of trade) are presented in the panels in the first column. An inequality shock lowers economic growth and terms of trade in panel (2,1), but the drop is smaller for terms of trade in panel (3,1).[10] The inequality shock lowers GDP growth and returns to normal within 10–12 years, but it has a clear effect on the terms of trade—it initially lower trade growth but then returns to normal quickly. The second column of Figure 1 presents impulse responses for the effect of a GDP growth shock, which raises inequality, as presented in panel (1,2), and returns to normal within 5–7 years. The growth shock has a negative effect on trade growth and takes a long time to return to normal. Finally, the effect of a trade shock is tabulated in column 3. The trade shock lowers inequality and then returns to normal quickly. On the other hand, the trade shock also has an initial lowering of GDP growth and returns to normal quickly as well. These effects are all small and do not seem to persist.

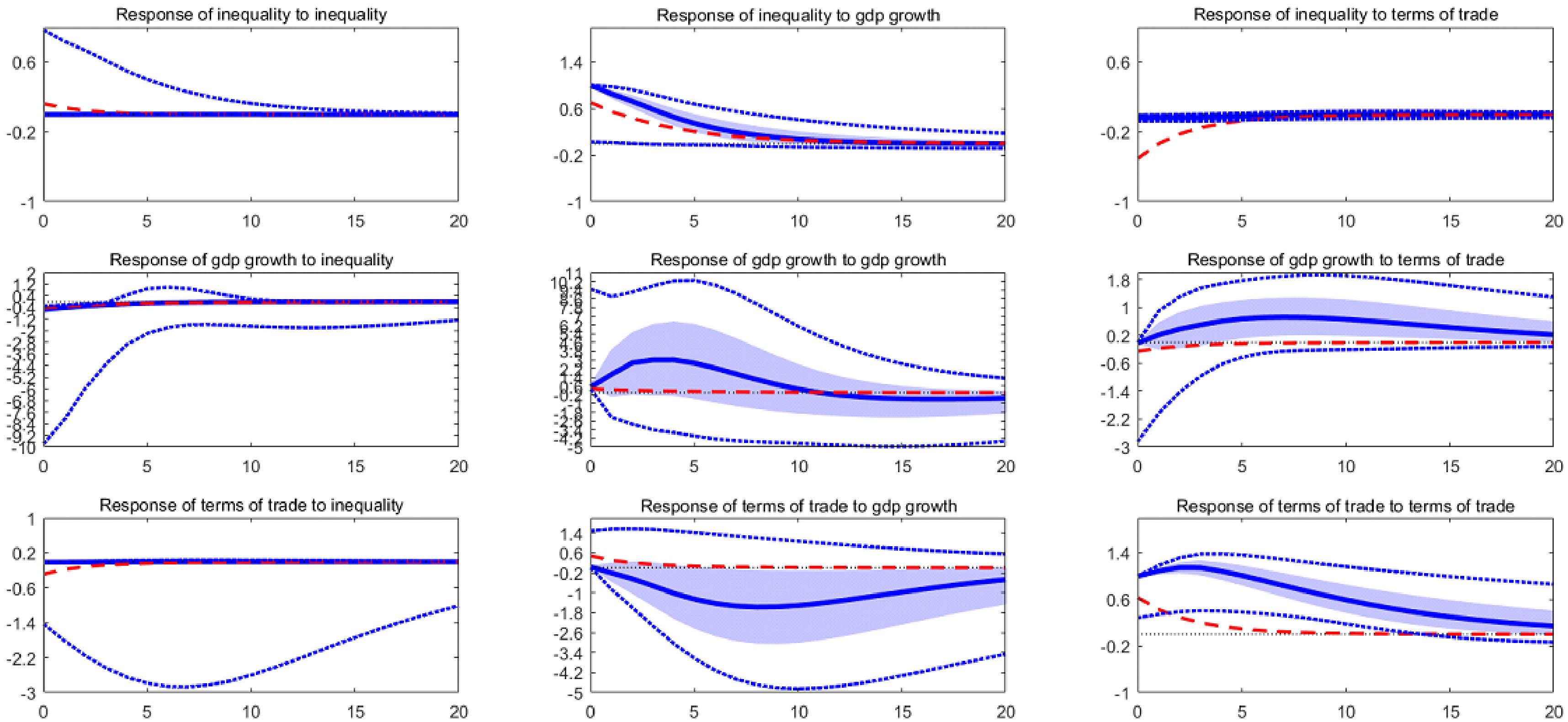
[10] Panels are referred to in a row–column format; for example, panel (3,1) is row 3, column 1.

Figure 1: China's structural IRFs for the three-variable VAR, using inequality measure perc(30:80)



Note: solid blue lines, posterior median; shaded regions, 75 per cent posterior credibility set; dotted blue lines, 95 per cent posterior credibility set; dashed red lines, prior median.
Source: authors' estimations based on data from CHARLS and WID.

Figure 2: China's structural IRFs for the three-variable VAR, using inequality measure perc(0:50)



Note: solid blue lines, posterior median; shaded regions, 75 per cent posterior credibility set; dotted blue lines, 95 per cent posterior credibility set; dashed red lines, prior median.
Source: authors' estimations based on data from CHARLS and WID.

For robustness, we estimate the models using another inequality measure, perc(0:50), presented in Figure 2.[11] The inequality shock again has very similar effects on both GDP growth and terms of trade—the inequality shock lowers GDP growth and also lowers the terms of trade, with a quicker return to normal than GDP growth. We observe the same effect that a GDP growth shock raises inequality and then returns to normal within 5–10 years. All effects are again small.

