The impact of macroeconomic uncertainty on inequality: An empirical study for the UK

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Abstract

The role of economic uncertainty on macroeconomic fluctuations has been studied extensively in the literature. In the aftermath of the financial crisis and in the process of its exit from the EU, the UK is facing high levels of uncertainty on future economic growth, investment, financial markets etc. In this paper we investigate whether macroeconomic uncertainty affects income, wage and consumption inequality. Our findings suggest that the measures of inequality increase in the aftermath of an uncertainty shock but decrease in the medium to long run, converging to lower levels. Macroeconomic uncertainty appears to account significantly for the variation of income and consumption inequality. Using detailed micro data we decompose households' income to investigate transmission channels where uncertainty shocks affect differently the percentiles of income and consumption distributions. The financial segmentation and portfolio channels appear to play an important role in this heterogeneous response.

Keywords: Macroeconomic uncertainty, income inequality, consumption inequality, SVAR

JEL codes: C32, D3, D8, E32.

1 Introduction

A decade after the Great Recession, most economies are recovering slowly with the world economic growth in upward trend. Unemployment levels are low, fiscal balances have been improved substantially and one would expect a similar picture for the levels of income and wage inequality. However, OECD (2016) warns that income inequality remains at record high levels in many countries despite declining unemployment and improving employment rates. Some key facts are persistent: long term unemployment in low income households,

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slow wage growth for low and middle earners but most importantly redistribution policies, which cushion the impact of crisis in its initial stage, have been weakened in many countries.

The picture in the UK appears to be different: the fast economic recovery was abruptly interrupted by the European Union membership referendum in June 2016, increasing the levels of economic and political uncertainty. Nevertheless, according to data on disposable income coming from the latest waves of the Family Expenditure Survey (FES, 2016), income inequality has not increased but remains to pre crisis levels. Cribb *et al.* (2017) show that in 2016 income inequality measures such as the Gini Coefficient and the 90:10 ratio are roughly at the same levels of 1990s. Their upward trend have been interrupted by the financial crisis in 2007-8 mainly due to loss of real earnings in high income households and rising social security benefits. While inequality measures for wage and total consumption have recovered some of their downward adjustments during the financial crisis (see Figure 1), income inequality still remains at low levels. Cribb *et al.* (2017) report that real earnings for median and high incomes have started to grow slowly while real benefits for low income families have slowed down. These facts lead some researchers to forecast that the equality gains obtained during the Great Recession would be reversed by 2016 (see for example Brewer *et al.*, 2013). However, this has not happened yet: income inequality in the UK (excluding the top and bottom 1%[1]) remains still at low levels.

The drivers of inequality have been extensively studied in the literature: Skill biased technological change, trade openness and globalisation, financial deepening and credit constraints, changes in labour markets structure and trade unions' strength influence inequality through a number of transmission mechanisms. These mechanisms vary in magnitude across developed and emerging economies and in the short to long run (see for example Acemoglu, 1998; Freeman, 2010; Roine *et al.*, 2009; Western and Rosenfeld, 2011; Card, 2001). Demographic factors and individual characteristics such as the level of education, return of schooling, family structure, gender, social mobility have been also found to be important drivers (e.g. Knight and Sabot, 1983; Cunha and Heckman, 2007)

The redistributive role of the government through progressivity in taxation and social security transfers is a strong determinant to equality especially for low income percentiles (e.g. Heathcote *et al.*, 2010). Finally, the role of monetary policy has been lately examined and findings suggest a positive impact of contractionary monetary policies and quantitative easing to inequality (Coibion *et al.*, 2017; Mumtaz and Theophilopoulou, 2017).

One of the factors which has been limited studied as a determinant of inequality is

[1] Cribb *et al.* (2017) find that the household income held by the top 1% has increased during the same time span and despite a substantial fall during the Great Recession, it has recovered fully and is at pre-crisis levels. The authors use different data sources for these calculations as FES and FRS suffer from under reporting of the top high incomes.

macroeconomic uncertainty. A number of studies[2] have found that uncertainty shocks affect macroeconomic fluctuations through their ability to affect consumption, savings and investment decisions. During periods of high uncertainty households decrease consumption or postpone purchase of durables and increase their buffer stock of savings. Firms may postpone investment in a wait and see state and prefer temporary to permanent workforce. The labour market is affected in terms of employment rate, hours worked and wage growth. Uncertainty directly affects financial markets which experience high volatility of returns. Credit conditions become tougher for firms and households who face greater difficulty to obtain credit and higher costs as risk premia increase. A question that arises naturally is whether households of different income, consumption and wage levels are affected by economic uncertainty in a similar way. However, most studies focus on the effects of uncertainty on aggregate data. As Deaton (2016) states: "While we often must focus on aggregates for macroeconomic policy, it is impossible to think coherently about national well-being while ignoring inequality and poverty, neither of which is visible in aggregate data."

Uncertainty shocks are found to amplify and prolong recessions. During recessions different percentiles of income, wage and consumption distributions are differently affected (Heathcote *et al.*, 2010). Guvenen *et al.* (2014) find that US low wage workers experience downward movements and high volatility in their wage while high earners experience only sluggish wage growth during economic slowdowns. Looking at the evolution of consumption inequality in the US, Attanasio and Pistaferri (2014) found lower consumption inequality during the Great Recession as the consumption of the 10^{th} percentile falls substantially during this period. Gambetti and De Giorgi (2017) observe procyclical behaviour of consumption inequality for the US especially for the right tail consumers who are more exposed to economic fluctuations. High consumption individuals are estimated to pay three times more the cost of the business cycle relatively to other consumers. Finally, when the researchers look at the impact of TFP and Economic Policy Uncertainty (EPU) on consumption distribution they find significant effects on the top end of the distribution. Top consumption percentiles reduce substantially their consumption levels in high EPU periods relatively to the low ones and thus inequality in consumption falls. The impact of the EPU on household income is also examined by Fischer *et al.* (2018) for the US states. The authors find that inequality falls in most states while there is high heterogeneity in

[2] There is a large literature on the channels by which uncertainty affects the economy. Some indicative studies include Bloom (2009), Bond et al. (2005), Bernanke (1983) on investment and productivity growth, Benito (2006) and Eberly (1994) on consumption behaviour, Arellano et al. (2016), Alessandri and Bottero (2017) on financial markets and credit conditions. For a literature review on the impact on economic fluctuations see Bloom (2014).

terms of magnitude and duration. Different income composition across states leads to heterogeneous responses and fall in inequality is observed when capital income is relatively higher.

To our knowledge, the last few studies are the only ones that look at the direct impact of uncertainty, mostly of the EPU, on macroeconomy[3]. This paper attempts to shed new light on the relationship between macroeconomic uncertainty and inequality. More specifically, we investigate whether macroeconomic uncertainty shocks affect earnings, income and consumption inequality in the UK. This paper has two distinctive features: First, a macroeconomic uncertainty index using a large macroeconomic and financial dataset has been constructed for the UK. Second, quarterly inequality measures have been constructed by using survey microeconomic data. Thus both macroeconomic uncertainty and inequality measures have been constructed by exploiting rich data environment, taking into account households' characteristics and macroeconomic activity.

By using a Structural Vector Autoregression (SVAR) we find that macroeconomic uncertainty shocks lead to lower inequality in earnings, income and consumption in the medium and long run. These results remain invariant to alternative specifications of the VAR. The uncertainty shock makes important contributions to forecast error variance in the inequality measures. In order to identify possible factors and channels of transmission which led to the observed fall in inequality we estimate a SVAR using data for households in different percentiles of each distribution. Results from this exercise suggest that the uncertainty shock decreases wages and income for households at the middle and high end of the distribution while households at the lower end are less affected due mainly to redistributive policies and social security. This is consistent with wealthier households deriving a comparatively larger proportion of their income from investments which falls substantially during periods of higher uncertainty.

The rest of the paper is structured as follows: Section 2 describes the variables used in the empirical analysis and the construction of inequality and uncertainty measures. Section 3 describes the estimation of the SVAR model and identification scheme. Section 4 presents the main results for earnings, income and consumption, discusses issues of heterogeneity and carries out robustness checks while Section 5 concludes.

[3] A recent theoretical study by Kasa and Lei (2017) focuses on the role of uncertainty on wealth inequality. The authors show that when top wealth agents confront Knightian uncertainty chose robust portfolio policies and invest a large part of their wealth in higher yielding assets while low wealth households chose safer assets as they are more risk averse. This investment behaviour amplifies wealth inequality. However, the results may vary substantially for income and consumption inequality in samples where the top 1% of households is excluded.

2 Data

In this section we describe the variables used from the Family Expenditure Survey (FES), the construction of measures of inequality and the construction of macroeconomic uncertainty measure for the UK.

2.1 The Family Expenditure Survey variables

The data for income wage and consumption are drawn from the Family Expenditure Survey (FES) from 1970 to 2016. The FES is an annual survey which provides detailed information on demographics, income, expenditure and consumption for on average of a representative sample of 7,000 UK households per year. The households who participate on FES are asked to keep a diary with their spending of a two week period. In 2001 FES merged with the National Food Survey and became the Expenditure and Food Survey (EFS) and with the Living Costs and Food Survey (LCFS) in 2008[4]. Even though the FES has been running from 1957 there are discontinuities and small samples prior to 1968 and for this reason solid inequality measures can be constructed from 1969. Some studies (see for example Foster, 1996, van de Ven, 2011) point out representation problems with the survey: FES tends to over represent mortgage holders, people living in the countryside, older households and under represents people living in council flats, institutions (e.g. retirement homes, military), no fixed address holders, ethnic minorities, self employed, manual workers and younger households. Compared to National Accounts, some sources of income such as earnings and social security benefits closely match National Accounts distributions while there is some under-reporting of investment income and self employment earnings (Banks and Johnson, 1998)

The variable we use for disposable income is defined as weekly household income net of taxes and national insurance contributions. It is summed across all members living in the same household. After keeping only the positive values and trimming, there are on average 6,900 households per year until 2006 and then the average drops to 5,600 per year. Thus, in total there are around 305,000 household income observations for the whole sample period. The income variable is equivalised for the family size by dividing the income of each household by the square root of the number of individuals living in the household.

