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

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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 strongly in 2011-15 with average annual growth of 4% (Balestra and Tonkin (2018)). During the Global Financial and European Sovereign Debt crises, the Bank of England lowered the Bank Rate towards zero and launched a Quantitative Easing (QE) programme in which it purchased £375 billion of financial assets from 2009 to 2012. In 2016 the Bank of England announced another round of QE to address issues of uncertainty due to Brexit and anemic economic growth.

Developments in wealth distribution have attracted renewed interest not only because its link to rising income inequality but its eminent role in smoothing consumption and maintaining a living standard above the poverty line: households with positive wealth holdings can keep their level of consumption stable when they experience loss of employment, health, assets, etc. while households with zero or negative wealth remain vulnerable to swings of the business cycle. On the other hand, income from physical and financial wealth such as rent, interest and dividends is on an upward trend and it is a significant proportion of total income, especially for households in the right tail of income distribution (Crossley *et al.* (2016)).

The role of public policies can be crucial for the wealth distribution. Countries with similar growth rates and market development can have a different evolution in income and wealth inequality due to different policies implemented (The World Inequality Report, 2018). While fiscal policy directly affects income and wealth distributions, the role of monetary policy has been largely considered neutral until recently, where a number of studies find significant distributional effects[1].

Monetary policy has heterogeneous effects on households' income and wealth through direct and indirect channels of transmission. An expansionary conventional or unconventional monetary policy directly affects interest payments and the value of financial assets respectively. The portfolio composition and maturity of assets and liabilities are crucial for heterogeneous responses to monetary policy shocks[2] (see Auclert (2017)).

Indirectly, a monetary expansion is expected to boost investment, employment and overall economic activity through the macroeconomic channel (e.g. Coibion *et al.* (2017), Mumtaz and Theophilopoulou (2017), Ampudia *et al.* (2018)). Studies on the Euro Area such as Lenza and Slacalek (2018) and Bunn *et al.* (2018) find this to be dominant in

[1] For a detailed survey on the literature examining the impact of central banks' policies on inequality see Colciago *et al.* (2018).

[2] If, for example, liabilities consist of short term or variable rate debt, a lower policy rate will benefit this type of debt issuers, while debt holders with maturing assets will face reinvestment risk, debt holders in variable rates and savers in current account deposits will be negatively affected. On the other hand, savers in time deposits or bond holders with long term maturities in fixed rates will not be directly affected.

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[3] and depends on a number of factors: portfolio and investment decisions of the fund, generosity of future real cash flows, longevity etc. Studies which take into consideration pension wealth are constrained to make simplifying assumptions about future cash flows and focus only on measured pension wealth.

The inflation induced by loose monetary policy harms fixed rate savings and debt securities holders, favouring mainly fixed rate borrowers. Doepke and Schneider (2006) find that rich households are adversely affected as they are the principal holders of long maturity interest bearing assets while Erosa and Ventura (2002) find that poor households are mostly affected as they hold most of their wealth in the form of cash.

In summary, the impact of monetary policy on household wealth is complex from a theoretical perspective as it affects wealth through the various transmission channels discussed above. In this paper we examine whether the expansionary monetary policy and the financial easing adopted during the crisis played a role in driving wealth inequality in the UK. To our knowledge this is a first attempt to examine the dynamic relationship between monetary policy shocks and wealth inequality measures. Most studies using wealth surveys are constrained by a limited number of waves and low frequency data. The methodology in these studies is a two-step approach: First, the impact of monetary policy shock on aggregate variables is estimated and then a number of assumptions concerning household's portfolio decisions, asset prices and returns is used to simulate the estimated impact on

[3]While lower discount rates rise the value of financial assets and a household may decide to sell in order to increase current consumption in the expense of future consumption, this is not the case for pension funds. If the value of pension pots increases, households cannot directly use future pension cash flows to finance current consumption.

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.

## 2 Data

In this section we describe the construction of wealth inequality measures as derived from the WAS.

### 2.1 Wealth Inequality Measures

The wealth inequality measures are calculated using the Wealth and Assets Survey, a longitudinal survey launched by the Office for National Statistics (ONS) in 2006. It gathers information about households' levels of assets, savings and debt, savings for retirement and factors which affect their financial planning. At present the WAS consists of five waves, with each wave covering two years with the last wave pertaining to the period 2014-16. ONS aims at a response from on average 20,000 households per wave and the response rate has been around 50-55% in all waves.

Total wealth in the WAS is the sum of private pension wealth, net financial wealth, net property wealth and physical wealth. In 2016 WAS estimates total wealth to be 12.73 billion GBP of which 42% consists of private pension wealth and 35% of property wealth. Private pension wealth considers any future current income from private pension schemes on which individuals or their spouses retain rights. Basic state pension is excluded. The two main private pension schemes are Defined Contribution (DC) and Defined Benefits (DB). DC pension wealth includes occupational and personal pensions while DB is expected income to be received from DB schemes based, for example, on final salary. Financial wealth is the value of formal and informal financial assets held by the household, net of any financial liabilities. It comprises savings and current accounts, ISAs, national saving certificates and bonds, gilts, shares, insurance products, employee shares and options, unit and investment trusts and children's assets. Physical wealth sums the value of contents in all properties of a household. This include all valuable items such as collectables, vehicles, art work, antiques etc. It is calculated at household level. Finally, Property wealth is respondents' net valuation of any property owned in the UK or abroad net of any outstanding loans or mortgages.

Note that while the WAS is the only data source which allows for the construction of UK wealth inequality measures at a frequency relevant for monetary policy, it does come with some caveats. Like most income and wealth survey studies, WAS suffers from low response rates and under-reporting in higher percentiles. In the WAS this problem is dealt by oversampling wealthier households. Using information from national income tax records, WAS flagged areas where at least one person had total wealth above a certain threshold. In this way wealthy households had a much higher probability to be selected for interview. Another problem that wealth surveys face is undervaluation of assets. Wealthy households may under-report financial assets for tax purposes or because of time lags between the response and the maturity, high price volatility of some financial assets, possession of intangible assets, etc. where its precise value is difficult to be estimated. Crossley *et al.* (2016) reports that a high percentage of households who owned business assets failed to provide a valuation of such assets giving incomplete responses. In an effort to produce more precise estimates, WAS removed business assets from the estimation of total wealth. This, however may undervalue total wealth in top percentiles.

For our benchmark measures of wealth inequality we use quantile ratios. The 80/20 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.

