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Monetary Policy and Inequality in the UK

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Abstract

The UK has experienced a dramatic increase in earnings and income inequality over the past four decades. We use detailed micro level information to construct historical measures of inequality from 1968 to 2008. We study whether monetary policy shocks played a significant role in explaining this increase before and after 1993. We find that contractionary monetary policy shocks lead to a deterioration in earnings and income inequality and contribute to its fluctuation. Our evidence suggest that this effect is smaller during the inflation targeting period.

Keywords: Inequality, Earnings, Income, Mixed Frequency Bayesian SVAR, Monetary Policy Shocks

JEL No. E2, E3, E4, E5

1 Introduction

The latest financial and sovereign crises left Western economies with rising levels of inequality. A number of studies (e.g. Belfield, Cribb, Hood and Joyce, 2014; Blundell and Etheridge, 2010, Brewer, Muriel and Wren-Lewis, 2009) present evidence of rising income inequality for the UK up to 2007-8. According to Belfield et al. (2014) the Gini coefficient for households' disposable income has increased over the last 45 years from 0.25 in 1967 to 0.36 in 2007-8. Similar trends appear for net labour earnings where the Gini increased from 0.32 in 1968 to 0.35 in 2008 (Brewer et al.,2009).

A growing area of research is trying to explain the rising trend and to identify the contributing factors. Skill based education and technological advances, changes in the family structure, employment status and occupation, structural reforms in the labour market, globalisation and increased international trade have all contributed to wage and income inequality (see for example Card, 2001; Bound and Johnson, 1992; Feenstra and Hanson, 2008). However, the above factors are only part of the story: trying to decompose changes in income inequality Brewer et al. (2009) find that a large amount of the UK income inequality for the period 1968-2007 remains explained and this amount is increasing to over 50% over the total variation towards the end of the period.

While fiscal policy has received substantial attention as contributing factor to inequality, the role of monetary policy is still to be decided. Earlier studies present a contradictory view on the matter: Galbraith (1998), for example, argues that strict inflation targeting policies caused a series of recessions, higher unemployment rates and therefore rise in inequality. On the other hand, as Coibion, Gorodnichenko, Kueng, and Silvia (2012) who review possible channels of monetary policy to inequality note that the expansionary monetary policy of Fed boosted share prices benefiting mainly shareholders, participants of financial markets and trade, who are usually the wealthier households. In addition, low income households hold most of their wealth in liquid assets which are the most vulnerable to inflation inducing monetary policies. Opposite effects have been also documented: Expansionary monetary policies and low interest rates favour borrowers who may be low income households while savers and lenders are adversely affected (Doepke and Schneider, 2006).

Hence monetary policy can have an ambiguous effect on inequality. The relationship complicates further by taking into account the sources of income of households. If policy affects wages and labour income more, then low income households will be affected more as wage is the most important source of income. If monetary policy substantially alters assets prices such as quantitative easing, financial wealth, which is an important source of income for high income households, will be highly affected.

A recent study by Coibion et al. (2012) investigates whether US monetary policy has contributed to changes in consumption and income inequality. The authors use household level data from the Consumer Expenditures Survey (CEX) since 1980 at quarterly frequency to construct their different measures of inequality and to see how they respond to monetary shocks as identified by Romer and Romer (2014). Their findings suggest that contractionary shocks significantly increase income, and wage inequality among US households.

The policies of Bank of England in the last decade were critical and shaped the British economy especially during the Great Recession. A direct link between the Bank of England and households is the bank rate which acts as a benchmark for a number of flexible rate mortgages. Belfield et al (2014) find that historically low interest rates in the period 2007-13 kept mortgage payments low which decreased housing costs by 37%. It is stressed that without this reduction in housing costs, the mean income would have fallen by 13% instead of 10% for the period. Home owners are towards the top of income distribution. However the amount of households benefited by low mortgage payments decreased the same period by 5% due to adverse economic conditions. Renters increased and also saw their proportion of income to rents increasing from 26% to 28%. Thus it is unclear if the expansionary monetary policy followed during the crisis supported the median disposable income and earnings or whether the benefits were limited to a small proportion of the population. .

In the present study we investigate whether monetary policy shocks have affected earnings and income inequality in the UK. The novelty of this paper is to use long time series for earnings and income -from 1967-2008- which includes a number of recessions where the Bank of England used a variety of policies. We look at the impact of monetary policy before and after 1993 separately when inflation targeting was introduced by the Bank of England. Most importantly, we use detailed micro data to construct the proxies for inequality from a number of data sources: the Family Expenditure Survey (FES) and Family Resources Survey (FRS) to construct a range of measures to proxy inequality for labour earnings, and the HBAI and BHPS to construct inequality proxies for household's disposable income.

Using a mixed frequency structural VAR we find that contractionary monetary policy shocks lead to a significant increase in earnings and income inequality. The effect is estimated to be more pronounced in the pre inflation targeting period and earnings inequality appear to be more affected by monetary policy. These results remain invariant to alternative specifications of the VAR. We find that the monetary policy shock makes important contributions to historical fluctuations in the inequality measures. These results have important policy implications at a time when the Bank of England is contemplating the possibility of contractionary monetary policy. Our results suggest that policy makers need to take redistributive affects of policy changes into account.

Section 2 describes the construction of the inequality measures and the data sets used. Section 3 describes the estimation of the mixed frequency structural VAR model and the identification scheme. Section 4 presents the main results for earnings and income inequality for the two sub samples and considers the contribution of the monetary policy shock to the evolution of inequality measures. It also investigates alternative specifications and models to test the robustness of the main results. Section 5 concludes.

2 Data

For labour earnings inequality measures we use two large household surveys: the Family Expenditure Survey (FES, 1968-2000) and the more resent Family Resource Survey (FRS, 2001-2013). The FES covers a representative sample of 7,000 households while the FRS enlarged this sample to 24,000 households on average annually (Brewer et al., 2009). Even thought some of the variables have very similar definitions in both data sets, the surveys per se have some differences in their income distributions. Dayal et al (2000) suggest the FRS over represents low income households and benefits receivers, while FES over represents mortgage holders, people living in the country and under represents people living in council flats.