The variable for gross wage is the normal gross wage from any type of occupation before taxes including national insurance contributions and other deductions and bonuses. Gross wage is at individual level, converted to weekly amounts[5]. Taking into account

[4] In 1993-94 the FES changes from calender year to financial year (April to March) and the EFS goes back to the calender year in 2006.

[5] If the individual works full time, the weekly payment is defined as earnings, while in the case of a part

only positive values there are on average 7,000 observations per year or around 320,000 observations over the 46 year period. Inequality measures constructed from data on wages have smaller measurement error than other forms of income.

The definition for the total consumption variable comes from National Accounts which is the sum of housing, food, alcohol, tobacco, fuel, light and power, clothing and footwear, durable household goods, other goods, transport, vehicles and services. Household's total consumption is divided by the number of people living in the household to construct consumption per capita.

The distributions of all three variables have been trimmed by removing the top and bottom 1%. Even though the tails of the distributions may give highly heterogeneous responses during economic uncertainty, they are likely to contain measurement errors as their inclusion causes erratic shifts in the inequality measures. Thus we follow the existing literature on this issue (see for instance Brewer and Wren-Lewis, 2012) and trim the tails by 1%. All variables have been deflated by the CPI.

2.2 Measures of Inequality

Three measures of inequality are constructed for each FES variable: the Gini coefficient of levels, which takes values between 0 (perfect equality) and 1 (perfect inequality), the cross sectional standard deviation of log levels which removes zero values, reducing this way sensitivity to extreme values and lastly the differences between individual percentiles of the cross sectional distribution of the log levels (e.g. $90^{th}P - 10^{th}P$, $50^{th}P - 10^{th}P$, etc.) for each period. An important feature of this dataset, which allows a closer observation of inequality responses, is the quarterly frequency of the inequality measures. This is achieved by assigning households to different quarters within a year based on the date of the survey interview (Cloyne and Surico, 2017).

Figure 1 shows the evolution of the Gini coefficient for disposable income, total consumption and gross personal wage from 1970 to 2016 for the UK. All measures depict an upward trend for the period examined with the most dramatic rise taking place in the second decade of the sample. More specifically, the sample period starts with a fall of inequality in the beginning of the 1970s which remains at low levels until the end of the decade. The observed fall in inequality is achieved mostly through labour earnings as high earners experienced fall of their real wages relative to low earners. This period is also characterised by an increase in relative earnings for women and pensioners, accompanied by monetary easing in the second half of 1970s (Nelson, 2001).

During the 1980s, the unemployment rate increased dramatically, peaking at 12% in

time or odd job, the last payment is counted.

1984. The same period is characterised by a dramatic increase of inequality especially in disposable income. This has been attributed to higher unemployment in low income households, lower working hours of the employed, more part time contracts and higher dispersion of wages between low and high earners (Brewer and Wren-Lewis, 2012).The highest rise observed was that of disposable income inequality. Even though income inequality was at its lowest in the beginning of the sample period, it catches up rapidly with consumption inequality in mid 1980s. Financial liberalisation and more consumption loans available enabled many low income households to achieve a level of consumption which was not entirely supported by their income.

Fall of investment income and the burst of the dotcom bubble in the beginning of 2000s, contributed to fall of inequality in income and earnings. In 2007 financial markets collapsed and the Great Recession which followed, caused a deep fall in all inequality measures, especially in consumption. During this period low income families experienced real increases in benefit income which is a substantial part of their total income while middle and high income families experienced large falls in their real earnings. Interestingly, the Gini coefficients for consumption and earnings rose substantially after 2010 while the one for disposable income remains at low levels. During the recovering period (2010-12), income inequality remained low mainly due to increase of employment among workless households (less individuals lived in a workless household) while employment rates in high income households did not change (Belfield *et al.*, 2017). During the last period of the sample (2013-16) income inequality remains low and unchanged (around 0.31). It is equal to 1985 levels although real earnings have started to grow slowly and real benefits have slowed down.

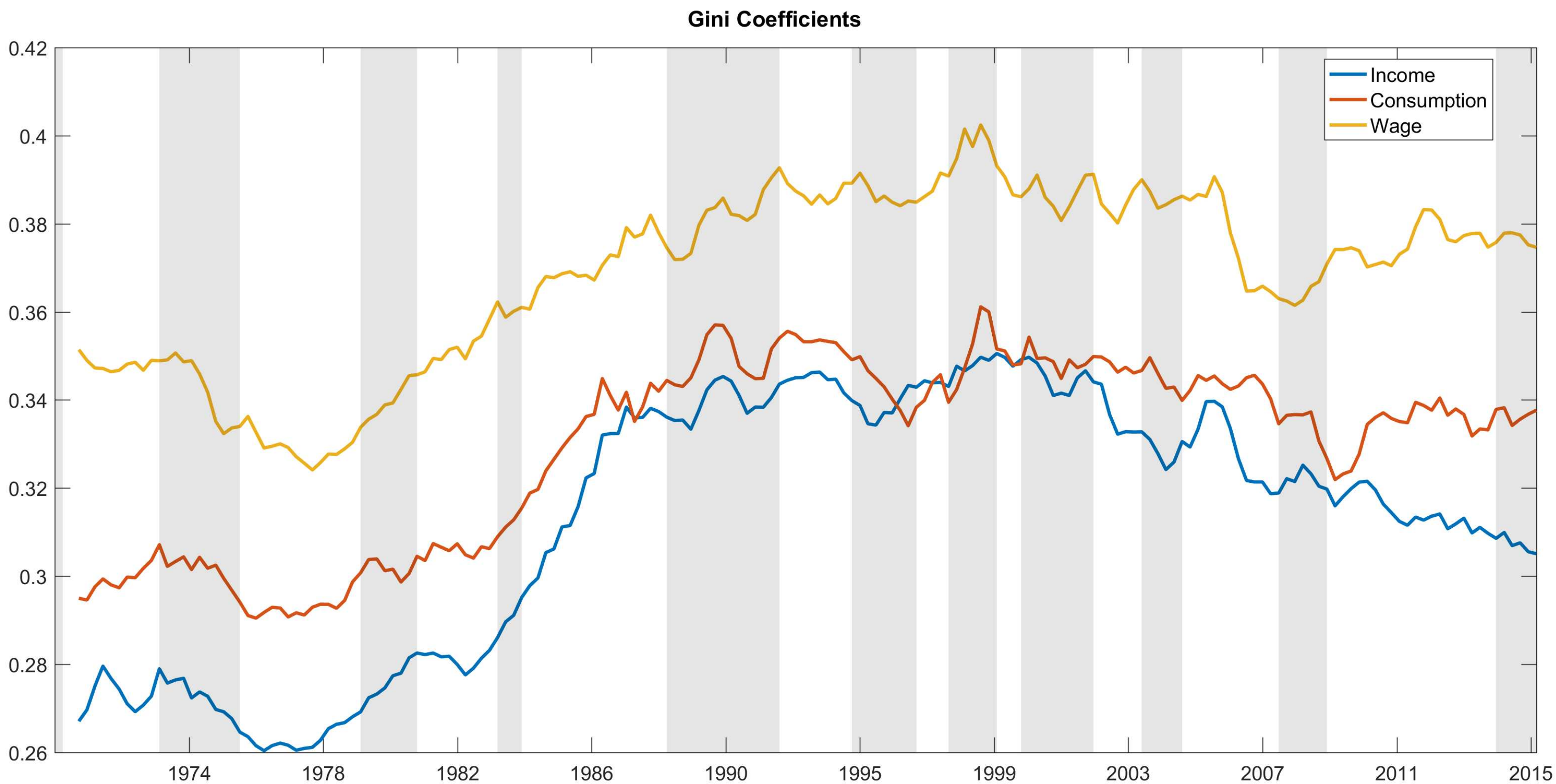

Figure 1: *The Gini Coefficient (4 quarter moving average) for disposable income, total consumption and gross wage for the UK from 1970 to 2016.* The data is from the Family Expenditure Survey (FES) and its successive surveys (see Section 2.1) Shaded areas represent recessions as identified by the OECD.