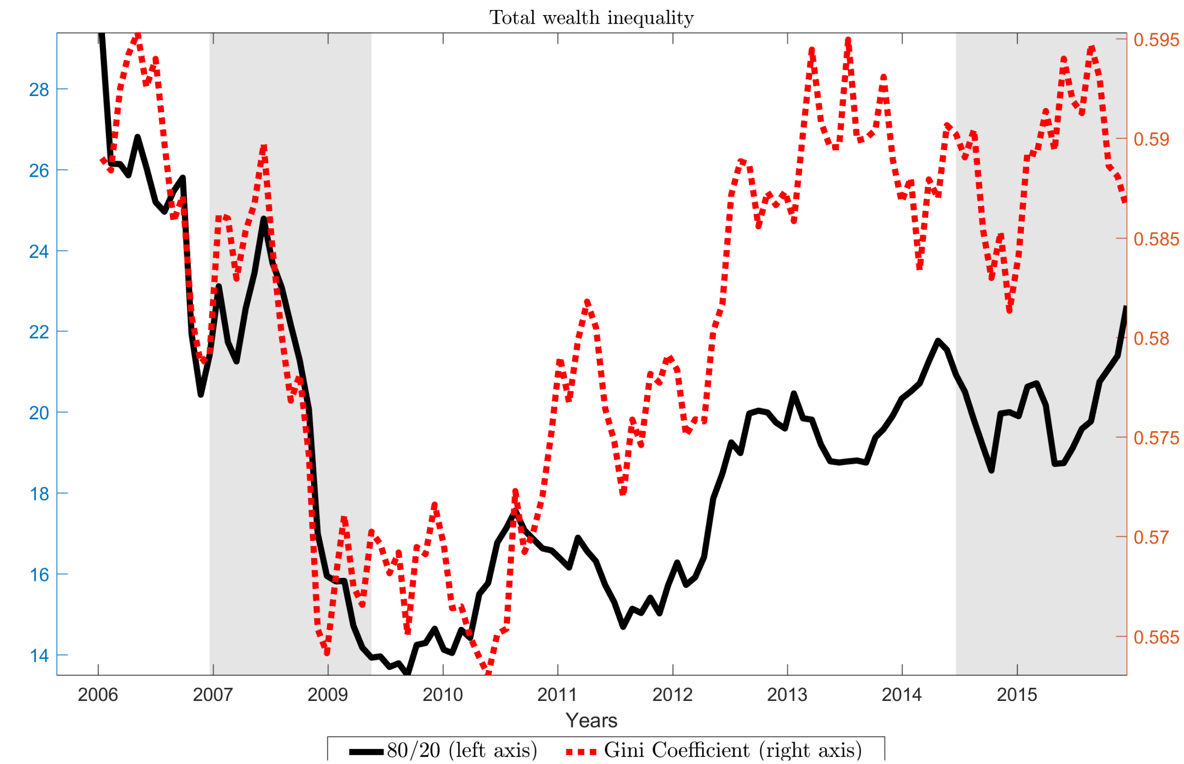


Figure 1: Gini coefficient (right axis) and the 80/20 ratio (left axis). Both series are smoothed using a 6 month moving average in the figure.

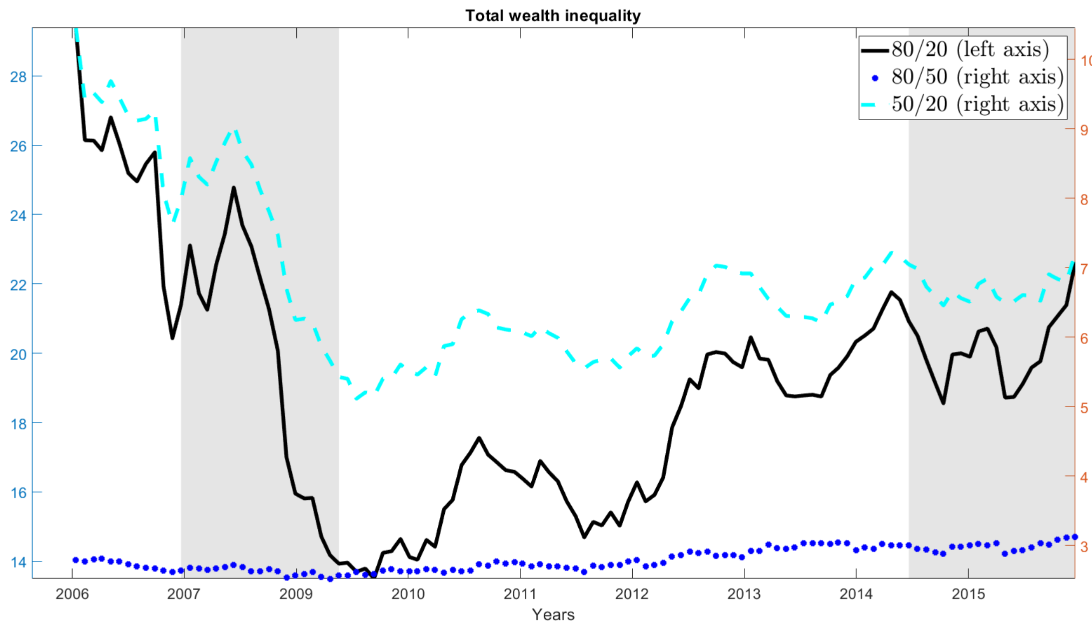


Figure 2: 80/20 (left axis) and 80/50, 50/20 (right axis). The measures are smoothed using a 6 month moving average in this figure.

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:

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

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.

$\underbrace{F_t}_{K\times 1}$ denotes a set of $K$ factors that summarise the information in $X_t$, $\Lambda$ 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 $AR\left(q\right)$ process:

$$v_{it} = \sum_{p=1}^{P} \rho_{ip} v_{it-p} + e_{it}, var(e_{it}) = r_i, R = diag\left([r_1, r_2, .., r_M]\right) \tag{2}$$

where $i = 1, 2, .., M$.

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:

$$Y_t = BX_t + u_t \tag{3}$$

where $X_t = [Y'_{t-1}, .., Y'_{t-P}, 1]'$ is $(NP+1) \times 1$ vector of regressors in each equation and $B$ denotes the $N \times (NP+1)$ matrix of coefficients $B = [B_1, ..., B_P, c]$. 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 $\Sigma$, and $q$ is an element of the family of orthogonal matrices of size $N$, satisfying $q'q = I_N$.

## 3.1 Identification of shocks

The structural shocks of the FAVAR model $\varepsilon_t$ are defined as:

$$\varepsilon_t = A_0^{-1} u_t, \varepsilon_t \sim \mathcal{N}(0, I_N) \tag{4}$$

where $A_0 = Aq$. The shock of interest is the first shock $\varepsilon_{1t}$ in the $N \times 1$ vector of shocks $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{\cdot t}]$, where $\varepsilon_{\cdot t}$ contains the remaining $N-1$ elements in $\varepsilon_t$. To identify the effect of $\varepsilon_{1t}$, we employ an instrument $m_t$ described by the following equation:

$$m_t = \beta\varepsilon_{1t} + \sigma v_t, \quad v_t \sim \mathcal{N}(0, 1) \tag{5}$$

where $\mathbb{E}(v_t\varepsilon_t) = 0$. The instrument is assumed to be relevant (i.e. $\mathbb{E}(v_t\varepsilon_{1t}) = \alpha \neq 0$) and exogenous (i.e. $\mathbb{E}(v_t\varepsilon_{\cdot t}) = 0$).

In our empirical application, the instrument to identify the monetary policy shock is taken from Gerko and Rey (2017) who use high frequency data on short-sterling (SS) futures to construct a proxy for a monetary policy shock. In particular, Gerko and Rey (2017) consider changes in SS futures during a tight window around monetary policy events. They argue, that changes in SS futures around the release of the minutes of the monetary policy committee meetings contain information regarding the future stance of conventional and unconventional monetary policy and provide evidence that suggests that this measure is a strong instrument for the policy shock. As in Gerko and Rey (2017), the monetary policy instrument $R_t$ is assumed to be the 5 year government bond yield.

The structure of the FAVAR model implies that the series in $X_t$ are driven by aggregate shocks $\varepsilon_t$ and idiosyncratic shocks $e_{it}$. When the survey-based wealth inequality series in $X_t$ are considered, our model captures the impact of aggregate shocks *net* of the effect of idiosyncratic disturbances that might proxy measurement error or differences in characteristics specific to the particular percentile group (see De Giorgi and Gambetti (2017)).

### 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 $\beta$ and $\sigma^2$ 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 $\varepsilon_{1t}$:

$$\rho^2 = \frac{\beta^2}{\beta^2 + \sigma^2} \tag{6}$$

In our benchmark model, the priors for $\beta$ and $\sigma^2$ are set to reflect the strong belief that the instruments are relevant and imply that $\rho \approx 0.5$. 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.

