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Monetary Policy and Wealth Inequality over the Great Recession in the UK. An Empirical Analysis

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Abstract

We use detailed micro information at household level from the Wealth and Assets Survey to construct measures of wealth inequality from 2005 to 2016 at the monthly frequency. We investigate the dynamic relationship between monetary policy and the evolution of wealth inequality measures. Our findings suggest that expansionary monetary policy shocks lead to an increase in wealth inequality and contributed significantly to its fluctuations. This effect is heterogenous across the wealth distribution with the monetary shock affecting the median household relative to the 20th percentile by a larger amount than the right tail. Our results suggest that the shock is transmitted through changes in net property and financial wealth that constitute the bulk of total wealth of households near the median of the wealth distribution.

Keywords: Inequality, Wealth, FAVAR, Monetary Policy Shocks

JEL No. D31, E21, E44, E52

1 Introduction

In the aftermath of the Great Recession a number of countries face increasing income and wealth inequality. During the Great Recession wealthy households experienced earnings and financial losses while automatic stabilisation policies were set off to support low income families. However, a decade after the global financial crisis this trend has been reversed and losses have been more than recovered. Across the 28 OECD countries, the Gini coefficient for disposable income has increased from 0.30 in 2006-7 to 0.32 in 2016-17 and 10% of households hold 52% of total wealth in 2015 (Balestra and Tonkin (2018)).

According to data by Alvaredo *et al.* (2018), wealth inequality in the UK as expressed by the share of top 10% was in a downward trend until the end of 1990s, when it reached its historical lower value. In the first half of 2000s wealth inequality remained mostly unchanged. During the Global Financial Crisis the ratio fell substantially while it recovered reducing income inequality but do not find any significant effects on wealth. There are further indirect ways through which monetary policy impacts wealth: It alters house prices and benefits home owners and mortgagors (Cloyne et al., 2016, Adam and Tzamourani (2016)). This may have an equalizing effect if these two groups cover a large part of population and if housing wealth is the largest component in poor households' portfolio (Casiraghi *et al.* (2018)). However, the rise of property prices can generate new types of inequalities between home and non home owners, mainly young earners with no parental gifts, who find increasingly difficult to enter the housing market (Piketty *et al.* (2018)).

Large scale assets purchase programmes lower gilt yields affecting large bond holders such as private pension funds. Pension fund schemes (especially Defined Benefit schemes) may experience disproportionate increase in their liabilities to the value of their assets leading to higher deficits. Lower gilt yields put also downward pressure on the return on annuities which implies lower pension income for their policy holders. As Bunn *et al.* (2018) note, the impact of monetary policy on pension wealth is very complex households' balance sheet. We follow a different methodology: By using the available waves in the Wealth and Asset Survey (WAS), we construct wealth inequality measures at monthly frequency to investigate the dynamic effects of conventional and unconventional monetary policy on wealth without the use of assumptions on future asset prices and households' decisions. Moreover, we employ a Factor Augment Vector Autoregression (FAVAR) model to take advantage of a rich macroeconomic environment and a large information set but also to account for measurement errors. The monetary policy shocks are identified using an external instrument approach.

Our main finding suggests that wealth inequality increases after an expansionary monetary policy shock with the wealth at the 80th percentile rising relative to wealth at the 20th percentile. The increase in inequality is largely driven by the left tail of the distribution: while the policy expansion pushes up the 50/20 ratio, the 80/50 ratio is relatively unaffected. We argue that the main driver of this result is that fact that (net) property wealth constitutes the largest proportion of wealth at the median of the distribution. Expansionary policy shocks push up house prices which have an impact on this component. Evidence for this assertion comes from the fact that the effects of monetary policy on wealth inequality become substantially smaller once the property wealth component is removed from the inequality measures. We also find that the policy shock has large effects on financial asset prices. This large impact has a positive effect on the financial wealth of households towards the right tail of the distribution and also contributes to the increase in inequality. Finally, the effect of monetary policy on physical wealth, the largest component of wealth in the least wealthy households, acts in the opposite direction and reduces the degree of the rise in inequality after the policy shock.

The rest of the paper is structured as follows: Section 2 describes the construction of the wealth inequality measures. Section 3 describes the estimation of the FAVAR model and the identification scheme. Section 4 presents the main results and section 5 concludes.

ratio compares the wealth of the top 20 percent of the population to the bottom 20 percent. The 80/50 and 50/20 ratios demonstrate how the wealthier and poorer percentiles move relative to the median. Other popular measures of inequality such as the Gini coefficient may be less useful in this setting. For example, the Gini coefficient requires positive values thus forcing the removal of households with negative wealth.[4] Moreover, OECD (2013) show that the Gini coefficient is sensitive to outliers in the wealth distribution with percentile ratios displaying more robustness as long as percentiles deep in the tails are not considered.

The wealth data used to construct these inequality measures is obtained from each wave of the survey. Following Cloyne and Surico (2016) and Mumtaz and Theophilopoulou (2017), we group households by their date of interview. The WAS sampling structure involves an initial draw of an annual sample of addresses grouped into primary sampling units (PSUs). These PSUs are then assigned to months at random. As described in the WAS Wave 1 user guide, this assignment is carried out ensuring that PSUs allocated to a month are evenly spread across the original sample and have an equal chance of being allocated to each month. In the second stage, from each PSU, addresses are sampled and assigned each month to the ONS interviewer panel. By selecting households that are interviewed each month, we obtain a sample of about 800 to 1200 households per month. We then construct the percentiles of their total wealth using survey weights.

[4] Another generic problem of the index is that it does not capture where in the distribution the inequlaity occurs. Thus two countries may have the same Gini index number in a certain year but the wealth allocation maybe very different across percentiles.

