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

The role of economic uncertainty on macroeconomic fluctuations has been studied extensively in the empirical literature; however, its distributional effects have received little attention. This paper attempts to fill this gap by investigating whether macroeconomic uncertainty affects income, wage, and consumption inequality in the United Kingdom. Our findings suggest that measures of inequality fall significantly to a macroeconomic uncertainty shock. Households in the middle and right tail of the income distribution appear to be more adversely affected relative to ones in the left tail. Income composition and households indebtedness explain a large part of the heterogeneous response. Uncertainty also appears to account significantly for the variation of income and consumption inequality.

JEL codes: C32, D3, D8, E32
Keywords: macroeconomic uncertainty, income inequality, consumption inequality, SVAR

Many recent studies have demonstrated that uncertainty shocks matter for business cycle fluctuations.[1] For example, Bloom 2009 shows in his seminal paper that shocks to the VXO reduce asset prices and lead to a fall in industrial production by 1%. Jurado, Ludvigson, and Ng (2015) demonstrate that macroeconomic uncertainty has large and persistent recessionary effects. While

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1. A parsimonious review of studies examining the interaction of uncertainty with various aspects of the economic activity can be found in Castelnuovo, Lim, and Pellegrino (2017).

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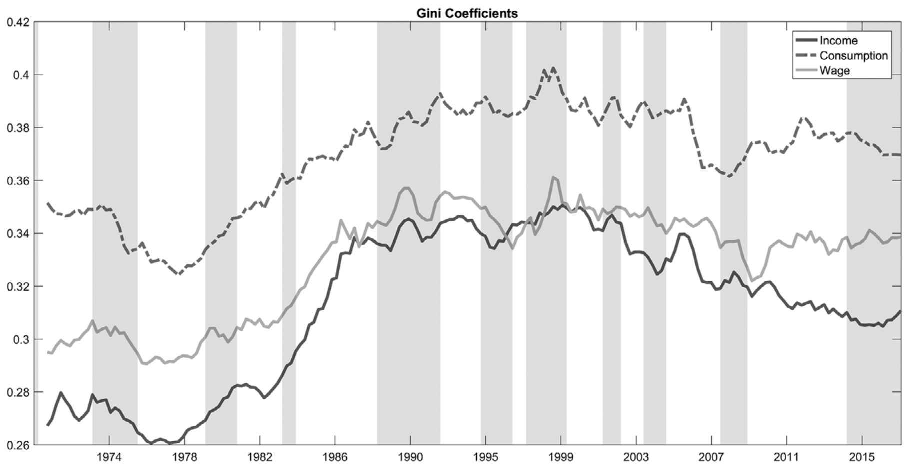

Fig 1. The Gini Coefficient (Four Quarter Moving Average) for Disposable Income, Total Consumption, and Gross Wage for the United Kingdom from 1970:Q1 to 2018:Q1. The Data Is from the Family Expenditure Survey (FES) and Its Successive Surveys (See Section 2.1). Shaded Areas Represent Recessions as Identified by the OECD.

this burgeoning literature has focused on aggregate macroeconomic and financial variables, the distributional effects of uncertainty shocks have been largely ignored. This omission is surprising as inequality remains at record highs in many OECD countries and an exploration of possible contributory factors is crucial. As uncertainty shocks affect asset prices and the real economy, it is likely that their impact on rich and poor households is not homogenous.

In this paper, we fill this gap in the literature and investigate the impact of uncertainty shocks on inequality. We focus on the United Kingdom, a country that has seen large changes in income, earnings, and consumption inequality and experienced several episodes of high uncertainty.[2] The UK encountered a dramatic rise of inequality measures in the 1980s, while a substantial drop occurred in the global financial crisis (see Figure 1). On the other hand, macroeconomic uncertainty appears to be high in the second part of the 1970s, during the financial crisis, and it is rising again in recent years (see Figure 2).

By using a battery of structural vector autoregression (SVAR) models, we show that macroeconomic uncertainty shocks lead to lower inequality in income, earnings, and consumption. A one standard deviation uncertainty shock reduces the Gini coefficient for income after one and a half years, reaching a trough of 0.5% within 4 years. Consumption inequality drops faster, after only two quarters from the shock, while it reaches its maximum decline of 0.6% in 2 years. The response of the wage measure is also negative. It takes 4 years for the Gini of gross wage to reach its maximum drop of −0.25%. The response of all measures to the shock is negative, significant, and persistent for a long time.

2. In addition, the availability of a long-run household survey data makes the United Kingdom an ideal candidate for this investigation from an econometric point of view.

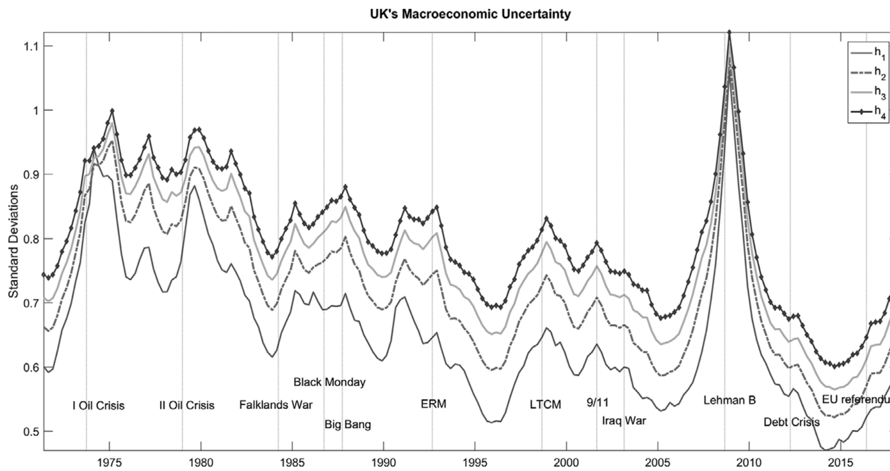

Fig 2. UK Macroeconomic Uncertainty for Horizons (h) One to Four Quarters Ahead. The Vertical Lines Indicate Major Economic and Political Events for the United Kingdom. The Data Are Quarterly and Span the Period 1971Q1:2018Q1.

To identify possible factors and channels of transmission that led to the observed fall in inequality, we estimate an SVAR using data for households in different quintiles of the income, earnings, and consumption distributions. Results from this exercise suggest that uncertainty shocks decrease wages and income for households at the middle and right tail of the distribution, while households at the left tail are less affected. Exploring the income composition channel, we find that wealthier households derive a relatively larger proportion of their income from earnings and investment proceeds that fall substantially during periods of higher uncertainty. Households in the left tail are less responsive as a large part of their income comes from social security benefits that are largely countercyclical. Another channel that sheds light on this heterogeneous response is households' indebtedness that is proxied by housing tenure. Results show that mortgagors, who are mostly in the middle and right tail of income distribution, are more responsive to uncertainty shocks and reduce their consumption relative to renters, who are mostly in the left tail.