We use two variables for labour earnings: Net Personal Earnings from the FES[1] (1968-2000/01) is defined as the normal net wage or salary from main occupation or any other occupation including the actual pay for people working less than 8 hours per week[2]. This includes occasional additions to pay such as net bonuses. Tax refunds are not included. Net Personal Earnings from the FRS (2001/2-2012/13) are simply defined as wage including overtime, bonus, commission or tips, after all deductions, the last time of payment. Note that from 1993 FES changes form calendar to financial (April to March) years and FRS follows this methodology. The change from one dataset to another has an impact on the data since we move from a dataset of 6,354 observations (2000/1, FES) to a much larger dataset of 23,648 observations (2002/3, FRS).

The second variable of labour earnings is Gross Personal Earnings which is the normal gross wage from any type of occupation before taxes, national insurance contributions and other deductions. Gross Personal Earnings from the FRS are defined as the total before any reductions gross wage

[1] Even though FES starts from 1961 the first years of the survey were problematic as the sample initially consisted of only 3,000 households and years 1964 and 1967 data are available only for the first two quarters resulting to 1,500 households in 1964. In addition data for labour earnings are not always available in the all the years before 1968.

[2] We have not included self employment income as it is defined as net profits from employment and profits are not included in this category. Instead it is included in household's income.

as shown on pay slip. Both variables for Earnings are at the individual level, converted to weekly amounts[3] which we have deflated to January 2005 prices. For the benchmark analysis and for sensitivity we use measures of Net Personal Earnings but we also control if there are any substantial differences with the pre tax variables. We consider only positive net and gross earnings.

For the measures of income inequality we draw from Households Below Average Incomes (HBAI, 1967-1991 and 1994/95 to 2012/13) by the Department for Work and Pensions. The HBAI compiles existing data from the FES prior to 1991 and from FRS after 1994-95. For the missing years between the two data sets we calculate the income from British Households Panel Survey (BHPS, 1992 and 1993). We follow HBAI's definition of income which is income net of taxes and benefit credits summed across all members living in the same household and it is referred throughout the text as Household's Disposable Income. Then this variable is equivalised for the family size and deflated taking as benchmark of living standard the income of a couple without dependent children deflated in 2012-13 prices. The inclusion of housing costs was a difficult decision as the amount a household is willing to spend on housing and living quality is a matter of taste and partially affected by policies. On the other hand, income after housing costs can be a good indicator for those who do not have many choices on their housing quality and income differentials do not reflect differences in market rents or housing quality such as the social rented sector and households on the lower part of income distribution. Even though our benchmark analysis is for income before housing costs (BHC) we also report results on the income after housing costs in the Appendix. The time period examined is 1967-2012/13 for income. The HBAI series moved from calendar years to financial years in 1994–95.

We focus our results to labour earnings inequality. Labour earnings have the advantage to be more clearly known to the respondents so the error band is much smaller than the one of income. On the other hand labour earnings is only one source of income which weight less for wealthier households who receive income form other sources. From a technical point of view, labour earnings are at the individual level and similarly defined in FES and FRS surveys so the constructed time series is more robust. Income, on the other hand, is in household level, needed to de scaled and equivalised and there were significant differences in definitions in the change of data sets. Using survey data over long periods entail a number of perils derived from the fact that questions change over the years and the way the answers are handled differs thorough the years. In the collection of data process we made every effort to select variables that were as closely as possible defined so to maintain consistency among different datasets.

The rest of the macroeconomic variables are UK's GDP in constant prices from the Office of National Statistics, the consumer price index (CPI) from the Bank of England's database with 2005 base year. The three month treasury bill rate and the real effective exchange rate are both from Global Financial data. Frequencies are annual.

[3] When the individual works full time, the weekly payment is defined as earnings, while in the case of a part time or odd job, the last payment is counted.

2.1 Measures of Inequality

We use three widely used measures of Inequality: The Gini coefficient of levels is perhaps the most commonly used measure of inequality which takes values between 0 (perfect equality) and 1 (perfect inequality). The second measure is the cross sectional standard deviation of log levels which drops out zero values reducing this way sensitivity to extreme values. The third measure is the difference between the 90th and the 10th percentile of each distribution in logs which also reduces sensitivity to the outliers at the top and bottom of the distributions and provides information about changes in the shape of the distributions. Figure 1 shows the evolution of these three measures for net and gross earnings and BHC and AHC disposable income. Earnings appear to fall in the second part of 70s following a sharp increase in the 80s. Even though the inequality in earnings is always higher in the sample, the rise of inequality is more pronounced in disposable income. Earnings seem to stabilize in 2000s and peak twice in the end of 1990s and in the recent financial crisis remaining at high levels since then. Income showed an abrupt increase in 80s and then another one in mid 90s and a high volatility in the decade of 2000 until it reached its higher point in 2010. It has been decreasing since then and in 2012 it was at the same levels of 90s. It is notable that although disposable income had a much lower Gini coefficient in the beginning of the sample in 1967 it caught up with the Gini of gross earnings which is the highest one in 2009. From all these four variables, the Gini of AHC income experience the highest rise.

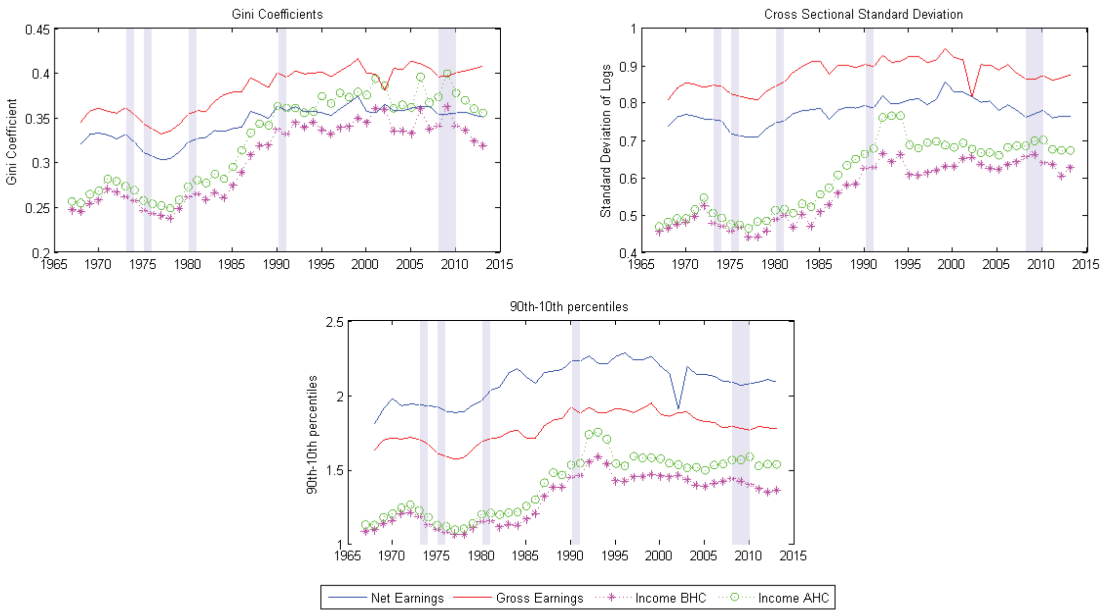

Figure 1: Inequality measures for disposable income and labour earnings in the UK