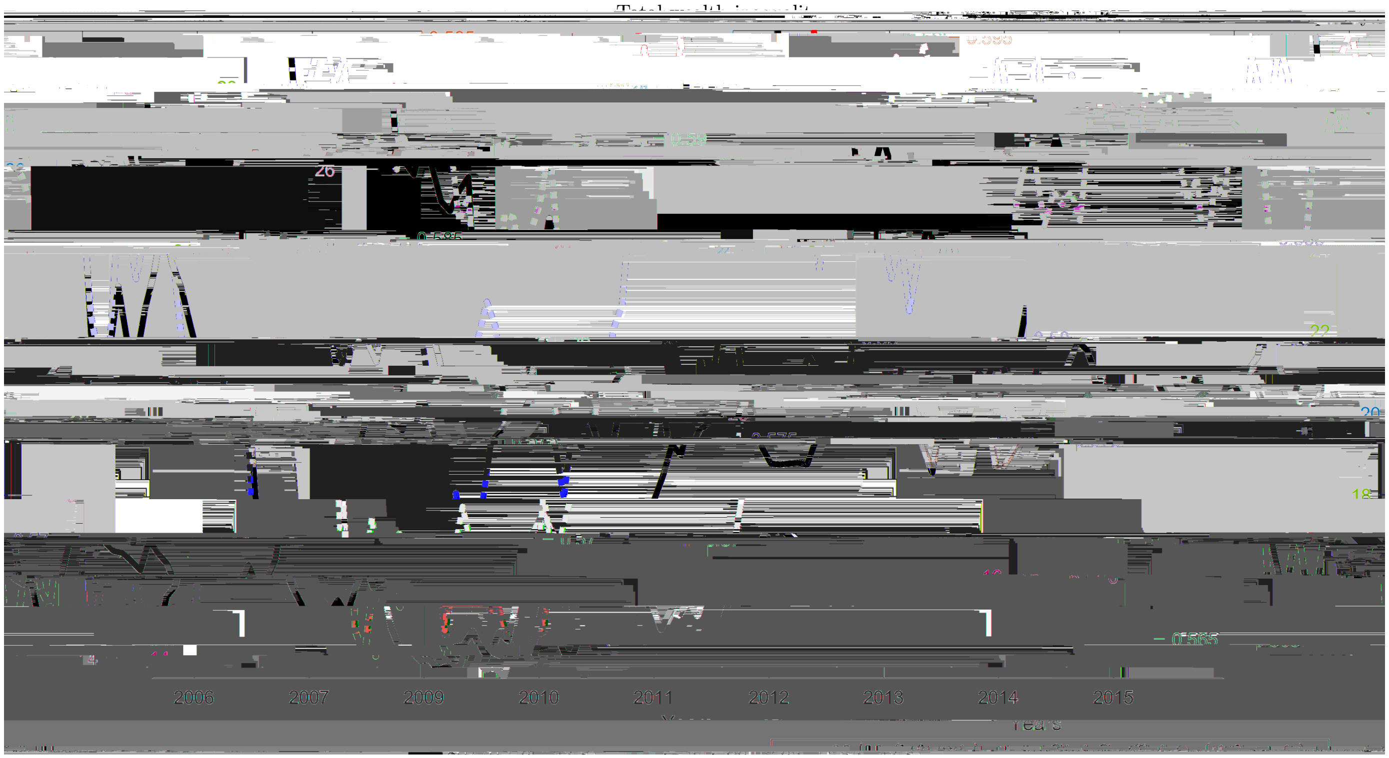


Figure 1: Gini coefficient (right axis) and the 80/20 ratio (left axis). Both series are smoothed using a 6 month moving average in the figure.

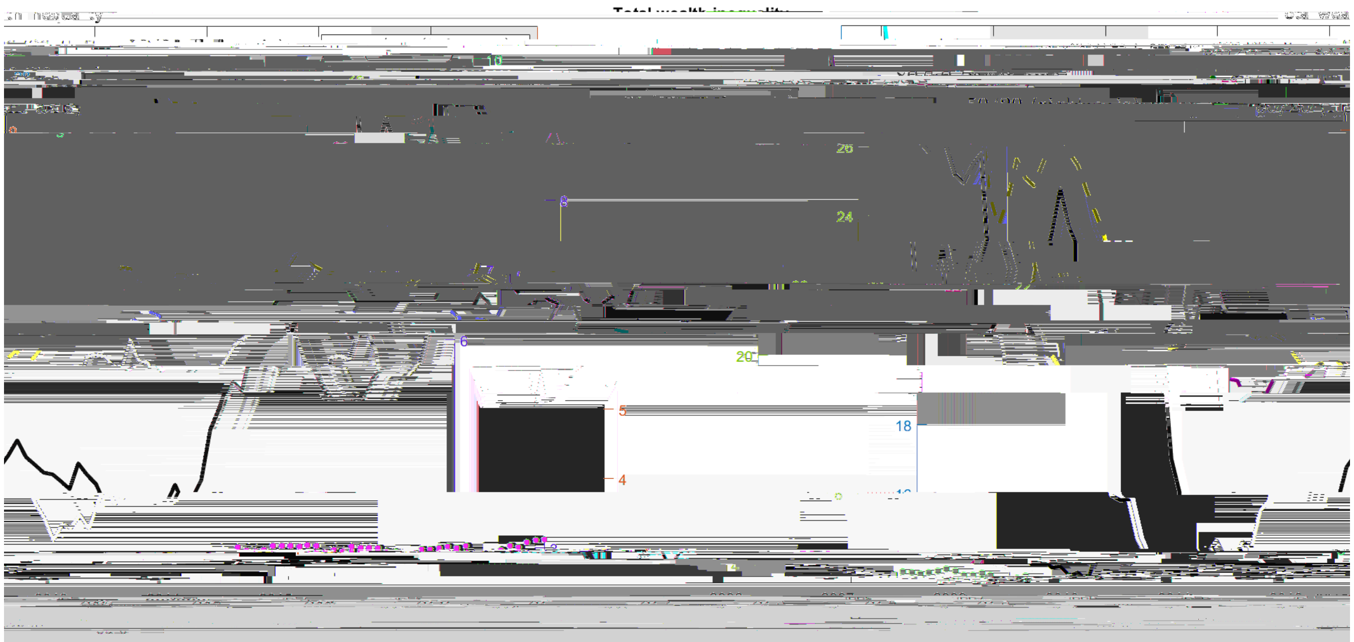


Figure 2: 80/20 (left axis) and 80/50, 50/20 (right axis). The measures are smoothed using a 6 month moving average in this figure.

The evolution of the benchmark measure of total wealth inequality can be seen in Figure 1. For the purposes of comparison, we also present the Gini coefficient. The two measures display a correlation of about 0.7 over the sample period and tend to move together fairly closely. Wealth inequality was declining during the pre-2007 period with 80/20 ratio falling to just above 20. The onset of the financial crisis coincided with a short-lived increase in the measures. However, after 2008, the inequality declined sharply with the 80/20 ratio almost half of its initial value. The remaining period is characterised by a largely sustained increase in the inequality measures with both the Gini coefficient and the 80/20 ratio moving towards their pre-2007 levels.

Figure 2 compares the 80/20 measure with the 80/50 and 50/20 measures. It is clear from the figure that the 80/20 measure is tracked by the 50/20 measure. In contrast, the 80/50 ratio, remains relatively flat over the sample period. This suggests that movements in total wealth inequality over this period are largely driven by changes in the wealth of the median household relative to the left tail of the distribution.

As discussed above, there were several changes in conventional and uncoventional monetary policy over this period. In the next section, we consider the effect of monetary policy shocks on measures of wealth inequality and investigate the channels of shock transmission.

