Dynamic and Asymmetric Response of Inequality to Income Volatility: The Case of the United Kingdom

Goodness C. Aye*, Giray Gozgor** and Rangan Gupta***

Abstract

Using the quarterly data of the United Kingdom (UK) for the period from 1975Q1 to 2016Q1, the paper analyses the dynamic and the asymmetric responses of inequality to the real gross domestic product (GDP) (income) volatility. For this purpose, we consider the bivariate Generalized Autoregressive Conditional Heteroskedasticity-in-mean (GARCH-M) Structural Vector Autoregressive (VAR) based models to examine the related relationship. Applying this method to the different measures of both income- and consumption inequality (i.e. the measures of the Gini, the standard deviation, and the 90-10 percentile differential), we find that income volatility has an increasing effect on inequality. Not only the real GDP volatility significantly increases inequality, but also its effect is asymmetric. In other words, inequality differently responds to the positive and the negative income growth volatility shocks. Moreover, the volatility in the GDP-inequality equation tends to amplify the positive dynamic response of inequality to a positive income shock, while diminishing the response of inequality to a negative income shock. The implications of these findings are also drawn.

Key Words: Inequality; income volatility; asymmetric shocks; impulse-response functions

JEL Classification Codes: C32; O11; O47

* Corresponding Author. Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. E-mail: goodness.aye@gmail.com.

** Istanbul Medeniyet University, Istanbul, Turkey E-mail: giray.gozgor@medeniyet.edu.tr.

*** Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. E-mail: rangan.gupta@up.ac.za.

1. Introduction

Inequality across the world has been rising and became more pronounced since the great global recession of 2008-2009. The UK is not an exception. The evidence of rising income inequality in the UK has been presented by a number of studies. For instance, Belfield et al. (2014) reported that the Gini coefficient for the UK. Household disposable income increased from 0.25 in 1967 to 0.36 in 2008. Similarly, Brewer and Wren-Lewis (2016) observed that the Gini coefficient for net labour earnings increased from 0.32 in 1978 to 0.35 in 2008. These findings corroborate that the evidence of Blundell and Etheridge (2010), which is also noted the historically rising trend in inequality in the UK. This trend has not been reversed as the net income Gini in the UK is 0.36 in 2015, according to the estimations by the Organisation for Economic Co-operation and Development (OECD) Income Distribution Database (OECD, 2018).

The precise drivers of increasing inequality are not well understood (Piketty and Saez, 2007). Many factors, which are interconnected, could play a role. These factors include the level of globalization, public policy (monetary and fiscal), international competition, decline of labour unions, supply-side economic models that favour greater individualization of pay over collective bargaining, structural changes in the labour market that favour the very highly skilled, increasing levels of private and inherited wealth, skill-biased technological change, the rise of pass-through businesses resulting in huge capital income accumulation, the great global recession of 2008-2009, and among many others (see e.g., Alvaredo, et al., 2013; Aye et al., 2018; Bunker, 2017; Gozgor and Ranjan, 2017; Moeller, et al., 2017; Mumtaz and Theophilopoulou, 2017; Rosenfeld, 2014; Stiglitz and Greenwald, 2014; Western and Rosenfeld, 2011). In this paper, we focus on a different factor and aim to examine the effect of income growth volatility on income inequality in the UK.

The growing interest in the relationship between the economic growth (income) volatility and the macroeconomic variables stems from the early paper by Ramey and Ramey (1995), which examined the nexus between the output volatility and the output growth rate. Ramey and Ramey (1995) found that countries with the higher volatility of output growth have a lower output growth rate. Inequality has also received a wide attention among the studied macroeconomic variables. While some studies–theoretical and empirical–have examined the effect of income volatility on inequality, others have examined the reverse effect of inequality on income volatility.