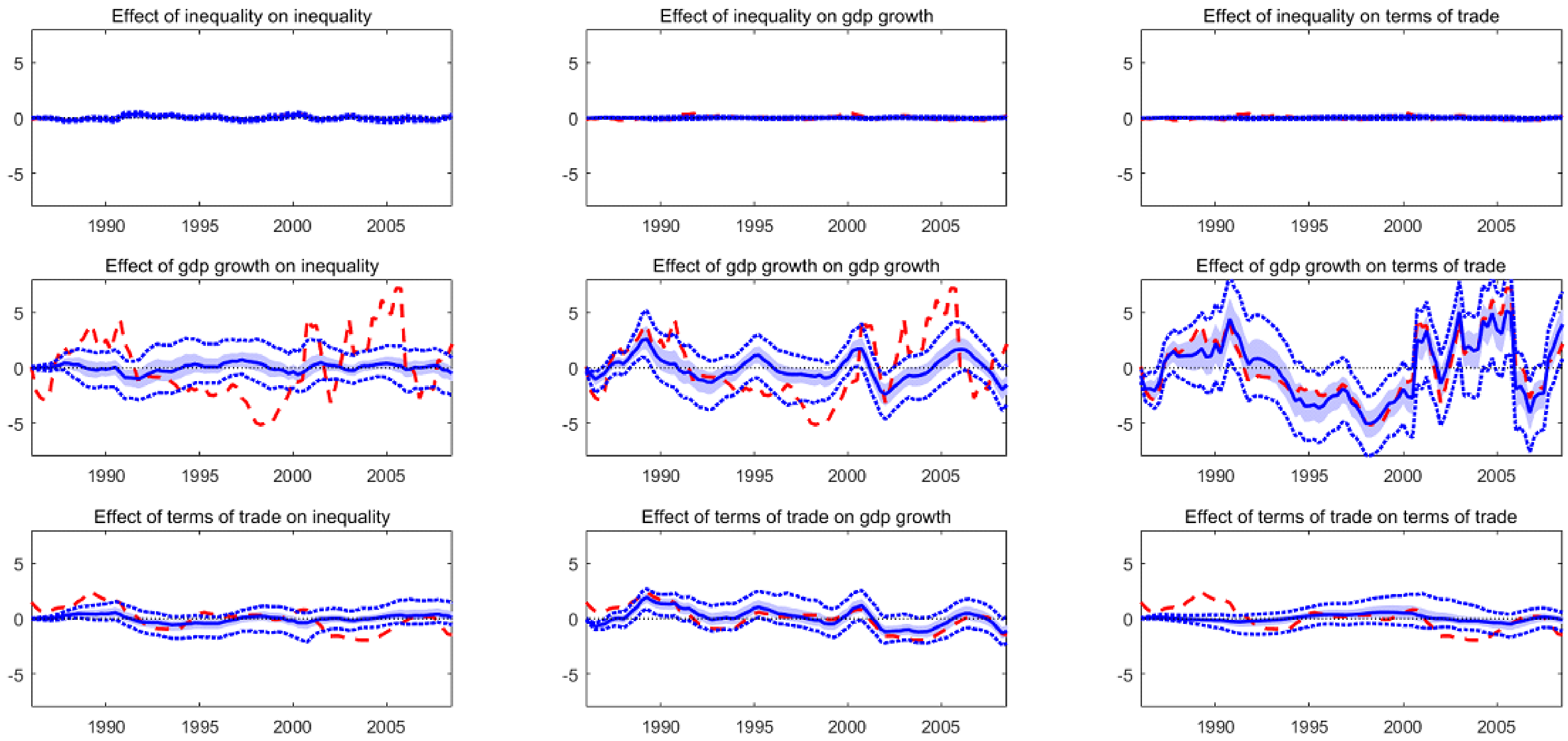
We are particularly interested in the size of the contribution of each of these shocks on inequality and growth. For this, we present the historical decomposition of all three variables (GDP growth, inequality, and terms of trade) in terms of the contributions of each of the separate structural shocks in Figures 3 and 4. The red dashed line in the panels records the actual value of our variable of interest being impacted upon by the shock (expressed as deviations from its mean). Thus, for the first row, the red line presents the actual value of inequality, and for the second and third rows, the actual values of GDP growth and terms of trade. The solid blue line is the portion attributed to the indicated structural shock and the dotted blue line represents the posterior credibility sets. The shaded regions and dashed lines denote 75 per cent and 95 per cent posterior credibility regions, respectively. In Figure 3 the first row gives us the posterior median contribution of the inequality shock on all three entities. We can see that an inequality shock barely has any impact upon GDP growth (panel (1,2)) and terms of trade (1,3). The second row gives us the decomposition of the contributions of the GDP growth shock, and the third row gives us the contributions of the shock in terms of trade. The GDP growth shock has a small effect on inequality (panel (2,1)). This is particularly the case in the late 1980s and early 1990s, and also later, in the late 1990s and late 2000s.

As a point of comparison, we have estimated the above estimations using a mean-dependent inequality measure, the Gini. Similar results are obtained when using the Gini as the inequality measure in Figure A2 in the Appendix.

Tables 1–3 summarize the average contribution of the three different types of shocks using variance decompositions. We report the contribution of each of the three structural shocks to the mean-squared error of a one-year-ahead forecast of each of the three variables. Table 1 summarizes the average contribution of the three different types of shocks using variance decompositions using the inequality measure perc(30:80). A GDP growth shock accounts for 1.85 per cent of the variance of inequality and, for comparison, about 6.08 per cent of the variance of terms of trade. An inequality shock, on the other hand, accounts for less than 1 per cent of variation in GDP growth (and 0.76 per cent for terms of trade). It is not surprising that an inequality shock doesn't have much of a sizeable impact on either of the two entities (GDP growth and trade). Trade shocks account for 0.6 per cent of the variability of GDP growth and 5.16 per cent of the variability of inequality. It is interesting to observe that a terms of trade shock has a more perceptible impact upon inequality than the effect of a GDP shock. All said, the sizes of both of the shocks on inequality is still quite small.

[11] We also generate IRFs for the inequality measure percentile share ratio 10th to 90th percentile shares (perc(10:90)). The IRFs are very similar to those presented in the paper and are available from the authors.

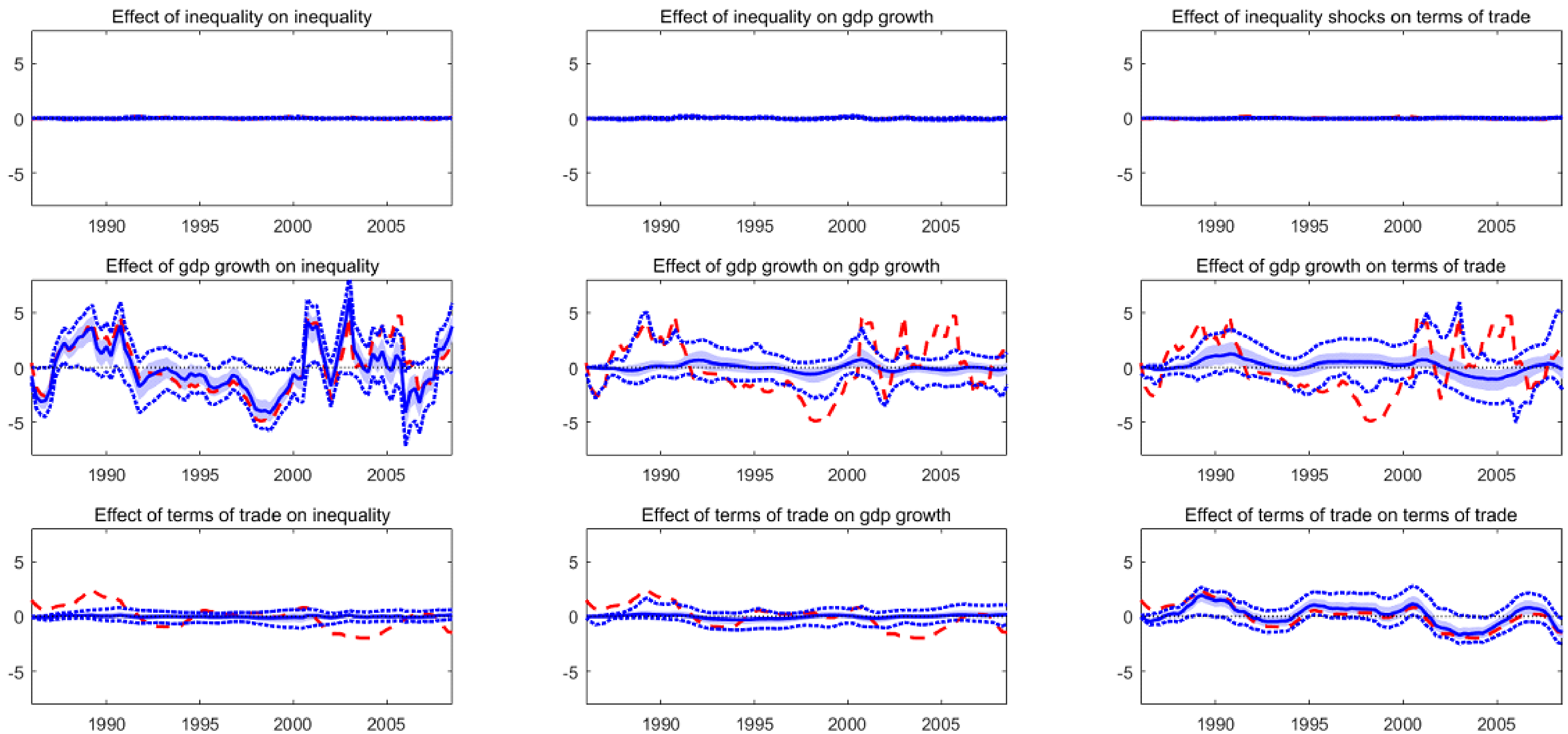
Figure 3: China's portion of historical variation in inequality (perc(30:80)), GDP growth, and terms of trade attributed to each of the structural shocks



Note: dashed red, actual value for the deviation of the variable of interest from its mean; solid blue, portion attributed to the indicated structural shock; shaded regions, 75 per cent posterior credibility sets; dotted blue, 95 per cent posterior credibility sets.