3 Empirical model

To estimate the impact of monetary policy shocks, we employ a Factor Augmented Vector Autoregression (FAVAR) as our benchmark model. The observation equation of the model is defined as:

$$\begin{pmatrix} R_t \\ X_t \end{pmatrix} = \begin{pmatrix} I & 0 \\ \Lambda^R & \Lambda \end{pmatrix} \begin{pmatrix} R_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ v_t \end{pmatrix} \tag{1}$$

where R_t denotes the policy interest rate. X_t is $M \times 1$ matrix of variables for the UK covering both aggregate macroeconomic and financial data *and* measures of wealth inequality, namely the 80/20 ratio, the 80/50 ratio and the 50/20 ratio. The 35 macroeconomic and financial series included in X_t are listed in the appendix. Note that the sample period is 2006M7 to 2016M6.

$\underbrace{F_t}_{K}$ denotes a set of K factors that summarise the information in X_t, Λ is a $M \times K$ matrix of factor loadings. Finally, v_t is a $M \times 1$ matrix that holds the idiosyncratic components. We assume that v_t follows an AR (q) process:

$$v_{it} = \sum_{p}^{P} \psi_{ip} v_{it-p} + e_{it}; \text{var}(e_{it}) = r_i; R = \text{diag}([r_1; r_2; ...; r_M]) \tag{2}$$

where $i = 1; 2; \ldots; M$.

Denoting the factors $\begin{pmatrix} R_t \\ F_t \end{pmatrix}$ by the $N \times 1$ vector Y_t, the transition equation can be described as:

$$Y_t = BX_t + u_t \qquad (3)$$

where $X_t = [Y_{t-1}'; \ldots; Y_{t-P}'; 1]'$ is $(NP + 1) \times 1$ vector of regressors in each equation and B denotes the $N \times (NP + 1)$ matrix of coefficients $B = [B_1; \ldots; B_P; c]$. The covariance matrix of the reduced form residuals u_t can be written as:

$\Sigma = (Aq)(Aq)'$ where A is the lower triangular Cholesky decomposition of Σ, and q is

3.2 Model estimation and specification

Following Bruns (2019) and Miescu and Mumtaz (2019), the FAVAR is estimated using a Gibbs sampling algorithm that is an extension of the algorithm proposed by Caldara and Herbst (2016) for proxy VARs. Details of the algorithm and the priors are presented in the technical appendix. As discussed in Caldara and Herbst (2016), the priors for and play an important role as they influence the reliability of the instrument. Mertens and Ravn (2013) define the reliability statistic as the squared correlation between m_t and ε_t:

$$= \frac{\quad}{+} \tag{6}$$

In our benchmark model, the priors for and are set to reflect the strong belief that the instruments are relevant and imply that 0.5. This prior belief is based on the evidence regarding the high relevance of the instrument presented in Gerko and Rey (2017). We show, in the sensitivity analysis below that an alternative identification scheme suggests results that are similar to benchmark.

The choice of the number of factors is a key issue with regards to specification of the model. We follow the general approach used in Bernanke *et al.* (2005): i.e. the benchmark model is estimated using $K = 6$. We present some robustness analysis regarding this choice below. The lag length P is set to 6 in the benchmark model as the number of time-series observations is fairly limited.