Theoretically, three different channels through which growth volatility could affect income and wealth distribution have been identified (Chang, et al., 2018; Huang et al., 2015). The first channel is the wage channel which relates to risk. Due to differing levels of risk tolerance, entrepreneurs may acquire more income and wealth than wage earners, since higher risk premium is associated with higher income. For instance, Caroli and García-Peñalosa (2002) argued that in a situation where the output becomes more volatile and hence marginal product and wages fluctuate due to random shocks, entrepreneurs will capture a greater share of output due to their risk-bearing ability while salaried workers will settle for a decreased salary to maintain constant wage. The second channel is the human capital channel and proposes that the wage volatility could affect the wage differential between the low- and the high-skilled workers. Checchi and García-Peñalosa (2004), established this in their study by showing that wage volatility causes a high degree of educational inequality, which consequently increases income inequality. The third channel is the labour supply decision mechanism. García-Peñalosa and Turnovsky (2005) proposed the stochastic endogenous growth model to explore the relationship between the volatility of growth and the distribution of factor income. In their model, the employment level is endogenously determined and the production structure allows for non-constant labour shares. Under realistic values of the degree of risk aversion, the greater output volatility increases saving and promotes growth, thereby raising (future) wages and the supply of labour. As a result, the return to capital rises and that to labour falls. Since capital endowments exhibit more unequal distribution than labour time, the change in relative factor prices will raise income inequality.

In addition, volatility can also make economic growth less favourable to the poor through for instance market imperfections, which makes it difficult for the poor to access financial and credit markets, thus affecting their occupational outcomes. In addition, the low-income individuals often depend on state grants and social services (Jeanneney and Kpodar 2011), have less diversified sources of income, possess lower qualifications, and are less mobile relative to the rich (Agénor, 2004; Chang, et al., 2018; Corak et al., 2014; Galor and Zeira, 1993; Laursen and Mahajan, 2005). These factors could widen the gap between the rich and the poor.

Empirically, a few studies have been conducted in an attempt to examine the effects of income growth volatility on inequality (Bahmani-Oskooee and Motavallizadeh-Ardakani, 2018; Breen and García-Peñalosa, 2005; Calderon and Yeyati, 2009; Eksi, 2017; Hausmann and Gavin, 1996; Huang et al., 2015; Konya and Mouratidis, 2006; Laursen and Mahajan, 2005; Whalley and Yue, 2009). In general, these studies found a positive effect of income volatility on inequality. However, whether the effect is asymmetric or symmetric is another question. We contribute to the existing literature by examining the relationship using the UK data. Also, our analysis is based on the disaggregated inequality data. Specifically, we consider both income- and consumption inequality, and we look at three different forms: i) the Gini income and consumption inequality, ii) the standard deviation of logs of income and consumption, iii) the difference between the 90 and 10th percentile of logs of income or consumption. The disaggregated inequality data enables us to identify, which measure and form of inequality are affected by the growth volatility and to what extent. This will help to properly guide policy decisions. In addition, we also analysed the asymmetric responses of inequality to income volatility. In other words, we investigate whether the positive and the negative income volatility has different effects on income inequality.

Among the empirical papers, our paper is closely related to Bahmani-Oskooee and Motavallizadeh-Ardakani (2018) and Huang et al. (2015). However, we differ from the paper of Bahmani-Oskooee and Motavallizadeh-Ardakani (2018), which analysed the asymmetric effect of income volatility on income inequality by using the nonlinear Autoregressive-Distributed Lag (ARDL) model and hence could only make inference on average effect. Also, their study may be subject to the generated regressors problem discussed by Pagan (1984). To address this issue, we used the GARCH-in-mean VAR model, which measures the conditional standard deviation of the forecast of the growth of the UK GDP as the measure of economic growth uncertainty. Furthermore, this method allows us to examine not only the average effect of income volatility on inequality but also the dynamic impulse responses to the positive and the negative growth volatility shocks over the different horizons. Another closely related paper is that of Huang et al. (2015), which examined the effect of income volatility on income inequality in the United States (U.S.) state-level disaggregated data by using the panel data models. Although their paper performed the asymmetric analysis, it was based on the univariate Exponential GARCH (EGARCH) model, which only looks at the univariate property (asymmetric behaviour) of the economic growth without conditioning this on inequality. At this stage, we conduct the bivariate analysis, which includes both income volatility and inequality in making inference about the asymmetric effect. Therefore, Huang et al. (2015) may also be influenced by the generated regressors problem. Moreover, different from the other empirical studies, our models are able to capture the dynamic response of inequality to income volatility with and without the GARCH-in-mean terms. We also used the higher frequency (quarterly) and national data. Note that those papers used the U.S. state level annual panel data.