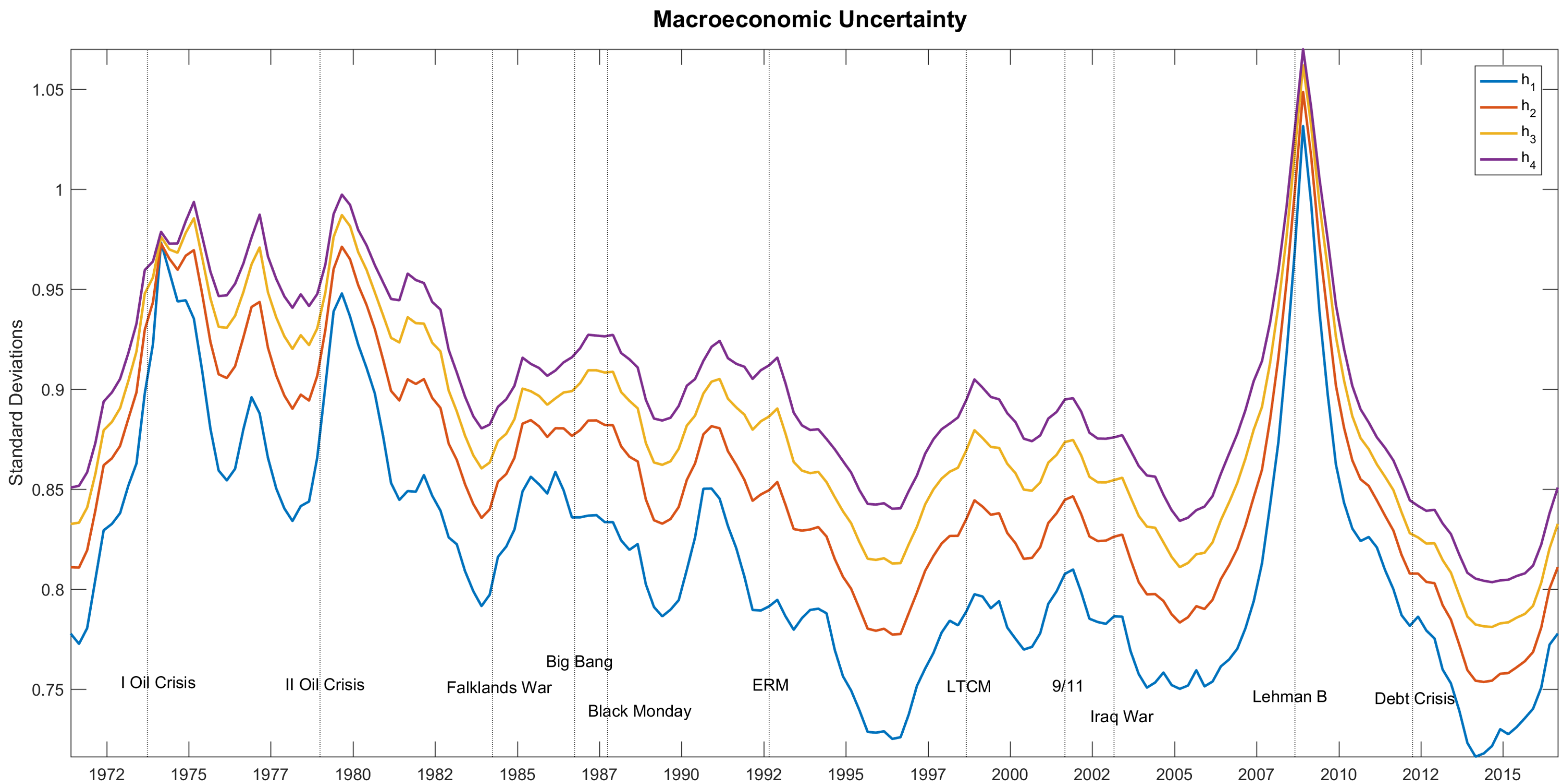

Figure 2: *UK Macroeconomic Uncertainty for horizons* (h) *one to four quarters ahead.* The vertical lines indicate major economic and political events for the UK. The data are quarterly and span the period 1971Q1:2016Q1

2.3 The Measure of Uncertainty

To construct the measure of macroeconomic uncertainty for the UK we follow closely the methodology described in Jurado, Ludvigson and Ng (2015). The main characteristics of this measure are that it is derived by using a large number of macroeconomic and financial variables, it is not related to the structure of theoretical models but most importantly it focuses on the evolution of the non forecastable component of each variable. The authors argue that when this component increases, the economy becomes less predictable and this is how uncertainty increases.

Summarising the model in Jurado *et al.* (2015), the h period ahead uncertainty $(U^y_{jt}(h))$ of the variable $y_{jt} \in Y_t = (y_{1t}...y_{Nyt})'$ is the conditional volatility of the non forecastable part of the future value of the series which is defined as:

$$U^y_{jt}(h) = \sqrt{E\left[y_{jt+h} - (Ey_{jt+h}|I_t)\right]^2 |I_t}, \tag{1}$$

where I_t is the information set available to economic agents at period t. If the expectation today on the forecast error of the variable y_{jt}, $y_{jt+h} - (Ey_{jt+h}|I_t)$ rises then the uncertainty on this variable rises as well. Note that the whole forecastable component of the variable y_j has been removed before calculating its conditional volatility, otherwise sizable forecastable variations will be mistakenly categorised as uncertainty. This is one of the main features of this uncertainty measure.

The measure of macroeconomic uncertainty can be constructed by using a weighted average of the uncertainty for each variable for period t:

$$U^y_t(h) \equiv p \lim_{Ny \longrightarrow \infty} \sum_{j=1}^{N_y} w_j U^y_{jt}(h) \equiv E_w\left[U^y_{jt}(h)\right], \tag{2}$$

where w_j are aggregation weights for each period. By using a large number of variables this measure is not based on the countercyclical volatility of an idiosyncratic shock but takes the common variation across all variables in the sample.

To obtain the estimates for the individual uncertainties in (1) and to construct the aggregate measure in (2) we first have to produce the forecast $E\left[y_{jt+h}|I_t\right]$ for each variable. The forecasted value of the variable y_j for the period $h \geq 1$ is given by the following factor augmented model:

$$y_{jt+1} = \phi^y_j(L)y_{jt} + \gamma^F_j(L)\hat{\mathbf{F}}_t + \gamma^W_j(L)\mathbf{W}_t + v^y_{jt+1},$$

where ϕ^y_j, γ^F_j and γ^W_j are finite order lag polynomials, $\hat{\mathbf{F}}_t$ are the factors coming from the information set available at time t I_t and it comprises the full data set of all macroeconomic, financial and global series, $\mathbf{W}_t$ are additional predictors. To generate time varying uncertainty in y_{jt}, the prediction error in y_{jt},and the forecast errors in factors $\hat{\mathbf{F}}$ and $\mathbf{W}$ are all allowed to have stochastic volatilities $\sigma_j^y, \sigma_k^F, \sigma_l^W$ for one step ahead forecast.

To obtain the forecasts for y_{jt}, a Factor Augmented Autoregression model (FAVAR) is employed. The stacked vectors in the FAVAR system are $Y_{jt} = (y_{jt}, y_{jt-1}...y_{jt+q-1})'$ and $\check{Z}_t \equiv (Z_t...Z_{t-q+1})'$ where Z is the vector which collects all factors estimated and additional predictors, $Z_t \equiv (\hat{\mathbf{F}}_t, \mathbf{W}_t)'$. The system has the following form:

$$\begin{pmatrix} \check{Z}_t \\ Y_{jt} \end{pmatrix} = \begin{bmatrix} \Phi^{\check{Z}} & 0 \\ \Lambda_j' & \Phi_j^Y \end{bmatrix} \begin{pmatrix} \check{Z}_{t-1} \\ Y_{jt-1} \end{pmatrix} + \begin{pmatrix} v_t^{\check{Z}} \\ v_{jt}^Y \end{pmatrix}. \tag{3}$$

A parametric stochastic volatility model has been employed to give to conditional volatilities of shocks $v_t^{\check{Z}}$ and v_{jt}^Y time variation. It is worth noting that the time varying volatilities of factors and predictors' errors create additional unforcasted volatility in y_{jt} and contribute further to its uncertainty. Thus, the time varying variance of the forecast error of both Y_{jt} and $\check{Z}_t$ is defined as:

$$\Omega_{jt}(h) = \Phi_j^Y \Omega_{jt}(h-1)(\Phi_j^Y)' + E_t\left(v_{jt+h}^Y \left(v_{jt+h}^Y\right)'\right).$$

After the variance of the forecast error has been derived, the h period ahead uncertainty for each variable y_{jt} can be easily computed following (1). Finally, the aggregate macroeconomic uncertainty can be calculated by (2).

2.4 Data for the macroeconomic uncertainty measure

The measure of macroeconomic uncertainty has been constructed by using 51 UK time series as described in Appendix II. These series try to cover various aspects of the UK economic activity spanning from 1970:Q1 to 2016:Q3. Even though there are many UK series starting as early as the 1950s not many run in a quarterly frequency and are continued until 2016. This was the main limitation for constructing a measure starting from 1970. A much larger number of quarterly series is available for a later date (for example starting form 1975). The areas covered in this dataset are the following: Output, Production and Investment, Employment, Housing, Trade, Prices, Interest and Exchange Rates, Financial Markets, Money and Credit, Government and World Macroeconomic Variables. Most series come from the Office of National Statistics (ONS), Global Financial Data (GFD), Bank of England (BOE), Organisation for Economic Co-operation and Development (OECD) and St. Louis Federal Reserve Economic Data (FRED). Series have been transformed and seasonally adjusted when needed. Details can be found in Appendix II.

The main specification in the empirical analysis below uses the following macroeconomic variables: (1) GDP per capita and in real terms (code=ABMI, ONS divided by population). (2) Inflation based on the Consumer Price Index (CPI). The CPI series is based on the seasonally adjusted harmonized index of consumer prices spliced with the retail price index excluding mortgage payments. (3) The three month treasury bill rate. Both series are obtained from the BOE Database (4) The Gini Coefficient for disposable income, gross wage and total consumption as described in Section 2.2 (5) the FTSEALL Index which is obtained from Global Financial Data and (6) the measure of macroeconomic uncertainty estimated by the model described in Section 2.3 and using the data described in Section 2.4 and Appendix II.

3 Empirical Model

In order to estimate the impact of uncertainty shocks on the constructed inequality measures we use a Structural VAR model. The benchmark model is defined as:

$$Z_t = c + \sum_{j=1}^{P} B_j Z_{t-j} + v_t, \tag{4}$$

where $v_t\tilde{\ }N(0, \Omega)$. The matrix of endogenous variables includes the standard set used for small open economies: i.e. the growth of real GDP per capita, CPI inflation, the three month treasury bill rate, the growth of the FTSE ALL index. The VAR model is augmented with the estimated index of uncertainty and each of the inequality measures described above, in order to estimate the impact of uncertainty shocks on inequality related to income, earnings or consumption. More specifications with alternative proxies for uncertainty and inequality have been tried in the sensitivity analysis. All variables except the interest rate and the inequality measure enter in log differences. The lag length P is set to 4 in the specifications above.