To our knowledge, this is one of the first papers to focus on the impact of uncertainty shocks on inequality.[3] The results of this study are important from a theoretical and policy perspective. Building on Cloyne and Surico (2017), they highlight the fact that liquidity constrained and indebted households are crucial for the transmission of uncertainty shocks. For policy makers, they provide guidance regarding the groups of agents who are likely to be more affected by increases in uncertainty as seen

3. There are only few studies so far which report some distributional effects of uncertainty, but this is not their main focus (e.g., Attanasio and Pistaferri 2014, DeGiorgi and Gambetti 2017). A subsequent study to the first version of this paper by Fischer, Florian, and Michael (2019), investigates this research question for U.S. data and find similar results for many U.S. regions.

during the financial crisis and the more recent pandemic. As an additional contribution, this paper constructs measures of uncertainty for the United Kingdom using a large macroeconomic and financial data set. This is combined with a long span of quarterly inequality measures constructed from household survey data to carry out the investigation.

The drivers of inequality have been extensively studied in the literature: Skill-biased technological change, trade openness and globalization, financial deepening and credit constraints, changes in labor 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, Roine, Vlachos, and Waldenstrom 2009, Western and Rosenfeld 2011, etc.). Demographic factors and individual characteristics such as the level of education, return of schooling, family structure, gender, and social mobility have also been found to be important drivers (e.g., Knight and Sabot 1983, Cunha and Heckman 2007).

The redistributive role of governmental policies through progressivity in taxation and social security transfers is a strong determinant to equality especially for low income quantiles. Finally, the role of monetary policy has been lately examined and findings suggest that conventional and unconventional monetary policy can have significant distributional effects (e.g., Coibion et al. 2017, Mumtaz and Theophilopoulou 2017).

One of the factors that has received little attention as a determinant of inequality is macroeconomic uncertainty. A number of studies[4] 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 labor market is affected in terms of employment rate, hours worked, and wage growth. Uncertainty directly affects financial markets that experience high volatility of returns. Credit conditions become tougher for firms and households, which face greater difficulty to obtain credit and incur 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 quantiles of income, wage, and consumption distributions are affected in a heterogeneous manner (Heathcote, Perri, and Violante (2010)). Looking at the

4. There is a large literature on the channels by which uncertainty affects the economy. For a literature review on its impact on economic fluctuations, see Bloom (2014).

evolution of consumption inequality in the United States, Attanasio and Pistaferri (2014) report lower inequality during the Great Recession as the consumption of the 10th quantile falls substantially during this period. DeGiorgi and Gambetti (2017) show that economic policy uncertainty (EPU) shocks have significant effects at the top end of the consumption distribution. Top consumption quantiles reduce substantially their consumption levels in high EPU periods relatively to the low ones. The impact of the EPU is also examined by Fischer, Florian, and Michael (2019) for the U.S. states. Different income composition across states leads to heterogeneous responses and fall in inequality is observed when capital income is relatively higher.

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 inequality measures, discusses issues of heterogeneity, and carries out robustness checks. Section 5 concludes.

1. 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 United Kingdom.

1.1 The Family Expenditure Survey Variables

The data for income, wage, and consumption are drawn from the Family Expenditure Survey (FES) from *1970:Q1 to 2018:Q1*. The FES is an annual survey that 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 spending diary for 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. Even though the FES has been running from 1957, there are discontinuities and small samples prior to 1970 and for this reason, solid inequality measures can be constructed from 1970 onward.

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[5] (Banks and Johnson (1998)). Blundell and Etheridge (2010), who compare a longer FES sample to National Accounts, find that FES strongly matches income and employment data and to certain extent consumption. There is some discrepancy in expenditure and the divergence increases since the early 1990s. The same phenomenon has been observed with the US CEX and according to the authors this is not because of selecting out high income households. In order to reduce the nonresponse bias, survey weights have been used for the construction of the inequality measures. Household data are weighted to compensate for nonresponse but also to match the population distribution in terms of age, sex, family composition and region.

The variable we use for disposable income is defined as weekly household income net of taxes and national insurance contributions.[6] It is summed across all members living in the same household. After keeping only the positive values and trimming, there are on average 7,000 households per year until 2007 and then the average drops to 6,000 per year. Thus, in total there are around 326,000 household income observations for the whole sample period. Income is equalized for 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.[7] Taking into account only positive values, there are on average 7,000 observations per year. Inequality measures constructed from data on wages have a smaller measurement error than other forms of income as the respondents have a more accurate information on this source.

The definition for the variable of total consumption 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.[8]

5. To test whether under-reporting from high income percentiles may bias the results, we use the annual Gini coefficient estimated by the WID World data and a mixed frequency VAR to estimate the impact of uncertainty. The results, which can be found in the online Appendix, Section 3.1, support the findings of the benchmark model.

6. The Gini for gross household income is also computed. We include it in the further robustness checks on the baseline SVAR, which can be found in the online Appendix, Section 3.2.

7. If 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.

8. Since the disposable income is equivalized and total consumption is per capita, they are not immediately comparable to each other. We have chosen these three variables following studies on UK income and consumption inequality such as Blundell and Etheridge (2010), Cloyne and Surico (2017), Brewer and Wren-Lewis (2016), Belfield et al. (2017), etc. The aim was not immediate comparability but to see the responses of three representative measures that have already been studied in the literature but in different frequencies and periods. In the sensitivity analysis of the benchmark model, total consumption has been

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 2016) and trim the tails by 1%. All variables have been deflated by the consumer price index (CPI). In the rest of the paper, the terms income, wage, and consumption refer to equivalized household disposable income, individual gross wage, and household total consumption per capita, respectively.

1.2 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 that removes zero values, thus reducing sensitivity to extreme values and lastly the differences between individual quintiles of the cross-sectional distribution of the log levels (e.g., 90th$P$ − 10th$P$, 50th$P$ − 10th$P$, etc.) for each period. An important feature of this data set, 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[9] (Cloyne and Surico (2017)).

Figure 1 shows the evolution of the Gini coefficient for disposable income, total consumption, and gross personal wage from 1970:Q1 to 2018:Q1 for the United Kingdom. All measures depict an upward trend for the period examined with the most dramatic rise taking place in the second decade. 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 labor earnings as high earners experienced fall of their real wages relative to low earners. This period is also characterized 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 1984. The same period is characterized 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 2016). The highest rise observed was that of disposable income

equivalized by the same equivalence scale of disposable income. The results can be found in the online Appendix, Section 3.3.