3 Estimation and identification

In order to estimate the impact of monetary policy shocks on the constructed inequality measures we use a Structural VAR model. Note, however, that the fact that the inequality measures are observed at an annual frequency complicates the SVAR analysis. As noted by Foroni and Marcellino (2014) a mismatch between the underlying time-scale of the SVAR model and the frequency of the data used can result in biased estimates of impulse responses. This problem is likely to apply to our application as monetary policy actions occur at a higher than annual frequency. In order to alleviate this problem we employ the mixed frequency VAR model introduced in Song and Schorfheide (2014) and incorporate quarterly macroeconomic data into the VAR model.

The benchmark VAR model is defined as

$$Z_t = c + \sum_{j=1}^{P} B_j Z_{t-j} + v_t \tag{1}$$

where $v_t \tilde{} N(0, \Omega)$. The matrix of endogenous variables Z_t contains the following set of variables:$Z_t = \{\hat{E}_t, Y_t\}$ where $\hat{E}_t$ denotes the quarterly estimate of the inequality measure under consideration and Y_t is a $T \times M$ matrix that contains quarterly data on real GDP, CPI, the short term interest rate and the nominal effective exchange rate in the benchmark case. As in Song and Schorfheide (2014), we make the assumption that the observed annual data on the inequality measure $E_{Y,t}$ is an average of the unobserved quarterly data:

$$E_{Y,t} = \frac{\hat{E}_t + \hat{E}_{t-1} + \hat{E}_{t-2} + \hat{E}_{t-3}}{4} \tag{2}$$

Let X_t denote a matrix of quarterly data where the first column is constructed such that it contains zeros apart from the fourth quarter of each year which contains the annual observation $E_{Y,t}$. The remaining columns of this matrix (denoted by $\bar{X}_t$) contain the quarterly data Y_t. Then using the assumption in equation 2, the following observation equation can be constructed

$$\begin{aligned} X_t &= \Xi z_t \text{ for } t = 4, 8, 12, ... \\ \bar{X}_t &= \Theta z_t \text{ for } t = 1, 2, 3, ... \end{aligned} \tag{3}$$

where $z_t = \{Z_t, Z_{t-1}, Z_{t-2}, Z_{t-3}\}'$. The first expression in equation 3 states that during periods when the annual observation $E_{Y,t}$ is observed, equation 2 applies and the coefficient matrix Ξ is defined as $\begin{pmatrix} 1/4 & 0_{1\times M} & 1/4 & 0_{1\times M} & 1/4 & 0_{1\times M} & 1/4 & 0_{1\times M} \\ 0 & 1_{1\times M} & 0 & 1_{1\times M} & 0 & 1_{1\times M} & 0 & 1_{1\times M} \end{pmatrix}$ with the second row of Ξ defining the identities implied by the observed quarterly data. The second expression in equation 3 applies when $E_{Y,t}$ is not observed and the corresponding entry in the first column of X_t is zero. In this case, the coefficient matrix equals:$\Theta = \begin{pmatrix} 0 & 1_{1\times M} & 0 & 1_{1\times M} & 0 & 1_{1\times M} & 0 & 1_{1\times M} \end{pmatrix}$.

3.1 Estimation

Equations 3 and 1 form a state-space model that is estimated using the Gibbs sampling algorithm described in Song and Schorfheide (2014). In this section we describe the key priors and summarise the algorithm.

3.1.1 Priors

The prior for the VAR coefficients $b = vec\left(c, B_j\right)$ is defined as $P(b)\tilde{}N(b_0, \Lambda)$ where $b_0 = b_{ols}$. The prior for the error covariance matrix is inverse Wishart (IW): $p\left(\Omega\right)\tilde{}IW\left(\Omega_0, T_0\right)$ where the scale matrix $\Omega_0 = \Omega_{OLS} \times T$. The OLS estimates b_{ols} and Ω_{OLS} are obtained using the quarterly data $Z_t = \{\bar{E}_t, Y_t\}$ where the quarterly data $\bar{E}_t$ is obtained using repeated annual observations. The prior tightness Λ and the degrees of freedom T_0 are chosen in order to ensure that the variance and dynamics of the posterior estimate of $\hat{E}_t$ do not display excessive volatility. In the benchmark model Λ is a diagonal matrix with diagonal elements equal to 0.1 while $T_0 = 50$. We stress that these relatively tight priors are used to ensure that the estimate of $\bar{E}_t$ is reasonable. The estimated impulse responses are robust to: (a) using a loose prior and (b) estimating a VAR that uses annual data. We show this in detail in the sensitivity analysis below.

3.1.2 Gibbs sampling algorithm

The Gibbs algorithm is based on draws from the conditional posterior distribution of b, Ω and $\hat{E}_t$. Note that these conditional posterior distributions are standard and apply to any state-space model (see for example Kim and Nelson (1999) and Blake and Mumtaz (2012).