We adopt a Bayesian approach to estimation and use a Gibbs sampling algorithm to approximate the posterior distribution of the model parameters. As discussed in Uhlig (2005), this approach offers a convenient method to estimate error bands for impulse responses. However, the prior used is flat and, therefore, the results reported are data driven. The estimation algorithm is described in detail in the Appendix I.

3.1 Identification of the uncertainty shock

The covariance matrix of the residuals Ω can be decomposed as $\Omega = A_0 A_0'$ where A_0 represents the contemporaneous impact of the structural shocks ε_t:

$$v_t = A_0 \varepsilon_t. \tag{5}$$

In the benchmark model we use Cholesky decomposition to calculate the A_0 matrix, ordering uncertainty last following Jurado *et al.* (2015). This implies that uncertainty shocks affect the rest of the variables after one period. In the robustness section we consider more variations of the benchmark model by trying alternative shock identification strategies (see Section 4.3). First we order macroeconomic uncertainty first to allow uncertainty to affect contemporaneously all other variables, following Bloom (2009). Second, following Ludvigson *et al.* (2018) we put sign and magnitude restrictions on the shocks during significant historical episodes and we restrict also the correlation among the shocks and financial variables. In all alternative identification strategies employed the results remain robust (see Figure 9).

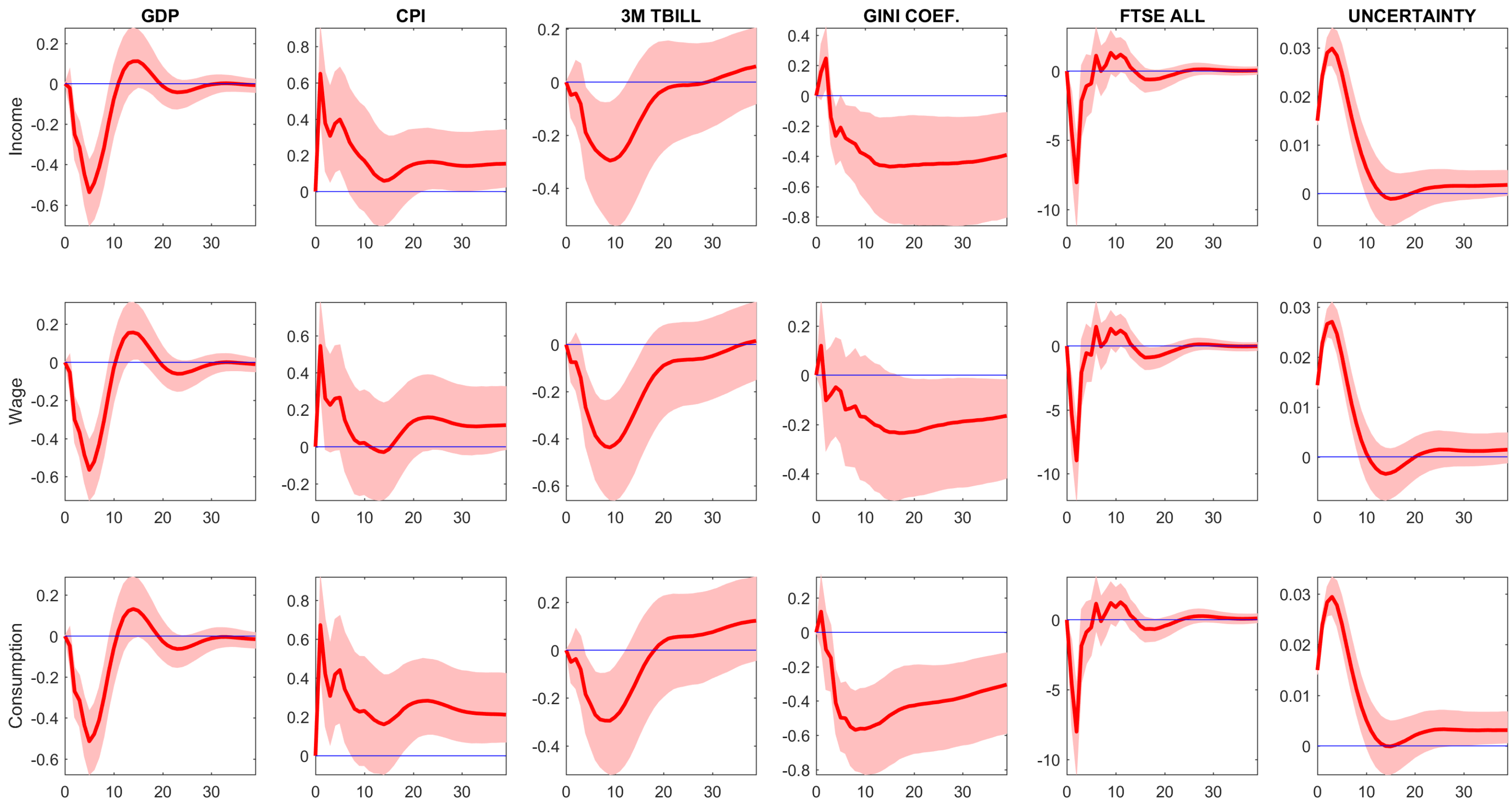

Figure 3: *Effects of the macroeconomic uncertainty shock on UK's macroeconomic variables.* The figure presents impulse response functions of macroeconomic variables to one standard deviation uncertainty shock. Each raw represents a SVAR model which has been augmented by the Gini Coefficient of Income, Wage and Consumption respectively. The vertical axis of each plot measures the response in percent. The horizontal axis indicates time in quarters. The red line is the median estimate and the shaded area is the 68% error band.

4 The response of inequality measures to uncertainty shocks

Figure 3 presents the results from the benchmark VAR model. Each row shows the response to a one standard deviation increase in uncertainty at $t = 0$ using the VAR model that includes the Gini coefficient on disposable income, gross wage and total consumption respectively.

The responses of the macroeconomic variables to uncertainty shock are the following: In the first model where the Gini coefficient of disposable income has been used as a measure of inequality, a one standard deviation macroeconomic uncertainty shock (a rise of 0.15 units of the uncertainty index) generates a 0.5 percentage point peak drop in output growth after a year, while the CPI inflation rate increases by 0.6 percent in the first quarter. This stagflation phenomenon is possibly due to the upward pricing bias channel where firms prefer to set prices toward the higher end of their price spectrum during periods of high uncertainty as it is less costly in terms of adjustment costs to increase them further if a large shock occurs (Fernández-Villaverde *et al.*, 2015). Mumtaz (2016) looks at the time varying impact of uncertainty shocks in the UK and finds a positive inflation response during the 1970s and 80s which becomes smaller in the subsequent two decades. The central bank seems to respond to the fall of output by lowering interest rates: the 3 month T-Bill rate falls, reaching a maximum drop of 0.3 percent after two years. The stock market experiences losses and the FTSEALL is negatively effected with peak response of 8 percent after two quarters. These variables follow similar behaviour in the other two models depicted in rows 2 and 3 of Figure 3 where the Gini coefficients for wage and consumption have been used as inequality measures.

The inequality measure in all three models follows an unexpected path: it increases in the short run but then it falls dramatically and remains at a lower level in the long run. More specifically, the Gini coefficient for income increases by 0.24 percent in the third quarter and then starts falling with peak drop of 0.5 percent after four years. The fact that income inequality increases in the short run may reflect a fall in labour supply and amount of hours worked. An increase in wage dispersion cannot fully explain the observed increase in income inequality in the short run as wages can be sticky and for the Gini of wage response, we cannot reject the null hypothesis of being equal to zero in the first quarters

The wage inequality, which follows a similar path to income but of a smaller magnitude, becomes statistically significant after 18 periods. When the standard deviation of log levels or the difference in percentiles are used as a measure of wage inequality, the IRF of wage follows a similar pattern but becomes significant after a year (see Figure 7). The more pronounced response is the one by the consumption inequality measure which has a maximum fall of 0.6 percent after about two years.

Overall we can summarise the benchmark findings as follows: A positive macroeconomic uncertainty shock increases the Gini coefficient of all variables in the short run but the null hypothesis can be rejected only in the case of disposable income. In the medium run, the Gini coefficients fall in lower levels and remain there for a long period. This response is robust in all specifications we tried in the sensitivity analysis and the null hypothesis that this effect is equal to zero can be rejected in all cases.

4.1 Heterogeneity of responses to uncertainty shocks

In order to understand the possible reasons behind the response of inequality measures shown in Figure 3 we consider how households and individuals at different points on the distribution respond to the uncertainty shocks identified above. In particular, for each variable, we consider households and individuals that fall within the following percentiles in a given quarter: $P_1 = \left[2^{nd} : 19^{th}\right], P_2 = \left[20^{th} : 39^{th}\right], P_3 = [40^{th} : 59^{th}], P_4 = [60^{th} : 79^{th}], P_5 = [80^{th} : 98^{th}]$. We then construct measures of average real wage, real income and real per-capita consumption within these percentiles. To examine how the shock affects the tails of each distribution relative to its median we also calculate the differences $P_5 - P_3$ and $P_3 - P_1$ These differences are then included in the SVAR along with the five macroeconomic variables used above and their response to the uncertainty shock is examined. The shock is identified by using the same recursive scheme as in the benchmark model.

The heterogeneous responses of the uncertainty shock in the distributions of income, earnings and consumption can be seen in Figure 4. In the first panel of Figure 4 the difference between P_1 (low income households) from its median (P_3) falls substantially and to a much higher magnitude than the difference between high income households from the median ($P_5 - P_3$). More specifically, the peak response of $P_3 - P_1$ is -1% after 10 periods while the one for $P_5 - P_3$ is about -0.5 % indicating that income inequality falls by more in the left part of the income distribution. Inequality in the right part of the distribution also falls but by a much smaller magnitude, indicating that high and median income households are affected by the shock in a similar way.