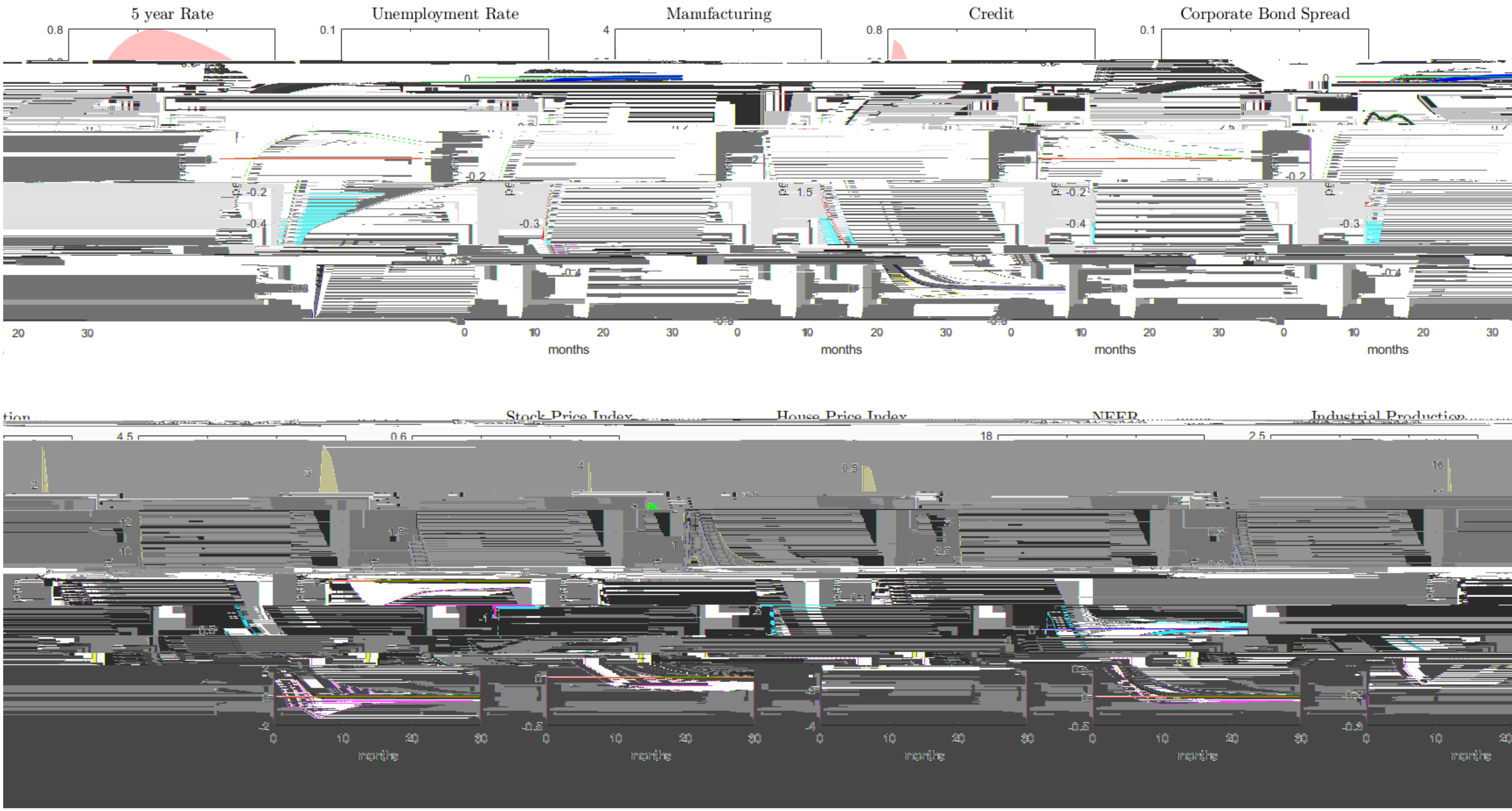


Figure 3: Impulse response of aggregate variables to a monetary policy shock

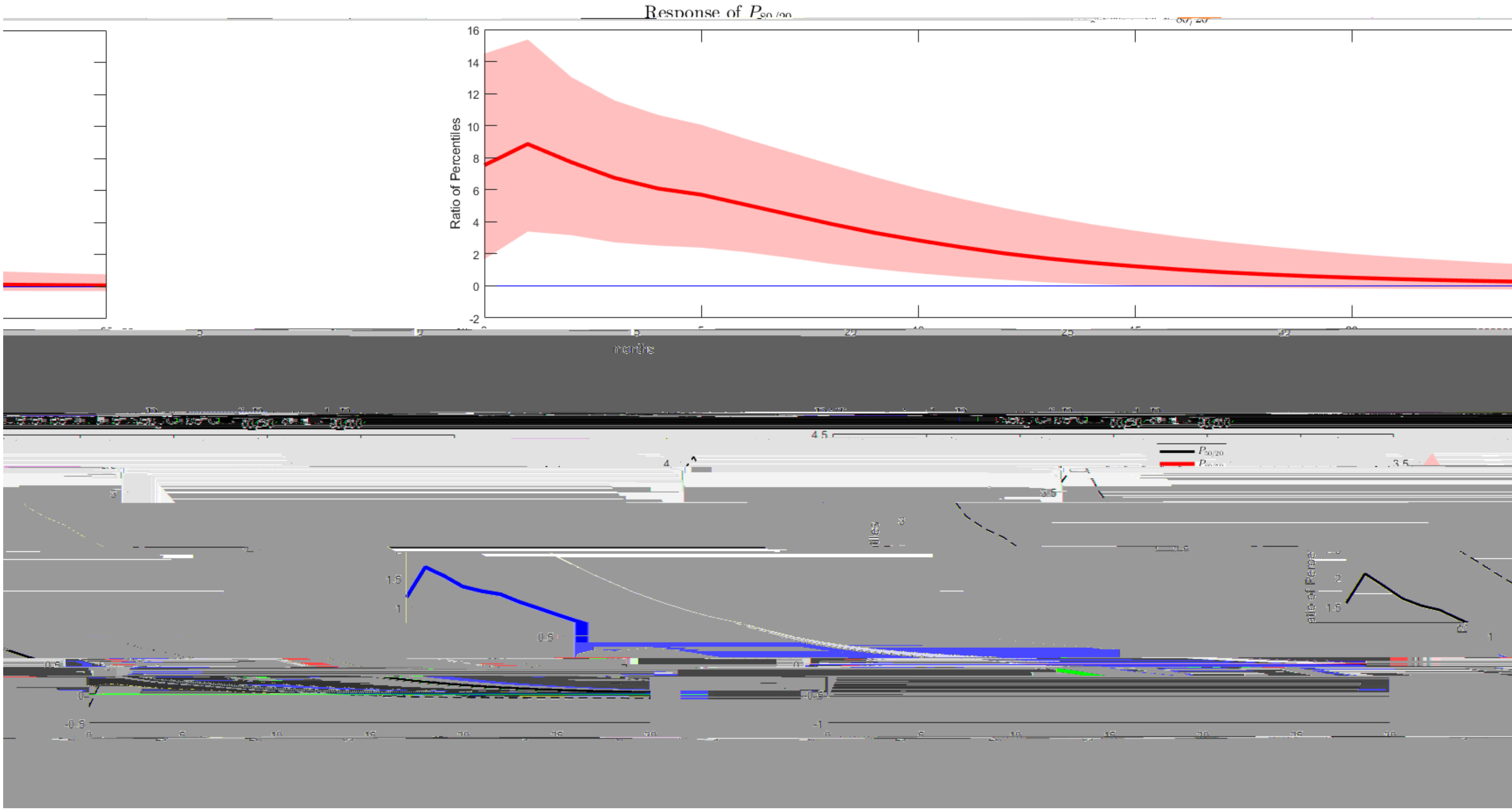
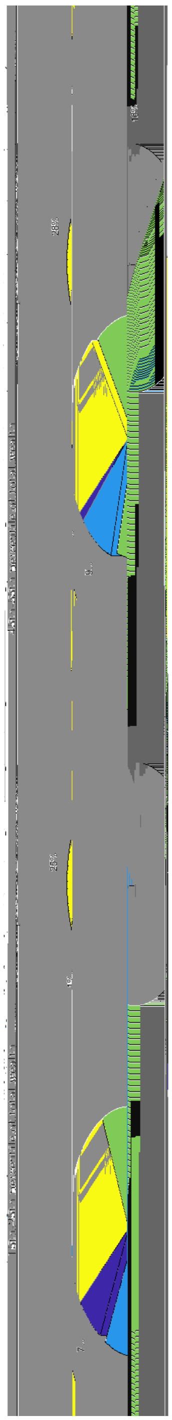