9. The number of households for each quarter is about one quarter of the annual observations. We do not observe large differences within quarters of the same year. Some differences between the first quarter and the rest can be observed for few years when the survey moves from the calendar year to fiscal year. Overall, the number of observations is evenly distributed among quarters in the same calendar or fiscal year.

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 liberalization and higher availability of consumption loans enabled many low-income households to achieve a level of consumption that 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 recovery 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 (2013–18), income inequality remains low and unchanged (around 0.30). It is equal to 1985 levels although real earnings have started to grow slowly and real benefits have slowed down.

1.3 The Measure of Uncertainty

To construct the measure of macroeconomic uncertainty for the United Kingdom, 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 nonforecastable component of each variable. The authors argue that when this component increases, the economy becomes less predictable and this is how uncertainty increases.

Summarizing the model in Jurado, Ludvigson, and Ng (2015), the h period ahead uncertainty ($U_{jt}(h)$) of the variable $y_{jt} \in Y_t = (y_{1t} \dots y_{Nyt})'$ is the conditional volatility of the nonforecastable part of the future value of the series that is defined as:

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

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 categorized as uncertainty. This is one of the main features of this measure.

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

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

where w_j are aggregation weights for the uncertainty of each variable y_j. 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 $E[y_{jt+h}|I_t]$ 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:

$$y_{jt+h} = \phi_j^y(L) y_{jt} + \gamma_j^F(L)\hat{\mathbf{F}}_t + \gamma_j^W(L)\mathbf{W}_t + v_{jt+h}^y,$$

where ϕ_j^y, γ_j^F, and γ_j^W 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 σ_j^y, σ_k^F, σ_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 $Y_{jt} = (y_{jt}, y_{jt-1} \ldots y_{jt+q-1})'$ and $\tilde{\Psi}_t \equiv (\Psi_t \ldots \Psi_{t-q+1})'$ where Ψ is the vector that collects all factors estimated and additional predictors, $\Psi_t \equiv (\hat{\mathbf{F}}_t, \mathbf{W}_t)'$. The system has the following form:

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

A parametric stochastic volatility model has been employed to give to conditional volatilities of shocks $v_t^{\tilde{\Psi}}$ 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 $\tilde{\Psi}_t$ 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).

1.4 Data Description

The measure of macroeconomic uncertainty has been constructed by using 64 UK and world time series as described in the online Appendix. These series try to cover various aspects of the UK economic activity spanning from 1970:Q1 to 2018:Q1. Even though there are many UK series starting as early as the 1950s, not many run in a quarterly frequency and are continued until 2018. This was the main limitation for constructing a measure starting from 1970. A much larger number of quarterly series is available from a later date. The areas covered in this data set 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 online Appendix, Section 2.

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 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 3-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 obtained from Global Financial Data, and (6) the measure of macroeconomic uncertainty estimated by the model in Section 2.3 and using the data described in this section.

2. EMPIRICAL MODEL

To estimate the impact of uncertainty shocks on the constructed inequality measures we use a structural VAR model. The benchmark model is defined as:

$$Z_t = c + \sum_{j=1}^{P} B_j Z_{t-j} + \upsilon_t, \qquad (4)$$

where υ_t $N(0, \Omega)$. The matrix of endogenous variables includes the standard set used for small open economies: that is, the growth of real GDP per capita, CPI inflation, the three month treasury bill rate, and 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.[10]

We adopt a Bayesian approach to estimation and use a Gibbs sampling algorithm to approximate the posterior distribution of the model parameters.[11] 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 online Appendix, Section 1.

2.1 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, Ludvigson, and Ng (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, Ma, and Ng (2018), we put sign and magnitude restrictions on the shocks during significant historical episodes and we also restrict the correlation among the shocks and financial variables. In all alternative identification strategies employed, the results remain robust (see Figure 11).

3. 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.

10. The choice of this lag length follows Bloom (2009) and Jurado, Ludvigson, and Ng (2015). It is also supported by the Akaike information criterion when selection between 1 to 4 lags. Alternative lag lengths have been tried in the online Appendix, Section 3.2, as robustness checks.

11. We use Bayesian estimation because it is a convenient method to construct error bands, it is more efficient for the larger VAR models, we consider in the robustness checks and because Bayesian methods are more robust in the presence of highly persistent variables ((Sims, Stock, and Watson 1990)). Frequentist estimates of the benchmark model are presented in Section 4 of the online Appendix. The results remain robust.

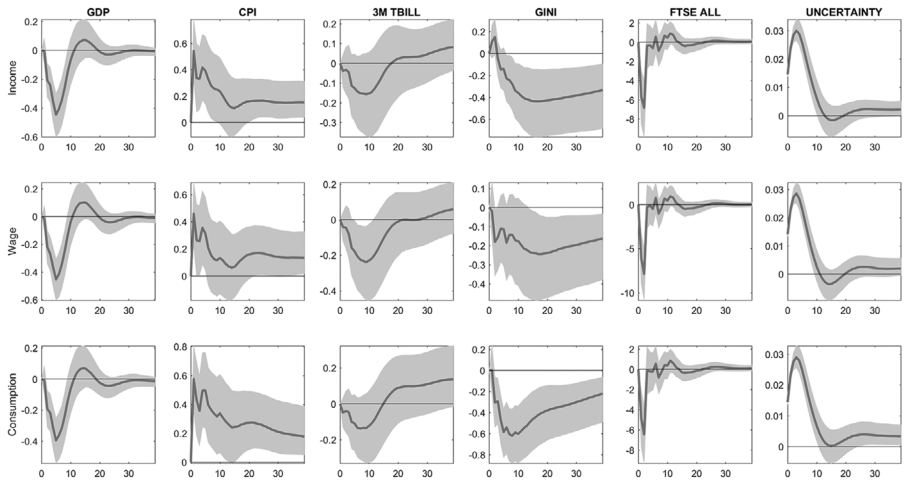

Fig 3. Effects of the Macroeconomic Uncertainty Shock.

NOTE: The figure presents impulse response functions of macroeconomic variables to one standard deviation uncertainty shock. Each row represents a SVAR model that 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.