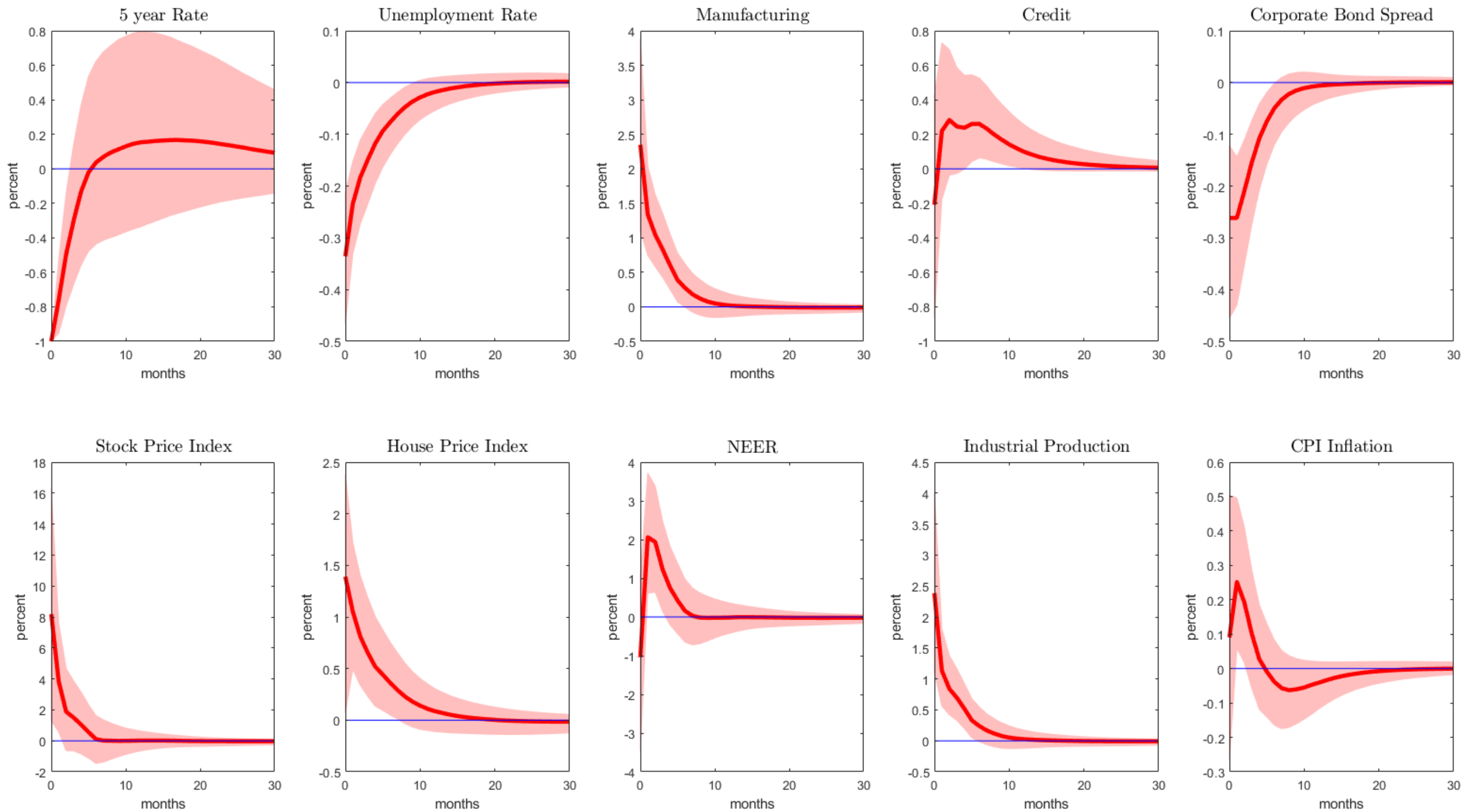


Figure 3: Impulse response of aggregate variables to a monetary policy shock

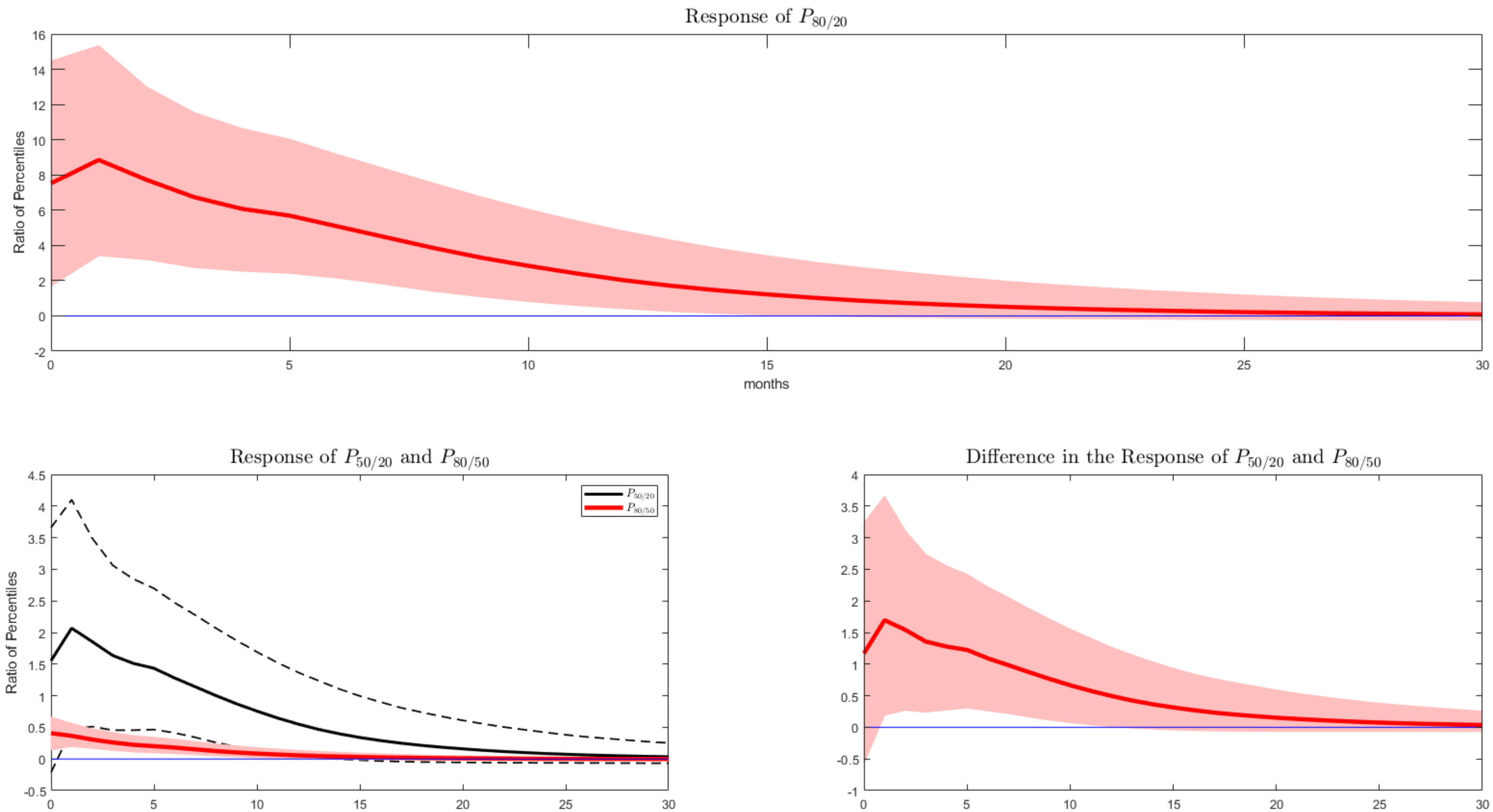


Figure 4: Response of total wealth

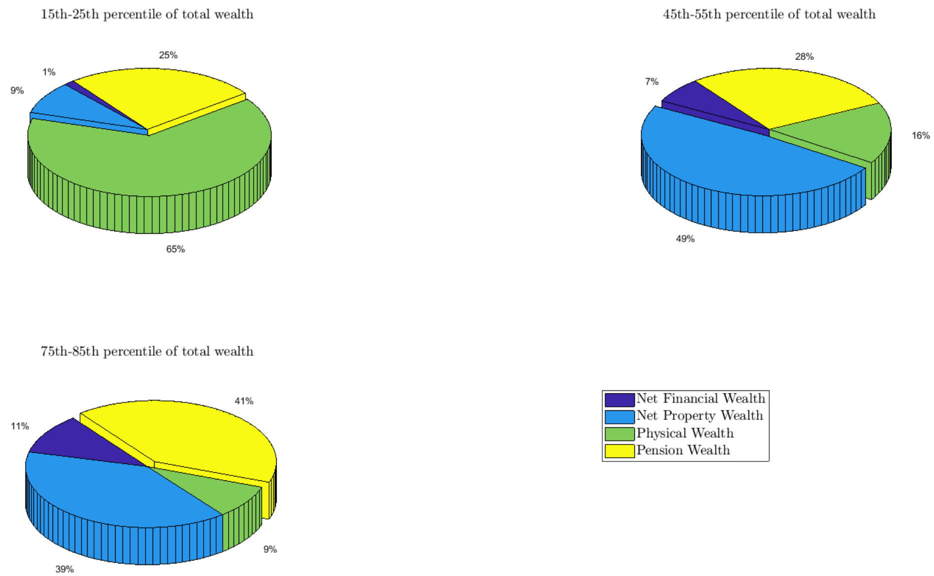


Figure 5: Decomposition of total wealth by selected percentiles.