Figure 4: Response of total wealth



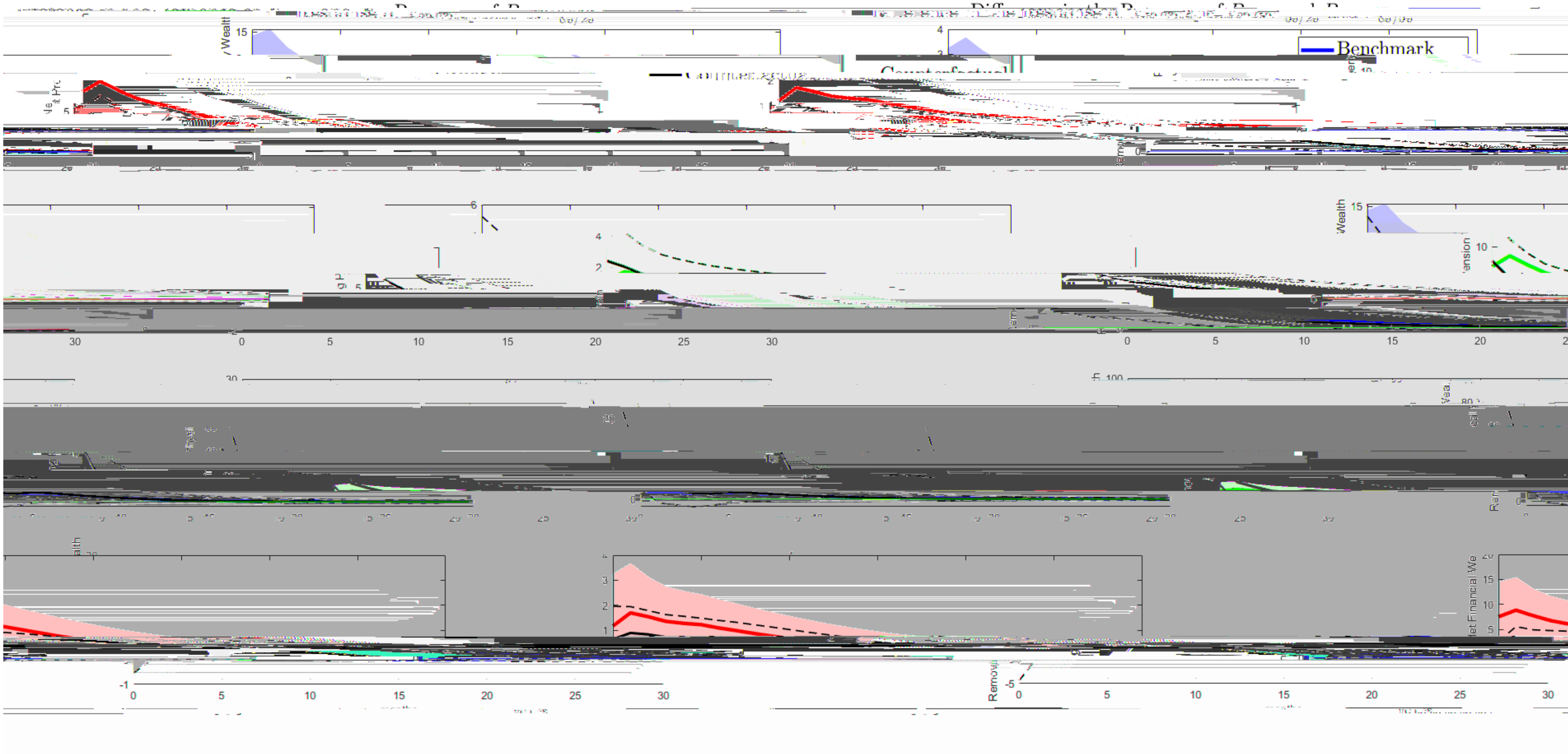


Figure 6: Comparison of benchmark results and those obtained when net property wealth is excluded.

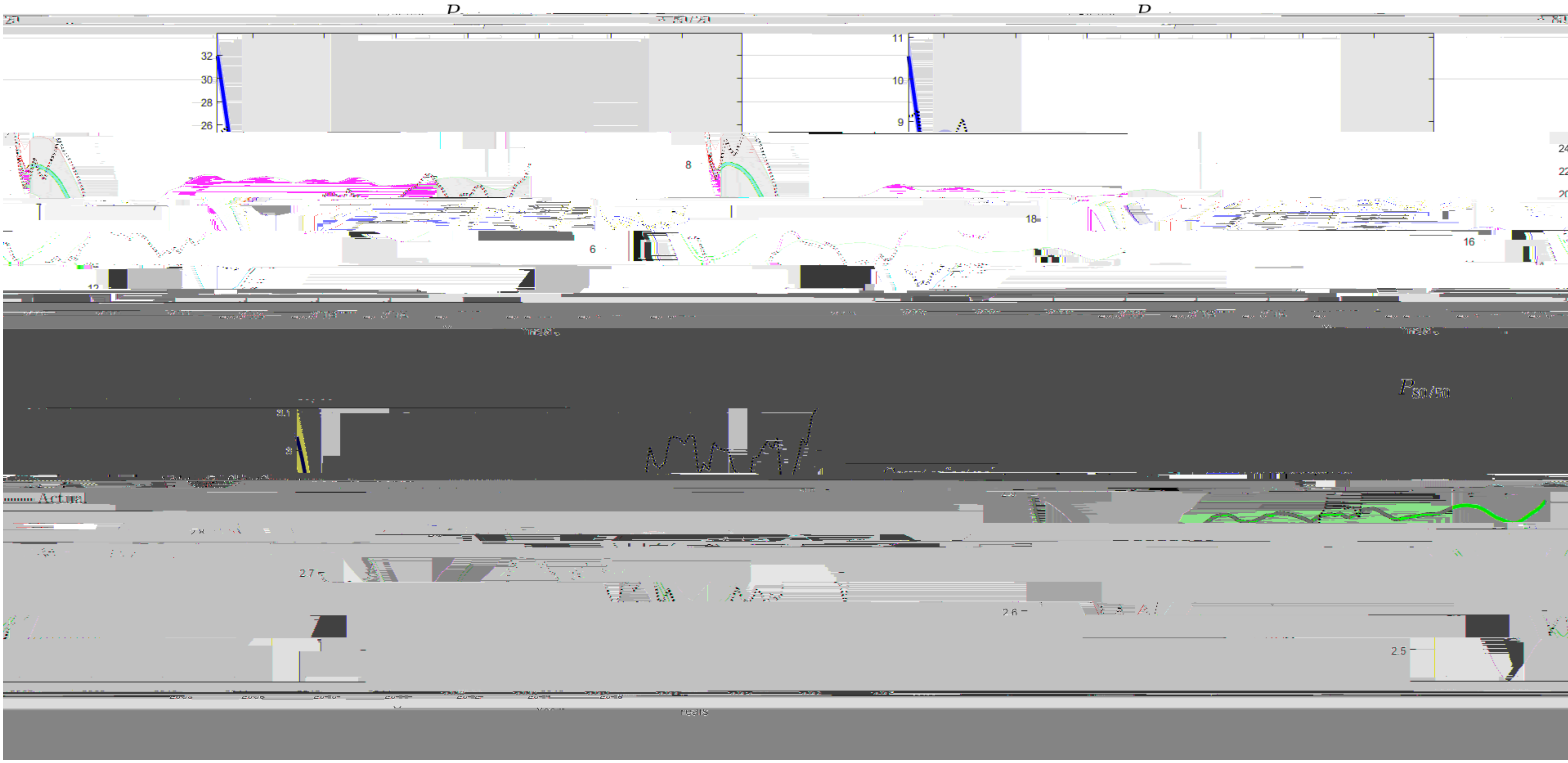


Figure 7: Counterfactual estimates of wealth inequality. The red lines and shaded area depict the counterfactual estimates (median and 68 percent error band) assuming that only the monetary policy shock is non-zero. The actual and counterfactual inequality measures are smoothed using a 6 month moving average.