Source: authors' estimations based on data from CHARLS and WID.

Figure 4: China's portion of historical variation in inequality (perc(0:50)), GDP growth, and terms of trade attributed to each of the structural shocks



Note: dashed red, actual value for the deviation of the variable of interest from its mean; solid blue, portion attributed to indicated structural shock; shaded regions, 75 per cent posterior credibility sets; dotted blue, 95 per cent posterior credibility sets.

Source: authors' estimations based on data from CHARLS and WID.

Table 1: China, decomposition of variance of four-years-ahead forecast errors, using inequality measure percentile share ratio (30:80)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	92.99%	1.85%	5.16%
	[0.001, 0.01]	[0.0001,0.0002]	[0.0001,0.0002]
GDP growth	0.68%	98.73%	0.60%
	[0.0001, 0.25]	[2.34,5.48]	[0.0001,0.19]
Terms of trade	0.76%	6.08%	93.16%
	[0.0001, 0.1]	[0.008,0.35]	[0.86,1.94]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

Source: authors' estimations based on data from CHARLS and WID.

As a robustness check, we repeat the above estimations using the other measures of inequality, perc(0:50) and perc(10:90), in Tables 2 and 3. The perc(0:50) inequality measure represents the bottom half of the income distribution and is popularly used in the policy applications literature. The perc(10:90) measure is also popular for focusing on the tails of the distribution, where it is not influenced by the dynamics of the centre of the distribution. The effect of a GDP growth shock on inequality and that of an inequality shock on GDP growth is quite similar to the earlier case using the perc(30:80) inequality measure. The proportion of the variation in inequality explained by GDP growth for both inequality measures is again less than 2 per cent. Likewise, the proportion of variation in GDP growth explained by inequality is also around 1 per cent for both inequality measures. We also present results using the Gini measure in the Appendix in Table A1, where we obtain very similar results.

Table 2: China, decomposition of variance of four-years-ahead forecast errors, using the inequality measure percentile share ratio (0:50)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	92.92%	2.08%	5.00%
	[0.001, 0.01]	[0.0001,0.0002]	[0.0001,0.0002]
GDP growth	0.74%	98.67%	0.59%
	[0.0001, 0.23]	[2.16,4.99]	[0.0001,0.17]
Terms of trade	0.74%	8.63%	90.63%
	[0.0001, 0.1]	[0.008,0.42]	[0.83,1.89]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

Source: authors' estimations based on data from CHARLS and WID.

Table 3: China, decomposition of variance of four-years-ahead forecast errors, using the inequality measure percentile share ratio (90:10)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	92.51%	1.58%	5.92%
	[0.001, 0.01]	[0,0.0001]	[0,0.0001]
GDP growth	0.71%	98.79%	0.50%
	[0.0001, 0.15]	[1.51,3.52]	[0.0001,0.11]
Terms of trade	0.76%	10.19%	89.00%
	[0.02, 0.1]	[0.00001,0.46]	[0.83,1.86]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

Source: authors' estimations based on data from CHARLS and WID.

Our conclusion above, that growth shocks account for a positive fraction of inequality fluctuations, corresponds with the literature. Variations in growth are positively associated with variations in inequality, as evinced by the recent literature using GMM and other regression approaches (see Halter et al. (2014) and Barro (2000) for studies that exploit the time dimension). The negative effect of an inequality shock on GDP growth is also documented in the panel regression applications literature (for example, see Forbes (2000), Knowles (2005) and Halter et al. (2014) for studies exploiting cross-sectional variation, and Bandyopadhyay (2020) for mean-dependent inequality measures). It is also clear from these studies that the effects must be small due to the very small size of the regression coefficients of inequality and growth in the regressions in these studies. These studies, however, do not emphasize or further analyse the cause of the small magnitude of these effects.

To examine a different country's growth and inequality experience, we now undertake our estimations for the USA. The growth and inequality experience has been vastly different in the USA due to a historically different policy framework compared to China. Figure A1 in the Appendix plots some selected inequality measures estimated for the USA and China.

In Figures 5 and 6 we present the structural IRFs for the USA, using the perc(0:50) and the perc(50:90) inequality measures.[12] A clear impact is observed for an inequality shock on GDP growth in panel (2,1): an inequality shock leads to a drop in GDP growth for both sets of results, perc(0:50) and perc (50:90). The red dashed lines plot the median of our prior distribution for impulse response functions for the 20 time periods. Again, the medians of our prior distribution for structural IRFs die out fairly quickly. The effects are small but do not seem to persist for long; for the effect of an inequality shock on growth, it lasts for 5–10 years. In panel (1,2) we record the effect of a growth shock on inequality. For both measures of inequality, the growth shock leads to a drop in inequality. For robustness, we also estimate the IRFs using the perc(10:90) and perc(99:100) measures, where we obtain similar results (available from the authors). We thus observe for both countries, and also for other countries we have worked with (the UK and France) that using different inequality percentile measures does not necessarily yield very different results. Bandyopadhyay (2020) shows that when using a large range of inequality measures, some inequality measures do result in different effects of a GDP shock on inequality.[13]

In order to identify the relative contribution of these structural shocks, we also present the historical decomposition of all three variables (GDP growth, inequality, and terms of trade) in terms of the contributions of the three different sources. Figures 7 and 8 present the variance decompositions in the nine panels, where the red dashed line records the actual value of our variable of interest being impacted by the shock (expressed as deviations from its mean). The solid blue line is the portion attributed to the indicated structural shock, the dotted blue line represents the posterior credibility sets, and the shaded regions and dashed lines denote 75 per cent and 95 per cent posterior credibility regions, respectively.