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, and the effect persists for around 10 quarters.[12] The CPI inflation rate responds by an increase of 0.5% 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 rise them further if a large shock occurs (e.g., Born and Pfeifer 2014, Fernandez-Villaverde et al. 2015).[13] Mumtaz (2016) looks at the time-varying impact of uncertainty shocks in the United Kingdom and finds a positive inflation response during the 1970s and 80s that 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

12. The responses of GDP growth and macrouncertainty, in terms of magnitude and persistence, are in line with the findings of Redl (2017) for the United Kingdom. Jurado, Ludvigson, and Ng (2015) also find high persistence of the response of U.S. production and employment; a persistence that is higher than other proxies of uncertainty such as the VXO index.

13. The model of Leduc and Liu (2016) suggests that uncertainty shocks resemble negative demand shocks. However, Fasani and Rossi (2018) show that this result depends on the calibration of the Taylor rule. A Taylor rule with interest rate smoothing leads to a positive response of the inflation rate.

a maximum drop of 0.15% after 2 years but only in the second specification, we can reject the null hypothesis of no response. The stock market experiences losses and the FTSEALL are negatively effected with peak response of 7% after two quarters. These variables follow similar behavior 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 SVAR models falls dramatically and the shock propagates for a long period of time. More specifically, the median response of Gini coefficient for income starts falling after two quarters from the shock but the response is significantly different from zero after six quarters. It reaches peak drop of about 0.5% within 4 years. Wage inequality falls slowly to the shock and up to −0.25% in 4 years. The more pronounced response is the one by the consumption inequality measure that shows a significant negative response in two quarters and has a maximum fall of 0.61% in 2 years. The long propagation of the shock to all inequality measures can be explained by the long and persistent impact of the macroeconomic uncertainty shocks on the economy, as documented by Jurado, Ludvigson, and Ng (2015) but also by the nature of the Gini coefficient that is a very slow moving and persistent variable. The slow and persistent response of the Gini coefficient to other types of shocks, such as monetary policy shocks, has been observed in the inequality literature (e.g., Furceri, Loungani, and Zdzienicka 2018, Castelnuovo, Lim, and Pellegrino 2017 and Inui, Sudo, and Yamada 2017).

Overall, we can summarize the benchmark findings as follows: A positive macroeconomic uncertainty shock reduces the Gini coefficients in the short to the medium run with the response persisting 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.

3.1 Heterogeneity of Responses to Uncertainty Shocks

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 uncertainty shocks. In particular, we construct the differences $P_{90} - P_{50}$ and $P_{50} - P_{10}$ for the log of income, wage, and consumption, where P_x denotes the variables at the x^{th} percentile. 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_{10} (low income households) from its median (P_{50}) falls substantially and to a much higher magnitude than the difference between high-income households from the median ($P_{90} - P_{10}$). More specifically, the median peak response of $P_{50} - P_{10}$ is −1% after 10 periods, while the one for $P_{90} - P_{10}$ is about −0.1%, indicating that income inequality falls by more in the left tail of the income

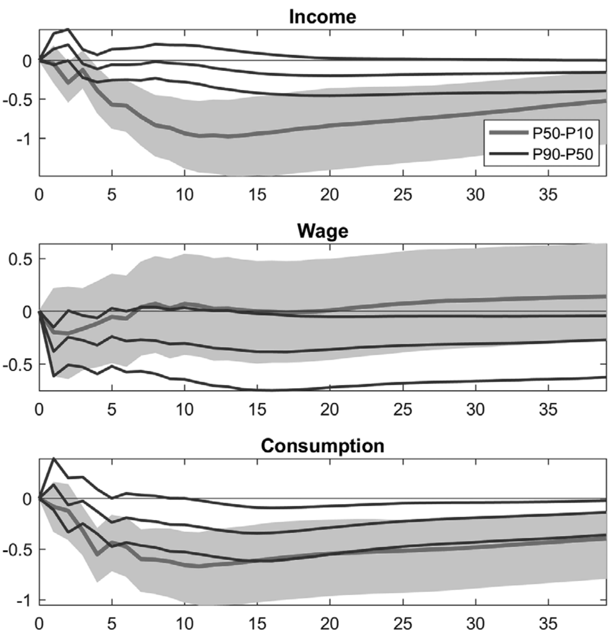

Fig 4. Distributional Effects of Macroeconomic Uncertainty Shocks by Percentiles.

Note: The figure reports the impulse response functions of log differences between the 50th and 10th percentile ($P50 - P10$, red solid line) and between the 90th and the 50th 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

distribution. Inequality in the right tail 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 findings of Coibion et al. (2017) for the U.S. and Mumtaz and Theophilopoulou (2017) for the United Kingdom, who decompose households' income. These studies find a higher percentage of income coming from financial investments and wages for high-income households, while low-income ones are partly supported by 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.

To check whether the income composition channel can explain the observed heterogeneous response, we decompose UK households' income from 1975 to 2015 to three main sources: wage, social security benefits, and investment

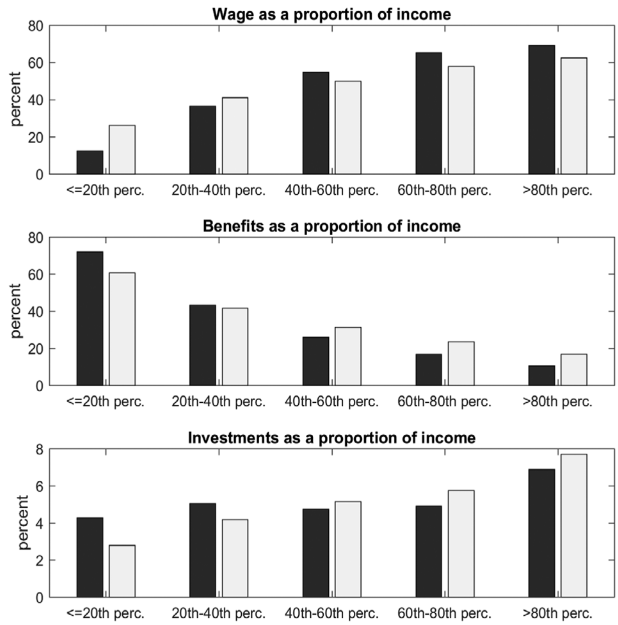

Fig 5. Sources of Income.

NOTE: The figure reports the proportions of gross wage, social security benefits, and investment income on gross income. Households are sorted into groups according to their income (blue bars) and consumption (yellow bars). The bars represent the average ratio in each quintile. The data used for this figure are 5 year averages over the period 1975–2015, from the FES.

income (Figure 5). In particular, for each variable, we consider households and individuals who fall within the following quintiles of income and consumption in a given quarter: $P_1 = [2^{nd} : 19^{th}]$, $P_2 = [20^{th} : 39^{th}]$, $P_3 = [40^{th} : 59^{th}]$, $P_4 = [60^{th} : 79^{th}]$, $P_5 = [80^{th} : 98^{th}]$. We then construct the average of the source of income in each group.