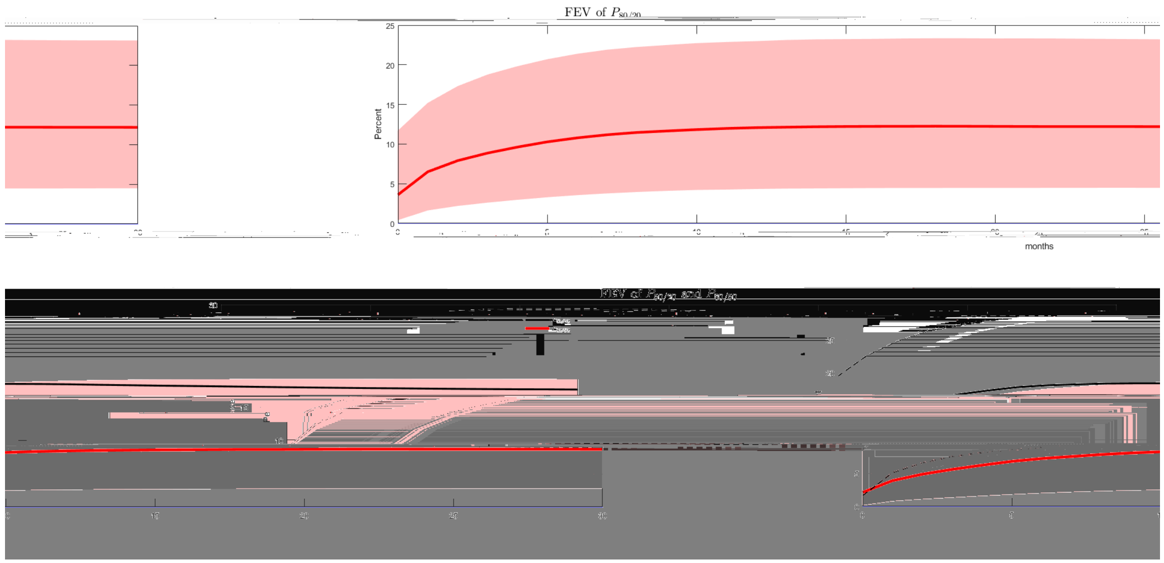


Figure 8: Contribution of the monetary policy shock to the forecast error variance (FEV) of wealth inequality measures.

4 Response to a monetary expansion

4.1 Impact on macroeconomic aggregates

Before considering the impact of the monetary shock on the wealth distribution we report its impact on economic aggregates. Figure 3 shows the response of selected aggregate macroeconomic and financial variables to a monetary policy shock scaled to reduce the five year rate by 100 basis points. The monetary expansion leads to a boost in real economic activity with an increase in manufacturing and industrial production and a decrease in the unemployment rate. There is some indication that CPI inflation rises after the shock. As in Gerko and Rey (2017), the shock is associated with financial easing – the corporate bond spread declines, the stock index and credit rises and the response of house prices is positive. The response of NEER indicates a depreciation on impact with a quick reversal. However, unlike Gerko and Rey (2017), we do not find a large response of the exchange rate to the shock. This possibly reflects the smaller sample used in our study. Overall, these estimates are consistent with the standard results regarding the macroeconomic impact of monetary policy shocks reported in the literature.

4.2 Impact on the distribution of wealth

We now turn to the estimated impact of this shock on the total wealth distribution. Figure 4 considers the response of the three measures of total wealth wealth inequality included in X_t, i.e. the ratio of percentiles denoted as: (i) $P_{\frac{80}{20}}$, (ii) $P_{\frac{80}{50}}$ and (iii) $P_{\frac{50}{20}}$. The top panel of the figure shows that after a monetary expansion wealth inequality increases. That is, the gap between the 80^{th}

to 55th percentile, 15th

role. When physical wealth is removed from the the inequality measures, their response increases substantially. As shown by the right panel, the response below the median is now substantially larger than benchmark. These estimates are consistent with the fact that physical wealth forms the largest component of total wealth for households in the left tail of the distribution. A monetary expansion may boost the wealth of these households through this component thus ameliorating the rise in wealth inequality. Once this component is removed, the gap between the left tail of the wealth distribution and the median widens substantially more than the benchmark case after a positive policy shock. While net financial wealth is a relatively smaller component of total wealth, it appears to play some role in the transmission of the shock. The last row of Figure 6 shows that the response of $\tilde{P}_{\frac{80}{20}}$ in this case is lower than that of $P_{\frac{80}{20}}$. This is possibly driven by the fact that the monetary shock has a relatively large impact on financial conditions – as shown in Figure 3, there is a large increase in stock prices after the shock and the corporate bond spread declines substantially. This appears to benefit households towards the right tail of the wealth distribution dis-proportionally.

In summary, this counterfactual analysis suggests that net property wealth and net financial wealth are key factors in the transmission of monetary expansions into higher wealth inequality. In contrast, physical wealth acts as ameliorating influence and reduces inequality by increasing the wealth of households on the left tail of the distribution.

4.3 Contribution of monetary policy shocks

To investigate the historical importance of the monetary policy shock we conduct a counterfactual experiment. For each iteration of the Gibbs sampler we simulate data for the wealth inequality measures P_P

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Monetary Policy and Wealth Inequality over the Great Recession in the UK. An Empirical Analysis (Technical Appendix)

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Abstract

Technical Appendix

1 Proxy FAVAR model

The observation equation of the FAVAR model is de…ned as

Z_t
X_t

where $E(v_t \varepsilon_t) = 0$.

1.2 Priors

We assume the following prior distributions:

1. We use a natural conjugate prior for the VAR parameters $b = vec(B^0)$; implemented via dummy observations (see Banbura et al. (2010)):

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\ _1\ _1 \ldots\ _N\ _N)}{} \\ 0_{N\ (P\ 1)\ N} \\ \ldots\ldots\ldots \\ diag(\ _1 \ldots\ _N) \\ \ldots\ldots\ldots \\ 0_{1\ N} \end{pmatrix}; \text{and } X_{D,1} = \begin{pmatrix} \frac{J_P\ diag(\ _1 \ldots\ _N)}{} & 0_{NP\ 1} \\ 0_{N\ NP+1} & \\ \ldots\ldots\ldots & \\ 0_{1\ NP} & I_1\ c \end{pmatrix} \qquad (7)$$

where $_1$ to

This system is conditionally linear and Gaussian. This system is conditionally linear and Gaussian. As m_t is observed, one can re-write the model using the conditional normal distribution. In particular, partition the covariance cov $\begin{matrix} u_t \\ m_t \end{matrix}$ $_b$ as:

$$\text{cov} \begin{matrix} u_t \\ m_t \end{matrix} \quad _b = \begin{matrix} _{u_t u_t} & _{u_t m_t} \\ ^0_{u_t m_t} & _{m_t m_t} \end{matrix} \tag{9}$$