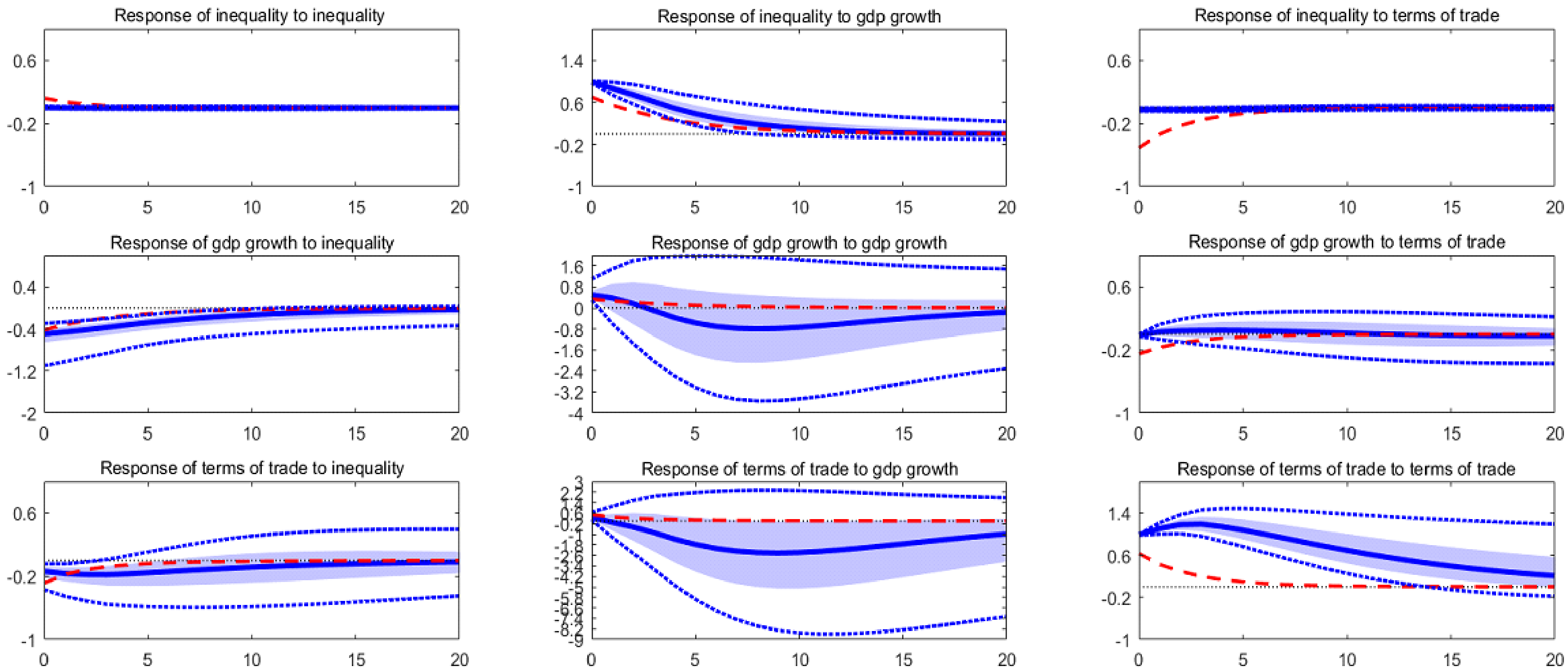
In the figures, the first row gives us the posterior median contribution of inequality shocks on all three entities. We observe a negligible effect of an inequality shock on GDP growth and trade compared to the China estimations. The effect of a GDP growth shock on inequality in panel (2,1) is a bit more observable, with an initial increase in inequality that gradually tapers out in the 1990s. The third row gives us the decomposition of the contributions of the trade shock: the effect of a trade shock on inequality (3,1) is quite small (given by the blue solid line), as is its effect on GDP growth. Similar results are obtained when using the Gini as the inequality measure (see Figure A2 in the Appendix).

These results are also revealed in Tables 4–6, which summarize the average contribution of the three different types of shocks using variance decompositions. The tables report the contribution of each of the three structural shocks to the mean-squared error of a one-year-ahead forecast of each of the three variables for three different types of inequality measures. We present estimates using three different percentile share inequality measures that reveal the similarities in their effects. We also present results using the Gini measure (as a mean-dependent inequality measure) in Table A2 in the Appendix. Results obtained with the Gini measure are very similar to those obtained with the percentile share ratios.

[12] We present results with perc(99:100) in place of perc(10:90) which was used for the China example simply for variety. Results with perc(10:90) for the USA are available from the authors; they are very similar to the perc(99:100) results presented.

[13] Bandyopadhyay (2020) shows that mean-independent inequality measures perform slightly differently from mean-dependent inequality measures in being impacted by a GDP growth shock.

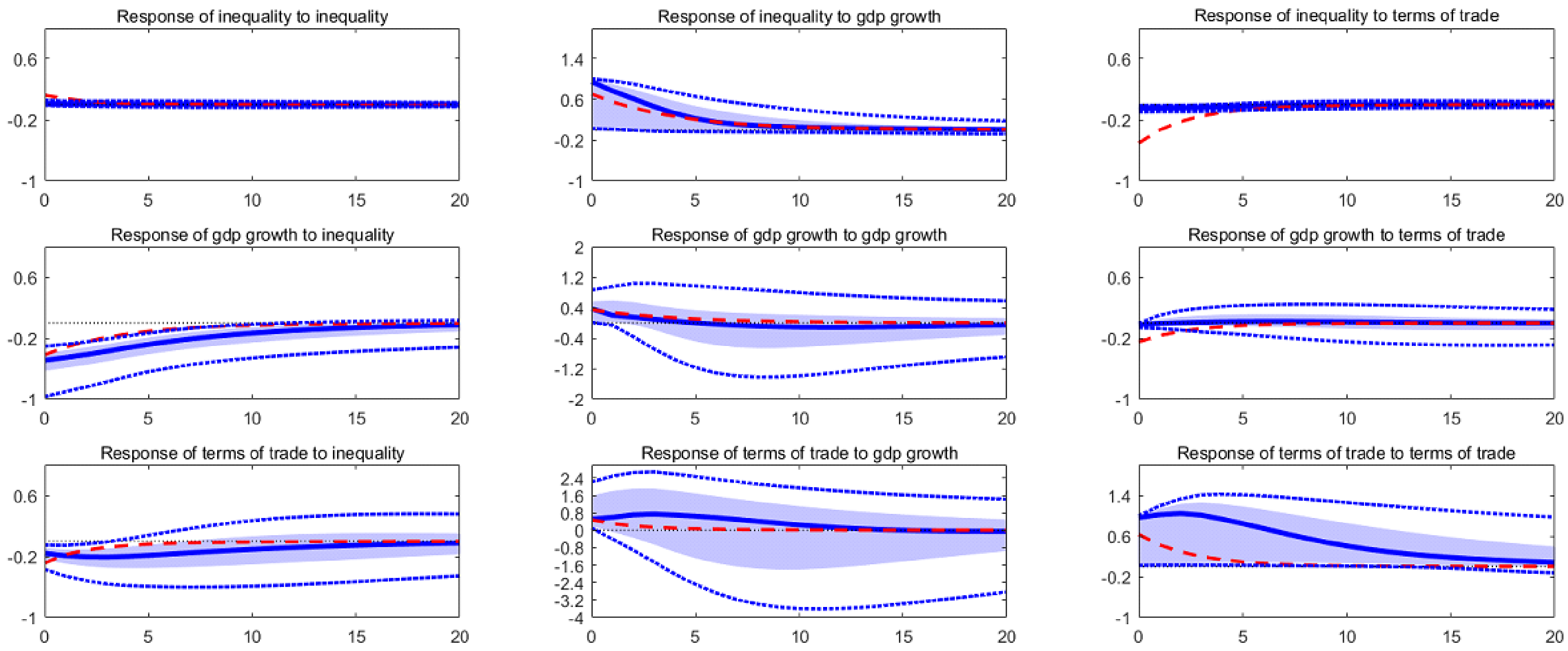
Figure 5: USA's structural IRFs for the three-variable VAR, using inequality measure perc(0:50)



Note: solid blue lines, posterior median; shaded regions, 75 per cent posterior credibility set; dotted blue lines, 95 per cent posterior credibility set; dashed red lines: prior median.

Source: authors' estimations based on data from WID.