The rest of the paper is organized as follows: Section 2 presents the empirical model. Section 3 presents the data. The results are discussed in Section 4, while Section 5 concludes.

2. Empirical Model

Our model is based on Elder (1995 and 2004) and Elder and Serletis (2010) and it is a bivariate quarterly model for the change of inequality measures and the GDP (income) growth volatility. It is also a structural VAR based model with the modifications for conditional heteroskedasticity in the parametric form of the bivariate GARCH-in-mean. It is assumed that the dynamics of the structural system can be summarized by a linear function of the variables of interest, and a term related to the conditional variance, which is given as:

$$\mathbf{B}y_t = \mathbf{C} + \boldsymbol{\Gamma}_1 \mathbf{y}_{t-1} + \boldsymbol{\Gamma}_2 \mathbf{y}_{t-2} + \ldots + \boldsymbol{\Gamma}_p \mathbf{y}_{t-p} + \boldsymbol{\Lambda}(\mathbf{L})\sqrt{\mathbf{H}_t} + \varepsilon_t \tag{1}$$

where dim ($\mathbf{B}$) = Dim (Γ_i) are p × p matrices, $\sqrt{\mathbf{H}_t}$ is a diagonal and $\boldsymbol{\Lambda}(\mathbf{L})$ is a matrix polynomial in the lag operator. $\mathbf{y}_t$ is a vector containing the GDP and inequality growth rates, $\varepsilon_t \parallel \Pi_{t-1} \sim \text{iid}\ (\mathbf{0}, \mathbf{H}_t)$ represents the uncorrelated structural disturbances in the system where Π_{t-1} is the available information set at time t-1.

The matrix of conditional standard deviations ($\sqrt{\mathbf{H}_t}$) is allowed to affect the conditional mean. A test of restrictions on the elements of $\boldsymbol{\Lambda}(\mathbf{L})$ that relates the conditional standard deviation of inequality, given by the appropriate element of $\sqrt{\mathbf{H}_t}$, to the conditional mean of $\mathbf{y}_t$ is performed. This enables us to test whether the GDP volatility affects inequality measures; if the GDP volatility has adversely affected inequality, a negative and statistically significant coefficient on the conditional standard deviation of the GDP in inequality equation will be found.

The conditional variance $\mathbf{H}_t$ is modelled as bivariate GARCH and is given as:

$$\mathbf{h}_t = \mathbf{C}_v + \sum_{j=1}^{J} \mathbf{F}_i vec(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{i=1}^{I} \mathbf{G}_i \mathbf{h}_{t-i} \tag{2}$$

$\varepsilon_t \sim \sqrt{\mathbf{H}_t}\mathbf{z}_t;\ \mathbf{z}_t \sim iidN(0, \mathbf{I}),$ where $\mathbf{C}_v$ is $\mathrm{N}^2 \times 1$ matrix, $\mathbf{F}$ and $\mathbf{G}$ are $\mathrm{N}^2 \times \mathrm{N}^2$ matrices and $\mathbf{h}_t = vec(\mathbf{H}_t)$. This specification does not however guarantee that $\mathbf{H}_t$ is positive definite. With a few restrictions and by re-dimensioning the variance function parameter matrices $\mathbf{F}$ and $\mathbf{G}$, the variance function reduces to the following equation:

$$diag(\mathbf{H}_t) = \mathbf{C}_v + \sum_{j=1}^{J} \mathbf{F}_i diag(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{i=1}^{I} \mathbf{G}_i diag(\mathbf{H}_{t-i}) \tag{3}$$