Then

$$u_t j m_t \sim N \quad _{ujm} ; \quad _{ujm} \tag{10}$$

where

$$\begin{aligned} _{ujm} &= \quad _{u_t m_t} (\quad _{m_t m_t}) \; ^1 m_t^0 \\ _{ujm} &= \quad _{u_t u_t} \quad _{u_t m_t} (\quad _{m_t m_t}) \; ^1 \; ^0_{u_t m_t} \end{aligned} \tag{11}$$

The model can be written as a standard VAR

$$\begin{aligned} Y_t &= (I_N \quad X_t^0) b + u_t j m_t ; \\ & u_t j m_t \sim N \quad 0 ; \quad _{ujm} \end{aligned}$$

where:

$$Y_t = Y_t \quad ^0_{ujm}$$

Thus the conditional posterior for b is normal: $N (M ; V)$ where:

$$\begin{aligned} M &= \text{vec} \quad x^0 x \quad ^1 \quad x^0 y \\ V &= \quad _{ujm} \quad x^0 x \quad ^1 \end{aligned}$$

with:

$$y = \begin{pmatrix} Y_t \\ Y_{D;1} \\ Y_{D;2} \end{pmatrix} ; x = \begin{pmatrix} X_t \\ X_{D;1} \\ X_{D;2} \end{pmatrix}$$

Step 2. $p(\; j \quad _{b_t} ; Y_{1:T} ; m_{1:T})$. We follow Caldara and Herbst (2016) and use a Metropolis step to sample .

(a) Draw a candidate $_{new}$ from the proposal $Q(:) = IW (u^0 u \; ; T + T_D \quad K)$. The proposal density is the conditional posterior distribution of the error covariance matrix in the case of a standard Bayesian VAR where u denotes the residuals $y \quad x \; M$ with $y = \begin{pmatrix} Y_t \\ Y_{D;1} \\ Y_{D;2} \end{pmatrix}$, T_D denotes the number of dummy observations and K denotes the number of regressors in each equation.

(b) Accept the draw with probability $\quad = \min \left[\frac{\frac{p(m_{1:t} ; Y_{1:t} ; \; _{new} ; \quad)}{Q(\; _{new})}}{\frac{p(m_{1:t} ; Y_{1:t} ; \; _{old} ; \quad)}{Q(\; _{old})}} ; 1 \right]$. Here $p(m_{1:t} ; Y_{1:t})$ denotes the joint posterior distribution.

Step 3. $p(q_1 j \quad _{q_1} ; Y_{1:T} ; m_{1:T})$. Following Caldara and Herbst (2016) we use a Metropolis step to sample q_1 :

(a) Draw a candidate from as $q_{1;new} = \frac{z}{kzk}$ where z is a $N \quad 1$ vector from the $N (0; 1)$ distribution

(b) Accept the draw with probability $\quad = \min \frac{P(m_{1:t} j Y_{1:t} ; q_{1;new} ; \quad _{q_1})}{P(m_{1:t} j Y_{1:t} ; q_{1;old} ; \quad _{q_1})} ; 1$

Step 4 $p \quad ; \quad j \quad _{[; \;]} ; Y_{1:T} ; m_{1:T}$. The structural shock of interest $"_{1t}$ can be calculated as $"_{1t} = A q_1 u$. Conditional on $_{[; \;]}$ equation 6 is a standard linear regression, so specifying a conditional Normal-

Gamma prior delivers a Normal-Gamma posterior. Particularly, we …rst draw $p(\ ^2 | \ _{[;\ ]}; Y_{1:T}; m_{1:T})$. Assuming an inverse-Gamma prior, this conditional posterior is also inverse-Gamma. As the prior is parameterised in terms of mean $_0$ and standard deviation v_0; it is convenient to draw the precision $\frac{1}{\ ^2}$ using Gamma distribution. Note that $\frac{1}{\ ^2}\ G(a; b)$ where $a = \frac{\ _1}{2}$; $b = \frac{2}{s_1}$. The parameters of this Gamma density are given by $_1 = \ _0 + T$ and $s_1 = s_0 + \hat{v}_t^0 \hat{v}_t$ where $\hat{v}_t = m_t \quad e_{1t}$. s_0 can be calculated as $2\ _0\ 1 + \frac{\ _0^2}{v_0^2}$ while $_0 = 2\ \ 2 + \frac{\ _0^2}{v_0^2}$: Moreover, assuming a prior for $\ | \ ^2; \ _{[;\ ]}$ $N(\underline{\ }; \underline{V}\ ^1)$, the posterior is also conditional Normal $p\ \ | \ _{[;\ ]}; \ ; Y_{1:T}; m_{1:T}\ \ N(\tilde{\ }; \tilde{V}\ ^1)$, where $\tilde{\ } = \tilde{V}\ ^1 \left[\sum_{t=1}^{T} m_t "_{1t} + \underline{V}\,\underline{\ } \right]$ and $\tilde{V} = \underline{V} + \frac{1}{\ ^2} \sum_{t=1}^{T} "^2_{1t}$:

Step 5 $H(\ | \ ; Y_{1:T}; m_{1:T})$. Given the factors F_t, the observation equation is set of M independent linear regressions with serial correlation

$$X_{it} = F_t \ _i^0 + v_{it}$$

where $_i$ denotes the ith row of the factor loading matrix. The serial correlaton can be dealt with via a GLS transformation of the variables:

$$\tilde{X}_{it} = \tilde{F}_t \ _i^0 + e_{it}$$

where $\tilde{X}_{it} = X_{it} \quad \sum_{p=1}^{P} \ _p X_{it\ p}$ and $\tilde{F}_{kt} = F_{kt} \quad \sum_{p=1}^{P} \ _p F_{kt\ p}$. The conditional posterior is normal $N(M; V)$:

$$V = \left[\ _0^{\ 1} + \frac{1}{r_i} \tilde{F}_t^0 \tilde{F}_t \right]^{\ i}; \text{the}$$

de…ned as:

$$f_t = \quad + \tilde{B} f_{t \;\; 1} + U_t$$

where $\tilde{B} = \begin{matrix} B_1 & & B_P \\ I_{N(P \;\; 1) \;\; NP} & & \end{matrix}$; $\quad = \begin{matrix} c \\ 0_{N(P \;\; 1)} \end{matrix}$; $U_t = \begin{matrix} u_t \\ 0_{N(P \;\; 1)} \end{matrix}$. The non-zero block of $cov(U_t)$ is given by $_{u_t u_t}$. In other words, over periods where the instrument is missing the correlation between the instrument and the residuals does need to be directly modelled.