1. Sample from $G\left(b\backslash\hat{E}_t, \Omega\right)$. Conditional on a draw of the quarterly data $\hat{E}_t$ and the covariance matrix Ω this conditional posterior is normal: $G\left(b\backslash\hat{E}_t, \Omega\right)\tilde{}N(M, V)$. Letting $X_t = \{1, Z_{t-1}, Z_{t-2}, ..Z_{t-p}\}$ and $\hat{b} = \left(X_t'X_t\right)^{-1} X_t'Z_t$ the moments are given by:

$$\begin{aligned} M &= \left(\Lambda^{-1} + \Omega^{-1} \otimes X_t'X_t\right)^{-1} \left(\Lambda^{-1}b_0 + \Sigma^{-1} \otimes X_t'X_t\hat{b}\right) \quad (4) \\ V &= \left(\Lambda^{-1} + \Omega^{-1} \otimes X_t'X_t\right)^{-1} \end{aligned}$$

2. Sample from $G\left(\Omega\backslash\hat{E}_t, b\right)$. The conditional posterior for Ω is IW with scale matrix $\bar{\Omega} = \Omega_0 + \left(Z_t - X_t\bar{b}\right)'\left(Z_t - X_t\bar{b}\right)$ where $\bar{b}$ denotes the draw of the VAR coefficients reshaped to be conformable with X_t.

3. Sample from $G\left(\hat{E}_t\backslash\Omega, b\right)$. Given a draw for b and Ω, equations 3 and 1 form a linear and Gaussian state space model and the Carter and Kohn (2005) algorithm can be applied to draw from the conditional posterior of $\hat{E}_t$. The distribution is given by: $\hat{E}_t\backslash Y_t, \Omega, b \sim N\left(E_{T\backslash T}, \tilde{P}_{T\backslash T}\right)$ and $\hat{E}_t\backslash\hat{E}_{t+1}, Y_t, \Omega, b \sim N\left(E_{t\backslash t+1,\hat{E}_{t+1}}, \tilde{P}_{t\backslash t+1,\hat{E}_{t+1}}\right)$ where $t = T-1, ..1$. A run of the Kalman filter delivers $E_{T\backslash T}$ and $\tilde{P}_{T\backslash T}$ as the filtered states and its variance at the end of the sample. Then one proceeds backwards in time to obtain $E_{t\backslash t+1,\hat{E}_{t+1}} = E_{t|t} + \tilde{P}_{t|t}\tilde{F}_t'\tilde{P}_{t+1|t}^{-1}\left(E_{t+1} - \tilde{\mu}_t - \tilde{F}E_{t|t}\right)$ and $\tilde{P}_{t|t+1,\hat{E}_{t+1}} = \tilde{P}_{t|t} - \tilde{P}_{t|t}\tilde{F}_t'P_{t+1|t}^{-1}\tilde{F}_t\tilde{P}_{t|t}$. Note that $\tilde{F}_t$ and $\tilde{\mu}_t$ denote the VAR coefficients on the lags and the constant in companion form corresponding to the equation for $\hat{E}_t$.

These steps are repeated 20,000 times with the last 2000 draws used for inference. Recursive means for the retained draws shown in the appendix display little fluctuation providing evidence in favour of convergence.

	GDP	CPI	Nominal Exchange Rate	Short-Term interest rate
Monetary Policy	≤ 0	≤ 0	≥ 0	≥ 0

Table 1: Sign Restrictions

3.1.3 Model specification and identification of the monetary policy shock

As mentioned above, the quarterly data in the model contains GDP, CPI, the nominal effective exchange rate and the three month T-bill rate. These variables represent the key data for a small open economy. In the benchmark model, the first three variables are included after linear de-trending. However, we show below that the results survive when levels or growth rates are used. We set the lag length to 4.

The model is estimated over two sub-samples:1968Q1 to 1993Q4 and 1993Q1 to 2008 Q1. This is primarily because the annual inequality data is measured over financial years in the post-1993 period. For example, the inequality data for 1993-1994 spans the period April 1993 to March 1994. The quarterly data in the model for this year is included from 1993Q1 to 1994Q2 thus making the structure of the data consistent with equation 2. Note also that 1993 marks a structural break in the practice of monetary in the UK. After the UK's exit from the ERM in September 1992, the Bank of England adopted an inflation target. In a seminal paper, Nelson (2001) shows that the post-inflation targeting period was marked by a monetary policy rule significantly different from the preceding period. Thus, from this perspective splitting the sample in 1993 may be warranted. Furthermore, we exclude the period after 2008 which features quantitative easing and unconventional monetary policy.

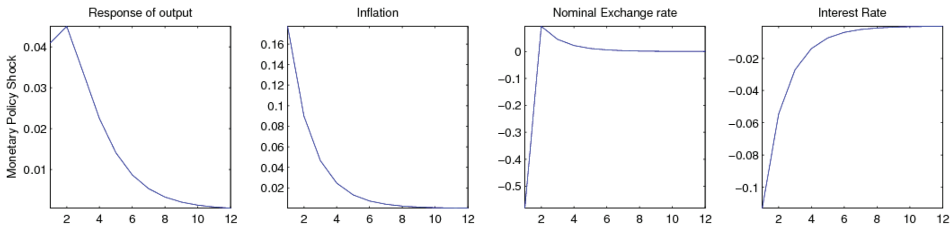

Figure 2: Impulse Responses to a Monetary Policy Shock

3.2 Identification

As mentioned, the benchmark structural analysis using the SVAR model is based on the identification of the monetary policy shock via contemporaneous sign restrictions summarised in Table **1.**

We motivate our sign restrictions using a structural, two-country model described in Lubik and Schorfheide (2006) – an estimated, open-economy extension of the standard, three-equation New Keynesian workhorse. The model-implied impulse responses to monetary policy shocks are given in Figure 2. In light of these impulse responses we impose the following on the contemporaneous impulse responses from the VAR: (1) contractionary monetary policy shocks are assumed to increase the nominal interest rate, reduce GDP, reduce CPI and lead to a nominal effective exchange rate (NEER) appreciation (an increase based on our definition of NEER) on impact.

The identification scheme is implemented as follows. We compute the structural impact matrix, denoted A_0, via the procedure introduced by Rubio-Ramírez et al. (2008). Specifically, let $\Sigma = PDP'$ be the eigenvalue-eigenvector decomposition of the SVAR's covariance matrix Σ, and let $\tilde{A}_0 \equiv PD^{\frac{1}{2}}$. We draw an $N \times N$ matrix K from the $N(0,1)$ distribution and then take the QR decomposition of K. That is, we compute Q and R such that $K = QR$. We then compute a structural impact matrix as $A_0 = \tilde{A}_0 \times Q'$. If A_0 satisfies the sign restrictions we keep it and use it to compute the impulse response functions and decompositions.