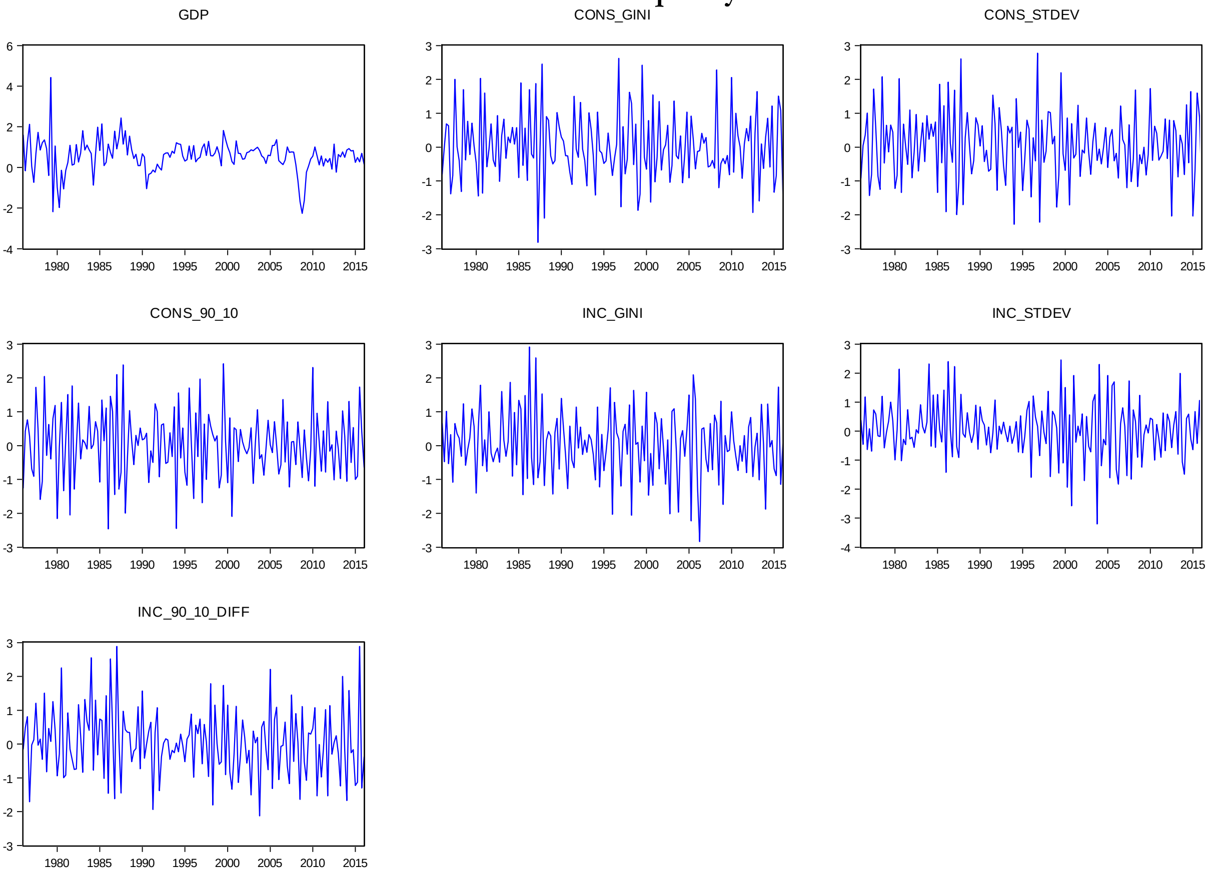
Where $diag$ is the operator that extracts the diagonal of a square matrix. The second and third terms on the RHS of Equation (3) are the ARCH and GARCH, terms respectively. The variance function given by Equation (3) is estimated with $J = I = 1$, which is the specification for a GARCH (1,1)-in-mean VAR model. The impulse responses calculated following Elder (2003) are simulated from the maximum likelihood estimates of the parameters of the model. The confidence intervals are generated by simulating 1000 impulse responses based on parameter values drawn randomly from the sampling distribution of the Maximum Likelihood Estimations (MLEs).[1]

[1] Further technical details about the model can be obtained from Elder and Serletis (2010).

3. Data

We used the quarterly real GDP and inequality data for the UK, spanning the period from 1975Q1 to 2016Q1 with the starting and ending dates solely determined by data available on inequality. The real GDP at the market prices were sourced from the Main Economic Indicators database of the OECD. The inequality measures are calculated using survey data on income and consumption from the family expenditure survey, which is available from the UK Data Service.[2] We considered both income and consumption forms of inequality. The income equalised inequality was obtained by dividing the total consumption per capita of a household by the square root of the number of people in a household. We used three measures of inequality: the Gini coefficient, the standard deviation of logs, and the difference between the 90 and 10th percentile of logs. All data as shown in Figure 1 and they were used in the logarithmic difference form to achieve stationarity and hence avoid spurious regression.