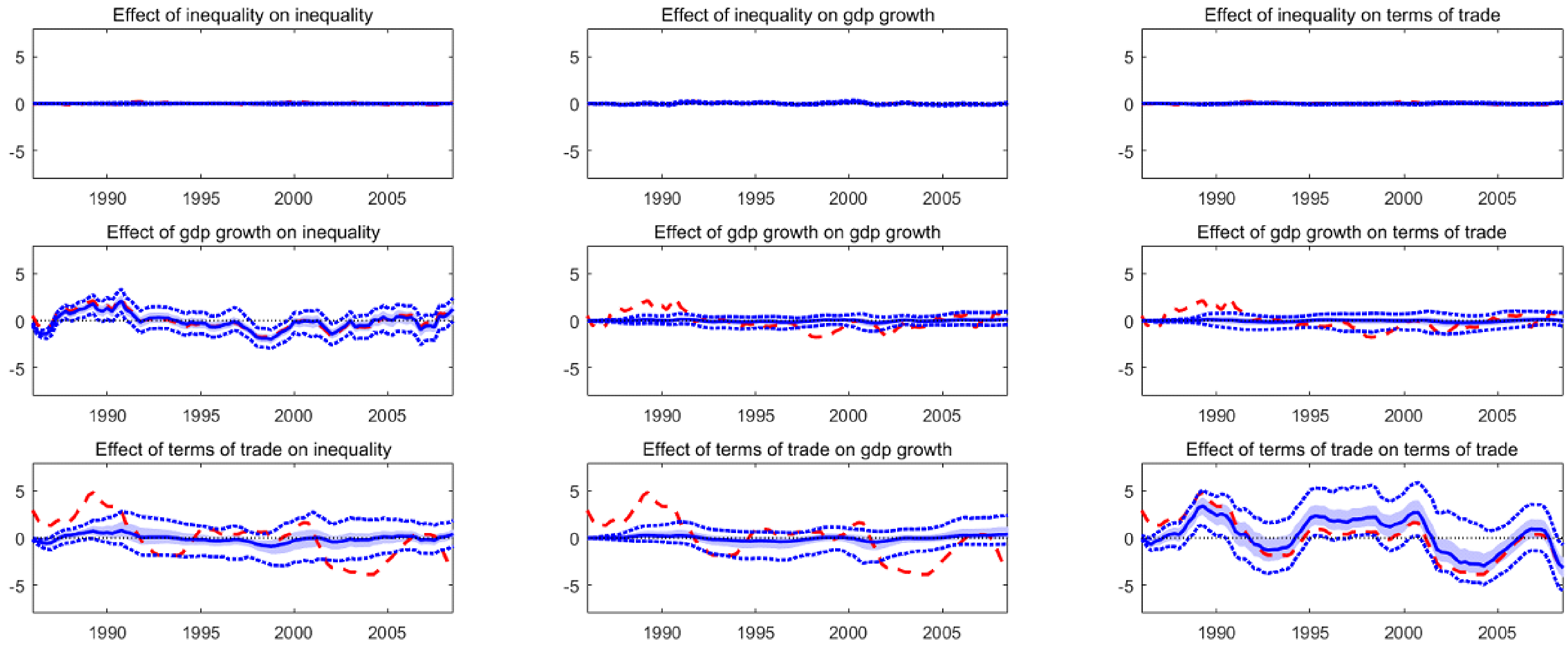
Figure 6: USA's structural IRFs for the three-variable VAR, using inequality measure perc(50:90)



Note: solid blue lines, posterior median; shaded regions, 75 per cent posterior credibility set; dotted blue lines, 95 per cent posterior credibility set; dashed red lines, prior median.

Source: authors' estimations based on data from WID.

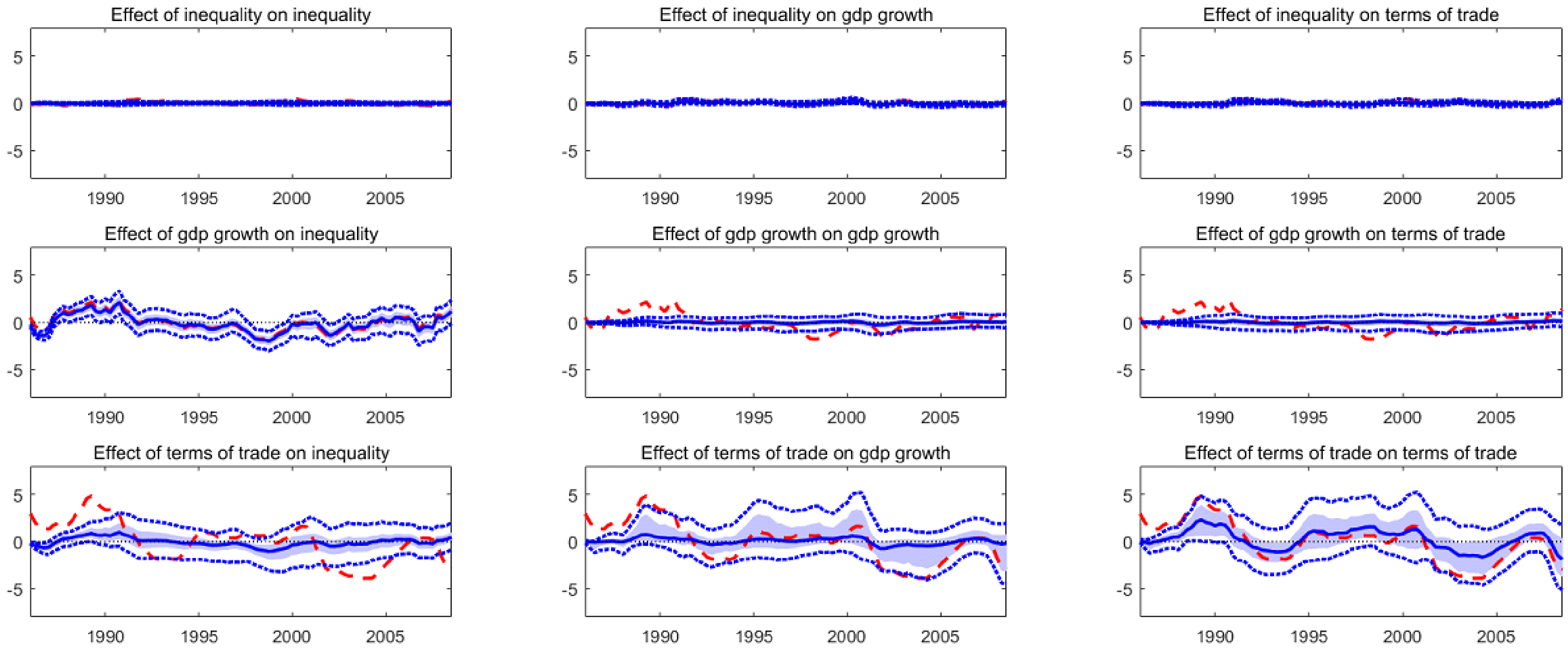
Figure 7: USA's portion of historical variation in inequality (perc(0:50)), GDP growth, and terms of trade attributed to each of the structural shocks



Note: dashed red, actual value for the deviation of the variable of interest from its mean; solid blue, portion attributed to indicated structural shock; shaded regions, 75 per cent posterior credibility sets; dotted blue: 95 per cent posterior credibility sets.

Source: authors' estimations based on data from WID.

Figure 8: USA's portion of historical variation in inequality (perc(50:90)), GDP growth, and terms of trade attributed to each of the structural shocks



Note: dashed red, actual value for the deviation of the variable of interest from its mean; solid blue, portion attributed to indicated structural shock; shaded regions, 75 per cent posterior credibility sets; dotted blue, 95 per cent posterior credibility sets.

Source: authors' estimations based on data from WID.