4 Impact of Monetary Policy on Earnings and Income Inequality

4.1 Impact on earnings inequality

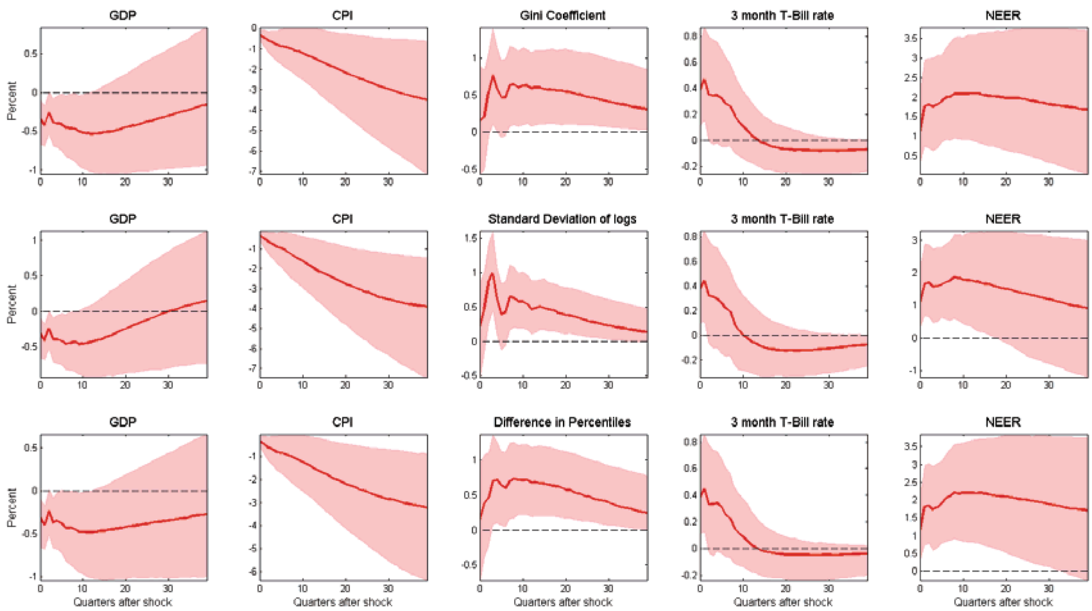

Figure 3: Impact of a monetary policy shock on earnings inequality pre-1993.

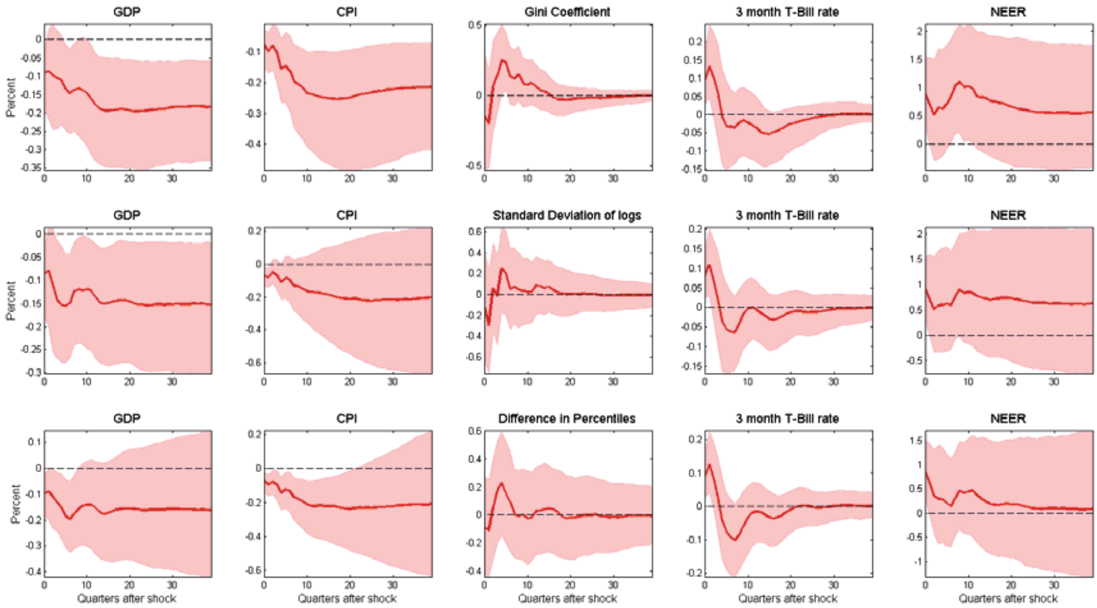

Figure 4: Impact of a monetary policy shock on earnings inequality post-1993.

Figure 3 presents the estimated response of the endogenous variables to a one standard deviation contractionary monetary policy shock in the pre-1993 period. The response of GDP, CPI and NEER is presented in cumulated form and thus represents the response of the level of these variables. The policy shock increases the short-term interest rate by 40 basis points. This in-turn leads to a decline in GDP and CPI of about 0.4% and 0.7%, respectively, at the one year horizon while the NEER appreciates by about 1.5%. In response to this contractionary policy shock, all three measures of earnings inequality increase. The magnitude of the increase is modest–about 0.7% to 1% at the one year horizon. However the hypothesis that the impact is zero can be clearly rejected. Note also that the impact of the shock on earnings inequality is estimated to be persistent.

Figure 4 presents the impulse responses estimated after the 1993 period. The impact of the great moderation is clearly reflected in the drop in the standard deviation of the monetary policy shock with the contemporaneous increase in the interest rate about 4 times smaller than in the pre-1993 period. It is interesting to note that the cumulated response of CPI is proportionally smaller over this sub-sample, a result highlighted by previous studies such as Castelnuovo and Surico (2006). In contrast, the response of the NEER is larger over the inflation targeting period confirming the result in Ellis, Mumtaz and Zabczyk (2014). The response of earnings inequality measures also changes over this sub-sample. First, the error bands are larger and the hypothesis that the impulse response is equal to zero can be rejected over most of the horizon. Second, the dynamics of the response are different relative to the pre-1993 period: The contemporaneous median response is negative, with the impact becoming positive after a year and then returning to base much faster than the pre-1993 estimate.

In short, the results in Figures 3 and 4 suggest that contractionary policy shocks have a positive impact on earnings inequality and this affect is larger and more persistent in the pre-inflation targetting period.