Figure 1.
Real GDP and Inequality Data



Notes: The prefix 'cons' stands for consumption while 'inc' stands for income. The suffix 'stdev' stands for the standard deviation, while '90_10' stands for the 90-10 percentile differential of income and consumption inequality series.

4. Empirical Results

The effect of income growth volatility on inequality measures is examined by using four lags in the Gini and the standard deviation forms of inequality related equations and two lags for the 90-10

[2] For the details of the data, visit (https://discover.ukdataservice.ac.uk/series/?sn=200016), (https://discover.ukdataservice.ac.uk/series/?sn=2000028).

percentile differential related equation as suggested by the Akaike Information Criterion (AIC). To test the suitability of the GARCH (1,1)-in-mean VAR model specification in capturing the features of the data, we compared its Schwarz Information Criterion (SIC) statistics with that of the standard parsimonious homoscedastic VAR. An improvement in the Schwarz criterion suggests strong evidence in favour of the bivariate GARCH (1,1)-in-mean VAR specification (Elder and Serletis, 2010). The results presented in Table 1, clearly shows the superiority of the GARCH (1,1)-in-mean VAR model over the traditional homoscedastic VAR for all variants of the GDP-income inequality equations.

Table 1.
Results of the Model Specification Test

Bivariate VAR Model	Schwarz Criterion Value	
	VAR	GARCH-in-mean VAR
Income Growth Volatility and Income Gini	842.253	801.068
Income Growth Volatility and Income Standard Deviation	826.716	776.918
Income Growth Volatility and Income 90-10 Percentile Differential	826.672	774.824

The plausibility of the GARCH-in-mean VAR specification is also confirmed by the point estimates of the variance parameters, which are reported in Table 2. The results in Table 2 support the rejection of the null hypothesis of no ARCH (F=0) and GARCH-in Mean (F = G = Λ =0) terms. Specifically, there is the significant evidence of the GARCH in inequality and the evidence of the ARCH in the real GDP volatility.

The primary coefficient of interest relates to the effect of the real GDP volatility on the inequality measures. The income volatility is captured by the conditional standard deviation of changes in real GDP $\sqrt{\mathbf{H}_t}$. The result, as presented in Table 3, shows that an increase in income volatility leads to the positive impact of over 0.4 on income inequality. Therefore, the null hypothesis that the true value of this coefficient is zero is rejected at the 1 % significance level, thus providing evidence to support the hypothesis that the higher income volatility tends to increase inequality in the UK.

The dynamic responses of the inequality measures to the GDP growth volatility are evaluated by using impulse responses, which are simulated from the maximum likelihood estimates of the parameters of the model. For comparability to those of a homoscedastic VAR, the magnitude of the impulse responses used to simulate the impulse response functions is based on a GDP shock that is equal to the unconditional standard deviation of the change in GDP. To examine whether the responses to positive and the negative shocks are symmetric or asymmetric, the response of income inequality to the positive and the negative income growth shock are simulated. The impulse responses (black lines) and the one-standard-deviation error bands (blue lines) are presented in Figures 2, 3, and 4. Looking at the income Gini inequality result in Figure 2 for instance, on one hand, the impulse responses indicate that a positive income shock tends to immediately and significantly increase inequality, inducing an upward revision in the income Gini inequality from about 25% at the moment of impact to positive 5% after 4 quarters. The dynamic effect of the positive income shock is also relatively persistent with the effect of dying off only after 6 quarters. The maximum response of the income standard deviation and the 90-10 percentile differential in Figures 3 and 4 respectively is about 15% with the impact also dying off after 6 quarters.

Table 2.
Coefficient Estimates for the Variance Function of the GARCH-in-mean VAR

Panel A:	**GDP Growth and Income Gini**			
	Conditional Variance	Constant	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$
GDP Growth Equation	$H_{1,1}(t)$	0.208***	0.718***	0.000
		(5.577)	(3.828)	
Income Gini Equation	$H_{2,2}(t)$	0.081	0.037	0.843***
		(0.937)	(0.888)	(6.026)
Panel B:	**GDP Growth and Income Standard Deviation**			
	Conditional Variance	Constant	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$
GDP growth Equation	$H_{1,1}(t)$	0.198***	0.763***	0.000
		(6.313)	(4.744)	
Income Standard Deviation Equation	$H_{2,2}(t)$	0.079	0.085	0.783***
		(0.900)	(1.097)	(4.027)
Panel C:	**GDP Growth and Income 90-10 Percentile Differential**			
	Conditional Variance	Constant	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$
GDP Growth Equation	$H_{1,1}(t)$	0.188***	0.777***	0.000
		(5.799)	(5.161)	
Income 90-10 Percentile Differential Equation	$H_{2,2}(t)$	0.615***	0.269*	0.107
		(4.201)	(1.767)	(0.532)