This can possibly reflect the fact that during periods of high uncertainty, high and median household incomes decrease while low incomes are partly supported by social security benefits. This argument is in line with the findings of Coibion *et al.* (2017) for the US and Mumtaz and Theophilopoulou (2017) for the UK who decompose households' income and find a higher percentage of income coming from financial investments and wages for high income households while low income households are partly supported by social benefits when they experience loss of income and wage in periods of economic slowdown. Similar results are depicted by Belfield *et al.* (2017) explaining why the UK experienced lower income inequality after the Great Recession.

In Figure 5 we decompose UK households' income and consumption from 1995 to 2015 to three main sources: wage, social security benefits and investment income. The decomposition reveals that wage is the main source of income for median (56%) and high percentiles (68-70%) and investment income has a significant contribution (around 7.5%) to the highest percentile. Social benefits, on the other hand, appear to be a very significant source of income and consumption for households in the first percentile (79.5%) while for the fifth percentile is less significant (11%). Thus median and high income households are more affected in terms of income and consumption during periods of high uncertainty and recession as wages and investment proceeds become more volatile while low income households are largely sustained by social security benefits.

In terms of wage distribution, we can see from the second panel of Figure 4 that the difference between low and median earners is decreasing about one year after the shock while the response of the difference among high earners is not statistically significant. This is in line with the findings of Heathcote *et al.* (2010) for the US earnings distribution. More specifically, the authors find that earnings dynamics are more important for high percentiles of the earnings distribution as their earnings are more volatile to the business cycle. On the other hand, labour market characteristics such as institutional constraints on minimum wage, unions' power and hours worked are more important for low percentiles. Therefore, uncertainty shocks can generate a decrease in earnings growth which is more pronounced and uniform for the second half of the earnings distribution such that $P_5 - P_3$ appears to be statistically insignificant while the low percentiles are more immune to wage drops due to institutional constraints. This is why $P_3 - P_1$ becomes smaller and earnings inequality falls in the first half of the income distribution.

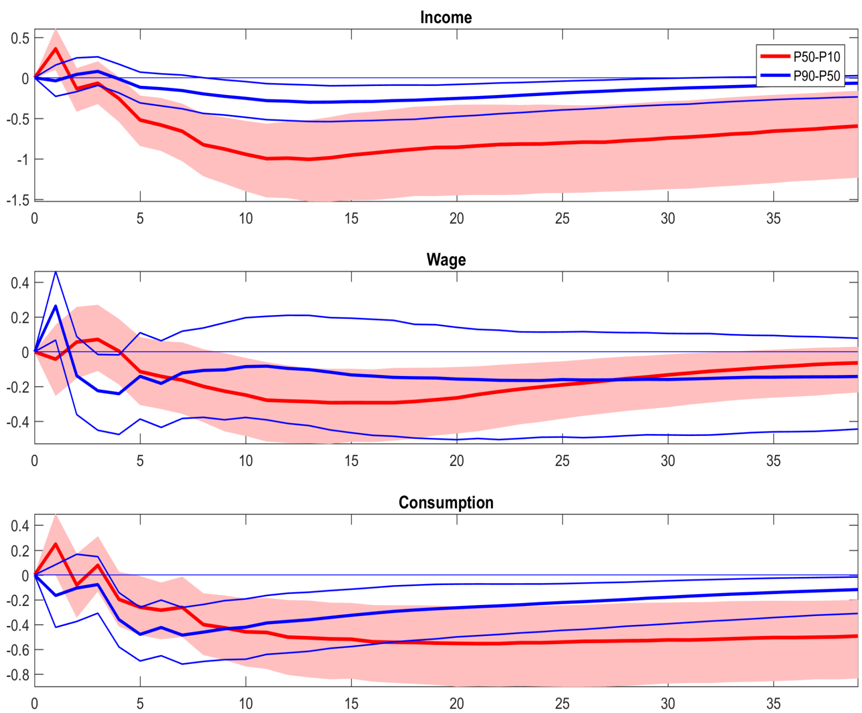

Figure 4: *Distributional effects of macroeconomic uncertainty shocks by percentiles.* The figure reports the impulse response functions of log differences between the 50^{th} and 10^{th} percentiles ($P50 - P10$, red solid line) and between the 90^{th} and the 50^{th} percentile ($P90 - P50$, blue central line) to one standard deviation uncertainty shock for the distributions of income, wage and consumption. The shaded area in the case of the $P50 - P10$ difference and the two external blue lines in the case of the $P90 - P50$ represent 68% error bands. The IRFs are measured in percentage changes (vertical axis) while the horizontal axis reports time in quarters.

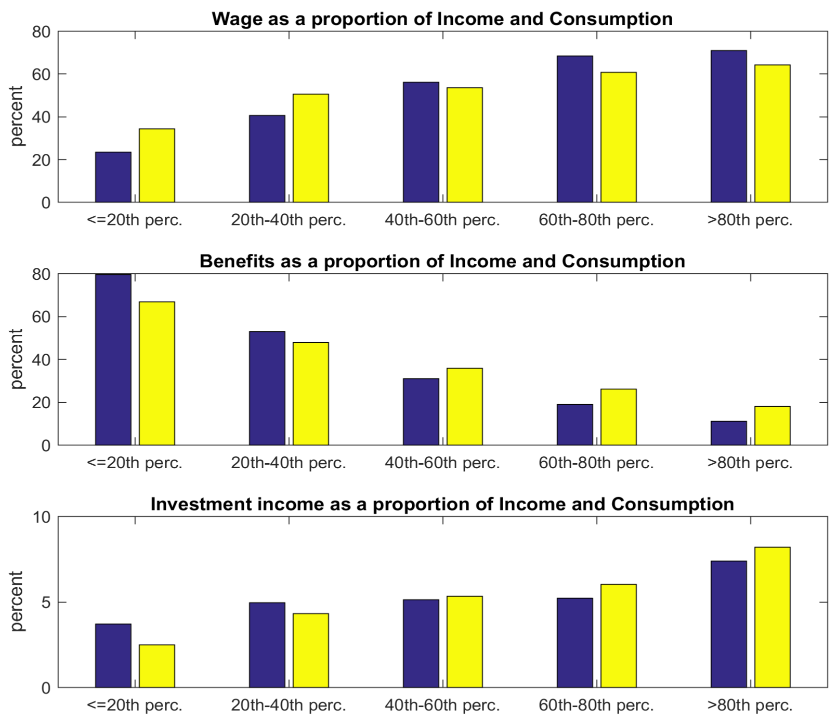

Figure 5: *Income and Consumption decomposition by percentile.* The figure reports the proportions of gross wage, social security benefits and investment income in Disposable Income (blue bars) and Total Consumption (yellow bars) for each percentile. The data used for this figure are 5 year averages over the period 1975-2015, from the FES.

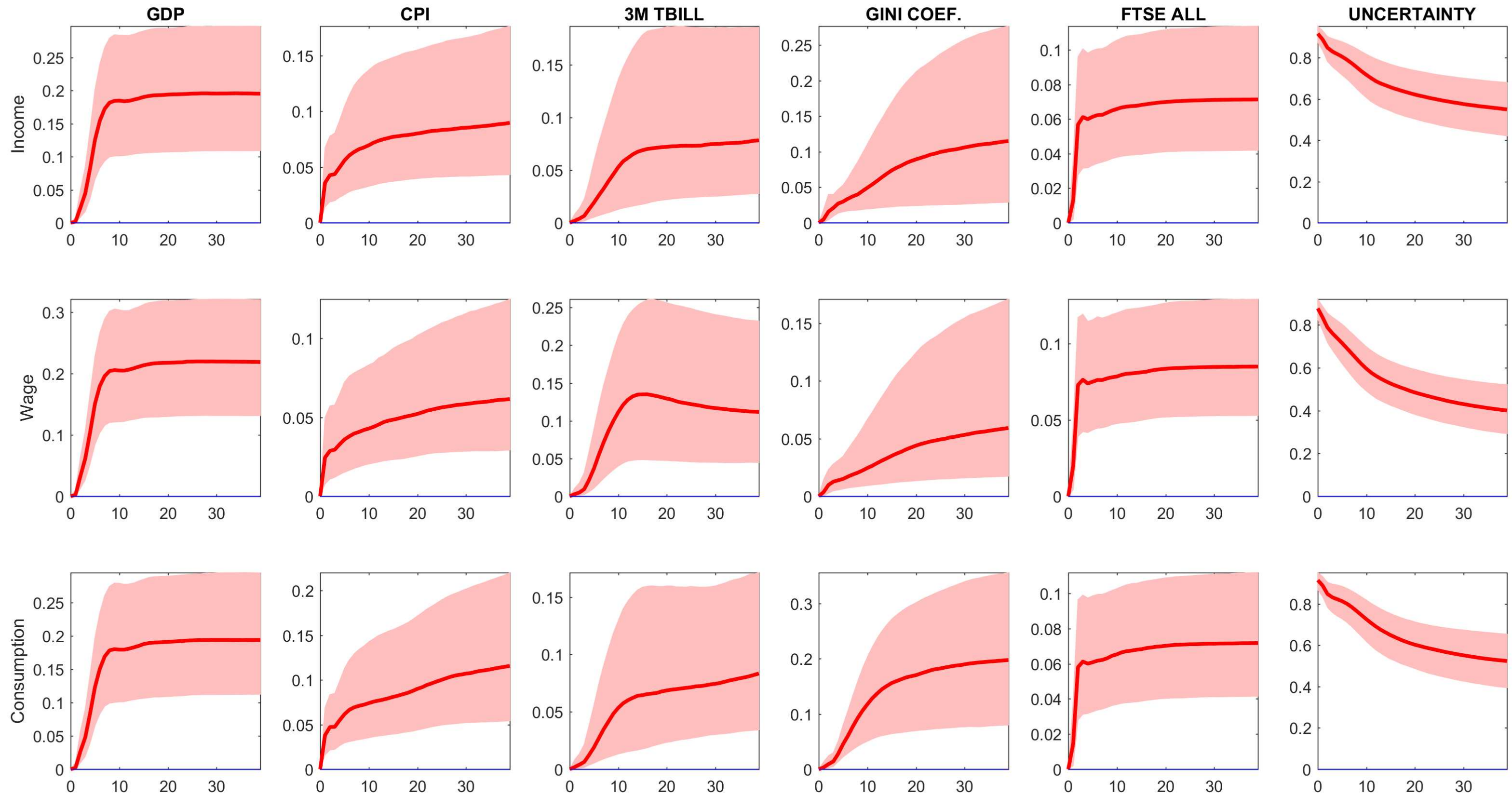

Figure 6: *Percentage contribution of uncertainty shocks to the forecast error variance (FEV) of all macroeconomic variables.* The fourth column reports the shock's contribution to the FEV of Gini Coefficients for income, wage and consumption respectively. The solid line is the median estimate and the shaded area is the 68% error band. The vertical axis measures percentage change and the horizontal time in quarters.