4.2 Impact on income inequality

The response of earnings inequality measures to this shock are reported in Figures 5 and 6. Overall the results are similar to those reported for the earnings inequality measures. Consider the results for the pre-inflation targeting period in Figure 5. A one standard deviation contractionary policy shock leads to persistent increase in the Gini coefficient. It is interesting to note that the magnitude of the increase is larger than that estimated for the Gini coefficient associated with earnings. The same features are evident for the response of the two remaining inequality measures–the response is persistent and somewhat larger than the corresponding earnings inequality measures. Figure 6 shows the response of income inequality estimated after the start of the inflation targeting. As in the case of earnings, evidence for the hypothesis that policy shocks increased inequality is weaker over this sub-sample. While the response of the Gini coefficient is briefly different from zero, the error bands for the remaining measures include zero over most of the horizon. Note that the persistence of the median inequality responses is also smaller over this sub-sample.

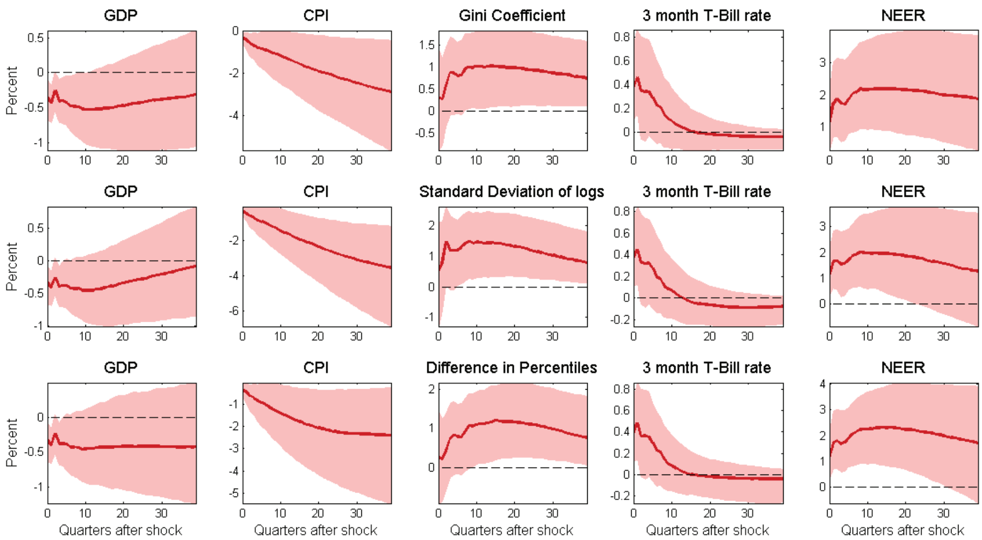

Figure 5: Impact of a monetary policy shock on income inequality pre-1994.

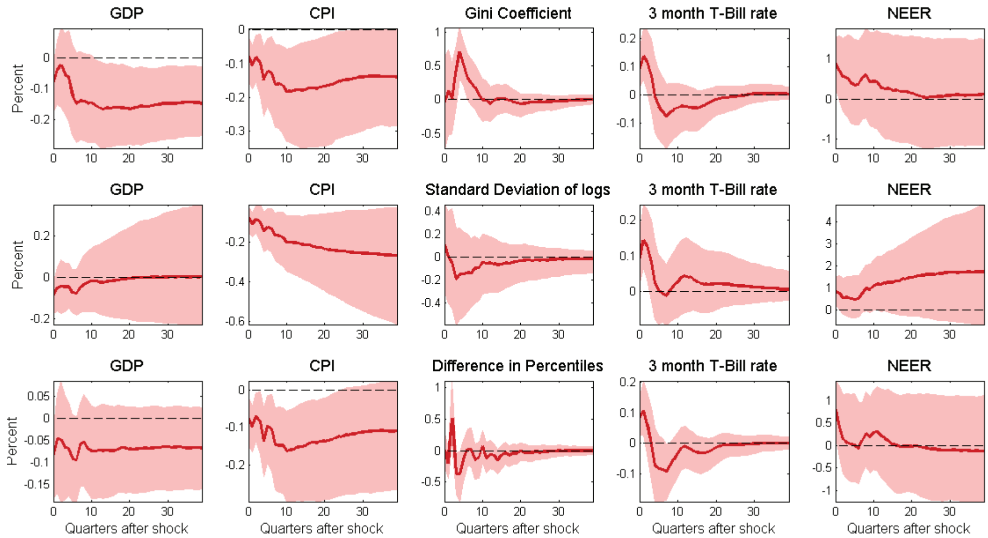

Figure 6: Impact of a monetary policy shock on income inequality post-1994.

4.3 Sensitivity Analysis

	Earnings	
	Pre-1993	Post-1993
	Gini Coefficient	Gini Coefficient
1 Q	11.4	11.9
1 yr	17.5	16.6
5 yrs	20.4	16.9
	Standard -Deviation	Standard -Deviation
1 Q	11.4	10.5
1 yr	24.6	13.8
5 yrs	26.3	10.5
	Difference in Percentiles	Difference in Percentiles
1 Q	12.8	11.0
1 yr	18.0	15.8
5 yrs	21.3	10.1
	Income	
	Pre-1993	Post-1993
	Gini Coefficient	Gini Coefficient
1 Q	12.3	10.7
1 yr	15.3	14.2
5 yrs	20.8	19.1
	Standard -Deviation	Standard -Deviation
1 Q	12.2	11.6
1 yr	16.8	14.7
5 yrs	24.6	13.7
	Difference in Percentiles	Difference in Percentiles
1 Q	11.5	10.6
1 yr	13.7	14.9
5 yrs	20.1	15.0

Table 2: Percentage Contribution of the monetary policy shock to the forecast error variance