The decomposition reveals that wage is the main source of income for median- (55%) and high-income quintiles (68-70%), while investment income has a significant contribution (around 7%) to the highest quintile. Social benefits, on the other hand, appear to be a very significant source of income and consumption for households in the first quintile[14] (71%), while for the fifth quintile is less significant (10%). 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

14. The percentage of benefits on disposable income for low-income households was very high in the first half of the sample but it falls substantially in the last two decades. These percentages are also in line with Banks and Johnson (1998), who show that the two main sources of income, earnings, and social security benefits follow closely the National Accounts.

investment proceeds decline[15] and become more volatile, while low-income households are largely sustained by social security benefits.

Examining the effect of the earnings heterogeneity channel, we can see from the second panel of Figure 4 that the difference between high tand median earners ($P_{90} - P_{50}$) is decreasing to the shock by -0.38%. The median response of the difference among median and low earners ($P_{50} - P_{10}$) is close to zero and the null hypothesis of no response cannot be rejected for the whole horizon. This is in line with the findings of Heathcote, Perri, and Violante (2010) for the U.S. earnings distribution. More specifically, the authors find that earnings dynamics are more important for high quintiles in the earnings distribution that are more volatile to the business cycle. On the other hand, labor market characteristics such as institutional constraints on minimum wage, unions' power, and hours worked are more important for low quintiles. Therefore, uncertainty shocks can generate a decrease in earnings growth that is more pronounced in the second half of the earnings distribution, while the low quintiles are more immune to wage drops due to institutional constraints. This can explain why the fall in earnings inequality largely takes place in the second half of the distribution.

Since uncertainty affects the relative price of financial assets and credit conditions, it can affect income and consumption behavior of households through the portfolio and savings redistribution channels. Highly indebted households who face liquidity constraints can change their consumption levels substantially when shocks affect their income. FES does not provide detailed data on holdings of financial assets and wealth. However, it does provide information on housing tenure of households. Cloyne and Surico (2017) claim that debt for housing is a strong proxy for household debt. This is because the indebtedness of a household may explain better than net wealth consumption decisions. For example, households who have high levels of debt through the purchase of a large durable good, such as a house, face liquidity constraints but at the same time can have net positive wealth (wealthy hand-to-mouth households).

To approximate households' net financial position, we follow Cloyne and Surico (2017) and group households according to their housing tenure into three groups: renters, mortgagors, and outright owners. Then, we take the difference between each two groups in terms of average income, wage, and consumption. Figure 6 shows the IRFs of the difference between mortgagors and renters to an uncertainty shock. In all three cases, the difference between the two groups falls, indicating that mortgagors are more negatively affected than renters.[16] The impact is stronger for

15. In an extended version of the benchmark model, we add investment and compensation of employees in the vector of endogenous variables. Both of these variables decline after an uncertainty shock. These results are available on request.

16. We also estimate the response of the difference between mortgagors and owners and between owners and renters. In both cases, the difference is falling to uncertainty shock. However, given that owners are similarly distributed across income and consumption distributions (see Figure 7), we cannot infer an improvement to equality.

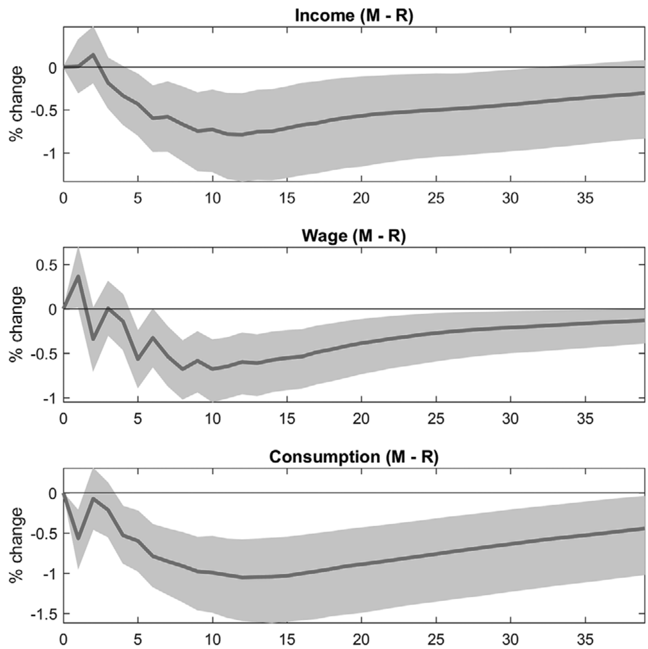

Fig 6. Dynamic Effects of the Macroeconomic Uncertainty Shock by Housing Tenure.

NOTE: The figure reports the impulse response functions of differences in the average income, wage, and consumption between mortgagors and renters to one standard deviation uncertainty shock. The shaded areas represent 68% error bands. The IRFs are measured in percentage changes (vertical axis), while the horizontal axis reports time in quarters.

consumption where mortgagors are worse off relative to renters by 1.2% after 2 years from the shock.

A natural question would be where the majority of renters, mortgagors, and owners stand in the income or consumption distributions. In Figure 7, we decompose each income and consumption quintile by housing tenure. We observe that mortgagors are more likely to lie in the median- and high-income quintiles, while renters in the low-income ones. The owners do not dominate any quintile as for many owners, their level of income is not directly related to their ownership (e.g., inherited property). This analysis shows that mortgagors, who often carry high levels of debt, are more adversely affected than the other two housing groups. Mortgagors are also likely to have high levels of income. Therefore, the financial position of a household, the level of indebtedness, and liquidity constraints can produce heterogeneous responses to an uncertainty shock with distributional implications.

Given that prices rise after an uncertainty shock, we examine the possibility that rental prices may also go up. In this case, renters who are typically liquidity-constrained households will be adversely affected through an increase in rents. However, we find that this is not the case for the UK rental prices and this

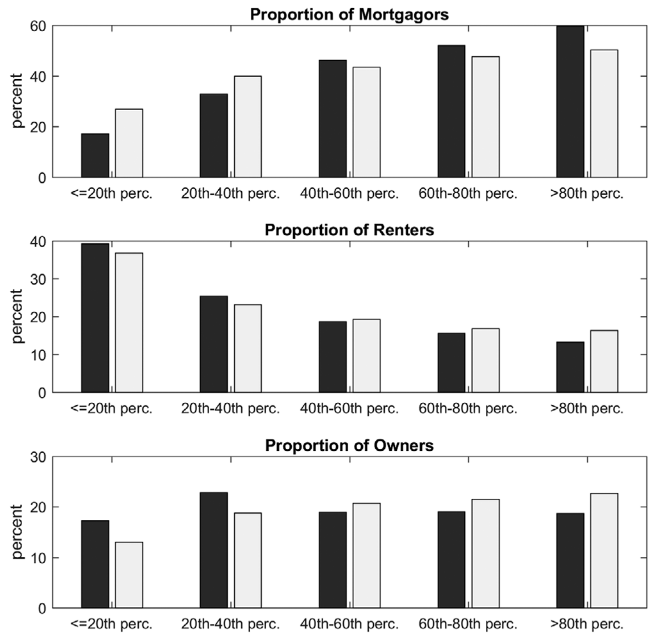

Fig 7. Housing Tenure.