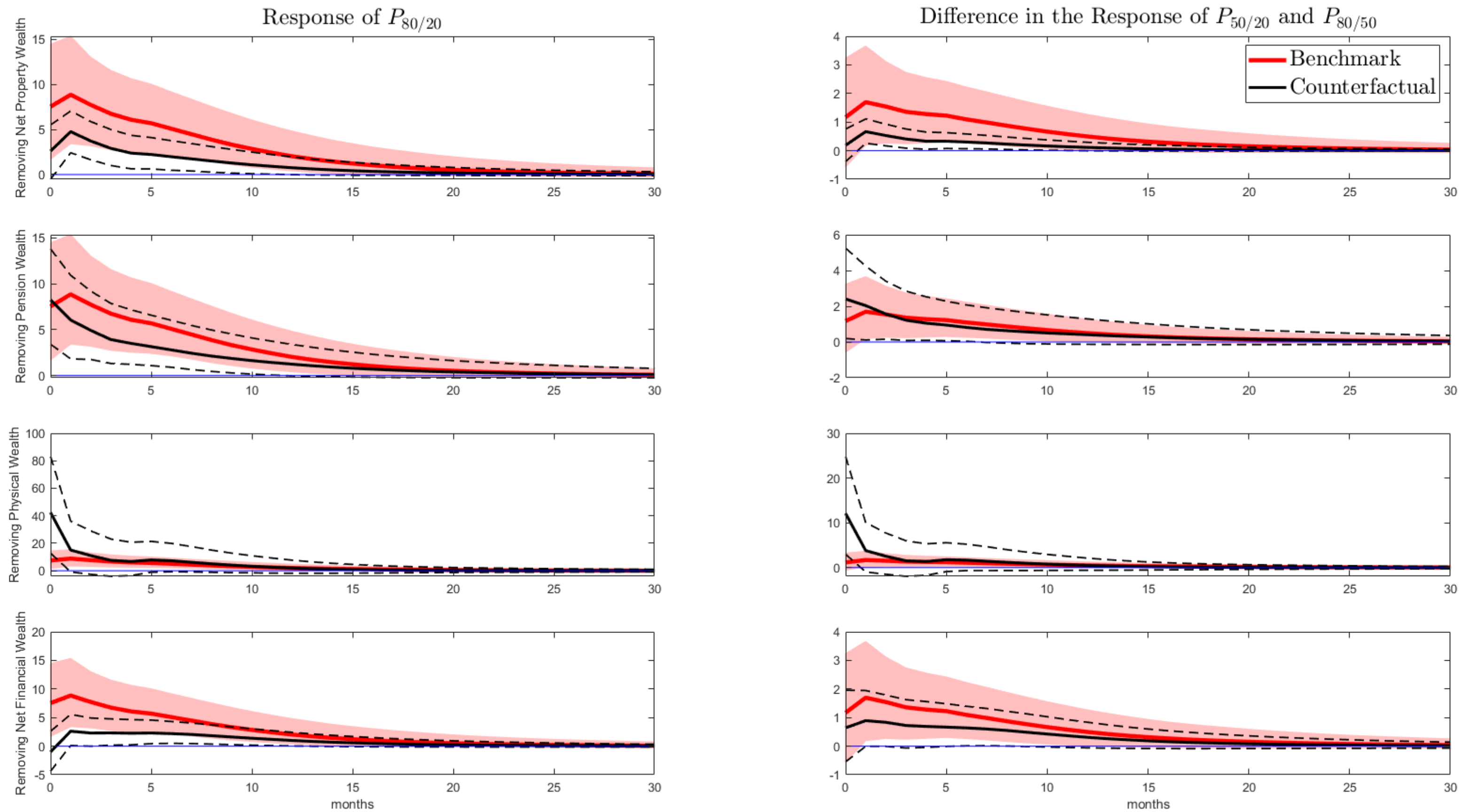


Figure 6: Comparison of benchmark results and those obtained when net property wealth is excluded.

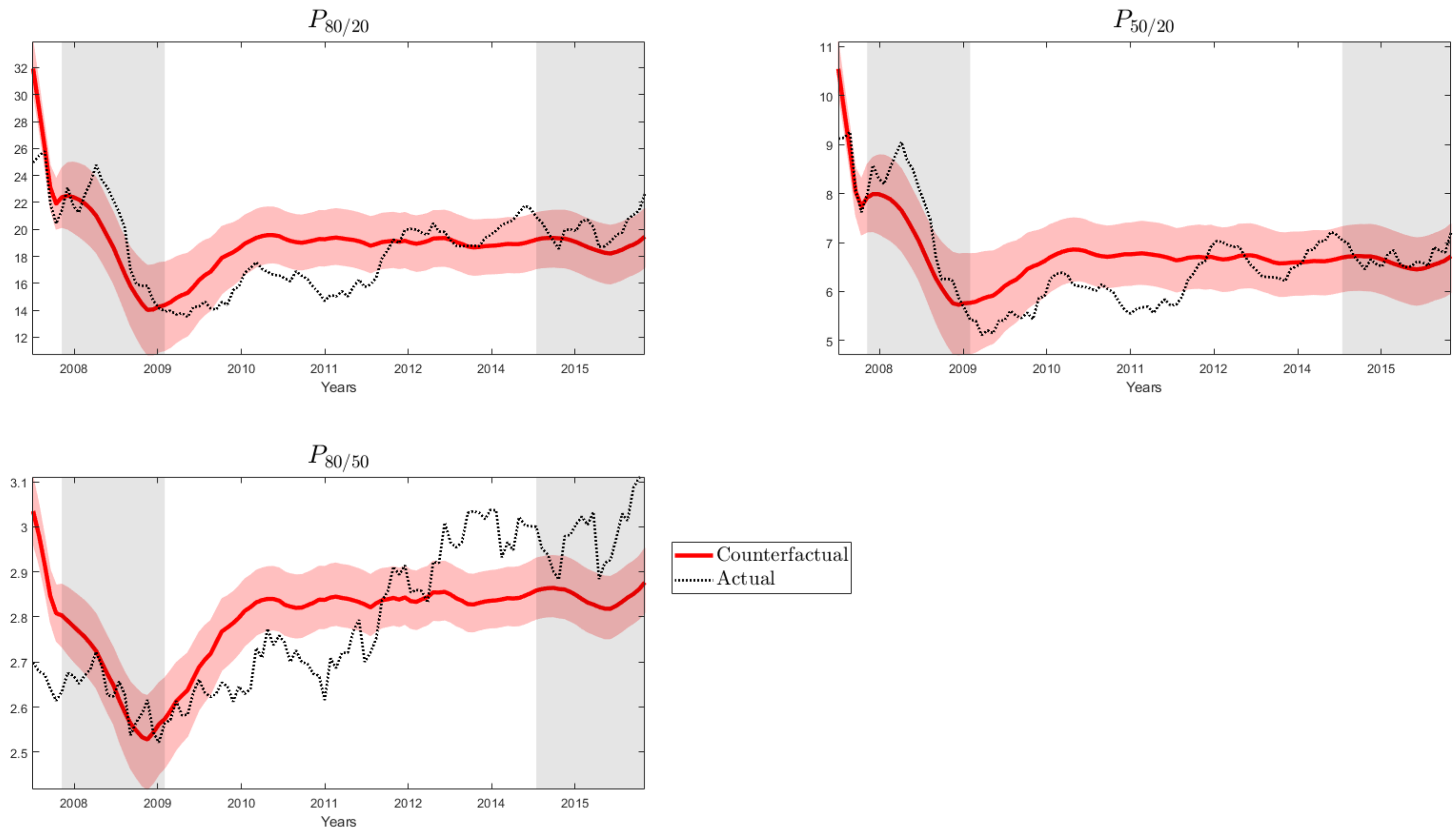


Figure 7: Counterfactual estimates of wealth inequality. The red lines and shaded area depict the counterfactual estimates (median and 68 percent error band) assuming that only the monetary policy shock is non-zero. The actual and counterfactual inequality measures are smoothed using a 6 month moving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