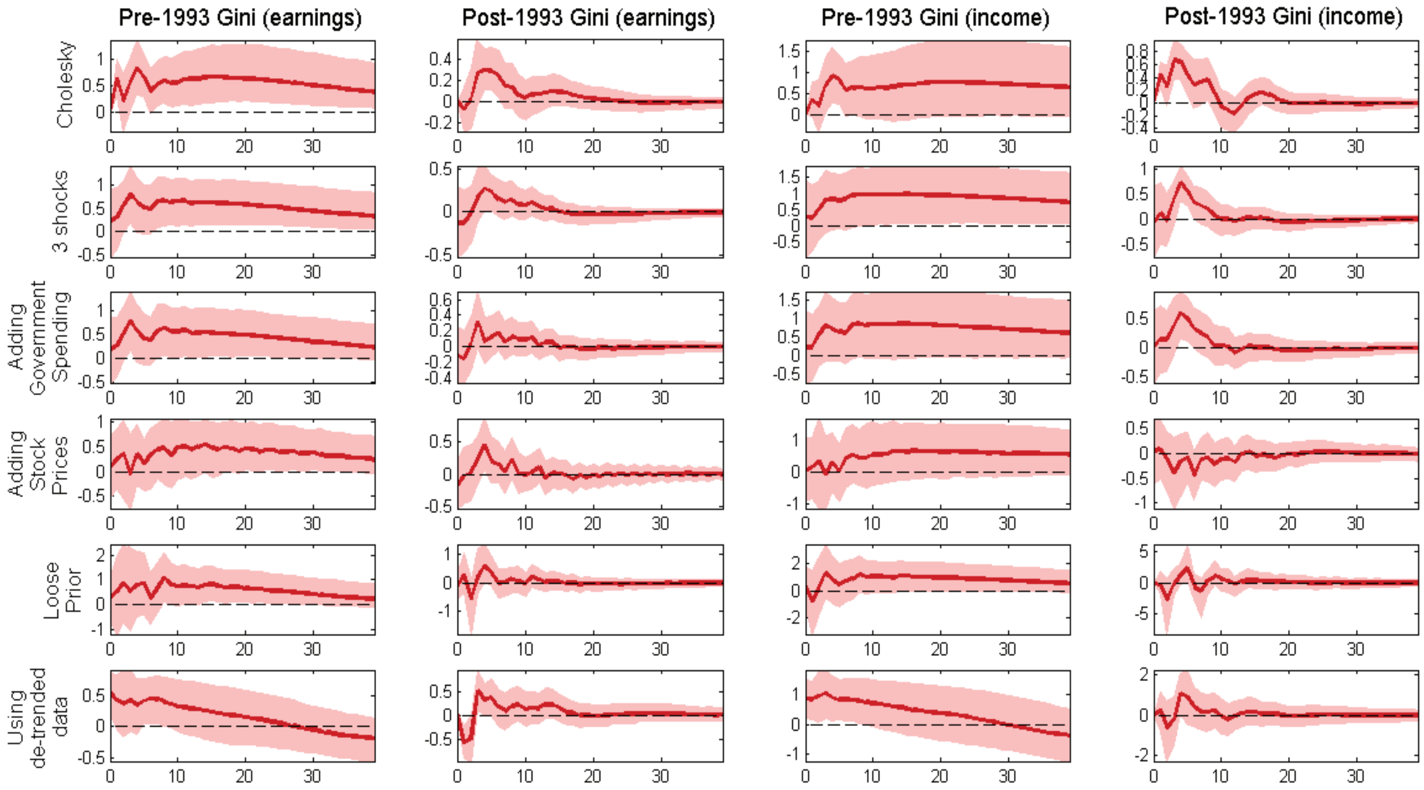

Figure 7: Sensitivity Analysis for the Gini Coefficient

The results presented above provide strong evidence that contractionary monetary policy shocks increased income and earnings inequality during the pre-inflation targeting period. Our results suggest that this transmission mechanism was weaker over the inflation targetting era. In this section we carry out an extensive sensitivity analysis to gauge the robustness of these results. In particular, we consider alternative identification schemes, different prior distributions and change the specification of the VAR model along various dimensions. The results of this exercise are presented in Figure 7, where each row displays the impulse response of the earnings and income Gini coefficient before and during the inflation targetting period.

The top two rows of the Figure consider two alternative identification schemes. The top rows shows results from the model where the monetary policy shock is identified using a Cholesky decomposition ordering the interest rate before GDP growth, inflation and the inequality measure but before the NEER which is a fast moving asset price and can thus be affected contemporaneously by policy shocks. The estimate impulse responses show that the results are stronger under this identification scheme. During the pre-inflation targetting period, the response of the Gini coefficient is persistent. The response in the second sample reverts to base quicker, but the hypothesis of a zero response can be rejected. The second row of the Figure displays estimates from the model where the original sign restriction scheme is augmented to include aggregate demand and supply shocks. The demand shock is identified by assuming that a positive shock increases GDP growth, inflation and interest rates on impact. In contrast, the supply shock is restricted to move GDP growth and inflation in opposite directions. The response of the Gini coefficient under this alternative scheme is close to the benchmark case.

The next two rows of Figure 7 add extra variables to the benchmark model to account for the possibility of missing variables. In particular, we add government spending to account for fiscal policy and stock prices to incorporate the possible effect of the financial sector. While the error bands are larger in these expanded models, the basic results survive. The impact of policy shocks on inequality in the pre-inflation targetting period is estimated to be persistent and the hypothesis of a zero response can be rejected for earnings. Given the limited degrees of freedom and the large number of state variables in the model, we take this as evidence in favour of the benchmark model.

The fifth row of the Figure considers the impact of the prior distributions on the results. In this estimation, we relax the prior significantly. In particular, the prior tightness Λ is changed from 0.1 to 10. As discussed above, this increases the variability of the quarterly estimate of the Gini coefficient substantially. However, the pre-inflation targetting responses shown in Figure 7 are still similar to the benchmark, especially for earnings. The final row of the Figure shows that the benchmark results survive if GDP, CPI and the NEER are included in the model in deviations from a linear trend.

In summary, the sensitivity analysis shows that the main results are fairly robust: there is strong evidence that contractionary monetary policy increased inequality during the pre-inflation targetting period.

4.4 Contribution of the monetary policy shock to inequality measures

Table 2 presents the contribution of the monetary policy shock to the forecast error variance of the earnings measures at the one quarter, one year and five year horizons. The top panels show the decomposition for the model with earnings inequality, both pre and post-1993 while the bottom three panels correspond to the model with income inequality. The Table shows that the monetary policy shock explains about 15% to 25% of the forecast error variance inequality measures at the one year horizon in the pre-inflation targetting period, with the percentage contribution slightly lower after 1993. It is interesting to note that the magnitude of these contributions match the estimates reported by Coibion et. al. (2014) for the US. The percentage contribution of this shock is also in line with the contribution of this shock to the macroeconomic variables included in the model.