NOTE: The figure reports the proportions of mortgagors, renters, and owners by quintiles of income (blue bars) and consumption (yellow bars). The data used for this figure are 5 year averages over the period 1975–2015 from the FES.

channel appears to be less important in our application. A simple VAR exercise indicates that the growth of rental prices falls in response to a macroeconomic uncertainty shock. The results are available in the online Appendix, Section 6.

3.2 The Contribution of Uncertainty Shocks to Inequality

Figure 8 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 up to 10% for income is smaller for wage, while for total consumption, it amounts to about 16% in the FEV at a 5-year horizon. Similar estimates are found when the standard deviation of logs or the difference of the 90th$P$ − 10th$P$ 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.

3.3 Robustness

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

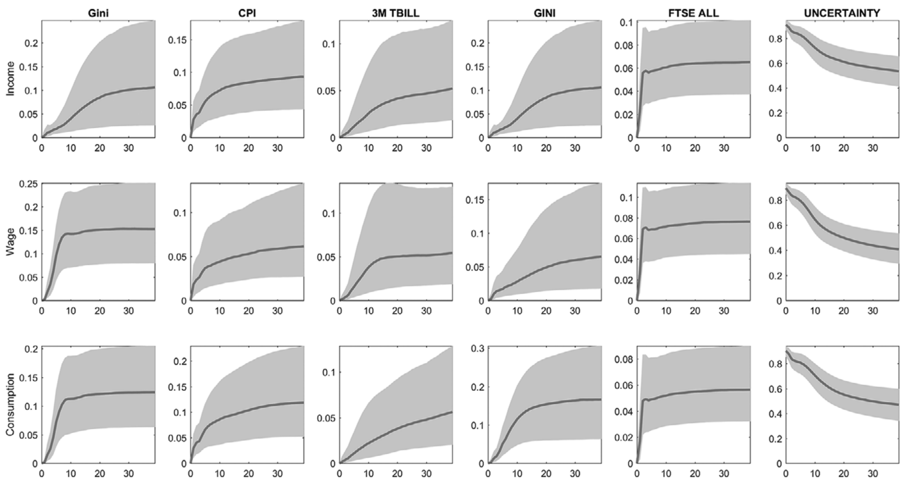

Fig 8. Percentage Contribution of Uncertainty Shocks to the Forecast Error Variance (FEV) of All Macroeconomic Variables.

NOTE: 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.

90th$P$ − 10th$P$ 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 90th and 10th percentiles. The advantage of the former is that it reduces 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 Gini coefficients in the benchmark specification and the impact is of same magnitude (see Figure 9, 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 quintiles 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 that is −0.5% (Figure 9, third column). In order to tackle issues with underreporting in high-income households, we use the Gini coefficient for pretax national income provided by the WID world data. The data are available in annual frequency and in a shorter time span. We use a mixed frequency VAR model to estimate the response and all IRFs can be found in Section 3.1 of the online Appendix. The results remain robust for income and the coefficient falls about 1% to the shock.

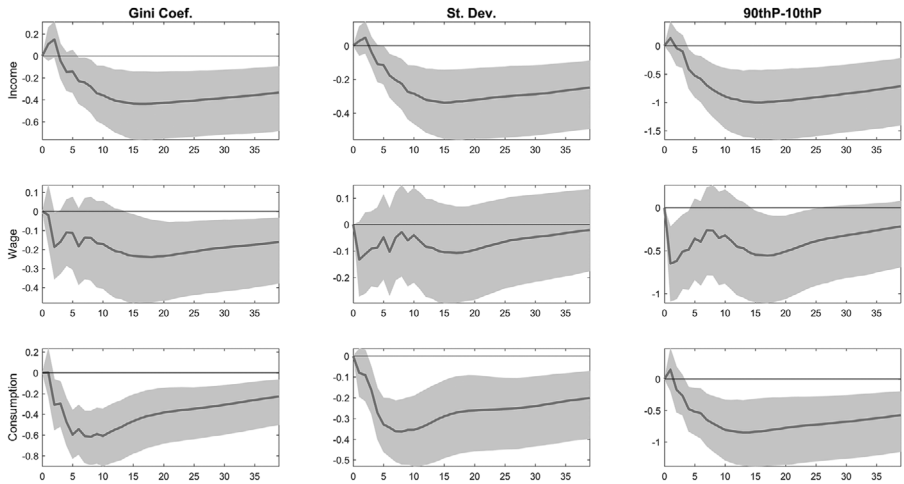

Fig 9. Sensitivity in the Measure of Inequality: The Impulse Response Functions of Gini Coefficients (First Column), Standard Deviation of log Levels (Second Column) and 90th$P$ − 10th$P$ (Third Column) to One Standard Deviation Uncertainty Shock.

NOTE: 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.

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 64 macroeconomic and financial time series to ensure orthogonality and solve recursively. The Granger causality test indicates that informational sufficiency is no longer rejected. The results remain similar to the benchmark experiment: As Figure 10 shows, the Gini coefficient falls for all three variables in a similar pattern and magnitude to benchmark.