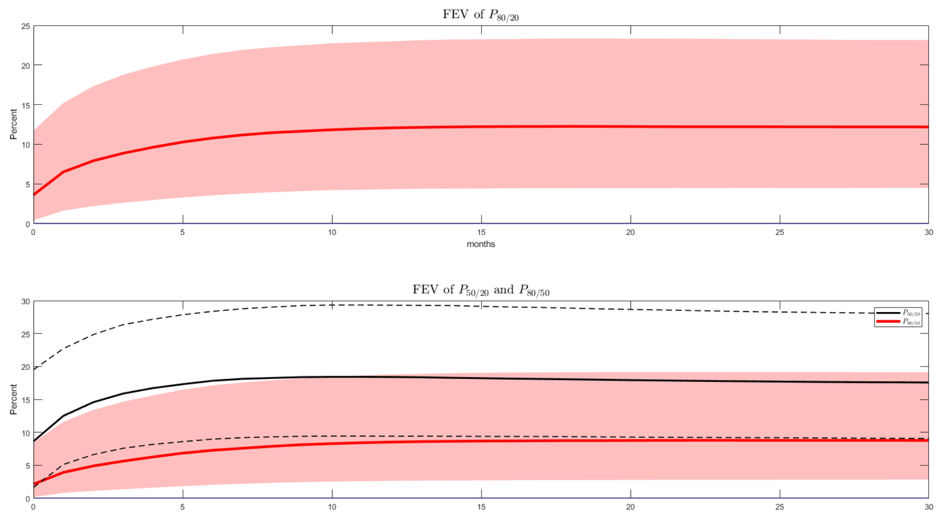


Figure 8: Contribution of the monetary policy shock to the forecast error variance (FEV) of wealth inequality measures.

# 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 $80^{th}$ percentile and the $20^{th}$ percentile rises with the ratio rising by about 8 units and the impact persisting for about one year. The bottom panels of the figure considers if this inequality is driven by changes above or below the median. While the difference between the $80^{th}$ percentile and the $50^{th}$ percentile increases, the magnitude of the increase is negligible. In contrast, the 50/20 measure rises more substantially. The bottom right panel shows that the difference between the two responses is different from zero in statistical terms. This suggests that wealth inequality is pulled up mainly by the increase in wealth towards the middle of the distribution relative to the $20^{th}$ percentile.

### 4.2.1 Channels of transmission

To investigate the heterogeneous responses of wealth percentiles to monetary policy shock we examine the composition of wealth across the distribution. Figure 5 shows the composition of total wealth around the median, the $20^{th}$ and the $80^{th}$ percentile of the wealth distribution. This is calculated by selecting households that fall within the intervals of $45^{th}$

to $55^{th}$ percentile, $15^{th}$ to $25^{th}$ percentile and $75^{th}$ to $85^{th}$ percentiles and then computing the average of each component of wealth expressed as a proportion of the total. The figure reports the mean of this estimate across the five waves of the survey.[5] Towards the left tail of the distribution, total wealth is dominated by physical wealth. Net property wealth and pension wealth form a large proportion of wealth for the percentiles towards the middle and the top of the distribution. In the former case, property wealth makes the largest contribution while pension wealth is the most important component in the latter. The composition of wealth may, therefore, be an important determinant of the transmission of the shock to wealth inequality.

In order to test this hypothesis, we re-estimate the benchmark FAVAR but replace $P_{\frac{80}{20}}, P_{\frac{80}{50}}$ and $P_{\frac{50}{20}}$ with measures that *exclude* one component of wealth. In other words, we group households in each month into the intervals used in Figure 5 . We then construct a 'counterfactual' measure of average wealth in each interval which excludes net housing wealth, pension wealth, physical wealth and net financial wealth, respectively. These measure are used to construct the ratios $\tilde{P}_{\frac{80}{20}}$ and $\tilde{P}_{\frac{50}{20}}$. $\tilde{P}_{\frac{80}{50}}$ denotes the ratio of this counterfactual wealth measure in the intervals given by the 75th to 85th percentile and 45th to 55th percentile of total wealth. Similarly, $\tilde{P}_{\frac{50}{20}}$ denotes the ratio in the intervals given by the 45th to 55th percentile and 15th to 25th percentile of total wealth. The use of intervals instead of exact percentiles is motivated by the fact that the counterfactual measure of wealth can be zero or negative at lower percentiles which impedes clear interpretation of the proposed ratios. This problem is alleviated by the use of averages within an interval. The left panels of Figure 6 compares the response of $P_{\frac{80}{20}}$ obtained from the benchmark model with that of $\tilde{P}_{\frac{80}{20}}$. The right panels compare the response of the difference $P_{\frac{50}{20}} - P_{\frac{80}{50}}$ with the counterfactual case $\tilde{P}_{\frac{50}{20}} - \tilde{P}_{\frac{80}{50}}$.

It is clear from the top row of the figure that once net property wealth is removed from the inequality measure, the impact of the policy shock declines substantially with the median response of total wealth inequality almost twice as small as benchmark. The top right panel of the figure shows that in the counterfactual case, the difference between the response of wealth inequality above and below the median becomes substantially smaller. These results support the argument that the net property wealth component is a key driver of the response of wealth inequality to monetary policy shocks. In contrast, when pension wealth is excluded from the inequality measures, the difference between the counterfactual response and the benchmark is much less pronounced. The third row of the figure shows that the impact of policy shocks on physical wealth also appear to play a major

[5] Using an interval around the percentiles of interest ensures that the estimates are based on a reasonably large number of households.

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 $P_{\frac{80}{20}}, P_{\frac{80}{50}}$ and $P_{\frac{50}{20}}$ from the FAVAR model assuming that only the identified monetary policy shock is non-zero. Figure 7 shows the six month moving average of the actual data and the estimate under the counterfactual scenario. If only the policy shock was non-zero, then positive innovations in the early part of the sample would have driven down the inequality measures faster. This is especially the case for the $P_{\frac{50}{20}}$ measure. However, for about two years after 2009, policy innovations were on average estimated to be negative reflecting the response to the financial crisis. As a consequence, the counterfactual estimates of inequality lie above the actual data over the years 2009 to the end of 2011.

In Figure 8, we show that contribution of the policy shock the forecast error variance (FEV) of the inequality measures. The shock makes a contribution of about five to fifteen percent to the FEV. It is interesting to note that the contribution is largest for the FEV of $P_{\frac{50}{20}}$ indicating that the policy shock is important for the left tail of the wealth distribution.

### 4.3.1 Robustness

We carry out a number of checks to test the robustness of the main results. The top panel of Figure 2 in the technical appendix 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. The results from this parsimonious model are very similar to the benchmark case. Similarly, increasing the number of factors to 8 does not change the results substantially. 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 the figure 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 $P_{\frac{50}{20}}$ measure.

## 5 Conclusions

This paper considers the impact of monetary policy on the distribution of wealth over the last two decades. The estimated impulse responses from a FAVAR model suggest that a monetary expansion is associated with an increases wealth inequality. The increase is largely driven by an increase in wealth at the median relative to the left tail of the distribution. An exploration of the components of total wealth indicates that the transmission of the monetary policy shock occurs via net property wealth and net financial wealth.

From a policy perpective, these results highlight the importance of the impact of monetary policy on the housing and financial market. With Brexit instigating a downturn in house and stock prices, the impact of this shock and the monetary policy response may have strong distributional consequences. In future work, it may be useful to investigate if shifts in the wealth and/or income distribution have an impact on the aggregate UK economy and if such structural changes alter the transmission of policy shocks.

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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 defined as

$$\begin{pmatrix} Z_t \\ X_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & \Lambda \end{pmatrix} \begin{pmatrix} Z_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ v_t \end{pmatrix} \tag{1}$$

where $Z_t$ denotes a set of 'observed' factors. $X_t$ is a $M \times 1$ vector of variables, $F_t$ denotes a $K \times 1$ matrix of unobserved factors while $\Lambda$ 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:

$$v_{it} = \sum_{p=1}^{P} \rho_{ip} v_{it-p} + e_{it}, var(e_{it}) = r_i, R = diag\left([r_1, r_2, .., r_M]\right) \tag{2}$$

where $i = 1, 2, .., M$.