1.5 Further results

Figure 1: Ine¢ ciency Factors

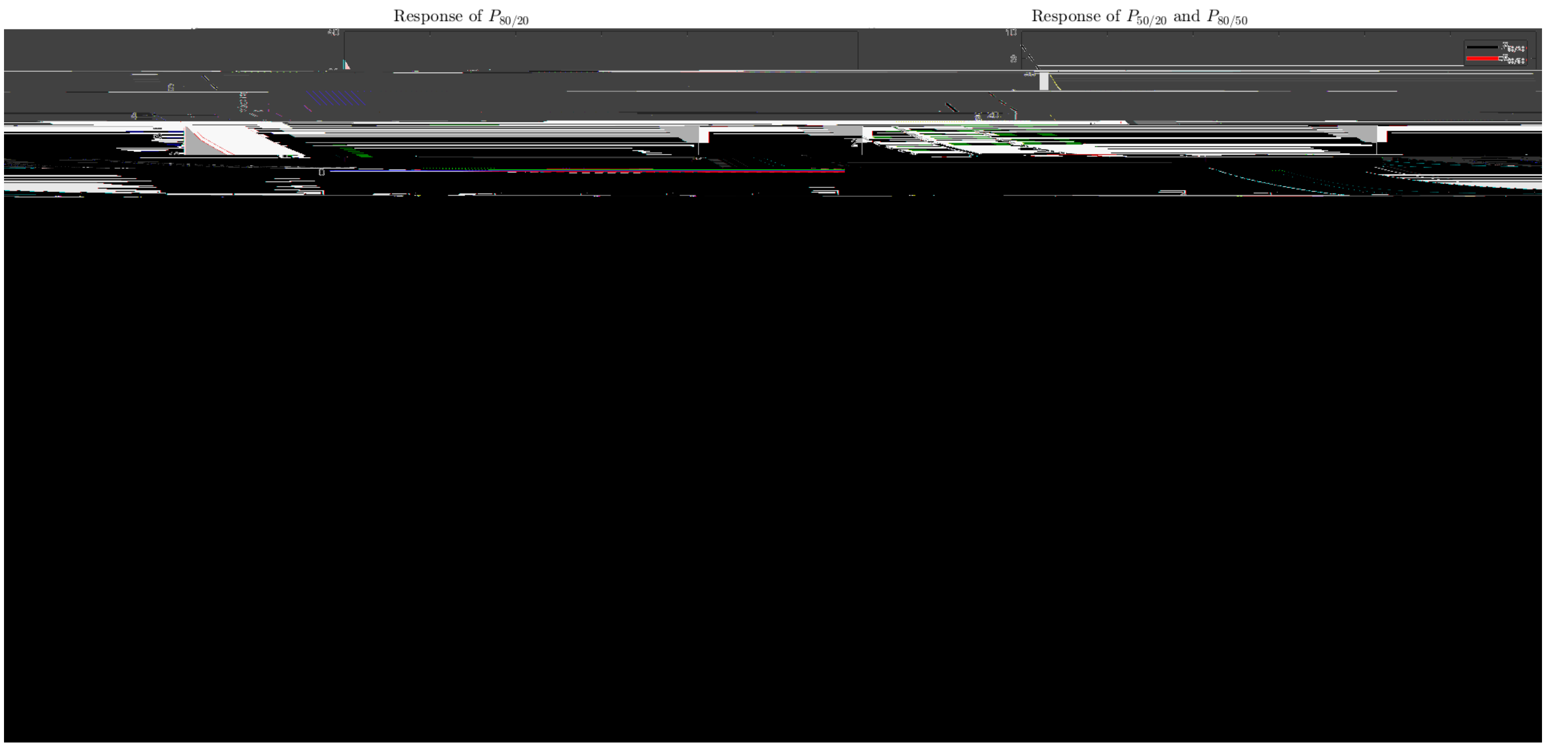

Figure 2: Robustness

Figure 1 shows the estimated inefficiency factors for the benchmark model. In most cases these are quite low suggesting some evidence for convergence. Figure 2 presents the robustness analysis. We carry out a number of checks to test the robustness of the main results. The top panel of Figure 2 plots the response of the wealth inequality measures from a version of the benchmark model that assumes that the number of factors is equal to 3. When the number of factors are increased to 8 in the second panel, the results are similar to benchmark.[1] Finally, the last row of the figure shows estimates from a FAVAR model where we use an alternative identification scheme. In particular, in this alternative model the five year rate is replaced by the shadow rate constructed by Wu and Xia (2016). Following Bernanke et al. (2005), the policy shock is identified via a recursive ordering under which this disturbance has no contemporaneous impact on slow moving variables (e.g. industrial production) but affects fast moving variables such as asset prices immediately. The last row of figure 2 shows that the response of the inequality measure $P_{\frac{80}{20}}$ to a reduction in the shadow rate is positive, albeit more sluggish than the benchmark case. The bottom right panel of the figure suggests that, as with the IV identification scheme, the impact of the shock is largest for the $P_{\frac{80}{20}}$ measure.

1.6 Data

Table 1 displays the data sources and transformations. GFD is global financial data and BOE is the Bank of England. Transformation code 1 denotes no transformation, 2 denotes log differences, while 3 denotes differences.

Remotes

Variable	Source	Transformation
Production of Total Industry	GFD	2
Composite Leasing Indicator	GFD	1
Retail Price Index	BOE	2
Consumer Con…dence	GFD	2
Business Con…dence	GFD	2
Retail Trade	GFD	2
Unemployment Rate	GFD	3
Manufacturing Production	BOE	2
Vacancies	BOE	2
Average Weekly Earnings	BOE	2
Producer Price Index	BOE	2
RPIX	BOE	2
M0 Money supply	BOE	2
Lending by Monetary Financial Institutions	BOE	2
3 Month Libor	BOE	3
T-Bill Rate	BOE	3
10 year Govt. Bond Yield Spread over Libor	BOE	1
20 year Govt. Bond Yield Spread over Libor	BOE	1
Corporate Bond Spread	BOE	1
Variable Mortgage rate spread over Bank rate	BOE	1
Credit Card Rate spread over Bank rate	BOE	1
Personal Loan rate spread over Bank rate	BOE	1
FTSE All Share Index	GFD	2
FTSE Non-industrials	BOE	2
Dividend Yield	GFD	2
Price Equity Ratio	GFD	2
House Price Index	Nation Wide	2
Brent Oil Price	GFD	2
Economic Policy Uncertainty	http://www.policyuncertainty.com/index.html	1
Nominal E¤ective Exchange Rate	BOE	2
Real E¤ective Exchange Rate	BOE	2
Canadian Dollar to Pound	BOE	2
Euro to Pound	BOE	2