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 realized volatility of FTSEALL that 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 (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 11, second column). Intuitively, large volatility shocks in financial markets will decrease income from financial assets and investments. This affects mostly households in high-income

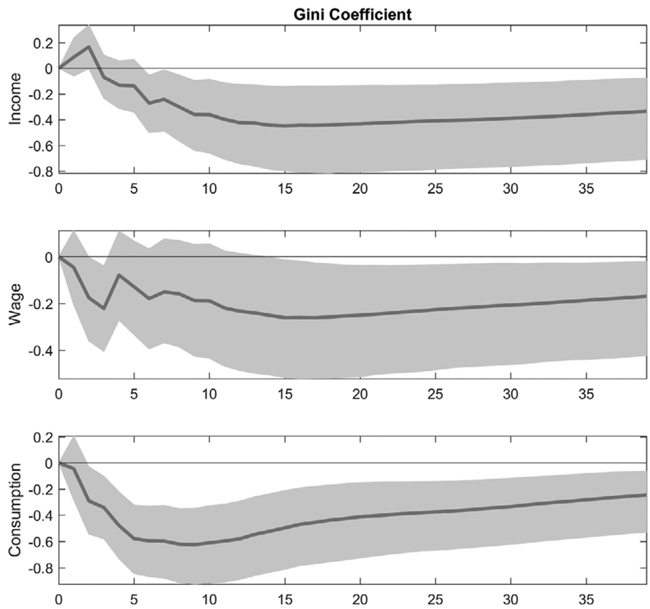

Fig 10. Sensitivity to the Information Set: The Impulse Response Functions of Gini Coefficients to One Standard Deviation Uncertainty Shock.

NOTE: 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 Band.

quintiles as it can be seen in income decomposition (Figure 5), decreasing this way income inequality.

The second proxy for uncertainty used is the EPU as defined in Baker, Bloom, and Davis (2016). The UK historical news-based index from the authors' website 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 11, third column. Even though this experiment uses a significantly smaller sample, different order and a different type of uncertainty simultaneously, the responses are in line to the benchmark scenario: inequality measures also fall to EPU shocks. Inequality for income falls after two quarters even though it briefly increases initially. The response of consumption inequality is similar to DeGiorgi and Gambetti (2017) findings for the U.S. The authors show that inequality of consumption falls to an EPU shock by 0.5% in the first 2 years but the null cannot be 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

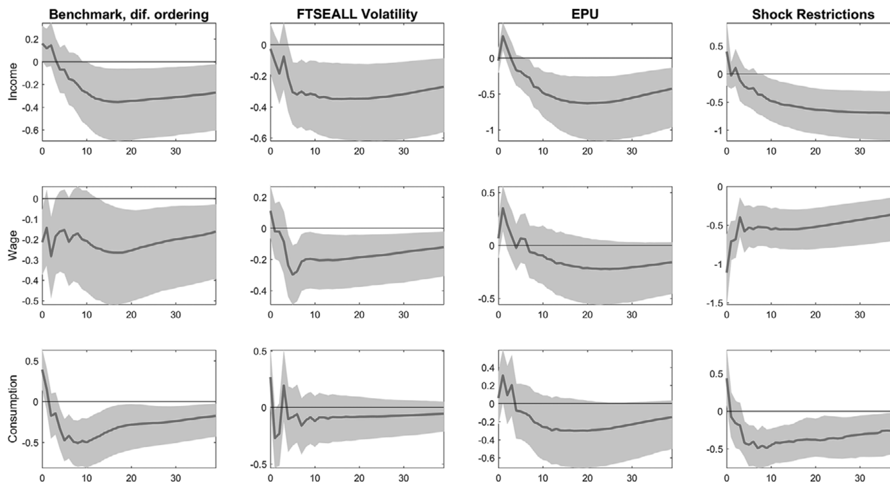

Fig 11. Sensitivity to the Information Set and Identification Strategy: The Impulse Response Functios of Gini Coefficients to One Standard Deviation Macroeconomic Uncertainty Shock.

NOTE: 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 IRFs 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.

first altering the order of variables in the recursive scheme and second 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 11, first column. The results of this experiment support the benchmark results. A macroeconomic uncertainty shock lowers inequality for income, wage, and consumption in a different recursive ordering of the variables.

Second, we put minimal sign restrictions on the A_0 matrix to impose that macroeconomic uncertainty and output move to 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, Ma, and Ng (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 that imply large positive shocks to output during that period.

As in Ludvigson, Ma, and Ng (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 11. All three IRFs of the Gini coefficients fall to the shock with a more pronounced drop in the wage measure. In both alternative identification schemes, the drop in inequality measures is clear, distinct, and persistent.

Additional robustness checks include the estimation of the baseline model by using OLS, alternative lag lengths on the SVAR variables (two and six lags), splitting the sample into two subsamples (before and after the introduction of inflation targeting by the BoE,1992Q3), and adding a linear time trend. The results remain qualitatively robust in all the above exercises and can be found in the online Appendix, Sections 3 and 4.

4. 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 United Kingdom.

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 United Kingdom. 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 15%.

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 labor and financial incomes are more exposed to economic fluctuations. Investigating further portfolio's channel of transmission and using the housing tenure as a proxy for household's indebtedness, we find that mortgagors are most affected by the shock. Highly indebted households who are cash constrained are more likely to adjust their levels of consumption to an uncertainty shock. On the other hand, macroeconomic uncertainty seems to play a small role in income fluctuations for households on the left tail of the distribution as social security benefits and institutional constraints seem to be more important determinants. This is also documented by decomposing the income distribution into its main sources.

These results may have a policy implication: In the postfinancial crisis, period, the nonincreasing levels of inequality observed in the United Kingdom may be related to high levels of uncertainty.[17] Economic uncertainty played an important role in suppressing the income growth of median- and high-income percentiles. In a more stable environment with lower economic and political uncertainty, these percentiles will enjoy a higher growth of investment income and earnings than low-income households. In this case, inequality will be higher and stronger redistributive fiscal policies will be needed.

LITERATURE CITED

Acemoglu, Daron. (1998) "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *Quarterly Journal of Economics*, 113, 1055–89.

Attanasio, Orazio, and Luigi Pistaferri. (2014) "Consumption Inequality over the Last Half Century. Evidence Using the New PSID Consumption Measure." *American Economic Review*, 104, 112–6.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. (2016) "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics*, 131, 1593–636.

Banks, James, and Paul Johnson. (1998) "How Reliable Is the Family Expenditure Survey? Trends in Incomes and Expenditures over Time." IFS Report, No. R57, The Institute for Fiscal Studies.

Belfield, Chris, Richard Blundell, Jonathan Cribb, Andrew Hood, and Robert Joyce. (2017) "Two Decades of Income Inequality in Britain: The Role of Wages, Household Earnings and Redistribution." *Economica*, 84, 157–79.

Bloom, Nicholas. (2009) "The Impact of Uncertainty Shocks." *Econometrica*, 77, 623–85.

Bloom, Nicholas. (2014) "Fluctuations in Uncertainty." *Journal of Economic Perspectives*, 28, 153–76.

Blundell, Richard, and Ben Etheridge. (2010) "Consumption, Income and Earnings Inequality in Britain." *Review of Economic Dynamics*, 13, 76–102.