Collecting the factors in the $N \times 1$ vector $Y_t$, the transition equation can be described as:

$$Y_t = BX_t + u_t \tag{3}$$

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

$$\Sigma = (Aq)(Aq)' \tag{4}$$

where $A$ is the lower triangular Cholesky decomposition of $\Sigma$, and $q$ is an element of the family of orthogonal matrices of size $N$, satisfying $q'q = I_N$.

### 1.1 Identification of shocks

The structural shocks of the FAVAR model $\varepsilon_t$ are defined as

$$\varepsilon_t = A_0^{-1} u_t, \varepsilon_t \sim \mathcal{N}(0, I_N) \tag{5}$$

where $A_0 = Aq$. The shock of interest is the first shock $\varepsilon_{1t}$ in the $N \times 1$ vector of shocks $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{\cdot t}]$, where $\varepsilon_{\cdot t}$ contains the remaining $N-1$ elements in $\varepsilon_t$. To indentify the effect of $\varepsilon_{1t}$, we employ an instrument $m_t$ described by the following equation:

$$m_t = \beta \varepsilon_{1t} + \sigma v_t, \quad v_t \sim \mathcal{N}(0, 1) \tag{6}$$

where $\mathbb{E}(v_t \varepsilon_t) = 0$.

## 1.2 Priors

We assume the following prior distributions:

1. We use a natural conjugate prior for the VAR parameters $b = vec(B'), \Sigma$ implemented via dummy observations (see Banbura *et al.* (2010)):

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1\sigma_1...\gamma_N\sigma_N)}{\tau} \\ 0_{N\times(P-1)\times N} \\ ............. \\ diag(\sigma_1...\sigma_N) \\ ............. \\ 0_{1\times N} \end{pmatrix}, and\ X_{D,1} = \begin{pmatrix} \frac{J_P \otimes diag(\sigma_1...\sigma_N)}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP+1} & \\ ............. & \\ 0_{1\times NP} & I_1 \times c \end{pmatrix} \tag{7}$$

where $\gamma_1$ to $\gamma_N$ denotes the prior mean for the coefficients on the first lag, $\tau$ is the tightness of the prior on the VAR coefficients, $c$ is the tightness of the prior on the constant terms and $N$ is the number of endogenous variables, i.e. the columns of $Z_t$. In our application, the prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable. We use principal component estimates of the factors $F_t$ for this purpose. We set $\tau = 0.2$. The scaling factors $\sigma_i$ are set using the standard deviation of the error terms from these preliminary AR(1) regressions. Finally we set $c = 1/1000$ in our implementation indicating a flat prior on the constant. We also introduce a prior on the sum of the lagged dependent variables by adding the following dummy observations:

$$Y_{D,2} = \frac{diag(\gamma_1\mu_1...\gamma_N\mu_N)}{\lambda},\ X_{D,2} = \begin{pmatrix} \frac{(1_{1\times P})\otimes diag(\gamma_1\mu_1...\gamma_N\mu_N)}{\lambda} & 0_{N\times 1} \end{pmatrix} \tag{8}$$

where $\mu_i$ denotes the sample means of the endogenous variables calculated using $F_t$.

2. The prior for the factor loadings $\Lambda$ is normal $\mathcal{N}(\Lambda_{i0}, \Sigma_0)$ where $\Lambda_0$ is set to zero and $\Sigma_0$ is a diagonal matrix with diagonal elements equal to 100.

3. The prior for $\rho = [\rho_1, \rho_2, ..\rho_P]$ is normal $\mathcal{N}(\rho_0, \Sigma_{\rho 0})$ where $\rho_0 = 0$ and $\Sigma_{\rho 0}$ is an identity matrix. The prior for $r_i$ is inverse Gamma $IG(T_0, D_0)$ where $T_0 = 1$ and $D_0 = 1e - 5$.

4. We assume a normal prior for $\beta$: $\mathcal{N}(\underline{\beta}, \underline{V})$. The prior for $\sigma^2$ is inverse Gamma with mean $\sigma_0$ and standard deviation $v_0$.

5. The initial conditions for the factors are $\mathcal{N}\left(Y_{0|0}, P_{0|0}\right)$ where $Y_{0|0}$ is set using the initial estimates of the factors obtained via prinicipal components and $P_{0|0}$ is an identity matrix.

## 1.3 Gibbs algorithm

The Gibbs algorithm samples from the following conditional posterior distributions.

Step 1. $p(b|\Xi_{-b_t}, Y_{1:T}, m_{1:T})$. We write the model in state-space form:

$$\begin{aligned} \begin{pmatrix} Y_t \\ m_t \end{pmatrix} &= \begin{pmatrix} I_N \otimes X_t' \\ 0 \end{pmatrix} b_t + \begin{pmatrix} u_t \\ m_t \end{pmatrix} \text{ observation} \\ b_t &= b_{t-1} \text{ transition} \end{aligned}$$

where $b = vec(B')$. The covariance matrix of the observation equation residuals is:

$$cov\left( \begin{matrix} u_t \\ m_t \end{matrix} \middle| \Xi_{-b_t} \right) = \begin{pmatrix} AA' & Aq_1'\beta \\ \beta q_1 A' & \beta^2 + \sigma^2 \end{pmatrix}$$

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 $cov\left(\begin{array}{c} u_t \\ m_t \end{array} \middle| \Xi_{-b}\right)$ as:

$$cov\left(\begin{array}{c} u_t \\ m_t \end{array} \middle| \Xi_{-b}\right) = \left(\begin{array}{cc} \sigma_{u_t u_t} & \sigma_{u_t m_t} \\ \sigma'_{u_t m_t} & \sigma_{m_t m_t} \end{array}\right) \tag{9}$$

Then

$$u_t | m_t \tilde{} \mathcal{N}\left(\mu_{u|m}, \Omega_{u|m}\right) \tag{10}$$

where

$$\begin{aligned} \mu_{u|m} &= \sigma_{u_t m_t} \left(\sigma_{m_t m_t}\right)^{-1} m'_t \\ \Omega_{u|m} &= \sigma_{u_t u_t} - \sigma_{u_t m_t} \left(\sigma_{m_t m_t}\right)^{-1} \sigma'_{u_t m_t} \end{aligned} \tag{11}$$

The model can be written as a standard VAR

$$\begin{aligned} Y^*_t &= \left(I_N \otimes X'_t\right) b + u_t | m_t, \\ & \quad u_t | m_t \tilde{} \mathcal{N}\left(0, \Omega_{u|m}\right) \end{aligned}$$

where:

$$Y^*_t = Y_t - \mu'_{u|m}$$

Thus the conditional posterior for $b$ is normal: $\mathcal{N}(M, V)$ where:

$$\begin{aligned} M &= vec\left(\left(x^{*'} x^*\right)^{-1} \left(x^{*'} y^*\right)\right) \\ V &= \Omega_{u|m} \otimes \left(x^{*'} x^*\right)^{-1} \end{aligned}$$

with:

$$y^* = \left(\begin{array}{c} Y^*_t \\ Y_{D,1} \\ Y_{D,2} \end{array}\right), x^* = \left(\begin{array}{c} X_t \\ X_{D,1} \\ X_{D,2} \end{array}\right)$$

Step 2. $p\left(\Sigma | \Xi_{-b_t}, Y_{1:T}, m_{1:T}\right)$. We follow Caldara and Herbst (2016) and use a Metropolis step to sample $\Sigma$.

(a) Draw a candidate $\Sigma_{new}$ from the proposal $Q(.) = IW\left(u^{*\prime} u^*, T + T_D - K\right)$. 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 $\tilde{y}^* - x^* M$ with $\tilde{y}^* = \left(\begin{array}{c} Y_t \\ Y_{D,1} \\ Y_{D,2} \end{array}\right)$, $T_D$ denotes the number of dummy observations and $K$ denotes the number of regressors in each equation.

(b) Accept the draw with probability $\alpha = \min\left[\frac{\frac{p\left(m_{1:t}, Y_{1:t}, \Sigma_{new}, \Xi_{-\Sigma}\right)}{Q(\Sigma_{new})}}{\frac{p\left(m_{1:t}, Y_{1:t}, \Sigma_{old}, \Xi_{-\Sigma}\right)}{Q(\Sigma_{old})}}, 1\right]$. Here $p\left(m_{1:t}, Y_{1:t}\right)$ denotes the joint posterior distribution.