4.2 The contribution of uncertainty shocks to inequality

Figure 6 plots the contribution of the macroeconomic uncertainty shock to the forecast error variance (FEV) of the Gini coefficients. The estimated median contribution of this shock ranges from around 10% at the three year horizon for income, is smaller for wage while for total consumption it amounts to about 20% in the FEV at a two year horizon. Similar estimates are found when the standard deviation of logs or the difference of the $90^{th}P = 10^{th}P$ are considered as measure of inequality. This suggests that uncertainty shocks make a contribution to inequality that is important both from an economic and statistical perspective.

4.3 Robustness of the results

We check the robustness of the results from three perspectives: First, we try different measures of inequality such as the standard deviation of log levels and the $90^{th}P - 10^{th}P$ difference. Second, to deal with the problem of informational deficiency in a conventional VAR we augment the benchmark VAR with factors extracted from the whole macroeconomic and financial data set. Third, we try different identification schemes for the uncertainty shock. Despite some differences in magnitude, overall the results remain robust in all cases.

Measures of Inequality: Two alternative measures of inequality are the standard deviation of the log levels of income, wage and consumption and the difference between the 90^{th} and 10^{th} percentiles. The advantage of the former is that it decreases the influence of outliers in highly skewed data while the latter compares directly two parts of the distribution without referring to the whole distribution and the statistics are easily read. By using the standard deviation of log levels we find similar results to the Gini coefficients in the benchmark specification and the impact is of the same magnitude (see Figure 7, second column). The fall in wage inequality is more pronounced and significant in this case. Similar impulse responses are produced when we use the difference in percentiles as a measure. In this case the magnitude is greater in all three variables, reaching, for example, -1% peak response in income compared to benchmark which is -0.5% (Figure 7, third column).

Informational sufficiency: To account for the fact that agents typically have access to a large information set while a conventional VAR can handle only a limited number of variables, we adopt the solution proposed by Forni and Gambetti (2014) and estimate a Factor Augmented VAR (FAVAR). We augment the benchmark VAR by two principal components computed by the 52 macroeconomic and financial time series to ensure orthogonality and solve recersively. The Granger causality test indicates that informational

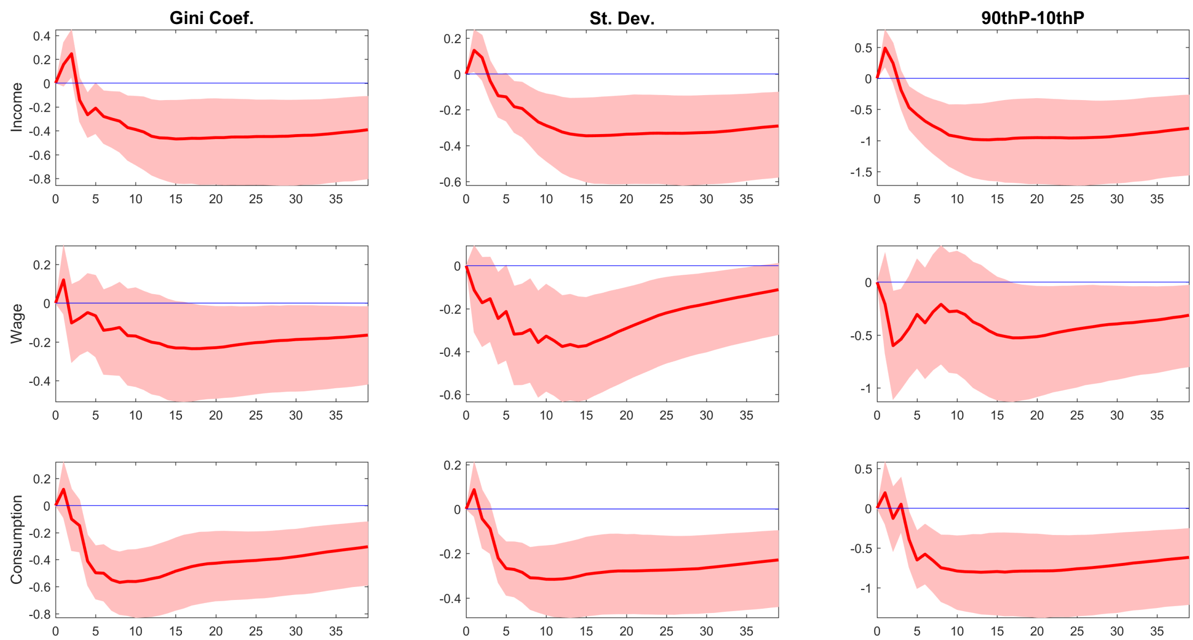

Figure 7: *Sensitivity in the measure of inequality*: The impulse response functions of Gini coefficients (first column), standard deviation of log levels (second column) and $90^{th}P - 10^{th}P$ (third column) to one standard deviation uncertainty shock. The vertical axis of each plot shows the response in percent. The red line is the median estimate and the shaded area is the 68% confidence bands.

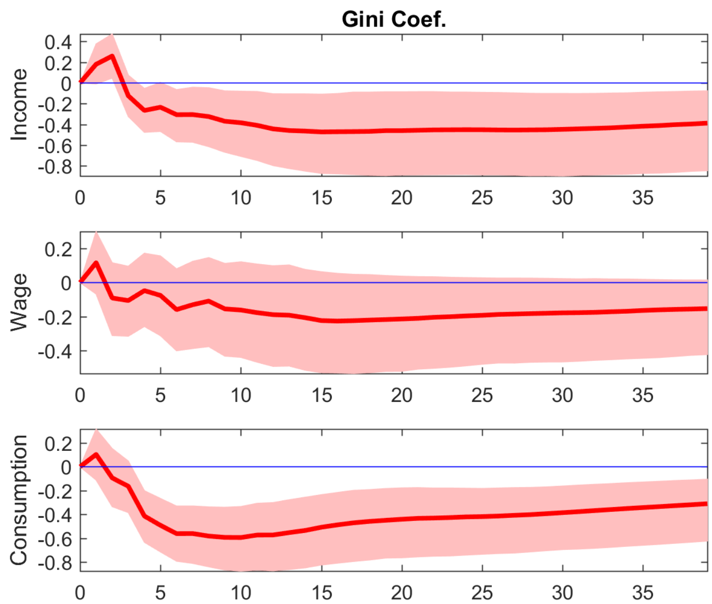

Figure 8: *Sensitivity in the information set*: The impulse response functions of Gini coefficients to one standard deviation uncertainty shock. Two principal components derived by a FAVAR model have been added in the benchmark VAR. The vertical axis of each plot shows the response in percent. The red line is the median estimate and the shaded area is the 68% confidence bands.

sufficiency is no longer rejected. The results remain similar to the benchmark experiment: As Figure 8 shows, the Gini coefficient falls for all three variables in a similar pattern and magnitude to the benchmark. In the case of gross wage, the null cannot be rejected.

Measures of Uncertainty: Next, we try two different proxies for the uncertainty measure. First, following Bloom (2009) we use the daily volatility of the FTSEALL index. The stock market volatility is constructed by using a quarterly average of the monthly realised volatility of FTSEALL which is HP detrended. A recursive identification strategy has been employed and the ordering of the variables has been altered to match Bloom (2009), ordering the returns of FTSEALL first, the stock market volatility second and keeping the inequality measure last. The impulse response functions of the main macroeconomic variables are similar to Bloom's (2009) and to the benchmark. The results indicate that stock market volatility shocks have a negative impact on Gini coefficients for income, wage and consumption (see Figure 9, second column). Intuitively, large volatility shocks in financial markets will decrease income from financial assets and investments. This affects mostly households in high income percentiles as it can be seen in income decomposition (Figure

5) decreasing this way income inequality. The Gini coefficient for consumption decreases in the short run. Consumption levels of households in low percentiles are sustained partly through social security while higher percentiles smooth their consumption patterns and temporary loss of income does not have a long run effect on their consumption (Mumtaz and Theophilopoulou, 2017).

The second proxy for uncertainty used is the Economic Policy Uncertainty (EPU) as defined in Baker, Bloom and Davis (2016). The UK historical news based index from the authors' web site has been used as it has the longer span but it ends in 2008. The newer series available start from 1997 and cannot be matched with the old ones as different newspapers have been used. In this experiment we use the same identification strategy and similar ordering to the authors by ordering EPU first. The results can be seen in Figure 9, third column. The impulse response functions are similar to the benchmark: inequality falls for all three variables in the long run. In the short run, there is an increase of Gini for income and wage which matches the benchmark results but in this case the null hypothesis can be clearly rejected.

Identification strategies of the macroeconomic uncertainty shock:

The benchmark model has been estimated by using a recursive identification scheme as described in Section 3.1. In this section we explore the sensitivity in the identification strategy by firstly altering the order of the variables in the recursive scheme and secondly by imposing event and correlation constraints on the structural shock in conjunction with sign restriction on the A_0 matrix.