Notes: Table reports the constants and the parameter estimates of ***F*** and ***G*** from the model given by Equations (1) and (3) with $\varepsilon_t \parallel \Pi_{t-1} \sim \text{iid}\ (0, H_t)$. Asymptotic t-statistics are in the parentheses. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.
Coefficient Estimates on Income Volatility

Measure of Inequality	Coefficient on $\sqrt{\mathbf{H}_t}$	T-Statistic
Income Gini	0.489***	2.781
Income Standard Deviation	0.481***	3.134
Income 90-10 Percentile Differential	0.461***	3.076

Note: *** indicates the significance level at the 1% level.

On the other hand, the dynamic response of income Gini inequality to a negative GDP growth shock also immediately caused income Gini inequality to decline by about 12% basis point before rising in the second quarter. The effect is significant and died off after 6 quarters. Similar observations are made for the income standard deviation and the 90-10 percentile differential.

Quantitatively, the effects of the positive and the negative income shocks are asymmetric since the responses are not equal in absolute terms. The positive income shock appears to have a larger effect than the negative income shock of equal size, especially for the Gini inequality. It is also observed that the response of inequality is different across the horizons with respect to both magnitude and sign pointing to the need for a dynamic response analysis as opposed to an average asymmetric effect.

Figure 2.
Response of Income Gini Inequality to Positive and Negative Income Growth Shock

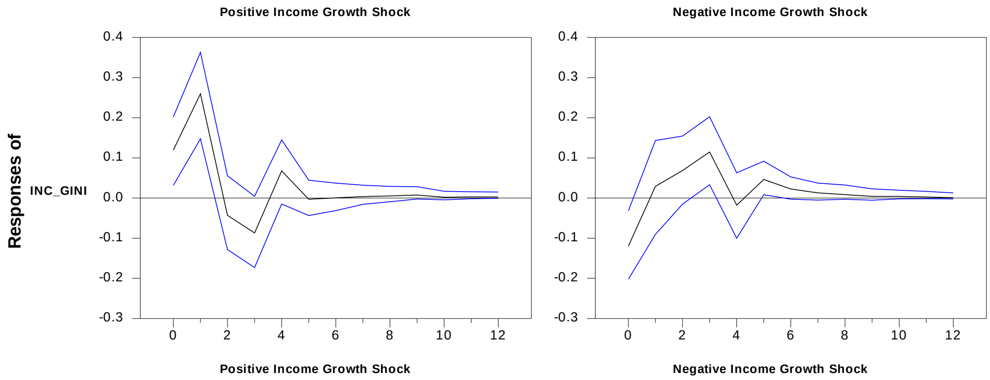


Figure 3.
Response of Income Standard Deviation to Positive and Negative Income Growth Shock