Step 3. $p\left(q_1 | \Xi_{-q_1}, Y_{1:T}, m_{1:T}\right)$. Following Caldara and Herbst (2016) we use a Metropolis step to sample $q_1$ :

(a) Draw a candidate from as $q_{1,new} = \frac{z}{\|z\|}$ where $z$ is a $N \times 1$ vector from the $\mathcal{N}(0,1)$ distribution

(b) Accept the draw with probability $\alpha = \min\left[\frac{P\left(m_{1:t} | Y_{1:t}, q_{1,new}, \Xi_{-q_1}\right)}{P\left(m_{1:t} | Y_{1:t}, q_{1,old}, \Xi_{-q_1}\right)}, 1\right]$

Step 4 $p\left(\beta, \sigma | \Xi_{-[\beta,\sigma]}, Y_{1:T}, m_{1:T}\right)$. The structural shock of interest $\varepsilon_{1t}$ can be calculated as $\varepsilon_{1t} = A q_1 u$. Conditional on $\Xi_{-[\beta,\sigma]}$ equation 6 is a standard linear regression, so specifying a conditional Normal-

Gamma prior delivers a Normal-Gamma posterior. Particularly, we first draw $p\left(\sigma^2|\Xi_{-[\beta,\sigma]}, Y_{1:T}, m_{1:T}\right)$. Assuming an inverse-Gamma prior, this conditional posterior is also inverse-Gamma. As the prior is parameterised in terms of mean $\sigma_0$ and standard deviation $v_0$, it is convenient to draw the precision $\frac{1}{\sigma^2}$ using Gamma distribution. Note that $\frac{1}{\sigma^2} \sim \mathcal{G}(a, b)$ where $a = \frac{\nu_1}{2}$, $b = \frac{2}{s_1}$. The parameters of this Gamma density are given by $\nu_1 = \nu_0 + T$ and $s_1 = s_0 + \hat{v}_t'\hat{v}_t$ where $\hat{v}_t = m_t - \beta e_{1t}$ . $s_0$ can be calculated as $2\sigma_0\left(1 + \frac{\sigma_0^2}{v_0^2}\right)$ while $\nu_0 = 2\left(2 + \frac{\sigma_0^2}{v_0^2}\right)$. Moreover, assuming a prior for $\beta|\sigma^2, \Xi_{-[\beta,\sigma]} \sim \mathcal{N}(\underline{\beta}, \underline{V}^{-1})$, the posterior is also conditional Normal $p\left(\beta|\Xi_{-[\beta,\sigma]}, \sigma, Y_{1:T}, m_{1:T}\right) \sim \mathcal{N}(\tilde{\beta}, \tilde{V}^{-1})$, where $\tilde{\beta} = \tilde{V}^{-1}\left[\sum_{t=1}^{T} m_t\varepsilon_{1t} + \underline{V}\underline{\beta}\right]$ and $\tilde{V} = \underline{V} + \frac{1}{\sigma^2}\sum_{t=1}^{T}\varepsilon_{1t}^2$.

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

$$X_{it} = F_t\Lambda_i' + v_{it}$$

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

$$\tilde{X}_{it} = \tilde{F}_t\Lambda_i' + e_{it}$$

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

$$\begin{aligned} V &= \left(\Sigma_0^{-1} + \frac{1}{r_i}\tilde{F}_t'\tilde{F}_t\right)^{-1} \\ M &= V\left(\Sigma_0^{-1}\Lambda_{i0} + \frac{1}{r_i}\tilde{F}_t'\tilde{X}_{it}\right) \end{aligned}$$

To account for rotational indeterminancy the top $K \times K$ block of $\Lambda$ is set to an identity matrix.

1. $H(r_i|\Xi_{-r}, Y_{1:T}, m_{1:T})$. The conditional posterior for $r_i$ is $IG(T_0 + T, e_{it}'e_{it} + D_0)$ where $T$ is the sample size.

2. $H(\rho|\Xi_{-r}, Y_{1:T}, m_{1:T})$. Given a draw of the factors, the AR coefficients are drawn for each $i$ independently. The conditional posterior is normal $\mathcal{N}(m, v)$

$$\begin{aligned} v &= \left(\Sigma_{\rho 0}^{-1} + \frac{1}{r_i}x_{it}'x_{it}\right)^{-1} \\ m &= V\left(\Sigma_{\rho 0}^{-1}\rho_0 + \frac{1}{r_i}x_{it}'y_{it}\right) \end{aligned}$$

where $y_{it} = v_{it}$ and $x_{it} = [v_{it-1}, .., v_{it-P}]$

3. $H(F_t|\Xi_{-F_t}, Y_{1:T}, m_{1:T})$. To draw the factors, we write the model in state-space form taking into account the covariance between $m_t$ and $u_t$ and the serial correlation in the idiosyncratic components. The observation equation is defined as:

$$\underbrace{\begin{pmatrix} Z_t \\ \tilde{X}_t \end{pmatrix}}_{x_t} = \underbrace{\begin{pmatrix} 1 & 0 & 0 & 0 & & 0 & 0 \\ 0 & \Lambda & 0 & \tilde{\Lambda}_1 & ,\ldots, & 0 & \tilde{\Lambda}_P \end{pmatrix}}_{H} \underbrace{\begin{pmatrix} Z_t \\ F_t \\ . \\ . \\ . \\ Z_{t-P} \\ F_{t-P} \end{pmatrix}}_{f_t} + \underbrace{\begin{pmatrix} 0 \\ v_t \end{pmatrix}}_{V_t}$$

where $\tilde{X}_t = \begin{pmatrix} X_{1t} - \sum_{p=1}^{P} \rho_{1p} X_{1t-p} \\ \cdot \\ \cdot \\ X_{Mt} - \sum_{p=1}^{P} \rho_{Mp} X_{Mt-p} \end{pmatrix}$. The blocks of the $H$ matrix contain the factor loadings multiplied by the negative of the corresponding serial correlation coefficient. For example $\tilde{\Lambda}_1 = \begin{pmatrix} -\Lambda_1 \rho_{11} \\ \cdot \\ \cdot \\ -\Lambda_M \rho_{M1} \end{pmatrix}$ where $\Lambda_i$ denotes the factor loadings for the $ith$ variable $X_{it}$. Finally, the variance of $V_t$ is $R = diag\left([0, r_1, .., r_M]\right)$. The transition equation is defined as

$$f_t - \tilde{\mu}_{u|m} = \mu + \tilde{B} f_{t-1} + U_t$$

where $\tilde{B} = \begin{pmatrix} B_1 & \cdot & \cdot & B_P \\ I_{N(P-1) \times NP} \end{pmatrix}, \mu = \begin{pmatrix} c \\ 0_{N(P-1)} \end{pmatrix}, U_t = \begin{pmatrix} u_t | m_t \\ 0_{N(P-1)} \end{pmatrix}, \tilde{\mu}_{u|m} = \begin{pmatrix} \mu_{u|m} \\ 0_{N(P-1)} \end{pmatrix}$. The non-zero block of $cov\left(U_t\right)$ is given by $\Omega_{u|m}$. In other words, the structure of the transition equation accounts for the relationship between the instrument and the reduced form residuals. Given this Gaussian linear state-space, the state vector can be drawn from the normal distribution using the Carter and Kohn (1994) algorithm.

## 1.4 Missing data for instrument

If the instrument has missing observations over some of the sample period and is only available for time periods $\tilde{T}$, some steps of the algorithm need to be modified to account for this:

Step 1 $p\left(b | \Xi_{-b_t}, Y_{1:T}, m_{1:\tilde{T}}\right)$ :The VAR model is written as:

$$\begin{aligned} Y_t^* &= \left(I_N \otimes X_t'\right) b + u_t | m_t, u_t | m_t \tilde{\ } \mathcal{N}\left(0, \Omega_{u|m}\right) \text{ if } m_t \neq nan \\ Y_t &= \left(I_N \otimes X_t'\right) b + u_t, u_t \tilde{\ } \mathcal{N}\left(0, \sigma_{u_t u_t}\right) \text{ if } m_t = nan \end{aligned}$$

In other words, the VAR model is heteroscedastic with the covariance matrix changing over time. This can be handled using a GLS step to draw $b$ from its conditional posterior distribution. The conditional posterior distribution for $b$ in this heteroscedastic setting is normal with mean and variance given by:

$$m = v\left(vec\left(\sum_{t=1}^{T}\left(X_t\left(y_t\right)'\left(\Omega_t\right)^{-1}\right)\right) + \left(S_0\right)^{-1} B_0'\right)$$

$$v = \left(\sum_{t=1}^{T}\left(\left(\Omega_t\right)^{-1} \otimes X_t X_t'\right) + \left(S_0\right)^{-1}\right)^{-1}$$

where:

$$\begin{aligned} y_t &= Y_t^*, \Omega_t = \Omega_{u|m} \text{if } m_t \neq nan \\ y_t &= Y, \Omega_t = \sigma_{u_t u_t} \text{if } m_t = nan \end{aligned}$$

and the mean and the variance of the prior for the coefficients is denoted by $B_0, S_0$ respectively.