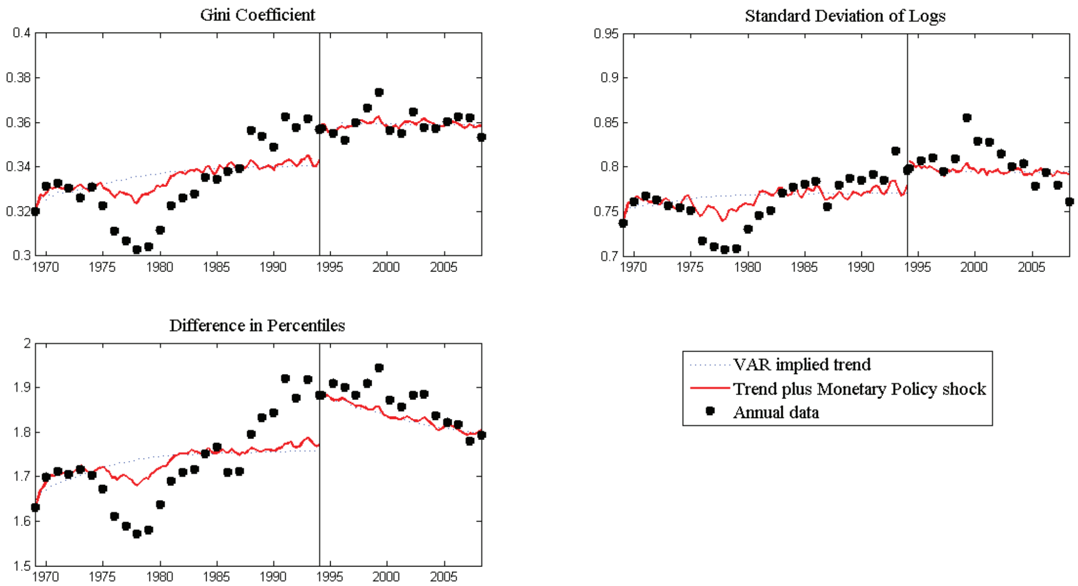

Figure 8: Historical decomposition of measures of earnings inequality.

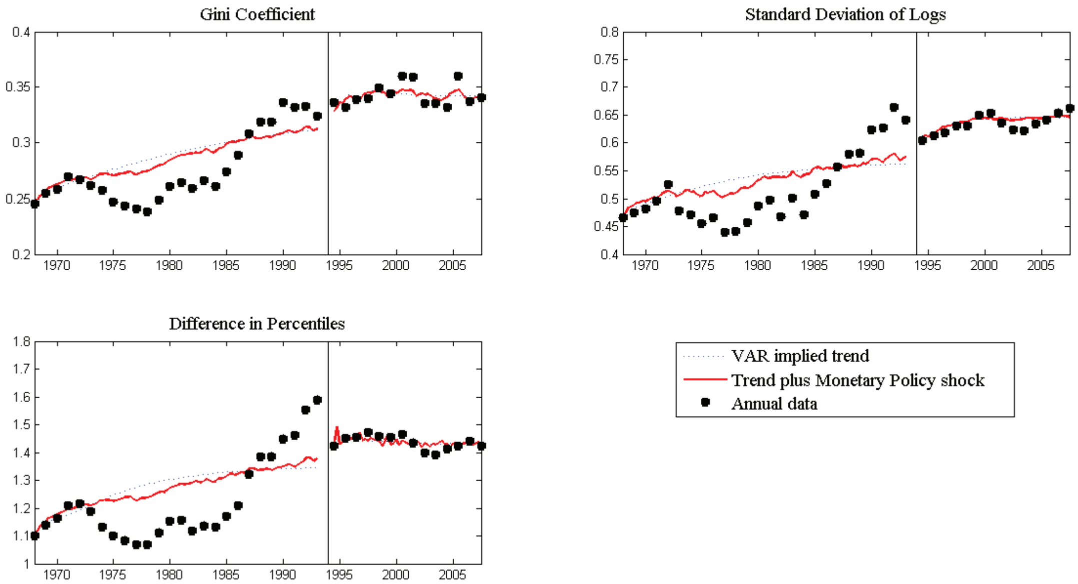

Figure 9: Historical decomposition of measures of income inequality.

Figure 8 shows the historical decomposition of the earnings inequality measures and displays the contribution of the monetary policy shock. Figure 9 displays the same estimates for income inequality measures. The black dotted symbols display the annual inequality data. The dashed blue line is the trend implied by the VAR coefficients and the vertical black line indicates the break in the data. The red line shows the trend plus the contribution of the monetary policy shock. Thus a deviation of the latter red line from the trend implies a contribution by the monetary policy shock.

The Figure clearly shows that the policy shock makes an important contribution in the pre-inflation targeting period. During the early 1970s, the policy shock contributed to the increase in inequality. During the mid-1970s, the UK government pursued expansionary monetary policy to stimulate the economy and relied on wage and price controls to hold down inflation (see Nelson 2001). This expansionary policy appears to have made a positive contribution, leading to a reduction in each income and earnings inequality measure below the trend. After 1980, as dis-inflationary monetary policy was introduced, earnings and income inequality increased. Our estimates provide some, albeit weak, evidence that the policy shock contributed to this increase. In the post-inflation targetting period, the contribution of the policy shock is close to zero, indicating that this shock was unimportant for inequality over this period.

5 Conclusions

This paper examines the impact of monetary policy shocks on earnings and income inequality in the UK. We build a historical time series for measures of labour earnings and income inequality from the FES FRS HBAI and BHPS databases. Using a mixed frequency structural VAR we show that shocks to monetary policy have a systematic positive impact on inequality measures. The impact appears to be stronger for the period before the adoption of inflation targeting policies by the Bank of England. The policy shock explains approximately 15-20% of the forecast error variance of inequality measures at the one year horizon. The historical decomposition suggests that monetary policy shocks played a role in explaining the fluctuations in inequality at key periods– monetary policy contributed to an increase in inequality during the early 1970s and to a decrease during the mid and the late 1970s. There is some evidence that the disinflation period in the early 1990s resulted in higher than trend inequality. After the introduction of inflation targeting policies the role of monetary policy to inequality measures appears weaker.

These results have important policy implications at a time when the Bank of England is contemplating the possibility of contractionary monetary policy. Our results suggest that policy makers need to take redistributive effects of policy changes into account.

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