First, we experiment with different ordering in the Cholesky decomposition and order the macroeconomic uncertainty first as in Bloom (2009). This implies that a shock in macroeconomic uncertainty has an instant effect in all other variables. This impact can be seen in Figure 9, first column. Figure 9 shows that the main results remain unchanged: increase in macroeconomic uncertainty improves the equality measure for income, wage and consumption in the long run. In the short run, only the Gini for consumption experiences briefly a small increase by 0.3%.

We put minimal sign restrictions on the A_0 matrix to impose that macroeconomic uncertainty and output move on opposite directions on the impact. However, these restrictions are not sufficient to disentangle uncertainty shocks from the rest of the shocks. Therefore, following the identification strategy in Ludvigson *et al.* (2018) we impose two types of shock-based restrictions: i) event constraints and ii) correlation constraints.

The event constraints impose the uncertainty shock to be larger than one standard deviation from their mean during the ERM crisis and Black Wednesday (1992Q4). The uncertainty shock is also restricted to be larger than one standard deviation at least once during the financial crisis (2008Q1-2009Q2). We also impose that shocks to GDP growth during the same period must be less than one standard deviation to exclude solutions which imply large positive shocks to output during that period.

As in Ludvigson *et al.* (2018), the uncertainty shock can affect stock premia and should be negatively correlated to stock returns. The correlation constraint is $\rho < -0.05$ implying a negative correlation between the uncertainty shock and stock returns. The results can be seen in the last column of Figure 9. All three IRFs of the Gini coefficients follow similar paths to the benchmark. In this identification scheme, the drop in inequality measures is clear, distinct and persistent.

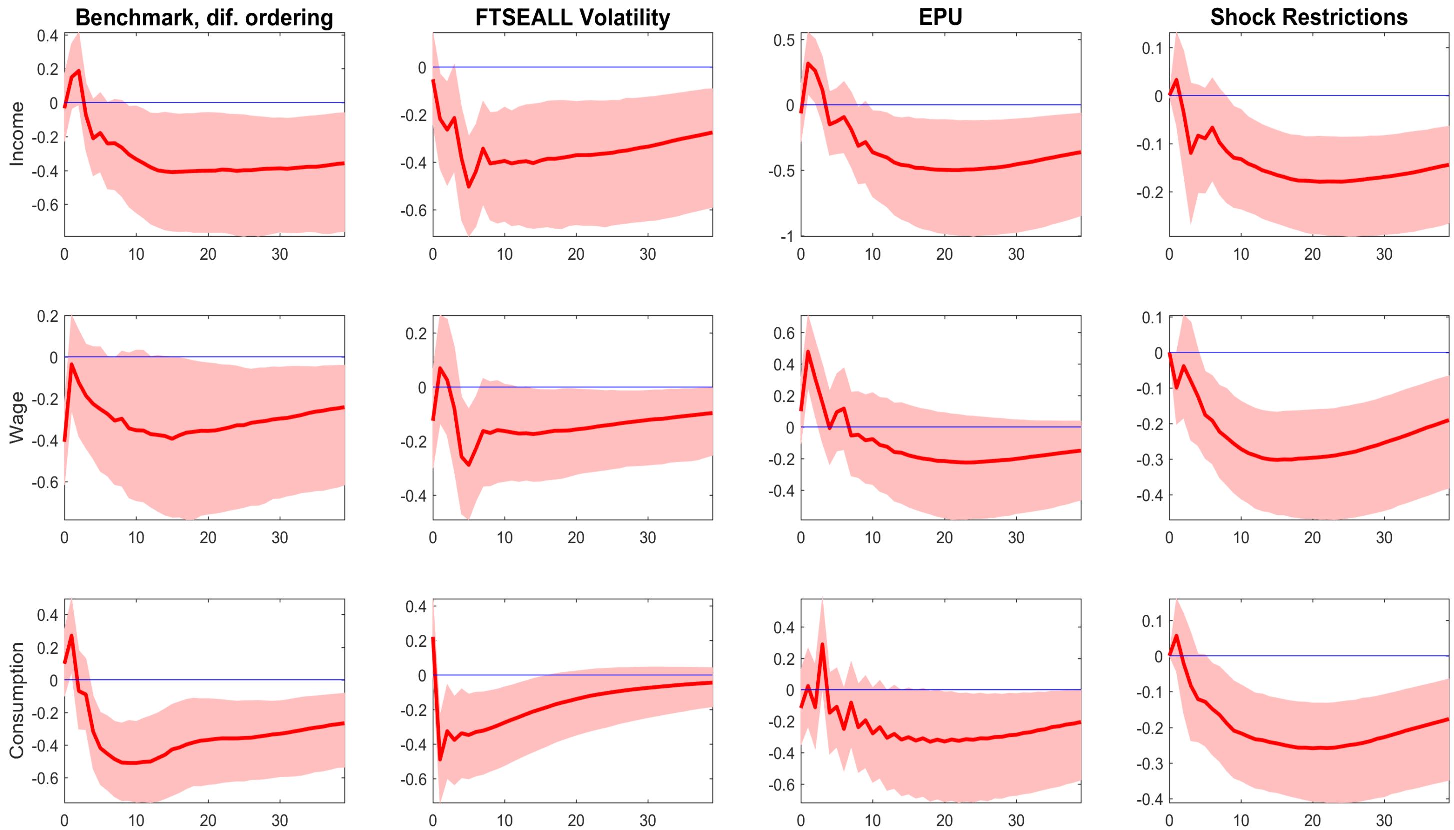

Figure 9: *Sensitivity in the information set and identification strategy*: The impulse response functions of Gini coefficients to one standard deviation macroeconomic uncertainty shock. The first column shows the results of a recursive ordering where the measure of uncertainty has been ordered first. For the results in the second column the daily volatility of the FTSEALL Index has been used as measure of uncertainty while in the third column the Economic Policy Uncertainty (EPU) Index has been used. The fourth column depicts results where shock-based restrictions have been used to identify the uncertainty shock. The vertical axis of each plot shows the response in percent. The red line is the median estimate and the shaded area is the 68% confidence bands.

5 Conclusions

A growing empirical literature has demonstrated the negative impact of uncertainty shocks on macroeconomic variables. However, little has been researched on its relationship with economic inequality and its distributional effects. This paper attempts to bridge this gap and sheds light on the impact of macroeconomic uncertainty on income, wage and consumption inequality for the UK.

We build quarterly historical time series for the measures of inequality exploring microeconomic data from the Family Expenditure Survey. We then use a data rich environment in terms of macroeconomic and financial time series to construct the uncertainty measure for the UK. By employing a structural VAR model we estimate the impact of uncertainty shocks on UK inequality. Our findings suggest that positive uncertainty shocks decrease inequality measures after about a year and this drop is significant and persistent. Our results remain robust in alternative measures of inequality, uncertainty, specifications of the model and identification strategies for the structural shock. Uncertainty shocks explain a significant proportion of the fluctuations in the inequality measures with a contribution to their variance estimated to be from 10 to 20 percent.

To explain this drop in inequality and understand distributional implications we examine how different percentiles of income, wage and consumption distributions react to the uncertainty shock. We find that households and individuals on the right part of distributions are the ones mostly affected by an increase in uncertainty. This is because their labour and financial incomes are more exposed to economic fluctuations. On the other hand, macroeconomic uncertainty seems to play a small role on income fluctuations for households in low percentiles as social security benefits and institutional constraints seem to be more important determinants. This is also documented by decomposing income and consumption distributions into their main sources.

Although macroeconomic uncertainty shocks have a well documented negative impact on the economy, we find that this is also the case for inequality. The main reason is that high income households seem to be more adversely affected through the portfolio composition and labour earnings channels than low income households who rely significantly on transfers during periods of economic slowdown.

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1 Appendix I: Estimation algorithm for Bayesian VAR

Consider the VAR model:

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

where $v_t \tilde{} N(0, \Omega)$. Following Uhlig (2005) we use Gibbs sampling to draw from the posterior of the VAR coefficients. The algorithm involves drawing successively from the conditional posterior distribution of the VAR coefficients and covariance. Note that while a Bayesian numerical approach is adopted, we employ flat priors and thus place all the weight on the information from the data. This section provides details on the algorithm used.

The VAR can be written compactly as:

$$Y_t = X_t B + v_t, \tag{2}$$

with $Y_t = Z_t$, $X_t = \{c_i, Y_{it-1}, Y_{it-2}..., Y_{it-p}\}$.Note that as each equation in the VAR has *identical* regressors, it can be re-written as:

$$y = (I_N \otimes X)\, b + V, \tag{3}$$

where $y = vec(Y_t)$ and $b = vec(B)$ and $V = vec(v_t)$..Assume that the prior for the VAR coefficients b is normal and given by:

$$p(b) \tilde{} N\left(\tilde{b}_0, H\right), \tag{4}$$

where $\tilde{b}_0$ is a $(N \times (N \times P + 1)) \times 1$ vector which denotes the prior mean while H is a is a $[N \times (N \times P + 1)] \times [N \times (N \times P + 1)]$ matrix where the diagonal elements denote the variance of the prior.