Bond, Stephen, Richhild Moessner, Haroon Mumtaz, and Murtaza Syed. (2005) "Microeconometric Evidence on Uncertainty and Investment." Mimeo, Institute for Fiscal Studies.

Born, Benjamin, and Johannes Pfeifer. (2014) "Policy Risk and the Business Cycle." *Journal of Monetary Economics*, 68, 68–85.

17. A historical decomposition of the Gini coefficients that compares the actual de-trended time series with counterfactual estimates where uncertainty shocks were set to zero shows that the counterfactual series are higher in the postfinancial crisis period. In other words, if there were no uncertainty shocks post-2009, inequality could be higher. The historical decomposition for the three coefficients can be found in the online Appendix, Section 5.

Brewer, Mike, and Liam Wren-Lewis. (2016) “Accounting for Changes in Income Inequality: Decomposition Analyses for the UK, 1978–2008.” *Oxford Bulletin of Economics and Statistics*, 78, 289–322.

Castelnuovo, Efrem, Guay Lim, and Giovanni Pellegrino. (2017) “A Short Review of the Recent Literature on Uncertainty.” *Australian Economic Review*, 50, 68–78.

Cloyne, James S., and Paolo Surico. (2017) “Household Debt and the Dynamic Effects of Income Tax Changes.” *Review of Economic Studies*, 84, 45–81.

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia. (2017) “Innocent Bystanders? Monetary Policy and Inequality.” *Journal of Monetary Economics*, 88, 70–89.

Cunha, Flavio, and James Heckman. (2007) “The Technology of Skill Formation.” *American Economic Review*, 97, 31–47.

De Giorgi, Giacomo, and Luca Gambetti. (2017) “Business Cycle Fluctuations and the Distribution of Consumption.” *Review of Economic Dynamics*, 23, 19–41.

Deaton, Angus. (2016) “Measuring and Understanding Behavior, Welfare, and Poverty.” *American Economic Review*, 106, 1221–43.

Department of Employment, Family Expenditure Survey, 1961 Colchester, Essex: UK Data Archive, August 1993. SN: 3042. https://doi.org/10.5255/UKDA-SN-3042-1

Fasani, Stefano, and Lorenza Rossi. (2018) “Are uncertainty shocks aggregate demand shocks?” *Economics Letters*, 167, 142–6.

Fernández-Villaverde, Jesús, Pablo Guerrón-Quintana, Keith Kuester, and Juan Rubio-Ramírez. (2015) “Fiscal Volatility Shocks and Economic Activity.” *American Economic Review*, 105, 3352–84.

Fischer, Manfred M., Huber Florian, and Pfarrhofer Michael. (2019) “The Regional Transmission of Uncertainty Shocks on Income Inequality in the United States.” University of Salzburg Working Paper Series.

Forni, Mario, and Luca Gambetti. (2014) “Sufficient Information in Structural VARs.” *Journal of Monetary Economics*, 66, 124–36.

Foster, Kate. (1996) “A Comparison of the Census Characteristics of Respondents and Non-Respondents to the 1996 FES.” London: Office for National Statistics; Survey Methodology Bulletin, 38.

Furceri, Davide, Prakash Loungani, and Aleksandra Zdzienicka. (2018) “The Effects of Monetary Policy Shocks on Inequality.” *Journal of International Money and Finance*, 85, 168–86.

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante. (2010) “Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967–2006.” *Review of Economic Dynamics*, 13, 15–51.

Inui, Masayuki, Nao Sudo, and Tomoaki Yamada. (2017) “Effects of Monetary Policy Shocks on Inequality in Japan.” Bank of Japan Working Paper Series, 17-E-3.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. (2015) “Measuring Uncertainty.” *American Economic Review*, 105, 1177–216.

Knight, John B., and Richard H. Sabot. (1983) “Educational Expansion and the Kuznets Effect.” *American Economic Review*, 73, 1132–6.

Leduc, Sylvain, and Zheng Liu. (2016) “Uncertainty Shocks Are Aggregate Demand Shocks.” *Journal of Monetary Economics*, 82, 20–35.

Ludvigson, Sydney C., Sai Ma, and Serena Ng. (2018) “Shock Restricted Structural Vector-Autoregressions.” Working Paper No. 23225, NBER.

Mumtaz, Haroon. (2016) "The Evolving Transmission of Uncertainty Shocks in the United Kingdom." *Econometrics*, 4, 1–18.

Mumtaz, Haroon, and Angeliki Theophilopoulou. (2017) "The Impact of Monetary Policy on Inequality in the UK. An Empirical Analysis." *European Economic Review*, 98, 410–23.

Nelson, Edward. (2001) "UK Monetary Policy 1972-97: A Guide Using Taylor Rules." Discussion Paper No. 2931, CEPR.

Redl, Chris. (2017) "The Impact of Uncertainty Shocks in the United Kingdom." Bank of England Working Papers 695, Bank of England.

Roine, Jesper, Jonas Vlachos, and Daniel Waldenström. (2009) "The Long-Run Determinants of Inequality: What Can We Learn from Top Income Data?" *Journal of Public Economics*, 93, 974–88.

Sims, Christopher, James Stock, and Mark Watson. (1990) "Inference in Linear Time Series Models with Some Unit Roots." *Econometrica*, 58, 113–44.

Uhlig, Harald. (2005) "What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure." *Journal of Monetary Economics*, 52, 381–419.

van de Ven, Justin. (2011) "Expenditure and Disposable Income Trends of UK Households: Evidence from Micro-Data." *National Institute Economic Review*, 218, 44–57.

Western, Bruse, and Jake Rosenfeld. (2011) "Unions, Norms, and the Rise in U.S. Wage Inequality." *American Sociological Review*, 76, 513–37.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure 1: *Effects of the macroeconomic uncertainty shock by using a mixed frequency VAR model.*

Figure 2: Sensitivity on the type of income in the benchmark SVAR model.

Figure 3: Sensitivity on consumption variable in the benchmark SVAR model.

Figure 4: Sensitivity in the lag length: The impulse response functions of Gini coefficients to one standard deviation uncertainty shock.

Figure 5: Sensitivity in subsamples: The impulse response functions of Gini coefficients to one standard deviation uncertainty shock in subsample I (1971Q2-1992Q3) and subsample II (1992Q4-2018Q1).

Figure 6: Adding a linear time trend.

Figure 7: *Effects of the macroeconomic uncertainty shock on the UK's macro variables.*

Figure 8: Historical decomposition of the VAR shocks to (de-trended) Gini coefficients.

Figure 9: Effects of the macroeconomic uncertainty shock to GDP and rental prices growth rates.

Table 1: Macroeconomic Data