Table 4: USA, decomposition of variance of four-years-ahead forecast errors, using the inequality measure percentile share ratio (50:90)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	86.97%	1.94%	11.1%
	[0.00, 0.06]	[0.00,0.02]	[0.01,0.03]
GDP growth	1.78%	97.36%	0.86%
	[0.03, 0.31]	[0.12,0.69]	[0.0001,0.11]
Terms of trade	1.3%	8.63%	90.07%
	[0.0001, 0.41]	[0.00,1.32]	[0.07,1.81]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

Source: authors' estimations based on data from WID.

Table 5: USA, decomposition of variance of four-years-ahead forecast errors, using the inequality measure percentile share ratio (10:90)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	74.63%	1.78%	23.59%
	[0.001, 0.04]	[0.00001,0.0002]	[0.00001,0.03]
GDP growth	1.24%	97.72%	1.04%
	[0.00001, 0.05]	[0.34,0.82]	[0.0001,0.04]
Terms of trade	4.82%	10.50%	84.68%
	[0.0001, 0.23]	[0.01,0.43]	[0.04,1.74]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

Source: authors' estimations based on data from WID.

Table 6: USA, decomposition of variance of four-years-ahead forecast errors, using inequality measure percentile share ratio (99:100)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	92.00%	1.49%	6.51%
	[0.001, 0.1]	[0.0001,0.002]	[0.0001,0.003]
GDP growth	0.83%	98.53%	0.65%
	[0.00001, 0.04]	[0.34,0.82]	[0.0001,0.03]
Terms of trade	6.41%	0.83%	92.76%
	[0.01, 0.35]	[0.0001,0.11]	[0.81,1.88]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

Source: authors' estimations based on data from WID.

We find that the effect of a GDP growth shock in all three tables accounts for similar amounts of the variation in inequality at under 2 per cent, and, by comparison, slightly more of the variance of terms of trade. An inequality shock also accounts for a very small amount of variation in GDP growth (under 2 per cent) and 3 per cent for the terms of trade. By contrast, the terms of trade shock seems to have a more perceptible effect on inequality, and some variation in its contribution for the different measures of inequality. The effects of all the shocks are thus quite comparable for China and the USA.

4 Discussion

There are several findings from our estimations which matter for both the policy-maker and the empirical researcher.

First, we find that a growth shock is inequality-increasing and an inequality shock is growth-reducing. We obtain this effect for both the USA and China. The two countries having very different policy structures, in particular China's drive towards poverty alleviation, does not seem to impact upon this relationship. This finding conforms with much of the earlier cross-country literature, as discussed in Section 2.

Second, perhaps the most striking finding is that the size of the effect of a GDP growth shock on inequality is very small. We also observe a similar very small effect of an inequality shock on GDP growth. This is the case for both China and the USA.[14] The effect of a terms of trade shock on inequality is larger in magnitude for all cases studied—for some cases by a factor of ten.

For China, the size of the effect of a growth shock on inequality explains less than 2 per cent of the variance in inequality for all the inequality measures tested. For the USA, a growth shock explains a similarly small amount of the variance of inequality: less than 2 per cent. The effect of an inequality shock is also very small for both countries. It is quite remarkable that the sizes of these effects for both countries are very similar, in spite of the two countries having different socioeconomic structures. The differences in the results for different inequality measures are also negligible.

This particular result of the size of the effect of GDP growth on inequality being small may be due to the lack of social mobility that has been highlighted for both the USA and China. The effects of a GDP growth spurt may take a very long time to have an impact upon inequality. At worst, the required channels via which a growth spurt could reduce inequality may not be adequately available for these countries.

Finally, we observe that the impact for all of the shocks (growth, inequality, and terms of trade) do not persist for very long. For both countries, and for all variables in the model, the shocks taper off in their effects within 10–15 years at the most. This result accords with that observed by Bandyopadhyay (2020) for a number of developed countries, including Denmark, Switzerland, and the UK.

For the policy-maker, the third finding, that the effects of the shocks are short, is good news. However, it also means that the socioeconomic effects of the shock need to be dealt with in the immediate aftermath of the shock, which is bad news. For all the impulse responses generated, there is an immediate increase in inequality after a growth shock (and an immediate drop in GDP growth after an inequality shock). Further modelling is thus required to identify which aspects of social wellbeing or which macroeconomic variables are most immediately impacted upon due to a growth or inequality shock.

That the size of the effects of inequality and growth shocks upon each other is only 2 per cent calls for a discussion. In terms of the simple arithmetic of the variance decomposition, it is easy to see from our empirical results that a terms of trade shock has a much larger impact upon inequality and growth compared to that of growth and inequality on each other for both countries. For the USA, in Tables 4 and 5, 11 per cent and 23 per cent of the variance in inequality is explained by the terms of trade shock, respectively. For the China results, around 5 per cent of variation in inequality is explained by a terms of trade shock. Compared to that, a GDP growth shock explains only 1.78 per cent of the variation in inequality for both countries, and around 1 per cent of growth is explained by an inequality shock. Other studies using this approach (e.g. Baumeister and Hamilton 2018) to measure the effects of monetary policy, domestic demand, and supply shocks on inflation reveal that 69 per cent of variation in inflation is explained by a supply shock and 28 per cent is determined by a demand shock. In contrast, a monetary policy shock only explains 5 per cent. Comparing our findings to these statistics for fiscal and monetary shocks, it is thus easy to conclude that the effects of inequality and growth shocks on each other are quite small.

That a growth shock or an inequality shock explains so little variation of inequality or growth, respectively, however, raises a worrying concern. The small size implies that these shocks are impacting upon other macroeconomic variables that are not included in the model—variables that have a clearer and direct impact upon social wellbeing or other macroeconomic aspects. In our estimations, for example, we find that the terms of trade shock explains the variation in inequality to a greater extent than a growth

[14] This result is also borne out with our empirical results for other countries we have tested (the UK and France, not presented).

shock. Thus, 'inequality and growth' empirical studies employing models that are solely devoted to the effect of changes in inequality upon growth (or changes in growth on inequality) should model a more elaborate system of equations, identifying pathways of the impact of growth and/or inequality shocks on a large number of variables.

In addition, the assessments undertaken in this paper would ideally be complemented with more country examples; for example, some fast-growing small economies at different stages of development, with high or low inequality. Smaller countries and middle-income/rank developing countries may have a different experience, and the size of a growth shock on inequality and vice versa may be larger. Some possible examples that may be interesting to study could be Vietnam, Korea, Botswana, South Africa, Argentina, Chile, or Brazil, to name a few.

5 Conclusion

In this paper we have examined the relationship between inequality and growth by estimating the impact of their individual shocks for two large countries, China and the USA. We use a Bayesian VAR approach to estimate the size and direction of the effects of the shocks and conclude three salient findings. First, we find that a growth shock is inequality-increasing. We also find that an inequality shock is growth-reducing. These two results conform with much of the empirical literature.

The second salient finding is that the sizes of these effects are strikingly small. Variance decompositions reveal that, at most, 2 per cent of the variations in growth are explained by an inequality shock. Likewise, we find that under 2 per cent of variation in inequality is explained by a growth shock.

The third finding is that the effects of these shocks dissipate within ten years. The results are remarkably similar for both countries. This result is also borne out by Bandyopadhyay (2020), who finds that the effects of a growth shock on inequality also dissipates in around ten years for three major developed countries (Denmark, Switzerland, and the UK). To ensure the robustness of our results, we use up to five inequality measures for the analysis, namely several percentile share ratios, each representing different parts of the income distribution. It is interesting that for both China and the USA the results are very similar for all inequality measures.