It can be shown that the *posterior distribution of the VAR coefficients* conditional on Σ is normal (see Kadiyala and Karlsson, 1998). That is the conditional posterior for the coefficients is given by $H\left(b|\Sigma, Y_t\right) \tilde{} N\left(M^*, V^*\right)$ where:

$$\begin{aligned} M^* &= \left(H^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1} \left(H^{-1}\tilde{b}_0 + \Sigma^{-1} \otimes X_t' X_t \hat{b}\right), \\ V^* &= \left(H^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1}, \end{aligned} \tag{5}$$

where $\hat{b}$ is a $(N \times (N \times P + 1)) \times 1$ vector which denotes the OLS estimates of the VAR coefficients in vectorised format $\hat{b} = vec\left(\left(X_t' X_t\right)^{-1} \left(X_t' Y_t\right)\right)$. The conjugate prior for the VAR covariance matrix is an *inverse Wishart distribution* with prior scale matrix $\bar{S}$ and prior degrees of freedom α.

$$p(\Sigma) \tilde{} IW\left(\bar{S}, \alpha\right). \tag{6}$$

Given the prior in equation 6, the posterior for Σ conditional on b is also inverse Wishart $H\left(\Sigma \backslash b, Y_t\right) \tilde{} IW\left(\bar{\Sigma}, T+\alpha\right)$ where T is the sample size and

$$\bar{\Sigma} = \bar{S} + \left(Y_t - X_t B\right)' \left(Y_t - X_t B\right). \tag{7}$$

Note that B denotes the VAR coefficients reshaped into $(N \times P + 1)$ by N matrix.

The Gibbs sampling algorithm for the VAR model consists of the following steps:

Step 1 Set priors for the VAR coefficients and the covariance matrix. As discussed above, the prior for the VAR coefficients is normal and given by $p(b) \tilde{} N\left(\tilde{b}_0, H\right)$. The prior for the covariance matrix of the residuals Σ is inverse Wishart and given by $IW\left(\bar{S}, \alpha\right)$. Set a starting value for Σ (e.g. the OLS estimate of Σ).

Step 2 Sample the VAR coefficients from its conditional posterior distribution $H\left(b|\Sigma, Y_t\right) \tilde{} N\left(M^*, V^*\right)$ where:

$$\underset{(N\times(N\times P+1))\times 1}{M^*} = \left(H^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1} \left(H^{-1}\tilde{b}_0 + \Sigma^{-1} \otimes X_t' X_t \hat{b}\right), \tag{8}$$

$$\underset{(N\times(N\times P+1))\times(N\times(N\times P+1))}{V^*} = \left(H^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1}. \tag{9}$$

Once M^* and V^* are calculated, the VAR coefficients are drawn from the normal distribution:

$$\underset{((N\times(N\times P+1))\times 1)}{b^1} = \underset{((N\times(N\times P+1))\times 1)}{M^*} + \left[\underset{(1\times(N\times(N\times P+1)))}{\bar{b}} \times \underset{(N\times(N\times P+1))\times(N\times(N\times P+1))}{\left(V^*\right)^{1/2}}\right]. \tag{10}$$

Step 3 Draw Σ from its conditional distribution $H\left(\Sigma \backslash b, Y_t\right) \tilde{} IW\left(\bar{\Sigma}, T+\alpha\right)$ where $\bar{\Sigma} = \bar{S} + \left(Y_t - X_t B^1\right)' \left(Y_t - X_t B^1\right)$ where B^1 is the previous draw of the VAR coefficients reshaped into a matrix with dimensions $(N \times P + 1) \times N$ so it is conformable with X_t.

2 Appendix II: Dataset for macroeconomic uncertainty

This section describes the data used for the construction of the macroeconomic uncertainty index. The 51 macroeconomic series included are selected to represent broad categories in the UK's economic and financial activity and some key global indicators. The main challenge for the data collection was the availability of UK series starting in 1970s with quarterly frequency. There is a higher availability for UK macroeconomic series starting in 1975. The series which were finally included are coming from the following data sources: Office of National Statistics (ONS), the Bank of England's long run database (BOE), OECD, Global Financial Data (GFD), St. Louis Federal Reserve Economic Data (FRED), .These categories include prices, financial markets, money and credit, government.

In the list below it can be found the short name of the series included in the macro data set, the code in the database of their origin, a short description and the transformation applied. The series span from 1970:Q1 to 2016:Q3.

The transformations are as follows: lv : no transformation (in levels), Δlv : first difference in levels, ln : natural logarithm, $\Delta \ln$: first difference of the natural logarithms.

The series have been also seasonally adjusted when necessary.

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Macroeconomic Data

ID	Description	Short Name	Transfor	Source
	Output, Production and Investment			
NPEN	Business Investment, SA	bus_invest	*Δln*	ONS
UKGFCF..D	Gross Fixed Capital Formation, SA	invest	*Δln*	GFD
GDPCGBR	Great Britain Real GDP in 2008 Pounds, SA	gdp	*Δln*	GFD
UKCNPER.D	Final Consumption Expenditure, SA	cons_exp	*Δln*	ONS
UKPERSAVE	Households Saving Ratio, SA	saving_r	*Lv*	ONS
UKPERDISD	Households Disposable Income, SA	disp_inc	*Δln*	ONS
UKPROFTSB	Total Gross Operating Surplus of Corporations, SA	oper_surp	*Δln*	ONS
UKNEWORDD	New Orders, Construction, New Work, Total, SA	n_ord_constr	*Δln*	ONS
GBRPROINDAIS	Production of Total Industry , SA	tot_prod	*Δln*	GFD
GDPCSGBR	Change in Stocks/Inventories (GDP Basis), SA	invent	*Lv*	GFD
	Employment			
UNGBRM	Great Britain Unemployment Rate, SA	unem	*Lv*	GFD
EMCPGBRQ	Great Britain Compensation of Employees, SA	comp_empl	*Δln*	GFD
A4YN	Output per worker, Whole Economy: % SA	output_worker	*Lv*	ONS
DMWR	Output per job, Whole Economy: % SA	output_job	*Lv*	ONS
DYDC	Workforce Jobs, Total, SA	workforce	*Δln*	ONS
	Housing			
GBRPERMITQIS	Permits Issued for Dwelling in United Kingdom, SA	perm_d	*Δln*	GFD
UKOCFIHSD	Housing, Constant Prices, SA, 2013 Prices	housing	*Δln*	OECD
	Trade			
UKEXNGS.D	Exports of Goods and Services, Const. Prices SA	exports	*Δln*	ONS
UKIMNGS.D	Imports, Goods and Services, Const. Prices SA	imports	*Δln*	ONS
UKCURBALB	Balance of Payments : Current Account Balance, SA	bop	*Δlv*	ONS
	Prices			
LEIGBRM	Composite Leading Indicators	com_lead_indic	*Lv*	GFD
CPGBRM	Retail Price Index Inflation Rate	rpi	*Δln*	GFD
CPGBRCM	Consumer Price Index	cpi	*Δln*	GFD
WPGBRM	Producer Price Index	ppi	*Δln*	GFD
UKGDPIPDE	Implicit Price Deflator	defl	*Δln*	ONS
CPEGBRM	Consumer Price Index Inflation Rate: Energy	cpi_enrg	*Δln*	ONS
RTGBRM	Total Retail Trade	ret_trade	*Δln*	GFD
K22A	Index of Production: Manufacturing, SA	manufa	*Δln*	ONS
BRT_D	Brent Crude Oil (USD per Barrel)	brent	*Δln*	GFD
	Financial data			
	Interest and Exchange Rates			
IMGBRD	Overnight Interest Rate	overnight_r	*Δlv*	GFD
ITGBR3D	UK 3-month Treasury Bill Yield	m3tbill	*Δlv*	GFD
IBGBR3D	UK 3-month Interbank Rate	m3interbank_r	*Δlv*	GFD
IGGBR5D	UK 5-year Government Note Yield	yield5	*Δlv*	GFD
IGGBR10D	UK 10-year Government Bond Yield	yield10	*Δlv*	GFD
IGGBR20D	UK 20-year Government Bond Yield	yield20	*Δlv*	GFD

ID	Description	Short Name	Transfor	Source
INGBRW	Corporate Bond Yields	corp_yield	*Δlv*	GFD
GBPUSD	US Dollars per British Pound	dol_pound	*Δln*	GFD
	Nominal Effective Exchange Rate	NEER	*Lv*	OECD
	Financial Markets			
_DFTASD	UK FT-Actuaries Dividend Yield (w/GFD extension)	divyield	*Lv*	GFD
_PFTASD	UK FT-Actuaries PE Ratio (w/GFD extension)	pe_ratio	*Δlv*	GFD
_TFTASD	UK FTSE All-Share Return Index (w/GFD extension)	dftseall	*Δln*	GFD
	Money and Credit			
	Break-adjusted monthly bank lending series excluding lending to intermediate OFCs	b_lending	*Δln*	BOE*
	Break-adjusted M4 series , 1880-2014, SA	m4	*Δln*	BOE*
FXRGBRM	Total Foreign Exchange Reserves exc Gold, SA	frn_resrv	*Δln*	GFD
MSGBRM1	M1 Money Supply, SA	m1	*Δln*	GFD
ILGBRMM	United Kingdom Mortgage Lending Rate	lend_rate	*Lv*	GFD
MSGBRM0	UK Bank of England Currency in Circulation, SA	currency	*Δln*	GFD
QGBPAM770A	Total Credit to Private Non-Financial Sector, SA	credit	*Δln*	FRED
	Government			
NMRY	General Govrn.: Final consumption expenditure: SA	gov_expend	*Δln*	ONS
RYFD	NET: UK public sector securities	net_pub_sec	*Lv*	ONS
JW2O	Total current receipts: Public sector excluding public	ps_receipts	*Δln*	ONS
JW2Q	Total current expenditure: Public sector excluding pu	ps_expend	*Δln*	ONS
	World			
	Real GDP Germany Index, SA	ger_gdp	*Δln*	OECD
	Real GDP France Index, SA	fr_gdp	*Δln*	OECD
	Real GDP US Index, SA	us_gdp	*Δln*	OECD
_SPXD	S&P 500 Composite Price Index (w/GFD extension)	sp500	*Δln*	GFD
_FFYD	USA Federal Funds Rate Market Rate	ffrate	*Lv*	GFD
IGUSA10D	USA 10-year Bond Constant Maturity Yield	us10yy	*Lv*	GFD
	US Consumer Price Index, SA	uscpi	*Δln*	OECD

* The long run database from the Bank of England has been used for these series