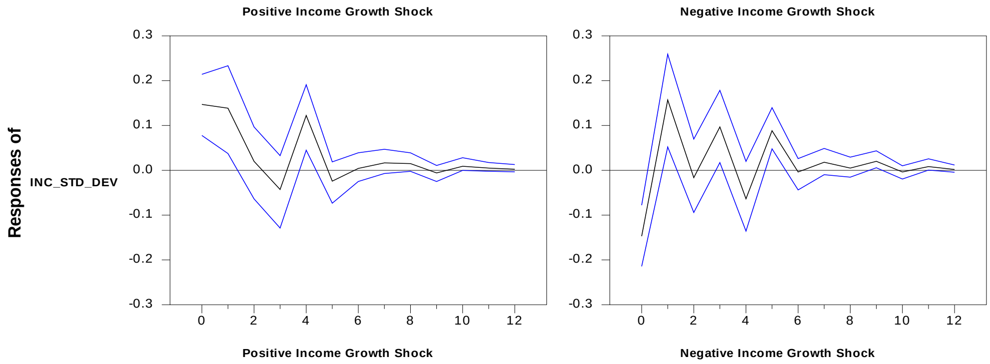
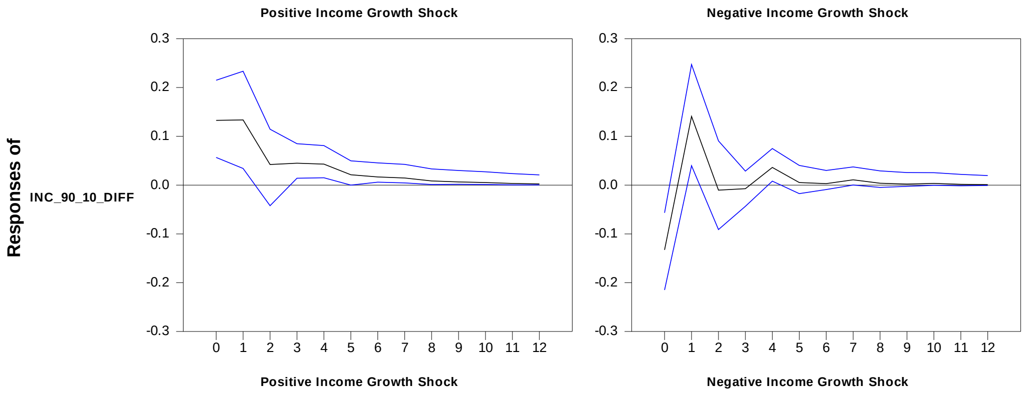


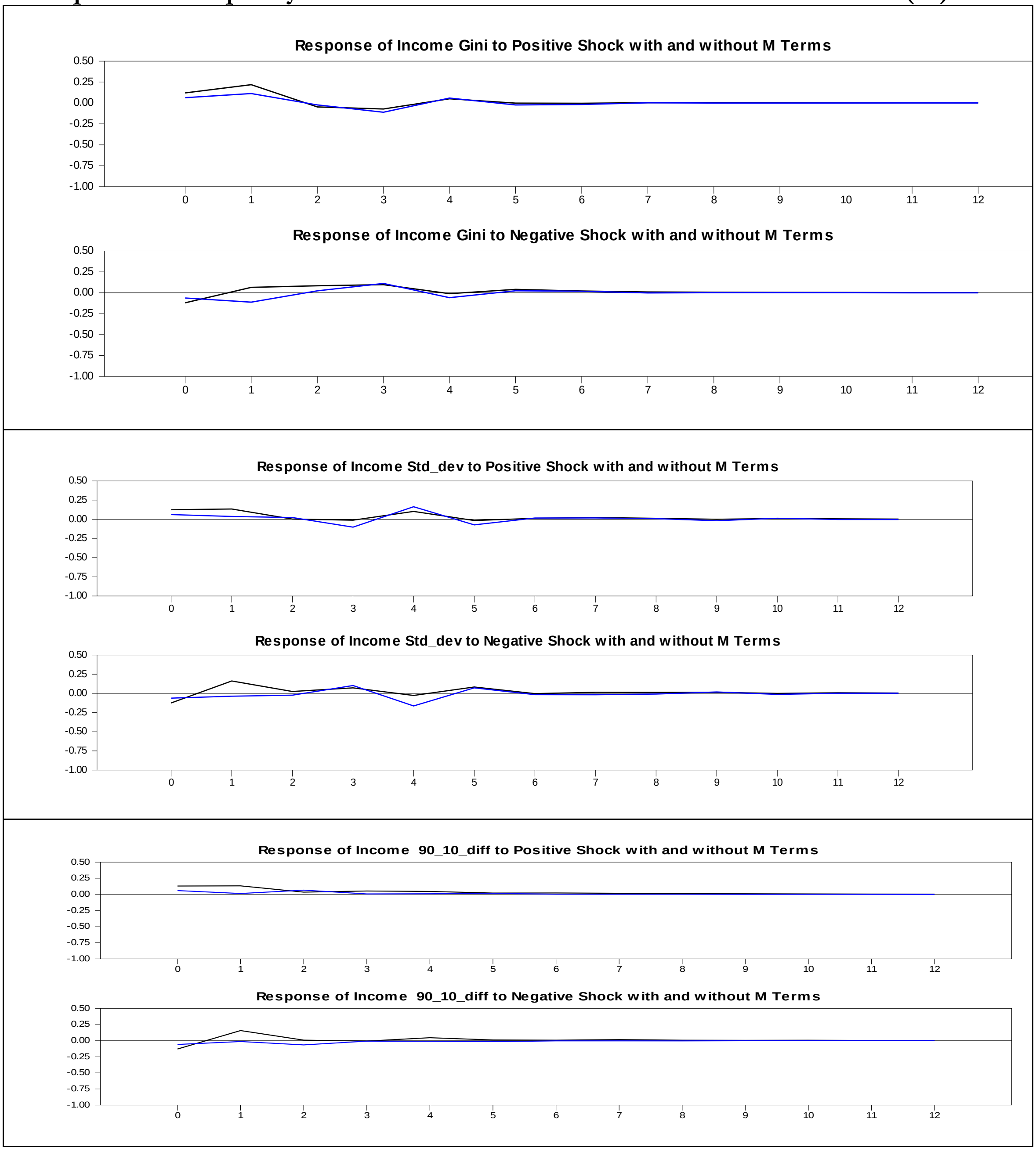
Figure 4.
Response of 90-10 Percentile Differential to Positive and Negative Income Growth Shock