The results obtained in the paper suggest that the inequality and growth relationship is likely a highly individual experience for each country and that it would be ideal for researchers and policy-makers to analyse countries on an individual basis rather than relying on a generalized result for all countries using a cross-country approach. While the findings in this paper accord with several conclusions in the empirical literature, one of the striking findings in this paper is that these effects have a short- to medium-term effect only. The effects of both growth and inequality shocks last for under ten years. It is possible that developed and developing countries will have different response times to these shocks.

The inequality-increasing effect of a growth shock and the growth-reducing effect of an inequality shock as obtained in this paper, however, will have long-term implications for other parts of the economy and society which are not modelled in this study. While the effects of these shocks themselves dissipate within ten years, the reduced growth or increased inequality as a result of these shocks will likely affect other variables such as inflation and unemployment. These effects could have greater long-term impact and thus could be investigated in further research.

The findings obtained in this paper would be more robust if extended using another standard measure of inequality, such as any other mean-dependent inequality measure, to observe the effects of the shocks tested in this paper for the same countries. Bandyopadhyay (2020) highlights that different inequality measures experience the effects of the GDP shocks in different ways. It would also be useful to observe whether other developed countries and developing countries have similar or different experiences.

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Appendix

Table A1: China, decomposition of variance of four-years-ahead forecast errors, using the inequality measure percentile share ratio (99:100)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	59.22%	8.89%	31.89%
	[0.23, 2.23]	[0.03,0.67]	[0.19,0.91]
GDP growth	1.03%	96.72%	2.25%
	[0.00001, 0.003]	[0.01,0.02]	[0.0001,0.01]
Terms of trade	3.48%	6.04%	90.48%
	[0.01, 0.21]	[0.41,1.98]	[2.79,6.13]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

Source: authors' estimations based on data from CHARLS and WID.

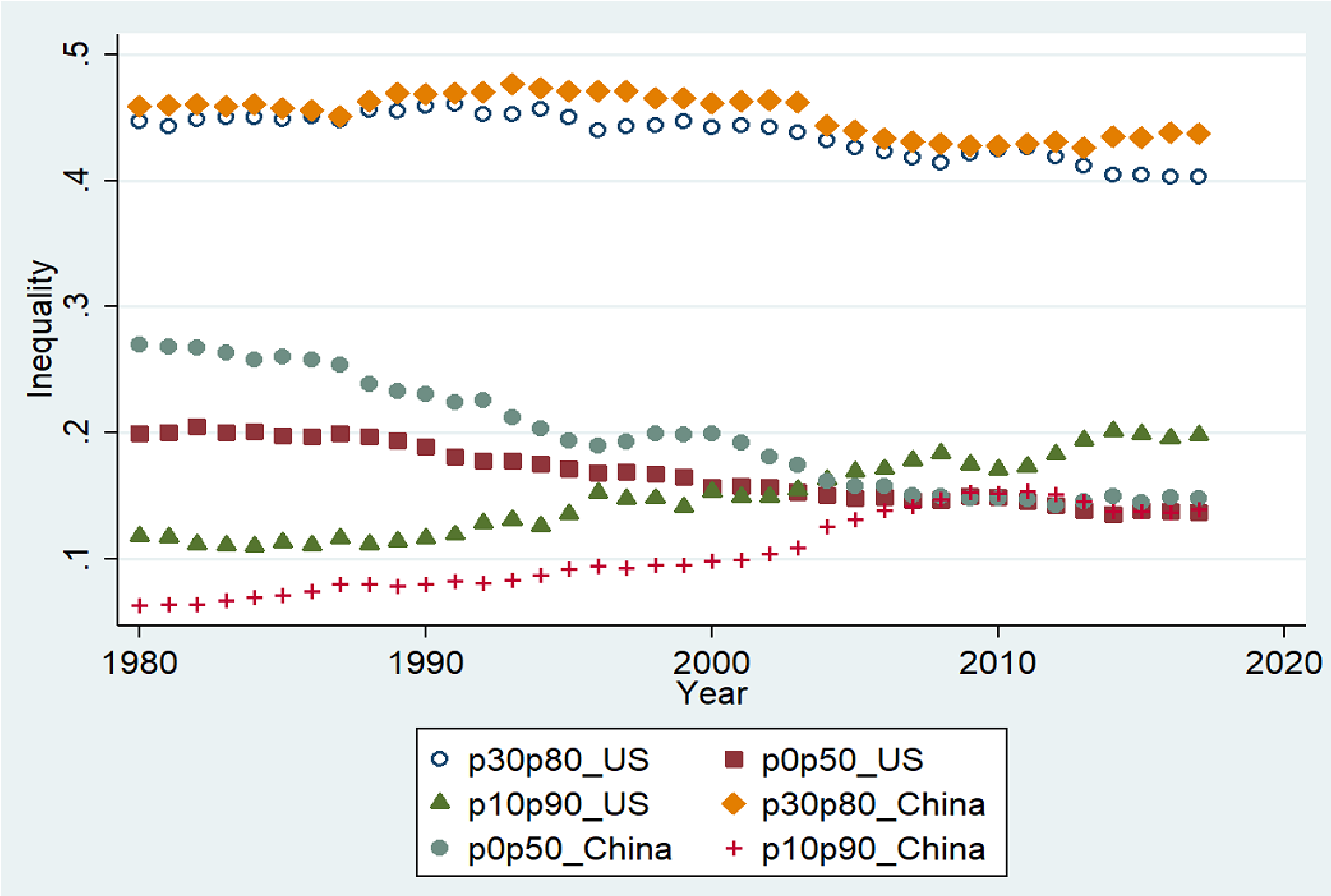
Table A2: USA, decomposition of variance of four-years-ahead forecast errors, using the inequality measure percentile share ratio (99:100)

	Inequality shock	GDP growth shock	Terms of trade shock
Inequality	95.27%	4.12%	0.61%
	[0.01, 0.6]	[0.00001,0.0001]	[0.00001,0.0001]
GDP growth	2.02%	96.79%	1.20%
	[0.00003, 0.00003]	[0.01,0.01]	[0.0001,0.0001]
Terms of trade	4.83%	3.85%	91.32%
	[0.03, 0.71]	[0.01,0.58]	[2.32,5.36]

Note: estimated contribution of each structural shock to the four-years-ahead median squared forecast error. Brackets indicate 95 per cent credibility intervals.