Steps 2,3,4 In the draws $p\left(\Sigma | \Xi_{-b_t}, Y_{1:T}, m_{1:\tilde{T}}\right), p\left(q_1 | \Xi_{-q_1}, Y_{1:T}, m_{1:\tilde{T}}\right), p\left(\beta, \sigma | \Xi_{-[\beta,\sigma]}, Y_{1:T}, m_{1:\tilde{T}}\right)$ only the non-missing values of the instrument are used.

Step 8. $H\left(F_t | \Xi_{-F_t}, Y_{1:T}, m_{1:T}\right)$: The transition equation for the state-space model changes when the instrument is missing. In this case, the transition equation is simpler and given by:The transition equation is defined as:

$$f_t = \mu + \tilde{B} f_{t-1} + U_t$$

where $\tilde{B} = \begin{pmatrix} B_1 & \cdot & \cdot & B_P \\ I_{N(P-1)\times NP} & & & \end{pmatrix}$, $\mu = \begin{pmatrix} c \\ 0_{N(P-1)} \end{pmatrix}$, $U_t = \begin{pmatrix} u_t \\ 0_{N(P-1)} \end{pmatrix}$. The non-zero block of $cov\left(U_t\right)$ is given by $\sigma_{u_t u_t}$. 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

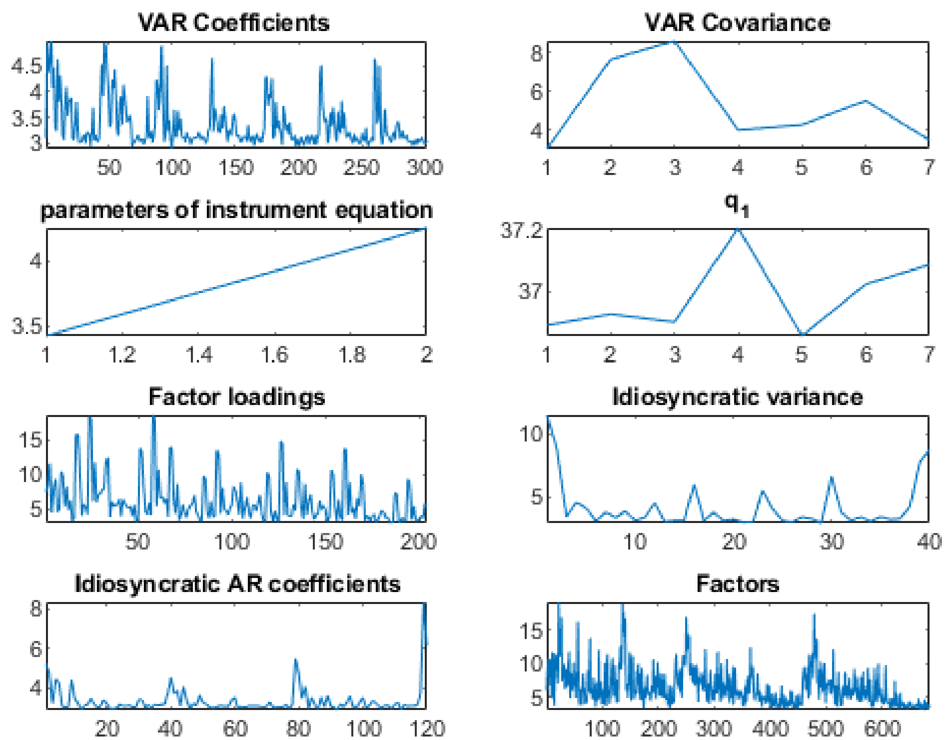


Figure 1: Inefficiency Factors

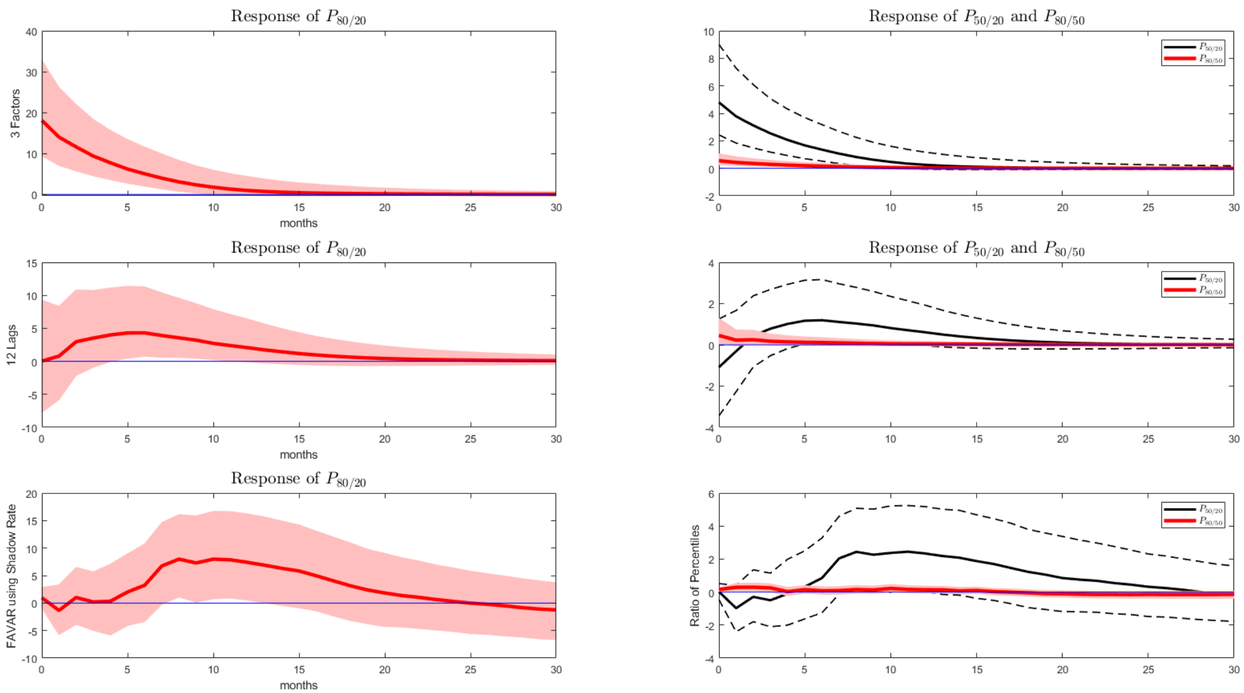


Figure 2: Robustness

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 Figure2 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 $P_{\frac{50}{20}}$ 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.

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[1] We use a lag length of 4 in this version as the number of endogenous variables in the transition equation of the model is substantially larger.

| Variable | Source | Transformation |
|---|---|---|
| Production of Total Industry | GFD | 2 |
| Composite Leasing Indicator | GFD | 1 |
| Retail Price Index | BOE | 2 |
| Consumer Confidence | GFD | 2 |
| Business Confidence | 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 Effective Exchange Rate | BOE | 2 |
| Real Effective Exchange Rate | BOE | 2 |
| Canadian Dollar to Pound | BOE | 2 |
| Euro to Pound | BOE | 2 |
| Yen to Pound | BOE | 2 |
| US dollar to Pound | BOE | 2 |
| Industrial Production Index | BOE | 2 |
| Consumer Price Index | BOE | 2 |
| 5 Year Government Bond Yield | GFD | 1 |

Table 1: Data used in the FAVAR