We also compared the responses of inequality to the positive and the negative income shocks with and without the Mean (M) terms. These results are presented in Figure 5 for the various measures of income inequality, where the error bands have been suppressed for clarity. A model that includes the Mean term accounts for the effect of the real GDP volatility, while the coefficients of the real

GDP volatility are constrained to zero in the model without the Mean terms. In Figure 5, the black lines represent the response of inequality to the real income shock after allowing the real GDP volatility into the inequality equation. The blue lines represent the response of inequality to the real income shock without allowing the real GDP volatility into the inequality equation. The results show that incorporating the Mean terms amplifies the responses of inequality to the positive GDP shock, while it dampens its response to a negative GDP shock. This finding is robust to all the measures of income inequality and hence confirms that income growth volatility significantly matters for inequality in the UK.

Figure 5.
Response of inequality to the Real Income Shock with and without Mean (M) Terms



Notes: The black lines represent the response of inequality following a real income shock after allowing income growth volatility into inequality equation. The blue lines represent the response of inequality following a real income shock without allowing income growth volatility into inequality equation.

For robustness check, we conducted the analyses using consumption inequality instead of income inequality measures. For brevity, we have presented only the impulse responses of consumption to the positive and the negative GDP growth volatility in the Appendix Figure I. The results are qualitatively similar to those of income inequality.

5. Conclusion

In this paper, we examined the dynamic and the asymmetric response of inequality to income volatility in the UK using the bivariate GARCH-in-Mean Structural VAR based model. The results provide the evidence of the positive effect of income volatility on inequality. The effect is found to be asymmetric as the magnitude of the impact of the positive income shock is qualitatively different from that of the negative income shock. This is more pronounced in the case of income Gini. These findings have important implications. The fact that the positive and significant relationship exists between income volatility and inequality poses a challenge to the debate that distributional targets may be incompatible with efficiency goals. Since stabilization policies have been one of the key objectives of monetary- and fiscal policy in many countries, including the UK, it is therefore important that such policies should equally be aimed at reducing the degree of income inequality in the UK. Again, given that income growth volatility may affect inequality through the wage, human capital, and labour supply channels, it is therefore pertinent for policymakers to address these issues. Policies that can restore full employment in the economy and sustain the same cannot be overstressed. Public investments in education and health care would go a long way to improve the skills and the productivity of the bottom 90% to 99% of the population. This will assist in preventing the wealthy getting wealthier while the poor get poorer. Moreover, policies that can help the poor to improve their risk bearing ability, such as insurance policies may contribute to reducing inequality gap. From an academic perspective, the findings point to the importance of analysing the asymmetric effect of income volatility using impulse responses, which are capable of tracking the response of inequality over time, since the response, could vary from one horizon to the other. Finally, future papers can analyse the other large developed and developing economies, such as China, Germany, and Japan.

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Appendix Figure I.
Response of Consumption Inequality to Positive and Negative Income Growth Shock