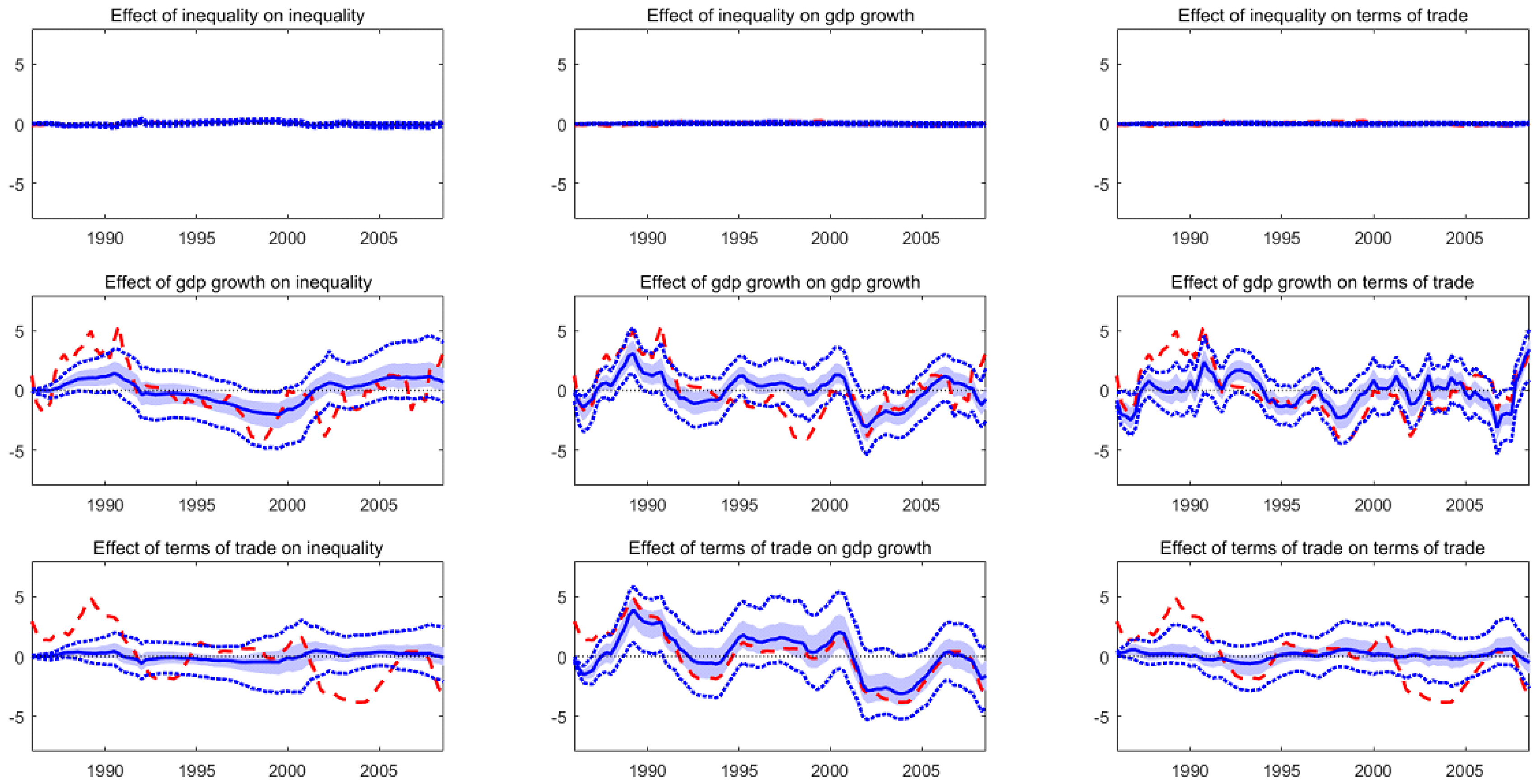
Source: authors' estimations based on data from WID.

Figure A1: Trends of selected inequality measures (percentile share ratios) for China and USA for 1979–2018



Source: authors' estimations based on data from CHARLS and WID.

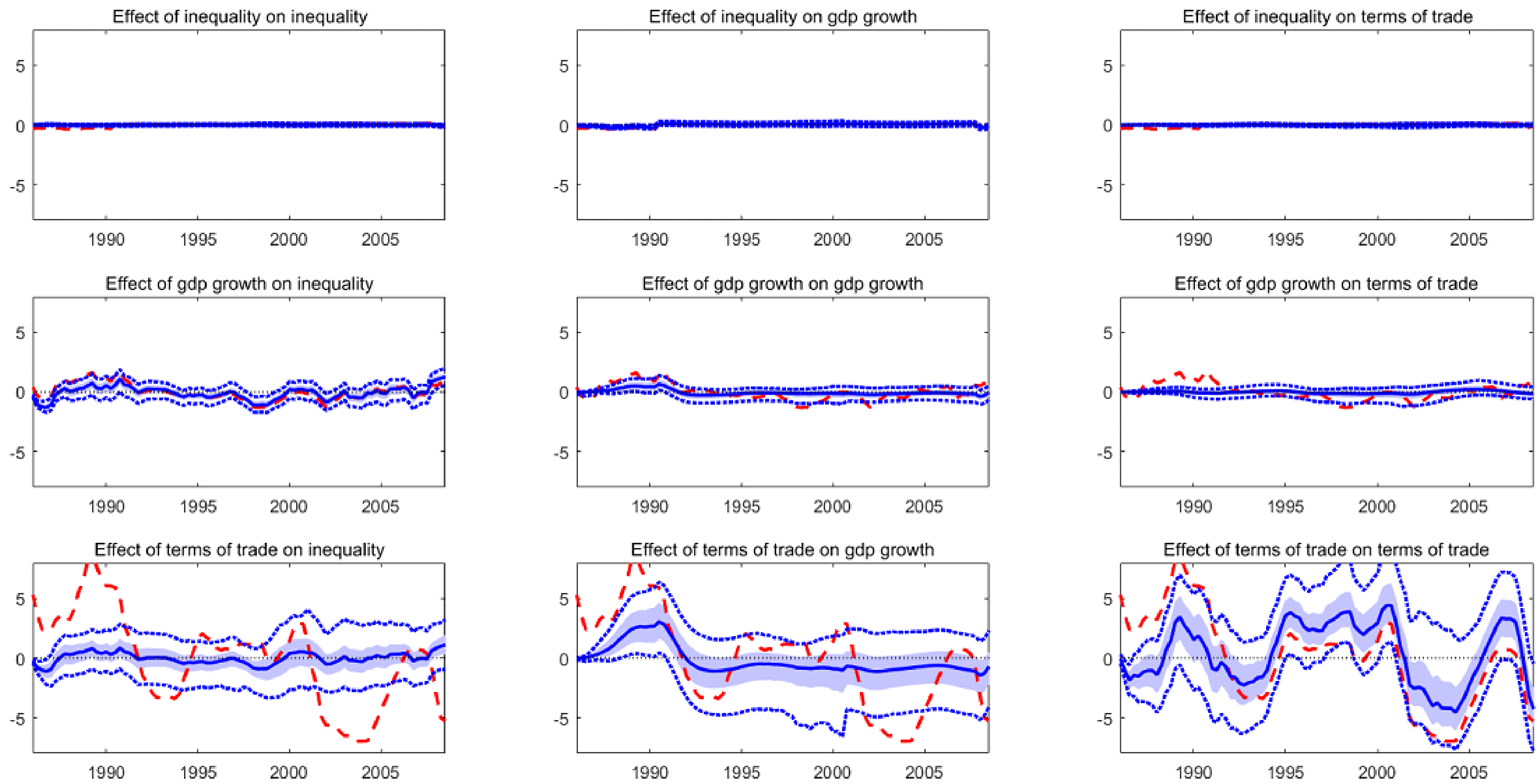
Figure A2: China's portion of historical variation in inequality (using the Gini), GDP growth, and terms of trade attributed to each of the structural shocks



Note: dashed red, actual value for the deviation of the variable of interest from its mean; solid blue, portion attributed to the indicated structural shock; shaded regions, 75 per cent posterior credibility sets; dotted blue, 95 per cent posterior credibility sets.

Source: authors' estimations based on data from CHARLS and WID.

Figure A3: USA's portion of historical variation in inequality (using the Gini), GDP growth, and terms of trade attributed to each of the structural shocks



Note: dashed red, actual value for the deviation of the variable of interest from its mean; solid blue, portion attributed to indicated structural shock; shaded regions, 75 per cent posterior credibility sets; dotted blue, 95 per cent posterior credibility sets.

Source: authors' estimations based on data from WID.